

Estimating direct rebound effects for personal automotive travel in Great Britain

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Keywords

rebound effects, transport, fuel efficiency, econometric models

Abstract

Direct rebound effects result from increased consumption of cheaper energy services. For example, more fuel-efficient cars encourage more car travel. This study is the first to quantify this effect for personal automotive travel in Great Britain. We use aggregate time-series data on transport activity, fuel consumption and other variables over the period 1970–2011 and estimate the direct rebound effect from the elasticity of vehicle kilometres with respect to: a) vehicle fuel efficiency (km/MJ); b) the fuel cost of driving (£/km); and c) road fuel prices (£/MJ). We estimate a total of 54 models, paying careful attention to methodological issues and model diagnostics. Taking changes in fuel efficiency as the explanatory variable, we find no evidence of a long-run direct rebound effect in Great Britain over this period. However, taking changes in either the fuel cost of driving or fuel prices as the explanatory variable we estimate a direct rebound effect in the range 10 % to 27 % with a mean of 18 %. This estimate is consistent with the results of US studies and suggests that one fifth of the potential fuel savings from improved car fuel efficiency may have been eroded through increased driving. We also show how the normalisation of distance travelled (per capita, adult or driver) affects the results obtained.

Introduction

Direct rebound effects relate to increased consumption of energy services whose effective price has fallen as a consequence of improved energy efficiency. For example, we expect more fuel-efficient cars to encourage more car travel, thereby offset-

ting some of the potential energy savings. The magnitude of such effects may vary widely between different energy services, between different social groups and over time, with long-term rebounds being of greatest interest for public policy [1]. Compared to the majority of energy services, the direct rebound effect for personal automotive transport is relatively well-studied since data on vehicle travel and fuel consumption is routinely collected by national and regional authorities. However, the evidence to date is overwhelmingly dominated by studies from the US [1–3]. Since road fuel prices, vehicle efficiencies and population densities are comparatively low in the US, while car ownership and usage are comparatively high, US results may not provide a reliable guideline for other countries.

For econometric studies, the most obvious measure of the direct rebound effect is the elasticity of demand for the relevant energy service (S) with respect to some measure of energy efficiency (ϵ): $\eta_\epsilon(S) = \delta \ln(S) / \delta \ln \epsilon$. For example, the energy service provided by private cars may be measured in vehicle kilometres, their fuel consumption (E) in megajoules (MJ) and their fuel efficiency ($\epsilon = S / E$) in km/MJ. As shown by Sorrell and Dimitropoulos [4], the elasticity of demand for fuel with respect to fuel efficiency ($\eta_\epsilon(E)$) is then given by:

$$\eta_\epsilon(E) = \eta_\epsilon(S) - 1 \quad (1)$$

If $\eta_\epsilon(S)$ is zero, an x % improvement in fuel efficiency should lead to an x % reduction in fuel consumption ($\eta_\epsilon(E) = -1$). But since improved fuel efficiency makes driving cheaper, some of the potential fuel savings may be ‘taken back’ through increased distance travelled ($\eta_\epsilon(S) \geq 0$ and $\eta_\epsilon(E) \geq -1$). This in turn may result from greater use of vehicles and/or induced increases in the vehicle stock which in turn may be associated

with (induced) changes in land use patterns that encourage greater car dependence. In practice, however, reliable data may not be available on vehicle fuel efficiency, or the limited variation in fuel efficiency in the available data sets may preclude robust inference. Hence, a more common approach is to estimate the direct rebound effect from one of three price elasticities, namely:

$\eta_{p_s}(S)$: the elasticity of demand for vehicle kilometres with respect to the fuel cost per kilometre (p_s);

$\eta_{p_e}(S)$: the elasticity of demand for vehicle kilometres with respect to the price of fuel (p_e); or

$\eta_{p_e}(E)$: the elasticity of demand for fuel with respect to the price of fuel.

Where: $p_s = p_e / \varepsilon$. Estimates of price elasticities may be more precise than estimates of efficiency elasticities if there is greater variation in the relevant explanatory variables. But the first two of these elasticities ($\eta_{p_s}(S)$ and $\eta_{p_e}(S)$) can only be considered equivalent to the efficiency elasticity ($\eta_\varepsilon(S)$) if fuel prices are exogenous, the demand for vehicle kilometres depends solely on the fuel price per kilometre, and consumers respond in the same way to improvements in fuel efficiency as they do to reductions in fuel prices [4]. While the first of these assumptions is reasonable, the second and third are less so [4]. For $\eta_{p_e}(E)$ to be equivalent to $\eta_\varepsilon(S)$ we need the additional assumption that fuel efficiency is constant – which is problematic for a study of rebound effects [5]. If fuel efficiency is instead influenced by fuel prices ($\varepsilon = f(p_e)$), the following inequality should hold [4]:

$$|\eta_{p_e}(S)| \leq |\eta_{p_s}(S)| \leq |\eta_{p_e}(E)| \quad (2)$$

If fuel efficiency depends upon fuel prices, then fuel efficiency is endogenous. Moreover, there may be other reasons why fuel efficiency is endogenous. For example, if drivers expect to travel long distances they may be more likely to choose a fuel-efficient car, thereby creating an additional positive correlation between vehicle kilometres and fuel efficiency that may bias estimates of the rebound effect [6]. Possible responses to this include finding suitable instrumental variables for fuel efficiency or estimating a simultaneous equation model that includes separate equations for the number of cars, the total distance travelled and the fuel efficiency of the car fleet. But adequate instruments can be difficult, if not impossible, to find [7] and lack of data may preclude the estimation of a full structural model. In view of this, Frondel and Vance [5] recommend using $\eta_{p_e}(S)$ as the ‘best’ measure of the direct rebound effect since fuel prices are more likely to be exogenous.

These difficulties have led to a variety of approaches to estimating the direct rebound effect for personal automotive transport, with most studies basing their estimates on the elasticity of vehicle kilometres with respect to the fuel cost per kilometre ($\eta_{p_s}(S)$). Sorrell *et al* [8] reviewed 17 of these studies, including seven using aggregate time-series and cross-sectional data, four using aggregate panel data and five using household survey data. All but one of these studies applied to the US. Despite wide differences in specifications and methodologies, most estimated the long-run direct rebound effect to lie in the range 10–30 %.

