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## Peak car and increasing rebound: A closer look at car travel trends in Great Britain

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### ABSTRACT

This paper uses econometric analysis of aggregate time-series data to explore how different factors have influenced the demand for car travel in Great Britain since 1970 and how the rebound effect has changed over that time. Our results suggest that changes in income, the fuel cost of driving and the level of urbanisation largely explain travel trends over this period – with recent reductions in car travel (peak car) being driven by a combination of the rising fuel cost of driving, increased urbanisation and the economic difficulties created by the 2008 financial crisis. We find some evidence that the proportion of licensed drivers has influenced aggregate travel trends, but no evidence that growing income inequality and the diffusion of ICT technology have played a role. Our results also suggest that the rebound effect from improved fuel efficiency has averaged 26% over this period and that the magnitude of this effect has *increased* over time. However, methodological and data limitations constrain the level of confidence that we can have in these results.

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## 1. Introduction

Per capita car travel reached a plateau or began to decline in several OECD countries after the millennium, following more than half a century of continuous growth (Schipper, 2011; Van Dender and Clever, 2013). In Great Britain (GB), per capita car travel reached a peak in 2002 and fell by 9% over the subsequent decade. Although the 2008 financial crisis accelerated this trend, it was clearly established several years before.

There has been much debate about the causes of this so-called ‘peak car’ phenomenon and the extent to which it represents a permanent or merely a temporary break with historic trends (Goodwin, 2012; Goodwin and Van Dender, 2013; Millard-Ball and Schipper, 2011; Newman and Kenworthy, 2011; Puentes and Tomer, 2008). Some authors, such as Bastian et al. (2016), argue that simple economic models based solely on changes in income and fuel prices “... are able to predict the plateau and decrease of car travel with quite remarkable accuracy...” (Bastian et al., 2016). Others consider these economic factors to be insufficient and focus instead on changes in demographics, spatial patterns, social norms and other variables (Garikapati et al., 2016; Metz, 2013; Wee, 2015). For example, Goodwin and Van Dender (2013) argue that: “...an aggregate model focusing on GDP effects and fuel prices is too crude to catch the diversity and dynamics underlying aggregate car travel demand and how it changes...”.

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Bastian et al. (2016) emphasise that their conclusions do not rule out the existence of alternative explanations, or imply that there been no changes in other variables such as lifestyle and attitudes, or demonstrate that those variables have no effect on travel patterns. Instead, they simply argue that there is no “...compelling evidence that one needs to assume something else than fuel price and GDP to explain the aggregate VKT development after 2003...”. Wadud and Baierl (2017) question Bastian et al.'s findings, arguing that their use of ‘out of sample’ forecasts is invalid. But in response, Bastian et al. (2017) argue that a longer time series is preferred for estimation and that a model estimated with a shorter time period nevertheless gives consistent results.

Over the last few years a remarkably wide range of factors have been cited as contributing towards ‘peak car’, although some have received more attention than others (DfT, 2015e; Goodwin, 2012; Newman and Kenworthy, 2011; Van Dender and Clever, 2013). They include, for example: increasing income inequality and the worsening economic situation of young people (Klein and Smart, 2017); the increased take-up of higher education opportunities amongst young people, thereby delaying their access to cars (DfT, 2015e); the changing age structure of the population, with a growing proportion of older people who tend to drive less (Goodwin, 2012); relative increases in the non-fuel costs of car ownership and use (e.g. insurance and parking) (DfT, 2015e; Le Vine and Jones, 2012; Rohr and Fox, 2015); the approach towards saturation levels of both car and driving license ownership (Delbosc, 2016; Goodwin, 2012; Le Vine and Jones, 2012); changes in company car taxation leading to reductions in the amount of subsidised car travel (Le Vine et al., 2013); the substitution of car transport by electronic communication, together with the growth of e-commerce, home-working and online shopping (McDonald, 2015; Metz, 2013; Wee, 2015); changing preferences regarding the ownership and use of cars relative to other goods and services (McDonald, 2015); the growing trend towards urbanisation, reversing the historic ‘flight to the suburbs’ (Headicar, 2013); increased congestion, especially on urban roads (DfT, 2015a); modal shifts encouraged by improvements in public transport, cycling and walking infrastructure (DfT, 2015e; Goodwin, 2012); the declining marginal utility of increasing average trip length (Metz, 2013); the levelling off of door-to-door car speeds coupled with relatively stable travel time-budgets (Metz, 2013); and the high rate of net immigration in the first decade of the 21st century, coupled with a lower propensity to drive amongst immigrant communities (Headicar, 2013).

Identifying the relative importance of these factors is very challenging, partly because the required data is often lacking but also because the different factors are highly interdependent. For example, substitution of car transport by ICT is more likely amongst young people, but these also face some of the biggest economic difficulties and are more likely to live in urban areas. Hence, while there is increasing amount of research on ‘peak car’, a consensus on the explanations of the phenomenon remains elusive. Moreover, the most recent data from the US and the UK suggests that car travel may be on the rise again – perhaps encouraged by an improving economic situation and falling oil prices (DfT, 2015d, 2016). If this trend continues, it would reinforce the argument that economic factors remain dominant.

### 1.1. Dynamic rebound

A second area of debate is the extent to which improvements in vehicle fuel efficiency ( $\varepsilon$ ) have encouraged more car travel ( $S$ ) – the so-called rebound effect. Fuel efficiency improvements make car travel cheaper which in turn may encourage both more car ownership and more car use. This phenomenon is commonly investigated through econometric analyses of aggregate data on fuel use and travel patterns, which allow the rebound effect to be estimated from the elasticity of distance travelled with respect to fuel efficiency ( $\eta_{\varepsilon}(S) = \partial \ln(S) / \partial \ln \varepsilon$ ) (Sorrell and Dimitropoulos, 2007a).<sup>1</sup> A finding that this elasticity exceeds zero implies that some of the potential fuel savings from the efficiency improvements have been ‘taken back’ by increased driving. In practice, reliable data on vehicle fuel efficiency is frequently unavailable, or does not vary enough to permit robust estimates. But since the source of the rebound is *cheaper* driving, an alternative (and more common) approach is to estimate the direct rebound effect from one of three *price* elasticities, namely: the elasticity of vehicle kilometres with respect to the fuel cost per kilometre ( $\eta_{p_s}(S)$ ); the elasticity of vehicle kilometres with respect to the price of fuel ( $\eta_{p_e}(S)$ ); and/or the elasticity of fuel consumption with respect to the price of fuel ( $\eta_{p_e}(E)$ ). These elasticities are only equivalent under certain assumptions (Sorrell and Dimitropoulos, 2007a; Stapleton et al., 2016), suggesting the need for caution when interpreting and comparing the results from different studies. Also, technical improvements in fuel economy (e.g. better aerodynamics) may have encouraged a shift towards larger and more powerful cars, but most studies overlook this owing in part to lack of data (Ajanovic et al., 2012; Knittel, 2009).

