Rebound Effects for Household Energy Services in the UK

Mona Chitnis,[a] *Roger Fouquet,*[b] *and Steve Sorrell*[c]

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 private vehicle travel. We use a unique database on the price and quantity demanded of these energy services over the past half century. We estimate a two-stage almost ideal demand system for household expenditure, using 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 private vehicle travel and ~90% for the other energy services. However, these effects are offset by negative indirect rebound effects—that is, indirect rebounds contribute additional emission savings. As a result, our estimates of combined rebound effects are generally smaller, namely 54% for lighting, 55% for heating, 41% for refrigeration and clothes washing, –12% for entertainment and computing, 44% for cooking and 69% for vehicle travel. We also find some evidence that rebound effects have declined over time. We provide some important caveats to these results, and indicate priorities for future research.

Keywords: Rebound effects, Linear almost ideal demand system, Energy efficiency

https://doi.org/10.5547/01956574.41.4.mchi

1. INTRODUCTION

Major investments in energy efficiency are central to tackling climate change and to driving green growth. 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 marginal cost of lighting which encourages consumers to use more lighting (e.g. to illuminate more areas to higher levels for longer periods), 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

a Corresponding author. Surrey Energy Economics Centre (SEEC), School of Economics, University of Surrey, UK. E-mail: m.chitnis@surrey.ac.uk.

b Grantham Research Institute on Climate Change, London School of Economics, UK.

c Sussex Energy Group, Science Policy Research Unit (SPRU), University of Sussex, UK.

improvements by consumers, the evidence base has three important limitations (Chitnis and Sorrell, 2015).

First, most studies focus upon rebound effects for car travel, since reliable data on the marginal cost and quantity demanded of other household energy services is much harder to obtain. 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, energy-efficient lighting may encourage consumers to use more lighting (a direct rebound effect), but any remaining savings on electricity bills will be re-spent on other goods and services. Since the provision of those goods and services necessarily involves energy use and emissions, either directly or indirectly along their global supply chains, this re-spending is associated with additional emissions that further offset the environmental benefits of the energy efficiency improvement (an indirect rebound effect).

Third, most of the studies that estimate indirect rebound effects focus on the *income* effects of energy efficiency improvements and neglect the associated *substitution* effects—or in other words, they rely upon expenditure elasticities rather than cross-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). Since goods may be either substitutes or complements to the energy service, the associated indirect rebound effects may either offset or amplify the original emission savings.

This paper seeks to overcome these limitations. We estimate the combined direct and indirect rebound effects from improvements in the energy efficiency of six different energy services in UK households, namely: i) space and water heating; ii) lighting; iii) cooking; iv) refrigeration and clothes washing; v) entertainment and computing; and vi) private vehicle travel (i.e. cars, motorbikes and vans). This approach is made possible by a unique database on the consumption and price of those services in the UK over the last half-century (Fouquet, 2008; Fouquet and Pearson, 2006). Our analysis involves estimating a two-stage demand system for household expenditure that includes these energy services as categories of expenditure. Our results suggest that rebound effects have eroded more than half of the potential emission savings from historical improvements in energy efficiency. We estimate that direct rebound effects have eroded as much as 90% of the potential emission savings, but we also find that indirect rebound effects are negative—that is, they contribute additional emission savings. For example, we find that improvements in the energy efficiency of lighting are associated with reductions in the consumption of heating, which contributes additional emission savings. As a result, the total (direct + indirect) rebound effect is less than the direct effect. However, we emphasise that our estimates are subject to considerable uncertainty, owing in part to the difficulty of including energy services within a household demand model.

The paper is structured as follows. Section 2 describes the background to our approach, and 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 direct plus indirect rebound effect. Section 2 describes the economic model used to estimate the elasticities while Section 3 summarises the econometric techniques employed. Section 4 summarises our data sources, and presents our estimates of the price and consumption of the six energy services over the period 1964–2015. Section 5 presents our results including our estimates of the own-price and cross-price elasticities for each energy service, together with the corresponding direct, indirect and combined rebound effects. Section 6 concludes by highlighting the limitations of our approach and providing some suggestions for future research.

2. ESTIMATING THE COMBINED REBOUND EFFECT

Estimates of the direct rebound effect from an efficiency improvement can be obtained from estimates of the own-price elasticity of demand for the relevant energy service (e.g. the own-price elasticity of lighting) (Sorrell and Dimitropoulos, 2007). Estimates of the indirect rebound effect from such improvements can be obtained by combining estimates of the elasticity of demand for other goods and services with respect to the price of the energy service (e.g. the elasticity of demand for heating with respect to the price of lighting), with estimates of the energy/emission intensity of those goods and services (Chitnis and Sorrell, 2015).

Both own and cross-price elasticity estimates can be obtained from a household demand model which specifies the expenditure on different categories of goods and services as a function of total expenditure, the price of each category and other variables. To estimate rebound effects, one of the expenditure categories must be the relevant energy service. For example, to estimate the direct and indirect rebound effects associated with energy efficient lighting, the model should include lighting as one of the categories of household expenditure, alongside other categories such as food and heating. This requires data on the price and expenditure share of each category of good and service, including lighting itself (Chitnis and Sorrell, 2015; Sorrell, 2010). The average price of lighting will, in turn, depend upon both the price of electricity and the 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 gross complements (gross substitutes) to lighting (see Annex A of Chitnis and Sorrell, 2015).

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 good and service. For energy services such as lighting, these primarily derive from the *direct* energy use and emissions associated with consumption of the relevant energy commodities—such as gas and electricity.[1] For other goods and services such as food and furniture, these 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 environmentally-extended input output models (Kitzes, 2013).

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 consumption and cost 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, Brännlund et al. (2007) estimate the combined rebound effect associated with efficiency improvements in household gas use by combining estimates of the own and cross-price elasticities of household 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 both direct and indirect rebound effect (Chitnis and Sorrell, 2015; Sorrell, 2010). Second, additional bias will be introduced if the relevant energy commodity provides more than one energy service (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; Hunt and Ryan, 2014).

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.

Chitnis and Sorrell (2015) use the own and cross-price elasticities of energy commodities to estimate combined rebound effects for UK households over the period 1964–2013. This leads to estimates of 41% for efficiency improvements affecting gas consumption, 48% for improvements affecting electricity consumption and 78% for improvements affecting vehicle fuel consumption. In what follows, we seek to improve upon Chitnis and Sorrell (2015) in two ways. First, we estimate elasticities with respect to the price of energy services rather than the price of energy commodities, thereby allowing individual energy services to be isolated and removing 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) private vehicle travel.

We also depart from Chitnis and Sorrell (2015) in two other ways. First, we estimate rebound effects in terms of carbon emissions rather than GHGs—although in practice this makes little difference to the results. 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). Hence, we estimate both direct and indirect rebound effects, but our estimates of the latter are incomplete.

The main reason for adopting this simplified approach is the limited degrees of freedom in our model which constrains the number of categories of goods and services that we can include. As a result, we prioritise obtaining accurate estimates of the cross-price elasticities between different energy services rather than between those energy services and other commodity groups. A second reason is that the results of Chitnis and Sorrell (2015) suggest that own and cross-price effects between different energy commodities (i.e. changes in direct emissions), account for more than 80% of the combined rebound effect—implying that the neglect of embodied emissions should not lead to large errors. Whether these errors are positive or negative will depend upon whether non-energy goods and services are substitutes or complements to the relevant energy service.

3. ANALYTICAL EXPRESSION FOR THE COMBINED REBOUND EFFECT

Let x represent total household expenditure on all goods and services (e.g. in £), q_z the quantity of energy service z purchased by households, p_z the 'energy cost' of that service (excluding capital costs and non-energy operating costs), q_i the quantity purchased of good or service i and p_i the unit price of that good i (we drop time subscripts for clarity). We define a total of $N+1$ categories of goods and services ($i = 1,...N$, plus the energy service z), and allow these other goods and services (i) to include both traded goods (e.g. furniture, clothes) and other energy services (heating, cooking). We can then write total household expenditure as:

$$x = p_z q_z + \sum_{i=1,2...N} p_i q_i \tag{1}$$

Where the first term represent the expenditure on the energy service and the second represent expenditure on all other goods and services.

Assume the household makes a costless investment that increases the energy efficiency (ε_z) of providing energy service z by $\varsigma = \Delta\varepsilon_z / \varepsilon_z$ ($\varsigma \geq 0$), thereby reducing the energy cost of that service by $\tau = \Delta p_z \,/\, p_z$ ($\tau \le 0$). Let Q represent the household's baseline carbon emissions, 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 from the energy efficiency improvement (R_{C_z}) is then given by:

$$R_{C_z} = \frac{\Delta H - \Delta Q}{\Delta H} = -\frac{\Delta G}{\Delta H} \tag{2}$$

The baseline carbon emissions for the household can be written as:

$$Q = x_z u_z^x + \sum_{i(i \ne z)} u_i^x x_i \tag{3}$$

Where $x_i = p_i q_i$ is the expenditure on commodity i (in £), u_i^x is the carbon intensity of that expenditure (in tCO_2/£) and x_z and u_z^x are the corresponding values of these variables for energy service z. In general, the carbon intensities may include both direct and embodied emissions, but we only include direct emissions in what follows.

