

Developing an index of vulnerability to motor fuel price increases in England

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Abstract

As the outlook for oil prices remains uncertain, this paper develops a method to assess which areas of England would be most vulnerable to future motor fuel price increases. Building on previous research, we define and operationalise three dimensions of vulnerability: exposure (the cost burden of motor fuel), sensitivity (income) and adaptive capacity (accessibility with modes alternative to the car). We exploit unique data sets available in England, including the 'MOT' vehicle inspection data and DfT Accessibility Statistics. This allows us to map vulnerability to fuel price increases at a spatially disaggregated level (Lower-layer Super Output Areas), taking into account motor-fuel expenditure for all travel purposes, and the ability of households to shift to other modes of travel. This is an advancement on the 'oil vulnerability' indices developed in previous international research.

1. Introduction

Despite increasing academic and public attention regarding the possibility of having reached 'peak car', passenger mobility in developed countries remains largely dominated by car use, although this varies considerably between spatial contexts. At a global level, motorisation and car use have increased massively in recent years, notably in rapidly developing countries such as China. Similarly, while much is made of the rise of new powertrains and alternative fuels, most of the private motor vehicle fleet consists of internal combustion engine (ICE) technology running on fossil fuels, and e.g. in the UK these will remain the majority of the fleet in-use until at least 2030 (CCC, 2015). In 2014, oil derived fuels accounted for 95% of final transport-related energy consumption in the EU (EEA, 2015)

As a result of this situation, passenger mobility in developed countries is currently largely dependent on the availability of cheap, oil derived fuels. This has raised concerns about the vulnerability of transport and urban systems to increases in motor fuel prices (Dodson & Sipe, 2007; Newman et al., 2009), notably in relation to large increases in the price of oil between the turn of the century and 2014 (Fig.1).

Oil prices have rapidly declined since late 2014 due to reduced global demand and increased supply of unconventional oil, and this has been reflected in real motor fuel prices (Fig.1). However, this should not diminish the concern about the vulnerability of passenger travel to fuel price increases, for at least three reasons. First, oil price fluctuations are notoriously hard to predict and may well happen again in the future (Alexander, 2017). At the time of writing, the World Bank (2016) forecasts a steady rise in the real price of oil from 2017 to 2025. Second, at least in the case of the UK (which is the focus of this study), real motor fuel prices are still relatively high in historical comparison (Fig.1).

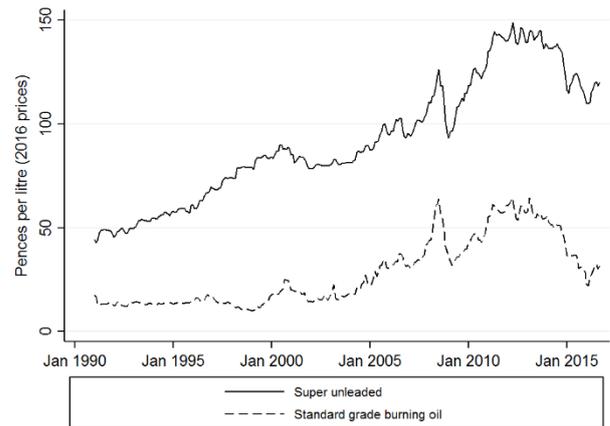


Figure 1 – Real monthly motor fuel¹ and oil prices in the UK, 1991 – 2016. Source: DBEIS (2016).

Finally, fluctuations in the basic cost of fuel are not the only driver of changes in motor fuel prices, as a significant proportion of retail fuel prices is typically accounted for by taxation (Chatterton et al., in press). Fig.1 shows a significant increase in the real price of fuel in the UK since the 1990s, in the absence of corresponding changes in the price of oil. This is due to the ‘fuel duty escalator’, an environmentally-motivated, automatic annual duty increase above the rate of inflation, which was introduced in 1993 and discontinued in 2000 following protests. This demonstrates that fuel prices can increase as a result of deliberate state interventions aimed at reducing the environmental impact of transport. Indeed, pricing measures are one of the key policy tools available for climate change mitigation in the transport sector. Therefore, an analysis of vulnerability to fuel price increases is crucial not only to assess the negative effects of oil-market induced spikes, but also for anticipating the distributional impacts of possible policy-induced increases in fuel prices.

A growing body of research (reviewed in the following section) suggests that the negative social impacts of fuel price increases are unevenly socially distributed. This paper contributes to this literature by developing a spatial metric of social vulnerability to fuel price increases for England. This is a novel contribution in at least three respects. First, as we illustrate in the next sections, due to the availability uniquely rich datasets for England, the metric proposed here is an advancement of previous international work on this topic. Second, while the UK has a rich tradition of research on transport and social exclusion, we are not aware of previous attempts to map spatial patterns of vulnerability to fuel price increases in Britain other than Lovelace and Philips' regional study (2014). Finally, this paper adds on previous work based on the MOT dataset (Chatterton et al., 2015; 2016; in press; Philips et al., 2017) in demonstrating the possible uses of vehicle inspection data for transport policy-relevant research.

In the remainder of this paper, we present a methodological discussion of a composite index to measure vulnerability in England. A more thorough analysis of the spatial patterns highlighted by the index will be the object of forthcoming work.

2. Background

Existing literature acknowledges that increases in motor fuel prices can negatively affect households, e.g. leading them to reduce necessary travel or to cut expenditure in other areas (e.g. Ortar, in press). These impacts are unevenly distributed among lines determined by both socio-economic and spatial factors. Accordingly, two types of quantitative empirical studies have been conducted.