Perhaps the most rigorous study was by Small and van Dender [6] who used panel data from US states over the period 1961–2001. Small and van Dender estimated a simultaneous equation model that allowed $\eta_{p_s}(S)$ to be derived, as well as a variant that allowed $\eta_\varepsilon(S)$ to be estimated. The variant performed relatively poorly, with the estimate of $\eta_\varepsilon(S)$ being small and statistically insignificant. Hence, Small and van Dender based their conclusions on their estimates of $\eta_{p_s}(S)$ – which suggested a long-run direct rebound effect of ~22 %. More recently, Greene [2] investigated the direct rebound effect for US transport over a similar time period, but using national time-series data instead. Similar to Small and van Dender, Greene failed to obtain a statistically significant estimate of $\eta_\varepsilon(S)$. However, his estimates of $\eta_{p_e}(S)$ suggested a long-run rebound effect of ~23 % – virtually identical to Small and Van Dender. Greene also tested and rejected the hypothesis that $\eta_{p_e}(S) = -\eta_\varepsilon(S)$ – thereby raising doubts about the validity of $\eta_{p_s}(S)$ as a measure of the direct rebound effect.

In summary, while an *efficiency* elasticity ($\eta_\varepsilon(S)$) may be the *preferred* measure of the direct rebound effect for personal automotive transport, most studies have either been unable to estimate this elasticity or have found the relevant coefficient to be statistically insignificant. In contrast, many studies have used one or more *price* elasticities ($\eta_{p_e}(S)$, $\eta_{p_s}(S)$ or $\eta_{p_e}(E)$) as *alternative* measures of the direct rebound effect and have commonly obtained statistically significant results. The reasons for these differences are unclear, but may be linked to the endogeneity of fuel efficiency, the limited variation of fuel efficiency in the available data sets and/or because consumers respond differently to changes in fuel prices than to changes in fuel efficiency (perhaps because fuel efficiency is correlated with other attributes of the energy service provided by private cars). While the absence of significant estimates of $\eta_\varepsilon(S)$ suggests a long-run direct rebound effect close to zero, the multiple estimates of price elasticities suggest that the long-run direct rebound effect lies in the range 10–30 %. These contradictory findings suggest the need for caution in interpreting the results of such studies.

Since the publication of the review by Sorrell [1], the literature on rebound effects has grown considerably. However, most of the estimates for personal automotive transport are in line with the above findings [e.g. 2,3,9,10]. Notable exceptions include Frondel *et al* [11,12] who find much larger rebound effects for car travel in Germany and Linn [13] who finds the same for the US. Linn’s study is also unique in obtaining statistically significant estimates of $\eta_\varepsilon(S)$ and in finding these to be *larger* than his estimates of $\eta_{p_e}(S)$. Recent US literature has indicated that the direct rebound effect may fall over time as incomes rise and car ownership and use approaches saturation levels [3,14,15].

All these studies use either aggregate panel data from US states or detailed micro-data on car ownership and use by individual households and the large number of observations in these datasets allows the specification of structural models that provide more precise parameter estimates. But since this type of data is not available for GB, we adopt a simpler approach using aggregate time-series data on car use and fuel consumption over the period 1970–2011. We develop a number of models with different specifications and use these to estimate and compare three different measures of the long-run direct rebound effect, namely $\eta_\varepsilon(S)$, $\eta_{p_s}(S)$ and $\eta_{p_e}(S)$. In addition, we explore how

different normalisations of our measure of distance travelled influence the results and pay careful attention to evaluating and comparing the statistical robustness of the estimated models.

Methodology

Our approach involves estimating a total of 54 models, each of which falls into one of 6 **Groups** – listed in Table 1. We first estimate two **base models** within each Group – one of which is a *static* specification and the second a *dynamic* specification. We then explore a number of **variants** of those models and use a series of **robustness tests** to choose the ‘best performing’ models. Below we explain in turn the definition of model Groups, the specification of base models, the specification of model variants and the robustness tests.

MODEL GROUPS

In common with most previous studies, we use the annual distance travelled by personal automotive vehicles (in vehicle kilometres) as our explained variable (S_t). In practice, changes in fuel economy may also influence the average load factor or average power and weight of cars, but these complexities are not addressed here.

Previous studies have not been consistent in their specification of distance travelled, either measuring it in absolute terms or normalising it to population, the number of adults or the number of licensed drivers. Changes in the age structure of the population, the propensity of young people to learn to drive and/or the proportion of female drivers will have different effects on the explained variable depending upon the normalisation used – thereby influencing the coefficients of the relevant models. For example, if the proportion of licensed drivers in the population is increasing, then normalising distance travelled to population may lead to a higher estimate of income elasticity than normalising to the number of drivers. To allow for this, we estimate and compare models using *all three* normalisations.

We then explore two **Types** of model (A and B) for annual distance travelled, namely:

- **Type A** models which include retail fuel prices (p_E) and fleet average fuel efficiency (ϵ) as separate explanatory variables, thereby allowing $\eta_{p_E}(S)$ and $\eta_{\epsilon}(S)$ to be estimated; and

- **Type B** models which combine fuel prices and fuel efficiency into a single explanatory variable, the fuel cost of driving ($p_S = p_E / \epsilon$), thereby allowing $\eta_{p_S}(S)$ to be estimated.

Type B models impose the hypothesis that the response to improved fuel efficiency is identical to the response to lower fuel prices, while *Type A* models allows this hypothesis to be tested. By estimating both types, we can compare the results obtained. This combination of two types of model and three normalisations of the explained variable leads to the six different model groups summarised in Table 1.

BASE MODELS

In common with most studies in this area, we specify the annual distance travelled (S_t) by personal automotive vehicles in Great Britain as a function of real equivalised household income (Y_t) and the real fuel cost of driving – whether specified in the Type A (p_E and ϵ) or Type B ($p_S = p_E / \epsilon$) forms. We also include a proxy variable for the level of congestion (C_t) on GB roads, together with a dummy variable (X_t) that is non-zero in years when there was an oil price shock. Using only four variables is appropriate given our limited number of observations.