To estimate the engineering effect (ΔH), we assume that 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 $\Delta x_z^H = q_z \Delta p_z$ ($\Delta x_z^H \le 0$ since $\Delta p_z \le 0$). Given that $\Delta p_z = \tau p_z$, $x_z = p_z q_z$ and $\Delta H = u_z^x \Delta x_z^H$, we obtain the following expression for the engineering effect:

$$\Delta H = u_z^x x_z \tau \tag{4}$$

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 re-spending effect is given by $\Delta x_z^G = p_z \Delta q_z$.[2] Adding in the change of expenditure on other commodity groups we obtain the following expression for the re-spending effect:

$$\Delta G = u_z^x \Delta x_z^G + \sum_{i(i \ne z)} u_i^x \Delta x_i \tag{5}$$

Assuming marginal changes, we can use elasticities to substitute for Δx_z^G and Δx_i in this equation. Let η_{x_z,p_z} represent the elasticity of expenditure on the energy service with respect to the energy cost of the energy service ($\eta_{x_z,p_z} = \partial \ln x_z \,/\, \partial \ln p_z$), and let η_{x_i,p_z} represent the elasticity of expenditure on commodity i with respect to the energy cost of the energy service ($\eta_{x_i,p_z} = \partial \ln x_i \,/\, \partial \ln p_z$). Then we can obtain:

$$\Delta G = u_z^x x_z \tau (\eta_{x_z,p_z} - 1) + \sum_{i(i \ne z)} u_i^x x_i \tau \eta_{x_i,p_z} \tag{6}$$

Substituting the expressions for ΔH (Equation 4) and ΔG (Equation 6) into Equation 2 and noting that $w_i = x_i \,/\, x$, we arrive at the following expression for the combined rebound effect:

$$R_{C_z} = (1 - \eta_{x_z,p_z}) - \sum_{i(i \ne z)} \psi_i \eta_{x_i,p_z} \tag{7}$$

Where:

$$\psi_i = \frac{u_i^x w_i}{u_z^x w_z} \tag{8}$$

2. The total change in expenditure on the energy service is the sum of the engineering and re-spending effects: $\Delta x_z = \Delta x_z^H + \Delta x_z^G$.

For ease of exposition, we typically express elasticities in terms of quantities (q_i) rather than expenditures (x_i). We can convert between the two as follows:

$$\eta_{q_i,p_i} = 1 - \eta_{x_i,p_i}; \text{ and } \eta_{q_i,p_j} = \eta_{x_i,p_j} \tag{9}$$

Substituting Equation 9 into Equation 7, we finally write the combined rebound effect as:

$$R_{C_z} = -\eta_{q_z,p_z} - \sum_{i(i \neq z)} \psi_i \eta_{q_i,p_z} \tag{10}$$

The first term in Equation 10 is the *direct* rebound effect for energy service z (R_{D_z}):

$$R_{D_z} = -\eta_{q_z,p_z} \tag{11}$$

For there to be no direct rebound effect, the own-price elasticity of energy service demand would need to be zero ($\eta_{q_z,p_z} = 0$). This elasticity can be further decomposed into a substitution effect and an income effect using the Slutsky equation: $\eta_{q_z,p_z} = \tilde{\eta}_{q_z,p_z} - w_z \eta_{q_z,x}$, where w_z is the share of energy service z in total household expenditure, $\eta_{q_z,x}$ is the expenditure elasticity of energy service z and $\tilde{\eta}_{q_z,p_z}$ is the *compensated* own-price elasticity of demand for energy service.

The second term in Equation 10 is the *indirect* rebound effect for energy service z (R_{I_z}):

$$R_{I_z} = -\sum_{i(i \neq z)} \psi_i \eta_{q_i,p_z} \tag{12}$$

The total indirect rebound effect is the sum of the indirect rebound effects associated with each individual goods and service (i). These in turn depend upon the elasticity of demand for the good or service with respect to the energy cost of the energy service (η_{q_i,p_z}) and the carbon emissions associated with expenditure on that good or service ($u_i^x w_i$) relative to those associated with expenditure on the energy service ($u_z^x w_z$) (Equation 8). Again, we can decompose the cross price elasticity into an income effect and a substitution effect ($\eta_{q_i,p_z} = \tilde{\eta}_{q_i,p_z} - w_z \eta_{q_i,x}$).

Goods and services that are gross complements to the energy service ($\eta_{q_i,p_z} < 0$) will contribute a positive indirect rebound effect, while those that are gross substitutes to the energy service ($\eta_{q_i,p_z} > 0$) will contribute a negative indirect rebound effect. Equation 12 demonstrates that goods and services with a small cross-price elasticity may nevertheless contribute a large indirect rebound effect if they are relatively carbon intensive and/or have a large expenditure share (and vice versa).

Note that the magnitude of the direct rebound effect is independent of the energy or emissions intensity of the energy service, 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 energy services and hence is sensitive to the metric used.

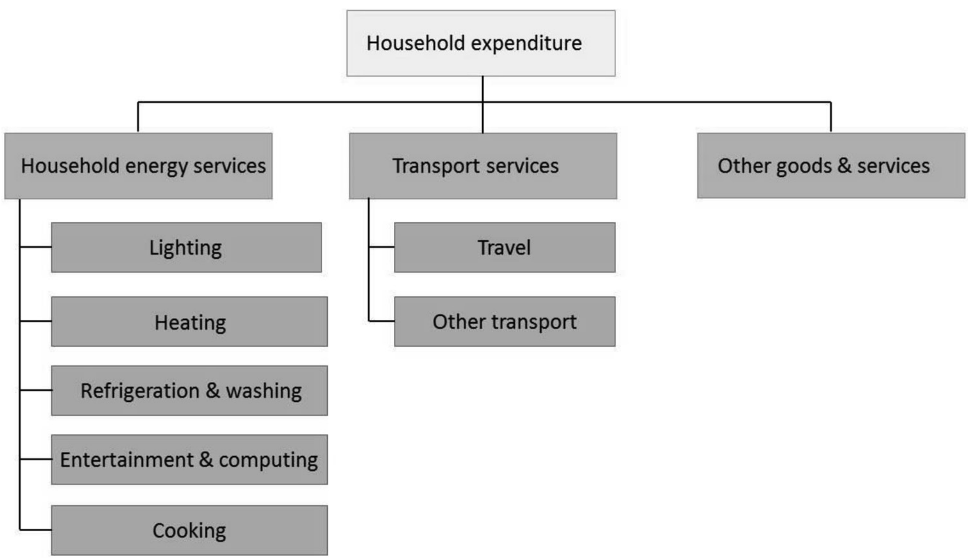
4. ECONOMETRIC MODEL

4.1 Two-stage budgeting

Estimates of the required elasticities (η_{q_z,p_z} and η_{q_i,p_z}) can be obtained from a household demand model estimated from annual survey data on household expenditures. But to obtain sufficient degrees of freedom, expenditures must be aggregated into a limited number of categories. A standard approach is to divide household expenditures into a number of *categories* of goods and services ($r = 1 \ldots R$), and then to subdivide expenditure on each category into a number of *subcategories ($i = 1, \ldots I^r$)*—with the number of subcategories (I^r) varying from one category to another. This approach assumes *weak separability* of preferences between categories—implying that household decisions on how much to spend on one category (e.g. food) are separate from decisions on how to allocate this expenditure between the goods and services within that category (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 the two-stage budgeting framework indicated in Figure 1. We assume households first allocate expenditure between three categories (household energy services, transport services, and other goods and services), and then distribute the expenditures on each of these categories (r) between individual subcategories (i). We define six subcategories of household energy services, and two subcategories of transport services, but we do not disaggregate the 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 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 private vehicle travel (cars, motorbikes and vans). In each case, the relevant expenditures relate to the 'energy cost' of the energy service ($x_z = p_z q_z$) and exclude the associated capital and non-energy operating costs. For vehicle travel, the latter costs form part of the 'other transport' subcategory (which also includes expenditures on public transport), while for household energy services these are included within the 'other goods and services' category.[3]

3. In practice, consumers first choose their energy systems and then choose how to operate those systems (Dubin and McFadden, 1984). As a result, expenditure shares will depend in part on the relative capital costs (past and present) of competing energy systems. While this endogeneity could potentially bias our estimates, we ignore it here owing to lack of data on the relative cost of different energy systems.

4.2 Specification

We specify our *base model* in two stages: first, a system of equations for the expenditure share of each category (r), and second a system of equations for the expenditure share of each sub-category (i) within each category.

Let x_t^r represent the expenditure on category r in period t, and let w_t^r represent the share of that category in total household expenditure (x_t):

$$w_t^r = \frac{x_t^r}{x_t} \tag{13}$$

In the *first stage*, we specify these expenditure shares as functions of total household expenditure, the price of each category and other variables:

$$w_t^r = \alpha^r + \theta^r t + \sum_{s=1,..R}\left(\gamma^{rs}\ln p_t^s\right) + \beta^r \ln\left(\frac{x_t}{P_t^L}\right) + \sum_{s=1,...(R-1)}\left(\lambda^{rs} w_{t-1}^s\right) + \upsilon_t^r \tag{14}$$

Where: r and s index over the categories ($R=3$); t is a time trend;[4] p_t^s is the price of the category s in period t; x_t is total expenditure per household in that period; 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, β^r and λ^{rs} are the unknown parameters and υ_t^r is the error term.

