UK ENERGY RESEARCH CENTRE

UKERC Review of Evidence for the Rebound Effect

Technical Report 2: Econometric studies

Working Paper

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Preface

This report has been produced by the UK Energy Research Centre's Technology and Policy Assessment (TPA) function.

The TPA was set up to address key controversies in the energy field through comprehensive assessments of the current state of knowledge. It aims to provide authoritative reports that set high standards for rigour and transparency, while explaining results in a way that is both accessible to non-technical readers and useful to policymakers.

This report forms part of the TPA's assessment of evidence for a **rebound effect** from improved energy efficiency. The subject of this assessment was chosen after extensive consultation with energy sector stakeholders and upon the recommendation of the TPA Advisory Group, which is comprised of independent experts from government, academia and the private sector. The assessment addresses the following question:

What is the evidence that improvements in energy efficiency will lead to economy-wide reductions in energy consumption?

The results of the project are summarised in a *Main Report*, supported by five in-depth *Technical Reports*, as follows:

1. Evidence from evaluation studies
2. Evidence from econometric studies
3. Evidence from elasticity of substitution studies
4. Evidence from CGE modeling studies
5. Evidence from energy, productivity and economic growth studies

A shorter *Supplementary Note* provides a graphical analysis of rebound effects. All these reports are available to download from the UKERC website at: www.ukerc.ac.uk/

The assessment was led by the Sussex Energy Group (SEG) at the University of Sussex, with contributions from the Surrey Energy Economics Centre (SEEC) at the University of Surrey, the Department of Economics at the University of Strathclyde and Imperial College. The assessment was overseen by a panel of experts and is extremely wide ranging, reviewing more than 500 studies and reports from around the world.

Technical Report 2: Econometric Studies focuses upon econometric estimates of the elasticity of demand for different types of consumer energy service such as household heating. Under certain assumptions, these estimates can provide good indication of the magnitude of the direct rebound effect for these energy services.

THE UK ENERGY RESEARCH CENTRE

Operating at the cusp of research and policy-making, the UK Energy Research Centre's mission is to be the UK's pre-eminent centre of research, and source of authoritative information and leadership, on sustainable energy systems.

The Centre takes a whole systems approach to energy research, incorporating economics, engineering and the physical, environmental and social sciences while developing and maintaining the means to enable cohesive research in energy.

To achieve this we have developed the Energy Research Atlas, a comprehensive database of energy research, development and demonstration competences in the UK. We also act as the portal for the UK energy research community to and from both UK stakeholders and the international energy research community.

Acknowledgements

Earlier versions of Section 2 of this report were presented at the 29th IAEE International Conference 'Securing energy in insecure times', held in Potsdam, Germany on the 7-10th June 2006 and the 6th BIEE Academic Conference, held at St. John's College, Oxford on the 20-21st September 2006. An updated version has been accepted for publication in *Ecological Economics* (Sorrell and Dimitropoulos, 2007). The authors gratefully acknowledge comments from Harry Saunders, John Feather, Blake Alcott, Brenda Boardman, Mark Barrett and Ed Steinmuller as well as from participants at both conferences and two anonymous referees. A debt is also owed to Lorna Greening and David Greene for their previous synthesis of empirical work in this area (Greening and Greene, 1998). The usual disclaimers apply.

Executive Summary

This report examines the evidence for direct rebound effects that is available from studies that use econometric techniques to analyse secondary data. The focus throughout is on consumer energy services, since this is where the bulk of the evidence lies. The evidence relevant to direct rebound effects for producers is discussed separately in *Technical Reports 3, 4 and 5*.

Direct rebound effects are sometimes estimated through quasi-experimental, or 'evaluation' studies in which the consumption of energy or useful work is measured both before and after an energy efficiency improvement. While a number of studies that use this approach are reviewed in *Technical Report 1*, this approach is relatively uncommon. An alternative approach uses econometric techniques to analyse secondary data sources that include information on the demand for energy, useful work and/or energy efficiency. This data can take a number of forms and can apply to different levels of aggregation, but is most useful when it applies to a single energy service. A key objective of such studies is to estimate *elasticities*, meaning the percentage change in one variable following a percentage change in another, holding other variables constant. Under certain assumptions, a number of these elasticities can be taken as estimates of either the short-run or long-run direct rebound effect for the relevant energy service.

The econometric literature is dominated by studies of personal automotive transportation and household heating, with very few studies of other energy services. The majority of studies have been conducted in the United States, with the evidence for direct rebound effects in developing countries being particularly weak.

This report clarifies the theoretical and methodological issues associated with such estimates, highlights the strengths and limitations of different approaches and summarises the available evidence for direct rebound effects for consumer energy services, paying particular attention to personal automotive transportation.

Defining the direct rebound effect

Direct rebound effects relate to individual energy services, such as heating, lighting and refrigeration and are confined to the energy required to provide that service. Improved energy efficiency will decrease the marginal cost of supplying that service and could therefore lead to an increase in consumption of the service. For example, consumers may choose to drive further following the purchase of energy efficient car because the price per kilometre has fallen. The resulting increase in energy service consumption will tend to offset the expected reduction in energy consumption provided by the energy efficiency improvement. The operation of direct rebound effects is discussed in more detail in the *Supplementary Report*.

Energy services are provided by a combination of energy commodities and associated equipment, including energy conversion equipment. A defining feature of an energy service is the *useful work* obtained, which may be defined and measured in different ways (e.g. vehicle, passenger or tonne kilometres) and decomposed in different ways (e.g. the product of the number, capacity and average utilisation of energy conversion devices). Energy services also have associated *attributes*, such as comfort, acceleration and prestige.

Different definitions of the independent variable (energy efficiency) and dependent variable (demand for useful work) for the direct rebound effect may lead to different conclusions regarding its size and importance. For example, most estimates of the direct rebound effect for passenger transport focus upon the increased demand for vehicle kilometres following an energy efficiency improvement. But this neglects changes in vehicle load factors and vehicle size.

Estimating the direct rebound effect

The econometric literature relevant to the direct rebound effect is technical and difficult to interpret. While this is partly a consequence of the variety of methodological approaches used, it also stems from a lack of clarity over basic definitions. Different studies use different definitions of the direct rebound effect, estimate the effect through a number of different measures, express these measures in a variety of ways and frequently fail to clarify the relationship between them. The situation is compounded by the fact that many of the relevant studies do not mention the rebound effect at all, since their primary focus lies elsewhere. These studies nevertheless provide elasticity estimates that, under certain assumptions, may be used as proxy measures of the direct rebound effect. A key objective of this report is therefore to clarify these different definitions and to develop a common terminology that aids interpretation of the relevant literature.

In principle, the direct rebound effect may be estimated from the elasticity of demand for either energy or useful work with respect to changes in energy efficiency. However, relatively few studies follow this approach, either because of data limitations or because the limited variation in the independent variable (energy efficiency) leads to high variance in the parameter estimates. Instead, rather more studies estimate the own-price elasticity of the demand for useful work (e.g. the elasticity of demand for vehicle kilometres with respect to the cost per kilometre). Since the price of useful work depends upon *both* energy prices and energy efficiency, the degree of variation in the independent variable is greater - with most of the variation typically deriving from historical or cross-sectional variations in energy prices. But the validity of this approach hinges upon the assumption that consumers respond in the same way to decreases in energy prices as they do to improvements in energy efficiency (and vice versa). In many cases this assumption is likely to be flawed.

It is also possible to estimate the direct rebound effect from the own-price elasticity of the demand for energy - thereby avoiding the need to collect data on the demand for useful work. But, unless energy efficiency is explicitly controlled for, this approach effectively assumes that: first, consumers respond in the same way to decreases in energy prices as they do to improvements in energy efficiency (and vice versa); and second, energy efficiency is unaffected by changes in energy prices. Both these assumptions are likely to be flawed, but the extent to which this leads to biased estimates of the direct rebound effect may vary widely from one energy service to another and between the short and long term.

Sources of bias when estimating the direct rebound effect

There are a number of potential sources of bias in econometric estimates of the direct rebound effect, several of which may lead the effect to be overestimated. The most important include the following:

- *Input costs*: Changes in energy prices are generally not correlated with changes in the costs of other inputs required to provide the relevant energy service. However, changes in energy efficiency may be - in particular, higher energy efficiency may require new equipment with higher capital costs. Hence, estimates of the direct rebound effect that rely primarily upon historical and cross-sectional variations in energy prices could overestimate the effect.
- *Asymmetry*: Energy price elasticities tend to be higher for periods with rising prices than for those with falling prices. One explanation is that higher energy prices induce technological improvements in energy efficiency, which also become embodied in regulations. Also, investment in measures such as thermal insulation is largely irreversible over the short to medium-term. But the appropriate proxy for improvements in energy efficiency is *reductions* in energy prices. Since many time-series studies incorporate periods of rising energy prices, the estimated price elasticities may overestimate the response to falling energy prices. Hence, estimates of the direct rebound effect that rely primarily upon variations in energy prices and do not control for asymmetry in demand responses could overestimate the effect.
- *Endogeneity*: Improvements in energy efficiency may encourage consumers to increase their consumption of useful work (e.g. driving further after purchasing an energy-efficient car). But at the same time, consumers who anticipate a high demand for useful work may also purchase more energy efficient conversion devices (e.g. buying an energy-efficient car because you expect to drive further). This suggests a potential circularity: i.e. the demand for useful work depends on the price of useful work, which depends upon energy efficiency, which depends upon the demand for useful work. The technical term for this is e*ndogeneity*, which means that the relevant variables (energy efficiency and useful work) are in part determined by each other. This can be addressed empirically through the use of simultaneous equation models and related techniques, but many studies do not use these. Hence, estimates of the direct rebound effect that do use appropriate techniques to control for endogeneity could potentially lead to biased estimates of the effect.
- *Time costs*: Consumers may be expected to take time costs into account when making decisions about the consumption of particular energy services. Time costs are conventionally measured by hourly wage rates, which have increased relative to energy prices throughout the past century. Indeed, increases in energy consumption in industrial societies may be partly driven by the substitution of energy for time. Some energy services involve trade-offs between energy efficiency and time efficiency, with higher (lower) energy efficiency implying lower (higher) time efficiency (e.g. compare rail to air travel). If wage rates continue to increase faster than energy prices in real terms, the rebound effect with respect to energy efficiency should become less important, since improvements in energy efficiency have an increasingly small impact on the total cost of useful work. Hence, for those energy services where trade-offs between energy and time costs are relevant, estimates of the direct rebound effect that do not control for increases in income could overestimate the direct rebound effect.

Consideration of time costs also points to another issue: increasing time efficiency may lead to a parallel 'rebound effect with respect to time' (e.g. faster cars encourage longer driving distances). So energy consumption may be increased, first, by trading off energy efficiency for time efficiency (e.g. choosing air travel rather than rail) and second, by the rebound effect with respect to time (e.g. choosing to travel further).

Summarising estimates of the direct rebound effect

The econometric literature relevant to the direct rebound effect is both relatively small and extremely diverse. Studies differ in their definition of independent and dependent variables, the methods of measuring those variables, the structural form employed, the type of data used and other relevant factors. Such diversity precludes a formal meta-analysis of quantitative results. Instead, we have simply described the methodology and approach of relevant studies, identified their strengths and weaknesses, highlighted key issues and summarised results. This leads to 'best guess' estimates for the long-run direct rebound effect for each service, in which greater weight is placed on the results from more rigorous studies (Table E.1). We have also reviewed estimates of the own price elasticity of energy consumption for different energy services, since under certain assumptions these may provide upper bounds for the direct rebound effect.

Table E.1 Estimates of the long-run direct rebound effect for consumer energy services in the OECD

End-Use	Range of Values in Evidence Base	'Best guess'	No. of Studies	Degree of Confidence
Personal automotive transport	3-87%	10-30%	17	High
Space heating	0.6-60%%	10-30%	9	Medium
Space cooling	1-26%	1-26%	2	Low
Other consumer energy services	0-39%	<20%	3	Low

Personal automotive transportation is the only area where the evidence is sufficiently strong to allow the magnitude of the direct rebound effect to be quantified with some confidence. Studies using aggregate time-series and cross-sectional data estimate the long-run direct rebound effect for personal automotive transport to be somewhere between 5% and 30%. Studies using aggregate panel data should provide more robust estimates owing to the greater number of observations, and these suggest direct rebound effects in the range 22% to 30%. Studies using disaggregate (i.e. household survey) data sources provide much less consistent estimates, ranging from 0% to 87%. However, the most rigorous of those reviewed estimates the long-run direct rebound effect to be 23%, which is consistent with the results of studies using aggregate data.

Overall, the review suggests that the long-run direct rebound effect for personal automotive transport lies somewhere between **10% and 30%**. The relative consensus on estimates, despite wide differences in data and methodologies suggests that the findings are robust. Also, the asymmetry of demand responses suggests that a value towards the lower end of this range is more likely. There is some evidence to suggest that the direct rebound effect for this energy service declines with income, but there is insufficient evidence to determine how it varies between different countries.

In contrast, the available evidence does not permit the direct rebound effect for space heating to be quantified with much confidence. While this is partly because space heating is inherently more complex, it is also because the topic has received insufficient attention. The studies reviewed here suggest direct rebound effects in the range **1.4 to 60%**, with considerable variation between different countries, households, fuels and types of energy efficiency improvement. The strong evidence for the price asymmetry of energy demand responses for space heating suggests that the mean effect may be towards lower rate end of the above range, but rebound effects appear to be higher for low-income groups. For the purpose of policy evaluation, a figure of **30%** would appear a reasonable assumption, which is consistent with the results of the evaluation studies reported in *Technical Report 1*.

There are a number of reasons why direct rebound effects for most other household energy services should be smaller than those for household heating. However, the econometric evidence is very poor, owing to measurement difficulties. Two rather dated studies of space cooling both suggest a direct rebound effect in the range **1%-26%**. However, both focus solely upon changes in equipment utilisation and therefore neglect the demand from 'marginal consumers' acquiring space cooling equipment for the first time, as well as any increases in the capacity of space cooling systems among existing users. While one study suggests direct rebound effects of up to 39% for other energy services, this estimate appears suspiciously high. A more rigorous study estimates the direct rebound effect for energy efficient washing machines to be less than **5%.** This figure is likely to be representative of other time-intensive energy services, such as those provided by dishwashers, vacuum cleaners and electronic appliances.

The evidence therefore suggests that direct rebound effects for consumer energy services are likely to be <u>low</u> to <u>moderate</u> in developed economies and may decline with income. Therefore, direct rebound effects should not undermine the objectives of energy efficiency programmes aimed at reducing the energy required to deliver particular energy services. However, these conclusions are subject to a number of qualifications, including the relatively limited time periods over which the effects have been studied, the frequent neglect of marginal consumers and the restrictive definitions of 'useful work' that are commonly employed.

Further research on the direct rebound effect

The current state of knowledge on direct rebound effects is insufficient for policy purposes. Research on direct rebound effects therefore needs to improve in rigour and expand in scope. This requires both good data sets and more robust methodologies that address the potential sources of bias indicated above. There is scope for studies of a greater range of consumer energy services, provided that individual appliances can be monitored. However, the policy issue here is not so much changes in short-term utilisation patterns, but changes in the number and capacity of conversion devices over the longer term.

Estimates of the direct rebound effect for personal automotive transport would benefit from more appropriate definitions of useful work. A study employing tonne-kilometres as the dependent variable appears feasible and could potentially capture the effect of increasing car sizes. Analysis is also needed of other modes of transport, including freight. There is also scope for more empirical work on the 'rebound effect with respect to time', especially in the area of transportation, and on the dependence of direct rebound effects on income.

The geographical bias of the evidence base also needs to be addressed. In particular, the evidence for rebound effects in developing countries remains very weak.

Contents

1 Introduction

Direct rebound effects relate to individual energy services, such as heating, lighting and refrigeration and are confined to the energy required to provide that service. Improved energy efficiency will decrease the marginal cost of supplying that service and could therefore lead to an increase in consumption of the service. For example, consumers may choose to drive further following the purchase of energy efficient car because the price per kilometre has fallen. The resulting increase in energy service consumption will tend to offset the expected reduction in energy consumption provided by the energy efficiency improvement.

While the existence of direct rebound effects is widely acknowledged, their magnitude is greatly disputed. Direct rebound effects are sometimes estimated through quasi-experimental, or 'evaluation' studies in which the consumption of energy or useful work is measured both before and after an energy efficiency improvement. While a number of studies that use this approach are reviewed in *Technical Report 1*, this approach is relatively uncommon. An alternative approach uses econometric techniques to analyse secondary data sources that include information on the demand for energy, useful work and/or energy efficiency. This data can take a number of forms and can apply to different levels of aggregation, but is most useful when it applies to a single energy service. A key objective of such studies is to estimate elasticities, meaning the percentage change in one variable following a percentage change in another, holding other variables constant. Under certain assumptions, a number of these elasticities can be taken as estimates of either the short-run or long-run direct rebound effect for the relevant energy service.

This report therefore examines the quantitative estimates of direct rebound effects that are available from studies using econometric techniques to analyse secondary data. The focus throughout is on consumer energy services, since this is where the bulk of the evidence lies.[1]

The report is structured as follows. Section 2 provides an in-depth examination of the different definitions of the direct rebound effect, including the strength and limitations of those definitions and the relationship between them. It develops a number of extensions to the basic definition and uses these to highlight some potential sources of bias in econometric estimates of the direct rebound effect. A key objective is to develop a common terminology that aids understanding of the relevant literature.

Section 3 sets out the criteria through which the empirical studies were selected and provides an overview of the various econometric approaches to estimating the direct rebound effect, including issues such as model structure, functional form and estimation techniques. This provides a useful basis for understanding and comparing the various studies discussed in the subsequent sections.

Sections 4 to 6 summarise the relevant empirical literature, addressing in turn personal automotive transportation, household heating and other consumer energy services. Each section begins by summarising the evidence on own-price elasticities of energy consumption

[1] The evidence relevant to direct rebound effects for producers is discussed separately in *Technical Reports 3, 4 and 5*.

for the relevant energy service, since these may provide an upper bound for the direct rebound effect. It then describes the methodology and approach of a number of studies that provide more accurate estimates of the effect, identifies their strengths and weaknesses, highlights key issues and summarises and compares the results. This leads to a 'best guess' estimate for the long-run direct rebound effect for each energy service, in which greater weight is placed on the results from more rigorous studies. Section 7 concludes.

2 The direct rebound effect: definitions, limitations and extensions

2.1 Introduction

The econometric literature relevant to the direct rebound effect is highly technical and difficult to interpret. While this is partly a consequence of the variety of methodological approaches used, it also stems from a lack of clarity over basic definitions. Different studies use different definitions of the direct rebound effect, estimate the effect through a number of different measures, express these measures in a variety of ways and generally fail to clarify the relationship between each measure. The situation is greatly compounded by the fact that many of the relevant studies do not mention the rebound effect at all, since their primary focus lies elsewhere. These studies nevertheless provide elasticity estimates that, under certain assumptions, may be used as proxy measures of the direct rebound effect. Taken together, these features inhibit understanding of the effect and the appropriate empirical approach to estimating its magnitude in different circumstances. They also make it very difficult to identify the relevance of different studies.

Hence, when first encountered the empirical literature is extremely confusing. While Greening and Greene (1998) provide a comprehensive and insightful review of this literature, they fail to clarify the key differences between each study in terms of the methodological approach adopted and elasticity measures used. As a result, they overlook a number of potential sources of bias in the empirical estimates.

This section seeks to address these weaknesses by identifying the different definitions of the direct rebound effect, clarifying the relationship between these definitions and highlighting some potential sources of bias in the empirical estimates. The aim is to develop a common terminology that aids understanding of the diverse literature discussed in the subsequent sections. The focus throughout is upon consumer energy services, since this is where the bulk of the econometric evidence lies.

This section is structured as follows. Section 2.2 presents a general ‘household production’ framework for characterising the demand for consumer energy services that helps to illustrate the different trade-offs involved. Section 2.3 shows how the direct rebound effect can be represented as the elasticity of energy demand with respect to energy efficiency and how it may be decomposed into the sum of elasticities for the number, capacity and utilisation of energy conversion devices. Section 2.4 identifies the relationship between the direct rebound effect and the own-price elasticity of the demand for ‘useful work’, as well as the own-price elasticity of the demand for energy, and shows why empirical studies using these definitions provide a primary source of evidence for the direct rebound effect.

Section 2.5 exposes the limitations of the above definitions, focusing on: a) the potential correlation between various input costs and improvements in energy efficiency; b) the endogeneity of energy efficiency and the implied need for simultaneous equation estimation; and c) the role of time costs and time efficiency in the production and consumption of energy services. It identifies some of the factors that need to be controlled for to obtain accurate estimates of the direct rebound effect and argues that the neglect of these factors by several existing studies may lead the direct rebound effect to be overestimated. Section 2.6 concludes.

2.2 Understanding the demand for energy services

The demand for energy (*E*) derives from the demand for energy services *(ES)* such as thermal comfort, refrigeration and motive power. These services, in turn, are delivered through a combination of energy commodities and the associated energy systems, including energy conversion devices. Consumers are assumed to derive utility from consuming these services, rather than from consuming energy commodities and other market goods directly. In practice, nearly all services require energy in some form, although energy may form a much smaller proportion of total costs for some services than for others.

An essential feature of an energy service is the *useful work* (*S*) obtained, which may be measured by a variety of thermodynamic or physical indicators (Patterson, 1996).[2] These indicators may, in turn, be decomposed in a variety of ways to reveal the relative importance of different contributory variables. For example, the useful work from the private cars owned by a group of households may be:

- measured in *vehicle kilometres* and decomposed into the product of the number of cars and the mean driving distance per car per year: $S = NO * UTIL$;
- measured in *passenger kilometres* and decomposed into the product of the number of cars (*NO)*, the mean driving distance per car per year (*UTIL*) and the average number of passengers carried per car (*LF*): $S = NO * UTIL * LF$; or
- measured (rather unconventionally) in *tonne kilometres* and decomposed into the product of the number of cars (*NO*), the mean driving distance per car per year (*UTIL*) and the mean (loaded or unloaded) vehicle weight (*CAP*): $S = NO * CAP * UTIL$.

In practice, the choice of indicator and associated decomposition will depend upon the objective of the analysis, the level of aggregation (e.g. household, sector, economy) and, most importantly, the availability of the relevant data. In much empirical work, measures of useful work are not decomposed.

It important to recognise that energy services also have broader *attributes* (*A*) that may be combined with useful work in a variety of ways. For example, all cars deliver passenger kilometres, but they may vary widely in terms of features such as speed, comfort, acceleration and prestige. The combination of useful work (*S*) with these associated attributes (*A*) may be considered to provide the full energy service: $ES = es(S, A)$.

Becker's 'household production' model provides a helpful framework for understanding the demand for energy services (Becker, 1965). In this model, individual households are assumed to <u>produce</u> energy services (*ES*) by combining energy commodities (*E*), capital equipment (*K*), other market goods (*O*) and some of the household's own labour, which may be measured by the amount of time (*T*) required. For example, mobility may be produced by the household through the combination of gasoline, a private car, expenditure on

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[2] See Technical Report 5 for a comprehensive discussion of thermodynamic, physical and economic measures of energy and energy efficiency, including a definition of output energy or 'useful work'.

maintenance and driving time. Similarly, a cooked meal may be produced through the combination of natural gas, a gas cooker, ingredients and cooking time.

The provision of useful work for a particular energy service may then be described by a production function, representing the maximum output that can be obtained from the currently available technology for a given level of energy and other inputs (Wirl, 1997). But the provision of broader attributes for a given amount of useful work is likely to require additional inputs; or, alternatively, for a given budget, the provision of broader attributes is likely to reduce the amount of useful work. To reflect this, the production function for energy service *i* may be written as:

$$ES_i = es_i[E_i, K_i, O_i, T_i; A_i] \qquad (2.1)$$

If a household's utility is assumed to depend solely upon these services, the utility function becomes:

$$U = u[ES_1, ES_2, ES_3, ...ES_n] \qquad (2.2)$$

The household may be assumed to be subject to the following income constraint:

$$V + T_W P_W \geq \sum_{i=1,n} (P_E E_i + P_O O_i + \delta_K K_i) \qquad (2.3)$$

Where V represents non-wage income; P_W represents the average wage rate; T_W represents the time spent in the labour market; P_E and P_O represent the unit price of energy and other goods respectively; and δ_K represents a discount factor (so $P_K = \delta_K K(A)$) gives the annualised capital costs). Households will also be subject to a second constraint on their available time:

$$T = T_W + \sum_{t=1}^{n} T_i \qquad (2.4)$$

Where T_i represents the time spent in producing services S_i. Becker (1965) argued that, since money and time are partly interchangeable through decisions on T_W, the income and time constraints can be collapsed into a single constraint. By substituting $T_W = T - \sum_{t=1}^{n} T_i$ into the budget constraint and rearranging , we obtain:

$$V + P_W T \geq \sum_{t=1}^{n} (P_E E_i + P_O O_i + \delta_K K_i + P_W T_i) \qquad (2.5)$$

Versions of Becker's 'household production' model form the basis of a substantial volume of empirical research (Juster and Stafford, 1991; Gronau, 1997). This includes numerous applications to energy use, although these studies frequently (and importantly) neglect the time inputs to energy services (Dinan, 1987; Willet and Naghshpour, 1987; Davis, 2004). The attraction of Becker's model for energy studies is that: first, it embodies the recognition that utility is derived from the consumption of energy services, rather than energy commodities; second it recognises that households have a joint role in both producing and consuming those services; and third, that time is an important (but often neglected) input into the production of those services. The implications that follow arguably offer greater insight into the determinants of energy-related behaviour than more conventional models of energy demand.

Becker's model rests upon a set of behavioural and other assumptions that may be criticised on a variety of grounds (Pollack and Wachter, 1975; Juster and Stafford, 1991).[3] Nevertheless, it offers a number of advantages over conventional models of household energy demand and predictions from the model appear broadly confirmed by empirical research (Juster and Stafford, 1991). The primary contribution of this model in the present context is to emphasise that consumption of an energy service involves three interrelated trade-offs, namely:

- between consumption of useful work versus consumption of other attributes of an energy service;
- between energy, capital, other market goods and time into the production of an energy service; and
- between consumption of different types of energy service.

This general framework forms the foundation for what follows.

2.3 The direct rebound effect as an energy efficiency elasticity

The energy efficiency (ε) of an energy system may be defined as $\varepsilon = S/E$, where E represents the energy input required for a unit output of useful work (however measured).[4] For example, a car may require ten litres of gasoline to drive one hundred kilometres. The *energy cost* of useful work (P_S) is then given by $P_S = P_E/\varepsilon$, where P_E represents the unit price of energy. This is one component of the *generalised cost* of useful work (P_G), which also includes other input costs, such as annualised capital costs (P_K), maintenance costs (P_M) and time costs (P_T) :

$$P_G = (P_E/\varepsilon) + P_K + P_M + P_T \qquad (2.6)$$

Consider a situation where the energy efficiency of an energy system is improved $(\Delta\varepsilon > 0)$, but the consumption and costs of non-energy inputs remain unchanged, together with the consumption of other attributes of the energy service. In the absence of a direct rebound effect, the demand for useful work would remain unchanged ($\Delta S = 0$) and energy demand would be reduced in proportion to the improvement in energy efficiency ($\Delta E/E = -\Delta\varepsilon/\varepsilon$). But the energy efficiency improvement lowers the energy cost per unit of useful work ($\Delta P_S < 0$) and hence also the total cost. Assuming that the energy service has a price elasticity in the normal range, consumers will demand more useful work ($\Delta S > 0$) and the proportional change in energy consumption will be less than the proportional change in energy efficiency ($\Delta E/E < -\Delta\varepsilon/\varepsilon$).

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[3] Including: the assumption that each market good or allocation of time is dedicated to the production of a single service; the notion that households are indifferent to the allocation of time, except as an input into the production of services; difficulties in defining what a service actually is (e.g. travel by car for a visit or the visit itself); the neglect of the fact that utility may be a function of producing as well as consuming a service; the implicit assumption of constant returns to scale in production; the difficulty in operationalising the model; the lack of good data on time use patterns; and the usual difficulties associated with models that assume 'hyper-rational', utility maximising individuals.

[4] The appropriate measure of energy efficiency depends upon the objectives of the analysis and is generally a property of the energy system, rather than just the energy conversion device. For example, the amount of heat required to maintain a particular internal temperature depends upon both of the thermodynamic efficiency of the heating system and the thermal integrity of the building.

The change in demand for useful work following a small change in energy efficiency may be measured by the *energy efficiency elasticity of the demand for useful work* ($\eta_\varepsilon(S)$):

$$\eta_\varepsilon(S) = \frac{\partial S}{\partial \varepsilon}\frac{\varepsilon}{S} \qquad (2.7)$$

In a similar manner, the change in energy demand following a small change in energy efficiency may be measured by the *energy efficiency elasticity of the demand for energy* ($\eta_\varepsilon(E)$):

$$\eta_\varepsilon(E) = \frac{\partial E}{\partial \varepsilon}\frac{\varepsilon}{E} \qquad (2.8)$$

Substituting $E = S/\varepsilon$ in the equation for $\eta_\varepsilon(E)$ and taking partial derivatives we can derive the following relationship between these two elasticities:[5]

Definition 1: $\eta_\varepsilon(E) = \eta_\varepsilon(S) - 1$

The elasticity of demand for useful work with respect to energy efficiency ($\eta_\varepsilon(S)$) has been commonly taken as a measure of the direct rebound effect (Berkhout, et al., 2000). The actual saving in energy consumption will only be equal to the predicted saving from engineering calculations when this elasticity is zero ($\eta_\varepsilon(S) = 0$). Under these circumstances, the elasticity of demand for energy with respect to energy efficiency ($\eta_\varepsilon(E)$) is equal to minus one. A positive direct rebound effect implies that $\eta_\varepsilon(S) > 0$ and $|\eta_\varepsilon(E)| < 1$. For example, a positive direct rebound effect for car travel implies that improvements in vehicle fuel efficiency lead to an increase in vehicle kilometres driven, with the result that the savings in energy consumption are less than predicted from engineering calculations alone. If the demand for useful work is inelastic ($0 < \eta_\varepsilon(S) < 1$) improvements in energy efficiency should reduce energy demand ($0 > \eta_\varepsilon(E) > -1$). But if the demand for useful work is elastic ($\eta_\varepsilon(S) > 1$), improvements in energy efficiency will <u>increase</u> energy consumption. This somewhat counterintuitive outcome is termed 'backfire' in the literature (Saunders, 1992).

Technological improvements in energy efficiency may, over time, lead to an increase in the number of energy conversion devices (*NO*), their average size (*CAP*), their average utilisation (*UTIL)* and/or their average load factor (*LF*). For example, people may buy more cars, buy larger cars, drive them further and/or share them less. Similarly, people may buy more washing machines, buy larger machines, use them more frequently and/or reduce the size of the average load. The equation for the energy efficiency elasticity of energy demand may therefore be decomposed in a variety of ways, depending upon data availability, the timeframe under consideration and the choice of measure for useful work (*S*). For example, if useful work is defined as the product of the number, average output capacity and average utilisation of energy conversion devices (*S=NO*CAP*UTIL*), the equation becomes:

$$\eta_\varepsilon(E) = [\eta_\varepsilon(NO) + \eta_\varepsilon(CAP) + \eta_\varepsilon(UTIL)] - 1 \qquad (2.9)$$

The relative importance of these variables may vary widely between different energy services and over time. For example, technological improvements in the energy efficiency of new refrigerators are unlikely to increase the average utilisation of the refrigerator stock (measured in hours/year) but could lead to an increase in both the number and average size

[5] See Annex A for derivations of this and subsequent definitions and formulae.

of refrigerators over time (since the cost per cubic metre of refrigeration has reduced). The majority of empirical estimates of the direct rebound effect relate to travel by private cars, where useful work is commonly measured in vehicle kilometres travelled and decomposed into the product of vehicle numbers and the mean distance travelled per car per year (Greene*, et al.*, 1999b; Small and Van Dender, 2005). An important consequence of this is that any increases in average vehicle weight as a result of energy efficiency improvements (e.g. more SUVs) as well as decreases in average load factor (e.g. less car sharing) will be overlooked.[6]

The marginal utility of energy service consumption is likely to decline with increased consumption, which should reduce the direct rebound effect from energy efficiency improvements. For example, direct rebound effects from improvements in the energy efficiency of household heating systems should decline rapidly once whole-house indoor temperatures approach the maximum level for thermal comfort. One implication, frequently observed in the policy evaluation literature, is that direct rebound effects will be higher among low income groups, since these are further from satiation in their consumption of individual energy services (Boardman and Milne, 2000).