In each model Group we estimate **base models** using both *static* and *dynamic* specifications. The former specify distance travelled as a function of the explanatory values in the same time period – thereby assuming that the observed demand is in equilibrium. But since responses to efficiency improvements and fuel price changes take time, this type of model may not adequately capture the long-run adjustments we are interested in. Hence we also investigate dynamic models in which distance travelled is specified as a function of historic values of the explained variables. To conserve degrees of freedom we use the standard ‘partial adjustment’ specification which simply adds a one period lag of the explained variable. In both cases we choose the standard double log (constant elasticity) formulation. The static and dynamic versions of each model type are then as follows:

Type A, static

$$\ln S_t = \beta_0^{AS} + \beta_1^{AS} \ln Y_t + \beta_2^{AS} \ln p_{E_t} - \beta_3^{AS} \ln \epsilon_t + \beta_4^{AS} X_t + \beta_5^{AS} C_t + u_t^{AS} \quad (3)$$

Table 1. Classification of model groups.

Group	Type	Rebound elasticity	Normalisation of vehicle kilometres
1	Type A	Fuel efficiency (km/MJ)	Per capita
2		Fuel prices (£/MJ)	Per adult
3			Per licensed driver
4	Type B	Fuel cost of driving (£/km)	Per capita
5			Per adult
6			Per licensed driver

Type A, dynamic

$$\ln S_t = \beta_0^{AD} + \beta_1^{AD} \ln Y_t + \beta_2^{AD} \ln p_{E_t} - \beta_3^{AD} \ln \varepsilon_t + \beta_4^{AD} X_t + \beta_5^{AD} C_t + \beta_6^{AD} S_{t-1} + u_t^{AD} \quad (4)$$

Type B, static

$$\ln S_t = \beta_0^{BS} + \beta_1^{BS} \ln Y_t + \beta_2^{BS} \ln p_{S_t} + \beta_3^{BS} X_t + \beta_4^{BS} C_t + u_t^{AS} \quad (5)$$

Type B, dynamic

$$\ln S_t = \beta_0^{BD} + \beta_1^{BD} \ln Y_t + \beta_2^{BD} \ln p_{S_t} + \beta_3^{BD} X_t + \beta_4^{BD} C_t + \beta_5^{BD} S_{t-1} + u_t^{BD} \quad (6)$$

Where S_t is vehicle or passenger kilometres travelled by the personal automotive fleet in Great Britain (GB) in year t , p_{E_t} is real average fuel prices (£/MJ), ε_t is fleet average fuel efficiency (vkm/MJ), p_{S_t} is real fuel costs per vehicle kilometre (£/vkm), Y_t is real equivalised household income, X_t is a dummy variable for the oil price shock years of 1974 and 1979, C_t is a proxy measure for road congestion and u_t is the error term. For illustration, the long-run elasticity of distance travelled with respect to the fuel cost of driving ($\eta_{p_S}(S)$) is given by β_2^{BS} in the static Type B model (Equation 5) and $(\beta_2^{BD}/(1-\beta_5^{BD}))$ in the dynamic version (Equation 6).

We form our proxy measure of congestion (C_t) by dividing the normalising variable for the explained variable (i.e. population, number of adults or number of licensed drivers) by the total road length in GB in that year. This is a relatively crude approach, but data on congestion in GB is of poor quality and actual congestion is likely to be endogenous [6]. Alternative methods for measuring congestion are discussed in [16]. We form our fuel consumption variable (E_t) by summing petrol and diesel consumption by cars and our fuel price variable (p_{E_t}) by weighting the price of each by their share of total car fuel consumption. This aggregation is necessary because our data on distance travelled does not distinguish between petrol and diesel cars. In practice, diesel cars tend to be more fuel-efficient, larger and more powerful than petrol cars, as well as being more intensively used [17]. The proportion of diesel cars in the GB fleet grew rapidly after 1990, and by 2011 diesels accounted for ~40 % of total GB car fuel consumption.

MODEL VARIANTS

With two base models (static and dynamic) in each of six Groups, this leads to a total of 12 base models. We then investigate *re-specifying* these models in four ways, described below.

Quadratic income variants

First, we investigate the addition of a *quadratic* term for log equivalised per capita income ($\ln Y_t$) to allow for the possibility of a 'peaking' relationship between income and distance travelled. Such a relationship is suggested by our data (Figures 1 and 2) and is consistent with the broader evidence on 'peak car' [18]. For illustration, the Type B static model becomes:

$$\ln S_t = \beta_0^{BS} + \beta_1^{BS} \ln Y_t + \beta_2^{BS} (\ln Y_t)^2 + \beta_3^{BS} \ln p_{S_t} + \beta_4^{BS} X_t + \beta_5^{BS} C_t + u_t^{AS} \quad (7)$$

The level of equivalised per capita income at which distance travelled starts to fall (Y_p) is then given by:

$$Y_p = \exp \left[\frac{-\beta_1^{BS}}{2\beta_2^{BS}} \right] \quad (8)$$

And the long-run income elasticity of distance travelled is given by:

$$\eta_Y(S) = \beta_1^{BS} + 2\beta_2^{BS} \ln Y \quad (9)$$

The equivalent expression for this elasticity in the dynamic model is:

$$\eta_Y(S) = (\beta_1^{BD} + 2\beta_2^{BD} \ln Y) / (1 - \beta_5^{BD}) \quad (10)$$

Hence, in the quadratic variants, the income elasticity varies with the level of per capita income and becomes negative when $Y > Y_p$. Below we evaluate this elasticity at the mean value of $\ln Y$ in our dataset.