Dimitropoulos et al. (2016) conducted a meta-analysis of the results from 76 primary studies in this area and found a mean long-run rebound effect of 32%. However, most of these estimates were from the US, with only Stapleton et al. (2016) providing estimates for GB. Also, most of the studies use a double log functional form that constrains the elasticities to be constant. In practice, the rebound effect may change over time or with increasing incomes, but few studies have investigated this. Fouquet (2012) provides a very long-run perspective and estimates that the own price elasticity of UK passenger transport demand fell from  $-1.5$  in 1850 to  $-0.6$  in 2010, while Small and Van Dender (2007) estimate that long-run rebound effect in the US was around 22% over the period 1960–2001, but fell to only 10.7% over the period 1997–2001. Greene (2012) confirmed Small and van Dender's estimate using aggregate time-series data, but a study by Hymel and

<sup>1</sup> The elasticity of fuel consumption with respect to fuel efficiency ( $\eta_{\varepsilon}(E)$ ) is then given by:  $\eta_{\varepsilon}(E) = \eta_{\varepsilon}(S) - 1$ .

Small (2015) found that the rebound effect had increased after 2000 – perhaps as a consequence of fuel price volatility and media coverage of rising fuel prices.

Similarly, few studies have investigated how the own-price elasticity of road fuel consumption ( $\eta_{p_E}(E)$ ) has changed over time or with increasing income. Hughes et al. (2006) estimate that fuel prices elasticities in the US were four to six times lower between 2001 and 2006 than between 1975 and 1980, partly as a consequence of the improved fuel efficiency of the US vehicle fleet. But this effect may be larger in the US than in other regions since the US has experienced proportionately larger changes in both fuel prices and vehicle fuel efficiency. In contrast, Bastian et al. (2016) find no evidence that fuel price elasticities have declined in the UK, Sweden, France, Germany or Australia since 1978, and instead find evidence that elasticities increased during periods of rising fuel prices, as well as during periods of rapid price change.

## 1.2. The contribution of this paper

In sum, there is strong evidence that per capita car travel has declined in several OECD countries over the 10–15 years, together with strong evidence that improvements in vehicle fuel efficiency have encouraged more car travel. But there is a lack of consensus on the causes of the former and on whether and how the rebound effect has changed over time. This paper therefore seeks to contribute to this literature in two ways: first, by investigating how different factors have influenced the demand for car travel in GB since 1970; and second, by investigating how the rebound effect has changed over that period.

Our approach involves the econometric analysis of aggregate, time-series data on travel patterns, fuel consumption and other variables in GB over the period 1970–2012.<sup>2</sup> We estimate a number of models with different specifications, systematically evaluate and compare the statistical robustness of these models and base our conclusions on the ‘best performing’ models. Our results suggest that changes in income, the fuel cost of driving and the level of urbanisation largely explain travel trends over this period. We also estimate a mean rebound effect of 26% and find some evidence that this effect has increased over time. However, the limited number of data points constrains the number of variables we can test and limits the confidence we can have in our results.

The following section describes our methodology, including the specification of the econometric models and the robustness tests used to select between them. Section 3 summarises the data sources and discusses the trends in the relevant variables. Section 4 presents the results, including the significance of different variables in explaining ‘peak car, the estimated rebound effect and how that effect has changed over time. Section 5 concludes by highlighting the limitations of the current approach and the priorities for future research.

## 2. Methodology

Our approach involves estimating a total of 17 econometric models - 9 of which have a static specification and the remainder a dynamic specification. Each model includes a different combination of explanatory variables, and we use a comprehensive series of robustness tests to select the ‘best performing’ models.

Our explained variable is the annual distance travelled ( $S_t$  – in vehicle kilometres) by personal automotive vehicles in GB. An alternative but less common measure would be passenger kilometres – which is the product of vehicle kilometres and average load factors. Cheaper driving (e.g. through improved fuel efficiency) may potentially encourage less lift sharing, higher car ownership, more vehicle kilometres and hence more fuel use with little change in passenger kilometres. However, Stapleton et al. (2016) found that the choice of passenger rather than vehicle kilometres made little difference to the estimated price and income elasticities.

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 (Sorrell and Dimitropoulos, 2007b). Changes in total population, the age structure of the population, the propensity of young people to learn to drive and/or the proportion of female drivers may have different effects on the explained variable depending upon the normalisation used. Again, Stapleton et al. (2016) found this choice made relatively little difference to the estimated price and income elasticities. Here we normalise to the number of adults: partly because this is the most common specification in the literature, and partly because the proportion of licensed drivers is one of the variables that we want to test.

Below we explain the specification of our two *base* models, together with fifteen *variants* of those models, the *robustness* tests used to select between them and the *sequence* of model testing (see Table 1).

### 2.1. Base models

Our base models specify annual distance travelled ( $S_t$ ) as a function of mean equivalised real household income ( $Y_t$ ), the real fuel cost of driving ( $p_s$ ) and a dummy variable ( $X_t$ ) that is non-zero for the oil price shock years of 1974 and 1979 (Table 2). Equivalisation adjusts for the significant changes in family size and composition since 1970, and we estimate the fuel cost of driving from the ratio of retail fuel prices ( $p_E$ ) to fleet-average fuel efficiency ( $\varepsilon$ ). This approach imposes the hypothesis that drivers respond in the same way to improved fuel efficiency as to lower fuel prices. Although widely

<sup>2</sup> We choose Great Britain (GB) rather than the UK since the required data is not available for Northern Ireland.

**Table 1**  
Variables in the base models.

Type	Variable	Symbol	Units
Explained	Vehicle kilometres per adult	$S_t$	vkm
Explanatory	Mean equivalised real household income	$Y_t$	£
	Fuel cost of driving	$p_{S_t}$	£/vkm
	Oil shock dummy	$X_t$	1 if $t = 1974$ or $1979$ . Zero otherwise

**Table 2**  
Additional explanatory variables.

Name	Symbol	Units
Median equivalised real household income	$\bar{Y}_t$	£
Proportion of adults in urban areas	$U_t$	$0 \leq U_t \leq 1.0$
Proportion of adults with driving licences	$L_t$	$0 \leq L_t \leq 1.0$
Proportion of households with internet access	$I_t$	$0 \leq I_t \leq 1.0$

employed, several studies have found only limited support for this hypothesis (Greene, 2012; Small and Van Dender, 2007; Stapleton et al., 2016). The alternative would be to include fuel prices and fuel efficiency as separate explanatory variables (Stapleton et al., 2016), but (as noted above) the limited variation in fuel efficiency within our dataset makes it difficult to obtain significant coefficients.<sup>3</sup> We therefore follow the bulk of the empirical literature in estimating the rebound effect from  $\eta_{p_s}(S)$ .