2.4 The direct rebound effect as a price elasticity

Since $P_S = P_E / \varepsilon$, raising (lowering) energy efficiency (ε) when energy prices (P_E) are constant should have the same effect on the energy cost of useful work (P_S) as falling (rising) energy prices when energy efficiency is constant. Under the ceteris-paribus assumptions given above, the effect on the total cost and hence the demand (*S*) for useful work should be symmetrical. If income and the price of other inputs are held constant, we can write the demand for useful work solely as a function of energy prices and energy efficiency: $S = s(P_E / \varepsilon)$. The demand for energy is then given by: $E = s(P_E / \varepsilon)/\varepsilon$. Assuming that energy prices are exogenous (i.e. P_E does not depend upon ε), we can differentiate this equation with respect to energy efficiency to give an alternative definition of the direct rebound effect:

Definition 2: $\eta_\varepsilon(E) = -\eta_{P_S}(S) - 1$

Hence, under these assumptions, the energy efficiency elasticity of energy demand ($\eta_\varepsilon(E)$) is equal to the *energy cost elasticity of demand for useful work* ($\eta_{P_S}(S)$), minus one. Effectively, the negative of the energy cost elasticity of demand for useful work ($\eta_{P_S}(S)$) is being used as a proxy for the energy efficiency elasticity of demand for useful work ($\eta_\varepsilon(S)$), which in turn is the primary definition of the direct rebound effect. If useful work is a normal good, we expect that $\eta_{P_S}(S) \leq 0$. For example, if the elasticity of vehicle km (*S*) with respect to energy cost per kilometre (P_S) is estimated as -0.10, then the elasticity of gasoline demand with respect to fuel efficiency can be estimated from Definition 2 as –0.90. This implies that the demand for gasoline will fall by only 9% if the fuel efficiency of vehicles

[6] The first of these rebound effects could be captured if useful work for private travel was measured in unloaded tonne kilometres rather than vehicle kilometres. This would be possible if data was available on the composition of the vehicle stock and the average unloaded weight of different types of vehicle. The second effect could be captured if useful work was measured in passenger kilometres rather than vehicle kilometres. This would require data on the average load factor of different types of vehicle. To capture both of these rebound effects, useful work would need to be measured in *loaded* tonne kilometres.

improves by 10% - or, alternatively, that 10% of the potential savings in gasoline consumption will be 'taken back' by increased distance driven.

As with Definition 1, Definition 2 may also be decomposed in a variety of ways, depending upon data availability and the choice of measure for useful work. For example, if useful work is defined as the product of the number, average output capacity and average utilisation of energy conversion devices, the equation becomes:

$$\eta_{\varepsilon}(E) = -[\eta_{P_S}(NO) + \eta_{P_S}(CAP) + \eta_{P_S}(UTIL)] - 1 \qquad (2.10)$$

A version of Definition 2 is derived by Khazzoom (1980), Berkhout *et al* (2000), Binswanger (2001) and Greene *et al* (1999a) and is generally used in preference to Definition 1 in empirical estimates of the direct rebound effect. For many energy services, the available data provides only limited variation in the independent variable for Definition 1 (ε), which leads to a high variance in the estimated elasticities while at the same time requiring energy prices to be controlled for. In contrast, the data frequently provides greater variation in the independent variable for Definition 2 (P_S), since this reflects both variations in energy efficiency and variations in energy prices. For many energy services, the historical and cross-sectional variations in the relevant energy commodity prices tend to be much greater than the corresponding variations in the energy efficiency of the relevant energy systems. Given the assumption that consumers respond in the same way to increases (decreases) in energy prices as to decreases (increases) in energy efficiency, Definition 2 provides a means to estimate the magnitude of direct rebound effects from energy efficiency improvements even in circumstances where the available data provides little or no variation in energy efficiency.

Empirical studies based upon Definition 2 require accurate measures of the energy cost of useful work (P_S) which depends upon both energy commodity prices and the energy efficiency of the relevant energy system ($P_S = P_E / \varepsilon$). But frequently, data on the energy efficiency of the relevant system is unavailable or of limited accuracy. An alternative approach, therefore, is to estimate the direct rebound effect from the elasticity of demand for useful work with respect to changes in energy prices alone ($\eta_{P_E}(S)$):

Definition 3: $\eta_{\varepsilon}(E) = -\eta_{P_E}(S) - 1$

As for Definition 2, Definition 3 relies upon the assumption that consumers respond in the same way to increases (decreases) in energy prices as to decreases (increases) in energy efficiency. In addition, unless energy efficiency is explicitly controlled for (i.e. $\eta_{P_E}(S)\big|_{\varepsilon}$), Definition 3 implicitly assumes that energy efficiency is <u>unaffected</u> by changes in energy prices (i.e. $\eta_{P_E}(\varepsilon) = 0$). If, instead, energy price changes induce changes in energy efficiency, the use of this measure to estimate the direct rebound effect could lead to bias since the change in the energy cost of useful work will not be directly proportional to the change in energy prices. However, Definition 3 is useful since it provides a means to estimate the magnitude of direct rebound effects even in circumstances where <u>no</u> data is available on energy efficiency.

Empirical studies based upon Definitions 2 and 3 still require accurate measures of the demand for useful work (S). But, depending upon how useful work is defined, this can be problematic. For example, the useful work from a domestic heating system could be defined as the average internal temperature of the house and measured directly using field thermometers or indirectly from thermostat settings. But the latter are notoriously inaccurate and can be a poor proxy for the thermal comfort of the occupants, which depends upon other variables such as humidity, airflow and the mean temperature of radiant surfaces (Greening and Greene, 1998). One reason that travel by private car is the most widely studied area for the direct rebound effect is that relatively good data is available on vehicle kilometres as a measure of useful work.

While obtaining measures of useful work (*S*) can be difficult, data is more commonly available on the energy demand (*E*) for the relevant energy service. For example, data may be available on the demand for gas for household heating. Again, if we assume that that energy efficiency is constant, the symmetry argument implied by the ratio $P_S = P_E / \varepsilon$ leads to an alternative definition for the direct rebound effect based upon the own price elasticity of energy demand ($\eta_{P_E}(E)$):

Definition 4: $\eta_{\varepsilon}(E) = -\eta_{P_E}(E) - 1$

It is this expression, rather than Definition 2, that was originally put forward by Khazzoom and is also used by Wirl (1997) in his comprehensive analysis of the economics of energy efficiency. Definition 4 shows that under certain assumptions, the direct rebound effect may be approximated by the own price elasticity of *energy* demand for the relevant energy service. As with Definition 3, Definition 4 relies upon the assumption that consumers respond in the same way to increases (decreases) in energy prices as to decreases (increases) in energy efficiency and that energy efficiency is unaffected by changes in energy prices.

The attraction of Definition 4 is that it avoids the need to collect data on either useful work or energy efficiency. It therefore provides a means for estimating direct rebound effects for a wider range of energy services. However, this definition is most useful when the energy demand in question relates to a single energy service (e.g. refrigeration). In practice, available measures of energy demand frequently apply to a collection of energy services (e.g. household electricity use), although techniques such as conditional demand analysis may allow the proportion of demand attributable to an individual service to be estimated (Parti and Parti, 1980).[7]

Empirical studies of the direct rebound effect for different energy services may use any of the above definitions, but the differences between studies are not always made clear. For example, in their comprehensive literature review of the rebound effect, Greening and Greene (1998) cite six econometric studies of household heating, but place particular weight on the methodologically rigorous studies of household survey data by Klein (1987), Hseuh and Gerner (1993) and Schwarz and Taylor (1995) (reviewed in Section 5).[8] As Table 2.1 makes clear, these three studies use different definitions of the dependent and independent variable, apply different methodologies and controls and focus upon different fuels. Only one

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[7] For example, Haas and Biermayr (2000) unbundled energy use for space heating from that for water heating by assuming that the latter was constant over the year, while the former depended upon external temperature.

[8] Greening and Greene (1998) cite 23 studies of household heating, but the majority of these are 'evaluation studies' which are discussed in *Technical Report 1*. Most of the heating studies are sponsored by US utilities and appear to be small-scale, short-term and methodologically weak. We have not been able to access these studies, which were originally reviewed by Nadel (1993). Greening and Greene simply reproduce Table 1 from Nadel (1993) and discuss a small number of additional econometric studies.

of the three studies (Schwarz and Taylor) represents an explicit investigation of rebound effects (the other two do not mention the term) and Greene and Greening's estimate of direct rebound effects is based upon a different elasticity measure in each case. Clearly, the existing literature is too small and diverse to allow a consistent approach to this issue.

Table 2.1 Varying estimates of the direct rebound effect for household heating

Study	**Dependent variable**	**Approach**	**Greening and Greene (1998) estimate the direct rebound effect from:**
Klein (1987)[1]	Proxy measure for *S* estimated from difference between thermostat setting and external temperature	Simultaneous estimation of a cost function for *S*, a demand function for *S* and an equation for the relative share of capital and fuel	$\eta_{P_G}(S)$
Hseuh and Gerner (1993)[2]	*E* estimated from energy bill. (No measure of *S* available)	Estimates an equation for the demand for *E.* incorporating engineering and other variables that affect the demand for *S*.	$\eta_{P_E}(E)$
Schwarz and Taylor (1995)[3]	Two proxy measures for *S:* thermostat setting and estimated demand for heat	Estimate a equation for the demand for *S*, that incorporates a variable representing the thermal resistance of the house	$\eta_{\varepsilon}(S)$

Notes:

1. Space heating demand is defined as the difference between the internal thermostat setting and the external temperature during the heating season. Klein specifies simultaneous equations for the total cost of space heat, the share of energy costs in total costs and the demand for space heat (*S*). Simultaneous equations are required because *S* appears in both the cost function and the factor share equation and individual household attributes affect both the production and consumption decision. The study estimates the elasticity of demand for space heat with respect to the generalised cost of space heat ($\eta_{P_G}(S)$), but Greening and Greene incorrectly interpret this as $\eta_{P_S}(S)$, thereby overestimating the direct rebound effect. The study does not mention the rebound effect specifically.

2. In principle, the reduced form equation should allow $\eta_{\varepsilon}(E)$ to be estimated - where ε represents the overall energy efficiency of the household, including both building fabric and energy conversion devices. But Hseuh and Gerner only quote the change in energy consumption following a physical change in one element of the system, such as increasing insulation thickness by one inch. So instead of $\eta_{\varepsilon}(E)$, Greene and Greening take the estimate of $\eta_{P_E}(E)$ as a measure of the direct rebound effect for electricity only, but the estimate for natural gas is ignored, although the gas equation provides more reliable estimates owing to the larger sample size.

3. The measure of energy efficiency is the thermal resistance of the house. The data and specification allows the energy efficiency elasticity of the thermostat setting and the energy efficiency elasticity of the demand for useful work to be estimated. The difference between each of these and -1 are taken as alternative measures of the direct rebound effect.

Following Definition 4, a number of authors have used new or existing estimates of the own-price elasticity of energy demand as approximate indicators of the magnitude of the direct rebound effect (Zein-Elabdin, 1997; Berkhout*, et al.*, 2000; Roy, 2000; Bentzen, 2004). This opens up a very large evidence base, as reviewed, for example by Espey (1998) and Dahl (1991). Most studies suggest that energy demand is relatively inelastic, with typical values ranging from -0.3 to –0.9 in the long run. Applying Definition 4, these figures suggest that some 30-90% of energy savings deriving from energy efficiency improvements may be 'taken-back' by the direct rebound effect. However, Definition 4 is likely to significantly overestimate the direct rebound effect for reasons discussed below. Also, elasticity estimates vary widely between different energy commodities, end-uses, sectors, countries and levels of aggregation; as well as increasing proportionately with the price level (Douthitt, 1989; Berkhout*, et al.*, 2000).

Of particular importance is the fact that elasticities tend to be higher for periods with rising energy prices than for periods with falling energy prices (Gately, 1992a; 1993; Dargay and Gately, 1994; 1995; Haas and Schipper, 1998). For example, Dargay (1992) found that the reduction in UK energy demand following the price rises of the late 1970s was five times greater than the increase in demand following the price collapse of the mid-1980s. Two explanations for this are that higher energy prices induce technological improvements in energy efficiency that are not reversed when energy prices fall, while investment in measures such as thermal insulation is largely irreversible over the short to medium-term (Grubb, 1995). Energy efficiency requirements may also become embodied in regulations that ensure that new investments maintain high standards, even in the absence of a price incentive. As a result, estimates of price elasticities based upon time-series data are likely to vary according to whether energy prices were rising, falling (or both) over the period in question (Haas and Schipper, 1998). In the case of the direct rebound effect, the appropriate proxy for energy efficiency improvements is *reductions* in energy prices. Hence, empirical estimates based upon periods of rising energy prices are likely to <u>overestimate</u> the size of the effect.

Econometric estimates based upon Definitions 2, 3 or 4 are a primary source of evidence for the direct rebound effect. Hence, the assumptions behind these definitions - and particularly the 'symmetry' argument - require careful scrutiny. The following three sections explore the limitations of these definitions in more detail, focusing on:

- the correlation between energy efficiency and other input costs, notably capital costs;
- the endogeneity of energy efficiency and the implied need for simultaneous equation estimation; and
- the role of time costs and time efficiency in the production and consumption of energy services.

2.5 Correlation between energy efficiency and other input costs

For an individual energy service, changes in energy commodity prices are unlikely to be correlated with changes in other input costs or with changes in the broader attributes of the energy service. But the same cannot be said about changes in energy efficiency. In many (although by no means all) cases, energy efficient conversion devices will have a higher capital cost than inefficient models (i.e. ε and K will be positively correlated). For example, UK building regulations now require high efficiency condensing boilers to be used when installing or replacing a domestic central heating system and these have historically cost some £200-300 more than a conventional boiler.

Khazzoom (1980) assumed this problem away by arguing that a more energy efficient appliance does not necessarily entail a greater initial cost and citing the lower cost of smaller and more fuel-efficient cars as an example. But in this case, the improvement in energy efficiency may have been achieved at the expense of other attributes of the energy service, such as carrying capacity and legroom (i.e. ε and *A* will be negatively correlated). In general, improvements in energy efficiency could result from energy-saving technological change, substitution between energy and other inputs in the production of useful work, or substitution between useful work and other attributes of the energy service. In practice, many energy services have multiple attributes (e.g. size, comfort, reliability, speed) and each attribute may have non-zero elasticity with respect to the energy cost of useful work. As Einhorn (1982) has argued, the long-term response to a reduction in energy costs will depend upon the trade-offs between useful work and these multiple attributes.

Khazzoom's neglect of capital costs has been challenged by several authors (Besen and Johnson, 1982; Einhorn, 1982; Henly, et al., 1988; Lovins, et al., 1988) who argue that it may lead empirical studies that rely upon Definitions 2, 3 or 4 to overestimate the direct rebound effect. Henly *et al* (1988) illustrate this clearly by including annualised capital costs (P_K) in the equation for energy demand. Assuming that capital costs are a function of energy efficiency, the basic identity becomes: $E = s[P_E/\varepsilon, P_K(\varepsilon)]/\varepsilon$. We can then derive[9] the following alternative definition of the energy efficiency elasticity of energy demand:

Extension 1: $\eta_\varepsilon(E) = -\left[\eta_{P_S}(S) - \left(\eta_{P_K}(S)\eta_\varepsilon(P_K)\right)\right] - 1$

Compared to Definitions 2-4 there is an additional term in brackets. This is the product of the elasticity of demand for useful work with respect to capital costs ($\eta_{P_K}(S)$) and the elasticity of capital costs with respect to energy efficiency ($\eta_\varepsilon(P_K)$). We expect the first of these to be negative: higher capital costs should reduce the long-run demand for useful work, largely because they should reduce the number of energy conversion devices ($\eta_{P_K}(NO) \leq 0$) and/or their average size ($\eta_{P_K}(CAP) \leq 0$ - assuming that capital costs are proportional to size). Under the assumption that energy efficient equipment is more expensive, the second term will be positive, making the product of these two expressions negative. The net result will be to reduce the absolute magnitude of the elasticity of energy demand with respect to energy efficiency ($|\eta_\varepsilon(E)|$). Hence, if energy efficient equipment is more expensive, the direct rebound effect may be *smaller* than suggested by studies that rely primarily upon historical or cross-sectional variations in energy prices and estimate the direct rebound effect from Definitions 2, 3 or 4. This is because the change in energy service demand following a change in energy prices will be different from that following a change in energy efficiency. In general, such studies will tend to overestimate the direct rebound effect. The size of this upward bias will depend upon the relative magnitude of the three separate elasticities.

The correlation between energy efficiency and capital costs may be expected to vary between energy services and over time. In areas such as computing, for example,

[9] See Annex 1

improvements in energy efficiency have long been associated with both improvements in service attributes and *reductions* in capital costs (Triplett, 1989). Also, higher capital costs will only reduce the direct rebound effect if the consumer faces the full cost of the purchase decision. If, for example, the additional cost of energy efficient conversion devices is fully subsidised, the higher initial cost should not affect the purchase decision. Furthermore, if government subsidies make energy-efficient devices *cheaper* than inefficient models, it is possible that the rebound effect will be amplified (i.e. if both $\eta_{P_K}(S)$ and $\eta_{\varepsilon}(P_K)$ are negative, their product will be positive). Moreover, the key variable may not be the initial cost of the equipment, but the discounted costs over the equipment lifetime, which depends upon consumer time preferences and the relative durability and lifetime of different models.

Consideration of the role of capital costs further highlights the importance of distinguishing between the number, capacity and utilization of energy service devices when estimating direct rebound effects. Once an appliance is purchased, the capital cost is sunk and hence should be irrelevant to the utilisation decision. But higher capital costs may lead to the purchase of fewer, smaller and/or different conversion devices, depending upon the trade-offs between different categories of input costs and between useful work and other output attributes. Holding output attributes constant, energy efficient conversion devices allow their owners to enjoy a greater consumer surplus in each time period, owing to the higher demand for useful work (Einhorn, 1982). But if the more efficient appliance is also more expensive than the inefficient alternative, it will only be purchased by an 'economically rational' consumer if the present value of the discounted stream of additional consumer surplus exceeds the present value of the additional capital cost. A mandatory requirement for new capital equipment to meet high standards of energy efficiency could mean that consumers will either: choose to delay replacing their existing equipment (if owned and if still working); choose to purchase smaller or different equipment; choose to purchase inefficient, second-hand equipment; or choose to go without the energy service altogether. The net effect on energy consumption for the relevant energy service over a particular period of time could therefore be ambiguous. But in all cases, the effect of the energy efficiency standard will be different from that of a change in energy prices, so an estimate of the direct rebound effect based upon the latter is likely to be incorrect.

It is also possible that improvements in energy efficiency will be associated with changes in other input costs, such as operation and maintenance (O&M) costs. If, for example, more efficient conversion devices are less reliable and more costly to maintain and operate, the effect of energy efficiency improvements on the demand for useful work will again be different from the effect of changes in energy prices. However, the evidence for a positive correlation between energy efficiency and O&M costs is absent for most energy services, and for some the correlation may be negative. In general, the magnitude and direction of the bias in estimating the direct rebound effect using Definitions 2, 3 or 4 will depend upon the degree and sign of the correlation between energy efficiency and all other categories of input costs. If they are positively correlated, the bias will be negative and the direct rebound effect may be overestimated, while if they are negatively correlated the bias will be positive and the rebound effect may be underestimated.

Even if improvements in energy efficiency are not associated with changes in other input costs, certain types of direct rebound effect may be constrained by the real or opportunity costs associated with increasing the demand for useful work. Two important examples are the opportunity cost of space (e.g. increasing refrigerator size may not be the best use of available space) and the opportunity cost of time (e.g. driving longer distances may not be the best use of available time). Both of these examples point to constraints on the demand for certain categories of useful work by individual households. However, space constraints may become less important over time if technological improvements reduce the average size of conversion devices per unit of useful work (e.g. computing) or if rising incomes lead to an increase in average living space (e.g. compare refrigerator sizes in the US and the UK) (Wilson and Boehland, 2005). In contrast, while technological improvements may reduce the time requirements per unit of useful work, the opportunity cost of time should *increase* with rising incomes. This illustrates, again, that direct rebound effects are not fixed, but vary over time and depend upon income and other factors. The relationship between time constraints and energy service consumption appears particularly important and is discussed further below.

2.6 Endogenous energy efficiency

Definitions 1-4 assume that energy efficiency is independent of the values of other independent variables – in other words, that it is *exogenous*. This follows naturally from Khazzoom's original focus on the effect of mandatory energy efficiency standards for household appliances. In practice, however, the system-wide level of energy efficiency is likely to be influenced by one or more of the other dependent variables – in other words, energy efficiency must be considered partly *endogenous*. In particular, energy efficiency may be expected to be a function of current and historical energy prices: $\varepsilon(P_E)$ (Greene*, et al.*, 1999b; Small and Van Dender, 2005). In the short term, increases in energy commodity prices may encourage consumers to utilise existing equipment in more energy efficient ways – such as increasing average load factor (e.g. car sharing), or adopting energy efficient operating practices (e.g. avoiding excessive speed). In the longer term, consumers may choose to purchase more energy efficient conversion devices, while producers may choose to devote expenditure to developing, improving and marketing such devices.

If the demand for useful work depends upon the energy cost of useful work ($S = s[P_E / \varepsilon]$) and energy efficiency depends upon energy prices ($\varepsilon = \varepsilon(P_E)$), the demand for energy for the relevant energy service may be represented as $E = S / \varepsilon = s[P_E / \varepsilon(P_E)] / \varepsilon(P_E)$. If we differentiate this expression with respect to energy prices and substitute the resulting expression for $\eta_{P_S}(S)$ into Definition 2, we obtain an alternative definition of the direct rebound effect that takes into account price-induced energy efficiency improvements:

Extension 2: $$\eta_\varepsilon(E) = -\left[\frac{\eta_{P_E}(E) + \eta_{P_E}(\varepsilon)}{1 - \eta_{P_E}(\varepsilon)}\right] - 1$$

Where the expression in square brackets represents the energy cost elasticity of the demand for useful work ($\eta_{P_S}(S)$).

Previous versions of this equation have appeared in Blair *et al* (1984b), Mayo and Mathis (1988) and Small and Van Dender (2005). In principle, Extension 2 provides an alternative method of estimating the direct rebound effect. Rather than estimating the energy cost elasticity of the demand for useful work, one could separately estimate the own price elasticity of energy consumption for the relevant energy service ($\eta_{P_E}(E)$) *and* the elasticity of energy efficiency with respect to energy prices ($\eta_{P_E}(\varepsilon)$). The resulting calculated value for the energy cost elasticity of the demand for useful work ($\eta_{P_S}(S)$) could then be used to estimate the direct rebound effect.

It is clear from Extension 2 that the energy cost elasticity of the demand for useful work ($\eta_{P_S}(S)$) will only be equal to the own price elasticity of the demand for energy for the relevant energy service ($\eta_{P_E}(E)$) if the energy price elasticity of energy efficiency is equal to zero ($\eta_{P_E}(\varepsilon)=0$). This is unlikely to be the case in practice. Annex 2 derives an expression for the relative magnitude of different price elasticities that should hold for all econometric estimates (see also Hanley *et al.* (2002)):

$$\left|\eta_{P_E}(S)\right| \le \left|\eta_{P_S}(S)\right| \le \left|\eta_{P_E}(E)\right| \le \left|\eta_{P_S}(E)\right| \qquad (2.11)$$

This relationship provides a valuable point of reference for the results from individual studies and is supported by evidence from recent surveys (Espey, 1998; Hanley*, et al.*, 2002; Graham and Glaister, 2004). It suggests that:

- The elasticity of demand for useful work with respect to the energy cost of useful work should be <u>greater</u> than the elasticity of the demand for useful work with respect to energy prices ($\left|\eta_{P_E}(S)\right| \le \left|\eta_{P_S}(S)\right|$). This shows that, relative to Definition 2, Definition 3 is likely to <u>underestimate</u> the magnitude of the direct rebound effect due to the neglect of price-induced energy efficiency improvements.
- The elasticity of demand for useful work with respect to the energy cost of useful work should be <u>smaller</u> than the elasticity of energy demand with respect to energy prices ($\left|\eta_{P_S}(S)\right| \le \left|\eta_{P_E}(E)\right|$). This shows that, relative to Definition 2, Definition 4 is likely to <u>overestimate</u> the magnitude of the direct rebound effect due to the neglect of price-induced energy efficiency improvements.

Equation 2.11 also suggests that the own price elasticity of energy demand for a particular energy service should provide an *upper bound* for the direct rebound effect for that service (since $\left|\eta_{P_S}(S)\right| \le \left|\eta_{P_E}(E)\right|$). This suggests that the voluminous literature on own price elasticities of energy demand may be used to provide an upper bound on the likely magnitude of direct rebound effects. This is an important result that is used subsequently in Sections 4 and 5.

It seems likely that energy efficiency will also be a function of other endogenous or exogenous variables in ways that could bias the results of empirical studies (Small and Van Dender, 2005). In particular, if consumers expect to have a high demand for useful work, they may be more likely to choose an energy-efficient conversion device in order to minimise the energy cost of useful work. For example, drivers may choose to purchase a more fuel-efficient car if they expect to drive long distances.[10] This may create a positive correlation between S and ε that is in addition to the positive correlation created by the direct rebound effect. If this is not corrected for in empirical studies, the magnitude of the

[10] This is a hypothesis to be tested. A counter argument could be that drivers will purchase larger cars if they expect to drive long distances, since these are more comfortable. As larger cars tend to be less fuel-efficient, this may lead to a negative correlation between S and ε.

direct rebound effect will again be overestimated. Moreover, as pointed out by Small and Van Dender (2005), this type of endogeneity makes the logic behind Definition 2 circular: the demand for useful work (*S*) depends upon the energy cost of useful work (P_S), which in turn depends upon energy efficiency (ε) which in turn depends upon the demand for useful work (*S*).

This simultaneous determination of an endogenous variable (ε) with another endogenous variable *(S)* can be captured empirically with a simultaneous equation model. This starts with a set of *n* equations for *n* endogenous variables, with each equation representing either a causal relationship or an equilibrium condition. Such models could be formulated in a variety of ways, depending upon data availability. Small and Van Dender (2005), for example, use aggregate data for each US state and establish separate equations for the number (*NO*) of private cars in each state, their total annual mileage (*S*) and the average fuel efficiency of the state vehicle fleet (ε). Small and Van Dender base their model upon the following generic assumptions regarding consumer choices:

- The total demand for useful work (*S*) is influenced by the number of energy conversion devices (*NO*), the energy cost of useful work ($P_S = P_E / \varepsilon$) and a number of exogenous variables (X_S).
- The number of energy conversion devices (*NO*) is influenced by the capital cost of those devices (P_K), the *anticipated* demand for useful work (*S*), the energy cost of useful work (P_E / ε) and a number of exogenous variables (X_N).
- The average energy efficiency of the stock of conversion devices (ε) is influenced by the price of energy (P_E), the anticipated demand for useful work (*S*), regulatory standards on the energy efficiency of new devices (R_ε) and a number of exogenous variables (X_ε).

This leads to the following set of ‘structural’ equations:

$$\begin{aligned} S &= s(NO,(P_E/\varepsilon),X_S) \\ NO &= no(P_K,S,(P_E/\varepsilon),X_{NO}) \\ \varepsilon &= \varepsilon(P_E,S,R_\varepsilon X_\varepsilon) \end{aligned} \qquad (2.12)$$

It is an empirical question as to whether a simultaneous equation model is appropriate for a particular energy service. In some cases, the joint dependence of some or all of the variables may either not hold or be sufficiently weak that it can be ignored. For example, Johansson and Schipper (Johansson and Schipper, 1997) assumed that mean driving distance per vehicle was a function of the number of vehicles and their average fuel efficiency, but argued that the latter did not depend upon mean driving distance because: ‘…..one chooses what distance to drive for a given vehicle stock with different characteristics, and not the other way round’ (Johansson and Schipper, 1997). In contrast, Small and Van Dender (2005), Greene *et al* (1999b) and Wheaton (1982) all formulate models in which energy efficiency is a function of the number of cars and distance driven and each find the relevant coefficients to be statistically significant.[11]

[11] However, Small and Van Dender find no support for the endogeneity implied by the second of the equations in (9), since the coefficients on P_S and *S* are not significant.

The key point, however, is that *if* joint dependence is relevant, the equations need to be estimated through an appropriate econometric technique, such as the use of instrumental variables. If, instead, one or more of the individual equations are estimated through ordinary least squares (OLS), the resulting coefficients will be biased and inconsistent owing to correlation between the endogenous variable and the error term. As an illustration, Small and Van Dender (2005) found that the use of OLS in their model overestimated the short and long-run direct rebound effects for car travel by 88% and 53% respectively (although factors other then endogeneity may have been involved).

The use of a simultaneous equation model provides a clearer understanding of the implications of changes in energy efficiency, whether induced by regulatory intervention, energy price increases or other factors. For example, a mandatory standard for the energy efficiency of new conversion devices will have a *direct* effect on the energy efficiency of the stock, through the third of the equations in (9). However, improvements in energy efficiency will also tend to increase the number of conversion devices (e.g. the number of cars), which in turn will increase the total demand for useful work. Improvements in energy efficiency should also increase the demand for useful work (e.g. the distance driven by each car) by reducing the associated energy costs. The net increase in the demand for useful work will in turn encourage higher energy efficiency. Hence, a change in an exogenous variable such as regulatory standards for energy efficiency may trigger a complex set of changes within the system until a new equilibrium is reached. If the behavioural assumptions given above hold, the total change in system-wide energy efficiency following the regulatory intervention will be greater than the direct change, as will the total change in the demand for useful work.

The structural equations may be solved to allow each of the endogenous variables to be written solely as functions of the exogenous variables, giving so-called 'reduced form' equations. However, many empirical estimates of the direct rebound effect use neither a structural equation system nor their reduced form solution. Instead, they employ what Small and Van Dender (2005) term a 'partially reduced form' equation for S, denoted here by the symbol $\hat{s}$. This includes energy efficiency indirectly via the energy cost of useful work, but does not include the number or capacity of conversion devices:

$$S = \hat{s}(P_K, (P_E / \varepsilon), X_{NO}, X_S) \qquad (2.13)$$

Since energy efficiency is endogenous, estimation of this equation by OLS is likely to lead to biased estimates of the direct rebound effect. Moreover, the bias will be compounded if (as is commonly the case), capital costs (P_K) or other input costs are correlated with either S or ε, but are omitted from the equation owing to lack of data.

2.7 Energy efficiency and time costs

The model summarised in Section 2.1 is based upon Becker's work on the allocation of time within household production (Becker, 1965). As Binswanger (2001) has argued, time costs and the efficiency of time use have important implications for energy use in general and the direct rebound effect in particular. However, empirical work in this area remains in its infancy (Jalas, 2002).

For consumers, time is a necessary input to the production and enjoyment of energy services. For example, it takes time to drive from one place to another; to purchase food; to prepare a meal; to wash, dry and iron clothes and so on. The total cost of time for a particular energy service will depend upon the opportunity cost of time and the amount of time required per unit of useful work. In the household production model, the cost of time is conventionally measured by the average hourly wage for the household (P_W) and hence should vary from one household to another. The amount of time required per unit of useful work may be measured by the efficiency of time use (θ), which depends upon the technology used. For example, a microwave oven is more time efficient than a conventional oven; a car is more time efficient than a bike;[12] an aircraft is more time efficient than a ship; and so on. The relationship between useful work and time consumption for a particular energy services may then be expressed as: $S = \theta T$, while the time cost per unit of useful work may be expressed as $P_T = P_W / \theta$. These expressions are entirely analogous to those used for energy consumption for a particular energy service (namely $S = \varepsilon E$ and $P_S = P_E / \varepsilon$).

Under these assumptions, the contribution of time costs to the full cost of an energy service should be inversely proportional to the time efficiency of the relevant technology and proportional to the wage rate. Similarly, the contribution of energy costs should be inversely proportional to the energy efficiency of the relevant technology and proportional to the energy price. Consumers may be able to choose between technologies with different combinations of energy and time efficiency in the provision of a particular energy service, and also between energy services with different levels of time and energy efficiency. The relative price of time and energy should influence the direction of technological innovation and encourage higher or lower levels of time/energy efficiency for individual energy services, as well as shifts towards the development of more or less time/energy efficient services.

