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Vulnerability to fuel price increases in the UK: A household level analysis



Giulio Mattioli^{a,*}, Zia Wadud^b, Karen Lucas^c

^a Sustainability Research Institute and Institute for Transport Studies, University of Leeds, Leeds LS2 9JT, United Kingdom

^b Institute for Transport Studies, Centre for Integrated Energy Research and School of Chemical and Process Engineering, University of Leeds, Leeds LS2 9JT, United Kingdom

^c Institute for Transport Studies, University of Leeds, Leeds LS2 9JT, United Kingdom

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ABSTRACT

In highly motorised countries, some sectors of the population own and use cars despite struggling to afford their running costs, and so may be particularly vulnerable to motor fuel prices increases, whether market-led or policy-driven. This paper proposes a novel, disaggregated approach to investigating vulnerability to such increases at the household level. We propose a set of indicators of ‘car-related economic stress’ (CRES), based on individual household level expenditure data for the UK, to identify which low-income households spend disproportionately on running motor vehicles, and to assess the depth of their economic stress. By subsequently linking the dataset to local fuel price data, we are able to model the disaggregated price elasticities of car fuel demand. This provides us with an indicator of each household’s adaptive capacity to fuel price increases. The findings show that ‘Low Income, High Cost’ households (LIHC) account for 9% of UK households and have distinct socio-demographic characteristics. Interestingly, they are characterised by very low responses to fuel price increases, which may cause them to compromise on other important areas of their household expenditures. Simulations suggest that a 20% increase in fuel prices would substantially increase the depth, but not the incidence of CRES. Overall, the study sheds light on a sector of the population with high levels of vulnerability to fuel price increases, owing to high exposure, high sensitivity and low adaptive capacity. This raises challenges for social, environmental and resilience policy in the transport sector.

1. Introduction

One of the major uncertainties for transport policy and practice concerns the level of future fuel prices, and thus their affordability for the domestic and commercial travellers. Oil derived fuels still account for the overwhelming majority of energy consumption in the transport sector (EEA, 2015), making it very exposed to oil price fluctuations. These may be sudden and hard to predict (Baumeister and Kilian, 2016; Gronwald, 2016; Alexander, 2017), although the longer-term outlook is for overall increases in the real price of crude oil worldwide (World Bank, 2016).

At the same time, climate change mitigation efforts may lead to higher motor fuel prices, as governments increase taxes and/or reduce fossil fuel subsidies (Ross et al., 2017). Whether market-led or policy-driven, increases in motor fuel prices have important effects on the transport system, including, crucially, on levels of car use (Bastian et al., 2016; Wadud and Baierl, 2017). They can be used to encourage modal shift, and to support compact city planning and transit-oriented development (De Vos and Witlox, 2013;

* Corresponding author.

E-mail addresses: G.Mattioli@leeds.ac.uk (G. Mattioli), Z.Wadud@leeds.ac.uk (Z. Wadud), K.Lucas@leeds.ac.uk (K. Lucas).

Guimarães et al., 2014; Gusdorf and Hallegatte, 2007; Ortuño-Padilla and Fernández-Aracil, 2013), as well as the uptake of more efficient and alternative fuel vehicle technology (Li et al., 2009; Schäfer et al., 2009; Wadud, 2014).

An issue that has received limited attention, however, is the hardships that motor fuel price increases may inflict upon some lower-income sectors of society. There is some research evidence to suggest that in highly motorised countries a number of households already struggle to afford the running costs of cars, while relying on car mobility to satisfy their accessibility needs (Belton Chevallier et al., 2018; Curl et al., 2018; Currie and Delbosc, 2011; Litman, 2016; Lucas, 2011; Mattioli, 2017; Mullen and Marsden, 2018; Ortar, 2018; Rock et al., 2016; Taylor et al., 2009). This can make these households particularly vulnerable to motor fuel prices increases, which is problematic from a social equity perspective. Also, from an environmental policy viewpoint, it may hinder the implementation of measures such as carbon taxes and the reduction of fossil fuel subsidies due to worries about social inequalities. It is possibly partly for this reason that, to date, most governments have been reluctant to substantially increase fuel prices, due to public and political non-acceptability issues (Lyons and Chatterjee, 2002; Ross et al., 2017), even though such increases would appear to be common-sense from an energy-reduction policy perspective.

In this paper, we put forward a set of indicators to assess the incidence and depth of ‘car-related economic stress’ (CRES) in the UK. We then use econometric modelling methods to estimate disaggregated price elasticities of fuel demand, which we take to be indicative of the degree of car dependence and adaptive capacity of individual households. Finally, we use these elasticity estimates to model the impact of fuel price increases on CRES in the UK.

In particular, the study makes two novel scientific contributions. First, it highlights the household characteristics associated with vulnerability to fuel price increases, complementing the emphasis of previous research on the importance of spatial factors. Second, it demonstrates how a social indicator approach to transport (un)affordability can be combined with econometric analysis to produce realistic estimates for future price-based scenarios. The proposed approach can be implemented in any jurisdiction where household expenditure and fuel price data with enough spatial and temporal variation is available, and has thus the potential to be used as a diagnostic and planning tool in transport, land use and social policy making, in the UK and elsewhere.

The article is structured as follows. Section 2 reviews the relevant literature. In Section 3, our approach is set out in detail, along with the data used. Section 4 presents the findings, which are discussed in Section 5. In Section 6 we draw conclusions and discuss policy implications.

2. Literature review

This study draws from and builds upon three contemporary strands of research: (i) transport and social exclusion, (ii) ‘oil vulnerability’ and (iii) the heterogeneity in the response to fuel prices. These are briefly reviewed below.

2.1. Transport, social exclusion, and affordability

Research on transport and social exclusion (Lucas, 2012; Ricci et al., 2016; Schwanen et al., 2015; Titheridge et al., 2014) investigates the causes and consequences of reduced access to key services and opportunities, highlighting for example the socio-economic factors associated with low levels of travel activity (Lucas et al., 2016a). Studies have generally focused on low-income carless households, given their limited opportunities to travel and accessibility to opportunities (e.g. Klein and Smart, 2017). Perhaps slightly less attention has been given to car-owning households, who may be struggling to afford the cost of their travel. However, rapidly fluctuating fuel prices, stagnating real incomes and increasing car ownership among low-income groups in many advanced economies has drawn increasing attention to questions of affordability within the transport sector (AAA, 2016; Guerra and Kirschen, 2016; Litman, 2016; Mattioli et al., 2017a). The costs of daily mobility, most notably by car, can have important negative impacts on household finances, leading households to curtail their expenditures in other essential areas, to restrict their activity spaces, and/or to tip them into debt, all of which can ultimately result in social exclusion (Belton Chevallier et al., 2018; Curl et al., 2018; Currie and Delbosc, 2011; Lucas, 2011; Mullen and Marsden, 2018; Ortar, 2018; Rock et al., 2016; Taylor et al., 2009; Walks, 2018).

Different terms are used in the literature to describe the condition of households who need to spend a disproportionately high share of their income to get where they need to go. These include ‘forced car ownership’ (Curl et al., 2018; Currie and Senbergs, 2007), ‘transport poverty’ (Gleeson and Randolph, 2002; Sustrans, 2012), ‘commuter fuel poverty’ (Lovell and Philips, 2014) and ‘transport affordability’ (Litman, 2016; Lucas et al., 2016b). In this paper, we use the term ‘car-related economic stress’ (CRES) (Mattioli and Colleoni, 2016) to refer to a subset of transport affordability problems, solely related to *expenditure on motoring*. Existing research on developed countries has largely focused on the affordability of owning and operating motor vehicles (Lucas et al., 2016b), reflecting the fact that motoring accounts for around 80% of all household spending on transport in OECD countries (Kauppila, 2011).

2.2. Oil vulnerability

Historically high oil prices between the early-2000s and 2014 have triggered a wave of studies into ‘oil vulnerability’ in urban areas, notably in Australia (Dodson and Sipe, 2007, 2008; Fishman and Brennan, 2009; Leung et al., 2015; 2018; Runting et al., 2011), but also increasingly in Europe (Büttner et al., 2013; Gertz et al., 2015; Lovell and Philips, 2014; Mattioli et al., 2017b; Nicolas et al., 2012). These set out to identify the areas where households would be most severely affected by motor fuel price increases, typically through the use of composite indicators at the small-area level.

Drawing on notions of ‘social vulnerability’ (Adger, 2006; Brooks, 2003), recent contributions (Büttner et al., 2013; Leung et al., 2015; 2018; Mattioli et al., 2017b) argue that oil vulnerability indicators should cover three elements: (i) *exposure* to fuel price

increases – assessed with measures of average expenditure on fuel in the area (or proxies such as car ownership and use); (ii) *sensitivity* – generally operationalised as average income levels; (iii) *adaptive capacity* – conceptualised as the viability of modes alternative to the car, i.e. the opposite of car dependence.

The adequate consideration of adaptive capacity is essential for an accurate assessment of vulnerability (Leung et al., 2015; 2018; Rendall et al., 2014; Runting et al., 2011), as good accessibility by alternative modes makes modal shift possible, reducing the need for car use (and hence oil vulnerability) even in areas where car travel is currently high. Due to limited data availability, however, several studies proxy car dependence with indicators of revealed car ownership and/or use (e.g. Akbari and Habib, 2014; Dodson and Sipe, 2007; Fishman and Brennan, 2009). As a result, what these studies actually map is car-related economic stress in the present time (i.e. areas where people are already spending too much on motoring), rather than what they claim to do, i.e. calculate the prospective expenditure and resilience of areas with reference to a future scenario where fuel prices are significantly higher (although of course there are clear overlaps between the two).

Furthermore, to date, the large majority of studies have investigated the oil vulnerability of spatial units, e.g. census tracts (Dodson and Sipe, 2007). Their findings generally show that low-income, car-dependent suburban and peri-urban areas are the most vulnerable. Insights into the socio-economic factors associated with vulnerability at the disaggregate level of households are still relatively rare (but see Lovelace and Philips, 2014; Nicolas et al., 2012).

A relevant finding of previous research is that oil vulnerability can be compounded or alleviated depending on urban socio-spatial configurations, i.e. the distribution of different income groups within city regions. The ‘regressive’ configuration of Australian metropolitan areas means that low-income households tend to live in the most car dependent areas, which further deepens their vulnerability (Dodson and Sipe, 2007). Studies in other jurisdictions such as Canada (Akbari and Habib, 2014) and New Zealand (Rendall et al., 2014) have shown markedly different patterns, with outer suburban areas characterized by higher incomes and thus lower vulnerability.