We estimate both *static* and *dynamic* base models. Static models specify distance travelled as a function of the explanatory values in the same time period – thereby implicitly assuming that the observed demand is in equilibrium. But since responses to efficiency improvements and fuel price changes take time, these models may not adequately capture the long-run adjustments that we are interested in. Hence we also investigate dynamic models that specify distance travelled as a function of both current and historic values of the explained variables. To conserve degrees of freedom we use a ‘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 base models are then:

*Static:*

$$\ln S_t = \beta_0^S + \beta_1^S \ln Y_t + \beta_2^S \ln p_{S_t} + \beta_3^S X_t + u_t \quad (1)$$

*Dynamic:*

$$\ln S_t = \beta_0^D + \beta_1^D \ln Y_t + \beta_2^D \ln p_{S_t} + \beta_3^D X_t + \beta_4^D S_{t-1} + u_t \quad (2)$$

The long-run elasticity of distance travelled with respect to the fuel cost of driving ( $\eta_{p_s}(S)$ ) is given by  $\beta_2^S$  in the static model and  $(\beta_2^D / (1 - \beta_4^D))$  in the dynamic model. This provides an estimate of the long-run direct rebound effect.

## 2.2. Model variants

We then estimate a number of *variants* of these models, using combinations of the additional explanatory variables indicated in Table 2. The rationale for each variant is summarised below.

### 2.2.1. Median income variant

Income inequality has grown in Great Britain since 1979, with the income distribution becoming more positively skewed. If the incomes of an increasing part of the population are growing more slowly than GDP, the rate of growth of car travel may become progressively decoupled from GDP. To test for this, we substitute *median* for mean equivalised household income, since the former has grown more slowly and is correlated with both total income and income inequality.

### 2.2.2. Urbanisation variant

Urban areas provide high-density living arrangements, easy access to desired destinations and good public transport alternatives to the private car. As a consequence, car ownership and use tends to be significantly lower in urban areas: for example, vehicle kilometres per person in inner London are only one quarter of those in rural areas (Headicar, 2013). While the growth in car travel during the late 20th century was correlated with the trend towards suburban living, this trend

<sup>3</sup> In an earlier study (Stapleton et al., 2016), we estimated a broader range of model specifications but failed to find a statistically significant estimate of the elasticity of vehicle or passenger kilometres with respect to fuel efficiency. Simple tests with the current specifications suggested similar results. The implications of this finding are discussed in Stapleton et al. (2016).

has reversed over the past 15 years – stimulated in part by urban regeneration initiatives and a policy of locating new housing developments on urban brownfield sites. This trend may have restrained the growth in car travel, and may also have been reinforced by other factors such as increasing restrictions on urban parking, significant investment in public transport infrastructure (especially within the major cities), growing congestion on urban roads and the increasing effectiveness of land use planning in restricting traffic growth (Bastian and Börjesson, 2015; Goodwin and Van Dender, 2013; Jahanshahi et al., 2015; Le Vine and Jones, 2012; Metz, 2013). For example, data from the English travel survey (DfT, 2015a) suggests that the largest reduction in traffic since 2000 has occurred on urban roads and that travel trends in London are increasingly different from those in the rest of the country. To test for this, we include a variable representing the proportion of the population living in the five largest British cities, namely London, Birmingham, Leeds, Glasgow and Sheffield.<sup>4</sup>

### 2.2.3. Quadratic income variant

Rising incomes were associated with increasing car travel during the latter half of the 20th century, but these two variables have become increasingly decoupled. This is despite household car ownership continuing to rise and remaining some way short of projected saturation levels (DfT, 2015c). Travel survey data (DfT, 2015a) suggests that both the average time spent travelling and the share of transport in total household expenditure have remained broadly stable since 1970, while the average trip distance has remained stable since the mid-1990s.<sup>5</sup> Metz (2013) argues that increases in average trip length now provide only limited gains in utility since current trip lengths allow much of the UK population to have good access to desired destinations. In addition, in the absence of an increase in average speed, any increase in utility from accessing more destinations will be offset by the decrease in utility from the additional time spent travelling. But while these arguments appear plausible, they do not explain the ~12% fall in the number of car trips since 1995/97 (DfT, 2015a).

Even if the required data were available, it is not possible to capture all these complexities within an aggregate time series model such as this. Hence, rather than testing for the individual effect of these (and other) variables, we proxy their net effect by testing for a quadratic relationship between log vehicle kilometres and log equivalised income. This allows the income elasticity to vary with the level of per capita income. The static model then becomes:

$$\ln S_t = \beta_0^S + \beta_1^S \ln Y_t + \beta_2^S (\ln Y_t)^2 + \beta_3^S \ln p_{S_t} + \beta_4^S X_t + u_t \quad (3)$$

The long-run income elasticity of distance travelled is then:

$$\eta_Y(S) = \beta_1^S + 2\beta_2^S \ln Y \quad (4)$$

### 2.2.4. Licensed driver variant

Changes in the proportion of licensed drivers in the population may also contribute to changes in per capita car travel. These changes may in turn be driven by urbanisation, changing demographics, the economic constraints faced by certain groups (e.g. the cost of insurance and tuition has grown faster than young people's incomes) and other factors. License ownership may be saturating, with ~74% of GB adults now holding a driving licence compared to 48% in 1975 (DfT, 2015a). There has been a decline in the proportion of young people holding a licence (possibly linked to changing norms about car ownership (McDonald, 2015)),<sup>6</sup> but this has been offset by a countervailing trend towards more retired people holding licences (DfT, 2015a).<sup>7</sup> The impact of these trends is complicated by the variation in driving patterns between age groups (e.g. men drive nearly twice as far as women, while average driving distance declines from age 50 onwards (DfT, 2015a)), as well as over time (e.g. female car owners now drive further than they did in the past, while male car owners drive less (Le Vine et al., 2013)). Again, it is not possible to capture all these complexities within an aggregate model of this type. Instead, we simply test a variant that includes a variable representing the proportion of adults in GB who hold a driving licence.

### 2.2.5. Dynamic rebound variant

Some of the factors that contribute to changes in the income elasticity of car travel may also affect price elasticities. For example, as incomes increase we would expect the opportunity cost of time to play a larger role in driving decisions and the fuel cost per kilometre to play a smaller role. This could reduce the response to changes in fuel prices and improvements in fuel efficiency, thereby leading to a fall in the rebound effect over time (Small and Van Dender, 2007; Sorrell and Dimitropoulos, 2007a). We test for such changes by including an interaction term between equivalised income and cost per kilometre, as follows (static model):

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

The long-run income and price elasticities then become:

<sup>4</sup> Data on urban areas more generally is less accurate, and would also conflate urban and suburban areas which are more diverse in terms of population density, infrastructure provision and transport patterns.

<sup>5</sup> These variables differ between socio-economic groups, but the overall average appears relatively stable. This recent UK experience is consistent with broader claims about the stability of travel time and money budgets (Metz, 2013; Mokhtarian and Chen, 2004; Schafer and Victor, 2000).

<sup>6</sup> Around 43% of people aged between 17 and 20 held a licence in 1995, compared to only 36% in 2012 (DfT, 2015a).