These considerations suggest that an increase in the cost of time (i.e. wages) relative to energy prices should induce a substitution away from time and toward energy in the production of individual services, as well as a substitution away from time-intensive services and towards energy intensive services.[13] Since, in real terms, wages have grown faster than energy prices within developed countries over most of the last century, this mechanism could be an important driver of increased energy consumption (Binswanger, 2001). With time costs forming a significant proportion of the total cost of many energy services, consumers and producers have sought ways to improve the time efficiency, rather than the energy efficiency, of service provision. So travel by private car has replaced walking, cycling and public transport; automatic washing machines have replaced washing by hand; fast food and ready meals have replaced traditional cooking; supermarkets (and more recently e-shopping and home delivery) have replaced the trip up the high street; email has postal services; and so on. Increases in aggregate energy consumption could therefore have been driven as much by the substitution of energy for time as by the overall increases in income.

The relative importance of time costs and energy costs may be expected to vary over time and between different energy services. One area where time costs are particularly important and relatively well researched is transport. For example, figures presented by Small (1992)

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[12] Assuming no road congestion. As with energy efficiency, time efficiency is a function of the overall energy system, which could have multiple users. While congestion is given for individual decisions, it is an endogenous variable for the system as a whole.

[13] Note that traditional consumer theory would only capture the second of these effects and that the model implies that increases in non-wage income would not encourage either type of substitution.

suggest that the average time costs for US car travel were more than three times total running costs, implying that they were more than six times the total fuel costs. If the value of time is proportional to the average wage, this ratio will be higher for high-income groups and may be expected to increase over time if real incomes continue to increase faster than energy prices. For other energy services, such as household heating for example, time costs may be a less significant determinant of demand. However, time costs for this service may have been much greater in the past when coal or wood fires were the norm, since time was required for preparing and lighting the fuel. In many developing countries, the time required to collect fuelwood remains an enormous burden.

In those cases where technology permits a trade-off between the two, time efficiency may be represented as a function of energy efficiency ($\theta(\varepsilon)$) or vice versa ($\varepsilon(\theta)$). By taking the first of these, we may write the energy demand for a particular energy service as: $E = s[P_S(\varepsilon), P_T(\theta(\varepsilon))]/\varepsilon$. This leads to an alternative definition of the direct rebound effect that takes into account the associated changes in time costs:

Extension 3: $\eta_\varepsilon(E) = -\left[\eta_{P_S}(S) + \left(\eta_{P_T}(S)\eta_\theta(P_T)\eta_\varepsilon(\theta)\right)\right] - 1$

Again, as compared to Definitions 2 and 3 there is an additional term in brackets. This is the product of the elasticity of demand for useful work with respect to time costs ($\eta_{P_T}(S)$), the elasticity of time costs with respect to time efficiency ($\eta_\theta(P_T)$) and the elasticity of time efficiency with respect to energy efficiency ($\eta_\varepsilon(\theta)$). We expect the first of these to be negative (higher time costs should reduce the demand for useful work) and the second to be positive (higher time efficiency should reduce time costs). However, the sign of the last elasticity is ambiguous: while substitution between energy and time implies that energy efficiency is negatively correlated with time efficiency, technological improvements may sometimes improve both (e.g. microwave ovens). However, in many cases greater energy (time) efficiency is likely to be achieved at the expense of lower time (energy) efficiency (i.e. θ and ε will be negatively correlated). For example, a sports car is less energy efficient than a Smart car; aircraft are less energy efficient than ships; washing machines are less energy efficient than hand-washing; and so on. In these circumstances, the resulting increase in time costs will offset the saving in energy costs leading to a smaller direct rebound effect with respect to improvements in energy efficiency. For example, while greater fuel efficiency may make driving cheaper, consumers may not be willing to spend the time driving greater distances. This suggests that, for those energy services where trade-offs between time and energy efficiency are relevant, empirical estimates based upon Definitions 2 and 3 and relying primarily upon historical or cross-sectional variations in energy prices may <u>overestimate</u> the magnitude of the direct rebound effect.

As with capital costs, the size of this upward bias will depend upon the relative magnitude of the different elasticities. One notable implication is that, for time-intensive energy services, direct rebound effects from improved energy efficiency may be expected to decrease over time. One of the few studies to show evidence for this is Small and Van Dender (Small and Van Dender, 2005), although their methodology was subsequently criticised by Harrison *et al* (2005).

If energy efficiency is influenced by energy prices and if improvements in energy efficiency are associated with changes in both time costs and capital costs, the appropriate expression for the direct rebound effect incorporates all three of the extensions developed above:

$$\eta_\varepsilon(E) = -\left[\left(\frac{\eta_{P_E}(E) + \eta_{P_E}(\varepsilon)}{1 - \eta_{P_E}(\varepsilon)}\right) - \left(\eta_{P_K}(S)\eta_\varepsilon(P_K)\right) + \left(\eta_{P_T}(S)\eta_\theta(P_T)\eta_\varepsilon(\theta)\right)\right] - 1 \qquad (2.14)$$

As pointed out by Binswanger (2001), the analogy between time and energy efficiency also suggests that there should be a parallel *rebound effect with respect to time*. Since improvements in the time efficiency associated with a particular service lower the cost of that service, there should be a corresponding increase in service demand that will offset the potential time savings. Again, transport provides a particularly good example: the potential time savings from faster modes of transport may be partly or wholly taken back by traveling greater distances. For example, in the UK, the time spent travelling increased by only 17% between 1975 in 2005, while the total distance travelled increased by 52% (Department of Transport, 2006). Similar patterns are likely to apply to other energy services (e.g. washing clothes more often), but may be less important if time costs form a smaller proportion of total costs, or if the assumptions of the simple Becker model (e.g. no joint production) do not apply.

The rebound effect with respect to time may be defined as an efficiency elasticity ($\eta_\theta(T) = \eta_\theta(S) - 1$) or as a price elasticity ($\eta_\theta(T) = \eta_{P_T}(S) - 1$) in a similar manner to the conventional direct rebound effect. Empirical investigation of this effect would similarly need to take into account the potential correlation between improvements in time efficiency and other input costs (including capital and energy costs); and the potential endogeneity of time efficiency (e.g. consumers may choose a more time efficient technology if they anticipate a high demand for the service). But in the absence of good data on time use patterns and time efficiency, such considerations remain academic.

Both the substitution of energy for time in the production and consumption of energy services, and the subsequent rebound effect with respect to time should act to increase overall energy consumption. Indeed, it is possible that these processes have had a more important influence upon aggregate energy consumption than the conventional direct rebound effect with respect to energy efficiency. Moreover, if wages continue to increase faster than energy prices, the substitution of energy for time may be expected to increase in importance, while the conventional direct rebound effect decreases in importance. To date, however, attention has focused disproportionately on the latter.

2.8 Summary

This section began by clarifying the distinction between energy inputs (*E*) and 'useful work' outputs' (*S*) and argued that 'energy services' (*ES*) comprise both useful work and other attributes (*A*). It then showed how the consumption of an energy service involved trade-offs between: first, the consumption of useful work and the consumption of those other attributes; second, the use of energy and the use of other inputs in the production of that energy service; and third, the consumption of different types of energy service.

The section then introduced the four definitions of the direct rebound effect in common use, identified their underlying assumptions and clarified the relationship between them. It distinguished:

- the 'engineering' definition of the direct rebound effect as the energy efficiency elasticity of the demand for energy or useful work (Definition 1);
- the 'economic' definition of the direct rebound effect as the energy cost elasticity of the demand for useful work (Definition 2);
- a first approximation to the direct rebound effect based upon the energy price elasticity of the demand for useful work (Definition 3); and
- a second approximation to the direct rebound effect, based upon the own-price elasticity of the demand for energy (Definition 4).

These definitions are summarised in Table 2.2. The appropriate choice for empirical work will depend upon the availability, accuracy and variability of the relevant data and a range of other considerations. In principle, in the absence of any data constraints, empirical studies using Definition 1 should estimate the direct rebound effect more accurately than those using Definition 2, while studies using Definition 2 should estimate the direct rebound effect more accurately than those using Definitions 3 or 4. In practice, however, there are far more estimates of the own price elasticity of energy demand (Definition 4) then there are of the other elasticities listed in Table 2.1. While Definition 4 provides a relatively poor approximation to the direct rebound effect, simple theoretical arguments suggest that it should provide an *upper bound* for the direct rebound effect (since, from Equation 2.11, $\left|\eta_{P_S}(S)\right| \leq \left|\eta_{P_E}(E)\right|$).

Table 2.1 Definitions of the direct rebound effect

Definition 1	$\eta_\varepsilon(E) = \eta_\varepsilon(S) - 1$
Definition 2	$\eta_\varepsilon(E) = -\eta_{P_S}(S) - 1$
Definition 3	$\eta_\varepsilon(E) = -\eta_{P_E}(S) - 1$
Definition 4	$\eta_\varepsilon(E) = -\eta_{P_E}(E) - 1$

Notes:
- Symbols in parentheses stand for elasticity numerators while subscripts represent elasticity denominators
- *S*: Useful work; *E*: Energy; P_S: Energy cost of useful work; P_E: Energy price; ε: energy efficiency.

This section has also shown how the different ways in which useful work is defined and measured can lead to different conclusions regarding the nature and size of the effect. For example, improvements in the energy efficiency of washing machines may lead to a different outcome in terms of weight of clothes washed per year than in terms of hours of use. If the demand for energy or useful work can be decomposed into its constituent elements, such as the number, capacity and utilisation of energy conversion equipment, the determinants of short and long-run direct rebound effects may be much better understood.

Many empirical estimates of the direct rebound effect are based upon Definitions 2, 3 or 4 rather than Definition 1 and rely either primarily (Definition 2) or entirely (Definitions 3 & 4) upon historical or cross-sectional variations in energy prices. This section has argued that such studies could potentially <u>overestimate</u> the magnitude of the effect. Three important factors that may contribute to this are:

- the anticipated positive correlation between energy efficiency and other categories of input costs, notably capital costs (Extension 1);

- the role of price induced energy efficiency improvements (Extension 2); and
- the anticipated negative correlation between energy efficiency and time efficiency and the corresponding implication that direct rebound effects may decline with income (Extension 3).

Consideration of these factors led to the derivation of three extensions to Definition 2 which are summarised in Table 2.2.

Table 2.3 Extensions of Definition 2

Extension 1 (capital costs)	$\eta_{\varepsilon}(E) = -\left[\eta_{P_S}(S) - \left(\eta_{P_K}(S)\eta_{\varepsilon}(P_K)\right)\right] - 1$
Extension 2 (endogneity)	$\eta_{\varepsilon}(E) = -\left[\dfrac{\eta_{P_E}(E) + \eta_{P_E}(\varepsilon)}{1 - \eta_{P_E}(\varepsilon)}\right] - 1$
Extension 3 (time costs)	$\eta_{\varepsilon}(E) = -\left[\eta_{P_S}(S) + \left(\eta_{P_T}(S)\eta_{\theta}(P_T)\eta_{\varepsilon}(\theta)\right)\right] - 1$

Notes:

- Symbols in parentheses stand for elasticity numerators while subscripts represent elasticity denominators
- *S*: Useful work; *E*: Energy; P_S: Energy cost of useful work; P_E: Energy price; ε: energy efficiency; θ: time efficiency

Combining all these extensions leads to the following expression:

$$\eta_{\varepsilon}(E) = -\left[\left(\frac{\eta_{P_E}(E) + \eta_{P_E}(\varepsilon)}{1 - \eta_{P_E}(\varepsilon)}\right) - \left(\eta_{P_K}(S)\eta_{\varepsilon}(P_K)\right) + \left(\eta_{P_T}(S)\eta_{\theta}(P_T)\eta_{\varepsilon}(\theta)\right)\right] - 1 \qquad (2.15)$$

Consideration of time costs also points to the potential importance of the substitution of energy for time in the provision of energy services, together with possibility of a parallel 'rebound effect with respect to time'. Both of these subjects deserve further research.

Two additional factors were identified that could potentially lead to upwardly biased estimates of the direct rebound effect. First, it was noted that energy price elasticities tend to be higher for periods with rising energy prices than for those with falling energy prices. Since the appropriate proxy for energy efficiency improvements is *reductions* in energy prices, empirical estimates using time-series data that include periods of rising energy prices could potentially overestimate the effect. Second, it was argued that energy efficiency cannot always be treated as exogenous since it may be influenced by other variables in ways that could bias the results of empirical studies. For example, if consumers expect to have a high demand for useful work, they may be more likely to choose an energy-efficient conversion device in order to minimise the energy cost of useful work. This may create a positive correlation between *S* and ε that is in addition to the positive correlation created by the direct rebound effect. If such endogneity is not corrected for in empirical studies, the magnitude of the direct rebound effect will again be overestimated.

Different studies address these factors in different ways and to a greater or lesser extent, with some of the best examples being recent US studies of personal automotive transport (Greene*, et al.*, 1999b; Small and Van Dender, 2005). The relative merits of different empirical approaches to estimating the direct rebound effect are discussed further in Section 3.

3 Econometric approaches to estimating the direct rebound effect

3.1 Introduction

Subsequent sections review a selection of empirical estimates of the direct rebound effect. The selected studies form a subset of a much larger literature that uses econometric techniques to estimates the own price elasticity of energy demand in different circumstances. All of this literature has some relevance to the direct rebound effect, but a comprehensive review would be wholly impractical. Instead, we confine attention to a relatively small number of studies that are considered to provide robust estimates of the direct rebound effect for particular energy services. This section sets out the criteria by which these studies were selected.

In an early survey of econometric studies of energy demand, Bohi and Zimmerman (1984) noted that: "…. the information is sometimes bewildering…because of the variety of techniques employed and the disparities among the results." In the 20 years since this comment was made, the literature has become even more confusing owing to the number of studies published, their increasing diversity and the introduction of new and highly sophisticated techniques such as cointegration (Madlener, 1996). This makes it difficult to provide a meaningful overview of the literature, or to compare the results of different studies.

While Bohi and Zimmerman's review covered the full range of econometric studies of energy demand in OECD countries, attention is confined here to a relatively small subset of this literature. Nevertheless, many of the same difficulties of interpretation arise. In particular, individual studies are found to vary widely in terms of:

- the definition and measurement of useful work and other relevant variables;
- the types of data employed (e.g. cross-section; time-series; panel; etc.);
- the model structure chosen (e.g. structural; reduced form; household production; etc.);
- the functional forms used (e.g. linear; double log; translog; etc.); and
- the estimation techniques used (e.g. Ordinary Least Squares; Generalised Least Squares etc.)

This section therefore reviews of the different choices available under each of the above headings. The aim is to provide a basis for understanding, categorising and comparing the empirical studies discussed in subsequent sections.

3.2 Identifying the econometric evidence base

Econometric estimates of the direct rebound effect use one of the three definitions derived in Section 2. This means that the relevant evidence base consists of econometric studies that estimate one or more of the elasticities listed in Table 3.1.

Table 3.1 Elasticities used in estimating the direct rebound effect

Symbol	**Name**
Definition 1	
$\eta_{\varepsilon}(E)$	Elasticity of the demand for energy with respect to energy efficiency
$\eta_{\varepsilon}(S)$	Elasticity of the demand for useful work with respect to energy efficiency
Definition 2	
$\eta_{P_S}(S)$	Elasticity of the demand for useful work with respect to the energy cost of useful work
Definition 3	
$\eta_{P_E}(S)$	Elasticity of the demand for useful work with respect to the price of energy
Definition 4	
$\eta_{P_E}(E)$	Elasticity of the demand for energy with respect to the price of energy

In practice, econometric estimates of energy efficiency elasticities ($\eta_{\varepsilon}(E)$ and $\eta_{\varepsilon}(S)$) are relatively uncommon, largely as a result of lack of data or insufficient variation in the independent variable. Instead, most empirical studies estimate one or more of the price elasticities ($\eta_{P_S}(S)$, $\eta_{P_E}(S)$ or $\eta_{P_E}(E)$), for the reasons given in Section 2.

There are an enormous number of empirical studies that use econometric methods to estimate the own-price elasticity of energy demand ($\eta_{P_E}(E)$) for different energy services, or groups of services, in different sectors and at different levels of aggregation.[14] However, as argued in Section 2, this elasticity is likely to provide a relatively poor approximation to the direct rebound effect since it effectively assumes that energy efficiency is unaffected by changes in energy prices ($\eta_{P_E}(\varepsilon)=0$). Hence, given both the size of this literature and its limitations as a measure of the direct rebound effect, we do not attempt a comprehensive literature review in Sections 4 and 5. Instead, we simply provide some indicative figures that are taken from meta-analyses of the own price elasticity of energy demand for a number of sectors and energy services. The reason for including these is that, as shown in Section 2.5, the own price elasticity of energy demand may under certain assumptions be considered as an *upper bound* for the direct rebound effect.[15] This finding is of some importance, since it means that this voluminous literature may be used to place some upper bounds on the likely magnitude of direct rebound effects for different energy services. This was precisely the approach taken by Khazzoom (1980), who pointed to evidence that the long-run own-price elasticity of energy demand for water heating, space heating and cooking exceeded (minus) unity, implying that energy efficiency improvements for these services could lead to backfire. However, literature reviews and meta-analyses generally suggest that energy demand is price inelastic, with values typically less than unity (Dahl, 1994; Atkinson, 1995; Espey, 1998; Graham, 2002; Hanly, 2002). Important exceptions include low income groups and consumers in developing countries, who are found to be more responsive to energy prices.

Own price elasticities for energy demand are most useful when the demand relates to a single energy service, such as refrigeration. They are less useful when (as is more common)

[14] For a good review, see Barker*, et al.*, (1995).

[15] Since from Equation 2.11: $\left|\eta_{P_S}(S)\right| \leq \left|\eta_{P_E}(E)\right|$).

the measured demand derives from a collection of energy services, such as total household energy consumption. In this case, a high (low) own price for energy demand may suggest that improvements in the 'overall' efficiency of energy use by households will lead to large (small) direct rebound effects.[16] It may also suggest that the direct rebound effect for the energy services that dominate overall household energy consumption (such as heating) may be large (small). But such aggregate data disguises the own price elasticity of energy demand for individual energy services. For example, it is possible that the energy demand for refrigeration is elastic – suggesting the possibility of large rebound effects - but if overall household energy demand is inelastic and if refrigeration forms only a small portion of that demand, then such a possibility is disguised.

A small number of econometric studies estimate either the energy price elasticity of the demand for useful work or the own-price elasticity of the demand for energy, but include some measure of energy efficiency in their specifications (i.e. $\eta_{P_E}(S)\big|_{\varepsilon}$ or $\eta_{P_E}(E)\big|_{\varepsilon}$). The behaviour being measured here is the short run response to a change in energy prices, conditional upon a particular level of energy efficiency, which results primarily from changes in equipment utilisation. A number of these studies are included in the review of literature in Sections 4 to 6, since they are considered to provide a reasonable approximation to the short run direct rebound effect. However, they do not provide estimates of long-run effects.

Given both the paucity of estimates of energy efficiency elasticities and the limitations of energy demand elasticities as a proxy for the direct rebound effect, the literature review in Sections 4 and 5 is largely confined to studies that estimate either:

- the elasticity of the demand for useful work with respect to the energy cost of useful work ($\eta_{P_S}(S)$); or
- the elasticity of demand for useful work with respect to the price of energy ($\eta_{P_E}(S)$) (with or without controlling for energy efficiency).

The direct rebound effect may be estimated from either of these this using Definitions 2 and 3. However, estimates of $\eta_{P_S}(S)$ are preferred to estimates of $\eta_{P_E}(S)$, since the latter may underestimate the direct rebound effect.[17]. Moreover, while a number of studies estimate either $\eta_{P_S}(S)$ or $\eta_{P_E}(S)$ for a particular energy service, only a portion of these refer explicitly to the direct rebound effect.

The primary focus on elasticities of demand for useful work constrains the scope of the review, since such estimates are only possible if data is available on a relevant measure of useful work, such as vehicle kilometres. This is only the case for a subset of (mostly household) energy services. As a consequence, the evidence base for the direct rebound effect is heavily biased towards personal transportation and household heating, where proxy measures of useful work are most readily available. These energy services form a significant component of final demand in OECD countries and may be expected to be relatively price elastic: first, because energy costs (P_S) form a relatively large proportion of the generalised cost of these services (P_G); and second, because energy costs are relatively visible to the

[16] Although in this case the relevant measure of useful work is a composite of several different services.

[17] Since from Equation 2.11: $|\eta_{P_E}(S)| \le |\eta_{P_S}(S)|$).

consumer through regular utility bills and visits to the petrol station.[18] To the extent that energy forms a smaller proportion of total costs for other energy services (e.g. clothes washing), and/or those costs are less visible to the user, standard theoretical arguments suggest that energy price elasticities – and hence rebound effects – should be lower for those services.[19] However, this hypothesis needs to be tested empirically.

Two other features of the econometric evidence base may be noted. First, there are practically no estimates of the own-price elasticity of the demand for useful work (e.g. lighting, heating, motive power) by producers. As a consequence, almost all of the discussion in Sections 4 and 5 focuses on household energy services. While there is an extensive literature on the own-price elasticity of energy demand for producers in different sectors, this is not reviewed in the current report. Rebound effects for producers are, however, the main focus of *Technical Reports 3, 4* and *5*, where alternative approaches to estimating such effects are investigated (see also the Supplementary Report).

Second, the evidence base is overwhelmingly biased towards OECD countries in general and the US in particular, reflecting in part the high quality data available in the latter. However, estimates from the US may not necessarily be generalised to other OECD countries. For example, higher residential densities and the greater availability of public transport alternatives may make the own-price elasticity of demand for personal automotive travel higher in European countries than in the US. Similarly, results from OECD countries cannot be generalised to the developing world, since both theoretical arguments and empirical evidence suggests that direct rebound effects may be greater for low-income groups, including 'marginal' consumers that did not previously have access to particular energy services (Zein-Elabdin, 1997; Roy, 2000).

3.3 Measurement issues

To estimate the elasticity of demand for useful work with respect to the energy cost of useful work ($\eta_{P_S}(S)$), empirical studies must have data on useful work (*S*), energy prices (P_E), energy efficiency (ε) and/or energy consumption (*E*). In principle, since $S = \varepsilon E$, data on two of these variables should allow the third to be calculated. If data is additionally available on the number (*NO*), capacity (*CAP*), utilisation (*UTIL*) and/or average load factor (*LF*) of the relevant conversion devices, the demand for useful work may be further decomposed (e.g. *S=NO*CAP*UTIL*LF*). However, this approach is only valid if the relevant variables have been independently and accurately determined. As shown by Schipper *et al* (1993), this is not always the case, even in well studied areas such as passenger transport.

For many energy services, the relevant data is simply unavailable, while for others the data must either be estimated or is subject to considerable measurement error. In the case of passenger transport, for example, several studies have misleadingly equated the total

[18] Information on household energy consumption and costs is nevertheless much less than could be desired. For example, Kempton and Montgomery (1982) have compared the information value of the average household energy bill to that of receiving a single monthly bill from the supermarket for 'food'. Recent developments in smart metering and electronic display technologies offer the opportunity to improve the information available to consumers, and this could potentially make the demand for energy services more price elastic.

[19] The second Hicks-Marshall rule of derived demand states that: " the demand for anything is likely to be less elastic, the less important is the part played by the cost of that thing in the total cost of some other thing, in the production of which it is employed"

consumption of gasoline with the consumption of gasoline by passenger cars (Schipper*, et al.*, 1993). This is incorrect when vehicles other than passenger cars use gasoline, (e.g. light trucks, motorcycles, mopeds, boats) and when many passenger cars use diesel.[20] However, estimating the relative proportion of each fuel going to each category of vehicle can be a source of error.

Compared to most energy services, passenger transport is relatively straightforward. In comparison, data on the energy consumption for individual household energy services is rarely available, except when those services are sub-metered as part of an evaluation exercise. Even when available, sub-metered data usually applies only to a subset of households and for a limited period of time and hence may need to be scaled up. Data on total household energy consumption is relatively accurate, but may need to be 'unbundled' to estimate the proportion going to lighting, water heating, cooking, refrigeration and so on. Techniques such as 'conditional demand analysis' estimate appliance-specific energy consumption by combining engineering models of individual end uses with data on energy consumption, appliance ownership and other variables (Parti, 1980). However, these approaches have only been used in a handful of studies of the direct rebound effect (Dubin*, et al.*, 1986; Dubin and Henson, 1988).

Measurement of useful work is extremely problematic, which partly explains the limited scope of the available studies. Aggregate measures are only available for a subset of services such as transport, while disaggregate measures may require expensive monitoring. In the case of household heating, a number of studies have monitored thermostat settings and internal temperatures for individual households (Greening and Greene, 1998). But as argued in *Technical Report 1*, only a portion of the internal temperature change in a building following certain types of energy efficiency improvement may be due to changes in thermostat settings. For example, daily average household temperatures will generally increase following improvements in thermal insulation, even if the heating controls remain unchanged. This is because insulation contributes to a more even distribution of warmth around the house, reduces the rate at which a house cools down when the heating is off and delays the time at which it needs to be switched back on (Milne and Boardman, 2000).

This example points to a generic issue regarding the appropriate definition and measurement of direct rebound effects, namely should this be based upon the total change in demand for useful work that follows an energy efficiency improvement, or only on the portion of this change that result from *behavioural* change by the relevant individuals. In the case of household heating, the former would correspond to changes in heat output as a result of the change in internal temperature while the latter would correspond to changes in heat output as a result of the change in thermostat settings. The preceding discussion has implicitly assumed that these two measures are identical, but the heating example illustrates that this may not always be the case. Moreover, to assess the full benefits of an improvement in household heating systems, the temperature change in each room of the building would need to be measured, while controlling for outside temperature, changes in occupancy and other factors. In addition, internal temperature is only one of the determinants of thermal comfort, with others including activity levels, air velocity and humidity (Frey and Labay, 1988). If, for example, an energy efficiency improvement reduces internal airflow as well as thermal loss, measured changes in internal temperature

[20] The latter is especially problematic in Europe, where diesel forms a large and increasing proportion of the fuel mix for passenger cars.

may not fully reflect changes in comfort. Measurement issues are therefore closely linked to the appropriate definition of the direct rebound effect.

If data on both energy consumption and useful work is available, energy efficiency can be estimated. Alternatively, the demand for useful work could be estimated from data on energy consumption and energy efficiency. Again, however, such data is difficult to obtain and subject to inaccuracy. In practice, the relevant measures of energy efficiency may depend upon a number of variables beyond the thermodynamic efficiency of particular conversion devices. This is evident, for instance, in most household heating studies where various energy audit data have to be included to accurately estimate the demand for space heating. Moreover, the thermodynamic efficiency of conversion devices is frequently absent from datasets and may have to be estimated using techniques such as ‘frontier analysis’ (Guertin, 2003). Some studies use relatively crude techniques: Douthitt (1986), for example, uses a dummy variable to indicate whether a furnace has been replaced or serviced in the current year and can therefore be assumed to be more energy efficient. This again shows the attraction of $\eta_{P_E}(S)$ or $\eta_{P_E}(E)$ as proxies for the direct rebound effect, since these can be estimated in the absence of data on energy efficiency.

Measurement difficulties are not limited to the above variables, but also apply to exogenous variables that affect the demand for energy, useful work or energy efficiency. These may include demographic or geographical factors, for example. Omission of such variables could lead to bias if they are correlated with the dependent or independent variables, while inclusion of such variables could lead to error if they are measured or estimated inaccurately. As a consequence, empirical estimates of elasticities may be expected to include some sort of bias (e.g. sampling, measurement or missing variables bias), which may be either positive or negative. If a sufficiently large number of estimates are available, this problem may be overcome by post-regression techniques such as meta-analysis, but in the case of the direct rebound effect the evidence base is too small and too diverse for this to be possible.

3.4 Types of Data

Four broad categories of data can be distinguished:

- *Cross-section:* a sample of households, states, countries or other units, ideally taken at random from a population at a given point in time. An example would be data on total gasoline fuel consumption and related variables for OECD countries in the year 2000.
- *Time-series:* a series of observations on several variables at regular intervals (e.g. monthly, annually) over a period of time. An example would be annual data on total gasoline fuel consumption and related variables for the UK over the period 1970 to 2000.
- *Pooled cross-section (or cross-sectional time-series):* a cross-sectional sample from the same population taken at two or more intervals in time. An example would be data on gasoline fuel consumption and related variables from a survey of households in 1995 and 2000. With a pooled cross-section, the units (households in this case) need not be the same in each sample period.

- *Panel:* similar to a pooled cross-section, but with data from the same units in each sample period. An example would be data on gasoline fuel consumption and related variables from each US state over a period 1972 to 2000.

For each category, a further broad distinction may be made between aggregate and disaggregate data sets. For energy studies, the level of aggregation ranges from household survey data to country level data collected by the national authorities. Panel and pooled cross-section data frequently apply to the household level, while cross-section and time-series data more commonly apply to the sectoral, regional or country level. Time-series data also varies in periodicity (e.g. monthly, quarterly, annual), the length of time covered and the particular time periods analysed.

All four types of data have been used to estimate the direct rebound effect although studies using cross-sectional and time-series data are more common than those using pooled cross-sectional and panel data. Annual time-series are particularly common in transportation studies and form the basis of a number of studies of the direct rebound effect for passenger transport (Greene, 1992; Jones, 1993; Schimek, 1996). Cross-section data from household surveys are more common in studies of household heating and other residential end-uses (e.g. Houthakker (1980)) although there are fewer applications to the direct rebound effect. Pooled cross-sections are also common, given the large number of repeated household surveys that have been collected, particularly in the US. A small number of studies use panel data for households, derived from repeated surveys of the same participants (Goldberg, 1996; Puller and Greening, 1999; Frondel*, et al.*, 2007). The US is particularly fortunate in that state-level data can be used to form an aggregate panel, providing variations in the relevant variables both across time and between different states. Compared to conventional aggregate time-series data this approach provides substantially more observations, while compared to disaggregate panel data this approach provides more information on the effects that are of interest to policymakers without having to conduct household surveys and scale up the results. This data therefore forms the basis of some of the most robust studies of direct rebound effects in transport, including Haughton and Sarkar(1996) and Small and Van Dender (2005).

Generally speaking, the analysis of time-series data is more challenging than the analysis of cross-sectional data, since the assumptions of the 'classical linear model' are more likely to be violated (Wooldridge, 2003). Of particular importance is serial correlation in the error terms - where the error in one period depends in part upon the errors in previous periods. However, time-series econometrics has improved significantly over the last two decades, with substantial improvements in the goodness-of-fit and explanatory power of testing routines.

Pooled cross-sectional data may have advantages over individual time-series estimates, notably because of the increased number of observations and hence degrees of freedom (Baltagi and Griffin, 1983). Panel data sets are more difficult to obtain than pooled cross-section data, but are more valuable still since the multiple observations on the same units allow the unobserved characteristics of those units to be controlled for. Models using pooled cross-section or panel data appear particularly well suited to estimating the impact of energy efficiency improvements.

3.5 Model structures

Four broad types of econometric model can be identified in the literature, namely: single equation models, structural models, discrete/continuous models, and household production models. Each is outlined below.

3.5.1 Single equation models

Many empirical studies employ a single equation for estimating the demand for either useful work or energy. The very simplest approach uses the price of energy (P_E) and income (Y) as independent variables, together with other exogenous variables such as weather conditions (X_i):

$$\begin{aligned} S &= f(P_E, Y, X_S) \\ E &= g(P_E, Y, X_E) \end{aligned} \tag{3.1}$$

The price and income elasticities estimated from such models include both short-run changes in equipment utilisation and long-run changes in equipment stock. However, the model does not allow these individual effects to be distinguished. The approach may also lead to biased results since relevant variables are excluded.

If data is available, an alternative approach is to also include measures of the number (NO), capacity (CAP) and/or the energy efficiency (ε) of the relevant stock of equipment as independent variables:

$$S = f(P_E / \varepsilon, CAP, Y, Z) \tag{3.2}$$

This approach can capture very short-run income and price elasticities, since it effectively measures changes in utilisation while holding equipment stock and energy efficiency constant. But the long-run effects are embedded in the variables for equipment stock (NO and/or CAP) and energy efficiency (ε) and hence cannot be identified without estimating separate equations for these variables (Dahl and Sterner, 1991). This requires a *structural* model, which is described further below. Moreover, as described in Section 2.5, estimation of Equation 3.2 by Ordinary Least Squares (OLS) can lead to bias because equipment stock and energy efficiency are likely to be endogenous and therefore correlated with the error term. For example, unobserved factors that cause the demand for useful work to be high may also cause energy efficiency to be high. This creates a negative correlation between the demand for useful work (S) and the energy cost of useful work ($P_S = P_E / \varepsilon$) which is additional to that implied by the relationship in Equation 3.2 (Small and Van Dender, 2005).