First, some studies take *households* (or individuals) as the unit of analysis, with vulnerability typically defined as spending more than a certain percentage of income on car travel. In a UK context, Lovelace & Philips (2014) estimate that 2 to 6% of York residents (depending on the residential area) spend more than 10% of their income on work travel. Mattioli, Wadud and Lucas (2016) estimate that approximately 9% of UK households have ‘high’ costs for running motor vehicles and ‘low’ residual income. These households also have low price

¹ Diesel prices are not depicted in Fig.1 but are very similar to super prices in both levels and trends.

elasticity of motor fuel demand, suggesting that they struggle to reduce their consumption in times of high prices.

A second line of enquiry has taken *areas* as the unit of analysis, highlighting spatial patterns of vulnerability (Akbari & Habib, 2014; Arico, 2007; Büttner et al., 2013; Dodson & Sipe, 2007; Fishman & Brennan, 2009; Leung et al., 2015; Rendall et al., 2014; Runting et al., 2011). This paper contributes to this second strand of research, which is often referred to as 'oil vulnerability'.

Most work in this area uses *composite indicators* to summarise the multiple constituent components of vulnerability in a single metric. The first step in the construction of a composite indicator is the identification of a sound theoretical framework to guide the selection of underlying indicators (OECD, 2008). While existing 'oil vulnerability' research often relies on 'ad-hoc' theoretical frameworks, more recent contributions (Büttner et al., 2013; Leung et al., 2015) have proposed to draw on conceptualisations of social vulnerability developed in research on climate change and natural hazards (e.g. Adger, 2006; Brooks, 2003). Adger (2006) defines vulnerability as "the state of susceptibility to harm from exposure to stresses associated with environmental and social change and from the absence of capacity to adapt" (p.268). In this context, vulnerability is seen as constituted by three components: *exposure*, i.e. "the nature and degree to which a system experiences (...) stress", *sensitivity*, i.e. "the degree to which a system is modified or affected by perturbations", and *adaptive capacity*, i.e. "the ability of a system to evolve in order to accommodate (stress) and to expand the range of variability with which it can cope" (p.270). In this paper, we draw on this tripartite conceptualisation of vulnerability to organise our review of previous 'oil vulnerability' studies (Table 1), and to guide the construction of a composite indicator for England (Section 4).

Dodson and Sipe's pioneering study of 'oil vulnerability' in Australian cities (2007) proposed a 'vulnerability index for petrol expenses rises' (VIPER), with two sub-dimensions: car dependence and economic status. Car dependence is assessed through indicators of car ownership and use in the area, while economic status is measured based on an area-based socio-economic index. High vulnerability areas are identified as those with high car dependence and low economic status. The empirical study finds high oil vulnerability levels in outer urban areas.

Subsequent work on 'oil vulnerability' has identified limitations in the original VIPER indicator, and proposed ways of improving it. First, the 'car dependence' dimension actually conflates two distinct dimensions. On one hand, measures of car ownership and use are used as proxies for household motor fuel consumption and related economic stress, i.e. as indicators of the area's *exposure* to the negative impacts of higher fuel prices. On the other hand, actual car ownership and use are also used as proxies for the *need* for car-based mobility, as a result of lack of access to, or poor viability of, alternative transport modes in the area. In the conceptualisation adopted here, this is equivalent to a lack of *adaptive capacity*, as residents would find it difficult to switch away from car use in response to higher fuel prices. Further research (Leung et al., 2015; Rendall et al., 2014; Runting et al., 2011) has argued that adaptive capacity needs to be adequately included in composite indicators of vulnerability to fuel price increases. This has generally been achieved through the inclusion of indicators of access to services and opportunities with alternative modes (typically public transport).

A second limitation of the VIPER index concerns indicators of exposure. Car ownership and use are only crude proxies for fuel expenditure in the area. Moreover, both Dodson & Sipe (2007) and many subsequent empirical studies use metrics of car use that refer to commuting only (as these are more readily available). However, commuting typically accounts for only a minority of car mileage (e.g. 37% in England in 2015 (DfT, 2016)). Subsequent work has attempted to refine oil vulnerability metrics by: (i) adopting more direct indicators of household fuel consumption or expenditure (sometimes based on modelling); (ii) taking into account travel for all purposes.

A third limitation of existing oil vulnerability indices concerns the indicators of adaptive capacity used. These generally include either measures of access to public transport *per se*, or measures of access to employment with modal alternatives. Only Rendall et al. (2014) provide a measure of accessibility to a range of essential services (including e.g. shopping, etc.). This, however, requires them to develop a method to combine accessibility analysis with activity modelling, which is both conceptually and computationally complex.