In one of the few existing studies on Europe, Büttner et al. (2013) find contrasting patterns: Munich (Germany) resembles the configuration of Australian cities, while Lyon (France) is characterized by wealthier periurban areas, which results in a more mixed spatial patterning of fuel price vulnerability. This is not surprising as European cities have a variety of urban socio-spatial configurations, due to historical factors (Kesteloot, 2005).

2.3. Heterogeneity in the price elasticity of motor fuel demand

There is a long tradition of research on the elasticity of aggregate car travel and fuel demand to changes in fuel prices (see e.g. Austin, 2008; Dahl and Sterner, 1991; Goodwin et al., 2004). More recently, a number of econometric modelling studies have demonstrated that this elasticity varies depending on e.g. trip purpose, geographical area, and a range of household and vehicle characteristics (Bastian and Börjesson, 2015; Cornut, 2016; Dillon et al., 2015; Gillingham, 2014; Gillingham et al., 2015; Kayser, 2000; Nicol, 2003; Santos and Catchsides, 2005; Wadud et al., 2009, 2010a, 2010b; West and Williams, 2004). The key over-arching findings from these studies suggest that demand is more elastic in urban and higher-density areas (Bastian and Börjesson, 2015; Cornut, 2016; Santos and Catchsides, 2005; Wadud et al., 2009, 2010a), which is generally attributed to lower levels of car dependence. Also, work trips appear to be less responsive than non-work trips (Dillon et al., 2015) while multiple-vehicle, multiple wage earner households tend to be more responsive, possibly as a result of within-household switching of vehicles (Wadud et al., 2010a).

The literature provides conflicting evidence on the relationship between income and fuel price elasticity. Among studies considering the elasticity of household fuel demand in the US, Kayser (2000) finds lower price responsiveness among low income households, while West and Williams (2004) and Wadud et al. (2010a) find the opposite pattern. Relevant to this study, Santos and Catchsides (2005) also find that the cost elasticity of vehicle-miles travelled in the UK declines with higher income. While many studies of heterogeneity are motivated by a concern for the distributional impacts and welfare implications of increases in the price of fuel, notably in relation to possible environmental taxes, this research remains rather disconnected from studies of transport-related social exclusion and oil vulnerability.

3. Approach, data and methods

3.1. Approach

The aim of this paper is to demonstrate a newly developed, disaggregated approach to the assessment of vulnerability to fuel price increases, which: (a) takes households, rather than geographical areas, as the unit of analysis, and (b) more fully accounts for levels of car dependence and adaptive capacity.

In order to assess adaptive capacity at the household level, we use disaggregated estimates of the price elasticity of fuel demand. This builds on the hypothesis that:

“car-dependent households would demonstrate an unwillingness or inability to change their behaviour in response to an input change, such as cost. The levels of car usage would be relatively unresponsive to changes in the cost of driving in a car-dependent household. This ... can be measured quantitatively, via the *price elasticity of demand for car use*, so it may be researchers’ best proxy to quickly gauge the levels of car dependence in a society”

(Gorham, 2002, p. 109, emphasis added).

The empirical study consists of three main steps. First, we propose indicators of CRES modelled on the official English indicator of domestic ‘fuel poverty’, and apply them to British family expenditure data (see Section 3.3 below). This allows us to quantify the number of households experiencing CRES, as well as the depth of their economic stress. We also investigate the spatial and socio-economic correlates of CRES with logistic regression models. In a second step, we link the fuel expenditure data to fuel prices at postcode district level for the period 2006–2012. The temporal and geographical variation in fuel price data allows us to model the disaggregated price elasticities of fuel demand (see Section 3.4 below). We are, thus, able to show how elasticities vary depending on household characteristics, and to estimate the price response of CRES households. In the third step, based on the estimation of unique price elasticity values for each household, we model changes in the prevalence and depth of CRES in a fuel price increase scenario.

3.2. Data

The analysis is based on the UK *Living Costs and Food Survey* (LCFS), a cross-sectional expenditure survey that has been conducted annually since 2006, with a final sample of approximately 5,000–6000 households per year. Interviews are spread over 12 months to ensure that seasonal variation is captured. The sample for Great Britain (excluding Northern Ireland) is clustered into primary sample unit corresponding to postal sectors. In 2012, the response rate was 52% in Great Britain (ONS, 2013). Weights are provided within the dataset to correct for non-response. The analysis in this paper takes into account of both non-response weights and sample clustering.

The LCFS collects information on household expenditure in two ways: all individuals aged 16 and over complete a two-week expenditure diary; infrequent or irregular expenditure (e.g. rent, vehicle insurance, home improvements, and package holidays) is captured through retrospective questions in the household questionnaire. In the final dataset, expenditure information is provided on a weekly-equivalent basis, with a detailed breakdown that is consistent with the international standard COICOP classification (Classification of Individual Consumption by Purpose). The dataset also includes detailed information on income from employment, benefits and assets in the most recent 12 months, as well as on a range of socio-demographic characteristics.

Geographic identifiers at the postcode unit level (e.g. LS2 9JT) are provided in the ‘Secure Access’ version of LCFS (ONS and DEFRA, 2016). We use these to match household records to Experian Catalist Historic Fuel Price Data, including weekly average unleaded petrol and diesel prices at the postcode district level (e.g. LS2) for the period 2006–2012. LCFS and fuel price data are matched based on year, month and postcode district.¹

The elasticity estimation part of our analysis is based on the pooled 2006–2012 LCFS dataset (N = 41,007), as this provides us with both spatial and temporal variation in fuel price data, as well as an ample sample size for robust disaggregated analysis.² In the remainder of the analysis, we use data for 2012 (N = 5,596), i.e. the most recent year for which both LCFS and fuel price data are available, as we aim to provide the most up-to-date estimates of the problem.

3.3. A ‘Low Income High Costs’ metric of car-related economic stress

In order to identify households in CRES, we adapt a methodology developed in the UK for the measurement of ‘fuel poverty’. The notion of fuel poverty refers to the affordability of domestic energy (most notably heating), and underpins well-established research and policy agenda (Boardman, 1991, 2010; Hills, 2012). The official definition of fuel poverty in England is currently based on the ‘Low Income High Costs’ (LIHC) indicator (Hills, 2012), henceforth referred to as the ‘Hills’ indicator’. This metric defines ‘fuel poor’ households as those who (a) have “required fuel costs that are above the median level” and (b) “were they to spend that amount they would be left with a residual income below the official poverty line” (i.e. 60% of the median) (Hills, 2012, p. 9). The depth of the problem is measured by the ‘fuel poverty gap’, defined as “the amounts by which the assessed energy needs of fuel poor households exceed the threshold for reasonable cost” (Hills, 2012, p.9). A number of studies have adapted fuel poverty indicators for transport affordability analysis (e.g. Berry et al., 2016; Lovelace and Philips, 2014; Mayer et al., 2014; Sustrans, 2012). This paper proposes one of such indicators, and applies it to the LCFS dataset. A detailed discussion of the rationale for choices in the construction of the indicator (including e.g. income and expenditure thresholds) is provided in Mattioli et al. (2017a).

In keeping with the logic of the Hills indicator of domestic fuel poverty, in our study we define LIHC households as those falling below an income threshold and above a cost threshold. We considered costs for ‘running motor vehicles’, as reported in the LCFS dataset, which includes motor fuels as well as other variable costs of motoring such as vehicle road tax, insurance, repairs, parking fees, etc.³ The cost threshold is defined as twice the median of the *cost share* of ‘running motor vehicles’ (i.e. the percentage of income spent on it) in the first year of the dataset (2006), which gives a threshold of 9.5%. We suggest that households with a cost burden higher than this should be considered as incurring *disproportionately high* expenditures for motoring. Twice-median thresholds like the

¹ There are 3,107 postcode districts in the UK, with an average of approximately 9,000 households per district. In cases where information on prices at the postcode district level was missing, the average value of prices for that month at the postcode area level was assigned (e.g. LS). As the LCFS dataset does not provide postcodes for households in Northern Ireland, all Northern Irish households were assigned average fuel price values for Northern Ireland as a whole.

² The dataset includes sufficient variation in the real per liter price of petrol (min: 0.77£; max: 1.19£; mean: 0.99£; std. dev.: 0.10£) and diesel (min: 0.86£; max: 1.27£; mean: 1.03£; std. dev.: 0.10£), which allows us to model the disaggregated price elasticities of fuel demand.

³ Fixed costs (e.g. vehicle purchase) are excluded from the analysis for two reasons. First, most sampled households do not report any expenditure for car purchase in the 12 months before the interview, while a minority reports very high values, and this might skew the analysis. Second, previous studies have shown that the purchase of a car is a luxury good, with wealthier households spending a higher share of their income on more expensive cars, which are also substituted more frequently (Demoli, 2015; Kauppila, 2011).

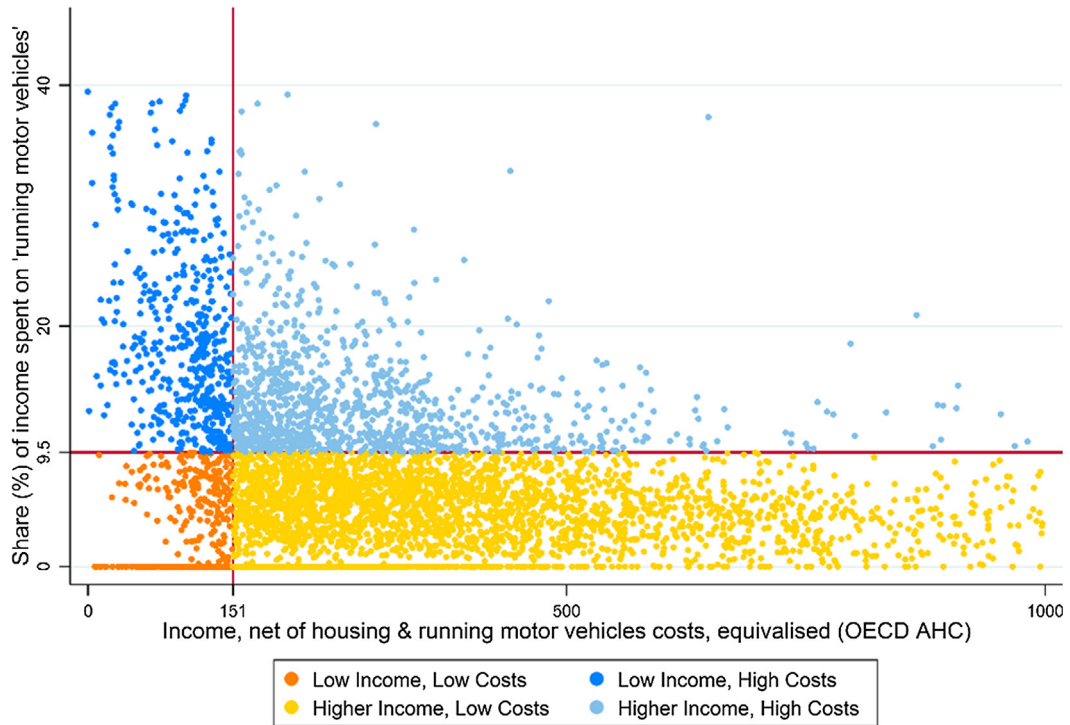


Fig. 1. Diagrammatical representation of the LIHC headcount indicator, based on data for 2012 (N = 5,596). Notes: extreme values (more than 40% income spent or £1000 weekly-equivalent income) are omitted from the graph for confidentiality reasons.

one adopted here are frequently used in fuel poverty research and in other areas to identify critically high values⁴ (Heindl and Schuessler, 2015; Liddell et al., 2012).