Equation 3.1 is a *static* model that is suitable for use with cross-sectional data. If it is assumed that demand is in equilibrium at the point of observation,[21] the resulting parameter estimates can be assumed to reflect long-run price and income elasticities. But a static model is only suitable for time-series data if demand can be assumed to adjust completely to changes in prices or income within the unit time period (e.g. one year). This is unlikely to be the case for most energy services, since adjustments to equipment capacity take place over periods of several years. To address this, a *dynamic* version of Equation 3.1 needs to be employed.

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[21] Or at least that the relationship between the explanatory variables has been approximately constant in the recent past.

The *partial adjustment* model is perhaps the most common dynamic model and is based on the assumption that consumers adjust their demand towards a desired level (S^*) over the long term. Since this adjustment process takes time, the actual change in the demand for useful work in a given time period is assumed to be proportional to the discrepancy between the desired value and the previous value:

$$S_t = S_{t-1} + \sigma(S_t^* - S_{t-1}) \qquad (3.3)$$

Where $0 \le \sigma \le 1$. The desired value of demand (S^*) is not observed, but may be eliminated by substituting Equation 3.3 into Equation 3.1 to yield an expression in terms of the observable variable S_t.

$$S_t = f(P_{E_t}, Y_t, Z_t, S_{t-1}) \qquad (3.4)$$

The result is an equation that includes a 'one period lag' of the dependent variable as an independent variable. When expressed in algebraic form, the coefficients of P_E and Y provide estimates of the short-run price and income effects, while the coefficient of the lagged dependent variable gives an estimate of the adjustment factor (σ). These may then be combined to give estimates of the long-run price and income elasticities (which should always be at least as large as the short-run elasticities).

The partial adjustment model implicitly assumes that each independent variable has a gradually and identically decreasing effect on the dependent variable over time.[22] In some circumstances this assumption may be inappropriate, so an alternative is to use a *distributed lag* model incorporating explict lags of one or more of the independent variables:

$$S_t = f(\sum_{i=1,k} P_{Et-i} \sum_{i=1,k} Y_{t-i}, \sum_{i=1,k} Z_{t-i}) \qquad (3.5)$$

Both of these approaches can lead to inefficient parameter estimates when there is colliniearity between the lagged variables and the current values of the other variables. Also, a major drawback of the distributed lag model is that the larger number of terms reduces the degrees of freedom and hence increases the standard error of the parameter estimates. In practice, the 'lag distribution' may take a number of standard forms and there is some debate in the literature as to which form is most appropriate in different circumstances (Puller and Greening, 1999).[23]

Single equation models in both static and dynamic forms provide the basis of a great many empirical estimates of the direct rebound effect. Examples include Greene (1992) and Orasch and Wirl (1997) for personal transport and Schwarz and Taylor (1995) and Haas*, et al.* (1998b) for household heating. Their popularity results from the fact that compared to other models, they require the least amount of information and are relatively easy to estimate. However, they do not distinguish explicitly between changes in equipment stock and changes in equipment utilisation and the distinction between short and long-run

[22] Taking the form of a declining geometric series $\sum_{i=1,n} ar^i$ where $r \le 1$

[23] Recent years have seen significant developments in dynamic modelling techniques, notably the introduction of cointegration models as a means to solve the problem of 'spurious regression' with time-series data (Madlener, 1996). Spurious regression may arise because both dependent and independent variables move in the same direction over time because of some common trend (Granger and Newbold, 1974). Standard models may indicate a high goodness of fit, not because of a true association between the variables but because of this common trend. The traditional way to deal with this is to include a time trend in the model, but this only acceptable if the common trend is deterministic rather than stochastic. Cointegration techniques can deal with this problem and estimate both short and long-run demand characteristics (Engle and Granger, 1987). However, to our knowledge, no studies have used such techniques to estimate direct rebound effects.

adjustments is based upon an arbitrary specification of the adjustment process (Bohi and Zimmerman, 1984). The final specification depends upon the trade-offs between the explanatory power of included or excluded variables, the number of degrees of freedom and the problem of multicollinearity. For instance, demographic variables might be expected to influence the demand for useful work, but the overall fit of the model can deteriorate when these variables are included in the final specification because of the loss of degrees of freedom and the possible correlation with other independent variables. Hence, researchers might prefer to slightly "bias" their results by omitting demographic variables in order to obtain a better overall fit of the model to the rest of the data.

3.5.2 Structural/simultaneous equation models

Structural models can provide a more illuminating approach to estimating direct rebound effects, but are less common owing to their greater data requirements.

As discussed in Section 2.1, the demand for useful work may be decomposed in a variety of ways to reveal the relative importance of different contributory variables. For example, the useful work (*S*) from household lamps could in theory be measured in lumen hours per year and decomposed into the product of the total capacity (*CAP*) of the lamp stock in lumens and the average utilisation of that stock (*UTIL*) in hours/year: [24] $S = CAP * UTIL$. If ε_m is a measure of the mean energy efficiency of the lamp stock in lumens/kW, the annual energy consumption (*E*) for household lighting (in kWh) is then given by: $E = CAP * UTIL * (1/\varepsilon_m)$.

Households can be assumed to make separate, but interrelated decisions on how many lamps to purchase, the energy efficiency of those lamps and how frequently to use them. For example, lamp utilisation may be expected to depend in part upon the energy efficiency of the lamps since this affects running costs, but at the same time the demand for energy efficiency may be expected to depend in part upon the expected utilisation. Unlike a single equation model, a *structural* model reproduces this decision-making structure explicitly, through the use of separate equations for capacity, utilisation and energy efficiency:

$$\begin{aligned} CAP &= f[P_K(\varepsilon), (P_E/\varepsilon_m), Y, X_C] \\ UTIL &= g[(P_E/\varepsilon_m), Y, X_U] \\ \varepsilon_m &= h[P_K(\varepsilon), P_E, UTIL, Y, X_\varepsilon] \end{aligned} \tag{3.8}$$

Where $P_K(\varepsilon)$ represents the capital cost of lamps, which is assumed to depend upon their energy efficiency (ε), and X_C, X_U and X_ε represent vectors of exogenous variables that influence the demand for lamp capacity, utilisation and energy efficiency respectively (several of which may be common to each).

In a structural model such as this, the dependent variables are endogenous in that they also appear on the right-hand side of the equation. The solution of a structural model therefore requires appropriate econometric techniques, such as two-stage least squares (2SLS). For cross-sectional data the static model represented by Equation 3.3 is appropriate, while for time-series or panel data the model may be specified in a dynamic form in a similar manner to that described above (most commonly by including a one period lag of each independent variable)

[24] A distinction could also be made between the number of lamps (*NO*) and their average capacity (*ACAP*) – so *S=NO*ACAP*UTIL.*

A key advantage of a structural model is that it allows the individual components of price and income elasticities, including the direct rebound effect, to be isolated. For example, it enables one to estimate how changes in utilisation and changes in capacity individually contribute to long-term changes in the demand for useful work or energy - something which is hidden by a single equation approach. The improved understanding of how the direct rebound effect operates may be useful, for example, when assessing the implications of energy efficiency standards for new equipment, since stock-wide energy efficiency is determined endogenously. However, the estimation of a set of structural equations such as this requires data on, amongst other things, the capacity, utilisation and energy efficiency of the equipment stock. For many energy services, this type of data is not available.

As argued by Small and van Dender (2005), the development of a structural model can highlight the potential limitations of many a single equation models. Since the structural model (Equation 3.8) is formed of three equations in three unknowns, it may be solved to express each endogenous variable solely as a function of the exogenous variables. This gives the so-called *reduced form* equations as follows:

$$\begin{aligned} CAP &= \tilde{f}[P_K(\varepsilon), P_E, Y, X_C, X_U X_\varepsilon] \\ UTIL &= \tilde{g}[P_K(\varepsilon), P_E, Y, X_C, X_U X_\varepsilon] \\ \varepsilon_m &= \tilde{h}[P_K(\varepsilon), P_E, Y, X_C, X_U X_\varepsilon] \end{aligned} \qquad (3.9)$$

Equation 3.9 shows that if any one of these variables is to be estimated using a single equation approach then (at least in principle) all of the relevant exogenous variables need to be included. For example, the capital cost of equipment should be included in an equation for equipment utilisation since it affects utilisation indirectly. The same applies to the estimation of useful work (*S*) or energy consumption (*E*) within a single equation. But in practice, many single equation models exclude these variables due to lack of data. At the same time, many of them *include* endogenous variables such as *CAP* or ε_m to give what Small and van Dender (2005) term a 'partially reduced form' model. In principle, such a model needs to be estimated using an instrumental variable technique (see below) to account for the endogeneity of these variables, but in practice this is rarely done. Hence, many single equation models could potentially lead to biased estimates.

Structural equation models have been most commonly applied to passenger transport, and a number of studies have estimated such models using aggregate data from the US (Archibald and Gillingham, 1981; Wheaton, 1982; Mayo and Mathis, 1988; Puller and Greening, 1999). The particular specification varies from one study to another, but typically separate equations are estimated for the number of vehicles and the annual distance driven (which may be specified in total or on a per-capita or per-driver basis) and the average stock-wide fuel efficiency. One of the best approaches of this type is Small and Van Dender (2005), who estimate such a model using aggregate cross-section time-series data from each US state. Other studies have used disaggregate data from household surveys and estimated models for the usage of individual cars within multi vehicle households – endogneity occurs here because the usage of one car depends upon the usage of others (Mannering, 1983; Golob*, et al.*, 1996). A particularly good example is Greene*, et al* (1998) who estimate separate equations for annual distance driven, fuel efficiency and fuel prices for households owning one, two, three and four vehicles respectively.[25] However, while this model estimates the demand for travel by households with different numbers of cars, it does not explain the decision of how many cars to own. This requires a *discrete/continuous* model, described next.

3.5.3 Discrete/continuous models

In many structural models, the number or capacity of the equipment stock is treated as a continuous variable. While this is appropriate for aggregate data, it may be inappropriate for modelling decision-making by individual households. For example, while the aggregate vehicle stock may vary continuously over time and between regions, the demand for cars by an individual household can only take a discrete number of values (e.g. from zero to a maximum of four per household). 'Discrete choice models' (or 'qualitative choice models') calculate the probability that a decision-maker will choose a particular alternative from a finite set of alternatives, given data observed by the researcher (Train, 1993). These models have been widely employed to predict the demand for various types of energy-using capital stock: for example, to predict whether a household will purchase air conditioning equipment, given data on income, fuel prices, demographic characteristics, external temperatures and other variables (Dubin and McFadden, 1984). The choice set can reflect both the number and capacity of the relevant equipment as well as other characteristics such as low or high energy efficiency (Hausman, 1979).

Once the equipment is purchased, the user will make a second decision on the utilisation of this equipment - for example, how many hours to run the air conditioning system each year. Unlike the first decision, the second may be represented by a continuous variable (*UTIL*). This second choice is *conditional* on the first (e.g. utilisation must be zero if no equipment is purchased) and in general may be expected to depend, at least in part, on the same exogenous variables as the first decision. For example, higher incomes may be positively correlated with both the ownership of air conditioning systems and the higher utilisation of those systems. Endogneity issues also arise, in a similar manner to those described above. For example, households whose dwellings for some unobserved reasons tend to become unusually hot are both more likely to purchase air conditioning systems and more likely to use them during hot weather.

Sophisticated methods have been developed for specifying and estimating models that describe such *discrete/continuous* situations and these have been applied to the estimation of direct rebound effects using household survey data (Dubin and McFadden, 1984; Mannering, 1985; Kayser, 2000). The general approach is to estimate an equation for the discrete choice of equipment, and then to estimate a second equation describing either the utilisation of this equipment or the demand for energy/useful work conditional upon the relevant equipment choice.[26] Since the values taken by the discrete variable cannot be taken as exogenous when estimating the equation for the continuous variable, appropriate estimation techniques such as 2SLS are again required. Typically, the choice probabilities

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[25] Fuel efficiency is endogenous for the reasons given in Section 2.5, while Greene *et al* argue (rather unconvincingly) that fuel prices are also endogenous because the consumer can choose between different gasoline stations.

[26] The discrete choice model relies upon 'conditional indirect utility functions' for each alternative which specify the maximum utility obtainable from a particular discrete alternative given prices and incomes (Train, 1993).

estimated from the discrete choice equation[27] are used as an instrumental variable (see below) for equipment ownership and equipment characteristics when estimating the utilisation equation. The endogeneity problem may be avoided, however, if the equipment is allocated to individual households as part of a controlled experiment (Davis, 2004).

As with structural models, the separation of the demand for energy into capital stock and utilisation components can help to clarify the differences between short and long-run direct rebound effects as well as the relative contribution of each factor. It may also allow the impact of specific policy measures such as equipment subsidies to be assessed.

3.5.4 Household production models

As illustrated in Section 2.1, the household production model provides an illuminating framework for exploring household energy demand, since it treats energy and capital as a means to provide energy services, with utility being derived from these services rather than from energy itself. Several researchers have estimated such models for household energy use (Archibald and Gillingham, 1981; Quigley and Rubinfield, 1989) although the key innovation introduced by Becker (1965) – namely the importance of time costs - has generally been overlooked. Moreover, even when time costs are ignored, the onerous data requirements of the household production approach have restricted its range of application.

A good illustration of this approach is provided by Klein (1987; 1988), who estimates a household production model for a household demand for space heat (useful work). Klein specifies the total cost of space heat as a function of the demand for space heat, the capital cost of energy efficiency (e.g. insulation), energy prices, the internal area of the house and heating degree days. Klein also specifies a second equation for the share of energy in the total cost of space heat, and a third equation for the demand for space heat as a function of household income, the price of space heat and other variables. These simultaneous equations are estimated using appropriate methods to give estimates for the elasticity of substitution between energy and capital in the production of space heat as well as price and income elasticities for the demand for space heat. On the basis of these, Klein estimates short and long-run elasticities for the demand for energy.

It is possible to incorporate dynamic adjustment into a household production framework in a similar manner to that indicated above. However, since these models require more detailed data on equipment costs than is generally available, their further application is dependent upon the availability of high quality micro data sets.

3.6 Functional Forms

The functional form refers to the manner in which the dependent variable is related to the independent variables (e.g. whether the relationship is linear or nonlinear). The options include the following:

Linear: $S = \beta_1 + \beta_2 P_E + \beta_3 Y$ $\quad (\eta_{P_E}(S) = \beta_2 P_E / S)$

Log-linear: $\ln S = \beta_1 + \beta_2 P_E + \beta_3 Y$ $\quad (\eta_{P_E}(S) = \beta_2 P_E)$

Double-log: $\ln S = \ln \beta_1 + \ln \beta_2 P_E + \ln \beta_3 Y$ $\quad (\eta_{P_E}(S) = \beta_2)$

[27] The final choice may be the outcome of a decision tree, with the probability of the final decision calculated from the product of the probability in each stage.

The linear functional form in real numbers is rarely used nowadays because of the advantages that are associated with the transformation of the data in natural logs. Hence, the most popular forms are log-linear or double-log.[28] Both are easy to specify and estimate and the resulting coefficients may be easily interpreted as short-run demand elasticities - with the standard errors providing measures of the variability of these estimates. An important drawback of the double-log specification is that it assumes that elasticities are constant and do not vary with the level of the independent variables or over the estimated sample period. It also imposes a multiplicative relationship between the variables,[29] which is not always justifiable on theoretical grounds (Plourde and Ruyan, 1985; Madlener, 1996). A 'Box-Cox test' may be used to test the relative appropriateness of different specifications, while a 'Box-Cox transformation' may be used to make such models more appropriate to the data - however, the resulting model must then be estimated using non-linear techniques such as 'maximum likelihood'.

While double-log specifications are more popular for the estimation of single equation and structural models, the *translog* specification is more popular for the estimation of cost functions and associated share equations within household production models (Christensen, *et al.*, 1973).[30] This form – which has become standard in empirical tests of production theory – has a strong basis in economic theory and imposes a minimum of restrictions on demand behaviour (Madlener, 1996). However, it is more difficult to estimate and interpret and frequently leads to a greater loss of degrees of freedom, because of the many parameters involved in estimation.[31]

3.7 Estimation Techniques

The wide variety of methodologies and datasets encourages the use of many different estimation techniques – with several studies using more than one technique and comparing the results. The main techniques found in the literature include:

- *Ordinary Least Squares (OLS)*: This is the standard approach, but the conditions required for these estimators to be unbiased and efficient are frequently violated. OLS results are sometimes provided solely for comparison.
- *Feasible Generalised Least Squares (FGLS):* This approach can deal with heteroskedasticity[32] in studies using cross-sectional data and is frequently used in time-series studies to correct for serial correlation in the error terms.
- *Instrumental variables (IV):* This provides a means to estimate model parameters when one or more explanatory variables are endogenous. The instrumental variable substitutes for the endogenous variable and must be partially correlated with the latter as well as uncorrelated with the error term.

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[28] Terminology here is inconsistent, since the double-log formulation is also referred to as log-linear.

[29] The double log formula implies that $S = \beta_1 P_E^{\beta_2} Y^{\beta_3}$

[30] The cost function is the dual of the production function. A brief discussion of the translog functional form is contained in Annex 1 of *Technical Report 3* and Annex 2 of *Technical Report 5*.

[31] This drawback is particularly important for dynamic specifications, since the introduction of lags further reduces the degrees of freedom.

[32] This means that the variance of the error terms depends upon the magnitude of the independent variables. As an example, the variability of food consumption increases with income. Heteroskedasticity makes estimation by OLS inefficient.

- *Two-stage least squares (2SLS):* This is an IV technique for structural equation models. The first stage is to estimate the 'reduced form' equations for each of the endogenous variables, in which each endogenous variable is expressed solely as a function of the exogenous variables. The second stage is to use the predicted values of the endogenous variables from the first stage as instrumental variables in the structural equations. The latter may then be estimated by OLS.
- *Three stage least squared (3SLS):* This is a related and more sophisticated approach that also takes into account the covariance between the error terms.
- *Fixed effects (FE), between effects (BE)) and random effects (RE)*: These techniques are all suitable for panel data and make different assumptions about whether and how the relevant parameters vary between units and over time.[33]
- *Logit/Probit/Tobit:* The Logit and Probit techniques are used when the dependent variable is binary, while the Tobit is used when the dependent variable is zero for a non-trivial portion of the population and takes continuous values for the remainder.
- *Maximum likelihood (ML):* This is suitable for the estimation of non-linear models as well as discrete models such as Tobit. Variations of the technique (like Full-Information ML or Limited Information ML) are also used.

3.8 Summary

Based upon the analysis in Section 2, the relevant evidence base for the direct rebound effect has been identified as econometric studies that estimate one or more of the elasticities listed in Table 3.1. In practice, however, estimates of energy efficiency elasticities are relatively rare, while estimates of the own price elasticity of the demand for energy (while numerous) provide a relatively poor approximation to the direct rebound effect. As a result, the literature survey in Sections 4 to 6 is largely confined to econometric estimates of the elasticity of the demand for useful work with respect to the energy cost of useful work and/or the price of energy. However, some estimates of the own-price demand for energy are also included, since in theory these provide an upper bound to the direct rebound effect.

The definition and measurement of key variables should be taken into account before any comparisons of empirical estimates are made. Given the above criteria, the econometric evidence base for direct rebound effects is largely confined to those energy services where useful work can be easily defined and measured. Even for these services, the particular measure of useful work vary from one study to another and may hide technical and behavioural factors that are relevant to direct rebound effects, such as changes in vehicle load factors. Measurement difficulties typically lead to many relevant variables being excluded and the measurement or estimation of the key variables of energy consumption, useful work and energy efficiency is usually far from straightforward.

Individual empirical studies also vary widely in terms of the type of data employed, the model structure chosen, the functional forms used and the estimation techniques employed. Table 3.1 summarises the different choices available. Note that the appropriate choice for

[33] *Fixed effects* controls for omitted variables that differ between cases but are constant over time; *between effects* controls for omitted variables that change over time but are constant between cases; and *random effects* allows for omitted variables that vary both over time and between cases.

functional form and estimation techniques depends upon the type of data and model structure.

It is difficult to make general statements regarding the relative methodological quality of different choices under each of these categories. Single equation models using aggregate cross-sectional or time-series data are the most popular and easiest to estimate, but they typically neglect the endogneity problem and do not separate the relative effect of changes in equipment capacity and changes in utilisation. Structural models perform better in this regard but have correspondingly greater data requirements, while discrete/continuous and household production models are more demanding still and are largely confined to disaggregate studies using comprehensive household survey data. Some model structures may be used to estimate both short-term and long-term direct rebound effects, while others may only estimate one or the other. Since the direct rebound effect can vary over time and have multiple repercussions within sectors, studies using pooled cross-section or panel data may be more likely to provide robust estimates. However, such data sets are less widely available. Examples of all these categories are included in the subsequent sections.

Table 3.2 Summary of econometric approaches to estimating the direct rebound effect

Category	**Choices available**
Type of data	*Aggregate versus Disaggregate* Cross-section; Time-series; Pooled cross-section; Panel
Model structure	*Static versus dynamic* Single equation; Structural; Discrete/continuous; Household production
Functional form	Linear Log-linear Double log Translog
Estimation technique	Ordinary Least Squares (OLS); Feasible Generalised Least Squares (FGLS); Instrumental Variables (IV); Two-stage least squares (2SLS); Three-stage least squares (3SLS); Fixed Effects (FE) and Random Effects (RE); Error Correction (ECM); Logit/Probit/Tobit; Maximum Likelihood (ML)

4 Evidence for direct rebound effects for personal automotive transportation

4.1 Introduction

The demand for motor fuels by passenger vehicles is one of the best studied areas in energy (and transport) economics. It is also the best studied areas for the direct rebound effect, partly because relatively good data is available on distance travelled as a measure of useful work. There is therefore greater consensus on the size of direct rebound effects for this energy service than for any other energy service. This is not to say that the empirical literature is without weaknesses, bias or controversies. For example, the methodological approaches are diverse, problems of measurement error are common there are far more studies of direct rebound effects in the US than in other OECD countries, and there is inconsistency between the results of studies using aggregate data and those using household survey data. Nevertheless, personal automotive transportation provides one of the few areas where the evidence base for the direct rebound effect is strong and where the size of the effect can be estimated with some confidence.

This section reviews this literature in some detail, using it to illustrate the broader methodological issues associated with obtaining econometric estimates of the direct rebound effect. It begins by reviewing the large empirical literature containing estimates of the fuel price elasticity of gasoline demand and the demand for travel In principle, these should provide upper and lower bounds on the size of the direct rebound effect. It then reviews a selection of studies that estimate either the elasticity of distance travelled with respect to fuel efficiency ($\eta_{\varepsilon}(S)$), or he elasticity of distance travelled with respect to the fuel cost per kilometre ($\eta_{P_S}(S)$). In principle, both of these should provide more accurate estimates of the direct rebound effect. These studies are organised according to the type of data they use, distinguishing between: a) aggregate time-series data or cross-sectional data; b) aggregate panel data; and c) disaggregate (household survey) data. The literature review is not entirely comprehensive, but includes the most prominent studies in this area and pays particular attention to those that are considered to be methodologically robust.

4.2 Setting bounds on the direct rebound effect for personal automotive transportation

A large number of studies estimate own-price elasticities of the demand for motor fuels (*E*) by passenger cars ($\eta_{P_E}(E)$), while a much smaller number of studies estimate price elasticities of the demand for distance travelled (*S*). Of the latter, the majority estimate the elasticity of demand for distance travelled with respect to the price of fuel ($\eta_{P_E}(S)$), while relatively few estimate either the elasticity of distance travelled with respect to fuel efficiency ($\eta_{\varepsilon}(S)$), or the elasticity of distance travelled with respect to the fuel cost per kilometre ($\eta_{P_S}(S)$).

The elasticity of distance travelled with respect to fuel efficiency ($\eta_{\varepsilon}(S)$) provides a direct measure of the rebound effect, while the elasticity of distance travelled with respect to the fuel cost per kilometre ($\eta_{P_S}(S)$) relies upon the assumption that the response to a change in fuel prices is equal and opposite to the response to a change in fuel efficiency. Whether this 'symmetry' assumption is valid is a key issue for the studies reviewed below. But the reason for making this assumption is both to increase the degrees of freedom and provide for greater variation in the independent variable. Many studies have insufficient variation in fuel efficiency (and/or excessive measurement error) to base estimates of the direct rebound effect on $\eta_{\varepsilon}(S)$ so they rely instead upon $\eta_{P_S}(S)$.

In principle, estimates of $\eta_{\varepsilon}(S)$ and/or $\eta_{P_S}(S)$ should provide the most accurate estimates of the direct rebound effect for personal automotive transportation. The studies are therefore discussed in detail in the following sections. However, for the reasons discussed in Section 2.5, estimates of the own-price elasticity of fuel demand ($\eta_{P_E}(E)$) should, in principle, provide an *upper bound* for the direct rebound effect, while estimates of the fuel price elasticity of distance travelled ($\eta_{P_E}(S)$) should provide a *lower bound*. Hence, it is useful to summarise these estimates in the case of personal automotive transportation.

Since personal automotive transportation is one of the best studied energy services, there are number of comprehensive reviews and meta-analyses of published elasticity estimates (Goodwin, 1992; Espey, 1998; Hanley*, et al.*, 2002; Graham and Glaister, 2004). These reviews cover a wide range of different countries and time periods, which may contribute to the large variance in results. For example, Hanley *et al* (2002) reviewed 69 studies containing 491 different elasticity estimates from more than 20 countries and regions spread over the period 1929 to 1991.

Table 4.1 summarises the mean values of the estimates of $\eta_{P_E}(E)$ from each of these reviews, while Tables 4.2 and 4.3 summarise the mean values of the estimates of $\eta_{P_E}(S)$. While Table 4.2 refers to studies of the <u>total</u> distance travelled by all automobiles[34], Table 4.3 refers to studies of the distance travelled <u>per vehicle.</u> In principle, the former should be greater than the latter since changes in fuel prices should also lead to changes in the number of vehicles. Table 4.4 summarises estimates of the elasticity of vehicle numbers with respect to the price of fuel ($\eta_{P_E}(NO)$), while Table 4.5 summarises estimates of the elasticity of fuel efficiency (per vehicle) with respect to the price of fuel ($\eta_{P_E}(\varepsilon)$). The tables distinguish between *static* models that provide only a single elasticity estimates and *dynamic* models which allow short and long-run elasticities to be identified (see Section 3.5.1). In each case, the tables show the mean of the estimates and the number of estimates on which this figure is based. In addition, the results from Hanley *et al* (2002) also show the range and standard deviation.

[34] The terms automobile, vehicle and car are used interchangeably in this section to refer to the privately-owned vehicles used for passenger travel. However, identifying measures for vehicle numbers, distance driven and fuel consumption for these vehicles is far from straightforward. For example, an increasing volume of passenger travel takes place in light trucks and vans that may also be used for the transport of light goods.

Table 4.1 Elasticity of automobile fuel consumption with respect to fuel prices ($\eta_{P_E}(E)$) - summary of empirical literature

	Dynamic		Static
	Short-run	**Long-run**	
Hanley et al (2002)			
Mean	-0.25	-0.64	-0.43
Standard deviation	0.15	0.44	0.23
Range	-0.01 to -0.57	0 to -1.81	-0.11 to -1.12
No. of estimates	46	51	24
Goodwin (1992)			
Mean	-0.27	-0.73	
No. of estimates	57	53	
Espey (1998)			
Mean	-0.26	-0.58	
No. of estimates	277	363	
Graham and Glaister (2002)			
Mean	-0.2 to - 0.3	-0.6 to -0.8	

Table 4.2 Elasticity of total distance travelled by automobiles with respect to fuel prices ($\eta_{P_E}(S)$) - summary of empirical literature

	Dynamic		Static
	Short-run	**Long-run**	
Hanley et al (2002)			
Mean	-0.10	-0.29	-0.31
Standard deviation	0.06	0.29	0.14
Range	-0.17 to -0.05	-0.63 to -0.10	-0.54 to -0.13
No. of estimates	3	3	7
Goodwin (1992)			
Mean	-0.16	-0.32	
No. of estimates	4	6	
Graham and Glaister (2002)			
Mean	-0.15	-0.3	

Table 4.3 Elasticity of distance travelled <u>*per automobile*</u> *with respect to fuel prices ($\eta_{P_E}(S)$) - summary of empirical literature*

	Dynamic		Static
	Short-run	**Long-run**	
Hanley et al (2002)			
Mean	-0.10	-0.30	-0.51
Standard deviation	0.06	0.23	-0.25
Range	-0.14 to -0.06	-0.55 to -0.11	-0.69 to -0.33
No. of estimates	2	3	2

Table 4.4 Elasticity of vehicle stock (automobile numbers) with respect to fuel prices ($\eta_{P_E}(NO)$) - summary of empirical literature

	Dynamic		Static
	Short-run	**Long-run**	
Hanley et al (2002)			
Mean	-0.08	-0.25	-0.06
Standard deviation	0.06	0.17	0.08
Range	-0.21 to -0.02	-0.63 to -0.10	-0.13 to -0.03
No. of estimates	8	8	3

Table 4.5 Elasticity of vehicle fuel efficiency with respect to fuel prices ($\eta_{P_E}(\varepsilon)$) - summary of empirical literature

	Dynamic		Static
	Short-run	**Long-run**	
Hanley et al (2002)			
Mean	0.08	1.1	0.30
Standard deviation	n/a	n/a	0.22
Range	n/a	n/a	0.89 to 0.04
No. of estimates	1	1	22

Some key points to emerge from these summaries are as follows:

- As Equation 2.11 predicts, the elasticities for fuel consumption are generally higher than the elasticities for distance travelled - by a factor of 1.5 to 2.0. This demonstrates that fuel prices have a considerable influence on fleet average fuel efficiency, both through short-term changes in driving styles and the pattern of journeys and long-term changes in the mean fuel-efficiency of new vehicles. Only a small number of (mostly static) studies estimates this effect directly, with the results being summarised in Table 4.5. This suggests that a 10% increase in fuel prices will lead to a 3% improvement in fleet average fuel efficiency.
- For both fuel consumption and distance travelled, the estimated long-run fuel price elasticities are found to be at least twice the size of the short-run elasticities, with the result from static models falling somewhere between the two. Given the limitations of static models, the results from dynamic models should perhaps be

given greater weight. However, the estimates of long-run price elasticities exhibit considerable variance.

- The range of estimates for the elasticity of total distance travelled with respect to fuel prices is comparable to that for the estimates of distance travelled per vehicle. However, in both cases, the number of relevant studies is relatively small.
- The results do not provide any strong evidence that price elasticities decline over time with increasing incomes – as would be expected from the theoretical considerations reviewed in Section 2.6. However, there is some evidence that price elasticities are related to price levels and were generally higher in the period immediately following the oil price shocks in the 1970s (Hanley*, et al.*, 2002).

Using the mean values of $\eta_{P_E}(E)$ suggests an *upper bound for the short-term direct rebound effect of 20-25% and an upper bound for the long-term effect of 80%*. Similarly, using the mean values of $\eta_{P_E}(S)$ suggest a *lower bound for the short-term direct rebound effect of 10-15% and an lower bound for the long-term effect of 30%*. In principle, the actual rebound effect should lie somewhere within this range. However, the mean values disguise a large variance in the results. For example, using the full range of estimates suggests that the upper bound for the long-run direct rebound effect lies somewhere between zero and 181%, while the lower bound lies somewhere between 10% and 61%. The breadth of this range is not very helpful. Also, the upper bound is likely to be a significant overestimate of the direct rebound effect since it neglects the effect of fuel prices on fuel efficiency – which appears to be substantial (Table 4.5).

Using Extension 2, the mean estimates of $\eta_{P_E}(E)$ (Table 4.1) and $\eta_{P_E}(\varepsilon)$ (Table 4.5) may be combined to give an estimate of the elasticity of distance travelled with respect to the fuel cost per kilometre ($\eta_{P_S}(S)$). This leads to an estimate of the long-run direct rebound effect in the range 18% (static estimates) to 49% (dynamic estimates). The upper value is higher than obtained from most studies that directly estimate $\eta_{P_S}(S)$ - reviewed in detail below. Also, these studies generally produce estimates of the long-run direct rebound effect that lie below the mean value of the lower bound (30%) implied by Table 4.2. Hence, direct estimates of $\eta_{P_S}(S)$ are not wholly consistent with the 'bounds' on the direct rebound effect calculated above.