As with most applications of LAIDS, we impose restrictions on the parameter values to ensure the results are compatible with consumer demand theory. The *adding-up* condition ensures that the expenditure shares sum to unity ($\sum_{r=1,..R} w_t^r = 1.0$) and is fulfilled if:[5]

$$\sum_{r=1..R}\alpha^r = 1;\ \sum_{r=1..R}\theta^r = 0\ \sum_{r=1..R}\beta^r = 0;\ \sum_{r=1..R}\gamma^{rs} = 0\ \forall s;\ \text{and}\ \sum_{r=1..R}\lambda^{rs} = 0\ \forall s \tag{15}$$

The *homogeneity* condition ensures that quantities demanded do not change if prices and income change by the same percentage amount. This is fulfilled if:

$$\sum_{s=1..R}\gamma^{rs} = 0\ \forall r \tag{16}$$

The *symmetry* condition follows from applying Shepard's Lemma to the expenditure function and ensures that the Slustky matrix is symmetric (Ryan and Plourde, 2009).[6] This is fulfilled if:

$$\gamma^{rs} = \gamma^{sr} \tag{17}$$

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

$$w_{it}^r = \frac{x_{it}^r}{x_t^r} \tag{18}$$

4. Similar to Hunt and Ryan (2015) we have added a time trend to the model, but for different reasons as explained in the paper.

5. In practice, the adding up restrictions are imposed by dropping one of the equations from the estimation.

6. 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.

We specify these expenditure shares (w_{it}^r) as functions of the category expenditure (x_t^r), the price of each subcategory ($\ln p_{it}^r$) and other variables:

$$w_{it}^r = \alpha_i^r + \theta_i^r t + \sum_{j=1,..k^r}\left(\gamma_{ij}^r \ln p_{it}^r\right) + \beta_i^r \ln\left(\frac{x_i^r}{P_t^{rL}}\right) + \sum_{j=1,...(k^r-1)}\left(\lambda_{ij}^r w_{jt-1}^r\right) + \upsilon_{it}^r \tag{19}$$

Where i and j index over the subcategories within category r ($i, j \in r$); k^r is the number of subcategories in category r (i.e. five for household energy services, two for transport services); p_{it}^r is the price of subcategory i in category r in period t; x_t^r is the expenditure on category r in period t; P_t^{rL} is the log-linear analogue of the Laspeyres price index for category r in period t; α_i^r, θ_i^r β_i^r and λ_{ij}^r are the unknown parameters and υ_{it}^r is the error term. We impose the adding up, symmetry and homogeneity restrictions in a similar manner to the first stage.

This specification departs from typical applications of LAIDS in three ways. First, we use a log-linear analogue of the Laspeyres price index (P_t^L) rather than the usual Stone price index (P_t). P_t is defined as the expenditure-share weighted sum of the prices for the individual aggregate categories where the weight varies over time:

$$\ln P_t = \sum_{r=1,\ldots,R} w_t^r \ln p_t^r \tag{20}$$

P_t is sensitive to the units of measurement for prices and quantities, which may seriously affect the approximation properties of the model (Moschini, 1995). Two alternatives to the Stone price index are the log-linear analogue of the Paasche price index (P_t^P) and the log-linear analogue of the Laspeyres price index:

$$\ln P_t^P = \sum_{r=1,\ldots,R} w_t^r \ln\left(\frac{p_t^r}{p_0^r}\right) \tag{21}$$

$$\ln P_t^L = \sum_{r=1,\ldots,R} w_0^r \ln p_t^r \tag{22}$$

When the prices are expressed as indices, Equations 20 and 21 should be equivalent. However, since the expenditure share (w_t^r) in both equations is endogenous, the use of these two price indices could result in biased estimates in LAIDS. The Laspeyres price index differs from the Stone and Paasche price indices by holding the expenditure share weights constant at their base year value ($t=0$). We therefore use a log-linear analogue of the Laspeyres price index to overcome the endogeneity problem.

Second, we include a time trend (t) to capture the effect of time-varying factors on expenditure shares, to reduce the risk of spurious correlation and to mitigate problems of serial correlation.

Third, we include lagged expenditure shares (w_{t-1}^s) of all the categories in the model. This also reduces problems of 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.

4.2 Elasticities

To estimate the short-run expenditure and price elasticities for each subcategory, we utilise the expressions derived for a two-stage budgeting model by Edgerton (1997). These calculate short-run 'total' elasticities from estimates of the 'between-category' and 'within-category' elasticities (see Chitnis and Sorrell (2015) for a full explanation and interpretation of this approach). We modify these expressions to allow for our use of a Laspeyres rather than a Stones price index,[7] leading to the formulae summarised in Table 1. Here: t_0 is the base year for the Laspeyres price index ($t_0 = 2012$); δ_{rs} (the kronecker delta) is unity when r=s (i.e. own-price elasticity) and zero otherwise; and δ_{ij}^r is unity when $i=j$ and zero otherwise. Note that some of the expenditure shares inTable 1 relate to the base year (t_0) and others to the current year (t). Note further that when subcategories i and j are in different categories ($r \neq s$), $\delta_{rs} = 0$ and the expression for the short-run total price elasticity reduces to:

$$\eta_{q_i,p_j,t} = \eta^r_{q_i,x_r,t}\eta_{q_r,p_s,t}w^s_{jt_0} \tag{23}$$

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

$$\eta_{q_i,p_j,t} = \eta^r_{q_i,p_j,t} + \eta^r_{q_i,x_r,t}(1+\eta_{q_r,p_r,t})w^r_{jt_0} \tag{24}$$

Table 1: Analytical expressions for the short-run between-category, within-category and total expenditure and price elasticities within a two-stage LAIDS model

Elasticity	Expenditure	Price
Between-category ($i \in r; j \in s; r \neq s$)	$\eta_{q_r,x,t} = 1 + \frac{\beta^r}{w^r_t}$	$\eta_{q_r,p_s,t} = \frac{\gamma^{rs} - \beta^r w^s_{t_0}}{w^r_t} - \delta_{rs}$
Within-category ($i, j \in r$)	$\eta^r_{q_i,x_r,t} = 1 + \frac{\beta^r_i}{w^r_{it}}$	$\eta^r_{q_i,p_j,t} = \frac{\gamma^r_{ij} - \beta^r_i w^r_{jt_0}}{w^r_{it}} - \delta^r_{ij}$
Total	$\eta_{q_i,x,t} = \eta^r_{q_i,x_r,t}\eta_{q_r,x,t}$	$\eta_{q_i,p_j,t} = \delta_{rs}\eta^r_{q_i,p_j,t} + \eta^r_{q_i,x_r,t}(\delta_{rs} + \eta_{q_r,p_s,t})w^s_{jt_0}$

Source: Edgerton (1997)

The elasticities in Table 1 depend upon the expenditure shares of each category (w^r_t) and subcategory (w^r_{it}), which vary from year to year. Hence, the short-run total elasticities also vary from year to year ($\eta_{q_i,x,t}$ and $\eta_{q_i,p_j,t}$). When estimating rebound effects, we calculate the elasticities using the mean expenditure shares of each subcategory over the whole period: $\overline{\eta}_{q_i,x}$ and $\overline{\eta}_{q_i,p_j}$.

Finally, we substitute the short-run elasticity estimates for energy service z ($\overline{\eta}_{q_z,p_z}$ and $\overline{\eta}_{q_i,p_z}$) into Equation 10 to give the short-run rebound estimates for that energy service.

5. DATA AND TRENDS

5.1 Data sources

We take data on prices and household expenditures for transport and other goods and services from *Consumer Trends* published by the UK Office of National Statistics (ONS). We obtain estimates of the quantity consumed (q_z), energy cost (p_z) and expenditure ($x_z = p_z q_z$) for our six energy services from the database constructed by Fouquet (2008, 2014) which combines information from a variety of sources. These estimates allow for energy services being supplied by more than one energy commodity (e.g. heating is supplied by both gas and electricity) and by more than one energy system (e.g. heating is supplied from both boilers and storage heaters); and reflect the changes in the mix of commodities and systems over time, as well as improvements in the energy efficiency

7. See for example Equations 62 and 63 in Barnett and Seck (2008).

of each system over time. The process of constructing this database is summarised in Annex A and explained in more detail in Fouquet (2014).

Our data is annual over the period 1964 to 2015 and we specify prices relative to a base year of 2012 (t_0) using implied deflators from the ONS. 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 vehicle 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 use the 'OECD modified equivalence scale' (Hagenaars et al., 1994) to equivalise total expenditure (x_t) and the expenditure on each category (x_t^r):

$$x_t = \frac{\overline{x}_t}{1+0.5a_t+0.3c_t} \qquad x_t^r = \frac{\overline{x}_t^r}{1+0.5a_t+0.3c_t} \tag{25}$$

Where $\overline{x}_t$ is the unadjusted total expenditure of UK households, $\overline{x}_t^r$ is the corresponding value for category r, a_t is the number of people over the age of 14; and c_t is the number of children. We take data on the size and composition of the UK populations from the ONS.

We take estimates of the carbon intensities (tCO_2/kWh) of fuels from BEIS (2016a) and the carbon intensity of electricity supply from BEIS (2016c) and combine these with our estimates of the fuel mix and expenditure share of each energy service to obtain estimates of the carbon intensity of expenditure on each energy service (u_{zt}^x). When estimating rebound effects, we use the mean carbon intensity of each energy service over the whole time period ($\overline{u}_z^x$), to ensure consistency with our elasticity estimates.