<sup>7</sup> Between 1995 and 2012, the proportion of people aged over 70 holding a driving licence increased from 30% to 58% (DfT, 2015a).

$$\eta_Y(S) = \beta_1^S + \beta_3^S \ln p_{S_t} \quad (6)$$

$$\eta_{p_S}(S) = \beta_2^S + \beta_3^S \ln Y_t \quad (7)$$

### 2.2.6. ICT variant

Several authors have highlighted the coincidence between the peak in per capita car travel and the explosion in the use of information and communication technologies (ICT). Survey data suggest a modest growth in home working since 2000 and a significant growth in internet shopping – which could have contributed to the reduction in the number of trips per household (McDonald, 2015; Metz, 2013; Wee, 2015). High-speed networks also allow people to use their smart devices in transit which could make public transport more attractive (Lyons and Urry, 2005; Wee, 2015). However, the evidence in this area is ambiguous, with some studies indicating substitutability between telecommunications and travel and others indicating complementarity (Choo et al., 2007a,b; Choo and Mokhtarian, 2007; Choo et al., 2005; Mokhtarian, 2009). Given limited data and degrees of freedom, we again test for this in a rather crude fashion by including a variable indicating the proportion of GB households with an internet connection. This acts as a proxy for the broader diffusion of ICT within the GB population.

### 2.2.7. Reduced variant

Several of the above variables are co-linear and their inclusion restricts the degrees of freedom within our small dataset. We therefore investigate removing variables that are individually and jointly insignificant at the 5% level – thereby optimising the trade-off between goodness of fit and complexity.

### 2.2.8. Co-integrated variant

With time series data it is common for one or more of the variables to be non-stationary, creating the risk of spurious regressions.<sup>8</sup> While this may be avoided by differencing the data, this would prevent the estimation of the long-run relationships we are interested in. 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. We therefore test the time series and residuals of our models for unit roots. If the variables are found to be non-stationary and co-integrated, this can be interpreted as an equilibrium relationship (Basso and Oum, 2007). In this circumstance, we re-estimate the ‘best performing’ static model using a specialised technique (‘canonical cointegrating regression – CCR’ (Park, 1992)).

## 2.3. Robustness tests

Econometric studies vary widely in their inclusion or otherwise of different diagnostic tests. Here we conduct a comprehensive set of 13 diagnostic tests on each of our models and use the results to form an overall *robustness score* (0–100%) for each model – with higher scores indicating ‘better’ models. The relevant tests and the associated scores are summarised in Table 3. We use two different weighting rules: the first based on our judgement of the ‘relative importance’ of each test, and a second giving equal weighting to each test – although the ranking of models is broadly the same in each case. For the CCR technique in Stage 9, we use the more limited set of six diagnostic tests summarised in Table 4.<sup>9</sup>

## 2.4. Modelling sequence

We estimate a total of **17** models (9 dynamic and 8 static), in the sequence summarised in Table 5. The selection of models relies upon the results of the diagnostic tests, with the ‘best’ model being carried forward at each stage. For example, if the inclusion of an urban population variable in Stage 3 leads to a model with a higher (lower) robustness score than in Stage 2, then the urban population variable is retained (omitted) in subsequent stages. Stage 8 takes the best performing model and removes variables that are individually or jointly insignificant, while Stage 9 re-estimates the best performing static model using the CCR technique.<sup>10</sup>

<sup>8</sup> 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.

<sup>9</sup> Some of the tests in Table 3 are not appropriate for the CCR technique, while others are not available with our software (EViews).

<sup>10</sup> Tests suggest that this methodology is not sensitive to the sequence in which variables are introduced.



**Table 3**  
Diagnostic tests and weighting rules.

No.	Test	Description	Unequal weighting	Equal weighting
1	Coefficient signs	Score if all statistically significant coefficients ( $p < 0.05$ ) have the expected signs	2	1
2	Coefficient magnitudes	Score if all statistically significant coefficients have plausible magnitudes	2	1
3	Serial correlation	Score if Lagrange multiplier (Breusch and Pagan, 1980) test with two lags suggests insignificant serial correlation of the residuals <sup>a</sup>	2	1
4	Heteroscedasticity	Score if Lagrange multiplier test (Breusch and Pagan, 1979) suggests insignificant heteroscedasticity of the residuals	1	1
5	Normality	Score if Jarque and Bera (1987) test suggests normally distributed residuals	1	1
6	Multicollinearity	Score if centred variance inflation factors (VIF) test suggest absence of multicollinearity <sup>b</sup>	1	1
7	CUSUM	Score if cumulative sum of recursive residuals is stable over time (Brown et al., 1975)	2	1
8	CUSUM of squares	Score if cumulative sum of recursive squared residuals is stable over time (Brown et al., 1975)	2	1
9	Akaike information criterion	Use Akaike (1974) information criterion (AIC) to evaluate the trade-off between goodness of fit and model complexity in each group of models. Score 1 for rank 1 or 2, 0.66 for rank 3 or 4, 0.33 for rank 5 or 6, zero for rank 7 or 8	Max of 1	Max of 1
10	Hannan and Quinn information criterion	Use Hannan and Quinn (1979) information criterion in a similar manner to AIC	Max of 1	Max of 1
11	Schwarz information criterion	Use Schwarz (1978) information criterion in a similar manner to AIC	Max of 1	Max of 1
12	RESET-1	Score if inclusion of squares of fitted values of explained variable significantly improves model fit (Ramsey, 1969)	2	1
13	RESET-2	Score if inclusion of squares and cubes of fitted values of explained variable significantly improves model fit (Ramsey, 1969)	2	1

<sup>a</sup> Used in preference to the Durbin-Watson test, since the latter is only operationalised with one lag and is not applicable where lagged explained variables are included.

<sup>b</sup> The centered VIF is the ratio of the variance of the coefficient estimate from the original equation divided by the variance from a coefficient estimate from an equation with only that regressor and a constant. This provides a measure of how much the variance is increased because of co-linearity with other variables.

**Table 4**  
Diagnostic tests and weighting rules for CCR estimation.

No.	Name	Description	Unequal weighting	Equal weighting
1	Coefficient signs	Score if all statistically significant coefficients ( $p < 0.05$ ) have the expected signs	2	1
2	Coefficient magnitudes	Score if all statistically significant coefficients have plausible magnitudes	2	1
3	Normality	Score if Jarque and Bera (1987) test suggests normally distributed residuals	1	1
4	Multicollinearity	Score if centred variance inflation factors (VIF) test suggest absence of multicollinearity	1	1
5	Stability	Score if Hansen (1992) test suggests stability of coefficient estimates over time	2	1
6	$R^2$	Use simple $R^2$ test to evaluate goodness of fit. For equal (unequal) weighting, score 2 (1) if $R^2 > 0.95$ and score 1.75 (0.875) if $R^2 > 0.90$	2	1

**Table 5**  
Modelling sequence.

Stage	Static	Dynamic
1	Base model	Base model
2	Median income variant	Median income variant
3	Urban population variant	Urban population variant
4	Quadratic income variant	Quadratic income variant
5	Licensed drivers variant	Licensed drivers variant
6	Dynamic rebound variant	Dynamic rebound variant
7	ICT variant	ICT variant
8	Reduced variant	Reduced variant
9	CCR variant	

### 3. Data

We take data on distance travelled by cars in GB ( $S_t$  – in vehicle kilometres) over the period 1970–2012<sup>11</sup> from the DfT (DfT, 2015a, 2015b), and data on UK car fuel consumption ( $E_t$  – in MJ) over the same period from DECC (2015).<sup>12</sup> Both time

<sup>11</sup> We excluded 2013 as household income data for that year was not available at the time the research was carried out.