A notable weakness of most of the studies included in these reviews is that they assume that the effect of a price reduction on demand is equal and opposite to the effect of a price increase. This is at odds with the literature on the price asymmetry of energy demand (Dargay, 1992; Gately, 1993), which includes studies of the road transport sector (Gately, 1992b; Walker and Wirl, 1993). For example, Dargay and Gately (1994) estimate the own-price elasticity of gasoline demand in the US transport sector to be -0.21 during periods of rising prices, but only -0.04 during periods of falling prices. For studies using time-series data, the extent to which neglect of this price asymmetry can lead to biased estimates of elasticities in general and the direct rebound effect in particular will depend upon the price trends (in real terms) over the period in question. Since an improvement in fuel efficiency corresponds to a reduction in fuel prices, it is possible that the direct rebound effect is significantly smaller than suggested by elasticities estimated during periods of rising fuel prices. The incorporation of asymmetric price responses should therefore be a priority for future research.

The following three sections review a selection of studies that estimate the price elasticity of distance travelled with respect to the fuel cost per kilometre ($\eta_{P_S}(S)$). Provided the studies are methodologically robust, they should provide a more accurate estimate of the direct rebound effect than the figures quoted in the above tables. The studies are grouped as follow:

- studies using either aggregate time-series data or aggregate cross-sectional data;
- studies using aggregate panel data; and
- studies using disaggregate (household survey) data.

4.3 Evidence from studies using aggregate time-series or cross-sectional data

This group of studies uses aggregate data on road fuel consumption; fuel prices, distance travelled and/or fleet average fuel efficiency taken from a either a single region or country over an interval of time (time-series), or a number of regions or countries at a single point in time (cross-section). Each study estimates the elasticity of the demand for travel with respect to the fuel cost per kilometre (P_S) – which is in turn estimated from the ratio of fuel prices to fleet average fuel efficiency (P_E/ε). The direct rebound effect may be estimated from this elasticity, but not all the studies mention the rebound effect explicitly. Although the studies vary greatly in terms of model structure and other factors, the estimated values for short and long-run direct rebound effects appear broadly comparable. Table 4.6 provides a summary of the studies reviewed.

One of the first studies to derive an estimate for the direct rebound effect from $\eta_{P_S}(S)$ was **Blair *et al.* (1984b)**. This used monthly time-series data from Florida covering the period 1948 to 1976. As with many studies from the 1970s and early 1980s, the available historical data provided relatively little variation in fuel prices in real terms. More recent studies that incorporate the effect of the second oil price shock of 1979-1982, together with the subsequent oil price collapse of 1986, benefit from greater variation in the independent variable.

Blair *et al* estimated a static equation for total distance travelled by the vehicle fleet as a function of fuel cost per kilometre, income and population, together with a second equation for fleet average fuel efficiency as a function of fuel prices and income. A third equation for the number of vehicles would have been useful, but was not feasible due to lack of data. Blair *et al* employ a linear functional form, which means that the estimates of $\eta_{P_S}(S)$ depend upon the particular values of fuel cost per kilometre and distance traveled. Using data from 1970, Greene (1992) puts their estimate of the direct rebound effect to be between 25% and 40% depending upon the method of estimation used (OLS and GLS respectively).

Mayo and Mathis (1988) use US national data covering the period 1958 to 1984, which includes the large increase in gasoline prices that followed the two oil shocks. Following Blair *et al*, they estimate equations for total distance travelled and fleet average fuel efficiency, but are able to distinguish short and long-run elasticities by using a dynamic specification incorporating a one period lag of the dependent variable. They justify omitting an equation for vehicle stock on the grounds that only income is significant in predicting vehicle numbers, although the more recent meta-analysis by Hanly *et al* (2002) suggests that this assumption is incorrect (Table 4.4).[35]

Mayo and Mathis find the short-run direct rebound effect to be 22% and the long-run effect to be 26%. However, the coefficient on the lagged dependent variable in their distance equation is not statistically significant (t=0.73), making the long-run estimate questionable (Greene, 1992). The distance equation is estimated using 3SLS, owing to the presence of 'serial correlation' in the error terms. Serial correlation means that the error in one time period is correlated with the error from one or more previous time periods, perhaps as a result of the influence of unobserved variables that persist over time. Identifying and correcting for serial correlation is a major issue in time-series econometrics and is relevant to many of the studies reviewed here.

A notable result from the Mayo and Mathis study is that US regulatory standards on 'corporate average vehicle fuel efficiency' (CAFE) were not found to have a statistically significant effect on either fleet average fuel efficiency or the demand for gasoline. But since the standards were imposed about the same time as a major increase in fuel prices occured, and also became more stringent as fuel prices increased in the early 1980s, it may be difficult to separate the two effects (Small and Van Dender, 2005). To the extent that comparable problems arise in other US studies, this could influence estimates of the direct rebound effect. In contrast, Greene (1996) argues that the CAFE standards were successful in improving on-road fuel economy in the US by 50% over the period 1975 to 1995.

Gately (1990) uses US national data over the period 1966-88 to estimate an equation for the total distance travelled by cars and light trucks. He employs a static, double-log equation to give an estimated direct rebound effect of 9%, for both the short and long term. An interesting feature of this study is the inclusion of a measure of the number of licensed drivers, rather than population. The ratio of the two varies significantly over time and the first should be more relevant to vehicle ownership and use. Gateley argues that omission of this variable in previous studies may have led the income elasticities of gasoline and travel demand to be overestimated.

One of the most rigorous studies of the direct rebound effect using aggregate data is that by **Greene (1992),** who uses US national data covering the period 1957-1989. Following Gately (1990), Greene estimates an equation for total distance traveled by cars and light trucks as a function of fuel cost per kilometre, income and the number of licensed drivers. Fleet average fuel efficiency is estimated from total car and light truck vehicle kilometres divided by the total fuel consumption of these vehicles. A notable feature of this study is the use of different model specifications to address two linked problems: namely the appropriate lag structure for dependent and/or independent variables and first order serial correlation in the error terms. The presence of the latter, which is confirmed, suggests that the appropriate model structure is one that contains one period lags of each independent variable as well as the dependent variable, although this reduces the degrees of freedom.

Greene finds that once serial correlation is accounted for, the coefficient on the lagged dependent variable is no longer significant. The surprising implication of this is that long-run direct rebound effects are no greater than the short-run effects, which Greene estimates to be between 5% and 15%. He argues that the reason other studies found significant long-run

[35] Table 4.4 suggests that fuel prices have a significant influence on vehicle numbers. However, these results derive from a small number of studies and hence should be treated with caution.

effects was that they failed account properly for serial correlation. Greene explains the absence of a long-run effect by noting that fuel costs account for less than 10% of long-run travel costs. If correct, similar conclusions should apply to an even greater extent to other household energy services where energy forms an even smaller proportion of (long-run) total costs.

Greene also finds that estimates of the direct rebound effect are relatively insensitive to the functional form of the equation used, as well as to the lag length and the particular lag structure. He also finds that the number of vehicles and the number of licensed drivers are so closely correlated that their respective effects on distance driven are indistinguishable – suggesting that a measure of one or the other should be sufficient. One particularly interesting result is that the direct rebound effect over the period 1978-89 is estimated to be only 5.9%, compared to 27.4% over the period 1966-77. This suggests that the direct rebound effect declines with income as theory predicts, but little confidence can be placed in this result as it is only statistically significant at the 10% level.

The value of Greene's study is further enhanced by **Jones (1993)** re-examination of Greene's data. While Jones confirms that the statistical model selected by Greene is valid, other models including those with the lagged dependent variables also appear consistent with the data. These give a long-run direct rebound effect of around 30%, which (in contrast to Greene's results) is approximately twice the short-run effect. One drawback with the dynamic models, however, is that they estimate the income elasticity of the demand for travel to be approximately zero, which seems implausible. In summarising his results, Jones notes that: "…..we are not completely sure about the long-run rebound effect, but if it does exist, it is probably not very large."

In a more recent study, **Schimek (1996)** uses US aggregate data for a longer time period than Greene and estimates a system of three equations for the number of vehicles, fleet average fuel efficiency and total distance travelled. Applying formal tests, Schimek is able to reject the possibility that endogeneity is biasing the results, which means he can avoid the use of simultaneous equation models and estimate each equation using OLS. This specification provides estimates for the direct rebound effect from both $\eta_{\varepsilon}(S)$ and $\eta_{P_E}(S)$, which are found to be approximately equal in magnitude and opposite in sign. This gives a short-run direct rebound effect of 5-7% and a much larger long-run effect of 21-29%.

All the above studies use aggregate data from the US, so the results may be specific to the US context. European countries for example have greater population density than the US, higher fuel prices, higher levels of fuel efficiency and greater scope for substitution to other transport modes, all of which may influence short-run price elasticities. Unfortunately, estimates of $\eta_{P_S}(S)$ from aggregate time-series data for other countries appear to be rare. However, an alternative approach is to use data from multiple regions or countries at a single instant of time. This may give wider variation in the relevant independent variables (e.g. fuel prices), although results may be influenced by inter-country differences which may not be measurable.

An early but relatively robust example of this approach is **Wheaton (1982),** who uses cross-section data from 25 countries for the year 1972 (i.e. prior to the first oil crisis). Wheaton develops separate equations for the number of vehicles per capita, the average distance travelled per vehicle and the average fuel efficiency of the vehicle fleet. The latter is estimated from sales weighted data on new car fuel efficiencies in each country, which provide a poor approximation to on-road fuel efficiency (Schipper*, et al.*, 1993)

Although Wheaton specifies a structural model, he estimates the three equations using OLS since tests show the relative absence of endogneity bias. This gives an elasticity of distance travelled with respect to fuel efficiency ($\eta_{\varepsilon}(S)$) of +0.06, suggesting a rebound effect of only 6%.[36] However, since the dependent variable is distance travelled per vehicle, the direct rebound effect may be expected to be smaller than in the other studies reviewed here (since $\eta_{\varepsilon}(NO)$ is not accounted for). Also, the reliability of the result depends upon the accuracy of the fuel efficiency estimates, which are questionable. In contrast to Schimek (1996), Wheaton finds that the elasticity of distance travelled with respect to fuel prices ($\eta_{P_E}(S)$) is significantly larger than the elasticity of the demand for travel with respect to fuel efficiency (($\eta_{\varepsilon}(S)$). The estimated magnitude of $\eta_{P_E}(S)$ is -0.5, suggesting a much larger direct rebound effect of 50%. The disparity between these two figures could result from measurement error or may suggest that the standard assumption regarding the equal and opposite effect of changes in fuel prices and changes in fuel efficiency is incorrect. This assumption is only tested in the small number of studies that have sufficient variability in both fuel prices and fuel efficiency to obtain statistically significant estimates of both elasticities. As will be seen below, Wheaton's study is not the only one to question the symmetry assumption.

One drawback with all the above studies is that they pay insufficient attention to the quality of data sources. Problems include the inappropriate use of total gasoline consumption as a proxy for the fuel consumed by automobiles, the uncertainties in estimates of distance driven obtained from roadside counts or surveys of vehicle users, and the uncertainties over the number of cars in use in each year (Sorrell, 1992; Schipper*, et al.*, 1993). For example, many countries measure automobile fuel consumption (*E*) as the residual after the estimated fuel consumption of trucks, buses and other vehicles is removed. This estimate is then *calibrated* against estimates of automobile fuel efficiency (ε) and total distance driven (*S*), thereby creating a circularity between the estimates of these three variables. Hence, using any two of these variables to estimate the third (as Wheaton does) may be inappropriate. These measurement difficulties may have been compounded by the increasing use of light trucks for personal transport in the US and the increasing penetration of diesel vehicles in Europe. While the difficulties can be resolved to some extent, the size of the measurement error may in some circumstances be comparable to the size of the variation in key variables.

In summary, studies using aggregate time-series and cross-sectional data estimate the long-run direct rebound effect for personal automotive transport to be somewhere between **5% and 30%**. While there is disagreement over the appropriate specification, particularly in relation to the appropriate treatment of serial correlation and lagged dependent variables, the limited number of data points available makes it difficult to settle the issue from this type of data alone. Also, since the available studies refer solely to the US and use relatively old data, it is not possible to establish whether any confidence whether price elasticities have declined over time or whether they are substantially different in other countries.

[36] From Table 2, using the 25 countries sample with undeflated prices (Wheaton, 1982).

Table 4.6 Estimates of the direct rebound effect for personal automotive transport using aggregate time-series or cross-section data

Author/year	**Short-run rebound effect**	**Long-run rebound effect**	**Country**	**Data**	**Model structure**	**Functional form**	**Estimation technique**	**Comments**
Blair (1984a)	25-40%	25 – 40%	US	Monthly TS for Florida 1967-76	Recursive (*S* and ε) Static	Linear	OLS and GLS	Early study with limited variation in the independent variable
Mayo and Mathis(1988)	22%	26%	US	TS 1958-84 National	Recursive (*S* and ε) Dynamic	Linear and Double log	3SLS	Coefficient on lagged dependent variable not significant.
Gateley (1992b)	9%	9%	US	TS 1966-88, National	Recursive (*S* and ε) Static	Double log, incorporating asymmetric effects	OLS	Uses drivers rather than population
Greene (1992)	5-19% (linear) 13% (log-linear)	5-19% (linear) 13% (log-linear)	US	TS 1957-89, National	Single equation (*S*) Static and dynamic	Linear and log-linear	OLS	Various models tested. Accounting for serial correlation made lagged dependent variable insignificant
Jones (1992)	13%	30%	US	TS 1957-89, National	Single equation (*S*) Static and dynamic	Linear and log-linear	OLS	Same data as Greene (1992)
Schmiek (1996)	5-7%	21-29%	US	TS National	Recursive (*S*, ε & *NO*) Dynamic	Double log	OLS	$\eta_{\varepsilon}(S)$ found to be equal and opposite to $\eta_{P_E}(S)$
Wheaton (1982)	6%	6%	25 OECD countries	XS 1972	Recursive (*S*, *NO* & ε) Dynamic	Double Log	OLS	Estimate based on $\eta_{\varepsilon}(S)$. Using $\eta_{P_E}(S)$ gives rebound effect of 50%

4.4 Evidence from studies using aggregate panel data

Some of the limitations of the above studies may be addressed through the use of aggregate panel data. This gives a much larger number of data points that includes both cross-sectional and temporal variations in the relevant variables. Both theory and empirical evidence suggests that panel data should provide more efficient parameter estimates (i.e. lower variance) (Baltagi and Griffin, 1983). The US is particularly fortunate in this respect since high quality time-series data is available from 50 different states as well as the District of Columbia, which may be combined to form a very large panel dataset. This section summarises two studies that estimate the rebound effect from cross-country panel data and two that use aggregate panel data from the US. The results are summarised in Table 4.7.

Orasch & Wirl (1997) use aggregate panel data from France, Italy and the UK covering the period 1971 to 1993. They estimate an equation for distance travelled as a function of fuel cost per kilometre, income and a one-period lag of the dependent variable. Their estimates of the short-run direct rebound effect are 10% for the UK and almost 20% for France and Italy, while the long-run equivalents are 27% for the UK and almost 30% for France and Italy.

Johansson and Schipper (1997) use cross-country panel data to study the determinants of automobile fuel demand in 12 OECD countries. They estimate a recursive system of equations for the number of vehicles, the mean fuel efficiency of the vehicle fleet and the mean annual driving distance per vehicle. They rule out the possibility of the simultaneous determination of fuel efficiency and driving distance on theoretical grounds, thereby avoiding the need for simultaneous equation techniques. However, since the possibility of bias is not investigated empirically, this assumption may be flawed. Also, they assume (but do not test) that changes in fuel prices have an equal and opposite effect on distance driven to changes in fuel efficiency - justifying this on the grounds of maximising the degrees of freedom.

Johansson and Schipper's study is notable for two reasons. First, very careful attention is paid to the quality of the data sources from each country, with fuel use being disaggregated between gasoline, diesel, LPG and CNG. This makes the study less vulnerable to measurement error than, for example, Orasch & Wirl (1997). Second, they use several different estimation methods, including OLS, GLS and 2SLS, and take some care in pointing out the possible drawbacks of each. In the case of the distance equation, the independent variables are strongly correlated, leading to a high variance on the parameter estimates and reduced confidence in the elasticity estimates.

The use of a structural system of equations allows the change in total distance driven to be decomposed into changes in distance driven per vehicle and changes in the vehicle stock. The former is found to be more important than the latter, with 'best value' elasticity estimates of -0.2 and -0.1 respectively. If the long-run direct rebound effect is measured on the basis of total distance driven by the vehicle fleet, this leads to a best guess estimate of 30% (with a range from 5% and 55%). In contrast, if the rebound effect is measured on the basis of distance driven per vehicle, this leads to a 'best guess' estimates of 20% (with a range from 5% to 35%.). Both estimates are at the upper end of the range in the literature and highlight the importance of the appropriate choice of dependent variable. The estimate of the long-run own-price elasticity of fuel demand (-0.7) is also at the upper end of the range.

Haughton and Sakar (1996) use US state-level data covering the period 1972 to 1991. They estimate seperate equations for fleet average fuel efficiency and kilometres driven per driver, with fuel consumption being calculated from the product of these two variables and the number of drivers. A 2SLS method is used to allow for simultaneous determination of these two variables, but this is not found to greatly influence the results. Although the authors refer to Greene's (1992) estimate of the direct rebound effect, they fail to note the difference between their dependent variable (kilometres per driver) and the one used by Greene (total vehicle kilometres). These two variables are not equivalent, since the same vehicle kilometres can be driven by two or more drivers. However, in contrast to the use of kilometres per vehicle for the dependent variable, this is unlikely to have a major influence on the estimated rebound effect.

Haughton and Sakar estimate a dynamic equation for fleet average fuel efficiency that includes a variable representing the highest real fuel price reached in the years preceding the current year. This implies that high fuel prices induce improvements in fuel efficiency that remain in place when fuel prices subsequently fall ('hysteresis'). They find that the current price of gasoline does not affect fuel efficiency unless it rises above its previous peak – demonstrating again the price asymmetry of energy demand.[37] They also include a variable representing the difference between the CAFE standard in the current year and the average fuel efficiency in 1975. However, the strong correlation between this variable and gasoline prices makes it difficult to separate the two effects, suggesting that alternative specifications of the CAFE standard need to be found (Small and Van Dender, 2005).

Distance driven per driver is estimated as a function of income, the fuel cost per kilometre, population density, the proportion of drivers in the total adult population[38] and a one period lag of the dependent variable. This leads to an estimated short run direct rebound effect of between 9% and 16%, and a long-run effect of 22%, with relatively little variation between different model specifications. Haughton and Sakar find serial correlation in the error terms, but unlike Greene (1992) they find that the coefficient on the lagged dependent variable is still significant when serial correlation is accounted for - implying that the long-run direct rebound effect is at least a third larger than the short-run effect. The advantages of Haughton and Sakar's panel dataset compared to Greene's time-series data gives some confidence in this conclusion.

Small and van Dender (2005) provide one of the most methodologically rigorous estimates of the direct rebound effect for passenger travel, incorporating a number of important innovations. As with Haughton and Sakar, they employ aggregate panel data from all 50 US states, but since this data covers a longer time period (1961-2001) their parameter estimates may be expected to be more precise. By estimating simultaneous equations for fleet average fuel efficiency, vehicle numbers and vehicle kilometres travelled (both of which are normalised to population rather than number of drivers), they provide one of the few studies to explicitly address the endogneity problem discussed in Section 2.5.

[37] While fuel prices are found to be significant, Haughton and Sakar observe that the link between US fuel prices and new car fuel efficiency may be weakening, as the US car market is becoming increasingly influenced by the demands of the European and Japanese markets.

[38] As a greater proportion of adults become drivers, the amount driven per driver is likely to fall. Secondary drivers tend to drive less as the total amount of driving is distributed more widely.

In this case, endogneity appears to be very important since, compared to the use of 2SLS and 3SLS, estimation of the individual equations by OLS leads to the short and long-run rebound effects being overestimated by 88% and 53% respectively (although it is possible that factors other than endogneity contribute to this).

In contrast to Haughton and Sakar, Small and van Dender represent the CAFE standards by a variable indicating the gap between the mandated fuel efficiency and an *estimate* of the fuel efficiency that would have been chosen in the absence of the standards. The latter is obtained from a partial adjustment model that incorporates pre-1977 data and estimates the demand for fuel efficiency as a function of fuel prices, taking into account the difference between the test performance of vehicles and their on-road fuel efficiency.[39] Small and van Dender are able to develop both short and long-run elasticity estimates through the use of a lagged dependent variable, but at the same time employ an estimation procedure that addresses the problem of serial correlation without introducing bias. Most importantly, by interacting the fuel cost per kilometre and income variables, they are able to allow for the fact that the response to changes in fuel costs may vary with income (since, as incomes increase, fuel costs account for a declining proportion of the generalised cost of car travel while time costs account for an increasing portion). This elasticity is also allowed to vary with spatial density and the level of fuel costs itself.

Small and Van Dender estimate the short-run direct rebound effect for the US as a whole to be 4.5% and the long-run effect to be 22%. The former is lower than most of the estimates in the literature, while the latter is close to the consensus.[40] However, they estimate that a 10% increase in income reduces the short-run direct rebound effect by 0.58% – as the theoretical considerations reviewed in Section 2.6 predict. Using US average values of income, urbanisation and fuel prices over the period 1997-2001, they find a direct rebound effect of only 2.2% in the short-term and 10.7% in the long-term - approximately half the values estimated from the full data set. If this result is robust, it has some very important implications. However, two-fifths of the estimated reduction in the rebound effect derives from the assumption that the magnitude of this effect depends upon the absolute level of fuel costs per kilometre. But since the relevant coefficient (on P_S^2) is not statistically significant, the claim that direct rebound effects have fallen is called into question.

Despite its methodological sophistication, Small and Van Dender's study is not without its problems. First, despite covering 50 states over a period of 36 years, the data provides relatively little variation in vehicle fuel efficiency making it difficult to determine its effect separately from that of fuel prices. This is illustrated by an alternative specification that allows for separate estimates of $\eta_{P_E}(S)$ and $\eta_{\varepsilon}(S)$. While $\eta_{P_E}(S)$ is found to be approximately equal to the original estimate of $\eta_{P_S}(S)$, $\eta_{\varepsilon}(S)$ is found to be small and statistically insignificant. Since $\eta_{\varepsilon}(S)$ is a more direct estimate of the direct rebound effect than $\eta_{P_S}(S)$, this could be interpreted as implying that the direct rebound effect is approximately zero. However, the new specification performs rather poorly overall, with

[39] Small and van Dender estimate that, in the absence of the standards, increases in fuel prices in real terms would have led to a gradually increasing demand for more fuel-efficient vehicles. As a result, while the CAFE standard is estimated to have been binding since 1997, its tightness has gradually diminished and was largely ineffective in 2001.

[40] They estimate the long-run, own-price elasticity of gasoline demand to be -0.43, which is also in the mid-range of recent studies (Table 4.1).

several of the coefficients becoming unstable with respect to the inclusion or exclusion of other variables. This leads Small and Van Dender to prefer the original specification and (as with most studies) to base their estimates of the direct rebound effect on $\eta_{P_S}(S)$.

Second, the difference between the estimated direct rebound effect in individual states and the national average depends upon the difference between the state's income and the national mean (i.e. states with higher incomes have rebound effects that are below the national mean). But as shown by Harrison *et al* (2005), this leads to the implausible result that the direct rebound effect in some states (including Connecticut and the District of Columbia) is negative. This raises questions about the validity of the results and particularly about the use of the model for projecting declining rebound effects in the future (since increasing incomes could make rebound effects negative in many states).

In summary, both cross-country and regional panel data provide substantially more observations than time-series or cross-sectional data and thereby provide a more robust basis for estimates of the direct rebound effect. Three of the studies reviewed above are very carefully done, incorporate important methodological innovations and should be given some weight in forming a judgement about the magnitude of the direct rebound effect for personal automotive transport. Johansson and Schipper's (1997) cross-country study gives results at the high end of the range in the literature (i.e. a best guess for the long-run direct rebound effect of **30%)**, while both Haughton and Sakar and Small and van Dender converge on a long-run value of **22%** for the US.

Small and van Dender's results provide a strong indication that the direct rebound effect declines with increasing income - as theory predicts. If so, this result has considerable importance for future policy in this area. However, their model has a number of weaknesses and their result is not supported by Hanley *et al*'s (2002) meta-analysis of other studies in this area. Hence, this issue should be a priority for further research.

Table 4.7 Estimates of the direct rebound effect for personal automotive transport using aggregate panel data

Author/year	**Short-run rebound effect**	**Long-run rebound effect**	**Country**	**Data**	**Model structure**	**Functional form**	**Estimation technique**	**Comments**
Orasch & Wirl, 1997	10-20%	27 – 30%	UK, France, Italy	Aggregate Panel (X-country) KOKO	Single equation (*S*) Dynamic	Double Log	OLS	
Johansson and Schipper (1997)		5 – 55% Best guess: 30%	12 OECD	Aggregate Panel (X-country)1973-1992	Recursive (*S*, ε, *NO*)	Double Log	Various	Careful attention to data quality. Equivalence of $\eta_{\varepsilon}(S)$ and $\eta_{P_E}(S)$ not tested.
Haughton and Sakar (1996)	9 – 16%	22%	US	Aggregate Panel (US states) 1973-1992	Simultaneous (*S*, ε)	Double Log	2SLS	Dependent variable is distance travelled by a driver.
Small and van Dender (2005)	4.5%	22%	US	Aggregate Panel (US states) 1961-2001	Simultaneous (*S*, ε, NO)	Double Log	3SLS	Dependent variable is distance travelled per-capita. Rebound effects estimated to decline with income. Tests suggest that $\eta_{\varepsilon}(S) \neq \eta_{P_E}(S)$.

4.5 Evidence from studies using disaggregate data

A number of studies have used household survey data to estimate elasticities of fuel and travel demand for passenger cars. While less common, this approach avoids some of the measurement difficulties associated with aggregate data (Schipper*, et al.*, 1993) and has the potential to provide very accurate data on distance travelled and fuel consumption. It also allows variations in demand patterns between different types of households and/or vehicles to be investigated, including in particular how the ownership of two or more vehicles can affect price responses (Mannering, 1983). The disadvantage is that the relevant datasets are generally larger and more difficult to handle, while the results may be less easy to generalise to the national level. Studies using disaggregate data also show greater variability in their estimates of the direct rebound effect; with several studies estimating rebound effects of 50% or more.

Disaggregate studies include those that use survey data from a single year (cross-section), those that use multi-year data from the same households (panel) and those that use multi-year data from a different sample of households in each sample year (pooled). This section contains examples of each and focuses upon a five studies that are considered to be methodologically robust. The results are summarised in Table 4.8.

Goldberg (1996) provides an impressively detailed study of the effect of the CAFE standards, drawing upon data from the US Consumer Expenditure Survey covering the period 1984-1990, together with additional information on new car fuel efficiency. The CES provides comprehensive information on household and vehicle characteristics including vehicle ownership, size, age, type, capital costs, operating costs and usage patterns, based upon odometer data from each car during each quarter. Following Durbin and McFadden (1984), Goldberg estimates a discrete/continuous model for the ownership and use of different types of vehicle. In the first stage, Goldberg estimates a four-stage nested logit model to give the probability of a household: buying a car; choosing between new and second-hand cars; choosing between one of nine categories of new car; and choosing between foreign and domestic models. The independent variables vary with each level but include capital cost, operating cost per kilometre, size, income and various demographic factors. In the second stage, Goldberg estimates an equation for the distance travelled by *new* cars, using the choice probabilities from the discrete choice equations as an instrumental variable for vehicle ownership and characteristics (second-hand cars are excluded, owing to lack of data on production year and hence fuel efficiency). The direct rebound effect can be estimated from this second equation using the estimated value of $\eta_{P_S}(S)$. This elasticity relates to new cars only and since it is conditional on the choice of a particular vehicle, Goldberg interprets it as a short-term direct rebound effect.

Using instrumental variables to estimate the second equation avoids potential endogneity bias. To examine the importance of this, Goldberg estimates a reduced form equation using OLS and compares the results with the instrumental variable estimation. The results suggest that the endogneity bias is significant. Without correcting for this bias, the direct rebound effect (using $\eta_{P_S}(S)$) averaged across all (new) vehicles is estimated to be 22%. However, once the instrumental variable approach is employed, the direct rebound effect becomes negative implying that higher fuel efficiency leads to *less* driving. But since the coefficient in this case is highly insignificant, Goldberg's results essentially imply that the direct rebound effect for new cars is zero. Goldberg's results also show that $\eta_{P_S}(S)$ for individual vehicles within multi vehicle households is larger than for single vehicle households, presumably because households can shift to more fuel-efficient vehicles.

There are a number of qualifications to this result. First, the results are short run, since they do not reflect the effect of fuel price/fuel efficiency changes on new vehicle purchases.[41] Second, the results apply to new cars alone, although it is not clear why direct rebound effects for used cars should be significantly different. Third, the data provides relatively little variation in fuel costs and hence may not reflect the hysteresis effects noted by Haughton and Sakar (1996).

Puller and Greening (1999) also use 9 years of data from the US Consumer Expenditure Survey (CES), but combine this with data on car fuel efficiency that is taken from a different source. Unlike Goldberg, this study includes all vehicles, estimates the distance travelled by each household rather than each vehicle, and uses a simultaneous equation model, rather than a discrete/continuous model. Since the CES is a 'rotating panel' data set (each household participates for one year), this means that the study only provides information on how households adjust to changes in fuel efficiency or fuel prices within one year. Puller and Greening justify this with reference to the meta-analysis by Espey (1996), which indicates that 70% of the response to changes in fuel prices occurs within one year. But this nevertheless limits the ability of the study to capture long-run changes in vehicle stock (as with the Goldberg study, although for different reasons).

Puller and Greening estimate simultaneous equations for the average fuel efficiency of each household (i.e. averaged across all vehicles) and the total distance travelled by each household, excluding business mileage (note that Goldberg included business mileage). The specification includes the current gasoline price and gasoline prices in the previous four quarters, together with income, demographic characteristics the price of new vehicles and the endogenous variables. Vehicle age is not included, although it is known to be strongly correlated with both fuel efficiency and vehicle utilisation. This is potentially important, since it could induce a spurious correlation between fuel cost per kilometre and distance travelled, by their mutual correlation with vehicle age (Greene*, et al.*, 1999a). The fact that attention is confined to non-business travel could also be important, since this may be expected to be more responsive to changes in the fuel cost per kilometre.

Based upon the estimated elasticity of distance travelled by the household with respect to fuel costs per kilometre ($\eta_{P_S}(S)$), Puller and Greening estimate the direct rebound effect to be 49%. This is significantly larger than the estimates from studies using aggregate data, despite the fact that it relates solely to the short to medium-term and despite the fact that it is based upon the same data as Goldberg's study, which estimates the direct rebound effect to be zero. Puller and Greening also estimate that a 1% increase in fuel prices would result in 0.22% decrease on-road in fuel efficiency (i.e. $\eta_{P_E}(\varepsilon) < 0$). The explanation given is that households respond to fuel price increases by cutting back on long journeys, such as vacations, which generally have higher fuel efficiency than short trips. Hence, higher fuel prices encourage households to reduce fuel consumption and fuel costs, but in doing so they

[41] From the discrete choice equation, Goldberg estimates that 1% increase in fuel efficiency increases the probability of buying a particular vehicle type by 10%. But she does not indicate the effect on the probability of buying any vehicle.

worsen average fuel efficiency. The same response is unlikely in the long term, since higher fuel prices should encourage the purchase of more fuel-efficient vehicles (Table 4.5).

The two equation model gives an own-price elasticity of gasoline consumption of -0.47, which is within the range of other studies.[42] However, the finding that the fuel price elasticity for fuel efficiency is negative means that Puller and Greening's estimates for $\eta_{P_S}(S)$ and $\eta_{P_E}(S)$ are not consistent with Equation 2.11. This provides a partial explanation for why the estimated direct rebound effect is so high, while the omission of a variable for vehicle age and the exclusion of business travel may provide additional explanations. Puller and Greening also estimate a single equation model for gasoline consumption, which gives a lower elasticity of -0.32. But many of the parameters of this equation are not significant, the model shows very poor goodness of fit and an alternative pooled model (including data points from all nine years) gives fuel price elasticities greater than unity which are considered implausible.

Greene *et al*. (1999a) is a very comprehensive and methodologically rigorous study, based upon US household survey data of vehicle ownership and use that covers six different years over the period 1979 to 1994 (i.e. pooled data with ~3000 households and ~6000 vehicles in each survey). The particular advantage of this study – at least in the US context - is the detailed treatment of multi-vehicle households.