Study reference	Exposure	Adaptive capacity	Sensitivity
<i>Dodson & Sipe (2007)</i>	(i) Proportion of households with two or more motor vehicles; (ii) Journey to work car modal share		Socio-economic index for areas (SEIFA)
<i>Arico (2007)</i>	(i) Journey to work car modal share; (ii) Proportion of total expenditure spent on transport	[Not considered]	(i) Vulnerable age group population (working population – ages 15 and over); (ii) Incidence of low income
<i>Fishman & Brennan (2009)</i>	(i) Average weekly fuel use; (ii) Percentage of weekday travel (for all purposes) using public transport, cycling or walking		Average personal income
<i>Runting et al. (2011)</i>	(i) Proportion of dwellings with two or more low-occupancy vehicles; (ii) Proportion of persons who travel to work by low occupancy vehicles; (iii) Average commuting distance for journey to work	Proportion of area with non-motorised access to public transport	Socio-economic index for areas (SEIFA)
<i>Büttner et al., 2013</i>	Munich: Vehicle-km per capita (estimated based on regional transport model) Lyon: Per capita commuting distance by private car (based on local travel survey)	Total number of accessible jobs within one hour by public transport at peak time	Munich: Average monthly income Lyon: Unemployment rate
<i>Akbari & Habib (2014)</i>	(i) Proportion of households with two or more vehicles; (ii) Proportion of trips (for all purposes) by car		(i) Median household income; (ii) Prevalence of low income after tax
<i>Lovelace & Philips (2014) ('Hybrid vulnerability index')</i>	Average proportion of individual's energy budget spent on commuting	(i) Distance to employment centre; (ii) Proportion of work trips made by car	[Not considered]
<i>Rendall et al. (2014)</i>	Average household car-related energy consumption / costs	Estimation of average 'minimum' required transport energy consumption	Median income
<i>Leung et al. (2015)</i>	(i) Average number of motor vehicles owned per dwelling; (ii) Oil-based fuel use of low-occupancy vehicles per commuting trip; (iii) Average commuting distance	(i) Proportion of mode share that does not consume oil; (ii) Proportion of area within 400m of public transport stop ranked by level of service on weekdays; (iii) Walkability indices; (iv) Employment density; (v) Proportion of area within 400m buffer of electric transport corridors	(i) Median weekly household income; (ii) Index of relative socio-economic disadvantage

Table 1 – Indicators used for the measurement of vulnerability to fuel price increases in previous studies

A final remark concerns indicators of sensitivity. In Dodson and Sipe's original study (2007) this was assessed by an area-based composite index (SEIFA) which included income alongside other dimensions (similarly e.g. to the British indices of Multiple Deprivation (DCLG, 2015)). This is arguably only an indirect measure of sensitivity to the economic stress arising from fuel price increases. Accordingly, several subsequent studies have used area-based income measures to assess the sensitivity dimension of vulnerability.

To sum up, a review of empirical research of transport 'oil vulnerability' shows an ongoing effort to develop metrics that are theoretically grounded, comprehensive, and accurate. Limitations in the availability of data at the small-area level, however, often result in the use of imperfect indicators of the underlying dimensions. Yet, as Dodson & Sipe note, "a more sophisticated analysis of suburban oil vulnerability could be undertaken if a better dataset was available that could reveal information about household socioeconomic status, vehicle and travel costs, and the access to and use of different modes" (2007, p.58). As we describe in the next section, such data is now available for England.

3. Data

The vulnerability index proposed in this paper draws on three main sources of data: (i) a vehicle inspection dataset (linked to a vehicle registration dataset); (ii) an area-based measure of median income; (iii) official government 'accessibility statistics'. These data sources are described in more detail in the remainder of this section.

Data collected through periodic (annual) technical inspections of motor vehicles is collected in a number of countries and is increasingly being made available to researchers and other users. In the UK, anonymised 'MOT' vehicle inspection test records have been published since 2010 (Cairns et al., 2014) and have been used for a range of travel behaviour analysis (Chatterton et al., 2015; 2016; in press; Philips et al., 2017). The application of mathematical methods (see Wilson et al., 2013a; 2013b) allows the estimation of annual mileage rates for each vehicle, based on odometer readings. As information on fuel type, engine size and vehicle age is also available with this data, it is possible to estimate fuel economy, annual fuel use and related expenditure for each vehicle (for details on methods see Chatterton et al., 2015; 2016; in press). Through linkage with data provided by the Driver and Vehicle Licencing Agency (DVLA) it is then possible to link private vehicle data to the residential location of the registered keeper. This is provided at the level of *Lower-layer Super Output Areas* (LSOAs - relatively socially homogenous areas of, on average, 700 households).

Estimates of median household income at the LSOA level are included in the public sector *Experian Demographic Data* provided by the UK Data Service (Experian Limited, 2007).

The final set of data used in this paper is drawn from the UK Department for Transport Official Accessibility Statistics. Since 2007 the government publishes annually official measures of the availability of transport to eight key sites and services at the LSOA level. The dataset includes estimates of the travel time required to the nearest key services, by different travel modes (car, public transport, walking and cycling). These are estimated "using information on public transport timetables, the road network, and information on actual average traffic speeds on the road network" (DfT, 2014, p.1). The availability of detailed accessibility statistics at the small-area level is a considerable asset for the spatial analysis of travel behaviour in England, as these do not need to be calculated from scratch (as it is the case in other countries – see e.g. Rendall et al., 2014; Siedentop et al., 2013), they are available in a standardised format in England, and are regularly updated.

While MOT data are available for the whole of Great Britain, in this paper we limit our analysis to England (32,840 LSOAs), as directly comparable accessibility statistics are unavailable for Scotland and Wales. In accordance with previous analyses of the MOT dataset (Chatterton et al., 2015; 2016; in press) we use data for 2011, as this allows linkage with a range of external data sources, including Experian income data. Data in the MOT dataset are based on LSOA boundaries from the 2001 Census, while income and accessibility statistics refer to updated 2011 boundaries. As a result, we have to exclude from the analysis 1,173 English LSOAs (3.57%) for which boundaries have changed.

4. Construction of composite indicator

As discussed above, we propose a composite indicator of vulnerability based on three dimensions: exposure, sensitivity and adaptive capacity. The construction of the indicator is summarised in Table 2 below.

