Understanding car ownership elasticities in England and Wales: Advancing the evidence base with new data sources

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Summary

This study presents global and local models explaining household car ownership elasticity in England and Wales based on new datasets from Experian household *median income* and 2011 Census released by UK Government agencies. Latest empirical evidence on car ownership elasticity across the area is based on 2001 Ward level household *average income* estimates and 2001 Census. In using different income estimates and new datasets, new evidence is compared with what we already know about car ownership elasticity. Geographically weighted regression is utilized to estimate and forecast car ownership elasticities at both Ward and Lower layer Super Output Areas. With our initial modelling in this paper, we suggest that future work should incorporate road worthiness tests data, at lower geographies when released, from Ministry of Transport (MOT) as a proxy for car ownership (and use) to undertake a comparative analysis towards deepening our understanding of car ownership (and use) trends to inform transport policy in England and Wales.

KEYWORDS: car ownership, median income, geographically weighted regression, elasticity, MOT test

1. Introduction

Existing 21st Century approaches used to estimate car ownership models may be grouped into two categories: a-spatial and spatial approaches. Most of the studies found fall in the a-spatial category (Clark and Finley, 2010; Clark, 2009; Dargay and Hanly, 2007; Dargay, 2002, 2001; Leibling, 2008; Litman, 2013; Whelan, 2007); with limited studies using a spatial approach (Clark, 2007a). Figure 1 indicates a range of a-spatial and spatial approaches employed in earlier studies whilst Figure 2 shows an overview of the variety of datasets used since 2000 to study car ownership in the UK.

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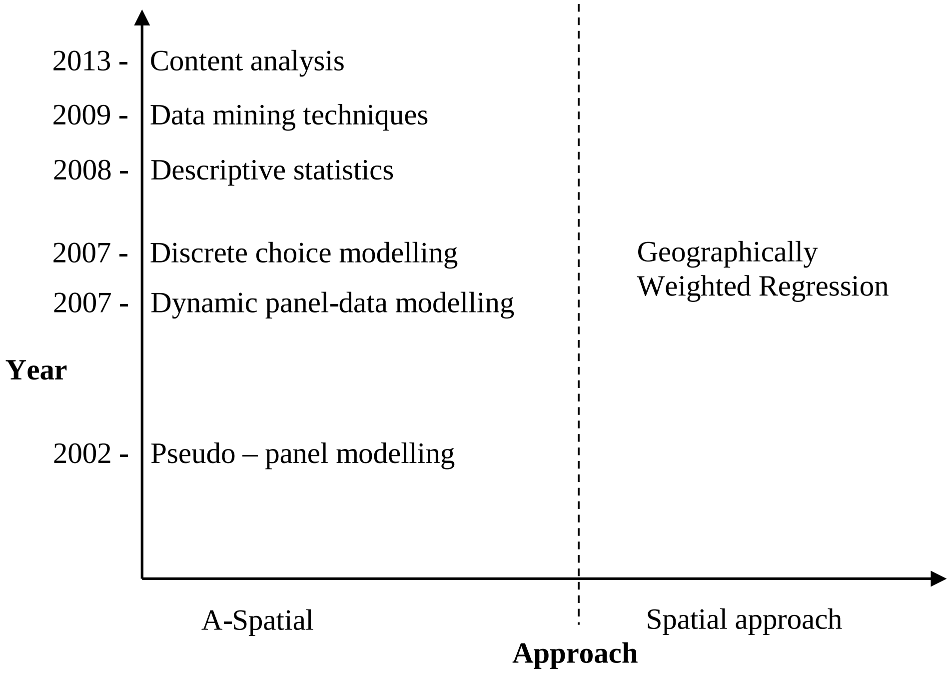