Greene *et al*. estimate different sets of simultaneous equations for households with one, two, three, four and five (!) vehicles. For single vehicle households there are three equations for distance driven, fuel efficiency and fuel prices,[43] while for two vehicle households there are two sets of three equations - and so on. These equations reflect two sources of endogenity. First, the fuel efficiency of a vehicle will depend upon its (expected) usage, while its usage will depend upon its fuel efficiency (Section 2.5). Second, the utilisation of one car will depend upon the utilisation of another (e.g. if you use one car to drive to the shops, you won't be using the other) (Mannering, 1983). Higher fuel prices may be expected to encourage greater use of the more fuel-efficient car in the household. Also, while the usage of one vehicle will directly affect the usage of a second vehicle, it will also <u>indirectly</u> affect the *on-road* fuel efficiency of that vehicle via its effect on usage.

Distance driven is estimated as a function of the on-road fuel efficiency of the vehicle, together with current gasoline prices and other household, vehicle and location variables including vehicle age. In turn, on-road fuel efficiency is estimated as a function of distance driven, current gasoline prices and other variables, including the average fuel efficiency of all cars produced in the model year of the relevant vehicle.[44] Current fuel prices affect on-road fuel efficiency through changes in how the vehicle is used. However, the model does not explain the decision of how many vehicles to own, or the choice of new-car fuel efficiency. As a result, it cannot be used to estimate the long-run own-price elasticity of gasoline consumption because it does not represent the effect of fuel prices on the fuel

[42] Since *E=S/ε*, taking logs and differentiating with respect to the fuel price gives: $\eta_{p_E}(E) = \eta_{p_E}(S) - \eta_{p_E}(\varepsilon)$.

[43] Fuel prices are claimed to be endogenous because drivers can react higher fuel prices by searching harder for cheaper fuel and because if you travel further you pass more petrol stations with a greater range of prices. Neither argument is convincing and the empirical evidence for this endogneity is weak.

[44] Unlike Puller and Greening, distance driven includes business use, although this is included as a right hand side variable.

efficiency of new vehicle purchases. Echoing Puller and Greening's results, Greene *et al* find that current fuel prices have a *negative* effect the on on-road fuel efficiency of vehicles, presumably because drivers cut back on long distance travel.

Greene *et al* test the hypothesis that consumers respond symmetrically to changes in fuel prices and changes in fuel efficiency. This is done by imposing the restriction that the coefficients of fuel prices and on-road fuel efficiency in the distance travelled equation sum to zero. This hypothesis is not rejected, lending support to the symmetry argument - and thereby supporting the findings of Schimek (1996) but not those of Wheaton (1982) or Small and van Dender (2005)). However, the R^2 for the distance traveled equation for one vehicle households is only 0.29 and the fact that the adjusted autocorrelation coefficients are consistently high for the fuel cost equation but not for the utilisation equation suggests potential misspecification.

By manipulation, Greene *et al* estimate the total system elasticity of household travel demand with respect to fuel efficiency ($\eta_{\varepsilon}(S)$) for each level of vehicle ownership. This is taken as a measure of the long-run direct rebound effect, since the data consists of different households in different circumstances spanning a 15 year time interval. This may be an underestimate, since the model does not represent the influence of fuel prices and fuel efficiency on the number of vehicles owned (including the purchase of a vehicle for the first time). Greene *et al* argue that this effect should be small because fuel costs form less than 10% of vehicle ownership costs (an argument that can be used for other energy services), but this is not supported by the results summarized in Table 4.4. Greene *et al* estimate the long-run direct rebound effect to range from 17% for three-vehicle households to 28% for one-vehicle households. Weighting by the distance driven by each type of household gives an average long-run direct rebound effect of 23%, which compares well with the estimates from aggregate data (including Haughton and Sakar (1996) and Small and van Dender (2005)). Since income growth leads to more households owning multiple vehicles, the results also suggest another reason why the direct rebound effect may decline with income,

West (2004) is the third study to use the US Consumer Expenditure Survey, this time for a detailed investigation of the distributional effects of vehicle pollution control policies. Unlike Goldberg (1996) and Puller and Greening (1999), this study uses cross-sectional data from a single year of the survey (1997), which is supplemented by additional information on vehicle fuel efficiency. The latter uses data from a survey of 667 vehicles in California as the basis of a regression equation on vehicle age and engine size.[45]

Following Goldberg, West estimates a discrete/continuous model for the ownership and use of different types of vehicle. In the first stage, West estimates a nested logit model that gives the probability of choosing one of 18 combinations of the number (between one and two), age and engine size of vehicle. Independent variables here include capital cost, *operating cost* per kilometre, income and various demographic factors. In the second stage, West estimates an equation for the total distance travelled by the household, using the choice probabilities from the discrete choice equation as an instrumental variable for vehicle ownership and characteristics.

[45] It is notable that each of the 3 studies which rely upon the US CES estimates the fuel efficiency of vehicles from a different data source.

As with Puller and Greening, the use of distance travelled by the household as the dependent variable means that study overlooks any response to fuel prices by shifting to the more fuel-efficient vehicle (in two-car households)[46] – although the study by Greene *et al* suggested that this is of some importance. Using the correction for endogeneity, West calculates the elasticity of demand for distance travelled with respect to the operating cost per kilometre of vehicles, conditional upon vehicle choice. Using the sample means of distance travelled, operating cost per kilometre and total expenditures, this gives an elasticity of -0.87. Operating cost is defined as the sum of fuel costs, maintenance costs and tyre costs per kilometre and is therefore greater than fuel costs alone.[47] The estimated magnitude of direct rebound effects therefore depends upon the share of fuel costs in total operating costs - which in turn will vary with the age and fuel efficiency of the vehicle. Since West does not provide a breakdown of operating costs at the sample mean, the best that can be said is that the study suggests an *upper bound* for the direct rebound effect of 87%. In practice, it appears likely that fuel costs will form at least half of the operating costs as defined here, suggesting a direct rebound effect of 40% or more. West's estimate of the direct rebound effect is therefore much larger than obtained from studies in using aggregate data.

Finally, **Frondel, *et al* (2007)** provide a rare example of a European study using household survey data. Their data source is the German Mobility Panel, comprising a group of households surveyed for a period of six weeks in spring in three consecutive years. Frondel *et al*'s sample of 293 single-car households is significantly smaller than in the studies reviewed above, but includes data on monthly distance driven, monthly fuel consumption, vehicle age and other demographic variables A notable feature of this study is the estimation of direct rebound effects from three different elasticities derived from three different models, namely: a) $\eta_{\varepsilon}(S)$ with fuel prices as a control variable; b) $\eta_{P_S}(S)$ imposing the restriction that the response to a change in fuel efficiency is equal and opposite to the response to a change in fuel prices ($\eta_{\varepsilon}(S) = -\eta_{P_E}(S)$); and c) $\eta_{P_E}(E)$ from a regression of fuel consumption on fuel prices and other variables. In the case of the second model, the null hypothesis of equal and opposite coefficients is not rejected, thereby lending support to the symmetry argument.

Frondel*, et al* (2007) also estimate each model in three different ways, namely fixed effects, between effects and random effects (see Section 3.7). Fixed-effects controls for time-invariant factors that vary across households while between-effects controls for household invariant factors that vary over time. Random effects allow for factors that vary both between households and over time.

What is notable about this study is that the estimates of the rebound effect appear remarkably insensitive to either the choice of elasticity measure or the choice of estimation method – thereby suggesting that they are robust. In all cases, the direct rebound effect is estimated to lie between 56% and 66%, which is significantly higher than the consensus

[46] The fuel efficiency of vehicles used by a two-car households is taken as a simple average, thereby implicitly assuming equal use of each vehicle.

[47] Insurance costs are not mentioned. West notes that time costs and expected accident costs are omitted from the definition of operating costs. Since the former is determined largely by income, regressions that include total operating costs give positive coefficients – implying that higher operating costs *increase* the demand for distance travelled. A better approach, therefore, is to exclude time costs from operating costs and include income as a separate variable. The dependence of rebound effects on income could then be investigated through the use of interaction terms (i.e. income*fuel costs).

values results from US studies. However, given the small sample size, it is not possible to judge whether this reflects any systematic difference between Germany and the US.

In summary, studies using disaggregate data sources provide much less consistent estimates of the direct rebound effect than those using aggregate data sources. Moreover, several of the estimates are significantly higher than those from aggregate data sources. While disaggregate data should avoid some of the measurement difficulties reported by Schipper *et al* (1993), the greater complexity of the models can create some difficulties of interpretation - especially when discrete/continuous models are used. It is notable that three of the studies use data from the US Consumer Expenditure Survey taken from overlapping periods, but nevertheless produce estimates of the direct rebound effect that range from **0% to 87%**. This diversity suggests that the results from disaggregate studies should be interpreted with a much greater caution.

Of the studies reviewed, Greene *et al* (1999) provides the most careful investigation of the direct rebound effect, albeit neglecting long-term changes in the vehicle stock. This study also produces an estimate of the long-run direct rebound effect (23%) which is consistent with the results of aggregate studies. As with the aggregate studies, there is again a strong bias towards studies from the US. While Frondel *et al*'s study is suggestive of large rebound effects in Germany, the small sample size, the lack of comparable studies from Europe and the inconsistency between these results and those of aggregate estimates of fuel price elasticities provide an insufficient basis to conclude that direct rebound effects are larger in Europe. Indeed, a number of theoretical considerations suggest that rebound effects should be smaller.

Table 4.8 Estimates of the direct rebound effect for personal automotive transport using disaggregate data

Author/year	**Short-run rebound effect**	**Long-run rebound effect**	**Country**	**Data**	**Model structure**	**Functional form**	**Estimation technique**	**Comments**
Goldberg, (1996)	0%		US	Rotating panel 1984-1990 (CES)	Discrete/ continuous	Double Log (utilisation equation)	Nested logit (discrete) & Instrumental variables (utilisation)	Utilisation of new cars only. If endogneity bias ignored, rebound effect estimated to be 22%
Puller and Greening (1999)	49%		US	Rotating panel 1980-1990 (CES)	Simultaneous equation (dynamic – single year)	Double log	2SLS	Find $\eta_{P_E}(\varepsilon) < 0$. Omission of vehicle age may lead to bias
Greene (1999)		23%	US	Pooled cross section (travel survey)	Simultaneous equation	Double log	3SLS	Rebound effects estimated for households owning 1 to 5 vehicles – quoted figure is weighted average. Find $\eta_{P_E}(\varepsilon) < 0$
West (2004)	87%		US	Cross-section (CES - 1997)	Discrete/ continuous	Double Log (utilisation equation)	Nested logit (discrete) & Instrumental variables (utilisation)	Rebound effect estimated from $\eta_{P_G}(S)$, so represents and upper bound
Frondel (2007)		56-66%	Germany	Panel	Single equation	Double log	Fixed/random effects	Rebound effect estimated from $\eta_{P_E}(S)$, $\eta_{\varepsilon}(S)$ and $\eta_{P_E}(E)$

4.6 Summary

Personal automotive transportation is one of the few areas where the evidence base is sufficiently strong to allow the magnitude of the direct rebound effect to be quantified with some confidence. This section summarises the main findings.

First, estimates of the own price elasticity of gasoline demand suggest a mean value of the upper bound for the long-term direct rebound effect of 80%. However, this mean value disguises a large variance in the results and using the full range of estimates suggests an upper bound of between 0 and 181%. The breadth of this range reflects the wide range of countries and time periods on which the estimates are based and hence is rather unhelpful. Moreover, the majority of these studies assume that the effect of a price reduction on demand is equal and opposite to the effect of a price increase. Studies that take price asymmetry into account typically find elasticities during periods of falling prices to be significantly smaller than those during periods of rising prices. The implication is that price elasticities - and hence direct rebound effects - may be <u>smaller</u> than suggested by many time-series studies.

In principle, estimates of the elasticity of distance travelled with respect to either fuel efficiency ($\eta_{\varepsilon}(S)$) or the fuel cost per mile $\eta_{P_S}(S)$ should provide an accurate estimate of the direct rebound effect. Estimates of the latter are more common in practice, owing to the greater variation in the independent variable (P_S) and the additional degrees of freedom this provides. However, these estimates rely upon the assumption that that the response to a change in fuel prices is equal and opposite to the response to a change in fuel efficiency. Few studies test this assumption explicitly and those that do are either unable to reject the null hypothesis that the two elasticities are equal, or find that the fuel efficiency elasticity is *less* than the fuel cost per mile elasticity. Again, the implication is that the direct rebound effect may be <u>smaller</u> than suggested by the results of many of the studies reviewed here.

The studies reviewed vary considerably in terms of the data used and the specifications employed. Most studies use aggregate data that can in principle capture long-term effects on demand like fuel efficiency standards or price-induced technical change. Disaggregated studies better describe household behaviour at the micro level. However, aggregate studies face numerous measurement difficulties, while disaggregate studies are more difficult to implement and produce results that are more difficult to generalise. Also, the relevant dependent variable varies between total distance travelled, distance travelled per capita, distance travelled per licensed driver and distance travelled per vehicle.

Studies using aggregate time-series and cross-sectional data estimate the long-run direct rebound effect for personal automotive transport to be somewhere between **5% and 30%**. While there is disagreement over the appropriate specification, the limited number of data points available makes it difficult to settle the issue from this type of data alone.

Aggregate panel data should provide a more robust basis for estimates of the direct rebound effect, owing to the greater number of observations. Johansson and Schipper's (1997) cross-country study gives a best guess for the long-run direct rebound effect of **30%**, while both Haughton and Sakar (1996) and Small and van Dender (2005) converge on a long-run value of **22%** for the US. Small and van Dender's study incorporates some important methodological innovations and suggests that the direct rebound effect declines with increasing income. However, their model has a number of weaknesses and the results are not supported by Hanley *et al*'s (2002) meta-analysis of estimates of $\eta_{P_E}(E)$ for personal automotive transport.

Studies using disaggregate data sources provide much less consistent estimates of the direct rebound effect and several of these estimates are significantly higher than those from aggregate data sources. Three US studies using comparable data sources produce estimates of the direct rebound effect that range from 0% to 87%. This diversity suggests that the results from disaggregate studies should be interpreted with a much greater caution. Greene *et al* (1999) appears the most rigorous of the studies reviewed and estimates the long-run direct rebound effect to be **23%**, which is consistent with the results of aggregate studies.

Taken together, the review suggests that the long-run direct rebound effect for personal automotive transport lies somewhere between **10% and 30%**. The relative consensus on estimates, despite wide differences in data and methodologies suggests that the findings are robust. Also, the asymmetry of demand responses and the limitations of the 'symmetry' assumption both suggest that the long-run direct rebound effect may be towards the lower end of this range.

The extent to which the direct rebound effect for this energy service declines with income remains unclear, although the methodologically rigorous studies by Small and van Dender (2005) and Greene *et al* (1999a) both suggest that it does. Measurement problems remain an issue for aggregate studies, as does the geographical bias towards the United States. The evidence reviewed here is insufficient to determine whether direct rebound effects are larger or smaller in Europe, but it is notable that the meta-analysis by Espey (1998) found no significant difference in long-run gasoline demand elasticities. Overall, it must be concluded that direct rebound effects in this sector have not obviated the benefits of technical improvements in vehicle fuel efficiency. Between 70 to 100% of the potential benefits of such improvements should be realised in reduced on-road fuel consumption.

5 Evidence for direct rebound effects for household heating

5.1 Introduction

After road transport, energy use by households is perhaps the best studied area in the economics of energy demand (Madlener, 1996). Since household energy demand is dominated by the use of fuel and/or electricity for space heating, the evidence on the economics of household heating is relatively good. As a result, the evidence for direct rebound effects for this energy service is also relatively good, although weaker than that for personal automotive transport.

As with all energy services, there are two broad approaches to estimating direct rebound effects for space heating. The first is to use a quasi-experimental research design that includes measurements of the change in demand for either useful work or energy consumption following an improvement in energy efficiency. A number of studies that use this approach for household heating are reviewed in *Technical Report 1*, which concludes that the methodological quality of most of these studies is relatively poor. Nevertheless, they suggest a direct rebound effect for household heating of around 30%, with higher values for low income groups

The second approach relies upon secondary data sources, frequently collected for other purposes, that include information on the demand for energy, useful work and/or energy efficiency and which use econometric techniques to estimate one or more of the elasticities listed in Table 3.1. Most of these studies do not mention the rebound effect explicitly. This section reviews a number of studies that follow this second approach, focusing upon those that are considered to be methodologically rigorous. While the studies have been selected through an extensive literature search, the coverage is not comprehensive. Compared to the evidence for personal automotive transport, these studies exhibit a greater range of methodological approaches and a greater diversity in empirical results.

Section 5.2 reviews the empirical literature estimating the own-price elasticity of the *total* demand for fuel and electricity by households ($\eta_{P_E}(E_{total})$). In principle, this should provide an indication of the upper bound for direct rebound effects for household energy services. However, unlike the corresponding estimates for personal automotive transport discussed in Section 4.2, these estimates apply to *all* household energy services and hence are less useful in setting bounds on the direct rebound effect for space heating.

Section 5.3 reviews some of the methodological challenges associated with estimating direct rebound effects for space heating, focusing upon the choice of elasticity measures and the factors contributing to variations in these measures between different types of household. Sections 5.4 and 5.5 then review a selection of studies that provide estimates of the elasticity of demand for energy use or useful work for space heating. In principle, each of these studies should provide a more accurate estimate of direct rebound effects for space heating than reliance upon estimates of $\eta_{P_E}(E_{total})$. However, the diversity of elasticity measures used reflects the rather patchy nature of the evidence base and makes it difficult to compare the results of different studies. Section 5.6 concludes.

5.2 Setting bounds on the direct rebound effect for household heating

5.2.1 The importance of heating in household energy consumption

Measured on the basis of thermal content, household heating dominates household energy demand in most OECD countries. In the UK in 2005, for example, space heating accounted for 60% of (delivered) household energy use, 72% of household fuel demand and 18% of electricity demand.[48] Natural gas was the dominant fuel for space heating, with electricity accounting for only 6.4%. However, the fuel mix for space heating varies widely from one OECD country to another, with electricity playing a significantly more important role in the US and Scandinavia and with district heating playing an important role in several northern European countries. Changes in energy prices may encourage consumers to switch fuels for space heating, while many households use two or more fuels for heating. Also, in countries and regions with warmer climates, energy use for space heating may be less important than that for space cooling. These factors contribute to a wide variation in energy price elasticities between different countries, regions and households.

Table 5.1 Household fuel use by end use in the UK (tonnes of oil equivalent - 2005)

	Space heating	Water	Cooking	Lighting and Appliances	Total
Solid fuel	468.7	201.7	26.7	-	697.1
Gas	23,536.0	8,791.4	691.4	-	33,018.8
Electricity	1,811.4	1,002.1	621.6	6,608.9	10,043.9
Oil	2,394.4	634.0	64.6	-	3,093.1
Total	28,210.5	10,629.2	1,404.3	6,608.9	46,853.0

Source: DTI (2007)

Table 5.2 Household fuel use by end use in the UK in 2005 (% of total - 2005)

	Space heating	Water	Cooking	Lighting and Appliances	Total
Solid fuel	67.2	28.9	3.8	-	100.0
Gas	71.3	26.6	2.1	-	100.0
Electricity	18.0	10.0	6.2	65.8	100.0
Oil	77.4	20.5	2.1	-	100.0
Total	60.2	22.7	3.0	14.1	100.0

Source: DTI (2007)

5.2.2 Heating elasticities and overall elasticities

As Table 5.2 suggests, space heating typically accounts for more than two thirds of household fuel use in the UK, with most of the remainder being used for water heating. In these circumstances, estimates of the own-price elasticity of total household fuel consumption using aggregate data should provide a rough indication of the own-price elasticity of fuel use for space heating (i.e. $\eta_{P_E}(E_{heat}) \approx \eta_{P_E}(E_{total})$). This may not be the case in other countries if electricity forms a greater share of energy use for space heating or if fuel use for non-heating purposes is proportionately more important. Similarly, if electricity

[48] Space and water heating combined accounted for 83% of UK household fuel demand. Since 1970, energy use for space heating in the UK has increased by 24%, for water heating by 15% and for lighting and appliances by 157%. Energy used for cooking has fallen by 16% (DTI, 2007).

provides the main energy source for space heating, the own-price elasticity of electricity use for heating may be roughly approximated by the own-price elasticity of total household electricity demand. Whether such approximations are appropriate for studies using disaggregate data sources will depend upon the particular households being studied.

Whether estimated for electricity or fuel, $\eta_{P_E}(E_{total})$ may not provide an upper bound for $\eta_{P_E}(E_{heat})$ since it is possible (indeed likely) that the own-price elasticity of other energy services (e.g., cooking and water heating) is less than $\eta_{P_E}(E_{heat})$. In these circumstances, $\eta_{P_E}(E_{heat})$ could exceed $\eta_{P_E}(E_{total})$, although in the case of fuel use the difference is unlikely to be large. Also, many households use more than one energy carrier for space heating and there may be scope for long-term substitution between different heating technologies. This suggests that $\eta_{P_E}(E_{heat})$ should be estimated for all heating fuels combined, excluding the fuel used for other energy services. But measurement difficulties preclude this option in most cases[49] and the demand response will depend upon the particular composition of price changes. If instead, price elasticities are estimated for each individual fuel, it is possible that $\eta_{P_E}(E_{heat})$ for all fuels combined could be less than $\eta_{P_E}(E_{total})$ for an individual fuel since an increase in the price of one fuel relative to another could induce substitution away from the fuel whose relative price has increased. These two considerations may therefore partially offset each other and their relative importance will depend in part upon the actual scope for fuel substitution and the extent to which the prices of different fuels are correlated.

Fuel use for heating is rarely sub-metered, but it may be estimated by subtracting the mean fuel demand during the summer months or by statistical analysis incorporating information on heating degree days, appliance ownership and other factors. Hence, in many cases it is possible to estimate $\eta_{P_E}(E_{heat})$ for individual fuels. In cases where a single fuel is used, $\eta_{P_E}(E_{heat})$ should provide an upper bound for the own-price elasticity of 'useful work' for space heating ($\eta_{P_S}(S_{heat})$), where a suitable measures for S_{heat} is kilowatt hours of heat output from the heating system. The latter measure, in turn, is a better proxy for the direct rebound effect.

It is difficult to make general statements on the short or long-run price elasticity of total household energy demand, since this depends upon the energy carrier, the type of household, the particular country or region and the level of household income. Also, price elasticities tend to change over time, to vary with the price level (with higher prices generally encouraging higher elasticities) and to be asymmetric (with a response to increasing energy prices generally being greater than the response to falling energy prices) (Kouris, 1982; Berkhout*, et al.*, 2000). To the extent that many studies rely upon double log specifications that implicitly assume that elasticities are constant, the latter effect may frequently be overlooked. Nevertheless, the estimates summarised below suggest that household fuel and electricity demand in OECD countries is price-inelastic (i.e. $|\eta_{P_E}(E_{total})| < 1$). This suggests that improvements in the energy efficiency of household energy services are unlikely to lead to backfire.

[49] Nesbakken (2001) is a notable exception.

5.2.3 The price elasticity of total household electricity demand

Generally speaking, there have been rather more studies of household electricity demand than household fuel demand. The majority of these apply to the US, where electricity forms a greater proportion of household heating demand than in Europe and where in many regions there is a large demand for electricity for space cooling. Studies of US electricity demand over the period 1945 to 1970 appeared to find very high price elasticities, although this may be partly a consequence of the rapid growth in electrical appliance ownership during this period.[50] For example, Wilson (1971) used a simple cross-sectional analysis of 77 US cities to estimate an own-price elasticity of electricity demand of -1.33. But with ownership of many durable goods reaching saturation levels, such estimates may no longer be valid.

More recent studies have generally provided lower estimates of price elasticities. For example, in their review of 18 studies, Bohi and Zinnerman (1984) estimated the short and long-run own-price elasticities of residential electricity demand to be -0.2 and -0.7 respectively. This review was recently updated by Espey and Espey (2004), who conducted a meta-analysis of 123 estimates of short-run price elasticities and 125 estimates of long-run price elasticities taken from 36 studies (again, mostly from the US).

Taken together, the mean values of these estimates suggests an upper bound for the short-term direct rebound effect for all household electricity services combined of 20-35% and an upper bound for the long-term effect of 80-85%.[51] However, these values disguise a large variance in the results between different countries, regions and households as well as between different methodological approaches. For example, using the full range of estimates suggests that the upper bound for the long-run direct rebound effect lies somewhere between between 4% and 225%, which is an even wider range than found for passenger transport. This upper bound is likely to be an overestimate of the direct rebound effect, both because the use of $\eta_{P_E}(E_{total})$ neglects the effect of electricity prices on energy efficiency (Equation 2.11) and because most of the studies neglect the price asymmetry of energy demand behaviour (discussed further below), However, it could also be an underestimate of the direct rebound effect for some electricity services since it represents a weighted average of all services, implying that some services will be more price elastic and some less.

5.2.4 The price elasticity of total household fuel demand

Evidence on the own price elasticity of household fuel demand is more variable and less robust than that for household electricity demand, although several studies suggest a lower price elasticity than for electricity. For example, in a study of UK households, Baker and Blundell (1991) estimate the mean weighted own-price elasticity for natural gas to be -0.41, -0.62 and -0.47 for winter, spring/ autumn and summer respectively, while the

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[50] With lower levels of appliance ownership, electricity is less of a necessity. This could lead to higher price elasticities than in the current period. Alternatively, the smaller range of options in terms of the energy efficiency of appliances compared to the current period could lead to lower price elasticities (Espey and Espey, 2004).

[51] The short-run elasticities ranged from -0.004 to -2.01, with a mean of -0.35 and a median of -0.28. The long-run elasticities ranged from -0.04 to -2.25, with a mean of -0.85 and a median of -0.81. The distribution of the results was skewed towards the lower end. The meta-analysis also allowed Espey and Espey to identify how factors such as data type and estimation methods influenced the results. For example: studies using non-US data estimated electricity demand to be less elastic in the short-run but more elastic in the long-run; short-run electricity demand was more inelastic during the energy crisis of the 1970, but not significantly different in the long-run compared with either before or after that time; and omission of the price of substitute fuels appeared to bias the results and lead to significantly lower estimates of long-run price elasticities.

corresponding figures for electricity were -0.67, -0.98 and -1.03. Similarly, following a review of four studies, Bohi and Zinnerman (1984) estimate the short and long-run own-price elasticities of US household gas demand to be -0.2 and -0.3 respectively, compared to -0.2 and -0.7 for electricity demand. This review points to an upper bound for the long run rebound effect for household fuel consumption in the range 20-70%, while corresponding figures from a cross-country analysis by the IEA suggest a figure in the range 25-40% (Vouyoukas, 1995).

Not all results follow this pattern, however. For example, in a review of US estimates of the own price elasticity of residential natural gas demand, Dahl (1993) finds short-run estimates in the range +0.02 to -0.88 and long-run estimates in the range +1.86 to -3.44. The corresponding estimates for heating oil suggested a short-run value of <-0.3, but a long-run value of a least -0.6 and possibly a more elastic demand than that for electricity. How much more is unclear, because simple dynamic models suggested an elastic price response with aggregate data but not with disaggregate data, whereas static models suggest the opposite. This area would clearly benefit from a meta-analysis of estimates comparable to that conducted by Espey and Espey for electricity.

5.3 Estimating the direct rebound effect for household heating

The estimated direct rebound effect for household heating will depend upon the type of household being studied and the choice of elasticity measure. Both these issues are discussed below.

5.3.1 Choice of households

The behavioural response to energy efficiency improvements or changes in fuel prices may be expected to vary widely between different demographic groups. In particular, low income households may be expected to be more sensitive to price changes, since energy forms a greater portion of their total expenditure. There is evidence for this from a number of sources, including Baker *et al* (1989), who find the own-price elasticity of gas (electricity) consumption by UK households to be two and a half times (two times) larger for the top income decile than for the lowest income decile. However, not all studies find this to be the case. For example, Nesbakken (1999) finds that the price elasticity of Norwegian household energy demand *increases* with income.[52]

In a similar manner, direct rebound effects may be expected to be larger for low income groups, since they may be expected to take back more of the energy efficiency improvements as improved comfort (Dumagan and Mount, 1993). Hence, a greater responsiveness to price changes among low income groups may result both from energy forming a greater proportion of total expenditure and the lower baseline level of thermal comfort (two factors which are related). Direct rebound effects following heating improvements are a key policy issue for the UK, where several million households live in 'fuel poverty' – defined as spending more than 10% of their income on energy. *Technical Report 1* reviews several UK-based evaluation studies that investigate this issue.

[52] The explanation offered is that the marginal utility of energy consumption is low for high income households. Thus, a reduction in energy consumption due to energy price increases only gives a small reduction in utility (e.g. no longer using the swimming pool). In contrast, the marginal utility of energy consumption is greater for low income households, since any curtailment would necessitate considerable reductions in comfort. Since plausible explanations can be found for both findings, it is essential to examine the data and methodology of each study.

Low income groups are also more likely to live in rental accommodation and may therefore have less control over the characteristics of energy using appliances - which are frequently chosen by the landlord instead. The response of such households to changes in energy prices may therefore be expected to be different from that of owner-occupiers. On the one hand, short-run elasticities (determined largely by decisions on equipment utilisation) may be expected to be higher than those for owner-occupiers since households in rental accommodation are typically on lower incomes. On the other hand, long-run elasticities (determined in part by decisions on new and replacement equipment) may be lower due to the occupants lack of control over investment decisions (Poyer and Williams, 1992). Baker and Blundell (1991) present some estimates of long-run energy price elasticities for the UK, disaggregated by type of tenure, which shows this pattern in the case of gas but not for electricity (Table 5.3).

Table 5.3 Estimates of the long-run own-price elasticity of UK household energy demand, broken down by type of tenure

Tenure	**Gas**	**Electricity**
Mortgaged	-0.640	-1.044
Owner-occupier	-0.481	-0.871
Council tenant	-0.330	-0.659
Rented accommodation	-0.333	-0.937

Source: Baker and Blundell (1991)

For high income households, saturation effects may be expected to reduce the direct rebound effect from improvements in the energy efficiency of household heating systems. These include an upper limit to temperature levels, heated space and the duration of use of heating equipment. This is analogous to the declining direct rebound effects for personal automotive transport, noted in Section 4, although in this case the primary cause is likely to be declining marginal utility rather than the declining importance of energy costs relative to time costs. However, saturation effects may be disguised in estimates of the (energy efficiency or price) elasticity of *total* household energy consumption, since there may be a corresponding increase in fuel/electricity consumption for other uses, such as patio heating.

5.3.2 Choice of elasticity measure

The *dependent* variable for an accurate estimate of the direct rebound effect should either be useful work (S_{heat}) or energy use (E_{heat}) for space heating. Energy use may be measured in kWh energy input to the heating system while useful work may be measured in kWh energy output. The relationship between the two may be expressed as $S_{heat} = \varepsilon_c E_{heat}$, where ε_c is the energy efficiency of the heating system.

However, the energy service provided by the heating system is thermal comfort. To a first approximation, this may be measured by the mean internal temperature (T_i) of the occupied areas of during the hours of occupation. It may be possible to directly monitor either the mean internal temperature of the occupied areas or the thermostat setting, but these two measures will not be equivalent. For example, daily average household temperatures will generally increase following improvements in the thermal insulation of buildings, even if the thermostat setting remains unchanged. This is because insulation contributes to a more even distribution of warmth around the house, reduces the rate at which a house cools down when the heating is off and delays the time at which it needs to be switched back on (Milne and Boardman, 2000). Also, thermal comfort is determined not just by internal temperature, but also by air velocity, humidity and other factors (Frey and Labay, 1988; Dewees and Wilson, 1990). Hence, if only internal temperatures or thermostat settings are monitored, the contribution of these other factors to improved thermal comfort will be overlooked.

The amount of useful work (S_{heat}) required to maintain a particular internal temperature will depend upon the heated area or volume (A), the difference between internal and external temperatures (T_i-T_o), occupancy levels (H), solar gain (G), the thermal resistance of the house (ε_h) and other factors (X): i.e. $S_{heat} = f(A,(T_i - T_o),H,G,\varepsilon_h)$. Hence, the energy use for space heating will depend upon both the energy efficiency of the heating system (ε_c) and the thermal resistance of the house (ε_h): i.e. $E_{heat} = g(\varepsilon_c,\varepsilon_c,A,(T_i - T_o),H,G,X)$. Thermal resistance, in turn, will depend upon a number of factors such as building materials, thickness of insulation, windows, air infiltration, humidity and so on. Hence, an appropriate *independent* variable for an estimate of the direct rebound effect could be ε_c, ε_h, a combination of the two, or one of the elements that comprise ε_h such as the level of roof insulation. Improvements in ε_h (e.g. better insulation) may affect any or all of the factors that determine thermal comfort while improvements in ε_c will generally only affect the amount of fuel required to provide a particular level of heat output. As a result, a change in ε_c may have a different effect on the demand for S_{heat} than a change in ε_h. Also, a change in one of the factors determining ε_h (e.g. cavity wall insulation) may have a different effect on the demand for S_{heat} than a change in another factor (e.g. window glazing). The estimated magnitude of the direct rebound effect may therefore be expected to depend upon the choice of independent variable.