Asymmetric variants

Second, we investigate the possibility of *asymmetric* responses to changes in either fuel prices (p_E – Type A) or driving costs (p_S – Type B). Asymmetric responses have been widely observed [19,20] and are typically ascribed to a combination of induced technical change, irreversible investments, habits and/or the embodiment of higher efficiency standards in regulations [5]. Our approach involves decomposing p_{E_t} (or p_{S_t}) as follows [21]:

$$p_{E_t} = p_{E_0} + p_{E_t}^r + p_{E_t}^f \quad (11)$$

$$p_{E_t}^r = \sum_t \max[0, (p_{E_t} - p_{E_{t-1}})] \dots \text{and} \dots$$

$$p_{E_t}^f = \sum_t \min[0, (p_{E_t} - p_{E_{t-1}})] \quad (12)$$

Here, $p_{E_t}^r$ ($p_{E_t}^f$) represents the cumulative effects of all increases (decreases) in price since the start of the sample: It is the coefficient on the latter that is relevant to rebound effects.

Reduced variants

Third, we investigate eliminating variables that are found to be insignificant¹ in the above specifications and then re-estimating these *reduced* models. This approach places a priority on parsimony. In practice, if the eliminated variables are co-linear they may be individually insignificant but jointly significant. For simplicity we do not test for this, but a test for multicollinearity forms one of our robustness checks.

1. Unless otherwise stated, the significance level in the reported results is 0.05 (5 %).

Co-integrated variants

Finally we investigate the stationarity of the time series in our 'best fitting' static models. With time series data it is common for one or more of the variables to be non-stationary, creating the risk of spurious regressions.² While this may be avoided by differencing the data, this would prevent the estimation of long-run relationships. But it is possible for two or more non-stationary variables to be *co-integrated*, meaning that certain linear combinations of these variables are stationary and that there is a stable long-run relationship between them. Co-integration techniques allow these relationships to be identified. Hence, we also test the time series and residuals in the 'best performing' static models for unit roots and, if found, re-estimate these *co-integrated* models using relevant techniques.

MODELLING SEQUENCE

This procedure leads us to estimate a total of **nine** models in each of the six groups, or **54 models in total**. Each group contains static and dynamic versions of the base, quadratic, asymmetric and reduced specifications, together with a single co-integrated specification. We estimate the co-integrated model with a specialised technique ('canonical co-integrating regression') and the remainder with OLS.

The procedure for selecting the models relies upon a comprehensive series of *robustness tests* that are described below. These tests are used to create an aggregate *robustness score* for each model which guides their selection at each stage. The procedure for selecting the model variants is as follows:

1. **Base models:** We first estimate the base static and dynamic models in each of the twelve groups (using OLS) and evaluate the robustness of each using the tests illustrated in Table 2 (*12 models in total*).
2. **Quadratic income variants:** We then add a quadratic term for log per capita income to each model and repeat the estimations and robustness tests. We compare the aggregate robustness score for each model in Stage 2 with the corresponding score for the model without the quadratic income term from Stage 1 and choose the best performing specification to take through to Stage 3 (*12 models in total*).
3. **Asymmetric variants:** We take the best performing model (base or quadratic) and add terms to allow for asymmetric price responses. We then repeat the estimations and robustness tests and also apply a Wald test to identify whether asymmetry is present. We select the Stage 3 specification over the Stage 1 or 2 specifications if the former has a higher robustness score AND the Wald test is significant. If not, we continue with the Stage 1 or Stage 2 specification. The selected models are taken through to Stage 4 (*12 models in total*).
4. **Reduced variants:** We take the selected models from Stage 3 and remove those coefficients which were found to be insignificant at the 5 % level– thereby creating 'reduced' specifications. We then repeat the estimations and robustness tests (*12 models in total*).
5. **Co-integrated variants:** Finally, we examine the results of the last four stages and select the 'best performing' static models in each of the six groups on the basis of their robustness scores. For each of these we test the data and residuals for unit roots using a method proposed by Phillips and Perron [22]. If the variables are found to be co-integrated we re-estimate the model using a co-integration technique proposed by Park [23]. In practice, all six 'best performing' models were found to be co-integrated³ and hence all were re-estimated at this stage (*6 models in total*).

ROBUSTNESS TESTS

To estimate the robustness of each model, we conduct a series of diagnostics tests and aggregate the results into an overall *robustness score* – with higher scores implying better models. In Stages 1–4, we evaluate each static and dynamic model against *thirteen* different diagnostic tests that are summarised in Table 2^{4,5,6}. We score the performance of each model against each of these tests and construct a weighted sum of results to obtain an overall score which we express in percentage terms. We use two different weighting rules: the first based on our judgement of the 'relative importance' of each test, and a second which gives equal weighting to each.

Some of these tests are not appropriate for co-integrated models, while others are not available for such models with our software (EViews). Hence, for the co-integrated models in Stage 5 we use a more limited set of *six* diagnostic tests summarised in Table 3. Tests for serial correlation and endogeneity are not included for the cointegrated models and there is some debate about whether our estimation technique ('canonical co-integrating regression') is immune to these [23–25]. CUSUM and CUSUM of squares are also not available for co-integrated models in EViews so instead we use a test that simultaneously identifies co-integrated time series and parameter stability (Hansen, 1992). Similarly, the three information criteria are not available, so we use a simple goodness of fit measure instead (R^2).

Data

We take data on distance travelled by cars in GB (S_t) over the period 1970–2011 from DTp [36], and data on UK car fuel consumption (E_t) over the same period from DECC [37]. Both time series include commercially rented vehicles (e.g. taxis) and company cars, since travel and fuel consumption by these groups are not independently identified.⁷ We scale the DECC data in proportion to the GB share in UK population

2. The mean and variance of a stationary process are constant over time and the covariance between two points depends only on the time distance between them and not the time period itself.

3. All variables in the best performing models (excluding the oil price shock variable) could not reject the null hypothesis of a unit root in levels form, but rejected the null in first differences. In all cases, the residuals reject the null hypothesis of a unit root in levels form.

4. Coefficient magnitudes, score for yes: Details about the boundaries used to operationalise this criterion are available from the authors.

5. Serial correlation, Lagrange multiplier: Used in preference to Durbin-Watson test because the latter is only operationalised with one lag and is not applicable where lagged explained variables are included.

6. Akaike information criterion: Models which are too complicated risk 'over-fitting' the data [31]. Alternative tests are available which define parsimony in terms of the complexity of model functional form [32].

7. Changes in the tax treatment of company cars are likely to have influenced both new-car purchases and car usage patterns.