<sup>12</sup> Since the volumetric energy density of gasoline is ~90% that of diesel, aggregating fuel consumption on an energy basis will lead to slightly different results than aggregating on a volumetric (or weight) basis. This is a minor concern for US studies since the majority of cars use gasoline. But the choice is more important for EU studies since diesel cars form a significant proportion of the fleet.

series include commercially rented vehicles (e.g. taxis) and company cars, since reliable data on travel and fuel consumption by these categories are not available over our full time period.<sup>13</sup> We scale the DECC data in proportion to the GB share in UK population and use this to estimate the average fuel efficiency of the GB car fleet ( $\varepsilon_t = S_t/E_t$  – in vkm/MJ).<sup>14</sup> An independent measure of this variable would be preferred, but unfortunately is not available.<sup>15</sup> We then take nominal gasoline and diesel prices from DECC (2014), convert these to 2012 prices with a ‘before housing costs deflator’ (Cribb et al., 2012) and construct an aggregate fuel price (in £/MJ) by weighting by the relative share of gasoline and diesel consumption in each year. Reflecting changes in fuel specifications, we use the price of 4\* gasoline before 1989 and the price of ‘premium unleaded’ gasoline after that date (Bolton, 2013). Finally, we form our fuel cost variable by dividing average fuel prices by fleet average fuel efficiency ( $p_{S_t} = p_{E_t}/\varepsilon_k$  – in £/vkm).

We take data on mean and median equivalised real household income ( $Y_t$ ) from IFS (2014), data on licensed drivers from DfT (2014, 2015d) and data on population and the number of households with internet access from ONS (2016). Where necessary, we use linear interpolation to adjust these series to end-of-year values. The use of equivalised incomes adjusts for changes in average family size and composition.

Trends in each of these variables are illustrated in Figs. 1–4. Vehicle kilometres per adult have approximately doubled since 1970, but the rate of growth slowed after the 1990 recession, subsequently plateaued and then declined (Fig. 1). The real fuel cost per vehicle kilometre ( $p_S$ ) fell between 1973 and 1990 and has since increased relatively slowly – with the effect of rising fuel prices and increasing taxation being offset by improvements in fleet average fuel efficiency (Fig. 1). Owing in part to high levels of road fuel tax in the UK, the range of variation in fuel cost per kilometre over this period is relatively small – which means that the variance of the estimated coefficients is likely to be relatively high.

Mean equivalised real household income doubled between 1970 and 2009, but then fell slightly following the financial crisis (Fig. 2). Median income has grown more slowly than mean income since 1983, with the gap increasing over time. The proportion of adults with driving licences rose steadily between 1970 and 1988 (driven in part by more women acquiring licences), but has now reached a plateau (Fig. 3). The proportion of adults living in the largest five cities fell between 1970 and 1997, but has since increased, reaching 18.1% in 2012 (Fig. 3). Finally, the proportion of households with an internet connection increased very rapidly after 1992 and had reached 83% by 2012 (Fig. 4).

## 4. Results

### 4.1. Model fit and diagnostic tests

We first consider the performance of the different models against the various diagnostic tests. Table 6 indicates the aggregate ‘robustness score’ of each static model, together with the variables included at each stage, while Table 7 presents the detailed results of the diagnostic tests on those models. Tables 8–10 do the same for the dynamic models.

Looking first at the static models, we make three observations. First, the overall robustness scores are relatively modest, with the ‘best’ specification (stages 6 and 8) scoring only 55% with the unequally weighted criteria and 62% with the equally weighted. All the static models suffer from serial correlation, which suggests the standard errors of the estimates may be underestimated – although the estimates should be unbiased. There is also evidence of collinearity between the variables, and the results of the RESET tests suggest potential misspecification.

Second, three of the variables tested – namely median rather than mean income, ICT access and quadratic income – failed to improve the performance of the models against the diagnostic tests and were therefore omitted in subsequent stages. In contrast, both the urbanisation variable and the proportion of licensed drivers improved model performance, so were included in subsequent stages.

Third, the highest scoring model under both weighting schemes (Stage 8) included mean income, fuel costs, urbanisation, the proportion of licensed drivers and the interaction term. This model was re-estimated with the CCR technique (Stage 9), but the results were very similar. The robustness score for Stage 9 is not directly comparable as it is based upon a different set of tests (Table 4).

The overall results from the static models suggest that changes in the level of urbanisation and the proportion of licensed drivers have influenced travel trends in GB, but that changes in income inequality and the diffusion of ICT technology have not played a significant role. The results also suggest that, after controlling for fuel cost, the level of urbanisation and the proportion of licensed drivers, there is little evidence that traffic growth has become decoupled from mean equivalised

<sup>13</sup> Company cars accounted for around 4% of the English car fleet in 2014, which is 31% less than in 95/97 (DfT, 2015a). The tax treatment of company cars became progressively less favourable after the mid-1990s which probably contributed to the reduction in distance travelled (Le Vine et al., 2013). For example, per capita mileage in company cars fell by ~37% between 95/97 and 2005/6, with the mileage per car falling by a quarter (Le Vine et al., 2013). Over the same period, the distance travelled by privately owned cars fell by only 11% (Le Vine et al., 2013). However, this trend appears to have largely run its course, and is unlikely to contribute to further reductions in total distance travelled.

<sup>14</sup> This aggregation is necessary because our data on distance travelled does not distinguish between gasoline and diesel cars. In practice, diesel cars tend to be more fuel-efficient, larger and more powerful than gasoline cars, as well as being more intensively used (Schipper and Fulton, 2009). An increasing proportion of diesel cars may therefore be associated with higher fleet average fuel efficiency and greater distance travelled. Diesel has also benefited from favourable tax treatment in the past (although no longer), creating the possibility of a further association with average fuel prices. This is a potential source of endogeneity bias, but lack of data on the proportion of diesel vehicles precludes a straightforward solution.

<sup>15</sup> See Schipper et al. (1993) for a discussion of the difficulties with this approach.



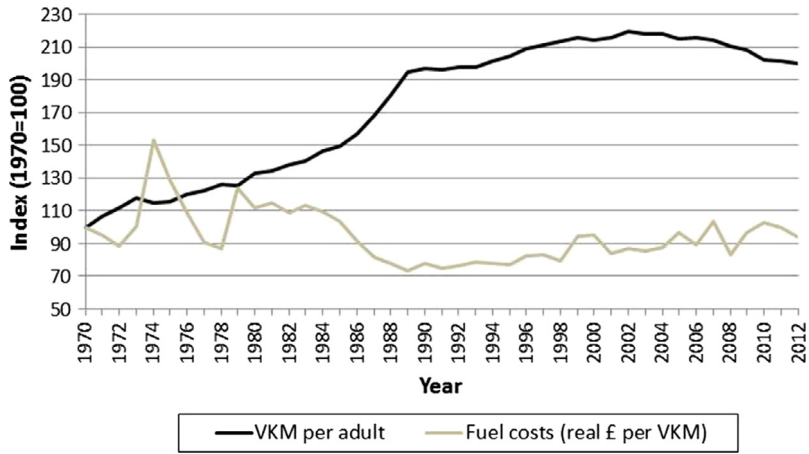


Fig. 1. Vehicle kilometres per adult and real fuel costs per kilometre in Great Britain 1970–2012.