Figure 1: Overview of car ownership study approaches in the 21st Century

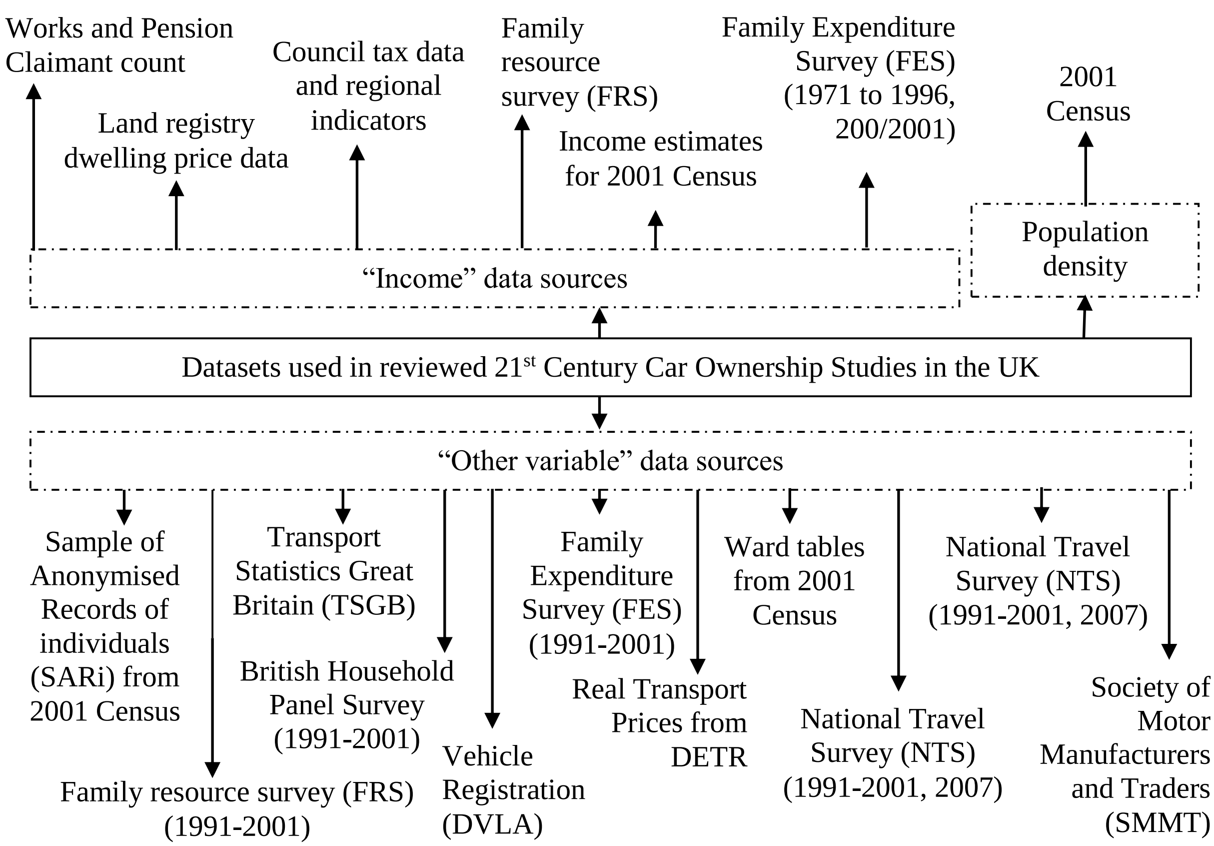

Figure 2: Sketch of datasets used in reviewed 21st Century Car Ownership Studies in the UK

ONS means Office for National Statistics; BHPS means British Household Panel Survey; DVLA means Driver and Vehicle Licensing Agency; DETR means Department for Environment Transport and the Regions.

The overarching research questions in this study comprise: 1) *What is the relationship between car ownership and household median income at both LSOA and Ward geographies*?; 2*) How does the strength of the relationship influence future elasticity scenarios of the number of cars in England and Wales?*; and, 3) *Does the modifiable area unit problem (MAUP) have an effect on the outcome of derived elasticity scenarios? Elasticity* is the measurement of how responsive an economic variable is to a change in another and could be considered a tool for measuring the responsiveness of one variable to changes in another. Elasticity has the advantage of being a unitless ratio, independent of the type of quantities being varied. In addressing these questions, a robust spatial analytical technique, geographically weighted regression (GWR), is used to estimate individual strength of the relationship for each LSOA and Ward along with future forecasts of the number of the size of vehicles in the area. The use of two geographies (i.e. LSOA and Ward) provides the empirical bases in addressing whether modified area unit problem (MAUP) has effect on the outcome of the future forecasts in this study; using at least two geographies is suggested (Flowerdew et al., 2008, p. 1254). The paper is divided into four main sections with this section inclusive: introduction, study area and data specification, analysis and results, and discussion and conclusion.