5.2 Estimated trends

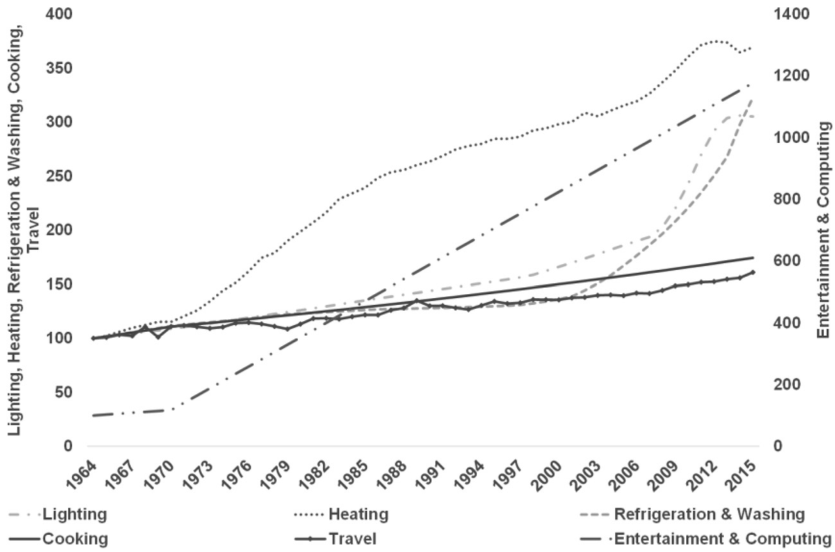
Here, we summarise our estimates of the energy cost and quantity consumed of each energy service over the period 1964–2015. Figure 2 indicates the estimated trends in energy efficiency, which represents the net effect of improvements in the efficiency of energy systems and changes in the mix of those systems for each energy service. For heating, average efficiencies (incorporating conversion efficiency and the thermal performance of the dwelling) improved more than three-fold between 1964 to 2015 (BEIS 2017)—driven in part by the shift from coal to gas, the increasing use of condensing boilers, and improvements in the thermal performance of the building stock. 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.[8]

We estimate that the efficiency of refrigeration and clothes washing improved more than three-fold between 1964 and 2015, with most of this improvement occurring since 2000 as a consequence of EU regulations. The energy efficiency of car travel 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 (right-hand axis)—although this estimate is particularly uncertain.

Figure 3 illustrates the estimated trends in the average 'energy input price' for lighting and appliances, cooking, heating and vehicle travel respectively. For lighting and appliances the trend

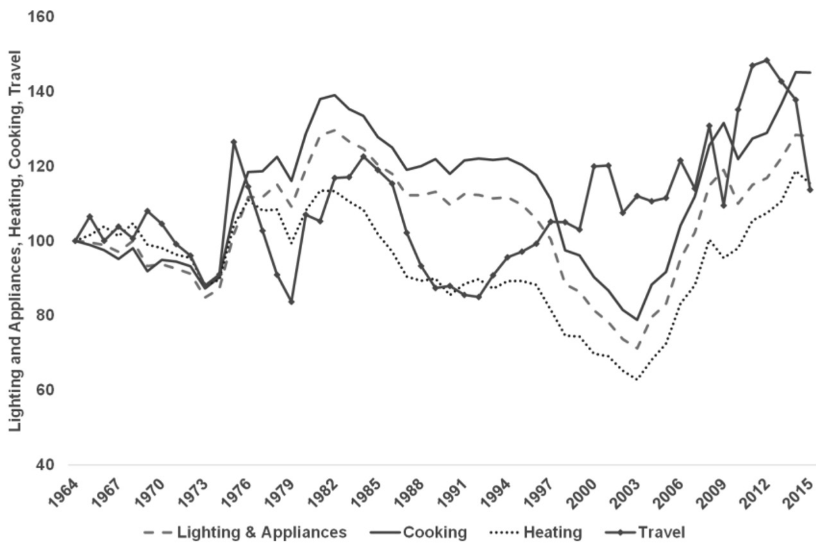
8. The slight dip in lighting efficiency in 2014 and 2015 was due to a decrease in the share of relatively efficient fluorescent strips and a modest increase in less efficient halogen lighting.

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



Note: The axis for entertainment and computing is on the right hand side of the figure.

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



represents the unit price of electricity, while for cooking, heating and vehicle travel the trend represents the quantity-weighted average unit price[9] of two or more energy commodities (see Annex A). 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).

The energy cost of energy services is the product of energy efficiency (Figure 2) and energy prices (Figure 3). The resulting estimates are illustrated in Figure 4. Between 1980 and 2003,

9. Standing and other charges are ignored.

a combination of falling energy prices and improving efficiencies led to significant reductions in the energy cost of household energy services. But higher energy prices after 2002 partly offset the continuing improvements in energy efficiency, with the result that the range of variation in energy costs (Figure 4) is less than the range of variation in energy efficiency (Figure 2) and energy prices (Figure 3). Throughout the period, there is a strong correlation in the energy cost trends for lighting and cooking and to a lesser extent heating. The energy cost of vehicle travel began to rise after 1991 with the modest improvements in vehicle efficiency being insufficient to offset rising fuel prices. In 2013, the energy cost of lighting was around 48% lower than in 1964, refrigeration and clothes washing 23% lower, entertainment and computing 88% lower, cooking 17% lower and heating only 20% lower.

Figure 4: Real energy cost of UK household energy services 1964–2015 (1964 = 100)

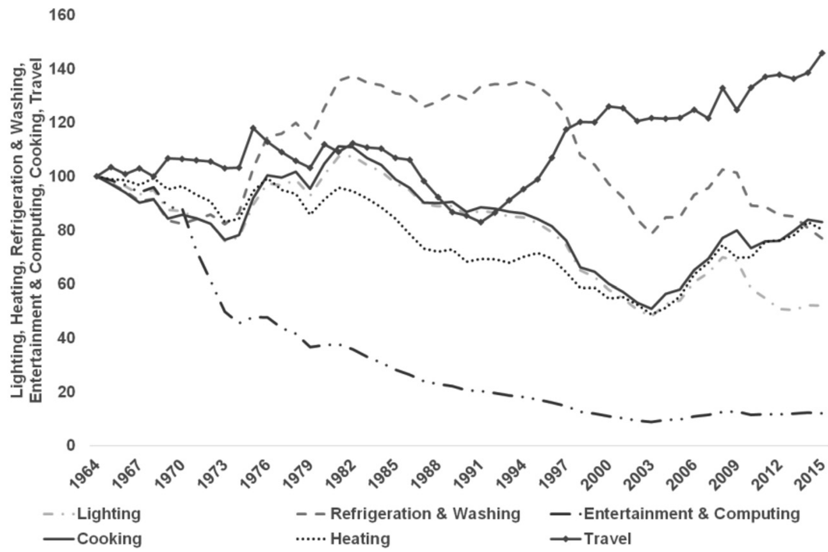
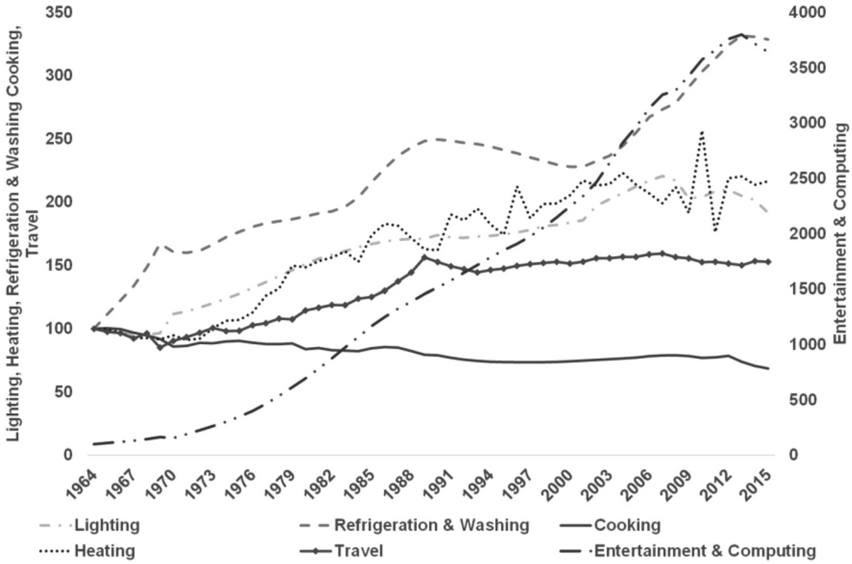


Figure 5 illustrates the resulting estimates of energy service consumption. The consumption of heating and lighting is estimated to have increased by a factor of four since the mid–1960s, while consumption of refrigeration and clothes washing increased seven-fold and entertainment and computing 100-fold. In contrast, consumption of cooking is estimated to have fallen by 30%—perhaps reflecting changing dietary preferences (e.g. ready-meals) and more eating out. Consumption of refrigeration and clothes washing appears to have accelerated after 2000, while consumption of other services has stabilised or even begun to decline. Note that the annual variations in heating consumption are related to variations in average winter temperatures.

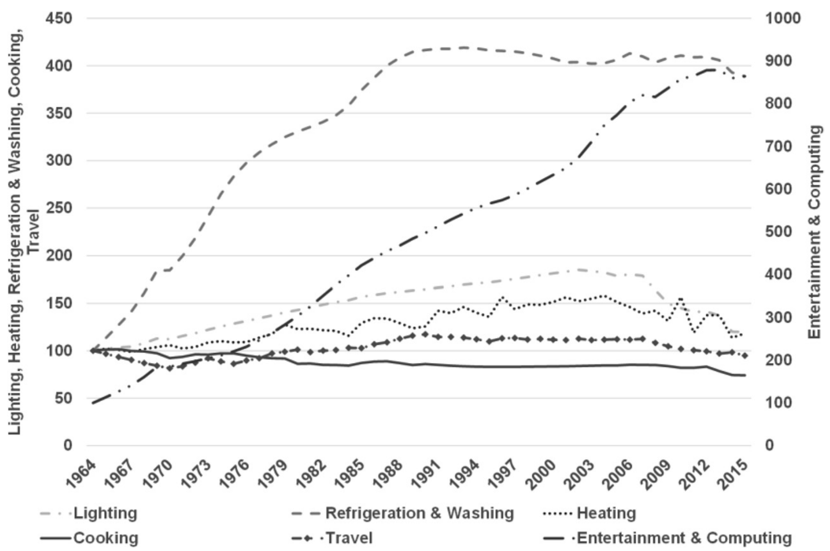
Finally, Figure 6 illustrates the estimated trends in energy consumption for each energy service. Energy consumption has grown slower than energy service consumption owing to improvements in energy efficiency. For example, energy use for heating was around 20% higher in 2015 than in 1964, while consumption of heating services was around 100% higher. For cooking, improvements in efficiency combined with reductions in cooking demand to reduce energy consumption by ~60%. For appliances, efficiency improvements moderated but did not offset the rise in service demand, with the result that energy use for refrigeration increased by 220% between 1964 and 2015, while that for clothes washing increased by 365% and for electronics by 765%. Energy use for computing increased by 110% between 2000 and 2015.