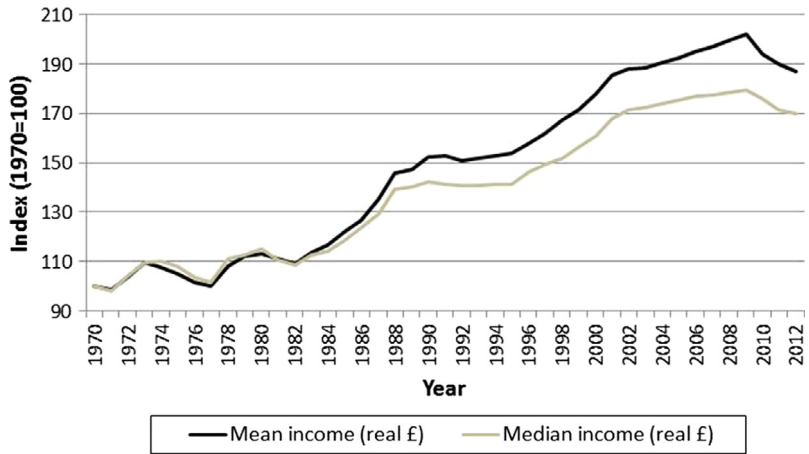


Fig. 2. Mean and median equivalised real household income in Great Britain 1970–2012.

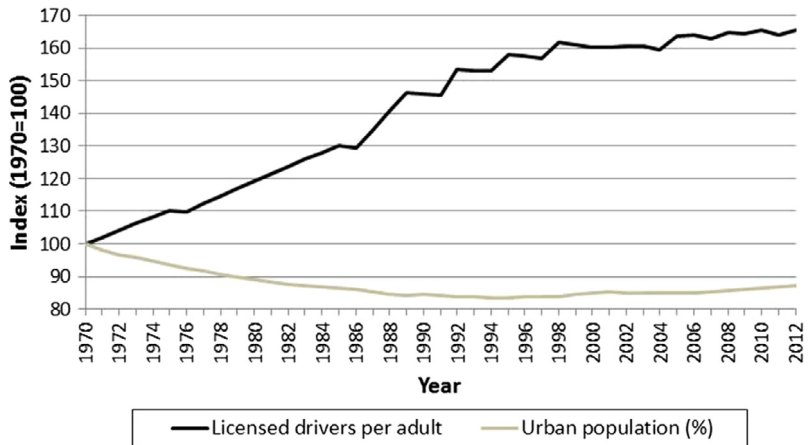


Fig. 3. Licensed drivers per adult and proportion of adults living in the five largest cities in Great Britain 1970–2012.

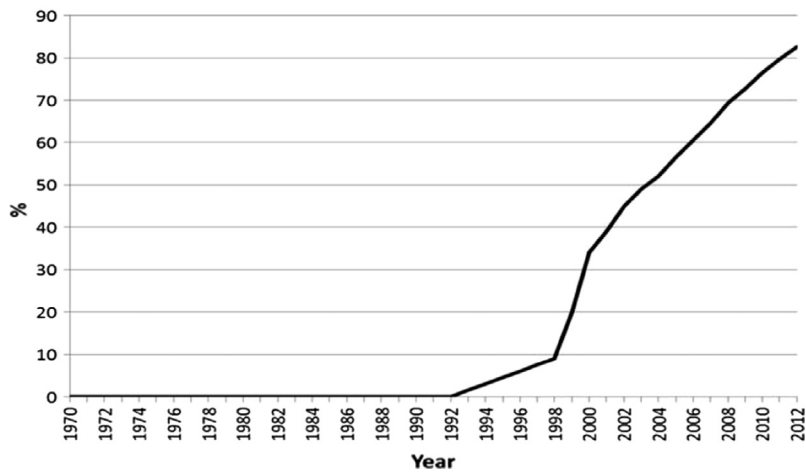


Fig. 4. Proportion of households with an internet connection in Great Britain 1970–2012.

Table 6

Robustness score and inclusion of variables—static models.

Stage	Score 1 (%)	Score 2 (%)	$\ln Y_t$	$\ln \tilde{Y}_t$	$\ln p_{S_t}$	$X_t$	$U_t$	$(\ln Y_t)^2$	$L_t$	$\ln Y \ln p_{S_t}$	$I_t$
1	45	46	*		*	*					
2	45	46		*	*	*					
3	50	54	*		*	*	*				
4	35	38	*		*	*	*	*			
5	50	54	*		*	*	*				
6	55	62	*		*	*	*		*	*	
7	50	54	*		*	*	*		*	*	*
8	55	62	*		*	*	*		*	*	
9	60	50	*		*	*	*		*	*	

Note: Stage 9 (CCR technique) uses a different set of diagnostic tests, so the score is not strictly comparable.

income. The interaction term also improves model performance; suggesting that the impact of fuel costs on driving patterns has varied with income – and vice versa.

Looking next at the dynamic models (Tables 9 and 10), we make two further observations. First, these models score significantly better against the diagnostic tests than do the static models, with the best specification (stage 3) scoring 95% against the unequally weighted criteria and 92% against the equally weighted. The results suggest that the inclusion of the lagged dependent variable reduces problems of both serial correlation and misspecification.

Second, the inclusion of the urbanisation variable improves model performance, but (in contrast to the static models) the inclusion of the licensed drivers variable does not. Again, the results provide little evidence that income inequality and ICT access have influenced travel trends. The best fitting dynamic model (Stage 3) explains travel trends using mean income, fuel costs, urbanisation, the oil shock dummies and the lagged dependent variable. In contrast to the static models, the interaction term between mean income and fuel costs does not improve model performance.

It is also important to consider the stationarity properties of the models. Table 10 summarises the results of two types of unit root tests on the residuals from the static models. The results are ambiguous, and should be interpreted with caution since the tests have only limited power with the number of observations used here. The results suggest that the variables in the 'preferred' static model (Stage 6) are co-integrated, thereby justifying the use of the CCR technique – and partly counterbalancing the low robustness score of this model relative to the dynamic models. The results of the diagnostic tests for Stage 9 are summarised in Table 11.

#### 4.2. Estimated coefficients

As Table 12 indicates, 13 of the 17 models produced statistically significant estimates of the long-run income elasticity of distance travelled. Overall, the results suggest that, *ceteris paribus* a 1% increase in equivalised real household income was associated with a 0.55% increase in vehicle kilometres over this period. The 'best performing' static model suggested a value of 0.40%, and the best performing dynamic model a value of 0.49%.