2. Study area and data specification

This study examines car ownership elasticities in England and Wales by using available datasets described in this section. We found available M.O.T tests datasets at the time of analysis too coarse (postcode district level) to use but we intend to include dataset (when released to the authors) in further analysis. Conducted literature review in this paper justifies the use of three key variables in our analysis; car ownership, income and population density.

2.1. Car ownership dataset

The car ownership data is taken from the 2011 Census (KS404EW) in the UK. The UK Census is taken every decade and the most recent is the 2011 Census. Car ownership at the household level is the number of cars or vans that are owned, or available for use, by one or more members of a household. This includes company cars and vans that are available for private use. It does not include motorbikes or scooters, or any cars of vans belonging to visitors. The count of cars or vans in an area relates only to households. Cars or vans used by residents of communal establishments are not counted. The Census gives an excellent snapshot of the country at a time. The 2001 Census version was only used to test results from previous study.

2.2. Household Median Income dataset

The availability of Household median income estimate, from Experian Limited, provided at LSOA geographies make analysis at LSOA level possible (Experian, 2011). Additionally, we argue that since one of the recent key findings from ONS suggest that growth in UK median household disposable income mirror closely growth in GDP from 1997 to 2012, using it to understand car ownership trends is more appropriate than household average income estimates (ONS, 2013). Further evidence is provided by Tim Harford, a UK Economist, that the median earnings in the UK, unlike US, have increased by 1.25% annually since 1968 (Harford, 2011). Average income estimates might not always reflect true income variations in economies where income disparities are wider. In the UK, although income inequality fell within 2011-2012 at its lowest since 25 years (Stewart and Osborne, 2013), the trend of income inequality is at alarming rate (EqualityTrust, 2013); and growing faster than any other rich country according to OECD with the top 10% having incomes 12 times greater than the bottom 10% (Ramesh, 2011). Given that income inequality is prevalent in the UK, we argue that median income estimates suggest a better reflection of "wealth" than average income estimates. Moreover, there seem to be no other recent relevant income data to use as the 2011 Census did not collect income information. The 2011 and 2004 median income estimates were used.

2.3. Geographic dataset and other explanatory variables

Two main geographies used are 2001 and 2011 Lower layer Super Output Areas (LSOAs) together with 2003 and 2011 Wards. Population density information from 2011 and 2001 Censuses were used in this study. Household structure and size could as well be used but this is not included due to possible co-linearity since it depends on number of people and number of household which are present in already chosen variables (Clark, 2007a); see Figure 2 for other data sources.

3. Analysis and results

3.1. Mapping significant clusters of car ownership, income and population density

As a first step, we explored areas in England and Wales where some Wards/LSOA with high car ownership can be determined to be statistically significantly ($p=<0.01$) different to the national household car ownership average. Applying Repley's K algorithm (a multi-distance spatial cluster analysis) gave a fixed distance of 17.5km exhibiting maximum spatial clustering effect which is used for the mapping in Figures 3 and 4. As shown in Figure 3 and Figure 4, there are differences in significant clusters at Ward and LSOA levels of analyses suggesting that further analysis at LSOA could provide more evidence to what we know at Ward level.