Table 2. Summary of diagnostic tests and scoring rules for the models in Stages 1–4.

No.	Name	Description	Weighting A	Weighting B
1	Coefficient signs	Do all statistically significant coefficients ($P < 0.05$) have the expected signs? Score for yes.	2	1
2	Coefficient magnitudes	Do all statistically significant coefficients have <i>plausible</i> magnitudes? Score for yes	2	1
3	Serial correlation	Lagrange multiplier with two lags used to test for serial correlation of the residuals [26]. Score for absence of serial correlation.	2	1
4	Heteroscedasticity	Lagrange multiplier used to test for heteroscedasticity of the residuals [26]. Score for absence of heteroscedasticity	1	1
5	Normality	Lagrange multiplier used to test for normality of the residuals [27]. Score for normally distributed residuals.	1	1
6	Multicollinearity	Centred variance inflation factors used to test for collinear variables. Score for absence of multicollinearity.	1	1
7	CUSUM	Cumulative sum of recursive residuals used to test for the stability of coefficient estimates over time [28]. Score for residual stability	2	1
8	CUSUM of squares	Cumulative sum of recursive squared residuals used to test the stability of coefficient estimates over time [28]. Score for residual stability.	2	1
9	Akaike information criterion	Akaike information criterion [29,30] used to evaluate the trade-off between goodness of fit and model complexity in each model group. Involves comparing and <i>ranking</i> the base, quadratic, asymmetric and reduced model variants in each group. Score 1 for rank 1, 0.5 for rank 2, 0.33 for rank 3 and 0 for rank 4.	Max of 1	Max of 1
10	Hannan and Quinn information criterion	Hannan and Quinn information criterion [33] used to evaluate the trade-off between goodness of fit and model complexity in each model group. Involves comparing and ranking the base, quadratic, asymmetric and reduced model variants in each group. Score 1 for rank 1, 0.5 for rank 2, 0.33 for rank 3 and 0 for rank 4.	Max of 1	Max of 1
11	Schwarz information criterion	Schwarz information criterion [34] used to evaluate the trade-off between goodness of fit and model complexity in each model group. Involves comparing and ranking the base, quadratic, asymmetric and reduced model variants in each group. Score 1 for rank 1, 0.5 for rank 2, 0.33 for rank 3 and 0 for rank 4.	Max of 1	Max of 1
12	RESET-1	Ramsey's regression specification error test used to determine whether the inclusion of 1 fitted term (e.g. squares of the explanatory variables) would better describe the data. Score for passing this test	2	1
13	RESET-2	Ramsey's regression specification error test used to determine whether the inclusion of 2 fitted terms (e.g. cubes and squares of the explanatory variables) would better describe the data. Score for passing this test.	2	1

and use this to construct our aggregate fuel efficiency variable ($\epsilon_i = S_i / E_i$). Schipper *et al* [38] provides an insightful discussion of the uncertainties and potential biases with this type of approach, but our data provides little alternative. We take nominal petrol and diesel prices from DECC [39], convert these to 2011 prices with a 'before housing costs deflator' [40] and construct an aggregate fuel price by weighting by the relative share of petrol and diesel consumption in each year. Reflecting changes in

fuel specifications, we use the price of 4* petrol before 1989 and the price of 'premium unleaded' petrol after that date [41]. We take data on mean equivalised real household income (Y_i) from IFS [42], population data from ONS [43] and data on licensed drivers and road length from DTp [36,44]. Where necessary, we use linear interpolation to adjust these data series to end of year values. The use of equivalised incomes adjusts for changes in average family size and composition.

Table 3. Summary of diagnostic tests and scoring rules for the models in Stage 5.

No.	Name	Description	Weighting A	Weighting B
1	Coefficient signs	Do all statistically significant coefficients ($P < 0.05$) have the expected signs? Score for yes.	2	1
2	Coefficient magnitudes	Do all statistically significant coefficients have <i>plausible</i> magnitudes? Score for yes	2	1
3	Normality	Lagrange multiplier used to test for normality of the residuals [27]. Score for normally distributed residuals.	1	1
4	Multicollinearity	Centred variance inflation factors used to test for collinear variables. Score for absence of multicollinearity.	1	1
5	Hansen	A test from Hansen [35] used to test the stability of coefficient estimates over time. Score for passing this test.	2	1
6	R^2	Simple R^2 test used to evaluate goodness of fit. For scoring system A (B), score 2 (1) if $R^2 > 0.95$ and score 1.75 (0.875) if $R^2 > 0.90$.	2	1

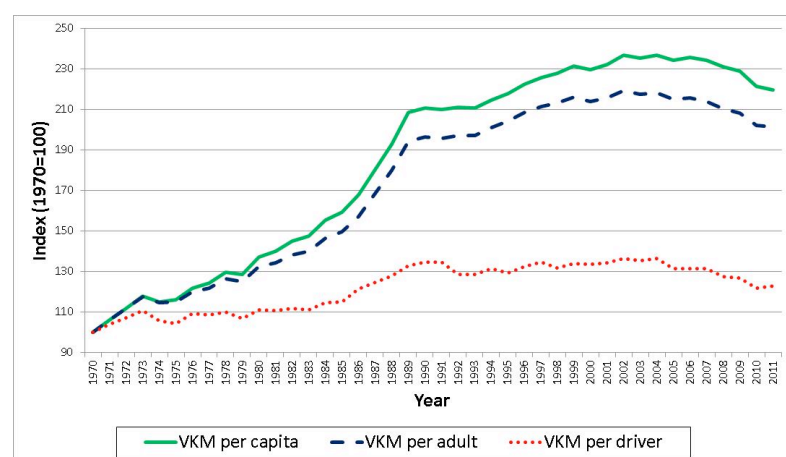


Figure 1. Trends in three measures of distance travelled in cars in Great Britain 1970–2011.

Trends in each of these variables are illustrated in Figures 1–2. Vehicle kilometres have approximately doubled since 1970, but the rate of growth slowed after the 1990 recession, subsequently plateaued and then declined (Figure 1). This pattern (‘peak car’) has been observed in several countries and typically predates the fall in per capita income that followed the 2008 financial crisis. This trend appears to be driven by a number of factors that are only partly captured by the (quadratic) income and congestion variables in our specifications [18].