With regard to income, we consider weekly-equivalent household income (including allowances), net of expenditure on housing and ‘running motor vehicles’. The reason for deducting housing costs is that they represent *necessary expenditures*, i.e. those which cannot be avoided, and which are highly variable across regions of the UK (Clarke et al., 2016). Income after housing costs is thus often considered as a preferable measure of disposable income, and as such it is used in Hills’ fuel poverty indicator. Following Hills (2012), we deduct ‘running motor vehicles’ costs (in addition to housing costs) from the household incomes. This is to take into account the additional households that are pushed over the poverty line by high motoring costs. To adjust for differences in household size and composition, we divide the remaining income by the modified OECD ‘after housing costs’ equivalence scale factors. Following common practice in the UK and the EU (see e.g. Eurostat, 2017; McGuinness, 2016) we set a poverty line at 60% of the median of the resulting income distribution, and adopt this as the income threshold.

Based on the combined cost and income thresholds we identify four groups (as illustrated graphically in Fig. 1): ‘Low Income High Costs’ (LIHC), ‘Low Income Low Costs’ (LILC), ‘Higher Income High Costs’ (HIHC) and ‘Higher Income Low Costs’ (HILC).⁵ LIHC households (in the upper left quadrant in Fig. 1) have disproportionately high expenditure on motoring (relative to income), and are left with disposable income below the poverty line after the costs of running motor vehicles are deducted. We adopt the headline count of LIHC households as a measure of the *extent* of car related economic stress. In Section 4.1, we use descriptive statistics and logistic regression models to identify the socio-demographic and geographic factors associated with membership of the LIHC group.

Drawing again on Hills (2012), we complement the indicator of extent with an indicator of the *depth* of the economic stress, i.e. how much more LIHC households spend as compared to the cost threshold. This measures the average severity of affordability problems among LIHC households, regardless of how many people fall into this group. The CRES gap is computed as follows:

$$GAP = \frac{\sum_{i=1}^N [(CBR_i - 9.5) / (100 - 9.5)]}{N} \tag{1}$$

where CBR_i is the cost burden ratio – i.e. the share of income spent on running motor vehicles – for LIHC household i , and N is the number of LIHC households. The metric can be interpreted as *the mean difference (in percentage points) between the cost burden ratio of*

⁴ Unlike the original LIHC metric, our indicator considers actual, rather than required, expenditure. This is because determining normative standards of required travel is a formidable challenge (Berry et al., 2016; Jouffe and Massot, 2013; Mattioli et al., 2017a; Mayer et al., 2014; ONPE, 2014; Stokes and Lucas, 2011; Titheridge et al., 2014), which is beyond the scope of this study.

⁵ It is important to stress that households in the ‘higher income’ groups do not necessarily have *high* income – residual income is just higher than in the ‘low income groups’, i.e. above the poverty line.

LIHC households and the cost threshold (normalised in the range 0–1⁶). This corresponds to the average distance between the dots in the upper-left quadrant of Fig. 1 and the horizontal line representing the 9.5% cost threshold.

3.4. Elasticity estimation

There are two approaches to modelling heterogeneous responses to price or income changes for different socio-economic groups. In the 'representative agent' approach, average consumption of different groups is observed over a long time period along with the changes in the average characteristics of the groups and other market variables (price and income) (e.g. Wadud et al., 2009). Studies that focus on the effect of socio-demographic characteristics on petrol demand generally tend to follow another approach, which involves using household level data on consumption and socio-economic characteristics. Household data is also useful if the results are later used for distributional analysis, as is the case here.

Several authors (e.g. Wadud et al., 2010a, 2010b; Romero-Jordan et al., 2014; Gillingham, 2014) have recently used the household level micro-dataset to understand motor fuel demand, an approach first proposed by Archibald and Gillingham (1980) using the household production theory. In this approach, a household's motor fuel demand is specified as a function of fuel price, household income, vehicle and household characteristics and other transport characteristics. This approach assumes a homogenous response, i.e. the elasticity of fuel demand with respect to fuel price (or income, or other variables) is the same across all households.

In order to accommodate the hypothesis that elasticities could vary among different household types this paper uses the approach adopted by Wadud et al. (2010a), interacting the socio-economic characteristics with fuel price (or income) in order to get an estimate of how they affect the relative elasticities. The specific characteristic still has a homogenous effect across all households of similar type (say, urban location), however, since those similar households will differ in another socio-economic characteristic (say, income), each household can have a *unique elasticity* in this specification. Whether the effects of the interacted socio-economic characteristics are significant or not can be determined using statistical tests. In order to accommodate the potentially different household types, in this study the general specification of fuel demand from personal vehicles has the form:

$$\ln F = \alpha + \beta_Y \ln Y + \beta_Y (\ln Y)^2 + \beta_{PY} \ln P \ln Y + \beta_P \ln P + \sum_{k=1}^3 \mu_k D_k + \sum_{k=1}^3 \gamma_k D_k \ln Y + \sum_{k=1}^3 \delta_k D_k \ln P + \varphi_L L \ln P + \sum_{m=1}^n \theta_m Z_m \quad (2)$$

where, F , P , and Y refer to fuel consumption of the household, retail price of fuel and income of the household respectively. The variables Z_m stands for socio-economic characteristics. The Greek characters refer to the parameters that need to be estimated from the data. We add squared of income (Y) to accommodate the possibility that income elasticity itself could change with higher income. We have also interacted income with fuel price (P) to understand the effect of income on price elasticities. A priori, it is expected that price elasticities would fall as income increases, as suggested by previous research (Wadud et al., 2010a).

The prime interest in this study is the response of the four different groups (LIHC, LILC, HIHC, HILC) to fuel price changes. In the model, three indicator variables (D_k), representing these groups, are included on their own as well as interacted separately with income and price (the fourth group remains the reference group⁷). Following earlier findings that households in urban areas are more price responsive, price is also interacted with an indicator variable for Central London (L), where public transport has higher patronage (DfT, 2015). We include a number of socioeconomic characteristics in the model, which have been associated with fuel demand in previous research (reviewed in Section 2.3). These include family size, presence of children or adults older than 64 years of age, location, gender of household reference person, number of vehicles in the household and whether any of the vehicles run on diesel. While education is generally a useful determinant, the LCFS dataset does not contain this variable for 2006.

In the UK in 2015, more than half of new personal vehicle fleet ran on diesel, although the share is smaller in the total vehicle stock. Diesel also has a larger energy content compared to petrol, which allows it to travel further per unit of volume of the fuel. Therefore, the diesel consumptions in the households are multiplied by 1.10, and energy (E) is used as the dependent model in the primary model (Model 3 in Table 3 below), where $E = \text{Petrol} + 1.1 \text{ Diesel}$.⁸ For the model where Fuel (F) is the dependent variable (Model 4 in Table 3 below), diesel and petrol fuel consumptions are simply added ($F = \text{Petrol} + \text{Diesel}$).

Note that in a traditional log-linear demand model the parameter estimates for $\ln Y$ and $\ln P$ will directly represent the income and price elasticities. However, as we have interacted income and fuel price with other variables, the parameter estimates for income (β_Y) or fuel price (β_P) do not represent income or price elasticity directly here. Instead the income and price elasticities –which would be unique for every household because of their differences in income and socio-economic groups – are to be calculated as derivatives of Eq. (2) with respect to income and price as follows (Eqs. (3) and (4)):

⁶ In order to avoid that the measure is skewed by extreme values, all values of CBR higher than 100 (i.e. spending more than 100% of their weekly equivalent income on running motor vehicles) are substituted with 100 in the calculation.

⁷ We acknowledge that the inclusion of these indicator variables in the model raises a potential issue of simultaneity. However we believe that this is not strong, as fuel consumption is only one among several factors that contribute to the definition of the four groups, and only in a rather indirect way. In detail: i) fuel costs are only a subset of the motoring costs considered in the 'cost burden' element of the classification – a whole range of other expenditure items are taken into account (e.g. vehicle road tax; vehicle insurance; car servicing; repairs; other motor oils; breakdown services; parking fees, tolls and permits; garage rent; costs for the annual vehicle roadworthiness test); ii) the 'cost burden' element of the classification is a ratio between total expenditure for running motor vehicles and income, further diluting the relationship between fuel consumption and group membership; iii) 'cost burden' is only one of the two elements that defined the classification, the other being equivalised residual income (i.e. after deducting housing and 'running motor vehicles' costs).

⁸ The conversion factor of 1.10 corresponds to the approximate ratio between the energy intensity of diesel (35.86 MJ/L) and petrol (32.18 MJ/L).

$$\text{Price elasticity} = \beta_p + \beta_{pY} \ln Y + \sum_{k=1}^3 \delta_k D_k + \phi_L L \quad (3)$$

$$\text{Income elasticity} = \beta_Y + 2\beta_Y \ln Y + \beta_{pY} \ln P + \sum_{k=1}^3 \gamma_k D_k \quad (4)$$

The interest in this study is not to generate an aggregate national level elasticity, but rather to generate estimates for households that already consume petrol or diesel for their transport needs. Therefore OLS can be used to estimate the model, even though households that do not consume fuel and thus do not own a vehicle are not included in the analysis sample.⁹ However, the errors are likely to be non-normal (and sometimes heteroskedastic), therefore the standard errors are modified using White's robust variance matrix.