We operationalise exposure as the 'cost burden' of motor fuel, i.e. the ratio between average per household expenditure on fuel and average income in the area. This can be thought of as a sort of area-based equivalent to the measures of the proportion of income spent on fuel often used in studies taking households as the unit of analysis (see Section 2). The left-hand panel in Fig. 2 maps variations in the cost burden in England in 2011, showing lower levels of exposure around the main city-regions, and particularly Greater London.

The method used to estimate annual expenditure on motor fuel for all vehicles in a LSOA is described in detail in Chatterton et al. (in press). In this analysis, we average total expenditure over the total number of households living in the area, i.e. including both households with and without cars. This is appropriate as our goal is to assess the vulnerability of the *area as a whole*, not just of motorised households living in the area. In other words, the observed cost burden value is a function of both the 'extent' of exposure within the area (i.e. the number of households with vehicles) and its 'depth' (i.e. the level of motor fuel expenditure among households with vehicles), without however distinguishing between the two. For an exploration of spatial patterns in the motoring expenditure of motorised households in England see Chatterton et al. (in press).

The patterns of spatial variation in the cost burden ratio illustrated in the left-hand panel in Fig.2 give a first indication of the geography of vulnerability to fuel price increases in England. However, it would be inappropriate to draw conclusions based on this indicator only. This is because areas with similar cost burden levels may have very different levels of income and/or very different levels of car dependence. In other words, areas that are

similarly exposed to motor fuel price increases may be very differently placed in terms of their ability to *maintain* current travel patterns by increasing fuel expenditure, or *adapt* them by switching to alternative modes (Rendall et al., 2014). This requires us to complement the cost burden measure with indicators of sensitivity and adaptability.

Dimension	Indicator	Variable	Data sources and year of reference
Exposure	Cost burden of motor fuel	Ratio between: (i) estimated mean expenditure on motor fuel per household; (ii) median income	MOT dataset (2011); DVLA Vehicle Stock Data (2011); Experian Demographic Data (2011)
Sensitivity	Income	Median income	Experian Demographic Data (2011)
Adaptive Capacity	Accessibility to key services by modes alternative to the car	Sum of estimated journey time to eight key services (employment centre, primary school, secondary school, further education establishment, general practitioner surgery, hospital, food shop, and town centre) by public transport or walking (whichever is the quickest)	DfT Accessibility Statistics (2011)

Table 2. Components of the composite indicator of vulnerability

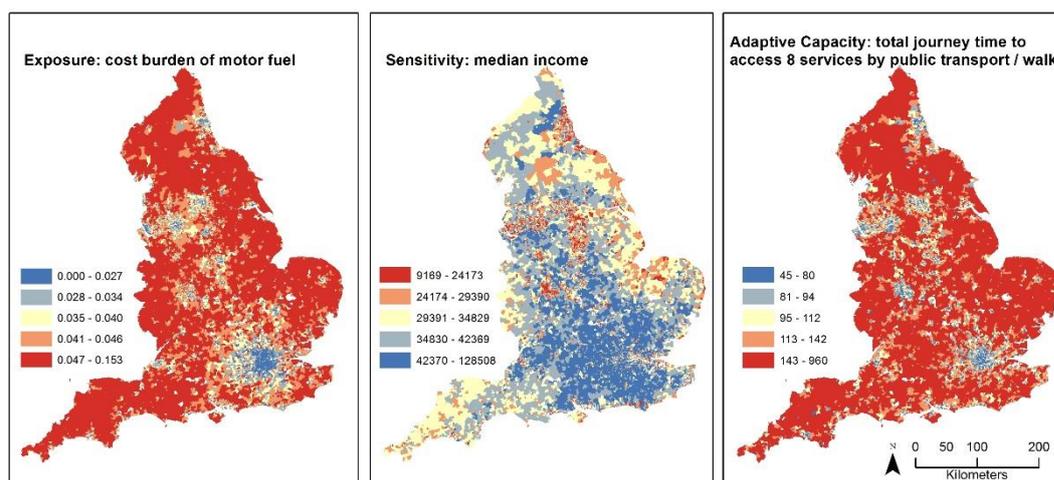


Figure 2. Maps of variations in the components of the vulnerability index in England (2011) by LSOA (keys based on quintiles)

In line with previous research, we operationalise sensitivity as (median) income in the area. The central panel in Fig. 2 maps income variations in England in 2011, showing a contrast between the richer South East and the rest of the country, with notable concentrations of low income around the core of city-regions in the North of England.

As shown in Table 2, median income appears twice in our composite indicator of vulnerability: first, on the denominator of the exposure indicator (cost burden ratio); second, as a separate indicator of sensitivity. This does not amount to double counting as low income areas where expenditure is high *relative to median income* (such as area A in Fig.3), should be considered as more vulnerable than areas with a similar cost burden, but higher median income (such as area B in Fig.3). If expenditure was not normalised by income, lower (absolute) levels of expenditure in low income areas may make low income areas appear less vulnerable than they actually are, leading to misleading conclusions. The approach adopted here reproduces the logic of the 'Low-Income High Costs' indicator proposed by Mattioli, Wadud and Lucas (2016) to measure vulnerability at the household level.