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



Note: The axis for entertainment and computing is on the right hand side of the figure.

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



Note: The axis for entertainment and computing is on the right hand side of the figure.

Having presented the trends in the consumption and price of energy services, we now summarise the results of the econometric analysis.

6. RESULTS

6.1 Parameter and elasticity estimates

Our two-stage model leads to three equations for the aggregate categories, five equations for the household energy services category and two equations for the transport category. We estimate each group as a system using the Iterative Seemingly Unrelated Regression method (ISUR) which is suitable for imposing cross-equation restrictions and corrects the estimates for any correlation of the error terms between equations. We impose the homogeneity and symmetry restrictions when estimating the equations in each group and impose the adding-up restriction by dropping one of the equations in each group. We estimate each system twice, dropping a different equation each time, in order to recover the standard errors for all parameter estimates.

Annex B summarises the parameter estimates for each group of equations. We see that the overall fit of the equations is good, with two thirds of the parameter estimates being statistically significant at the 5% level, with both the group and household energy services equations having an adjusted R^2 exceeding 90%, and with the transport group equations having an adjusted R^2 exceeding 70%.

To interpret the parameter estimates we need to derive the elasticities. Annex C summarises the between-group and within-group elasticity 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 short-run total expenditure ($\overline{\eta}_{q_i x}$) and total price ($\overline{\eta}_{q_i p_z}$) elasticities for each of our six energy services—which are summarised in Table 2. We then insert the total price elasticity estimates into Equation 10 to derive estimates of the short-run direct and indirect rebound effects for each energy service.

From Table 2 we observe that the estimated expenditure elasticities are all greater than 0.86, and for heating and 'refrigeration and clothes 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 (2014),[10] while our estimate of the expenditure elasticity of heating is approximately 40% larger. Hence, our estimates appear rather high.

The estimated own-price elasticities for the energy services are indicated in the main diagonal of Table 2 (in bold). These all have the expected sign but are again larger than anticipated: namely, –0.7 for heating, –0.5 for vehicle travel and ~–0.9 for the other energy services. 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 vehicle travel are at the upper end of the range found in the literature (Dimitropoulos et al., 2018; Galvin, 2015; Madlener and Hauertmann, 2011). The own-price elasticities for the services provided by electricity are all very similar, despite the diverging trends in the energy cost of these services (Figure 4).

Table 2 also indicates the estimated cross-price elasticities between the six energy services. Looking first at the signs of the elasticities we observe that vehicle travel is estimated to be a gross complement to household energy services ($\overline{\eta}_{q_i,p_z} < 0$), while the individual household energy services are estimated to be gross substitutes ($\overline{\eta}_{q_i,p_z} > 0$). This suggests, for example, that improved lighting efficiency is associated with increased vehicle travel but reduced consumption of heating. The increased emissions associated with the former offset the savings from energy efficient lighting, while the avoided emissions associated with the latter increase those savings. 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)

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

is associated with a ~0.35% reduction in demand for other household energy services, but only a 0.03% increase in vehicle travel demand.

Table 2: Estimated short-run total expenditure elasticity and total price elasticity for each energy service

		Price elasticity ($\overline{\eta}_{q_i,p_z}$)					
Energy service (z)	**Expenditure Elasticity ($\overline{\eta}_{q_i,x}$)**	Lighting	Heating	Refrigeration & clothes washing	Entertainment & computing	Cooking	Vehicle travel
Lighting	0.96	**–0.95**	0.37	0.09	0.08	0.03	–0.04
Heating	1.29	0.03	**–0.70**	0.06	0.06	0.03	–0.06
Refrigeration & clothes washing	1.10	0.04	0.34	**–0.92**	0.07	0.04	–0.05
Entertainment & computing	0.86	0.04	0.39	0.09	**–0.91**	0.05	–0.04
Cooking	0.97	0.02	0.36	0.08	0.08	**–0.93**	–0.04
Vehicle travel	0.89	–0.003	–0.03	–0.01	–0.01	–0.003	**–0.54**

Note: Each row represents an equation. For example, a 1% increase in the price of lighting is associated with a 0.95% reduction in lighting consumption and a 0.37% increase in heating consumption. We estimate these elasticities using the mean expenditure shares over the full time period.

6.2 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 (Equation 12 and Table 4). The results suggest very large direct rebound effects, namely: 70% for heating, 54% for vehicle travel and >90% for the other energy services. Again, these are larger than the majority of estimates in the literature.

Table 3 also summarises the estimated indirect rebound effects between each pair of energy services (e.g. between heating and lighting), while Table 4 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 effect associated with heating offsets the direct rebound effect (i.e. contributes additional emission savings), while that associated with vehicle travel amplifies the direct rebound effect (i.e. further erodes emission savings).

The sum of indirect rebound effects over all energy services is significant (Table 4). For example, we estimate the total indirect rebound effect for lighting to be –41%. This offsets the estimated direct rebound effect of 95% for lighting to leave a combined rebound effect of 54%. Similar comments apply to the other household energy services—and in the case of entertainment and computing, the indirect rebound is larger than the direct rebound, leading to a negative combined rebound effect. Heating provides the largest contribution to the indirect rebound effect (Table 3) as a consequence of: first, the large cross-price elasticity between other energy services and heating (Table 2); and second, the high carbon intensity and large expenditure share of heating (Equation 8).

For vehicle travel, the direct and indirect rebound effects have the same sign, so the combined rebound effect is larger than the direct effect. Overall, we estimate a combined rebound effect of 54% for lighting, 55% for heating, 41% for refrigeration and clothes washing, –12% for entertainment and computing, 50% for cooking and 69% for vehicle travel.

One notable feature of the results is the similarity of the estimated direct and indirect rebound effects for lighting; 'refrigeration and clothes washing'; cooking; and entertainment and computing (though the latter has a larger indirect rebound). While each is wholly or partly provided by electricity, we would expect the results to diverge given the different character of each service and the varying trends in the energy cost per unit of service (Figure 4). Given the similarity of these results, we re-estimated the model with the three entirely electric energy service categories combined. This leads to *lower* estimates of the combined rebound effect (Table 5), namely: 24% for lighting and appliances, 50% for heating, 44% for cooking and 49% for vehicle travel. These lower estimates primarily derive from lower estimates of the direct rebound effect and suggest that the results are sensitive to the level of aggregation used. This demonstrates the need for caution in interpreting and inferring from the results.

We also estimated the combined rebound effects for each energy service in 1964 and 2015 (Table 6). 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, we estimate the combined rebound for lighting has fallen from 36% in 1964 to 7.5 % in 2015, that for refrigeration and clothes washing has fallen from 59% to 7.5 %, and that for vehicle travel has fallen from 71% to 50%. These changes reflect the net effect of changes in price elasticities, budget shares and carbon intensities—and the results suggest that the direct rebound effects have remained relatively stable while the (negative) indirect rebound effects have increased.

Table 3: Estimated short-run direct and indirect ($R_{I_z i}$) rebound effects for each energy service

	Rebound effect (%)					
Energy service (*z*)	Lighting	Heating	Refrigeration and clothes washing	Entertainment & computing	Cooking	Vehicle travel
Lighting	**94.8**	–30.0	–6.2	–3.6	–2.3	1.4
Heating	–3.8	**70.2**	–5.6	–3.4	–3.7	1.4
Refrigeration & clothes washing	–5.4	–38.6	**92.4**	–4.6	–4.9	1.8
Entertainment & computing	–9.7	–73.1	–14.2	**90.8**	–9.5	3.4
Cooking	–2.6	–31.8	–6.1	–3.9	**93.1**	1.5
Vehicle travel	0.8	11.0	1.6	0.6	0.8	**53.7**

Note: Figures in bold on the main diagonal represent the direct rebound effect (R_{D_z}) for that energy service, while other figures represent the indirect rebound effect between one energy service and another ($R_{I_z i}$).