The mean income elasticity from the static models was 20% higher than that from the dynamic models – which is arguably consistent with the interpretation that static models provide long-run equilibrium estimates, while dynamic models

**Table 7**  
Results of diagnostic tests – static models.

Model	Coefficients		Standard				Stability		Parsimony			Functional Form		Robustness score 1 (%)	Robustness score 2 (%)
	Signs <sup>□</sup>	Magnitudes <sup>□</sup>	No serial correlation	Homoscedasticity	Normality	No imperfect multicollinearity	CUSUM	CUSUM of Squares	Akaike I criterion	Schwarz criterion	Hannan-Quinn	RESET 1	RESET 2	Aggregated <b>unequally weighted</b> performance (%)	Aggregated <b>equally weighted</b> performance (%)
1	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Fail	7	7	7	Fail	Fail	45	46
2	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Fail	8	8	8	Fail	Fail	45	46
3	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Fail	6	6	6	Fail	Fail	50	54
4	Pass	Pass	Fail	Pass	Pass	Fail	Fail	Fail	5	5	5	Fail	Fail	35	38
5	Pass	Pass	Fail	Pass	Pass	Fail	Pass	Fail	4	3	4	Fail	Fail	50	54
6	Pass	Pass	Fail	Pass	Pass	Fail	Pass	Fail	2	2	2	Fail	Fail	55	62
7	Pass	Pass	Fail	Pass	Pass	Fail	Pass	Fail	3	4	3	Fail	Fail	50	54
8	Pass	Pass	Fail	Pass	Pass	Fail	Pass	Fail	1	1	1	Fail	Fail	55	62

**Table 8**

Robustness score and inclusion of variables – dynamic models.

Stage	Score 1 (%)	Score 2 (%)	$\ln Y_t$	$\ln \tilde{Y}_t$	$\ln p_{S_t}$	$X_t$	$S_{t-1}$	$U_t$	$(\ln Y_t)^2$	$L_t$	$\ln Y \ln p_{S_t}$	$I_t$
1	40	38	*		*	*	*					
2	40	38		*	*	*	*					
3	95	92	*		*	*	*	*				
4	80	77	*		*	*	*	*	*			
5	85	77	*		*	*	*	*		*		
6	90	85	*		*	*	*	*		*	*	
7	75	69	*		*	*	*	*				*
8	90	85	*		*	*	*	*				

provide intermediate-run estimates (Basso and Oum, 2007). For comparison, a review of international studies by Goodwin et al. (2004) found a mean income elasticity estimate of 0.5 from static models and 0.3 from dynamic models.

In contrast to our previous work (Stapleton et al., 2016), only one model (dynamic model 4) produced a coefficient estimate (of  $-0.03$ ) for the price shock dummy that was statistically significant at the 5% level. However, many of the estimates were significant at the 10% level and the inclusion of this variable improved model performance against the diagnostic tests.

The urbanisation variable was found to be highly significant within all relevant models (Table 13). Overall, the results suggest that a 1% increase (decrease) in the proportion of the GB population living in the five largest cities was associated with a 1.7% decrease (increase) in distance travelled over the period. The 'best performing' static model suggested a value of  $-1.3\%$ , and the best performing dynamic a value of  $2.0\%$ . These estimates appear surprisingly high, even allowing for the much lower levels of car ownership and use within the major cities. A possible explanation is that the urbanisation variable is co-linear with other, non-included variables that also affect distance travelled. There may also be an asymmetric relationship between urbanisation and distance travelled that we have not tested for (see Table 14).

The variable representing the proportion of licensed drivers was found to be significant in the four static models in which it was included, but not in the dynamic models (Table 15). Since the latter performed better against our diagnostic tests, the evidence for the significance of licensed drivers appears weaker than that for urbanisation. On average, the results suggest that a 1% increase in the proportion of licensed drivers was associated with a 0.5% increase in distance travelled over this period.

Overall, 15 of the 17 models produced statistically significant estimates of the long-run rebound effect ( $\eta_{ps}(S)$ ), with a mean estimate of 26% (Table 15). In other words, the results suggest that, on average, a 1% decrease (increase) in fuel cost per kilometre was associated with a 0.26% increase (decrease) in vehicle kilometres over this period. The 'best performing' static model suggested a value of 0.19%, and the best performing dynamic a value of 0.34%. For comparison, our earlier work based upon 108 different econometric models provided a mean long-run estimate for GB of 19% (range 9% to 36%), while a meta-analysis of 76 (mostly US) studies by Dimitropoulos et al. (2016) provided a mean long-run estimate of 32%. However, as noted in the introduction, comparison between these results is complicated by differences in the definition of the rebound effect, the normalisation of the relevant variables, the region and time period under study and the data types and methodologies employed (Sorrell, 2007; Sorrell and Dimitropoulos, 2007b; Sorrell et al., 2009).

The static models produced estimates of the rebound effect that were on average 25% smaller than those from the dynamic models. This finding is consistent with the results of a meta-analysis of traffic and fuel price elasticities by Goodwin et al. (2004), who found exactly the same percentage difference between the results of the two types of models. Goodwin et al. further observe that transport modellers have tended to base their elasticity assumptions on the results of dynamic rather than static models and hence may be underestimating the income elasticity of distance travelled and fuel consumption, while at the same time overestimating the price elasticity.

Finally, the interaction term between income and fuel costs was found to be individually significant in the three static models in which it was included (together with the CCR model) and jointly significant in the single dynamic model in which it was included. The dynamic models score better against the diagnostic tests than the static models. However, since the inclusion of the interaction term in the dynamic models did not improve model performance, this gives us only medium confidence that the rebound effect varies with income. Moreover, the coefficient on the interaction term is negative, suggesting that the rebound effect *increases* with income – the opposite of that found for the US by Greene (2012) and Small and Van Dender (2007). The static models suggest that a 1% increase in equalised income was associated with 0.3% increase in the rebound effect over this period – with the CCR model suggesting a stronger relationship and the dynamic model a weaker one (Fig. 5).

## 5. Summary and conclusion

This paper has explored how different factors have influenced the demand for car travel in Great Britain since 1970 and how the rebound effect has changed over that time. Our results suggest that changes in income, the fuel cost of driving and the level of urbanisation largely explain travel trends over this period – with peak car being driven by a combination of the rising fuel cost of driving, increased urbanisation and the economic difficulties created by the 2009 recession. We find some

**Table 9**  
Results of diagnostic tests – Dynamic models.

Model	Coefficients		Standard				Stability		Parsimony			Functional Form		Robustness score 1	Robustness score 2
	Signs <sup>□</sup>	Magnitudes <sup>□</sup>	No serial correlation	Homoscedasticity	Normality	No imperfect multicollinearity	CUSUM	CUSUM of Squares	Akaike I criterion	Schwarz criterion	Hannan-Quinn	RESET 1	RESET 2	Aggregated <b>unequally weighted</b> performance (%)	Aggregated <b>equally weighted</b> performance (%)
1	Pass	Fail	Pass	Pass	Pass	Fail	Fail	Pass	7	7	7	Fail	Fail	40	38
2	Pass	Fail	Pass	Pass	Pass	Fail	Fail	Pass	8	8	8	Fail	Fail	40	38
3	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	2	2	2	Pass	Pass	95	92
4	Pass	Pass	Pass	Pass	Pass	Fail	Fail	Pass	1	1	1	Fail	Pass	80	77
5	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	5	5	5	Pass	Pass	85	77
6	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	4	4	4	Pass	Pass	90	85
7	Pass	Pass	Pass	Pass	Pass	Fail	Fail	Pass	6	6	6	Pass	Pass	75	69
8	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	3	3	3	Pass	Pass	90	85