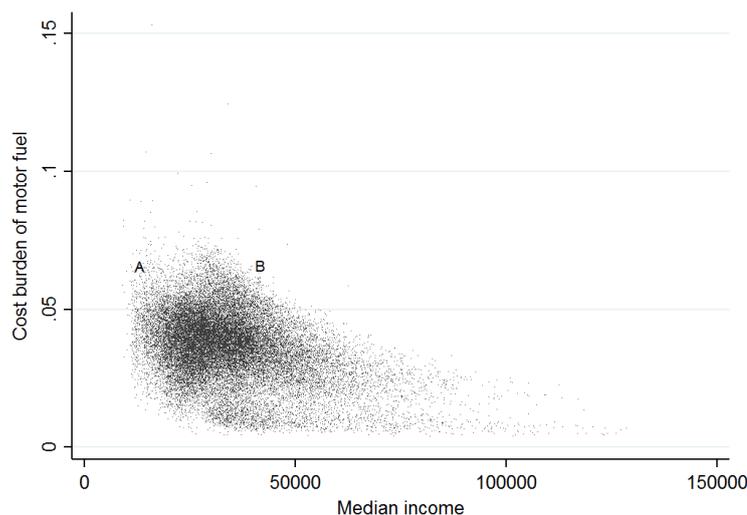


Figure 3. Cost burden of motor fuel by Experian median income for LSOAs in England (2011)

The final component of the index proposed here is an indicator of adaptive capacity. We operationalise this as the level of accessibility to key services by modes alternative to the car. This can be conceptualised as the opposite of 'structural' car dependence in the area (Mattioli, Anable & Vrotsou, 2016; Siedentop et al., 2013). It is important to note that switching to non-car modes is not the only possible adaptive response for households exposed to increases in motor fuel prices. Over the longer term, households may for example change their residential location to avoid the economic stress of 'enforced' car ownership and use in car dependent areas (Motte-Baumvol et al., 2010), or substitute their vehicle with a more fuel-efficient one. Therefore, the indicator used here is better suited to capture 'short term' adaptive capacity (Leung et al., 2015) to fuel price 'shocks'²; it is less well suited (although still relevant) to assess the capacity to adapt to more gradual fuel price increases that are maintained over a long period. Possible limitations notwithstanding, the adoption of an indicator of adaptive capacity based public transport and walking accessibility is consistent with previous oil vulnerability research. At the same time, the measure adopted here constitutes an improvement over the indicators reviewed in Table 1, as it takes into account access to several types of destination, rather than just employment.

We calculate accessibility measures for LSOAs in England using data from the UK Department for Transport LSOA Accessibility Statistics 2011 (DfT, 2012). We take into consideration the time required to travel to the nearest destination in eight different categories: employment centre, primary school, secondary school, further education establishment, general practitioner surgery, hospital, food shop, and town centre. These destinations are justified for use in the statistics because "being able to access employment, educational opportunities and essential services is key to people's well-being, life chances and social inclusion" (Kilby & Smith, 2012, p.6). This argument was articulated in the influential report of the Social Exclusion Unit on transport and social exclusion (SEU, 2003) and adopted into 'accessibility planning' policy from 2004.

We use the statistic mean minimum travel time by public transport (including walk access and egress) or walking if walk time is shorter to each destination. We do not consider cycling as the mode share of cycling is very low in England (2% of trips and 1% of distance in 2014 (DfT, 2016)), not everyone has a bike and has physical capability to cycle (Philips, 2014), and there is evidence to suggest that cycle ownership is less likely in more deprived areas (Anable 2010). Also, integrating measures of time by public transport/walking and cycling would require the development of ad-hoc methods, complicating the calculations. We assume walking time to be a reasonable proportional proxy for accessibility by non-motorised modes.

In order to assess accessibility to all eight key destinations, for each LSOA we sum the travel time by public transport or walking (whichever is the quickest) to the nearest destination of each type. The summary measure obtained can be interpreted as the total travel time (one-

² A fuel price shock may be defined as a scenario in which fuel prices increase by 50% within one year (Oxford Economics, 2011).

way) required to access all eight key destinations by modes alternative to the car from that LSOA³. The right-hand panel in Fig. 2 maps variations in total travel time in England in 2011, showing better levels of accessibility in and around the main city-regions and rail corridors.

One possible concern in adding up travel time values for different destinations is that these have very different distributions, with e.g. hospitals and secondary schools requiring typically more travel time than GP surgeries and primary schools (DfT, 2012). As a result, differences in total travel time between LSOAs may be driven mostly by services that are typically further away in space and time. To control for this effect, we computed a 'corrected' measure of total travel time as follows. First, for each of the eight services, travel time was converted to a z-score (number of standard deviations by which the observation is above the mean), obtaining a variable with a mean of zero and standard deviation of one. This converted the eight travel time variables to a common scale. In a second step, the z-scores were summed together to create a 'corrected' total travel time measure. Since the corrected and non-corrected measure are highly correlated (Pearson's $r=0.981$), we opted for using the non-corrected one, as it is easier to interpret.

A second sensitivity test was carried out to explore whether a more sophisticated measure of car dependence could be computed based on the available data. Besides travel time by public transport and walking, DfT accessibility statistics also provide the time required to access services by car. Based on both sets of data, we computed for each LSOA the *difference* between the time required to access services by car and by public transport/walking. This can be seen as a measure of the *additional time* that individuals would have to travel if they had to switch from the car to alternative modes. Ultimately, however, we decided to use total travel time by alternative modes, for three reasons. First, the two measures are highly correlated ($r=0.875$), and visual inspection of the resulting maps suggests that they highlight rather similar spatial patterns. Second, for a number of LSOAs we found a negative difference, i.e. longer travel time by car than public transport/walking, even in the absence of an obvious reason for it. Third, the 'total travel time' measure is easier to interpret.

Based on the results of the sensitivity tests, we conclude that total travel time to services by public/transport walking is a good proxy for the level of car dependence at the LSOA level, and we employ it as the adaptive capacity component of the vulnerability index.