Table 4: Estimated short-run direct, total indirect and combined rebound effects for each energy service

Energy service (*z*)	**Direct (R_{D_z})**	**Indirect (R_{I_z})**	**Combined (R_{C_z})**
Lighting	94.8	–40.7	54.1
Heating	70.2	–15.1	55.1
Refrigeration & clothes washing	92.4	–51.7	40.6
Entertainment & computing	90.8	–103.1	–12.3
Cooking	93.1	–42.9	50.2
Vehicle travel	53.7	14.9	68.6

Table 5: Estimated short-run direct, total indirect and combined rebound effects for each energy service—lighting and appliances combined (%)

Energy service (*z*)	**Direct (R_{D_z})**	**Indirect (R_{I_z})**	**Combined (R_{C_z})**
Lighting and appliances	83.1	–59.3	**23.8**
Heating	64.4	–15.6	**48.8**
Cooking	96.2	–52.4	**43.7**
Vehicle travel	56.8	–8.1	**48.7**

Table 6: Estimated short-run direct, total indirect and combined rebound effects for each energy service in 1964 and 2015

	1964			2015		
Energy service (z)	**Direct (R_{D_z})**	**Indirect (R_{I_z})**	**Combined (R_{C_z})**	**Direct (R_{D_z})**	**Indirect (R_{I_z})**	**Combined (R_{C_z})**
Lighting	93.4	–57.4	36.1	93.7	–86.2	7.5
Heating	68.5	–12.2	56.2	64.9	–13.7	51.1
Refrigeration & clothes 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
Vehicle travel	44.2	27.6	71.8	44.5	6.1	50.6

6.3 Alternative specifications

To assess the robustness of these results, we experimented with a number of alternative specifications.[11] First, we included a measure of 'heating degree days' (HDD), to capture weather-related influences on energy demand. The estimated coefficient was generally insignificant and including this variable had only a minor effect on the estimated rebound effects. Hence, to preserve degrees of freedom, we omitted HDD from the model

Second, we estimated the model using the Stone rather than the Laspeyres price index, which led to similar coefficients for the prices and time trend but different coefficients for total expenditure and lagged expenditure shares. This suggests that the results are sensitive to the price index used. We prefer the Laspeyres index for the reasons given in Moschini (1995), and the endogeneity issue arising from the use of Stone price index..

Third, we estimated the model without the lagged expenditure shares. This specification suffered from serial correlation (LM test), suggesting that the inclusion of lags improves the statistical performance.

Fourth, similar to Hunt and Ryan (2015), we added a quadratic time term (t^2) to capture non-linear trends over time. We found the relevant coefficient to be statistically insignificant and very small (<0.0000 for most categories), so we omitted this term from the specification.

Fifth, we experimented with dropping different categories of lagged expenditure shares to avoid co-linearity (e.g. dropping the heating expenditure share rather than the cooking expenditure share in Equation 19). This had no effect on the estimated coefficients for the time trend, total expenditures and category prices—and hence the estimated short run rebound effects were unchanged. However, the coefficients for the lagged expenditure shares varied from one specification to another—implying that estimates of long-run price elasticities and hence long-run rebound effects will depend upon which equation is dropped. Comparable instability was found by Edgerton (1997), who chose to only report short run elasticities as a result. We do the same here—so all of our results are for short-run effects.

Finally, we replaced the lagged expenditure shares of all categories with the lagged expenditure share of the same category only (e.g. we replaced $\sum_{s=1,\dots(R-1)}\left(\lambda^{rs}w_{t-1}^{s}\right)$ in Equation 14 with $\lambda^{r}w_{t-1}^{r}$). This provides a simpler specification of adjustment dynamics, but has the drawback that the speed of adjustment is constrained to be the same for all categories in order to satisfy the adding-up restriction (Ryan and Plourde, 2009).[12] Table 7 compares the results of this specification with those from our base model.

11. Full results are available from the authors on request.

12. The coefficient on the lagged expenditure share must be the same for all equations in the same group. That is: $\lambda^r=\lambda$ for all r in Equation 14 and $\lambda_i^r=\lambda^r$ for all i in Equation 19.

It is clear from Table 7 that the estimated rebound effects are sensitive to the model specification. Looking more closely, we find the two specifications provide comparable estimates of direct rebound effects but different estimates of indirect rebound effects. These in turn result from different estimates of the cross-price elasticities ($\overline{\eta}_{q_i,p_z}$). Comparing the elasticity estimates for the alternative specification (Table 8) with those from the base model (Table 2), we find the differences are small in absolute terms but proportionally large (e.g. from 0.04 to 0.08). The estimated cross-price elasticity between heating and other energy services is much larger than the others; and since heating has the largest expenditure share (w_i) and highest carbon intensity (u_i^x), it provides the largest contribution to the indirect rebound effect (Table 3). Hence, our estimated rebound effects are sensitive to relatively small differences in the estimated cross price elasticities associated with household heating. This highlights the importance of heating in determining the size of the overall rebound effect, but also reduces the level of confidence that we can have in our results.

Table 7: Comparing rebound estimates from the base model with those from an alternative specification with only a single lagged expenditure share

	Base model (all category lags)			**Variant (own category lag)**		
Energy service (z)	**Direct**	**Indirect**	**Combined**	**Direct**	**Indirect**	**Combined**
Lighting	94.8	–40.7	**54.1**	97.0	–22.2	**74.8**
Heating	70.2	–15.1	**55.1**	83.3	–7.9	**75.3**
Refrigeration & clothes washing	92.4	–51.7	**40.6**	96.6	–29.1	67.5
Entertainment & computing	90.8	–103.1	**–12.3**	93.9	–55.3	**38.6**
Cooking	93.1	–42.9	**50.2**	95.4	–22.5	**73.0**
Vehicle travel	53.7	14.9	**68.6**	53.5	4.9	**58.4**

Table 8: Estimated short-run price elasticities for each energy service from an alternative specification with only a single lagged expenditure share

	Price elasticity ($\overline{\eta}_{q_i,p_z}$)					
Energy service (*z*)	Lighting	Heating	Refrigeration & clothes washing	Entertainment & computing	Cooking	Vehicle travel
Lighting	**–0.97**	0.16	0.04	0.04	0.002	–0.02
Heating	0.02	**–0.83**	0.04	0.04	0.02	–0.02
Refrigeration & clothes washing	0.02	0.14	**–0.97**	0.03	0.02	–0.02
Entertainment & computing	0.03	0.25	0.06	**–0.94**	0.03	–0.01
Cooking	0.002	0.16	0.04	0.04	**–0.95**	–0.02
Vehicle travel	0.0002	0.002	0.0003	0.0003	0.0002	**–0.54**

7. CONCLUSIONS

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. Rebound effects have been estimated 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. In contrast to earlier work (e.g. Chitnis and Sorrell, 2015), this study does not assume 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 energy cost 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 energy efficiency. The only exception is vehicle travel, where the price per kilometre in 2015 was ~14% higher than in 1964.

The results from our base model suggest, first, that the direct rebound effects from energy efficiency improvements over this period have been very large—for example, 94% for lighting, 70% for heating and 54% for vehicle travel. While few other studies have estimated these effects, our estimates are larger than most in the literature.

Second, our results suggest that the indirect rebound effects associated with other energy services are also significant—for example: +15% for vehicle travel, –15% for heating, –52% for refrigeration and clothes washing and –41% for lighting. These indirect effects *offset* the direct rebound effect for household energy services, but *amplify* the direct rebound effect for travel. This is because we estimate household energy services to be gross substitutes for each other, and vehicle travel to be a gross complement to those services. The net result is that we estimate combined rebound effect to be smaller than the direct rebound effect for household energy services, but larger for vehicle travel. Overall, we estimate a combined rebound effect of 54% for lighting, 55% for heating, 41% for refrigeration and clothes washing, –12% for entertainment and computing, 50% for cooking and 69% for vehicle travel. These results suggest that around a half of the potential emission savings from improved energy efficiency over this period have been 'taken back' by consumer responses to cheaper energy services.

However, there are multiple caveats to these results. First, our sensitivity tests suggest that the estimates of indirect and hence combined rebound effects are sensitive to the model specification. In particular, small variations in the estimated cross-price elasticities associated with heating have a large influence on the estimated indirect rebound effect. This demonstrates how changes in heating consumption can dominate the rebound effect from different types of efficiency improvement, but also reduces the level of confidence that we can have in our results.

Second, our re-estimation of the model with aggregated categories of energy services suggests that the results are also sensitive to the level of aggregation used. This sensitivity may derive in part from the small share of total expenditure accounted for by individual energy services. While the LAIDS model is widely used, most applications focus upon goods that have a relatively large share of household expenditure. In contrast, the share of energy commodities is relatively small, and the share of individual energy services is smaller still. This makes it challenging to estimate rebound effects with this type of model.

Third, there are considerable difficulties in compiling estimates of the energy cost and quantity demanded of household energy services over this period—and particularly for years prior to 1970. The resulting uncertainties reduce the level of confidence we can have in our estimates—especially for categories such as entertainment and computing which are difficult to measure and where the quality of data is particularly poor.

Fourth, the limited number of observations in our model prevents us from including additional covariates and necessitates the imposition of separability assumptions that could potentially bias the results. However, this is a generic feature of multistage budgeting models.

Fifth, some of our 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. Our estimates of expenditure elasticities are also relatively high.

Finally, 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 modify our estimates of the total rebound effect.

Future work should seek to address 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 (e.g. Chitnis and Sorrell, 2015; Dimitropoulos et al., 2016; Mizobuchi, 2008). For example, Brännlund et al. (2007) estimated rebound effects in excess of 100%. At this stage, it is not clear whether these large estimates reflect a bias 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 reinforces the need to investigate rebound effects more carefully. If rebound effects are as large as our results suggest, improved energy efficiency is likely to contribute much less to emission reductions than is commonly assumed. If so, greater weight may need to be given to carbon pricing or to promoting low carbon energy supply. However, to have more confidence in this conclusion, further improvements are required in the empirical estimation of combined rebound effects.

ACKNOWLEDGMENTS

The authors acknowledge the helpful comments from the reviewers. Roger Fouquet gratefully acknowledges support from the Grantham Foundation and the ESRC through the Centre for Climate Change Economics and Policy (CCCEP). Steve Sorrell would like to acknowledge the support of UK Research and Innovation (UKRI) through a grant to the Centre for Research on Energy Demand Solutions (grant number EP/R035288/1).