4. Results

4.1. LIHC indicator

In 2012, 9.4% of UK households were classified as 'Low Income, High Costs' (LIHC). The rest of the population was distributed among 'Low Income, Low Costs' (10.1%), 'Higher Income, Low Costs' (62.0%) and 'Higher Income, High Costs' (18.5%). The 'gap' metric value for LIHC households was 0.161 (on a scale from 0 to 1). This means that LIHC households spend on average approximately 24% of their income on running motor vehicles, i.e. more than twice the 'high cost' threshold.

Table 1 shows the incidence of the four groups for different sectors of the population (with the variables corresponding to the predictors in the regression models of Table 2 below, plus car ownership). It shows that the incidence of LIHC is rather similar across population socio-economic sectors, exceeding 15% only among households with unemployed members and those with a non-white reference person. Further analysis (not reported here for the sake of brevity) shows that 67% of households who are in poverty (after housing costs) and own cars belong to the LIHC group. Conversely, 67% of LILC households do not own cars.

Table 2 presents the results of two logistic regression models, both including the same predictors. The models aim to (i) identify the characteristics that distinguish LIHC households from the average of the population, as well as (ii) the drivers of 'high costs' among the low-income population. To this end, Model 1 uses the full 2012 sample, and models the probability of belonging to the LIHC group, as opposed to any other group in our classification. Model 2 models the probability of belonging to the LIHC group, rather than LILC. The independent variables cover socio-demographics (household composition, age, employment, gender, and ethnic origin) as well as degree of urbanisation of the residential area.¹⁰ Previous research has found these factors to be associated with low income, car ownership and use (e.g. Lucas et al., 2016a; Mattioli, 2014, 2017; Stokes and Lucas, 2011). In addition, we include two housing-related variables: the category of dwelling (as a proxy for the density of the built environment in the neighbourhood), and tenure (in order to investigate the relationships with home ownership and housing expenditure). Note that we are unable to include a number of variables in the model (e.g. income, housing costs, car ownership), as these were used to define the outcome variable (or are strongly related to it), and so including them would raise endogeneity issues.

The low goodness of fit of Model 1 suggests that overall the predictors do not discriminate well between LIHC and the rest of the sample. This is consistent with the fairly even incidence of LIHC across population socio-economic sectors shown by descriptive statistics (Table 1). Despite the poor fit, Model 1 shows that households with children, with unemployed members, and those living in rural areas or Northern Ireland are significantly more likely to belong to the LIHC group. So do households with a reference person who is between 30 and 49 years old, male or non-white. Households living in a flat or with mortgages are significantly less likely to have low income and high costs.

Model 2 compares 'Low Income High Costs' households to 'Low Income Low Costs' households. This highlights factors associated with car-related economic stress among the low-income population. The model has better goodness-of-fit, suggesting that LIHC households differ more from other low-income households than from the average British household. A comparison of Model 1 and 2 shows that, while some variables have similar effects in both models (presence of children, age, gender, rurality) other coefficients change sign or significance. The presence of employed members has a negative effect in Model 1, but a positive effect in Model 2, while the opposite change is observed for the 'unemployed members' dummy. This can be interpreted as follows: LIHC households, like other low-income households, are overrepresented among those with unemployed and non-employed members. However, the 'working poor' are more likely than other low-income households to face high motoring costs. Incidentally, this suggests that for some households, employment-based income is not enough to get them out of poverty, after the cost burden of running motor vehicles is accounted for.

A similar pattern is observed for ethnicity: non-white households are overrepresented among low-income groups, but a non-white background does not significantly increase the likelihood of high motoring costs among the poor. Conversely, the presence of

⁹ It must be noted that, while the exclusion of carless households from the analysis raises potential sample selectivity problems (see e.g. Kayser, 2000), the interest here is on the 'actual effects' of fuel price, i.e. the effects on actual fuel consumption among those who own and use cars (see Frondel and Vance, 2009).

¹⁰ The variable we use is based on the ONS 2011 Rural-Urban classification for England and Wales (ONS, 2013) and the Scottish Government Urban Rural Classification (Granville et al., 2009). As no urban-rural variable is available for households in Northern Ireland, we group them in a separate category. Within Great Britain, we distinguish between the London Metropolitan area, 'other metropolitan areas' (in the North East, North West, Yorkshire and the Humber, West Midlands and Glasgow), 'other urban areas' (other areas classified as urban but outside of metropolitan areas), and 'rural areas'.

Table 1

Distribution of the 'income/motoring costs' indicator among different sectors of the population in 2012 (percentage values) (N = 5,596).

		LIHC	LILC	HILC	HIHC	Total
Total		9	10	62	19	100
Variable	Level					
Household size	1	8	14	65	13	100
	2	9	7	63	21	100
	3	9	9	60	22	100
	4 or more	12	12	57	20	100
Children	None	8	10	63	18	100
	1 or more	12	10	60	18	100
Full-time or self-employed members	None	13	18	57	13	100
	1 or more	7	4	66	23	100
Part-time employed members	None	9	11	63	17	100
	1 or more	11	9	58	23	100
Unemployed members	None	9	8	64	19	100
	1 or more	17	29	42	12	100
Age of household reference person (HRP) ^a	15–29	9	20	53	17	100
	30–49	10	8	63	18	100
	50–65	10	8	60	22	100
	65 +	8	10	66	16	100
Recipients of DLA (mobility) ^b	None	9	10	61	19	100
	1 or more	9	6	70	15	100
Ethnic origin of HRP	White	9	9	63	19	100
	Non white	16	19	50	15	100
Sex of HRP	Male	10	9	61	21	100
	Female	9	12	64	15	100
Category of dwelling	Detached	10	4	62	24	100
	Semi-detached	10	7	61	21	100
	Terraced	10	15	59	16	100
	Flat/other	7	15	66	12	100
Tenure type	Owned outright/rent free	10	8	61	21	100
	Owned with mortgage/rental purchase	7	3	66	23	100
	Local Authority/Housing Association rented	10	17	62	10	100
	Other rented	12	21	54	13	100
Type of area	London	10	12	66	13	100
	Other metropolitan areas	10	12	62	16	100
	Other urban	8	10	64	18	100
	Rural	12	7	56	26	100
	Northern Ireland	15	8	51	26	100
Cars and vans in household	None	1	27	71	1	100
	1	14	7	61	18	100
	2 or more	9	1	56	33	100

Notes:

^a The household reference person (HRP) is the householder who is legally responsible for the accommodation or has the higher income (ONS, 2013b).

^b In the UK individuals are eligible for the mobility component of the Disability Living Allowance (DLA) if they have walking difficulties.

members with mobility difficulties is not significantly associated with LIHC in Model 1, but increases the probability of a low-income household facing high costs in Model 2, possibly by increasing reliance on cars.

With regard to housing, Model 2 shows that living in terraced housing or flats significantly reduces the probability of LIHC (as compared to LILC). Also, living in a (public or private) rented accommodation is associated with a significant negative effect in Model 2, but not in Model 1. This suggests that LIHC households, like other low-income households, are overrepresented among renters, but home ownership is associated with high motoring costs among poor households.

The relationship between LIHC and type of area deserves further comment. Outside of Northern Ireland, the incidence of LIHC is relatively homogenous across the urban rural-spectrum (Table 1). This partly reflects higher poverty rates in metropolitan and urban areas. Among low-income households, the incidence of LIHC is indeed significantly higher in rural areas (49%) than in London (32%), other metropolitan (30%) and urban areas (32% - detailed figures not reported for the sake of brevity). The net association between rurality and LIHC is confirmed by the coefficients in Model 2, which also show no significant difference between London, metropolitan and other urban areas. There are two possible explanations for this. The first is that part of the built environment effect is picked up by the category of dwelling variable (as the share of flats and terraced houses is higher in metropolitan areas and particularly in London). The second is that the urban-rural variable used here is a rather broad-brush categorisation (Pateman, 2011), which may mask considerable variation within each area. However, we are unable to include more detailed variables (such as public transport accessibility or job density) due to the data limitations of the LCFS.

Having described the incidence patterns of CRES in the UK, in the next section we present the results of the estimation of the elasticity of fuel demand.

Table 2

Parameter estimates for the logistic regression for the probability of belonging to the LIHC group in 2012.

Model		Model 1		Model 2	
Outcome		LIHC		LIHC	
Base outcome		Rest of the sample		LILC	
Variable	Level	Coef.	Std. error	Coef.	Std. error
Household size (reference category: 1)	2	0.178	0.138	0.577 ^{***}	0.182
	3	0.028	0.206	-0.131	0.285
	4 or more	0.237	0.226	-0.567 [*]	0.337
Children (reference category: None)	1 or more	0.294 [*]	0.176	0.738 ^{***}	0.28
Full-time or self-employed members (reference category: None)	1 or more	-1.106 ^{***}	0.154	0.891 ^{***}	0.197
Part-time employed members (reference category: None)	1 or more	-0.012	0.121	0.347 [*]	0.189
Unemployed members (reference category: None)	1 or more	0.476 ^{***}	0.17	-0.309	0.201
Age of HRP (reference category: 15–29)	30–49	0.320 [*]	0.193	0.482 [*]	0.248
	50–65	0.205	0.211	0.453 [*]	0.268
	65 or older	-0.468 ^{**}	0.237	0.017	0.313
Recipients of DLA (mobility) (reference category: None)	1 or more	-0.208	0.195	0.786 ^{**}	0.311
Ethnic origin of HRP (reference category: White)	Non-white	0.642 ^{***}	0.165	0.189	0.242
Sex of HRP (reference category: Male)	Female	-0.263 ^{**}	0.113	-0.307 ^{**}	0.149
Category of dwelling (reference category: Detached)	Semi-detached	0.056	0.135	-0.346	0.232
	Terraced	-0.015	0.148	-0.996 ^{***}	0.237
	Flat/other	-0.472 ^{**}	0.195	-1.067 ^{***}	0.285
Tenure type (reference category: Owned outright/rent free)	Owned with mortgage/rental purchase	-0.377 ^{**}	0.156	0.001	0.247
	Local Authority/Housing Association rented	-0.182	0.169	-0.522 ^{**}	0.23
	Other rented	0.09	0.177	-0.813 ^{***}	0.235
Type of area (reference category: London)	Other metropolitan areas	0.057	0.172	-0.123	0.24
	Other urban areas	-0.089	0.151	-0.284	0.208
	Rural	0.461 ^{***}	0.161	0.477 [*]	0.25
	Northern Ireland	0.678 ^{***}	0.258	0.422	0.422
Diagnostics					
N		5,596		1,081	
McFadden's Pseudo R ²		0.062		0.15	

Notes: upon request of the data provider, the constant terms are omitted to prevent disclosure risks for models with all explanatory categorical variables.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

4.2. Elasticity estimation results

Table 3 presents the parameter estimates for our econometric model of fuel demand. Model 3 and 4 both have an R^2 in excess of 0.42, indicating a good fit. Other potential explanatory factors (annual trend, monthly dummies, age of household reference person) did not improve the fit via Adjusted R^2 , AIC or BIC, therefore we excluded them from the final model.