Having selected the indicators, the next step in the construction of a composite indicator is their aggregation in a single measure (OECD, 2008). This step entails methodological choices with regard to the *normalisation* and the *weighting* of the indicators, which are discussed below.

When indicators have different measurement units (as is the case here), normalisation of data is required to render the variables comparable, i.e. to avoid that variables with a larger scale (e.g. in our case, income) outweigh the others. Various methods of normalisation exist (OECD, 2008, p.30), some of which have been used in previous 'oil vulnerability' studies:

- a. *standardisation* of indicators based on mean and standard deviation (see above)
- b. *categorical scale* methods, whereby, for each indicator, a score is assigned based on the percentiles of the distribution of the indicator across cases
- c. *Min-Max* normalisation methods subtract the minimum value and divide by the range of the indicator values, resulting in a variable in the range 0-1 (OECD, 2008, p.30)

To test sensitivity, we computed three versions of the composite indicator, based on the three normalisation methods above (categorical scale with score 1-10, based on deciles). The results show very high correlation between the three resulting indices (Spearman's rank correlation coefficients $r_s > 0.95$). We opt for the standardisation method, as it preserves information about variance in the original indicators and is easier to interpret. For instance, composite indicator values at or around zero suggest an average situation on all dimensions vulnerability (or a situation where indicators offset each other). Very positive (negative) values correspond to high (low) vulnerability.

³ DfT travel time statistics have a two hour cut-off, i.e. any journey longer than this is given a value of 120 minutes but should be qualitatively interpreted as not accessible. As a result, the measure of 'total travel time' adopted here may underestimate travel time in the areas with the lowest levels of accessibility.

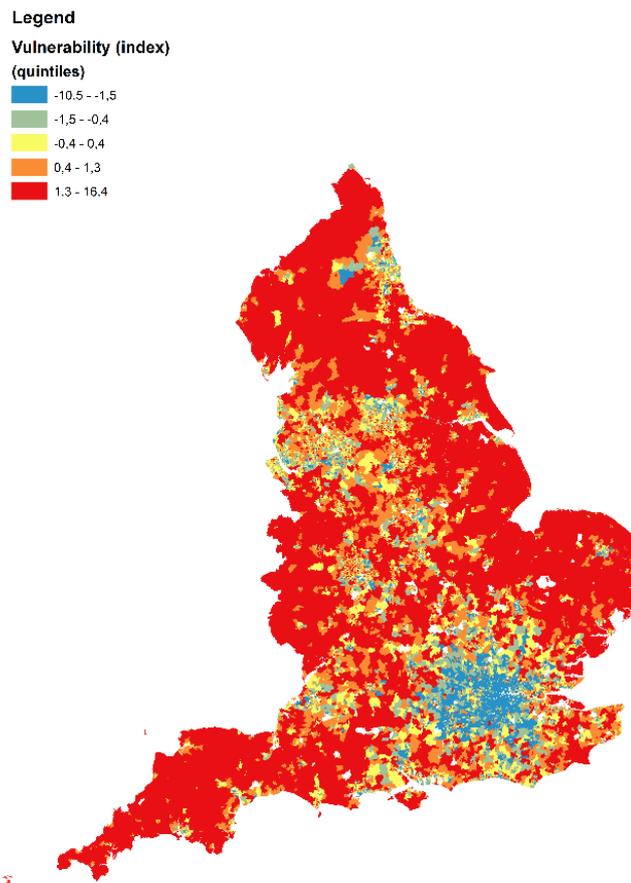


Figure 4. Map of variations in the composite indicator of vulnerability to fuel price increases in England (2011) by LSOA (key based on quintiles).

The normalisation procedure ensures that indicators are on a common scale. Yet, it may be sensible to assign different weights to different indicators, if that is consistent with the theoretical framework adopted. Previous studies have typically (either explicitly or implicitly) given equal weights to each sub-dimension of oil vulnerability, and equal weighting is indeed the most common approach for composite indicators (OECD, 2008, p.31). In the absence of a clear theoretical rationale for adopting unequal weights, we adopt the same approach here. Weighting may be adapted in the future if further research were to demonstrate the need for unequal weights.

In the framework adopted here, high vulnerability to fuel price increases (VFP) results from high exposure (E), high sensitivity (S) and low adaptive capacity (AC), as illustrated in the formula below (adapted from Leung et al., 2015):

$$(2) \quad VFP = E + S - AC$$

Since some of the indicators adopted here are scaled in the opposite direction (sensitivity is the opposite of income and adaptive capacity is the opposite of travel time by alternatives), the following formula is adopted:

$$(3) \quad VFP = cost\ burden - income + travel\ time$$

The most vulnerable areas are therefore defined as those with high cost burden of motor fuels, low income and high levels of car dependence. The values of the resulting index are mapped in Fig.4, with classes based on quintiles of the distribution. The map shows lower

levels of vulnerability in Greater London and the South East, as well as in the core of most Northern city-regions. High vulnerability prevails in lower density (and therefore larger) LSOAs, which explains the prevalence of red coloured areas in Fig.4.

5. Conclusion: potential applications of the composite indicator

A substantive discussion of the spatial patterns of vulnerability highlighted by the index is beyond the scope of this paper, and will be the object of a forthcoming article. Instead, in this section, we review possible applications of the composite indicator in future research.