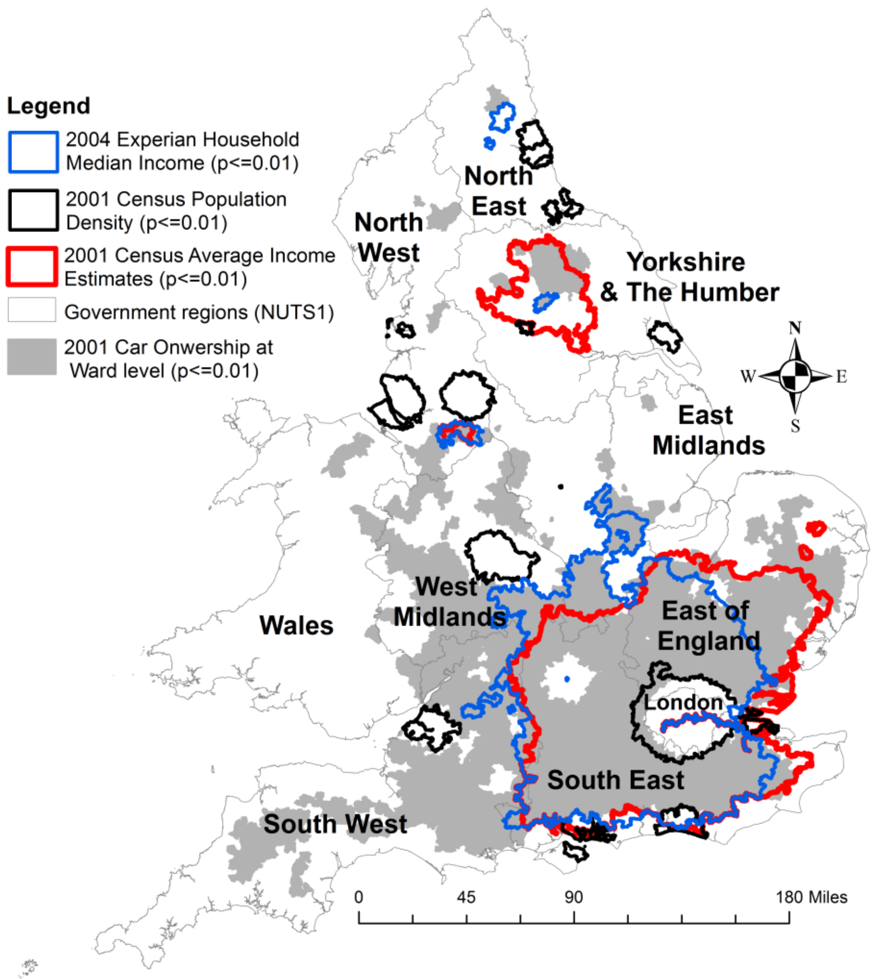

Figure 3: Statistically significant (p<=0.01) clusters of car ownership, population density, average and median income in England and Wales (Ward)