Results show that demand for transport energy increases with the number of members and number of vehicles in the household. Presence of children or elderly people in the household reduces the energy consumption, possibly because their travel demand is not as high as for active adults. Households in metropolitan areas have a lower energy consumption compared to those in other, smaller urban areas. Demand for fuel for car users in Greater London is not statistically different from those in other urban areas. As expected rural households use more fuel for their travel, as do those located in Northern Ireland.

Households that own at least one diesel vehicle consume more energy compared to those with petrol vehicles only. Generally diesel owners are a self-selected group: those who expect to travel more tend to purchase diesel vehicles because of their better fuel economy and corresponding lower running costs. Households with female household reference person (HRP – see note a, Table 1) consume less energy.

Table 4 presents the price and income elasticities of an average household in each of the four groups identified in the previous section, evaluated at median income of that specific group and median fuel price over the whole sample. It shows that households in the LIHC group have the lowest price response. This suggests that households in car-related economic stress, who already spend a disproportionate share of income on motoring, will increase expenditure even more if faced with a fuel price spike, further eroding disposable income. LIHC households also have the lowest income elasticity, indicating they spend a larger share of any additional income on other consumption (or saving) compared to other households, while LILC and HIHC have the highest income elasticity.

Table 3
Regression results for household fuel demand (based on pooled 2006–2012 sample).

Model Equation		Model 3 Energy equation		Model 4 Fuel equation	
Variable	Level	Coef.	Std. error	Coef.	Std. error
Income		−1.008***	0.322	−1.042***	0.323
Income (squared)		0.047***	0.008	0.047***	0.008
Fuel price		−2.481***	0.424	−2.526***	0.425
Fuel price * Income		0.267***	0.069	0.273***	0.069
(interaction term)					
Household size		0.112***	0.012	0.113***	0.012
Children	1 or more	−0.042***	0.011	−0.043***	0.011
(reference category: None)					
No. of members 65 years old or older	1 or more	−0.098***	0.009	−0.099***	0.009
(reference category: None)					
No. of cars and vans in household		0.151***	0.011	0.157***	0.011
Sex of HRP	Female	−0.014*	0.008	−0.013*	0.008
(reference category: Male)					
Type of area	London	0.012	0.013	0.013	0.014
	Other metropolitan areas	−0.048***	0.011	−0.048***	0.011
	Rural	0.070***	0.009	0.071***	0.009
	Northern Ireland	0.087***	0.014	0.086***	0.014
(reference category: Other urban areas)					
LIHC groups	LIHC	−0.113	0.901	−0.161	0.903
	HILC	1.134	0.841	1.133	0.843
	HIHC	−0.231	0.853	−0.275	0.855
(reference category: LILC)					
Interaction terms between LIHC groups and Income	LIHC * Income	−0.372***	0.049	−0.369***	0.049
	HILC * Income	−0.296***	0.044	−0.295***	0.045
	HIHC * Income	−0.135***	0.045	−0.131***	0.045
(reference category: LILC)					
Interaction terms between LIHC groups and Fuel price	LIHC * Fuel price	0.675***	0.185	0.681***	0.185
	HILC * Fuel price	0.157	0.173	0.156	0.173
	HIHC * Fuel price	0.382**	0.174	0.387**	0.175
(reference category: LILC)					
Interaction term between Type of area and Fuel price	London * Fuel price	−0.028***	0.004	−0.028***	0.004
(reference category: Other urban)					
No. of diesel vehicles in household	1 or more	0.216***	0.008	0.138***	0.008
(reference category: None)					
Constant		10.875***	1.952	11.106***	1.956
Diagnostics					
N		25,913		25,913	
R ²		0.44		0.43	
AIC		42799.09		42948.20	
BIC		43003.1		43152.26	

Notes: All continuous variables are transformed into natural logs.

Income and fuel prices are expressed in real prices (year 2005).

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

Table 4
Groupwise price and income elasticities and standard errors (all elasticities measured at respective group median income).

	Energy model		Fuel model	
	Price elasticity	Income elasticity	Price elasticity	Income elasticity
1. LILC	−0.967 (0.158) ^{2,3,4}	0.747 (0.042) ^{2,3}	−0.980 (0.158) ^{2,3,4}	0.746 (0.043) ^{2,3}
2. LIHC	−0.334 (0.097) ^{1,3}	0.360 (0.025) ^{1,3,4}	−0.341 (0.097) ^{1,3}	0.362 (0.025) ^{1,3,4}
3. HILC	−0.560 (0.045) ^{1,2}	0.539 (0.012) ^{1,2,4}	−0.568 (0.046) ^{1,2,4}	0.539 (0.012) ^{1,2,4}
4. HIHC	−0.411 (0.063) ¹	0.700 (0.017) ^{2,3}	−0.415 (0.064) ^{1,3}	0.703 (0.017) ^{2,3}

Notes:

- All values are statistically significant at the 0.01 level.

- Items in superscript indicate which values are significantly different from each other (Wald test at the 0.05 level).

Table 5
Values of CRES indicators in 2012 and in two price increase scenarios (N = 5,596).

CRES indicators	2012	Scenario 1 (no price response)	Scenario 2 (individual price response)
<i>Extent: headline count (%)</i>			
Low Income, Low Costs (LILC)	10.1%	9.6%	10.1%
Low Income, High Costs (LIHC)	9.4%	10.2%	9.6%
Higher Income, Low Costs (HILC)	62.0%	58.2%	60.6%
Higher Income, High Costs (HIHC)	18.5%	22.0%	19.8%
Total	100.0%	100.0%	100.0%
<i>Depth</i>			
CRES gap (for LIHC group)	0.161	0.176	0.174

This is consistent with the findings of [Wadud et al. \(2010a, 2010b\)](#), who have found low income elasticity for low income groups in the US.

Unlike LIHC, ‘Low Income Low Costs’ households have the highest price response, i.e. the greatest adaptive capacity. This may be due to low levels of commuting for these households and low levels of car dependence in the residential area: LILC households are overrepresented among households with non-employed members and among those living in higher-density urban areas, which are better served by public transit options ([Table 1](#)).

4.3. Price increase simulations

The third step of the analysis is to simulate how the CRES indicators would be affected by large changes in fuel prices. [Table 5](#) compares the extent (percentage of LIHC households) and depth (CRES gap value, last row in [Table 5](#)) of car-related economic stress in 2012 with two hypothetical scenarios.

In Scenario 1 (‘no price response’), fuel prices increase by 20%, and this results in an increase of 20% in expenditure on fuel for every household. This is a deliberately constructed unrealistic scenario, where household fuel demand is totally inelastic, i.e. any increase in price is matched by an equivalent increase in expenditure, and elasticities are equal for all households. In Scenario 2 (‘individual price response’), the elasticity estimation results presented in the previous section are used to estimate unique price elasticity values for each household. These values are then used to estimate how much household fuel consumption and expenditure would change as a result of a 20% increase in fuel prices. This is a more realistic scenario, as it takes into account that most households will reduce their demand in response to a price increase, as well as differences in elasticity between households. This approach is better suited to assess the welfare and distributional impacts of fuel price increases, as it takes into account behavioural responses¹¹ ([Santos and Catchesides, 2005](#); [West and Williams, 2004](#)).

[Table 5](#) shows that the headline count of LIHC households would increase from 9.4% to 10.2% in a scenario where fuel prices and expenditure both increase by 20%. However, there is barely any increase at all in Scenario 2 (9.6%), in which the elasticity of fuel price demand is taken into account. It must be noted, however, that the share of ‘Higher Income, High Cost’ households increases in both scenarios, although more markedly in Scenario 1. Finally, the depth of economic stress for LIHC households would increase by virtually the same amount in both in Scenario 1 and 2.

This suggests that even large increases in fuel prices would not be reflected in a substantial increase in the headline count of LIHC households. Due to the relative inelasticity of their fuel demand, however, any increase in fuel prices would result in a deepening of the car-related economic stress that they experience – i.e. households who are already in a critical situation would spend even more on fuel. The implication is that they would have to find these additional funds either by reducing their expenditures in other areas of the household budget, or that they would need to borrow the money from somewhere and tip over into (at least short term) debt.

The impact of a 20% fuel price increase is illustrated graphically in [Fig. 2](#), which replicates [Fig. 1](#) while showing, for each household, an arrow connecting their actual motoring expenditure in 2012 with their estimated expenditure in Scenario 2.¹² It shows that very few households tip over into the LIHC group, as most LILC households barely move across the plot area (due to high price response), while the expenditure increases among HIHC households are generally not large enough to bring them below the poverty line. On the other hand, LIHC households show a rather large movement toward the upper left corner of the graph, indicating a further deterioration of their affordability situation. Also, quite a few HILC households who are near the cost threshold in 2012 tip over into the HIHC group, possibly due to relatively low price elasticity for this group. This suggests that, if the income threshold was set higher (i.e. further to the right in [Fig. 2](#)), the LIHC headcount indicator would be more sensitive to changes in fuel prices.

5. Discussion

Our analysis has provided three indicators for the assessment of vulnerability to motor fuel price increases, namely i) the extent of

¹¹ In both scenarios, The LIHC headline count and gap metrics are recalculated based on increased expenditure, although the cost burden threshold remains fixed at 9.5%. This is necessary to ensure that the metrics satisfy the dynamic properties of affordability measures ([Heindl & Schüssler, 2015](#)).

¹² Note that by construction the dots in [Fig. 2](#) can only ‘move’ upwards and leftwards within the scatterplot. This is because, by definition, a fuel price increase cannot result in either an increase in income or a reduction in motoring expenditure.