First, the framework adopted here could be used to investigate how the different dimensions of vulnerability interact with each other. Initial work on Australian cities has shown a 'regressive' urban structural effect, whereby low income and high car dependence are strongly co-located in the urban periphery (Dodson & Sipe, 2007). Similar work on city-regions in New Zealand (Rendall et al., 2014) and continental Europe (Büttner et al., 2013), however, has highlighted different patterns (Mattioli & Colleoni, 2016). The set of indicators proposed here allows the investigation of this relationship in English city-regions. Similarly, previous research on Australian cities has suggested that areas with high vulnerability are also characterised by lower rates of diffusion of diesel and other alternative energy vehicles, and thus worse average fuel economy of the vehicle fleet, which further compounds their situation (Li et al., 2017). The MOT and DVLA datasets employed here allow the investigation of this relationship for England, as they include detailed information on vehicle characteristics and fuel economy.

Second, the methodology developed in this paper could form part of a broader indicator framework around vulnerability and adaptive capacity to changes in transport cost and availability, containing more sophisticated adaptive capacity measures for both motorised modes and walking and cycling (Philips et al., in press; Rendall, 2011). These in turn may be used to assess the distributional impact of policy changes. For example, subsidies to local bus services have been drastically cut in the UK since 2010, and this may have weakened the resilience of areas which, according to our analysis, had high pre-existing levels of vulnerability.

Third, our indicator of vulnerability to fuel price increases would benefit from being contextualised with other, non-transport indicators available at a spatially disaggregated level. For example, a joint analysis of the vulnerability index and the official Indices of Multiple Deprivation (DCLG, 2015) may reveal to what extent the measure proposed here captures a phenomenon that is distinct and non-overlapping with other, more widely acknowledged forms of disadvantage. A joint analysis with official metrics of housing affordability would help identify areas affected by both problems, contributing to international debates on the combined burden of housing and transport costs (e.g. Renne & Sturtevant, 2016). Similarly, the spatial relationship between vulnerability to fuel price increases in the transport and domestic sectors may be worth exploring. Previous work based on MOT data has shown a spatial association between high energy consumption for car usage, domestic gas and electricity in England and Wales (Chatterton et al., 2016). A joint analysis of the index proposed here and official LSOA-level estimates of domestic 'fuel poverty' (DECC, 2016) may answer the question whether different forms of 'energy-related economic stress' overlap spatially.

More broadly, spatial patterns of socio-economic status and living standards within metropolitan areas are attracting increasing attention in the UK (Clarke, 2016; Hunter, 2016), in a context marked by the ongoing devolution of powers to city-regions and a trend towards the suburbanization of poverty. While the importance of transport costs for household budgets is typically acknowledged, there is still a dearth of empirical analysis of this aspect at a spatially disaggregated level. The metric proposed here could thus contribute to inform policy debates on socio-spatial inequalities within English city regions.

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⁴ See <http://www.bettertransport.org.uk/save-our-buses>

References

- ADGER, W. N. (2006) Vulnerability. *Global Environmental Change*. 16(3), p. 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. *International Journal of Environmental Science and Technology*. 11(8), p. 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*. Abingdon: Routledge.
- ANABLE, J. (2010) *Analysis of walking and cycling activity and its relationship to social-economic status (Monitoring and Evaluation of the Smarter Choices Smarter Places Programme, Working paper 2010/01)*. Scottish Government.
- ARICO, R. S. M. (2007) *Measuring the oil vulnerability of Canadian cities*. Doctoral dissertation, Simon Fraser University.
- BROOKS, N. (2003) Vulnerability, risk and adaptation: A conceptual framework. *Tyndall Centre for Climate Change Research Working Paper*, 38, p. 1-16.
- BÜTTNER, B., WULFHORST, G., CROZET, Y. & MERCIER, A. (2013) The impact of sharp increases in mobility costs analysed by means of the Vulnerability Assessment. *13th World Conference on Transport Research*, Rio de Janeiro, July 15-18, 2013.
- CAIRNS, S., WILSON, R.E., CHATTERTON, T., ANABLE, J., NOTLEY, S. & MCLEOD, F. (2014) *Using MOT tests data to analyse travel behaviour change – scoping report*. Transport Research Laboratory.
- CCC (2015) *The fifth carbon budget, The next step towards a low-carbon economy*. Committee on Climate Change.
- CHATTERTON, T., ANABLE, J., BARNES, J. & YEBOAH, G. (2016) Mapping household direct energy consumption in the United Kingdom to provide a new perspective on energy justice. *Energy Research & Social Science*. 18, p. 71-87.
- CHATTERTON, T., ANABLE, J., CAIRNS, S. & WILSON, E. (in press). Financial implications of car ownership and use: a social and spatial distributional analysis. *Transport Policy*.
- CHATTERTON, T., BARNES, J., WILSON, E., ANABLE, J & CAIRNS, S. (2015) Use of a novel dataset to explore and social variations in car type, usage and emissions, *Transportation Research Part D*, 39, p. 151-164.
- CLARKE, S. (2016) *City Living. Devolution and the living standards challenge*. Resolution Foundation.
- DBEIS (2016) Road fuel and other petroleum product price statistics. [<https://www.gov.uk/government/collections/road-fuel-and-other-petroleum-product-prices>, accessed on 22 August 2016].
- DCLG (2015) *The English Indices of Deprivation 2015*. Department for Communities and Local Government.
- DECC (2016) *Sub-regional fuel poverty, 2016. Statistical methodology*. Department of Energy and Climate Change.
- DFT (2012) *Accessibility Statistics 2011*. Department for Transport.
- DFT (2014) *Accessibility Statistics 2013*. Department for Transport.
- DFT (2016) *National Travel Survey: England 2015*. Department for Transport.
- DODSON, J., & SIPE, N. (2007) Oil vulnerability in the Australian city: Assessing socioeconomic risks from higher urban fuel prices. *Urban Studies*. 44(1), p. 37-62.
- EEA (2015) *Evaluating 15 years of transport and environmental policy integration*. EEA Report No 7/2015.
- EXPERIAN LIMITED. (2007). Experian Demographic Data, 2004-2005 and 2008-2011. [data collection]. UK Data Service. SN: 5738, <http://dx.doi.org/10.5255/UKDA-SN-5738-1>
- FISHMAN, E. & BRENNAN, T. (2009) Oil vulnerability in Melbourne. *Institute for Sensible Transport*.
- HUNTER, P. (2016) *Towards a suburban renaissance: an agenda for our city suburbs*. The Smith Institute.
- KILBY, K. & SMITH, N. (2012) *Accessibility Planning Policy: Evaluation and Future Directions. Final Report*. Atkins & Centre for Research in Social Policy.
- 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 Australian Cities Conference*.