Energy efficiency elasticities may not provide a suitable basis for estimating the direct rebound effect owing to lack of data, measurement error or insufficient variation in the relevant measure of energy efficiency. But as described in Section 2, the direct rebound effect may also be estimated from the energy cost elasticity of the demand for useful work for space heating ($\eta_{P_S}(S_{heat})$) *provided* it is reasonable to assume that the change in demand for useful work following a change in energy efficiency is equivalent to that following a change in energy prices, but opposite in sign. This assumption appears more likely to hold for changes in ε_c rather than changes in ε_h, since the latter may change thermal comfort in a variety of ways independently of conscious behavioural change, while the former may not. More generally, the use of price elasticities is likely to lead to different estimates of the direct rebound effect than the use of energy efficiency elasticities.

The direct rebound effect may also be estimated from the own-price elasticity of the demand for energy for space heating ($\eta_{P_E}(E_{heat})$), but this measure is likely to overestimate the effect owing to the neglect of price-induced improvements in energy efficiency (Box 5.1). However, more accurate estimates of the short-run direct rebound effect may be obtained if energy efficiency can be controlled for within the specification - $\eta_{P_E}(E_{heat})\big|_{\varepsilon}$ - where ε refers to ε_h, ε_c or (preferably) both. This elasticity effectively captures short-run changes in equipment utilisation in response to changes in energy prices. Under certain assumptions, this may be comparable to the change in equipment utilisation in response to changes in energy efficiency.

Box 5.1 The importance of price-induced improvements in energy efficiency

A study by Haas and Schipper (1998) shows how the neglect of price-induced energy efficiency improvements can lead to the rebound effect being overestimated. Haas and Schipper estimate own-price elasticities of total household energy demand ($\eta_{P_E}(E_{total})$) in ten OECD countries over the period 1970-1993. Elasticities are estimated over the whole period, the period of rising energy prices from 1970 to 1982 and the period of falling energy prices from 1982 onwards.

The estimates are rather lower than the consensus in the literature, but the interesting point is the dependence of the results upon the time period chosen. For example, in the case of the US the estimates are -0.09 (1972-92), -0.32 (1970-82) and zero (1982-92) respectively. Generally, the estimated price elasticities are much higher for the period of rising prices (1970-82) than for the period as a whole. Moreover, for the period of falling energy prices (1982-92) most estimates are not significantly different from zero. Haas and Schipper interpret this result as evidence of irreversible improvements in energy efficiency induced during the period of rising energy prices, such as fitting loft insulation and tightening building regulations. Haas and Schipper also estimate another set of equations which incorporate measures of the energy efficiency of different household consumption activities. These provide a better statistical fit to the data and indicate much smaller price elasticities (i.e. $\eta_{P_E}(E)\big|_{\varepsilon} < \eta_{P_E}(E)$).

The implication of Haas and Schipper's results is that the price elasticity of household energy consumption is significantly smaller during periods of declining prices than during periods of rising prices. Since energy efficiency improvements are analogous to periods of declining energy prices, the long-run direct rebound effect may be overestimated if it is based upon energy price elasticities estimated from time series data that includes periods of rising energy prices.

Estimates of long-run energy efficiency elasticities may differ from estimates of short-run elasticities owing to long-run adjustment in the number, capacity and utilisation of the relevant conversion devices (e.g. boilers) and/or behavioural adaptation to higher temperature internal environments. While structural models can identify the relative contribution of these different factors, single equation models cannot. However, with the exception of low income groups, most households own heating systems of sufficient capacity to heat the occupied areas to an acceptable temperature. In these circumstances, the long-term adjustments in the number and capacity of conversion equipment in response to improvements in energy efficiency may be relatively small. Hence, estimates of long-run energy efficiency elasticities may be comparable to short-run estimates, since both derive primarily from changes in equipment utilisation. In turn, estimates of $\eta_{P_E}(E_{heat})\big|_{\varepsilon}$ may provide a suitable proxy for both the short and long-run direct rebound effect.

Hence, this summary suggests that, depending upon the availability and variability of data, a range of elasticity estimates could potentially be used as a proxy for the direct rebound effect for space heating, including:

- $\eta_{\varepsilon_c}(S_{heat})$: the elasticity of demand for useful work with respect to the energy efficiency of the heating system.
- $\eta_{\varepsilon_h}(S_{heat})$: the elasticity of demand for useful work with respect to the energy efficiency of the building.

- $\eta_{\varepsilon_c}(E_{heat})$: the elasticity of demand for energy for space heating with respect to the energy efficiency of the heating system.
- $\eta_{\varepsilon_h}(E_{heat})$: the elasticity of demand for energy for space heating with respect to the energy efficiency of the building.
- $\eta_{P_S}(S_{heat})$: the elasticity of demand for useful work with respect to the energy cost of useful work ($P_S = P_E / \varepsilon_c$)
- $\eta_{P_E}(E_{heat})\big|_{\varepsilon}$: the own-price elasticity of demand for energy for space heating controlling for the energy efficiency of the building and/or the heating system.

The following two sections summarise a number of studies that estimate one or more of these elasticities. Each of these studies may be used to derive an estimate of the direct rebound effect, although most of the studies do not mention the rebound effect explicitly. Several of these estimates were previously cited in the literature review by Greene and Greening (1998), but they did not clarify the differences between them.

All of the studies rely upon disaggregate (i.e. household survey) data corresponding to a wide range of geographical areas and time periods which contributes to the diversity of results. The discussion seeks to highlight the methodological issues associated with estimating direct rebound effects for household heating, as well as summarising the empirical results. The studies are grouped under two headings, namely single equation models and multiple equation models.

5.4 Evidence from single equation models

These studies estimate the demand for either energy or useful work as a function of various engineering, economic and demographic variables, compiled from household surveys and related data sources. Studies using cross-sectional data are the most common, although studies using pooled cross-section or panel data are also available. The number and type of independent variables varies widely from one study to another, as does the accuracy of measurement of these variables and the methodological approach. If such studies are to be used to accurately estimate the direct rebound effect they must including variables representing the energy efficiency of the building (ε_h) and/or the energy efficiency of the relevant heating equipment (ε_c). Importantly, only three of the studies mention the rebound effect explicitly.

Douthitt's (1986) rigorous study of the demand for heating fuel in Canada is notable for both allowing the price elasticity to vary with the level of prices and for paying explicit attention to potential selection bias. The data source is a cross-sectional sample of 370 households from across Canada conducted in 1981-82. The households are classified according to the main fuel use for space heating (oil, gas or electricity) and the proportion of fuel use attributable to space heating (E_{heat}) is estimated. This estimate then forms the dependent variable for a dynamic single equation model, with the independent variables including current and lagged fuel prices, variables relating to the energy efficiency of the house (ε_h) such as the thermal resistance of the walls, the average daytime internal temperature and demographic factors such as the number of occupants. The model provides a reasonable fit to the data for each fuel group (adjusted R^2 between 0.37 and 0.76) with most variables being significant. Douthitt's sample is biased towards those utilities with complete billing records and Greene and Greening (1998) discount the results for that reason. But problems of selection bias are likely to be found in many studies using survey data and Douthitt (1986) is one of the few studies to both explicitly test for this and to use a procedure proposed by Heckman (1979) to correct for it.

Although in principle, the model could provide an estimate of $\eta_{\varepsilon_h}(E)$, this is not quoted (largely because the rebound effect is not Douthitt's primary interest). Instead, Douthitt quotes short and long-run[53] estimates of $\eta_{P_E}(E_{heat})\big|_{\varepsilon_h}$ for each fuel. Taking this as a proxy for the direct rebound effect suggests a short-run effect of between 10% (gas) and 17% (electricity). The long-run effect is estimated by setting the lagged fuel price equal to the current fuel price (Donnelly and Diesendorf, 1985) and leads to an estimate of between 25% (gas) and 60% (electricity). A notable result is that the estimated elasticities vary widely with the price level faced by each household, being higher for those consumers facing higher than average prices. For the latter, the results suggest a long-run direct rebound effect of between 24% (oil heating) and 93% (electrical heating) – which suggests that improvements in the efficiency of electrical heating systems for these consumers may achieve few energy savings.

In a rare study of the direct rebound effect for space heating, **Hseuh and Gerner (1993)** estimate an equation for the household demand for fuel incorporating variables determining the cost of warmth. This specification allows the short-run direct rebound effect to be estimated from $\eta_{P_E}(E)\big|_{\varepsilon}$, although the presentation of the model makes the results difficult to interpret. The study uses cross-sectional data from the 1980-81 US Residential Energy Consumption Survey (RECS) which includes information on the demographic characteristics of the participating households, the thermal characteristics of their houses, appliance ownership and other variables. Attention is confined to owner-occupied, single-family detached houses using a single fuel for heating, leading to sample sizes of 1028 (gas heating) and 253 (electrical heating) respectively.

Hseuh and Gerner specify an equation for the demand for the main heating fuel (E_{total}) as a function of heating and cooling degree days, income, fuel prices, the number of occupants, various parameters determining the size and energy efficiency of the building (ε_h), binary variables for the ownership of seven types of appliances (air-conditioners, ovens, water heaters, refrigerators and freezers), data on the size of those appliances and cooling degree days (interacted with the binary variable for ownership of air-conditioners. The model provides a reasonable fit the data with adjusted R^2 of 0.51 (electricity) and 0.59 (gas).

In principle, the model should allow $\eta_{\varepsilon_h}(E_{total})$ to be estimated, but Hseuh and Gerner only quote the estimated change in energy consumption following a particular physical change in one of the elements determining ε_h - such as increasing the thickness of roof insulation by one inch. Comparing these estimates with those of engineering model suggests direct rebound effect of between 30% and 100% depending upon the type of measure and the

[53] Based on Donnelly and Diesendorf (1985), the long-run effect is estimated by setting the lagged fuel price equal to the current fuel price.

geographical region. However, this may be an overestimate of the direct rebound effect since the engineering estimates may be incorrect.

The model also allows the own-price elasticity of total fuel demand to be estimated, conditional on ε_h and a particular pattern of appliance ownership - $\eta_{P_E}(E_{total})\big|_{\varepsilon_h}$. However, this estimate does not control for the energy efficiency of either the heating system (ε_c) or the appliances. Hseuh and Gerner interpret this as a short-run elasticity, corresponding primarily to changes in the utilisation of heating equipment following changes in energy prices. Greening and Greene (1998) use the estimate of $\eta_{P_E}(E_{total})\big|_{\varepsilon_h}$ for electrically-heated homes as a proxy for the direct rebound effect for space heating, suggesting a short-run effect of 35%. However, they ignore the corresponding estimate of 58% for gas heated homes, despite the gas equation performing better as a result of the smaller sample size. Also, the appropriate proxy for the direct rebound effects for space heating is $\eta_{P_E}(E_{heat})\big|_{\varepsilon_h}$ which will be larger than $\eta_{P_E}(E_{total})\big|_{\varepsilon_h}$. The range of 35-58% could therefore be taken as a lower bound for the direct rebound effect for space heating implied by this study.

Schwarz and Taylor (1995) provide a rare example of a study that includes measurements of thermostat settings as a dependent variable - although the source and accuracy of these measurements is not made clear. As with Hseuh and Gerner, they use data from the US RECS, in this case applying to 1984-85 and confined to single family households that have a thermostat on their main heating equipment - leading to a sample size of 1188. Low income households are excluded, which may mean that the study underestimates direct rebound effects for households overall.

Schwarz and Taylor estimate an equation for thermostat setting (T_i) as a function of energy prices, external temperatures (T_o), heated area (A), household income and an estimate of the overall thermal resistance of the house (ε_h) obtained by combining RECS data with an engineering model. The energy output from the heating system (S_{heat}) is estimated from the product of heated area and the difference between internal and external temperature, divided by the thermal resistance of the house ($S_{heat} = A(T_i - T_o)/\varepsilon_h$). Since Schwarz and Taylor are able to derive a proxy estimate of S_{heat} using data on building energy efficiency (ε_h), they do not use any data on actual energy consumption for space heating.

Their equation allows the (building) energy efficiency elasticity of the thermostat setting ($\eta_{\varepsilon_h}(T_i)$) and the corresponding energy efficiency elasticity of the demand for useful work ($\eta_{\varepsilon_h}(S_{heat})$) to be estimated. The former represents a behavioural response to lower heating costs (as a result of better insulation) while the latter represents the corresponding change in demand for useful work - which may not result solely from behavioural change by the occupants. Other factors which may affect heating costs, such as the thermal energy efficiency of the boiler (ε_c), were not included in the specification, but these would only lead to biased estimates if they were correlated with the included variables.

The average value of $\eta_{\varepsilon_h}(T_i)$ ranged from 0.6% to 2.0% depending upon house size and climate – with larger responses in big houses in cold climates. The resulting rebound (or takeback) effect, based upon $\eta_{\varepsilon_h}(S_{heat})$ varied between 1.36% and 3.41%, which is smaller than most other studies in the literature. The behavioural response ($\eta_{\varepsilon_h}(T_i)$) is considerably smaller than the 'physical' response ($\eta_{\varepsilon_h}(S_{heat})$), which is consistent with theory (Milne and Boardman, 2000) provided that a linear relationship between S and T_i can be assumed. Since this is a cross-sectional study, the results may be interpreted as a long-run effect.

Haas *et al.* (1998a) present some estimates of the direct rebound effect for household heating from a cross-sectional survey of ~400 Austrian households. **Haas and Biermayr (2000)** provide some additional analysis of this data, together with estimates of the direct rebound effect taken from a number of other sources – their main argument being that the different sources are broadly consistent in their results. Both studies are marred by unconventional terminology (e.g. service factor), unhelpful notation and insufficient attention to the content and quality of data sources. For example, the sample size is quoted as ~400 households in Haas *et al.* (1998a) and ~500 in Haas and Biermayr (2000) and the source of data on both the energy efficiency of the heating system (ε_c) and the overall thermal integrity of the building (ε_h) is unclear. Also, the estimates of internal temperature are based upon self-reports by the occupants and hence must be considered of questionable accuracy.

The portion of total fuel use that is used for space heating (E_{heat}) is estimated from a simple regression incorporating heating degree days. This is then used as the dependent variable in a regression incorporating ε_h, ε_c, P_E, heating degree days (again), number of occupants, internal area, income, internal temperature and type of heating system (central or non-central heating). This leads to three estimates of the direct rebound effect, namely 20% from $\eta_{P_E}(E_{heat})$, 48% from $\eta_{\varepsilon_c}(E_{heat})$ and 22% from $\eta_{\varepsilon_h}(E_{heat})$. Haas and Biermayr also estimate the energy use for space heating as a polynomial function of ε_h and find a concave relationship that departs from the simple linear relationship that would be expected in the absence of a direct rebound effect. The magnitude of the direct rebound effect can be estimated from difference between the polynomial and linear curves and suggests an effect in the range 15-30% - which is broadly consistent with the elasticity estimates. These results suggest that the magnitude of the direct rebound effect varies with the initial level of energy efficiency, the amount of improvement in energy efficiency and the type of energy efficiency improvement. Importantly, they also find that changes in energy prices (and by implication, changes in the price of useful work) only have an impact on the demand for useful work when energy prices exceed a certain threshold.

Guertin *et al.* (2003) provides some valuable estimates of the direct rebound effect for three aggregate categories of energy service in Canadian households – namely household heating, hot water and appliances/lighting. They use cross-sectional data from 440 low-rise single-family dwellings (188 gas heated and 252 electricity heated) located in seven provinces and dating from 1993. This includes comprehensive data on demographics and appliance ownership. By examining seasonal demand patterns and other factors, they are able to estimate the energy consumption for space heating, hot water and appliances/lighting as well as the average internal temperature during the heating season. Also, by the use of 'frontier analysis' they are able to estimate the energy efficiency of gas boilers and other conversion technologies (ε_c). This enables them to construct separate equations for the energy demand for space heating (E_{heat}) and the demand for useful work ($S_{heat} = \varepsilon_c E_{heat}$).

On the basis of research by Douthitt (1989) and others, Guertin *et al.* restrict the own-price elasticity for heating and other energy services to be linear function of income. Using $\eta_{P_S}(S_{heat})$ suggests a direct rebound effect for household heating in the range 29% (high-income groups) to 47% (low income groups), with a sample average of 39%.[54] Since this is a cross-sectional study, the results may be interpreted as a long-run effect. The comparable estimates for $\eta_{P_E}(E_{heat})$ are 34% (high-income groups) to 51% (low income groups) and 43% (sample average) showing again how the use of this measure could lead the direct rebound effect to be overestimated. The higher price elasticities for low income groups appear to result from a combination of the higher share of energy expenditure in total expenditure, the higher share of heating in total energy expenditure and the higher price of useful work owing to slightly lower energy efficiencies. Oddly, the results suggest that low income households have higher than average internal temperatures, while high income households have lower temperatures.

In summary, the selected studies provide estimates of the short-run direct rebound effect for space heating in the range **10-58%** and estimates of the long-run direct rebound effect in the range **1.4%-60%** (Table 5.4). The coincidence of these ranges is arguably consistent with the argument that the primary source of direct rebound effects for household heating is changes in the utilisation of heating equipment. The diversity of results partly reflects the diversity of countries, regions and household types being studied, but is also strongly influenced by the different variables used in each study, the measurement errors associated with these variables and the different methodological approaches to estimation. Most importantly, only three of the studies directly address the rebound effect and the measures used to estimate this effect (selected either by the authors or ourselves) varies widely from one study to another. Indeed, the number of measures used exceeds the number of studies! This diversity demonstrates that the econometric literature has yet to develop a consistent approach to this issue.

[54] The variation in $\eta_{P_S}(S_{heat})$ between income groups was much greater for space heating than for other energy services.

Table 5.4 Estimates of the direct rebound effect for household heating using single equation models

Author/year	**Short-run rebound effect**	**Long-run rebound effect**	**Country**	**Data**	**Functional form**	**Estimation technique**	**Comments**
Douthitt (1986)	10-17%	35-60%	Canada	Cross section 1980-1981 SS: 370	Double log	OLS	RE estimated from $\eta_{P_E}(E_{heat})\big|_{\varepsilon_h}$. Elasticities vary with price level.
Hseuh and Gerner (1993)	35% (electric) 58% (gas)	-	US	Cross-section 1980-1981 SS: 1028 Gas, 253 Electricity	Double log	OLS	Equation for E_{total} incorporating engineering variables determining cost of S_{heat} RE estimated from $\eta_{P_E}(E_{total})\big|_{\varepsilon_h}$
Schwarz and Taylor (1995)	-	1.4 - 3.4%	US	Cross-section 1984-1985 SS: 1188	Double log	OLS	Measure of thermostat setting (T_i) and level of thermal insulation allows estimates of $\eta_{\varepsilon_h}(T_i)$ & $\eta_{\varepsilon_h}(S_{heat})$
Haas *et al.* (1998)	-	15-48%	Austria	Cross-section SS: ~400	Double log	OLS	RE estimated from a number of sources, including $\eta_{P_E}(E_{heat})$, $\eta_{\varepsilon_c}(E_{heat})$ & $\eta_{\varepsilon_h}(E_{heat})$
Guertin *et al.* (2003)	-	29-47%	Canada	Cross section 1993 SS: 440 (188 gas; 252 elec.)	Double log	OLS	Use of frontier analysis to estimate ε_c. RE estimated from $\eta_{P_S}(S_{heat})$ where $P_S = P_E/\varepsilon_c$

5.5 Evidence from multiple equation models

The determinants of the direct rebound effects for space heating may be better understood with the use of multiple equation models, including the structural, discrete-continuous and household production approaches described in Section 3. However, while there are an increasing number of applications of these approaches to space heating, they generally do not include data on either ε_c or ε_h. Hence, while the studies provide good estimates of $\eta_{P_E}(E_{total})$, they are less useful for estimating the direct rebound effect.

A number of authors have applied the discrete-continuous model to space heating (Nesbakken, 1999; Halvorsen and Larsen, 2001; Liao and Chang, 2002). The pioneering studies in this area is by **Dubin and McFadden (1984)**, who develop a discrete-continuous model of the demand for heating systems and the derived demand for energy. While methodologically rigorous and widely cited, the complexity of this model and the associated notation system make interpretation difficult. Dubin and McFadden (1984) use cross-sectional data from a sample of 313 households undertaken in 1975. They first estimate an equation for the probability of choosing a gas or electric heating system, based upon relative fuel prices, capital costs, income, average annual demand and other variables. Gas heating systems have higher capital costs but lower operating costs and tend to be chosen by higher income households. The estimated probability from this discrete choice model is then used as an instrumental variable in an equation for the demand for electricity, conditional upon the choice of heating system. Dubin and McFadden show how the failure to use instrumental variables in this second equation can lead to biased estimates of the price and income elasticities of energy demand.

Using the estimates of $\eta_{P_E}(E_{total})$ for electrically heated households, the short-term direct rebound effect can be estimated to lie between 25% and 31%. The long-term estimates of $\eta_{P_E}(E)$ are smaller, as they allow for switching from electricity to gas. However, since the study contains no information on ε_c or ε_h., these figures must be considered as an upper bound for the direct rebound effect.

Nesbakken (2001) provides a more recent example of this approach, using cross-sectional data from a sample of 551 Norwegian households in 1990. This differs from the Dubin and McFadden study number of ways including: focusing solely upon the energy consumption for space heating; allowing choice between four heating technologies (namely electricity only; electricity and oil; electricity and wood; and electricity, oil and wood); estimating the choice of space heating equipment at one point in time jointly with the utilisation that equipment at a later point in time; and estimating these equations simultaneously rather than sequentially. The estimates of $\eta_{P_E}(E_{heat})$ are based upon changes in the average energy price and are conditional on the choice of heating system. They vary between -0.15 for electricity+oil+wood and -0.55 for electricity only, suggesting that elasticities are lower when there is greater flexibility to switch fuels. Using the average value for $\eta_{P_E}(E_{heat})$ across all households suggests a short-term direct rebound effect of 21%. But again, this figure must be considered as an upper bound since the study contains no information on ε_c or ε_h.

There are fewer examples of household production models since the data requirements are onerous. The only example we have found relevant to rebound effects in household heating is **Klein (1987; 1988)**. However, Klein uses the same household survey data as, for example, Hseuh and Guerner (1993) and Schwarz and Taylor (1995), which in turn is comparable in detail to the household survey data used by Douthitt (1986) and others. Klein has to supplement this with engineering models of the thermal performance of buildings, together with data on the capital cost of energy efficiency improvements, both of which may be subject to error. Nevertheless, this suggests that there may be scope for the wider application of this approach.

Klein uses US national household survey data from 1973 and 1981. The former is from a survey conducted on behalf of the US Federal Energy Administration while the latter is the 1981 RECS. Both surveys provide detailed information on energy consumption, energy expenditure, demographic characteristics, appliance ownership and the thermal characteristics of the buildings. The availability of data on thermostat settings allows the demand for space heat (S_{heat}) to be estimated from the difference between external temperature and desired internal temperature. The energy use for space heating (E_{heat}) is estimated from billing data after subtracting the 'baseload' demand in the summer months. The thermal performance of the household (ε_h) is estimated from data on thermal insulation and secondary glazing, and the annualised capital cost of these measures (P_K) is estimated from data on installation costs. Similarly, the energy cost of useful work (P_S) is estimated by allocating fuel costs among the (estimated) baseload, space heating and space cooling demands and adjusting for differences in the average combustion efficiency (ε_c) between different fuels (i.e. household specific measures are not available). The sum of P_K and P_S provides an estimate of the 'generalised' unit cost of space heat (P_G) for each household (i.e. combining energy and annualised capital costs).

Klein then specifies an equation for the total cost of space heat (C) as a function of P_E, P_K, S_{heat}, the size of the housing unit and heating degree days.[55] Differentiating this equation with respect to energy prices leads to a second equation for the share of energy costs in the generalised cost of space heat. A third equation expresses the demand for space heat as a function of generalised costs (P_G), income, number of household members and heating degree days. Since the demand for space heat appears as an explanatory variable in the cost equations, and the cost of space heat appears as an explanatory variable in the demand equation, the model needs to be estimated using simultaneous equation techniques (Klein uses 3SLS).

The results indicate that the elasticity of demand for space heat with respect to the generalised cost of space heat ($\eta_{P_G}(S_{heat})$) is -0.43 in 1973 and -0.44 in 1981. Klein argues that this represents the short-run behaviour of households, since it is *conditional* on the existing capital stock. While Greening *et al* (1998) quote these figures as estimates of the direct rebound effect for space heating, this appears to be incorrect. The rebound effect should instead be estimated from the elasticity of demand for space heat with respect to the *energy* cost of space heat ($\eta_{P_S}(S)$). Using mean values of the energy cost of useful work, this can be calculated as -0.287 in 1973 and -0.251 in 1981. Hence, Klein's model suggests short-run direct rebound effects for household heating in the range 25% to 29%.

[55] This equation uses the 'translog' functional form that is widely used within neoclassical production theory (see *Technical Report 3*).

In summary, the multiple equation studies reviewed here give estimates of the short run direct rebound effect in the range **15% to 55%,** with Klein's estimates of an effect in the range **25% to 29%** being the most reliable (Table 5.5). These results are consistent with those from the single equation studies reviewed in the previous section.

Table 5.5 Estimates of the direct rebound effect for household heating using multi-equation models

Author/year	**Short-run rebound effect**	**Long-run rebound effect**	**Country**	**Data**	**Functional form**	**Estimation technique**	**Comments**
Dubin and McFadden (1986)	25-31%		US	Cross section 1975 SS: 313	Discrete-continuous	Logit (discrete) & Instrumental variables (utilisation)	Electrically heated households. RE estimated from $\eta_{P_E}(E_{heat})$. No control for energy efficiency
Nesbakken (2001)	15-55% (average 21%)		Norway	Cross section 1990 SS: 551	Discrete-continuous	Logit (discrete) & Instrumental variables (utilisation)	Various fuel combinations. RE estimated from $\eta_{P_E}(E_{heat})$. No control for energy efficiency
Klein (1987; 1988)	25-29%		US	Pooled cross section: 1973-81 SS: 2157	Household production	3SLS	Simultaneous estimation of a cost function for S, a demand function for S and an equation for the relative share of capital and fuel. RE estimated from $\eta_{P_S}(S_{heat})$, which in turn is estimated from $\eta_{P_G}(S_{heat})$,

5.6 Summary

In contrast to personal automotive transport, the available evidence from econometric studies does not permit the direct rebound effect for space heating to be quantified with much confidence. While this is partly because space heating is inherently more complex than personal automotive transport it is also because the topic has received insufficient attention in the econometric literature. However, there is no evidence to suggest that energy efficiency improvements for space heating will lead to backfire for the majority of households.

The results from the studies reviewed here suggest direct rebound effects in the range **1.4 to 60%.** The diversity of results suggests that quoting a single number for the rebound effect for space heating could be misleading, since the effect appears to vary greatly with the type of household, fuels used and type of energy efficiency improvement. Many of the estimates quoted here are based upon price elasticities, but these may provide a less accurate estimate of the direct rebound effect than in the case of personal automotive transport. Also, the strong evidence for the price asymmetry of energy demand responses for space heating suggests that the true effect may be towards lower rate end of the above range. Nevertheless, for the purpose of policy evaluation, a figure of **30%** for the direct rebound effect for household heating would appear a reasonable assumption, which is consistent with the results of the evaluation studies reported in *Technical Report 1*.

6 Evidence for direct rebound effects for other household energy services

6.1 Introduction

A number of theoretical considerations suggest that direct rebound effects for most other household energy services should be less than those for household heating. For example, compared to household heating:

- energy typically forms a smaller proportion of the total costs of useful work;
- the total cost (excluding time costs) of useful work typically forms a small proportion of total household expenditure; and
- the energy cost of useful work is typically relatively invisible to the consumer.

In principle, all these factors should contribute to low own-price elasticities $\eta_{P_E}(E)$ for these energy services, in both the short and long-run. Price elasticities may also be low if the service is to some extent essential for everyday life (a 'necessity good'). Cooking, water heating and clothes washing arguably fall into this category, although in each case there is scope for some variation in utilisation patterns in response to changes in energy prices. Other services, such as consumer electronics, are not necessity goods, but may nevertheless have low own price elasticities for the reasons given above.

In the UK, other household energy services are commonly grouped under three headings, namely water heating, cooking, and lighting/appliances. In 2007, water heating accounted for 26.6% of UK household fuel use and 10% of electricity use, while cooking accounted for only 2.1% of fuel use and 6.2% of electricity use (DTI, 2007). The generic category of lighting/appliances accounted for 60.6% of electricity consumption, broken down as follows: lighting (14.2%), fridges/freezers (13.4%); consumer electronics (13.3%); ICT (7.9%); and washing equipment (11.4%) (DTI, 2007). A similar breakdown may be anticipated in other countries or regions with a comparable climate to the UK. However, in warmer countries space cooling may form a substantial component of household electricity demand.

It is difficult to directly measure either useful work or energy consumption for these energy services, while the estimation of energy consumption from billing data is prone to error. As a result, the econometric evidence for direct rebound effects for other household energy services is extremely poor. This section summarises just four relevant studies, each of which is considered to be methodologically robust. Two of these studies are for space cooling and two for other energy services.

6.2 Direct rebound effects for space cooling

Space cooling forms a large and increasing proportion of household electricity consumption in warmer regions and the demand for space cooling has much in common with that for space heating. In 2001, 78% of US households owned space cooling equipment of some kind, up from 58% in 1981. The trend was towards central space cooling and away from room units. In the US as a whole, space cooling accounted for more than 11% of electricity consumption. While per capita ownership of space cooling equipment is lower in most other OECD countries, it appears to be growing rapidly.

The estimation of rebound effects of space cooling raises comparable measurement issues to that for space heating. For example, internal temperatures may only be one of the determinants of thermal comfort, with factors such as relative humidity also playing an important role. Rebound effects may also be expected to differ between room and central space cooling units, and may vary with electricity price levels and external temperatures. In particular, rebound effects may lower when systems are required to run at full capacity to maintain an acceptable internal temperature.

Despite the importance of space cooling in many regions, we have only been able to find two econometric studies of direct rebound effects, namely Hausman (1979) and Dubin *et al.* (1986).

Hausman (1979) develops a sophisticated discrete-continuous model of the demand for room air-conditioners and the associated use of the equipment. The data source is a 1978 survey of 1985 households across the US, which includes comprehensive details of appliance ownership and characteristics, together with socio-economic data and electricity consumption. A subsample of 51 households had the energy consumption of their room air-conditioners individually metered (E_{cool}), of which 46 provided usable data. Hausman also conducts a separate analysis of the market for room air-conditioners, which yields an estimate of the capital cost of room air-conditioners as a function of capacity and energy efficiency (ε_c).

The data permits the electricity consumption of the equipment to be estimated as both quadratic and double log functions of capacity, cooling degree days, electricity prices and energy efficiency. However, using the measured value of energy efficiency to estimate the direct rebound effect could lead to endogeneity bias, since households that anticipate a high level of utilisation may be expected to purchase a more efficient model (thereby creating a correlation between the consumption of useful work and ε_c that is in addition to that created by the direct rebound effect). To avoid this, Hausman uses other variables to form an instrumental variable for ε_c. While the energy efficiency of the dwelling (ε_h) may also be expected to influence equipment utilisation patterns, this is not measured or controlled for. However, while ε_h may be correlated with ε_c, it is less likely to be correlated with the instrumental variables that substitute for ε_c.

On the basis of estimates of $\eta_{P_E}(E_{cool})$ for the mean of the sample, both the quadratic and double-log specifications suggest a short-run direct rebound effect of ~4% (ie conditional upon the choice of air conditioning equipment). However, the quadratic specification also gives an estimate of $\eta_{\varepsilon}(E_{cool})$ which suggests a much larger direct rebound effect of 26.5%. Since this is a cross-sectional study, the latter may be taken as an estimate of the long-run effect. While long-run effects may be expected to be larger than short run effects, this appears insufficient to explain the magnitude of the difference between the two estimates - thereby raising questions about the appropriateness of $\eta_{P_E}(E_{cool})$ as a proxy.