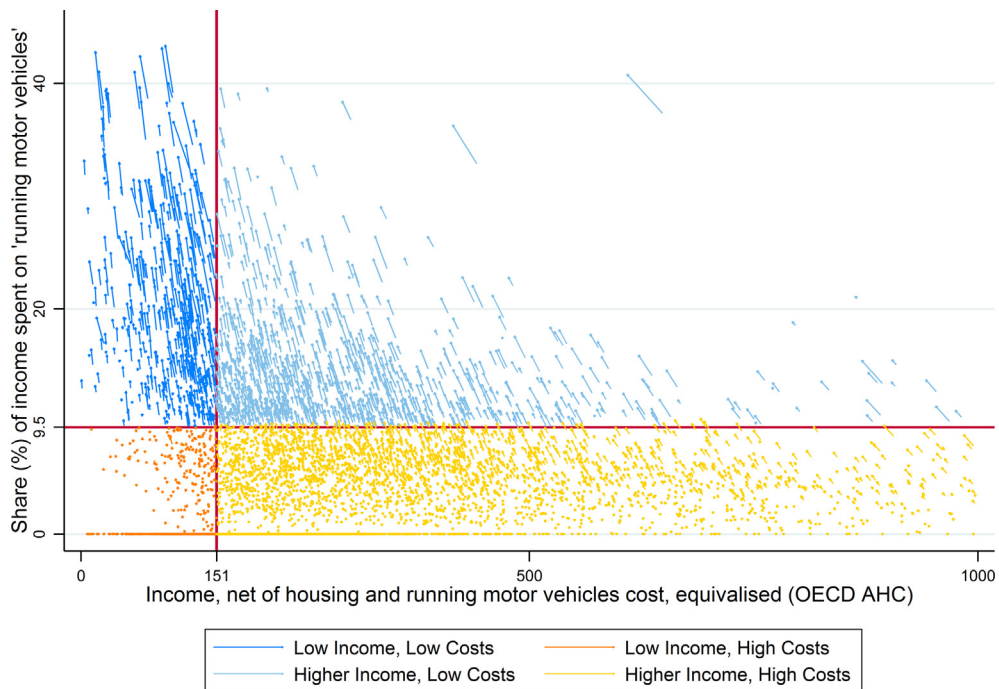


Fig. 2. Changes in motoring expenditure and residual income in Scenario 2 (N = 5,596). Notes: extreme values (more than 40% income spent or £1000 weekly-equivalent income in 2012 data) are omitted from the graph for confidentiality reasons.

CRES (percentage of households in LIHC group), ii) the depth of CRES (gap between average expenditure on motoring of LIHC households and high-cost threshold), and iii) the price elasticity of motor fuel demand for LIHC households. These indicators are related to the three dimensions of the vulnerability framework. The main finding of our analysis is to show the presence of a distinct population sector characterised by low income, high motoring costs, and low response to fuel price changes – i.e. with high *exposure*, high *sensitivity* and low *adaptive capacity* to fuel price increases. These households, which are consequently considered to be in car-related economic stress, accounted for 9.4% of UK households in 2012, corresponding to roughly 2.5 million households. Most low-income households who own cars are included in this group, which suggests that for poor UK households car ownership tends to result in economic stress.

The broad finding that part of the low-income population is reliant on cars, spends disproportionate amounts on motoring, and would be badly affected by fuel price increases is consistent with previous research from the UK (Chatterton et al., 2018; Froud et al., 2002; Lucas, 2011; Santos and Catchesides, 2005) and elsewhere (Berry et al., 2016; Demoli, 2015; Kayser, 2000). Our analysis goes beyond previous research in demonstrating a structured and comprehensive approach to investigating car-related economic stress and vulnerability to fuel price increases, based on quantitative data at the household level. This allows us to quantify the incidence and depth of the problem, to describe the affected population, and to model the impacts of fuel price changes within an integrated assessment framework.

Our findings suggest that households in CRES share some characteristics with other low-income households (e.g. lower employment rates, overrepresentation of ethnic minorities), while at the same time differing from them in a number of respects. Notably, some of the factors associated with high costs among low-income households (e.g. presence of employed household members, middle adulthood, and home ownership) tend to make them more similar to the average of the UK population, putting them on the ‘edge of social inclusion’. Overall, we find remarkably little variation in the incidence of CRES across socio-demographic groups, which can be explained by the counteracting effects discussed above.

We also find few differences in the incidence of CRES across types of area and, while as expected there is an association between CRES, low-density building types and rurality, this is not particularly strong. Perhaps this is because in the UK deprivation tends to be concentrated in urban areas and near city centres, where car dependence is lower (Bailey and Minton, 2018; Eurostat, 2015; Hunter, 2016; Pateman, 2011; Rae, 2012; Stokes, 2015), and this confounds the observed relationship between CRES and urbanity. This would demonstrate the key role played by urban socio-spatial configurations in determining spatial patterns of CRES and fuel price vulnerability, as discussed in Section 2.2. A complementary explanation is that, unlike most previous research on oil vulnerability, our analysis considers the entirety of household expenditure on running motor vehicles, including e.g. parking costs. Nicolas and Pelé (2017) have shown that high parking costs in urban cores can partially offset the spatial gradient of motoring costs, which otherwise tend to be higher in periurban areas.

Taken together, the results of this study suggest that the affordability of motoring costs is an issue that cuts across various social groups and types of area, and should not be considered as an exclusively peri-urban or rural problem, particularly in the UK. In this

regard, it supports recent research by [Curl et al. \(2018\)](#), which found high levels of ‘forced car ownership’ and related financial distress in disadvantaged urban communities in Glasgow. Also, our findings concerning the socio-demographic and spatial factors associated with CRES are remarkably consistent with Mattioli’s study of ‘forced car owners’ (i.e. households who own cars despite being in material deprivation), which has used living conditions data for the UK ([Mattioli, 2017](#)). This suggests that these broad findings are robust to the use of different sources of data and empirical definitions.

Our analysis of the heterogeneity of fuel demand elasticity allows us to provide further insights into CRES. The fact that households with low income and high costs have low response to fuel price changes may be explained by an inability to switch to more fuel-efficient household vehicles, as most of them own a single car only. However, it may also suggest that they have already reduced their car travel to the bare minimum, that what remains fulfils essential functions that cannot be cut, and that they are highly car dependent for these trips, having no other viable transport option available to them in the areas where they live ([Kayser, 2000](#); [Wadud et al., 2009](#)).

While our data do not allow a direct investigation of travel behaviour, we can hypothesize that a large part of the fuel consumption of LIHC households is for commuting, work-related or for livelihood. They are more likely to include employed members than other low-income households, and previous research suggests that the price elasticity of commuting may be lower than that of other trips ([Dillon et al., 2015](#)). Based on national travel survey data for Great Britain, [Stokes and Lucas \(2011\)](#) identify a group of low-income, working households who travel to work predominantly by car but make very few non-work journeys, and suggest that this may be due to affordability reasons ([Stokes, 2015](#)). The overlap between in-work poverty and CRES is interesting in light of the current UK’s Conservative Government’s welfare policy discourse, which sees ‘Just About Managing’ (JAMs) ([Schmuecker, 2016](#)) or ‘Ordinary Working Families’ ([BBC, 2017](#)) as most deserving of additional financial support.

The findings also show that households in CRES have the lowest income elasticity of demand. This may suggest that high motoring costs lead them to compromise on other important areas of their household expenditures, so that any income increase is used to increase non-fuel consumption ([Wadud et al., 2009](#)). Previous research has shown that the ‘motoring poor’ are willing to make important financial sacrifices to maintain car ownership and use ([Curl et al., 2018](#); [Deutsch et al., 2015](#); [Demoli, 2015](#); [Froud et al., 2002](#); [Mattioli, 2017](#); [Taylor et al., 2009](#)), reducing expenditure on basic needs such as heating ([Desjardins and Mettetal, 2012](#); [Ortar, 2018](#)) and food ([Gicheva et al., 2007](#)), and taking up debt ([Walks, 2018](#)).

The simulation results suggest that the number of households in CRES would remain substantially unchanged even in a scenario where fuel prices increase by 20%. This is partly because most other households appear to have more latitude to reduce fuel demand in response to price changes, which prevents them from tipping over the critical thresholds. However, the average depth of economic stress for the affected households would increase, reflecting the relative inelasticity of their response to price changes. This highlights the importance of assessing both the incidence and the depth of this problem. On the other hand, our findings suggest that price increases would result in a more substantial increase in the number of households facing high costs for motoring but who are not poor (i.e. have residual income above the official poverty line), and HIHC households are also characterised by relatively low response to fuel price increases. Adopting a less stringent definition of low income would therefore likely highlight the vulnerability to fuel price increases of households on medium to low incomes.

6. Conclusion

Our analysis demonstrates a new empirical approach to the investigation of CRES and vulnerability to fuel price increases by using disaggregated analysis at the household level and relating this to actual gasoline prices in their precise geographical locations. It also brings together concepts and methods from different, and hitherto fragmented, scientific disciplinary and policy arenas, such as social deprivation, urban resilience, fuel poverty, and energy economics. By adopting this disaggregated (household-level) approach, we have been able to highlight that there is a socio-economic dimension to vulnerability to fuel price increases. While low-density and rural areas tend to be more vulnerable, within each area certain types of households stand to lose the most from price spikes. Even among the low-income group, some households are more likely to spend a disproportionate share of income on motoring, and less likely to be able to reduce their car travel or fuel consumption.

This approach leads to different policy recommendations. Previous research has highlighted the ‘oil vulnerability’ of low-income settlements in car-dependent suburban and peri-urban areas, emphasising the need for compact city and transit oriented land use development, as well as for improved public transport provision in the areas where these households are located. Our analysis has highlighted the link between CRES and a number of socio-economic factors including e.g. in-work poverty, mobility difficulties and access to home ownership among low-income households. This suggests different entry points for local and national policy action including housing and welfare policies (e.g. in-work and disability benefits). The goal should be to ensure that the achievement of social inclusion in key areas, such as employment and housing, does not come at the price of CRES and curtailed expenditure on other household necessities.

More broadly, however, the issue of CRES raises a conundrum for social, environmental and resilience policy in the transport sector. At first sight, the findings of this study may seem to provide empirical backing for campaigns to reduce fuel taxes. Yet, on the longer term, low levels of fuel taxation increase car dependence and vulnerability, e.g. by encouraging urban sprawl and discouraging fuel-efficient car choices, while also increasing the sensitivity of pump prices to fluctuations in global oil markets. Also, a sustained policy of fossil fuel tax reductions is hardly defensible in light of international climate agreements.