Fleet average on-road fuel efficiency has improved by ~67 % since 1970 with most improvements occurring after 1980 (Figure 2). Retail fuel prices were volatile during the 1970s and have since been on an upward trend. The range of variation in these variables in GB over the last 40 years has been less than in the US owing to: first, the relatively higher efficiency of the GB vehicle fleet; second, the absence of fuel efficiency regulations in GB; and third, the much higher taxation of road fuels in GB (~60 % of retail price) which dampens the impact of oil price fluctuations. The fuel price trends since 1990 have increased the average fuel cost per kilometre while the fuel efficiency trends have reduced it, with the result that the real fuel cost per vehicle kilometre (p_s) has remained fairly constant since that

date. Such factors are likely to make the estimation of rebound effects more difficult for GB than for the US, since there is less variation in the relevant explanatory variables.

Figure 2 shows that equivalised real per capita income doubled between 1970 and 2009, but fell slightly following the financial crisis. Road building has kept up with population growth throughout this period, but not with the growth in the number of drivers, leading to a 65 % increase in the ratio of drivers to road length (~89 drivers per km in 2011). This is likely to have increased congestion, although factors such as the degree of urbanisation, traffic management will also affect congestion trends.

Results

In this section we report and interpret the most relevant results from the 54 modelling runs. We focus upon statistically significant estimates of the relevant coefficients and give priority to the more robust models. Specifically, we report in turn: the coefficient estimates; the significant estimates of rebound effects; and the relationship between rebound estimates and model robustness. Full results are available from the authors.

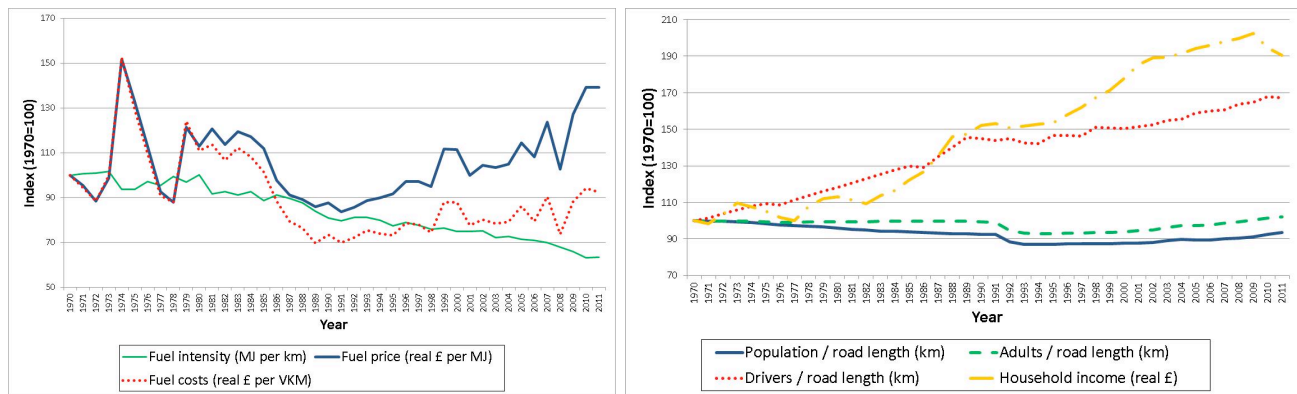


Figure 2. Trends in a) fuel intensity, real fuel prices and real fuel cost per kilometer for cars; and b) real equivalised household income and road congestion for Great Britain 1970–2011.

COEFFICIENT ESTIMATES

As shown in Table 4, we obtained 39 statistically significant estimates of the long-run income elasticity of distance travelled, ranging from 0.18 to 0.83. The results suggest that, on average, a 1 % increase in equivalised per capita income was associated with a 0.51 % increase in distance travelled over this period. As expected, normalising distance travelled to the number of licensed drivers led to lower estimates of income elasticity, but there was little difference between the results for static, dynamic and co-integrating specifications. For comparison, a review of international studies by Goodwin et al [45] found a mean estimate for income elasticity of 0.5 from static models and 0.3 from dynamic models (both for vehicle kilometres) while a UK study by Dargay [21] produced estimates in the range 0.95 to 1.12.

The quadratic specifications performed well, with 33 significant estimates of the level of mean equivalised household income at which vehicle kilometres began to fall – ranging from £457 to £639. The estimate of £532/week was slightly lower than the mean equivalised income in 2003 – although the latter fell after 2008.

We obtained 18 statistically significant estimates of the long-run elasticity of distance travelled with respect to our proxy measures of ‘congestion’. Estimates ranged from -1.47 to -0.85 and suggest that, on average, a 1 % increase in these proxies was associated with a 1.25 % reduction in vehicle kilometres over this period. Although road length per driver changed more than road length per person and per adult over this period (Figure 2), the coefficient on the former was not significant in any of the relevant models. However, this difference may result in part from the explained variable being normalised to the same measure as the congestion proxy in each model (i.e. people, adults or drivers). US studies [3,6] have yielded substantially smaller estimates for these proxies, but congestion is likely to be lower in the US since there is around three times more road space per driver.

We obtain 23 statistically significant estimates of the oil price shock coefficient, ranging from -0.068 to -0.041. On average, these suggest that the 1974 and 1979 oil price shocks were associated with a contemporaneous 5.2 % reduction in vehicle kilometres. Despite applying to GB, our mean estimate for this variable is close to recent estimates from the US [2,3,6].

The most important results are the coefficients relevant to rebound effects. These are summarised below.

REBOUND ESTIMATES

Estimates of the direct rebound effect can be obtained from the coefficients on fuel efficiency (ϵ) or fuel prices (p_E) in the Type A models, or the coefficient on the fuel cost of driving (p_S) in the Type B models. Tables 7 and 8 list those estimates that were found to be statistically significant with plausible magnitudes and signs, and also indicate the robustness score of the relevant model. The estimates are listed in descending order of model robustness within each category.