REFERENCES

Ajanovic, A., L. Schipper and R. Haas (2012). "The impact of more efficient but larger new passenger cars on energy consumption in EU-15 countries." *Energy* 48: 346–355. https://doi.org/10.1016/j.energy.2012.05.039.

Alfredsson, E.C. (2004). "'Green' consumption—no solution for climate change." *Energy* 29: 513–524. https://doi.org/10.1016/j.energy.2003.10.013.

Barnett, W.A. and O. Seck (2008). "Rotterdam model versus almost ideal demand system: will the best specification please stand up?" *Journal of Applied Econometrics* 23: 795–824. https://doi.org/10.1002/jae.1009.

BEIS (2016a). *Digest of UK Energy Statistics*. HMSO, London.

BEIS (2016b). *Energy Consumption in the United Kingdom*. London.

BEIS (2016c). *Historical electricity data 1920 to 2015*. London.

Bjelle, E.L., K. Steen-Olsen and R. Wood (2018). "Climate change mitigation potential of Norwegian households and the rebound effect." *Journal of Cleaner Production* 172: 208–217. https://doi.org/10.1016/j.jclepro.2017.10.089.

Brännlund, R., T. Ghalwash and J. Nordström (2007). "Increased energy efficiency and the rebound effect: effects on consumption and emissions." *Energy economics* 29: 1–17. https://doi.org/10.1016/j.eneco.2005.09.003.

Brockway, P.E., J.R. Barrett, T.J. Foxon and J.K. Steinberger (2014). "Divergence of trends in US and UK aggregate exergy efficiencies 1960–2010." *Environmental science & technology* 48: 9874–9881. https://doi.org/10.1021/es501217t.

Chan, N.W. and K. Gillingham (2015). "The microeconomic theory of the rebound effect and its welfare implications." *Journal of the Association of Environmental and Resource Economists* 2: 133–159. https://doi.org/10.1086/680256.

Chitnis, M. and S. Sorrell (2015). "Living up to expectations: Estimating direct and indirect rebound effects for UK households." *Energy Economics* 52: S100–S116. https://doi.org/10.1016/j.eneco.2015.08.026.

Cullen, J.M. and J.M. Allwood (2010). “Theoretical efficiency limits for energy conversion devices.” *Energy* 35: 2059–2069. https://doi.org/10.1016/j.energy.2010.01.024. https://doi.org/10.1021/es102641n.

Cullen, J.M., J.M. Allwood and E.H. Borgstein (2011). “Reducing energy demand: what are the practical limits?” *Environmental Science & Technology* 45: 1711–1718.

DCLG (2014). *Live tables on househhold projections Department Communities and Local Government*, London.

Deaton, A. and J. Muellbaeur (1980). *Economics and Consumer Behaviour*. Cambridge University Press.

Deaton, A. and J. Muellbauer (1980). “An Almost Ideal Demand System.” *The American Economic Review* 70: 312–326.

DfT (2016). *Transport Statistics Great Britain*. London.

Dimitropoulos, A., W. Oueslati and C. Sintek (2016). *The rebound effect in road transport: a meta-analysis of empirical studies.* OECD Environment Directorate, Paris, France.

Dimitropoulos, A., W. Oueslati and C. Sintek (2018). “The rebound effect in road transport: A meta-analysis of empirical studies.” *Energy Economics* 75: 163–179. https://doi.org/10.1016/j.eneco.2018.07.021.

Dubin, J.A. and D.L. McFadden (1984). “An econometric analysis of residential electric appliance holdings and consumption.” *Econometrica* 52: 345–362. https://doi.org/10.2307/1911493.

Edgerton, D.L. (1997). “Weak separability and the estimation of elasticities in multistage demand systems.” *American Journal of Agricultural Economics* 79: 62–79. https://doi.org/10.2307/1243943.

Fouquet, R. (2008). *Heat, power and light: revolutions in energy services*. Edward Elgar Publishing.

Fouquet, R. (2012). “Trends in income and price elasticities of transport demand (1850–2010).” *Energy Policy* 50, 62–71. https://doi.org/10.1016/j.enpol.2012.03.001.

Fouquet, R. (2014). “Long-run demand for energy services: Income and price elasticities over two hundred years.” *Review of Environmental Economics and Policy* 8: 186–207. https://doi.org/10.1093/reep/reu002.

Fouquet, R. and P.J. Pearson (2006). “Seven centuries of energy services: The price and use of light in the United Kingdom (1300–2000).” *The Energy Journal* 27:139–178. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol27-No1-8.

Galvin, R. (2015). *The rebound effect in home heating: A guide for policymakers and practitioners*. Routledge. https://doi.org/10.4324/9781315696942.

Hagenaars, A.J., K. De Vos and M. Asghar Zaidi (1994). *Poverty statistics in the late 1980s: Research based on micro-data*. Eurostat.

Hunt, L.C. and D.L. Ryan (2014). “Catching on the rebound: Why price elasticities are generally inappropriate measures of rebound effects.” Surrey Energy Economics Centre (SEEC) Discussion Papers (SEEDS) 148, School of Economics, University of Surrey. https://doi.org/10.1016/j.eneco.2015.05.006.

Hunt, L.C. and D.L. Ryan (2015). “Economic modelling of energy services: Rectifying misspecified energy demand functions.” *Energy Economics* 50: 273–285.

Kitzes, J. (2013). “An introduction to environmentally-extended input-output analysis.” *Resources* 2: 489–503. https://doi.org/10.3390/resources2040489.

Klonaris, S. and D. Hallam (2003). “Conditional and unconditional food demand elasticities in a dynamic multistage demand system.” *Applied Economics* 35: 503–514. https://doi.org/10.1080/00036840210148058.

Koomey, J.G., H.S. Matthews and E. Williams (2013). “Smart everything: Will intelligent systems reduce resource use?” *Annual Review of Environment and Resources* 38: 311–343. https://doi.org/10.1146/annurev-environ-021512-110549.

Madlener, R. and M. Hauertmann (2011). “Rebound effects in German residential heating: Do ownership and income matter?” FCN Working Papers 2. E.ON Energy Research Center, Future Energy Consumer Needs and Behavior (FCN). https://doi.org/10.2139/ssrn.1887030.

Mizobuchi, K. (2008). “An empirical study on the rebound effect considering capital costs.” *Energy Economics* 30: 2486–2516. https://doi.org/10.1016/j.eneco.2008.01.001.

Moschini, G. (1995). “Units of measurement and the Stone index in demand system estimation.” *American Journal of Agricultural Economics* 77: 63–68. https://doi.org/10.2307/1243889.

Murray, C.K. (2013). “What if consumers decided to all ‘go green’? Environmental rebound effects from consumption decisions.” *Energy Policy* 54: 240–256. https://doi.org/10.1016/j.enpol.2012.11.025.

Ryan, D. and A. Plourde (2009). *Empirical modelling of energy demand, in*: Evans, J., Hunt, L.C. (Eds.), International Handbook on the Economics of Energy. Edward Elgar, Cheltenham, UK. https://doi.org/10.4337/9781849801997.00011.

Saunders, H.D. and J.Y. Tsao (2012). “Rebound effects for lighting.” *Energy Policy* 49, 477–478. https://doi.org/10.1016/j.enpol.2012.06.050.

Shukur, G. (2002). “Dynamic specification and misspecification in systems of demand equations: a testing strategy for model selection.” *Applied Economics* 34: 709–725. https://doi.org/10.1080/00036840110048465.

Sorrell, S. (2007). *The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency*. UK Energy Research Centre, London.

Sorrell, S. (2010). "Mapping rebound effects from sustainable behaviours: key concepts and literature review." SLRG Working Paper 01-10. Sustainable Lifestyles Research Group (SLRG), University of Surrey.

Sorrell, S. and J. Dimitropoulos (2007). "The rebound effect: Microeconomic definitions, limitations and extensions." *Ecological Economics* 65: 636–649. https://doi.org/10.1016/j.ecolecon.2007.08.013.

Thomas, B.A. and I.L. Azevedo (2013). "Estimating direct and indirect rebound effects for U.S. households with input–output analysis. Part 2: Simulation." *Ecological Economics* 86: 188–198. https://doi.org/10.1016/j.ecolecon.2012.12.002.

Tsao, J.Y., H.D. Saunders, J.R. Creighton, M.E. Coltrin and J.A. Simmons (2010). "Solid-state lighting: an energy-economics perspective." *Journal of Physics D: Applied Physics* 43: 354001. https://doi.org/10.1088/0022-3727/43/35/354001.

Turner, K. (2013). "Rebound effects from increased energy efficiency : a time to pause and reflect." *The Energy Journal* 34: 25–42. https://doi.org/10.5547/01956574.34.4.2.

ANNEX A: CONSTRUCTING ESTIMATES OF THE CONSUMPTION AND ENERGY COST OF ENERGY SERVICES

Here we summarise the process of constructing estimates of the quantity consumed (q_z) and energy cost (p_z) of six energy services in UK households. Further details are provided in Fouquet (2008, 2014).

It is useful to consider energy services such as heating and private vehicle 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 thermal comfort. Here 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 the quantity of energy service delivered (q_z) to the quantity of 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 varies from one energy commodity to another (e.g. coal versus gas boilers) and changes over time. Similarly, the quantity of energy services supplied by different energy commodities and/or energy systems also changes over time (e.g. a shift from coal to gas for heating, or from compact fluorescents to LEDs for lighting).