On the other hand, our findings suggest that environmental policies increasing motor fuel prices, while arguably beneficial on the longer term, are likely to cause considerable hardship among certain sectors of the population in the short term. This reduces the public and political acceptability of such policy interventions. Ultimately, the only way out of the impasse is to ensure that

households with limited financial resources do not have to rely on private fossil fuel based vehicles for the satisfaction of basic needs in everyday life. The analysis in this paper, along with previous research, suggests that this is not the case in the UK at present. It could suggest that if such policies were to be enacted, the best welfare option move might be to subsidise the ownership of electric vehicles for CRES households, thus reducing their fuel cost at the point of use.

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References

- AAA, 2016. Transport Affordability Index. Australian Automobile Association.
- Adger, W.N., 2006. Vulnerability. *Glob. Environ. Change* 16 (3), 268–281.
- Akbari, S., Habib, K.N., 2014. Oil vulnerability in the greater Toronto area: impacts of high fuel prices on urban form and environment. *Int. J. Environ. Sci. Technol.* 11 (8), 2347–2358.
- Alexander, S., 2017. The paradox of oil: the cheaper it is, the more it costs. In: Dodson, J., Sipe, N., Nelson, A. (Eds.), *Planning After Petroleum. Preparing Cities for The Age Beyond Oil*. Routledge, Abingdon.
- Archibald, R., Gillingham, R., 1980. An analysis of the short-run consumer demand for gasoline using household survey data. *Rev. Econ. Statistics* 62 (4), 622–628.
- Austin, D., 2008. Effects of gasoline prices on driving behavior and vehicle markets. Congressional Budget Office.
- Bailey, N., Minton, J., 2018. The suburbanisation of poverty in British cities, 2004–16: extent, processes and nature. *Urban Geography* (in press).
- Bastian, A., Börjesson, M., 2015. Peak car? Drivers of the recent decline in Swedish car use. *Transp. Policy* 42, 94–102.
- Bastian, A., Börjesson, M., Eliasson, J., 2016. Explaining “peak car” with economic variables. *Transp. Res. Part A* 88, 236–250.
- Baumeister, C., Kilian, L., 2016. Forty years of oil price fluctuations: Why the price of oil may still surprise us. *J. Econ. Perspect.* 30 (1), 139–160.
- BBC, 2017. Reality Check: What are ‘ordinary working families’? 13 April 2017 [Available at <http://www.bbc.co.uk/news/education-39590198>, accessed on 19 May 2017].
- Belton Chevallier, L., Motte-Baumvol, B., Fol, S., Jouffe, Y., 2018. Coping with car dependency: a system of expedients used by low-income households on the outskirts of Dijon and Paris. *Transp. Policy* 65, 79–88.
- Berry, A., Jouffe, Y., Coulombel, N., Guivarch, C., 2016. Investigating fuel poverty in the transport sector: toward a composite indicator of vulnerability. *Energy Res. Social Sci.* 18, 7–20.
- Boardman, B., 1991. Fuel Poverty: from Cold Homes to Affordable Warmth. Pinter Pub Limited.
- Boardman, B., 2010. Fixing Fuel Poverty: Challenges and Solutions. Earthscan, Abingdon.
- Brooks, N., 2003. Vulnerability, risk and adaptation: a conceptual framework. Tyndall Centre for Climate Change Research Working Paper, 38, pp. 1–16.
- Büttner, B., Wulforth, G., Crozet, Y., Mercier, A., 2013. The impact of sharp increases in mobility costs analysed by means of the Vulnerability Assessment. In: 13th World Conference on Transport Research, Rio de Janeiro, July 15–18, 2013.
- Chatterton, T., Anable, J., Cairns, S., Wilson, R.E., 2018. Financial Implications of Car Ownership and Use: a distributional analysis based on observed spatial variance considering income and domestic energy costs. *Transp. Policy* 65, 30–39.
- Clarke, S., Corlett, A., Judge, L., 2016. The housing headwind. The impact of rising housing costs on UK living standards. *Resolut. Found.*
- Cornut, B., 2016. Longitudinal analysis of car ownership and car travel demand in the Paris region using a pseudo-panel data approach. *Transp. Res. Procedia* 13, 61–71.
- Curl, A., Clark, J., Kearns, A., 2018. Household car adoption and financial distress in deprived urban communities: A case of forced car ownership? *Transp. Policy* 65, 61–70.
- Currie, G., Delbosc, A., 2011. Mobility vs. affordability as motivations for car-ownership choice in urban fringe, low-income Australia. In: Lucas, K., Blumenberg, E., Weinberger, R. (Eds.), *Auto Motives: Understanding Car Use Behaviours*. Emerald, Bingley.
- Currie, G., Senbergs, Z., 2007. Exploring forced car ownership in metropolitan Melbourne. Australasian Transport Research Forum 2007.
- Dahl, C., Sterner, T., 1991. Analysing gasoline demand elasticities: a survey. *Energy Econ.* 13 (3), 203–210.
- Desjardins, X., Mettetal, L., 2012. L’habiter périurbain face à l’enjeu énergétique. *Flux* 89 (90), 46–57.
- Deutsch, J., Guio, A.C., Pomati, M., Silber, J., 2015. Material deprivation in Europe: Which expenditures are curtailed first? *Soc. Indic. Res.* 120 (3), 723–740.
- De Vos, J., Witlox, F., 2013. Transportation policy as spatial planning tool; reducing urban sprawl by increasing travel costs and clustering infrastructure and public transportation. *J. Transp. Geogr.* 33, 117–125.
- DfT, 2015. National Travel Survey: England 2014. Statistical release. Department for Transport, London.
- Demoli, Y., 2015. The social stratification of the costs of motoring in France (1980–2006). *Int. J. Automot. Technol. Manage.* 15 (3).
- Dillon, H.S., Saphores, J.D., Boarnet, M.G., 2015. The impact of urban form and gasoline prices on vehicle usage: Evidence from the 2009 National Household Travel Survey. *Res. Transportation Econ.* 52, 23–33.
- Dodson, J., Sipe, N., 2007. Oil vulnerability in the Australian city: assessing socioeconomic risks from higher urban fuel prices. *Urban Studies* 44 (1), 37–62.
- Dodson, J., Sipe, N., 2008. Shocking the suburbs: Urban location, homeownership and oil vulnerability in the Australian city. *Housing Studies* 23, 377–401.
- EEA, 2015. Evaluating 15 years of transport and environmental policy integration. EEA Report No 7/2015.
- Eurostat, 2015. Quality of life by degree of urbanisation. Eurostat. [http://ec.europa.eu/eurostat/statistics-explained/index.php/Quality_of_life_by_degree_of_urbanisation].
- Eurostat, 2017. Statistics explained. Eurostat. [<http://ec.europa.eu/eurostat/statistics-explained>].
- Fishman, E., Brennan, T., 2009. Oil vulnerability in Melbourne. Australasian Transport Research Forum.
- Frondel, M., Vance, C., 2009. Do high oil prices matter? Evidence on the mobility behavior of German motorists. *Environ. Resour. Econ.* 43, 81–94.
- Froud, J., Johal, S., Leaver, A., Williams, K., 2002. Not enough money: The resources and choices of the motoring poor. *Competition Change* 6 (1), 95–111.
- Gertz, C., Maaß, J., Guimarães, T. (Eds.), 2015. Auswirkungen von steigenden Energiepreisen auf die Mobilität und Landnutzung in der Metropolregion Hamburg. Ergebnisse des Projekts CLAN – Energiepreisentwicklung und Landnutzung. Institut für Verkehrsplanung und Logistik, Hamburg.
- Gicheva, D., Hastings, J., Villas-Boas, S., 2007. Revisiting the income effect: gasoline prices and grocery purchases, NBER Working Paper Series 13614. National Bureau of Economic Research.
- Gillingham, K., 2014. Identifying the elasticity of driving: Evidence from a gasoline price shock in California. *Regional Sci. Urban Econ.* 47, 13–24.
- Gillingham, K., Jenn, A., Azevedo, I.M., 2015. Heterogeneity in the response to gasoline prices: Evidence from Pennsylvania and implications for the rebound effect.