Importantly, *none* of the Type A models provided a statistically significant estimate of the elasticity of vehicle or passenger kilometres with respect to fuel efficiency ($\eta_\epsilon(S)$). In other words, *using the preferred measure of the long-run direct rebound effect, we find no evidence improvements in fuel efficiency have led to an increase in distance travelled in GB over the last 40 years*. As noted earlier, two of the most rigorous US studies reached exactly the same conclusion [2,6]. However, *we do find evidence that reductions in fuel prices have led to an increase in distance travelled ($\eta_{p_E}(S)$)*. As shown by Table 5, 11 of the Type A models provided statistically significant estimates of $\eta_{p_E}(S)$, with co-integrating specifications scoring higher against our robustness criteria and with no significant results from the dynamic models. These results imply a long-run direct rebound effect in the range **11 % to 22 %, with a mean of 17 %**.

Table 5 also suggests that normalising distance travelled the number of drivers leads to lower estimates of the direct rebound effect, while normalising to the number of adults leads to higher estimates (although here the difference is smaller). One possible interpretation of the former is that lower driving costs encourage more people to gain licenses and purchase cars, as well as to drive those cars further. But to test this hypothesis properly we would need to estimate a full structural model.

We also find evidence that a reduction in the fuel cost of driving ($p_S = p_E / \epsilon$) has led to an increase in distance travelled, with 17 of the Type B models providing statistically significant estimates of $\eta_{p_S}(S)$ (Table 6). More models provided significant estimates of $\eta_{p_S}(S)$ than $\eta_{p_E}(S)$, despite fuel prices varying more than the fuel cost of driving over the last 20 years (Figure 3). Dynamic models provided slightly larger estimates (Table 8). The results imply a long-run direct rebound effect **in the range**

Table 4. Mean estimates of the elasticity of distance travelled with respect to equivalised per capita income.

	Per capita	Per adult	Per driver	Mean
VKM	0.57 (12/18)	0.57 (13/18)	0.39 (14/18)	0.51 (39/54)

Note. Each table entry is the mean of the statistically significant estimates in that category, while the numbers in brackets indicate the fraction of models in each category that provided statistically significant estimates.

Table 5. Estimated rebound effects for fuel prices ($\eta_{p_e}(S)$).

	Per capita	Per adult	Per driver	Mean
VKM	17.9 % (3/9)	20.5 % (4/9)	13.8 % (4/9)	17.2 % (11/27)

Note. Each table entry is the mean of the statistically significant estimates in that category, while the numbers in brackets indicate the fraction of models in each category that provided statistically significant estimates.

Table 6. Estimated rebound effects for fuel cost per kilometre ($\eta_{p_s}(S)$).

	Per capita	Per adult	Per driver	Mean
VKM	18.8 % (5/9)	21.7 % (7/9)	14.4 % (5/9)	18.7 % (17/27)

Note. Each table entry is the mean of the statistically significant estimates in that category, while the numbers in brackets indicate the fraction of models in each category that provided statistically significant estimates.

11 % to 27 %, with a mean of 19 %.⁸ Again, normalising distance travelled to the number of drivers appears to lead to lower estimates of the direct rebound effect, while normalising to the number of adults leads to larger estimates.

In summary, if we were to base our estimates on $\eta_e(S)$ we would conclude that the long run direct rebound effect was approximately zero over this period, while if we to base o A estimates on either $\eta_{p_e}(S)$ or $\eta_{p_s}(S)$ we would conclude that it lay in the range **10 to 27 %**, with a mean of **18 %**. The estimates vary with the specification and measures used, but appear slightly lower when distance travelled is normalised to the number of drivers rather than to the number of adults or people and slightly higher when rebound is estimated with respect to the fuel cost per mile, rather than fuel prices. However, there is a significant overlap in the range of estimates for each specification and measure.

These results are consistent with the majority of studies in this area, most of which apply to the US and measure the direct rebound effect from $\eta_{p_s}(S)$. Hence, the differences in population density, land use patterns, car ownership and other variables between the US and the UK do not appear to have a significant influence on the estimated direct rebound effect. But as noted by Greene [2] and Small and van Dender [6], there is an important discrepancy between estimates of the direct rebound effect based upon efficiency elasticities and those based upon price elasticities. To explore this point further, we applied a Wald Test

to 41 of the 54 Type A models⁹ to test the hypothesis (imposed in the Type B models) that the elasticity of distance travelled with respect to fuel prices was equal and opposite to the elasticity of distance travelled with respect to efficiency ($\eta_{p_e}(S) = -\eta_e(S)$). The results were ambiguous. Specifically:

- The coefficients on the two variables were not found to be significantly different in 8 of the 20 models, but in these cases the coefficient on fuel efficiency was always insignificant although mostly of the expected sign (in 6 of the 8 models).
- Conversely, the coefficients on the two variables were found to be significantly different in the remaining models, but in these cases the coefficient on fuel efficiency was usually statistically significant but always the 'wrong' sign (implying that more efficient cars encourage less driving).

Following Greene [2], we conclude that the evidence in support of the hypothesis that consumers respond in the same way to improved fuel efficiency as to lower fuel prices is weak – despite the importance of this hypothesis for empirical estimates of the direct rebound effect. Greene speculates that one reason for this result is that the lower running costs of fuel-efficient cars are offset by higher vehicle purchase costs – related in the US case to the requirements of CAFE. But not only does this argument rely upon the questionable assumption that driving decisions are based upon the long-run cost per kilometre (including discounted capital costs), it also assumes that more fuel-efficient

8. Short-run estimates from the dynamic models range from 5.4 % to 8.3 % (average = 6.8 %).

9. The test was not applied to models where fuel efficiency and / or price had been removed from their specifications in Stage 4.

cars are more expensive. The opposite may be the case in the UK, since fuel-efficient cars are commonly smaller and cheaper. An alternative explanation is that the consumer response to improved fuel efficiency systematically deviates from the orthodox economic model. If this applies more generally, it has important implications for the determinants and magnitude of rebound effects.