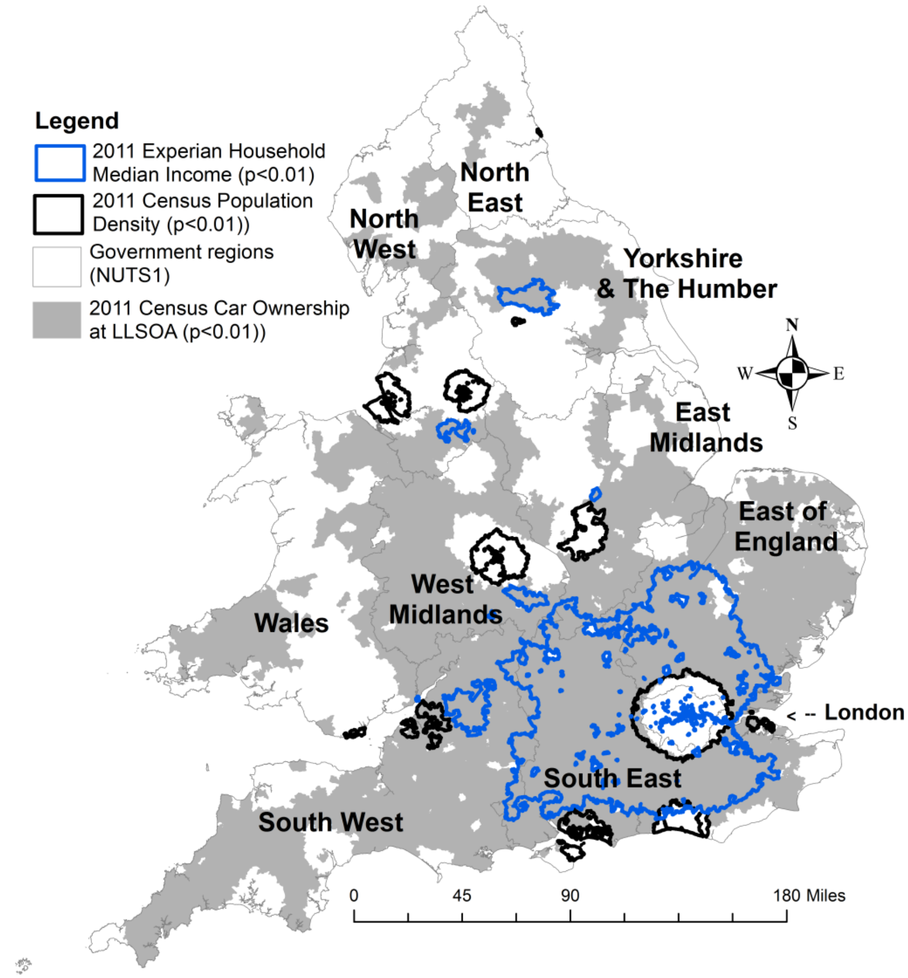

Figure 4: Statistically significant (p<=0.01) clusters of car ownership, population density, and median income in England and Wales (LSOA)

3.2. Car Ownership Models estimation with income and population density

3.2.1. Global models estimation at LSOA and Ward geographies

Logarithmic regression technique is used here to model car ownership with Experian's household median income and Census population density by comparing Clark's study which used 2001/2002 average income estimates data at Ward level along with other parameters. The comparison is done loosely with awareness that the income datasets are different in both studies but, the expectation is that these parameters should be reasonably close despite approximately two year's difference in income datasets and inherent estimation process. The average car ownership per household computed for the 8,805 Wards was still the same (1.223) as in Clark's study (which used 8,837 Wards). Results of global logarithmic regression model of car ownership at 2003 version of Ward geography (with 2004 Experian Median Income) show an adjusted R of .762:

$$\begin{aligned} &cars\ per\ household\ = \\ &\underset{(0.063)}{-5.051} + \underset{(0.006)}{0.638}\ Ln(2004\ Median\ Income) - \underset{(0.001)}{0.104}\ Ln(2001\ Population\ Density) \end{aligned} \quad \text{Eq.1}$$

The value of 0.52 (i.e. 0.638/1.223) shows that 10% rise in household median income gives rise to a 5.2% increase in car ownership at ward level across England and Wales. This is about 0.9% difference in prediction when the estimated household average income is used at ward level across England and Wales as shown in Clark's study. The average car ownership per household across England and Wales at LSOA is 1.19. Results of logarithm regression model of car ownership at LSOA geography (2011 Experian Income) show an adjusted R of .637:

$$\begin{aligned} &cars\ per\ household = \\ &\underset{(0.038)}{-3.585} + \underset{(0.004)}{0.503}\ Ln(2011\ Median\ Income) - \underset{(0.001)}{0.144}\ Ln(2011\ Population\ Density) \end{aligned} \quad \text{Eq.2}$$

The value of 0.42 (i.e. 0.503/1.19) shows that 10% rise in household median income gives rise to a 4.2% increase in car ownership at LSOA level across England and Wales. The coefficient of the median income parameter is reduced which in-turn affects the elasticity parameter for the prediction. Results of logarithm regression model of car ownership at 2011 Ward geography (2011 Household Median Income) show an adjusted R of .539:

$$\begin{aligned} &cars\ per\ household = \\ &\underset{(0.024)}{1.156} + \underset{(0.002)}{0.050}\ Ln(2011\ Median\ Income) - \underset{(0.002)}{0.147} Ln(2011\ Population\ Density) \end{aligned} \quad \text{Eq.3}$$

The average car ownership per household at 2011 Ward geography is 1.3. The value of 0.04 (i.e. 0.05/1.3) suggests that 10% rise in household median income gives rise to a 0.4% increase in car ownership at LSOA level across England and Wales.