- Energy Econ. 52, S41–S52.
- Gleeson, B., Randolph, B., 2002. Social disadvantage and planning in the Sidney context. *Urban Policy Res.* 20, 101–107.
- Goodwin, P., Dargay, J., Hanly, M., 2004. Elasticities of road traffic and fuel consumption with respect to price and income: a review. *Transport Rev.* 24 (3), 275–292.
- Gorham, R., 2002. Car dependence as a social problem - A critical essay on the existing literature and future needs. In: Black, W.R., Nijkamp, P. (Eds.), *Social Change and Sustainable Transport*. Indiana University Press, Bloomington.
- Granville, S., Mulholland, S., Staniforth, J., 2009. *Use and Understanding of the Scottish Government Urban Rural Classification*. Scottish Government. [<http://www.gov.scot/Resource/Doc/281343/0084923.pdf>, accessed 22 November 2017].
- Gronwald, M., 2016. Explosive oil prices. *Energy Econ.* 60, 1–5.
- Guerra, E., Kirschen, M., 2016. Housing plus transportation affordability indices: uses, opportunities, and challenges. *OECD/ITF Discussion Paper 2016–2114*.
- Guimaraes, T., Maaß, J., Gertz, C., 2014. Integrating a land use transport model with a serious game for supporting planning decisions under rising energy prices. *Transp. Res. Procedia* 4, 241–254.
- Gusdorf, F., Hallegatte, S., 2007. Compact or spread-out cities: Urban planning, taxation, and the vulnerability to transportation shocks. *Energy Policy* 35 (10), 4826–4838.
- Heindl, P., Schüssler, R., 2015. Dynamic properties of energy affordability measures. *Energy Policy* 86, 123–132.
- Hills, J., 2012. *Getting the measure of fuel poverty. Final Report of the Fuel Poverty Review*. London: CASE report 72.
- Hunter, P., 2016. *Towards a suburban renaissance: an agenda for our city suburbs*. The Smith Institute.
- Jouffe, Y., Massot, M.-H., 2013. Vulnérabilités sociales dans la transition énergétique au croisement de l'habitat et de la mobilité quotidienne. 1er Congrès Interdisciplinaire du Développement Durable. Namur, Belgium.
- Kayser, H.A., 2000. Gasoline demand and car choice: estimating gasoline demand using household information. *Energy Econ.* 22 (3), 331–348.
- Kaupilla, J., 2011. Ten stylised facts about household spending on transport. *ITF / OECD Statistical Paper No. 1/2011*.
- Kesteloot, C., 2005. Urban socio-spatial configurations and the future of European cities. In: Kazepov, Y. (Ed.), *Cities of Europe. Changing contexts, local arrangements, and the challenge to urban cohesion*. Blackwell, Oxford.
- Klein, N.J., Smart, M.J., 2017. Car today, gone tomorrow: The ephemeral car in low-income, immigrant and minority families. *Transportation* 44 (3), 495–510.
- Leung, A., Burke, M., Cui, J., Perl, A., 2015. *New approaches to oil vulnerability mapping for Australian cities: the case of South-East Queensland, the 200km city*. State of Australasian Cities Conference 2015.
- Leung, A., Burke, M., Cui, J., 2018. The tale of two (very different) cities - Mapping the urban transport oil vulnerability of Brisbane and Hong Kong. *Transportation Research Part D* (in press).
- Li, S., Timmins, C., Haefen, R.H.V., 2009. How do gasoline prices affect fleet fuel economy? *Am. Econ. J.: Econ. Policy* 1 (2), 113–137.
- Liddell, C., Morris, C., McKenzie, S.J.P., Rae, G., 2012. Measuring and monitoring fuel poverty in the UK: National and regional perspectives. *Energy Policy* 49, 27–32.
- Litman, T., 2016. *Transportation Affordability. Evaluation and Improvement Strategies*. Victoria Transport Policy Institute.
- Lovelace, R., Philips, I., 2014. The 'oil vulnerability' of commuter patterns: A case study from Yorkshire and the Humber, UK. *Geoforum* 51, 169–182.
- Lucas, K., 2011. Driving to the headline. In: Lucas, K., Blumenberg, E., Weinberger, R. (Eds.), *Auto Motives: Understanding Car Use Behaviours*. Bingley, Emerald.
- Lucas, K., 2012. Transport and social exclusion: Where are we now? *Transp. Policy* 20, 105–113.
- Lucas, K., Bates, J., Moore, J., Carrasco, J.A., 2016a. Modelling the relationship between travel behaviours and social disadvantage. *Transp. Res. Part A* 85, 157–173.
- Lucas, K., Mattioli, G., Verlingheri, E., Guzman, A., 2016. Transport poverty and its adverse social consequences. *Proceedings of the Institution of Civil Engineers – Transport*, vol. 169, pp. 353–365.
- Lyons, G., Chatterjee, K. (Eds.), 2002. *Transport Lessons from the Fuel Tax Protests of 2000*. Ashgate, Farnham.
- Mattioli, G., 2014. Where sustainable transport and social exclusion meet: Households without cars and car dependence in Great Britain. *J. Environ. Plann. Policy Manage.* 16 (3), 379–400.
- Mattioli, G., 2017. 'Forced Car Ownership' in the UK and Germany: socio-spatial patterns and potential economic stress impacts. *Social Inclusion* 5 (4), 147–160.
- Mattioli, G., Colleoni, M., 2016. Transport disadvantage, car dependence and urban form. In: Pucci, P., Colleoni, M. (Eds.), *Understanding Mobilities for Designing Contemporary Cities*. Springer, Heidelberg.
- Mattioli, G., Lucas, K., Marsden, G., 2017a. Transport poverty and fuel poverty in the UK: From analogy to comparison. *Transp. Policy* 59, 93–105.
- Mattioli, G., Philips, I., Anable, J., Chatterton, T., 2017b. Developing an index of vulnerability to motor fuel price increases in England. 49th Annual Universities' Transport Study Group Conference, 4–6 January 2017, Dublin.
- Mayer, I., Nimal, E., Nogue, P., Sevenet, M., 2014. The two faces of energy poverty: a case study of households' energy burden in the residential and mobility sectors at the city level. *Transp. Res. Procedia* 4, 228–240.
- McGuinness, F., 2016. *Poverty in the UK: statistics*. House of Commons Briefing Paper no. 7096.
- Mullen, C., Marsden, G., 2018. The car as a safety-net: narrative accounts of the role of energy intensive transport in conditions of housing and employment uncertainty. In: Hui, A., Day, R., Walker, G. (Eds.), *Demanding Energy*. Palgrave Macmillan, Hampshire.
- Nicol, C.J., 2003. Elasticities of demand for gasoline in Canada and the United States. *Energy Econ.* 25 (2), 201–214.
- Nicolas, J.P., Pelé, N., 2017. Measuring trends in household expenditures for daily mobility. The case in Lyon, France, between 1995 and 2015. *Transp. Policy* 59, 82–92.
- Nicolas, J.-P., Vanco, F., Verry, D., 2012. Mobilité quotidienne et vulnérabilité des ménages. *Revue d'Economie Regionale & Urbaine* 2012 (1), 19–44.
- ONPE, 2014. *Premier rapport de l'ONPE. Définitions, indicateurs, premiers résultats et recommandations*.
- ONS, 2013. *The 2011 Rural-Urban Classification For Small Area Geographies: A User Guide and Frequently Asked Questions*. Office for National Statistics. [<http://www.ons.gov.uk/ons/external-links/other/rural-urban-classification-2011-user-guide.html>, retrieved on 22 November 2017].
- ONS, 2013. *Living Costs and Food Survey. Volume A: Introduction*. Office for National Statistics.
- ONS, DEFRA, 2016. *Living Costs and Food Survey, 2006–2014: Secure Access*. [data collection]. 7th Edition. UK Data Service. SN: 7047, <http://doi.org/10.5255/UKDA-SN-7047-7>.
- Ortar, N., 2018. Dealing with energy crises: Working and living arrangements in peri-urban France. *Transp. Policy* 65, 72–78.
- Ortuño-Padilla, A., Fernández-Aracil, P., 2013. Impact of fuel price on the development of the urban sprawl in Spain. *J. Transp. Geogr.* 33, 180–187.
- Pateman, T., 2011. Rural and urban areas: comparing lives using rural/urban classifications. *Regional Trends* 43 (1), 11–86.
- Rendall, S., Page, S., Krumdieck, S., 2014. Voila! a new measure of oil vulnerability for cities. 1st International e-Conference on Energies.
- Rae, A., 2012. Spatially concentrated deprivation in England: An empirical assessment. *Regional Stud.* 46 (9), 1183–1199.
- Ricci, M., Parkhurst, G., Jain, J., 2016. Transport policy and social inclusion. *Social Inclusion* 4 (3), 1–6.
- Rock, S., Ahern, A., Caulfield, B., 2016. The economic boom, bust and transport inequity in suburban Dublin, Ireland. *Res. Transportation Econ.* 57, 32–43.
- Romero-Jordan, D., del Rio, P., Burguillo, M., 2014. Modelling fuel demand for passenger cars in Spain: A dynamic panel data analysis using the Generalised Method of Moments. *J. Transport Econ. Policy* 48 (2), 315–332.
- Ross, M.L., Hazlett, C., Mahdavi, P., 2017. Global progress and backsliding on gasoline taxes and subsidies. *Nat. Energy* 2, 1–6.
- Runting, R., Corcoran, J., Leung, A., Pullar, D., 2011. Oil vulnerability: the effect of non-metropolitan areas and master planned estates in South East Queensland 2001–2006. *Australian Planner* 48 (3), 117–130.
- Santos, G., Catchesides, T., 2005. Distributional consequences of gasoline taxation in the United Kingdom. *Transp. Res. Rec.: J Transp. Res. Board* 1924, 103–111.
- Schäfer, A., Heywood, J.B., Jacoby, H.D., Waitz, I.A., 2009. *Transportation in a Climate-Constrained World*. MIT Press, Cambridge, Massachusetts.
- Schmuecker, K., 2016. Who are Prime Minister May's 'just about managing' and what would help them?. Joseph Rowntree Foundation [Available at <https://www.jrf.org.uk/blog/who-are-prime-minister-mays-just-about-managing-and-what-would-help-them>, accessed on 19 May 2017].
- Schwane, T., Lucas, K., Akyelken, N., Solsona, D.C., Carrasco, J.A., Neutens, T., 2015. Rethinking the links between social exclusion and transport disadvantage through the lens of social capital. *Transp. Res. Part A* 74, 123–135.
- Sustrans, 2012. *Locked out. Transport poverty in England*. [Online] Available from: <http://www.sustrans.org.uk/lockedout>. [Accessed: 25th November 2015].

- Stokes, G., 2015. 27 Incomes, accessibility and transport poverty. In: Hickman, R., Bonilla, D., Givoni, M., Banister, D. (Eds.), *International Handbook on Transport and Development*. Elgar.
- Stokes, G., Lucas, K., 2011. *National travel survey analysis*. University of Oxford, Transport Studies Unit, Working Paper No. 1053.
- Taylor, J., Barnard, M., Neil, H., Creegan, C., 2009. *The Travel Choices and Needs of Low Income Households: the Role of the Car*. The National Centre for Social Research.
- Titheridge, H., Christie, N., Mackett, R., Hernández, D.O., Ye, R., 2014. *Transport and Poverty. A Review of the Evidence*. University College London, London.
- Wadud, Z., 2014. New vehicle fuel economy in the UK: Impact of the recession and recent policies. *Energy Policy* 74, 215–223.
- Wadud, Z., Baierl, M., 2017. Explaining “peak car” with economic variables: A comment. *Transp. Res. Part A* 95, 381–385.
- Wadud, Z., Graham, D.J., Noland, R.B., 2009. Modelling fuel demand for different socio-economic groups. *Appl. Energy* 86, 2740–2749.
- Wadud, Z., Graham, D.J., Noland, R.B., 2010a. Gasoline demand with heterogeneity in household responses. *Energy J.* 31, 47–74.
- Wadud, Z., Noland, R.B., Graham, D.J., 2010b. A semiparametric model of household gasoline demand. *Energy Econ.* 32 (1), 93–101.
- Walks, A., 2018. Driving the poor into debt? Automobile loans, transport disadvantage, and automobile dependence. *Transp. Policy* 65, 137–149.
- West, S.E., Williams, R.C., 2004. Estimates from a consumer demand system: implications for the incidence of environmental taxes. *J. Environ. Econ. Manage.* 47 (3), 535–558.
- World Bank, 2016. *World Bank Commodities Price Forecast*. [<http://pubdocs.worldbank.org/en/764161469470731154/CMO-2016-July-forecasts.pdf>, accessed 20 September 2016].