ROBUSTNESS TESTS

We also explored the relationship between the aggregate robustness score of each model and the estimated size of the rebound effect. This relationship is illustrated in Figure 4 which includes all 28 statistically significant long-run rebound estimates. Here,

open circles indicate robustness scores for 'Weighting A' and shaded circles 'Weighting B' (Figure 3). The figure suggests that the estimated size of the rebound effect is not systematically related to the robustness of the model. Using both the 'weighting A' and 'weighting B' results, this relationship was found to be statistically insignificant using three different correlation methods.

Conclusions

This study has sought to quantify the long-run direct rebound effect for personal automotive transport in Great Britain over the last 40 years. By estimating a range of models we are able to compare estimates of the rebound effect using different elas-

Table 7. Statistically significant estimates of the elasticity of vehicle kilometres with respect to fuel prices ($\eta_{pe}(S)$).

Specification	Metric	Robustness score (%)	Elasticity	Rebound effect (%)
Co-integrated	Capita	90	-0.181	18.1
Static Asymmetric	Capita	83	-0.200	20.0
Static Reduced	Capita	70	-0.155	15.5
Co-integrated	Adult	90	-0.197	19.7
Static Asymmetric	Adult	83	-0.210	21.0
Static Reduced	Adult	80	-0.173	17.3
Static Base	Adult	25	-0.222	22.2
Co-integrated	Driver	88	-0.145	14.5
Static Reduced	Driver	72	-0.138	13.8
Static Quadratic	Driver	53	-0.106	10.6
Static Base	Driver	33	-0.164	16.4
Mean		70	-0.172	17.2

Table 8. Statistically significant estimates of the elasticity of vehicle kilometres with respect to fuel cost per kilometre ($\eta_{ps}(S)$).

Specification	Metric	Robustness score (%)	Elasticity	Rebound effect (%)
Co-integrated	Capita	90	-0.176	17.6
Static Asymmetric	Capita	85	-0.198	19.8
Dynamic Asymmetric	Capita	71	-0.268	26.8
Static Reduced	Capita	68	-0.154	15.4
Static Base	Capita	20	-0.146	14.6
Dynamic Reduced	Adult	95	-0.235	23.5
Co-integrated	Adult	90	-0.189	18.9
Dynamic Asymmetric	Adult	85	-0.266	26.6
Static Asymmetric	Adult	85	-0.206	20.6
Dynamic Quadratic	Adult	78	-0.230	23.0
Static Reduced	Adult	78	-0.169	16.9
Static Base	Adult	30	-0.221	22.1
Co-integrated	Driver	88	-0.131	13.1
Static Reduced	Driver	61	-0.129	12.9
Static Quadratic	Driver	52	-0.109	10.9
Static Asymmetric	Driver	51	-0.122	12.2
Static Base	Driver	33	-0.229	22.9
Mean		68		18.7

ticities, different normalisations of the explained variable and different specifications. There are three conclusions.

First, our data do not support the hypothesis that consumers respond in the same manner to improvements in fuel efficiency as they do to reductions in fuel prices. If changes in fuel efficiency are taken as the appropriate explanatory variable, we find **no** evidence of a long-run direct rebound effect in GB over the last 40 years. However, if changes in either the fuel cost of driving or fuel prices are taken as the appropriate explanatory variable we find **good** evidence of a direct rebound effect, with most estimates lying in the range **10 % to 27 %** with a mean of **18 %**. These estimates are consistent with those obtained by most studies of this topic – although these primarily relate to the US.

Second, we find **good** evidence that estimates of rebound effects are larger when distance travelled is normalised to population or the number of adults rather than to the number of drivers. This may be because lower driving costs encourage more people to gain licenses and purchase cars – but to test this properly would require a full structural model. Earlier studies of this topic have not been consistent in their normalisation of distance travelled which can complicate the comparison of results.

Third, we found **some** evidence that the elasticity of distance travelled with respect to fuel cost per mile was greater than the elasticity of distance travelled with respect to fuel prices. This is consistent with theoretical expectations (Equation 2) and demonstrates how the choice of measure for the direct rebound effect can influence the results obtained. If, as Frondel and Vance [5] argue, the elasticity with respect to fuel prices is preferred, then many of the estimates in the literature may overestimate the direct rebound effect.

Since this is the first study of this type for Great Britain, there is considerable scope for improving the analysis. Specific issues to investigate include: improving the treatment of congestion; investigating the effect of company car taxation and the shift to diesel cars; and exploring whether and how the direct rebound effect has changed over time. The last issue is particularly important, since the growing evidence for ‘peak car’ implies that improvements in vehicle fuel efficiency may have much less impact on distance travelled than in the past. This phenomenon is partly captured by our quadratic specifications which associate increases in income with *reductions* in distance travelled once income exceeds a certain level. However, the underlying reasons for this trend are unclear and it is possible that a future period of economic stability and lower fuel prices will stimulate renewed traffic growth.

Finally we observe that no previous study has explored the relationship between the multi-dimensional diagnostic performance of models and the estimated magnitude of coefficients. Although we find little evidence that less robust models produce systematically biased results, this issue is worthy of further investigation.

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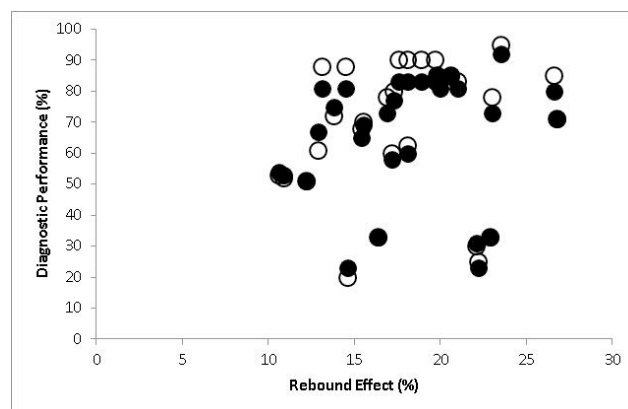


Figure 3. Relationship between the estimated size of the rebound effect and the robustness score of the model.

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Acknowledgements

This research was funded by the Research Council's UK Energy Programme through a grant to the Centre on Innovation and Energy Demand (CIED), Ref. EP/K011790/1. We are grateful for comments provided by Michael Coulon, Zia Wadud and anonymous reviewers.