**Table 10**  
Results of unit root tests on residuals.

Stage	Augmented Dicky Fuller	Phillips Peron
1. Base	Rejected in 1d	Rejected in 1d
2. Median income	Rejected in 1d	Rejected in 1d
3. Urban population	Rejected in 1d	Rejected in 1d
4. Quadratic income	Rejected in levels	Rejected in levels
5. Licensed drivers	Rejected in levels	Rejected in 1d
6. Rebound varying by income	Rejected in levels	Rejected in levels
7. Internet	Rejected in levels	Rejected in levels
8. Reduced	Rejected in levels	Rejected in levels

**Table 11**  
Results of diagnostic tests – CCR model.

Coefficients		Standard		Stability	Goodness of fit	Robustness score 1	Robustness score 2
Signs	Magnitudes	Normality	No implicit multicollinearity	Hansen test	Goodness of fit	Aggregated <b>unequally weighted</b> performance (%)	Aggregated <b>equally weighted</b> performance (%)
Pass	Pass	Fail	Fail	Fail	Pass (5%)	60	50

**Table 12**  
Mean estimates of the elasticity of distance travelled with respect to equivalised real household income.

Static	Dynamic	CCR	Mean
0.61 (7/8)	0.50 (6/8)	– (0/1)	0.55 (13/17)

Note: Each table entry is the mean of the individually or jointly 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 13**  
Mean estimates of the elasticity of distance travelled with respect to the proportion of the GB population living in the five largest cities.

Static	Dynamic	CCR	Mean
–1.52 (6/6)	–1.95 (6/6)	–1.10 (1/1)	–1.69 (13/13)

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

evidence that the proportion of licensed drivers has influenced aggregate travel trends, but no evidence that growing income inequality and the diffusion of ICT technology have played a role. While our results do not wholly support Bastian *et al's* contention that "... GDP per capita and fuel price are able to explain most of the trends in vehicle kilometres per capita..." (Bastian *et al.*, 2016), they are consistent with their argument that travel trends amongst different socio-economic groups have partially cancelled out. Our results are also consistent with the claim that economic recovery and low fuel prices could encourage renewed traffic growth – particularly since we find the income elasticity of car travel to be significantly larger than the price elasticity.

Our results also suggest that the rebound effect from improved fuel efficiency averaged 26% over this period – which is consistent with the results of other studies. Contrary to expectations, we find some evidence that the magnitude of this effect has *increased* over time, and is now more than twice as large as it was in 1970. This contradicts the results of two US studies (Greene, 2012; Small and Van Dender, 2007), but it is important to note that: first, our estimates are based upon the fuel cost per kilometre and hence reflect responses to both fuel efficiency improvements and changes in fuel prices; and second, the variation in fuel cost per kilometre has been much smaller in GB than in the US over this period. In any event, this result reinforces the argument that rebound effects should be taken account of when estimating the impact of policies such as fuel efficiency standards.



**Table 14**

Mean estimates of the elasticity of distance travelled with respect to the proportion of licensed drivers in the GB population.

Static	Dynamic	CCR	Mean
0.52 (4/4)	0 (0/6)	0.62 (1/1)	0.54 (5/11)

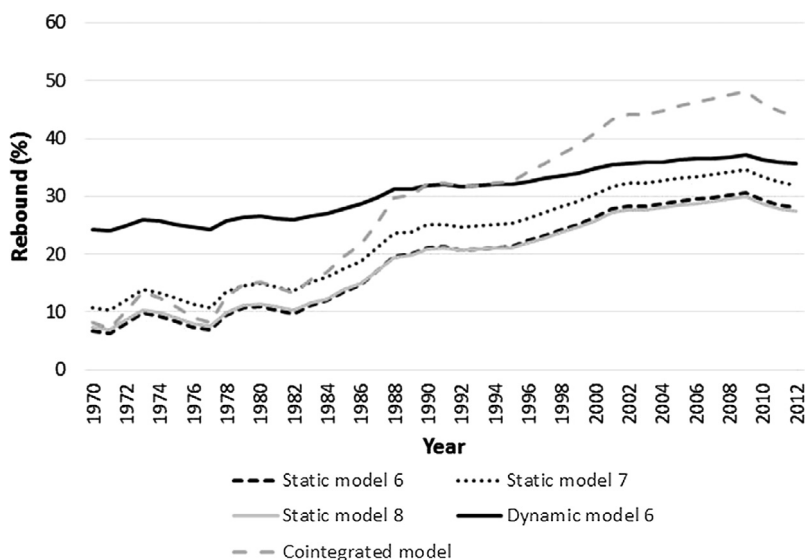
Note: Each table entry is the mean of the individually or jointly statistically significant estimates in that category, while the numbers in brackets indicate the fraction of models in each category that provided statistically significant estimates.

**Table 15**

Mean estimates of the long-run elasticity of distance travelled with respect to fuel cost per kilometre (the rebound effect).

Static	Dynamic	CCR	Mean
0.22 (8/8)	0.30 (6/8)	0.29 (1/1)	0.26 (15/17)

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.

**Fig. 5.** Changes in the rebound effect over time.

Overall, methodological and data limitations severely constrain the range of variables that we can test for with this approach, as well as the level of confidence that we can have in our results. For example: our use of aggregate timeseries data severely limits the degrees of freedom available; we do not have data on key variables such as company car ownership; we did not test for possible asymmetric responses to changes in fuel prices (Dargay, 2007); and our use of a lagged dependent variable in the dynamic models potentially introduces bias (Keele and Kelly, 2006). Also, technical improvements in fuel efficiency (e.g. improved aerodynamics) may have encouraged a shift towards larger and more powerful cars over this period, but this trend is not captured in our dataset.

These limitations are common to most econometric studies of travel trends that use aggregate timeseries data and are only partially mitigated by our systematic use of diagnostic tests. Hence, to obtain a deeper understanding of both the peak car and rebound phenomena, it is essential to utilise a broader range of data sources, together with a broader range of research methodologies. For example, much can be learnt from the analysis of national and regional travel survey data (DfT, 2015e; Headicar, 2013) and consumer expenditure data (Moshiri and Aliyev, 2017), especially when used in combination (Kuhnimhof et al., 2012b) or when compiled for a group of countries (Kuhnimhof et al., 2012a; Schipper and Johansson, 1997). Moreover, since the peak car phenomena remains relatively new, the inclusion of more recent data within such studies can improve the level of confidence in the results. In sum, there is still much work to do to uncover the drivers of recent travel trends.

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