Fouquet (2008, 2014) 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 Z types of energy service ($z = 1,..Z$) within the population of UK households. We designate these estimates by φ_{zedt}. This dataset also includes estimates of the energy efficiency of each system/commodity combination (ε_{zedt}) together with the unit price of the relevant energy commodities (p_{et}). The quantity of energy service z produced by commodity e and system d in year t is then given by: $q_{zedt} = \varphi_{zedt}\varepsilon_{zedt}$, and the energy cost of that energy service is given by: $p_{zedt} = p_{et} / \varepsilon_{zedt}$. The 'total cost' of the energy service also include the non-energy operating costs and discounted capital costs, but in our two-stage budgeting model 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 z consumed in year t (q_{zt}) is then given by summing over the relevant system/commodity combinations:

$$q_{zt} = \sum_{e=1,..E} \sum_{d=1,..D} q_{zedt} \tag{26}$$

The energy cost of energy service z in year t is given by the weighted average of the energy cost of the energy service from each system/commodity combination:

$$p_{zt} = \sum_{e=1,..E} \sum_{d=1,..D} \left(\frac{q_{zedt}}{q_{zt}} \right) p_{zedt} \tag{27}$$

We can define and measure energy services in a variety of ways. Here, we use the following measures for the quantity consumed 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

Our starting point in constructing these time series is BEIS (2016b), who 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 (2014).[13] 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 9). 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 (φ_{zedt}).

Table 9: 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 (2014), we use a variety of sources to obtain corresponding estimates of the energy efficiency of each system/commodity combination (ε_{zedt}). For example using and updating Fouquet (2014), 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

13. Briefly, we use data on the consumption of energy commodities from previous editions of the Digest of United Kingdom Energy Statistics and make assumptions about the share of different end-uses by extrapolating backwards in time from the 1970 share estimates provided by BEIS (2016b). In doing so, we also integrate historical information about different appliance markets. For the period from 1964 to 1970, the estimated shares change little.

for halogens, fluorescent strip lighting, compact fluorescents and LEDs, and use Equations 26 and 27 to estimate the total consumption and effective price of lighting in UK households since 1964.

In the case of refrigeration and clothes washing, we use data from DCLG (2014) on the UK stock of refrigerators and washing machines (Table 9) 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 energy rating of residential dwellings over the period 1970–2015, 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. We assume the rate of efficiency improvement prior to 1970 was only one quarter of the rate after 1970, reflecting the greater concern about energy efficiency after that date. While simplistic, these estimates appear broadly consistent with the exponential improvements in the energy efficiency of computing technology reported by Koomey et al. (2013) and suggest that the energy efficiency of the combined category of entertainment and computing has improved twelve-fold between the 1960s and 2015. These estimates are then combined with the price of electricity and data from BEIS (2016b) to construct indices of the cost of entertainment and cost of computing from 1964. These are combined by weighting by the share of energy consumption for each service to give a time-series for the cost 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 total electricity use for appliances multiplied by the consumption of electricity for appliances—based on data from Fouquet (2014).

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). Fouquet (2012) estimates the annual costs of car travel between 1971 and 2008 and finds that fuel accounted for 28–40% of the total. Fouquet (2012) provides further detail on the method for estimating the price of vehicle travel. 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 considerable uncertainty—particularly for refrigeration and clothes washing, and entertainment and computing. Improving the accuracy of these estimates should be a priority for future research.

ANNEX B: PARAMETER ESTIMATES

Table B.1: Parameter estimates for the categories

				γ^{rs} Category prices			λ^{rs} Lagged budget shares		
Expenditure share	α^r Intercept	θ^r Time trend	β^r Expenditure	Household energy services	Transport services	Other goods and services	Household energy services	Transport services	$\overline{R}^2$
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)	(0.0024)	(0.0034)	(0.0038)	(0.0761)	(0.0351)	
Transport services	–0.0059	0.0004**	–0.0208*	–0.0057*	0.0239**	–0.0182*	0.1903	0.8175***	0.94
	(0.0129)	(0.0001)	(0.0107)	(0.0034)	(0.0099)	(0.0098)	(0.1343)	(0.0670)	
Other goods and services	0.9884***	–0.0001	0.0154	–0.0109***	–0.0182*	0.0291***	–0.7178***	–0.8896***	0.93
	(0.0148)	(0.0001)	(0.0121)	(0.0038)	(0.0098)	(0.0109)	(0.1579)	(0.0746)	

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. The lagged expenditure share of 'other goods and services" is dropped to avoid co-linearity.

Table B.2: Parameter estimates for the subcategories of household energy services

		Expenditure shares				
Parameter	Variable	Lighting	Heating	Refrigeration & clothes washing	Entertainment & computing	Cooking
α^r	Intercept	0.2643***	–0.8697**	0.4870***	0.1512	0.9672***
		(0.0963)	(0.3526)	(0.1478)	(0.1125)	(0.1104)
θ^r	Time trend	0.0018***	–0.0109***	0.0036***	0.0036***	0.0019***
		(0.0003)	(0.0012)	(0.0005)	(0.0004)	(0.0003)
β^r	Category expenditure	–0.0153**	0.0598***	–0.0085	–0.0206***	–0.0154**
		(0.0060)	(0.0227)	(0.0093)	(0.0073)	(0.0067)
γ_{ij}^r	Price-lighting	0.0010***	–0.0000	0.0004***	0.0001	–0.0014***
		(0.0004)	(0.0002)	(0.0001)	(0.0001)	(0.0005)
	Price-heating	–0.0000	0.0019***	–0.0005***	–0.0005***	–0.0008***
		(0.0002)	(0.0004)	(0.0002)	(0.0001)	(0.0002)
	Price-refrigeration & clothes washing	0.0004***	–0.0005***	0.0002***	0.0001	–0.0001
		(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
	Price-entertainment & computing	0.0001	–0.0005***	0.0001	0.0004***	–0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	Price-cooking	–0.0014***	–0.0008***	–0.0001	–0.0000	0.0024***
		(0.0005)	(0.0002)	(0.0001)	(0.0001)	(0.0007)
λ_{ij}^r	Lag share-lighting	–0.0230	3.0646***	–1.2923***	–0.4854**	–1.2639***
		(0.1897)	(0.6791)	(0.2933)	(0.2126)	(0.2220)
	Lag share-heating	–0.3248***	2.1054***	–0.5085***	–0.2564**	–1.0158***
		(0.0903)	(0.3353)	(0.1403)	(0.1036)	(0.1045)
	Lag share-refrigeration & clothes washing	–0.2203**	1.2415***	0.4328***	–0.4000***	–1.0540***
		(0.0860)	(0.3417)	(0.1414)	(0.1023)	(0.0967)
	Lag share-entertainment & computing	–0.9623***	4.6474***	–1.7589***	–0.2692	–1.6571***
		(0.1662)	(0.6346)	(0.2558)	(0.1930)	(0.1883)
$\overline{R}^2$		0.94	0.93	0.96	0.99	0.98

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. The lagged expenditure share of ‘cooking” is dropped to avoid co-linearity.

Table B.3: Parameter estimates for the subcategories of transport

		Expenditure shares	
Parameter	Variable	Vehicle travel	Other transport
α^r	Intercept	0.2390*** (0.0774)	0.7610*** (0.0774)
θ^r	Time trend	–0.0006 (0.0004)	0.0006 (0.0004)
β^r	Category expenditure	0.0145 (0.0242)	–0.0145 (0.0242)
γ_{ij}^r	Price—vehicle travel	0.0937*** (0.0116)	–0.0937*** (0.0116)
	Price—other transport	–0.0937*** (0.0116)	0.0937*** (0.0116)
λ_{ij}^r	Lag share—vehicle travel	0.2569*** (0.0693)	–0.2569*** (0.0693)
$\overline{R}^2$		0.73	0.73

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. The lagged expenditure share of 'other transport" is dropped to avoid co-linearity. The coefficients of both equations have the opposite sign but the same absolute value because of adding up and symmetry restrictions (except for intercept).

ANNEX C: BETWEEN GROUP AND WITHIN GROUP ELASTICITY ESTIMATES

Table C.1: Between-group expenditure elasticity estimates ($\overline{\eta}_{q_r x}$)

	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 ($\overline{\eta}_{q_r p_s}$)

	Between-group price elasticity		
	Household energy services	Transport	Other goods and services
Household energy services	–0.4661	–0.2095	–0.5025
Transport	–0.0405	–0.7859	–0.0071
Other goods and services	–0.0134	–0.0241	–0.9807

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

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

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

	Within-group price elasticity					
	Lighting	Heating	Refrigeration & clothes washing	Entertainment & computing	Cooking	Travel
Lighting	–0.9760	0.1103	0.0288	0.0248	–0.0042	—
Heating	–0.0062	–1.0555	–0.0137	–0.0136	–0.0080	—
Refrigeration and clothes washing	0.0068	0.0344	–0.9900	0.0088	0.0033	—
Entertainment & computing	0.0177	0.1559	0.0364	–0.9590	0.0184	—
Cooking	–0.0048	0.0953	0.0212	0.0225	–0.9616	—
Travel	—	—	—	—	—	–0.5935

IAEE INTERNATIONAL ASSOCIATION *for* ENERGY ECONOMICS
WWW.IAEE.ORG

The IAEE is pleased to announce that our leading publications exhibited strong performances in the latest 2018 Impact Factors as reported by Clarivate. The Energy Journal achieved an Impact Factor of 2.456 while Economics of Energy & Environmental Policy saw an increase to 2.034.

Both publications have earned SCIMago Journal Ratings in the top quartile for Economics and Econometrics publications.

IAEE wishes to congratulate and thank all those involved including authors, editors, peer-reviewers, the editorial boards of both publications, and to you, our readers and researchers, for your invaluable contributions in making 2018 a strong year. We count on your continued support and future submission of papers to these leading publications.