Dubin *et al.* (1986) provide a rigorous examination of the direct rebound effect for space cooling, based upon a quasi-experimental study conducted by the Florida Power and Light company in 1981. The study involved a random sample of 504 single-family households, each with central electric heating and air-conditioning. These were assigned to one of four experimental groups, namely: upgraded insulation; upgraded insulation and a high-efficiency central air-conditioner; upgraded insulation and a high-efficiency heat pump; and a control group. The upgrades were provided free of charge.

The experimental design did not include before and after measurements of energy consumption in each household, but instead used econometric techniques to explore the cross-sectional variation in consumption across the sample in the year following equipment installation. Total electricity consumption in each household was monitored, together with the monthly consumption of the heat pump or air-conditioner. The study also included comprehensive surveys of the structural features of each dwelling, together with demographic data and the level of appliance ownership.

This design ensured that the energy efficiency of the air conditioning equipment (ε_c) was an exogenous variable, thereby circumventing the endogeneity problem highlighted in Section 2.6. An additional advantage was to create a much larger variation this variable than would have been obtainable through a cross-sectional study of existing households - very few of whom owned high-efficiency central air-conditioners in 1981. Combined with the variation in unit electricity prices (P_E) within the sample this led to considerable variation in the energy cost of useful work ($P_S = P_E / \varepsilon_c$). In addition, the data on the structural features of each dwelling permitted relatively accurate estimates of ε_h to be made with the help of an engineering model. For space conditioning, this was expressed as the change in kWh of useful work from the air conditioner (S_{cool}) per degree change of the thermostat setting for cooling ($\varepsilon_h = \Delta S_{cool} / \Delta(T_i - T_o)$).

With the help of an engineering model, Dubin *et al.* are able to estimate the electricity use for space cooling in each household (E_{cool}). Combining this with data on the energy efficiency of the relevant cooling equipment (ε_c) gives the monthly consumption of useful work for cooling (S_{cool}) This was then used as the dependent variable in econometric equation, whose independent variables included income, the number of occupants and the cost associated with a 1° change of the internal thermostat setting ($P_E / \varepsilon_c \varepsilon_h$). Hence, unlike the household heating studies reviewed in Section 5, the independent variable in this study was a combination of ε_c and ε_h.

Dubin *et al.* estimate this equation separately for each season, with sample sizes varying from 214 to 396 (owing to missing data). Overall, the equations show a large amount of unexplained variation (e.g. adjusted R^2=0.07) On the basis of $\eta_\varepsilon(E_{cool})$, Dubin *et al.* estimate the direct rebound effect to be 1-2% during summer months and up to 13% during the remainder of the year. This seasonal variation is revealing, since it suggests that both energy price elasticities and direct rebound effects are greater when average daily temperatures are lower and air-conditioning units are not running at full capacity. Similar results are reported for both heating and cooling by Poyer and Williams (1992), which suggests that the number of heating and cooling degree days is an important but frequently neglected source of variation in demand behaviour. Hence, the extent to which Hausman's results provide an indication of anticipated behaviour in other regions will depend in part upon relative climatic conditions.

In summary, the two studies reviewed here suggest a direct rebound effect for space cooling in the range **1%-26%**. While the first study focuses upon variations in ε_c, the second incorporates variations in both ε_c and ε_h. While both of these studies are methodologically rigorous, they are also dated, use relatively small sample sizes and were conducted during periods of rising electricity prices. Moreover, both studies focus solely upon changes in equipment utilisation. To the extent that ownership of this technology is rapidly increasing in many countries (owing to income growth, technical improvements, falling capital costs, changes in climatic conditions and other factors) demand from 'marginal consumers' may be an important consideration, together with increases in the capacity of space cooling systems among existing users. Hence, unlike household heating (where most households have a system of sufficient capacity), this may make the long-term direct rebound effect for space cooling significantly higher than suggested by these two studies.

6.3 Direct rebound effects for other energy services

Only two methodologically rigorous studies of direct rebound effects for other household energy services have been identified, namely Guertin *et al.* (2003) and Davis (2007). Guertin *et al.* (2003) estimates rebound effects for both water heating and other energy services combined, while Davis (2007) estimates rebound effects for clothes washing.

The study of 440 single-family Canadian households by **Guertin *et al.* (2003)** was described earlier in Section 5. In addition to the results for household heating reported earlier, Guertin *et al.* also estimate the own price elasticity of energy demand for hot water and for all other energy services combined (i.e. appliances and lighting). By combining seasonal demand patterns with comprehensive cross-sectional data on building type and appliance ownership, Guertin *et al.* are able to estimate the energy consumption for hot water and appliances/lighting. A potential source of error is the assumption that the ratio of energy consumption for hot water to that for appliances/lighting is the same in all households. Guertin *et al.* use 'frontier analysis' to estimate the energy efficiency of electricity and gas water heaters (ε_c), but assume that the energy efficiency of appliances and lighting is 100%. These assumptions allow them to construct separate equations for the demand for energy and useful work for water heating and other services. A notable feature of the model is that price elasticities are restricted to be a linear function of income.

The models account for 40-50% of the variation in the dependent variable. High-income households were found to have higher than average energy demands for appliances and lighting, while low-income households have lower than average. The demand for energy for water heating was insensitive to income.

For water heating, the estimates of $\eta_{P_S}(S)$ suggest a direct rebound effect in the range 34% (high-income groups) to 38% (low income groups), with a sample average of 36%. Since this is a cross-sectional study, the results may be interpreted as a long-run effect. The comparable estimates for $\eta_{P_E}(E)$ are 33% (high-income groups) to 39% (low income groups), with a sample average of 36%. Hence, for water heating (unlike space heating), this studies suggests that $\eta_{P_E}(\varepsilon)$ is relatively small and $\eta_{P_E}(E)$ provides a good proxy for the rebound effect.

For other energy services combined, the estimates of $\eta_{P_S}(S)$ suggest a direct rebound effect in the range 32% (high-income groups) to 49% (low income groups), with a sample average of 41%. Since appliance efficiency was assumed to be 100%, the estimates of $\eta_{P_E}(S)$ are identical.

These results are surprising, since they suggest that the own price elasticity of other energy services *exceeds* that for water and space heating[56] - despite the strong theoretical arguments in favour of lower price elasticities given above. While this may partly be a consequence of the assumption that the energy efficiency of the relevant conversion devices is 100% (and hence, implicitly that $\eta_{P_E}(\varepsilon)=0$), this seems insufficient to account for all the difference. It is also notable that the price elasticities for both water heating and other energy services show much smaller variation with income than those for space heating.

Davis (2007) provides a unique example of an estimate of direct rebound effects for household clothes washing - which together with clothes drying accounts for around one tenth of household energy consumption in the US. The estimate is based upon a US government-sponsored field trial of high-efficiency washing machines involving 98 participants.

Participants in the trial received a high-efficiency clothes washer free of charge. As with Dubin *et al.* (1986), the quasi-random replacement of capital equipment effectively made the energy efficiency of the clothes washer an exogenous variable, thereby circumventing the endogeneity problem highlighted in Section 2.6. Also, while participation in the trial was voluntary, both the utilisation of existing washers and the associated consumption of energy and water was monitored for a period of two months prior to the installation of the new washer, thereby allowing any household-specific variations in utilisation patterns to be controlled for. Taken together, these features of the study meant that unbiased estimates of the own-price elasticity of clothes washing - $\eta_{P_G}(S)$ - could be obtained.

The monitoring allowed household-specific estimates to be made of the consumption of detergent, water, electricity for the motor, energy for water heating and energy for drying for each kg of clothes washed, both before and after the installation of the new machine. These estimates showed a mean saving of 41% in water consumption and 48% in energy consumption per kg of washed clothes. By including data on the unit cost of water, energy and detergent the marginal cost of clothes washing for each household could be estimated (P_G). This was then used as the primary independent variable in an equation for the demand for clean clothes in kg/day (S), thereby allowing $\eta_{P_G}(S)$ to be estimated. Davis found that the demand for clean clothes increased by an average of 5.6% after receiving the new washers, largely as a result of increases in the weight of clothes washed per cycle rather than the number of cycles. This relatively small direct rebound effect suggests that only a small portion of the gains from energy efficient washing machines will be offset by increased utilisation.

This estimate of the direct rebound effect takes into account all the cost savings from the new washer, including savings in water and detergent costs. It highlights the fact that many energy efficiency improvements will be associated with reductions in other input costs (see

[56] The corresponding figures for space heating were 29% (high-income groups), 47% (low income groups) and 39% (sample average).

Technical Report 5). However, while $\eta_{P_G}(S)$ could be the most relevant variable for policy purposes, only a portion of this effect results from the saving in energy costs alone. If, instead, the estimate of the direct rebound effect was based upon $\eta_{P_S}(S)$, the estimated effect would be smaller. Indeed, Davis estimates $\eta_{P_E}(E)$ for electricity and propane use to be -0.02 and ~0.0 respectively, which suggests a direct rebound effect close to zero.

The above elasticity estimates do not include the time costs associated with washing clothes, which is approximately the same for both efficient and inefficient washers. Based upon time-use survey data, Davis estimates that time costs form 79-92% of the total cost of washing clothes. The results therefore support the theoretical prediction that, for time intensive activities, even relatively large changes in energy efficiency should have little impact on demand, since they lead to relatively small changes in the total cost of useful work (P_G). Similar conclusions should therefore apply to other time-intensive energy services that are both produced and consumed by households, including those provided by dishwashers, vacuum cleaners, televisions, power tools, computers and printers.

In summary, the two studies reviewed above produce rather contrasting results. Guertin *et al.* estimate long-term direct rebound effects for both water heating and appliances/lighting in the range **32-49%**, while Davis estimates short-term direct rebound effects for clothes washing of less than **5%.** While rebound effects may be expected to be larger in the long-term, this explanation seems insufficient to account for the difference between the two results. The study by Davis is the more rigorous of the two, involving a quasi-experimental design in which energy efficiency is exogenous and household-specific effects are controlled for. Since these results are also more consistent with theoretical predictions, they may be given greater weight. However, this study is confined to clothes washing, while Guertin *et al.* examines a composite of household energy services.

Table 6.1 Estimates of the direct rebound effect for space cooling

Author/year	**Short-run rebound effect**	**Long-run rebound effect**	**Country**	**Data**	**Functional form**	**Estimation technique**	**Comments**
Hausman (1979)	4%	26.5%	US	Cross section 1978 SS: 46	Discrete-continuous	Nested logit (discrete) & Instrumental variables (utilisation)	Room air-conditioners individually metered. RE estimated from $\eta_{\varepsilon_c}(E_{cool})$.
Dubin *et al.* (1986)	1 – 26%		US (Florida)	Cross section 1981 SS: 214-396	Discrete-continuous	Nested logit (discrete) & Instrumental variables (utilisation)	RE estimated from $\eta_{\varepsilon}(E)$. Energy efficiency is a composite of ε_c and ε_h

Table 6.2 Estimates of the direct rebound effect for other household energy services

Author/year	**Short-run rebound effect**	**Long-run rebound effect**	**Country**	**Data**	**Functional form**	**Estimation technique**	**Comments**
Guertin *et al.* (2003)		34-38% (water) 32-49% (appliances/ lighting)	Canada	Cross section 1993 SS: 440	Double log	OLS	ε_c estimated using frontier analysis. RE estimated from $\eta_{P_S}(S)$ where $P_S = P_E / \varepsilon_c$
Davis *(*2007)	<5.6 clothes washing		US	Panel 1997 SS: 98	Double log	Fixed effects	RE estimated from $\eta_{P_G}(S)$. Quasi-experimental study, so ε_c is exogenous

6.4 Summary

In theory, direct rebound effects for most other household energy services should be smaller than those for household heating. The reasons include: energy forming a smaller proportion of the total costs of useful work; the total cost of useful work forming a smaller proportion of total household expenditure; and the energy cost of useful work being relatively invisible to the consumer. However, it is difficult to directly measure either useful work or energy consumption for these energy services, while the estimation of energy consumption from billing data is prone to error. As a result, the econometric evidence for direct rebound effects for other household energy services is very poor.

Two rather dated studies of space cooling both suggest a direct rebound effect in the range **1%-26%**. However, both focus solely upon changes in equipment utilisation and therefore neglect both demand from 'marginal consumers' and increases in the capacity of space cooling systems among existing users. A study by Guertin et al. (2003) suggests a direct rebound effect of **34-38%** for water heating and **32-39%** for appliances/lighting, but both of these estimates appear suspiciously high. A more rigorous study by Davis (2007) estimates a direct rebound effect for clothes washing of **<5%**. As well as being more reliable, this estimate may be more representative of direct rebound effects from time-intensive energy services, such as those provided by dishwashers, vacuum cleaners and electronic appliances.

7 Summary and conclusions

This report has examined the evidence for direct rebound effects that is available from studies that use econometric techniques to analyse secondary data. The focus throughout has been on consumer energy services, since this is where the bulk of the evidence lies.

The econometric literature was found to be hard to interpret, partly as a result of lack of clarity over basic definitions. Different studies use different definitions of the direct rebound effect, estimate the effect through a number of different measures, express these measures in a variety of ways and frequently fail to clarify the relationship between them. The situation is compounded by the fact that many of the relevant studies do not mention the rebound effect at all, since their primary focus lies elsewhere. These studies nevertheless provide elasticity estimates that may, under certain assumptions, be used as proxy measures of the direct rebound effect. A key objective of this report, therefore, has been to clarify these different definitions and to develop a common terminology that aids interpretation of the relevant literature.

The direct rebound effect may be estimated from the elasticity of demand for either energy or useful work with respect to either energy efficiency, the energy cost of useful work or energy prices. However, the assumption that consumers respond in the same way to decreases in energy prices as they do to improvements in energy efficiency (and vice versa) is likely to be flawed and could lead to biased estimates of the effect. Reasons for this include:

- *Input costs*: Changes in energy efficiency may be correlated with changes in other input costs, while changes in energy prices may not.
- *Asymmetry*: Energy price elasticities tend to be lower for periods with falling prices than for those with rising prices and it is the former that is the more appropriate proxy for improvements in energy efficiency.
- *Endogeneity*: Energy efficiency and the demand for useful work are in part determined by each other. Unless this is controlled for, estimates of the effect could be biased.
- *Time costs*: For many energy services, direct rebound effects may decline in importance in the future, owing to time costs increasing in importance relative to energy costs.

Evidence for the direct rebound effect for automotive transport and household heating within developed countries is relatively robust. Evidence for direct rebound effects for other consumer energy services is much weaker, as is that for energy efficiency improvements by producers. Evidence is particularly weak for energy efficiency improvements in developing countries although theoretical considerations suggest that direct rebound effects in this context will be larger than those in developed countries.

Under certain assumptions, estimates of the own-price elasticity of energy demand for an individual energy service should provide an upper bound for the direct rebound effect for that service. If the measured energy demand relates to a group of energy services (e.g. household fuel demand), the own price elasticity should provide an approximate upper bound for the weighted average of direct rebound effects for those services. Since the demand for energy is generally found to be inelastic in OECD countries, the long-run direct rebound effect for most energy services should be less than 100%.

Table 7.1 summarises the results of our literature review.

Table 7.1 Estimates of the long-run direct rebound effect for consumer energy services in OECD countries

End-Use	**Range of Values in Evidence Base**	**'Best guess'**	**No. of Studies**	**Degree of Confidence**
Personal automotive transport	3-87%	10-30%	17	High
Space heating	1.4-60%%	10-30%	9	Medium
Space cooling	1-26%	1-26%	2	Low
Other consumer energy services	0-39%	<20%	3	Low

Personal automotive transportation is the only area where the evidence is sufficiently strong to allow the magnitude of the direct rebound effect to be quantified with some confidence. Overall, the review suggests that the long-run direct rebound effect for personal automotive transport lies somewhere between **10% and 30%**. The relative consensus on estimates, despite wide differences in data and methodologies suggests that the findings are robust. Also, the asymmetry of demand responses suggests that a value towards the lower end of this range is more likely. There is some evidence to suggest that the direct rebound effect for this energy service declines with income, but there is insufficient evidence to determine how it varies between different countries.

In contrast, the available evidence does not permit the direct rebound effect for space heating to be quantified with much confidence. While this is partly because space heating is inherently more complex, it is also because the topic has received insufficient attention. The studies reviewed here suggest direct rebound effects in the range **1.4 to 60%**, with considerable variation between different countries, households, fuels and types of energy efficiency improvement. The strong evidence for the price asymmetry of energy demand responses for space heating suggests that the mean effect may be towards lower rate end of the above range, but direct rebound effects appear to be higher for low-income groups. For the purpose of policy evaluation, a figure of **30%** would appear a reasonable assumption, which is consistent with the results of the evaluation studies reported in *Technical Report 1*.

There are a number of reasons why direct rebound effects for most other household energy services should be smaller than those for household heating. However, the econometric evidence is very poor, owing largely to measurement difficulties. Two rather dated studies of space cooling both suggest a direct rebound effect in the range **1%-26%**, but these neglect the demand from 'marginal consumers' acquiring space cooling equipment for the first time, as well as any increases in the capacity of space cooling systems among existing users. A rigorous study estimates the direct rebound effect for energy efficient washing machines to be less than **5%** and this figure is likely to be representative of many other time-intensive energy services, such as those provided by dishwashers, vacuum cleaners and electronic appliances.

All econometric estimates should be treated with caution. As Dahl (1993) has noted: "…. despite our attempts, it appears that demand elasticities are like snowflakes, no two are alike." Aside from the difficulties of estimation, behavioural responses are known to be contingent upon technical, institutional, policy and demographic factors that vary widely between different groups and over time. Demand responses are known to vary with the level of energy prices, the origin of price changes (e.g. exogenous versus policy induced), expectations of future prices, saturation effects and other factors. The past is not necessarily a good guide to the future in this area, and it is possible that the very long-run responses may exceed those found in empirical studies that rely upon data from relatively short time periods.

Nevertheless, the evidence suggests that direct rebound effects for consumer energy services are likely to be low to moderate in developed economies and may decline further in the future. Therefore, direct rebound effects should not undermine the objectives of energy efficiency programmes aimed at reducing the energy required to deliver particular energy services. However, these conclusions are subject to a number of qualifications, including the relatively limited time periods over which the effects have been studied, the frequent neglect of marginal consumers and the restrictive definitions of 'useful work' that are commonly employed.

The current state of knowledge on direct rebound effects must be considered insufficient for policy purposes. Hence, research on direct rebound effects needs to improve in rigour and expand in scope. This requires both good data sets and more robust methodologies that address the potential sources of bias indicated above. There is scope for studies of a greater range of consumer energy services, provided that individual appliances can be monitored. Estimates of the direct rebound effect for personal automotive transport would benefit from more appropriate definitions of useful work. A study employing tonne-kilometres as the dependent variable appears feasible and could potentially capture the effect of increasing car sizes. Analysis is also needed of other modes of transport, including freight. There is also scope for more empirical work on the 'rebound effect with respect to time', especially in the area of transportation, and on the dependence of direct rebound effects on income. The geographical bias of the evidence base also needs to be addressed, including in particular studies of consumer energy services in developing countries.

Annex A – Mathematical deriviations

Derivation of Definition 1

Given $S = \varepsilon E$

$$\eta_\varepsilon(E) = \frac{\partial(\frac{S}{\varepsilon})}{\partial \varepsilon}\left(\frac{\varepsilon}{S/\varepsilon}\right) = \left(-S\frac{1}{\varepsilon^2} + \frac{1}{\varepsilon}\frac{\partial S}{\partial \varepsilon}\right)\left(\frac{\varepsilon^2}{S}\right) = \frac{\partial S}{\partial \varepsilon}\frac{\varepsilon}{S} - 1$$

Or: $\eta_\varepsilon(E) = -\eta_\varepsilon(S) - 1$

Decomposing Definition 1

Given $S = \varepsilon E$ and $S = NO*CAP*UTIL$

$$\eta_\varepsilon(E) = \frac{\varepsilon}{E}\left[-\frac{(NO*CAP*UTIL)}{\varepsilon^2} + \frac{1}{\varepsilon}\left((NO*CAP)\frac{\partial UTIL}{\partial \varepsilon} + (NO*UTIL)\frac{\partial CAP}{\partial \varepsilon} + (CAP*UTIL)\frac{\partial NO}{\partial \varepsilon}\right)\right]$$

Substituting $E = (NO*CAP*UTIL)/\varepsilon$ and cancelling terms:

$$\eta_\varepsilon(E) = -1 + \left(\frac{\varepsilon}{UTIL}\frac{\partial UTIL}{\partial \varepsilon} + \frac{\varepsilon}{CAP}\frac{\partial CAP}{\partial \varepsilon} + \frac{\varepsilon}{NO}\frac{\partial NO}{\partial \varepsilon}\right)$$

Or: $\eta_\varepsilon(E) = [\eta_\varepsilon(NO) + \eta_\varepsilon(CAP) + \eta_\varepsilon(UTIL)] - 1$

Derivation of Definition 2

Given $E = S(P_S)/\varepsilon$ and $P_S = P_E/\varepsilon$ and assuming that P_E is exogenous, we have:

$$\eta_\varepsilon(E) = \frac{\partial E}{\partial \varepsilon}\frac{\varepsilon}{E} = \frac{\varepsilon}{E}\left[-\frac{S}{\varepsilon^2} + \frac{\partial S}{\partial P_S}\frac{\partial P_S}{\partial \varepsilon}\right] = \frac{\varepsilon}{E}\left[-\frac{S}{\varepsilon^2} - \frac{1}{\varepsilon}\frac{P_E}{\varepsilon^2}\frac{\partial S}{\partial P_S}\right]$$

$$= -\frac{S}{\varepsilon E} - \frac{P_E}{\varepsilon^2 E}\frac{\partial S}{\partial P_S} \quad = -1 - \frac{P_S}{S}\frac{\partial S}{\partial P_S}$$

Or: $\eta_\varepsilon(E) = -\eta_{P_S}(S) - 1$

Derivation of Definition 4

Given $E = S(P_S)/\varepsilon$ and $P_S = P_E/\varepsilon$ we have:

$$\eta_{P_S}(S) = \frac{\partial S}{\partial P_S}\frac{P_S}{S} = -\frac{\partial(\varepsilon E)}{\partial(P_E/\varepsilon)}\frac{P_E/\varepsilon}{\varepsilon E}$$

But if energy efficiency is held constant the above relationship becomes:

$$\eta_{P_S}(S) = \frac{\partial E}{\partial P_E}\frac{P_E}{E} = \eta_{P_E}(E)$$

Or: $\eta_{\varepsilon}(E) = -\eta_{P_E}(E) - 1$

Derivation of the relative magnitude of price elasticities

Starting with the identity $E = \frac{S[P_E / \varepsilon(P_E)]}{\varepsilon(P_E)}$, the energy cost elasticity of the demand for useful work may be expressed as:

$$\eta_{P_S}(S) = \frac{P_S}{S}\frac{\partial S}{\partial P_S} = \frac{P_S}{S}\left[\varepsilon\frac{\partial S}{\partial P_S} + E\frac{\partial \varepsilon}{\partial P_S}\right] = \frac{P_S}{E}\frac{\partial E}{\partial P_S} + \frac{P_S}{\varepsilon}\frac{\partial \varepsilon}{\partial P_S}$$

Or:

$$\eta_{P_S}(E) = \eta_{P_S}(S) - \eta_{P_S}(\varepsilon)$$

We expect that $\eta_{P_S}(\varepsilon) \geq 0$ (higher costs for useful work encourages higher energy efficiency). In contrast, we expect that $\eta_{P_S}(S) \leq 0$ (higher prices reduce demand). Hence we expect that:

$$\left|\eta_{P_S}(E)\right| \geq \left|\eta_{P_S}(S)\right|$$

By a very similar process we can show:

$$\eta_{P_E}(E) = \eta_{P_E}(S) - \eta_{P_E}(\varepsilon)$$

And hence we can argue that:

$$\left|\eta_{P_E}(E)\right| \geq \left|\eta_{P_E}(S)\right|$$

From Extension 2 we have: $\eta_{P_S}(S) = \frac{\eta_{P_E}(E) + \eta_{P_E}(\varepsilon)}{1 - \eta_{P_E}(\varepsilon)}$. Rearranging we obtain:

$$\eta_{P_E}(E) = \eta_{P_S}(S)\left[1 - \eta_{P_E}(\varepsilon)\right] - \eta_{P_E}(\varepsilon)$$

In most cases we would expect $1 \geq \eta_{P_E}(\varepsilon) \geq 0$ and $0 \geq \eta_{P_S}(S) \geq -1$. This implies that:

$$\left|\eta_{P_S}(S)\right| \leq \left|\eta_{P_E}(E)\right|$$

Combining the above three relationships, we obtain:

$$\left|\eta_{P_E}(S)\right| \leq \left|\eta_{P_S}(S)\right| \leq \left|\eta_{P_E}(E)\right| \leq \left|\eta_{P_S}(E)\right|$$

Derivation of Extension 1

Including the capital costs of new equipment (P_K), the basic identity becomes:

$$E = s[P_S(\varepsilon), P_K(\varepsilon)]/\varepsilon$$

Taking derivatives with respect to energy efficiency, we have:

$$\frac{\partial E}{\partial \varepsilon} = -\frac{S}{\varepsilon^2} + \frac{1}{\varepsilon}\frac{\partial S}{\partial \varepsilon} = -\frac{S}{\varepsilon^2} + \frac{1}{\varepsilon}\left[\frac{\partial S}{\partial P_S}\frac{\partial P_S}{\partial \varepsilon} + \frac{\partial S}{\partial P_K}\frac{\partial P_K}{\partial \varepsilon}\right] = -\frac{S}{\varepsilon^2} - \frac{P_E}{\varepsilon^3}\frac{\partial S}{\partial P_S} + \frac{1}{\varepsilon}\frac{\partial S}{\partial P_K}\frac{\partial P_K}{\partial \varepsilon}$$

Multiply through by ε / E to obtain $\eta_\varepsilon(E)$:

$$\frac{\partial E}{\partial \varepsilon}\frac{\varepsilon}{E} = -\frac{S}{\varepsilon E} - \frac{P_E}{\varepsilon^2 E}\frac{\partial S}{\partial P_S} + \frac{1}{E}\frac{\partial S}{\partial P_K}\frac{\partial P_K}{\partial \varepsilon} = -1 - \frac{P_E/\varepsilon}{\varepsilon\ E}\frac{\partial S}{\partial P_S} + \frac{1}{E}\frac{\partial S}{\partial P_K}\frac{\partial P_K}{\partial \varepsilon}$$

$$\frac{\partial E}{\partial \varepsilon}\frac{\varepsilon}{E} = -1 - \frac{P_S}{S}\frac{\partial S}{\partial P_S} + \frac{\varepsilon}{S}\frac{\partial S}{\partial P_K}\frac{\partial P_K}{\partial \varepsilon}$$

Multiplying numerator and denominator of the last term with P_K, we have:

$$\frac{\partial E}{\partial \varepsilon}\frac{\varepsilon}{E} = -1 - \frac{P_S}{S}\frac{\partial S}{\partial P_S} + \left(\frac{P_K}{S}\frac{\partial S}{\partial P_K}\right)\left(\frac{\varepsilon}{P_K}\frac{\partial P_K}{\partial \varepsilon}\right)$$

Or: $\eta_\varepsilon(E) = -1 - \eta_{P_S}(S) + [\eta_{P_K}(S)\eta_\varepsilon(P_K)]$

Derivation of Extension 2

If energy efficiency depends upon energy prices, the basic identity can be written as follows:

$$E = \frac{S}{\varepsilon} = \frac{S(P_S)}{\varepsilon(P_E)} = \frac{s[P_E/\varepsilon(P_E)]}{\varepsilon(P_E)}$$

Use the product and chain rules to differentiate this with respect to energy commodity prices:

$$\frac{\partial E}{\partial P_E} = -\frac{S}{\varepsilon^2}\frac{\partial \varepsilon}{\partial P_E} + \frac{1}{\varepsilon}\left[\frac{\partial S}{\partial P_S}\frac{\partial P_S}{\partial P_E} + \frac{\partial S}{\partial P_S}\frac{\partial P_S}{\partial \varepsilon}\frac{\partial \varepsilon}{\partial P_E}\right]$$

$$\frac{\partial E}{\partial P_E} = -\frac{S}{\varepsilon^2}\frac{\partial \varepsilon}{\partial P_E} + \frac{1}{\varepsilon}\left[\frac{\partial S}{\partial P_S}\frac{1}{\varepsilon} - \frac{\partial S}{\partial P_S}\frac{P_E}{\varepsilon^2}\frac{\partial \varepsilon}{\partial P_E}\right] = -\frac{S}{\varepsilon^2}\frac{\partial \varepsilon}{\partial P_E} + \frac{1}{\varepsilon^2}\frac{\partial S}{\partial P_S} - \frac{P_E}{\varepsilon^3}\frac{\partial S}{\partial P_S}\frac{\partial \varepsilon}{\partial P_E}$$

Multiplying both sides by P_E/E to switch into elasticity forms:

$$\frac{\partial E}{\partial P_E}\frac{P_E}{E}=-\frac{S}{\varepsilon^2}\frac{P_E}{\varepsilon}\frac{\partial \varepsilon}{\partial P_E}+\frac{1}{\varepsilon^2}\frac{P_E}{\varepsilon}\frac{\partial S}{\partial P_S}-\frac{P_E}{\varepsilon^3}\frac{P_E}{E}\frac{\partial S}{\partial P_S}\frac{\partial \varepsilon}{\partial P_E}$$

Noting that $S=\varepsilon E$ and $P_S=P_E/\varepsilon$, we can simplify:

$$\frac{\partial E}{\partial P_E}\frac{P_E}{E}=-\frac{P_E}{\varepsilon}\frac{\partial \varepsilon}{\partial P_E}+\frac{P_S}{S}\frac{\partial S}{\partial P_S}-\frac{P_S}{S}\frac{\partial S}{\partial P_S}\frac{P_E}{\varepsilon}\frac{\partial \varepsilon}{\partial P_E}$$

Expressing each term as an elasticity, we obtain:

$$\eta_{P_E}(E)=\eta_{P_S}(S)-\eta_{P_E}(\varepsilon)\left[1+\eta_{P_S}(S)\right]$$

Or alternatively: $\eta_{P_S}(S)=\dfrac{\eta_{P_E}(E)+\eta_{P_E}(\varepsilon)}{1-\eta_{P_E}(\varepsilon)}$

Substituting into Definition 2 gives:

$$\eta_\varepsilon(E)=-\left[\frac{\eta_{P_E}(E)+\eta_{P_E}(\varepsilon)}{1-\eta_{P_E}(\varepsilon)}\right]-1$$

Derivation of Extension 3

Including time costs and assuming time efficiency (θ) is a function of energy efficiency (ε) we have:

$$E=s[P_S(\varepsilon),P_T(\theta(\varepsilon))]/\varepsilon$$

Taking derivatives with respect to energy efficiency, we have:

$$\frac{\partial E}{\partial \varepsilon}=-\frac{S}{\varepsilon^2}+\frac{1}{\varepsilon}\left[\frac{\partial S}{\partial P_S}\frac{\partial P_S}{\partial \varepsilon}+\frac{\partial S}{\partial P_T}\frac{\partial P_T}{\partial \theta}\frac{\partial \theta}{\partial \varepsilon}\right]=-\frac{S}{\varepsilon^2}-\frac{P_E}{\varepsilon^3}\frac{\partial S}{\partial P_S}+\frac{1}{\varepsilon}\frac{\partial S}{\partial P_T}\frac{\partial P_T}{\partial \theta}\frac{\partial \theta}{\partial \varepsilon}$$

Multiply through by ε/E to obtain $\eta_\varepsilon(E)$:

$$\frac{\partial E}{\partial \varepsilon}\frac{\varepsilon}{E}=-\frac{S}{\varepsilon E}-\frac{P_E}{\varepsilon^2 E}\frac{\partial S}{\partial P_S}+\frac{1}{E}\frac{\partial S}{\partial P_T}\frac{\partial P_T}{\partial \theta}\frac{\partial \theta}{\partial \varepsilon}$$

Multiply the third term by ($\theta P_T/\theta P_T$) and rearrange:

$$\frac{\partial E}{\partial \varepsilon}\frac{\varepsilon}{E}=-1-\frac{P_S}{S}\frac{\partial S}{\partial P_S}+\left(\frac{P_T}{S}\frac{\partial S}{\partial P_T}\right)\left(\frac{\theta}{P_T}\frac{\partial P_T}{\partial \theta}\right)\left(\frac{\varepsilon}{\theta}\frac{\partial \theta}{\partial \varepsilon}\right)$$

Or: $\eta_\varepsilon(E)=-1-\eta_{P_S}(S)+[\eta_{P_T}(S)\eta_\theta(P_T)\eta_\varepsilon(\theta)]$

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