-
- LI, T., SIPE, N. & DODSON, J. (2017) Motor vehicle fleets in oil vulnerable suburbs. A prospect of technology innovations. In DODSON, J., SIPE, N., & NELSON, A. (eds.), *Planning after petroleum. Preparing cities for the age beyond oil*. Abingdon: Routledge.
- LOVELACE, R. & PHILIPS, I. (2014) The 'oil vulnerability' of commuter patterns: A case study from Yorkshire and the Humber, UK. *Geoforum*. 51, p. 169-182.
- MATTIOLI, G., ANABLE, J. & VROTSOU, K. (2016) Car dependent practices: Findings from a sequence pattern mining study of UK time use data. *Transportation Research Part A*. 89, p. 56-72.
- MATTIOLI, G. & COLLEONI, M. (2016) Transport disadvantage, car dependence and urban form. In PUCCI, P. & COLLEONI, M. (eds.), *Understanding Mobilities for Designing Contemporary Cities*. Wiesbaden: Springer.
- MATTIOLI, G., WADUD, Z. & LUCAS, K. (2016) Developing a Novel Approach for Assessing the Transport Vulnerability to Fuel Price Rises at the Household Level, *14th World Conference on Transport Research*, 10-15 July 2016, Shanghai, China.
- MOTTE-BAUMVOL, B., MASSOT, M. H. & BYRD, A. M. (2010) Escaping car dependence in the outer suburbs of Paris. *Urban Studies*. 47(3), p. 604-619.
- NEWMAN, P., BEATLEY, T. & BOYER, H. (2009) *Resilient cities: responding to peak oil and climate change*. Washington: Island Press.
- OECD (2008) *Handbook on Constructing Composite Indicators. Methodology and User Guide*. Organisation for Economic Co-Operation and Development.
- ORTAR, N. (in press) Dealing with energy crises: Working and living arrangements in peri-urban France. *Transport Policy*.
- OXFORD ECONOMICS (2011) *Fossil fuel price shocks and a low carbon economy*. Report for the Department of Energy and Climate Change
- PHILIPS, I. (2014) *The potential role of walking and cycling to increase resilience of transport systems to future external shocks: creating an indicator of who could get to work by walking and cycling if there was no fuel for motorised transport*. PhD thesis, University of Leeds.
- PHILIPS, I., ANABLE, J., CAIRNS, S., EMMERSON, P. & CHATTERTON, T. (2017) A Spatial typology of car usage and its local determinants in England. *49th Annual Universities Transport Study Group Conference*, 4-6 January 2017, Dublin.
- PHILIPS I, CLARKE G & WATLING D. (in press) A Fine Grained Hybrid Spatial Microsimulation Technique for Generating Detailed Individuals from Multiple Data Sources: An Application to Walking and Cycling, *International Journal of Microsimulation*
- RENDALL, S., PAGE, S., REITSMA, F., VAN HOUTEN, E. & KRUMDIECK, S. (2011). Quantifying Transport Energy Resilience. *Transportation Research Record*. 2242, p. 72–80.
- RENDALL, S., PAGE, S. & KRUMDIECK, S. (2014) Voila! A new measure of oil vulnerability for cities. *1st International e-Conference on Energies*, 14-31 March 2014.
- RENNE, L. & STURTEVANT, L. A. (2016) Background, Outline, Emerging Themes, and Implications for Housing and Transportation Policy. *Housing Policy Debate*. 26(4-5), p. 563-567.
- 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), p. 117-130.
- SEU (2003) *Making the connections: final report on transport and social exclusion*. London: Office of the Deputy Prime Minister.
- SIEDENTOP, S., ROOS, S. & FINA, S. (2013) Ist die "Autoabhängigkeit" von Bewohnern städtischer und ländlicher Siedlungsgebiete messbar? *Raumforschung und Raumordnung*. 71(4), p. 329-341.
- WILSON, R. E., CAIRNS, S., NOTLEY, S., ANABLE, J., CHATTERTON, T. & MCLEOD, F. (2013a) Techniques for the inference of mileage rates from MOT data. *Transportation Planning and Technology*. 36(1), p. 130-143.
- WILSON, R. E., ANABLE, J., CAIRNS, S., CHATTERTON, T., NOTLEY, S. & LEES-MILLER, J. D. (2013b). On the estimation of temporal mileage rates. *Transportation Research Part E*. 60, p. 126-139.
- WORLD BANK (2016) World Bank Commodities Price Forecast. [<http://pubdocs.worldbank.org/en/764161469470731154/CMO-2016-July-forecasts.pdf>, accessed 20 September 2016].
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