3.2.2. Local model estimates at LSOA and Ward geographies

Here, we are interested in finding out if any systematic spatial pattern exists in error estimates in the global regression models (Equation 2 & 3); our solution for eliminating any systematic pattern is the utility of Geographically Weighted Regression (GWR) technique in modelling these variables. GWR generates spatially calibrated regression models by generating separate regression equation for features in a sample data being investigated to explain the extent of spatial variation. Fotheringham et al. (2002) provide detail discussion of GWR. Even when spatial autocorrelation is identified, or not, in a global model, literature suggest that global measures tend to be misleading and that the use of localised version of spatial autocorrelation technique be used in the examining spatial arrangements of data (Fotheringham et al., 2002, pp. 14–15). Spatial autocorrelation still existed in the error estimates after the global logarithmic regression. Clark argued that goodness of fit for his case (i.e. at 2003 Ward level using 2001 Census data) improved from about 75.3% to 90.1% at 5% of neighbours (i.e. number of Wards) and it was due to considering the spatial component of the regression model. Thus, the use of spatially calibrated regression models provides better explanation than a-spatial regression regimes. The result from our calculation at 2011 LSOA suggests an improvement of goodness of fit from about 63.7% to 83.8% at 5% of neighbours. In using 2011Ward level values, the goodness of fit in our case improved from about 53.9% to 74.9% at 5% of neighbours.

3.2.3. Estimating number of cars and vans under six elasticity scenarios

We estimated the change in local and national car ownership of a 10% rise using household median income, and population density as co-variable, to show the effect of using different elasticity estimates. Table 1 shows results from six scenarios of predicted size of the national and London cars and fleets. Our results from the computed mean of car ownership elasticity ($\eta_{co} = 0.42$), from equation 2, which is a constant global elasticity assuming car ownership behaviour across England and Wales, suggest that relative increases of cars and van fleets, using 2011 LSOA level median income data, reflect similar differences (i.e. about 1.9% = 5.9-4.0) when 2001 Ward level specific elasticity ($\eta_{co} = 0.744/y_i$) is used as reported (i.e. about 1.9% = 8.6-6.7) by Clark (2007a, p. 195). However, our computation using 2011Ward specific elasticities from (η_{co} = 0.05/yi), gave relatively bigger difference (i.e. about 3.4% = 4.1- 0.7) for England and Wales and London. This might mean that average income affects predictions in London more than in England and Wales as Clark (2007a, p. 194) argues that “estimated national [i.e. England and Wales] parameter value of 0.744 is too high for the London situation”.

Scenario	England and Wales	London (excluding the City of London)
Number of cars and vans	27,294,656	2,662,722
Car and van fleet size after a 10% increase in median incomes		
Scenario 1: Using mean car ownership elasticity ($\eta_{co} = 0.423$) with respect to 2011 LSOA median income for prediction	28,386,442 (+4.0)	2,819,823 (+5.9)
Scenario 2: Using mean car ownership elasticity ($\eta_{co} = 0.039$) with respect to 2011 Ward median income for prediction	27,376,540 (+0.3%)	2,676,036 (+0.5%)
Scenario 3: The third scenario is to assume LSOA specific elasticities from ($\eta_{co} = 0.503/y_i$), which takes account of local circumstances but still assumes a uniformly estimated value for the strength of the relationship between car ownership and median incomes	28,604,800 (+4.8%)	2,849,113 (+7.0%)
Scenario 4: The fourth scenario is to assume 2011Ward specific elasticities from ($\eta_{co} = 0.05/y_i$), which takes account of local circumstances but still assumes a uniformly estimated value for the strength of the relationship between car ownership and median incomes	28,413,737 (+4.1%)	2,681,361 (+0.7%)
Scenario 5: The fifth scenario is the most flexible at LSOA level, it uses the locally (LSOA) estimated GWR median income parameters when estimating the elasticity $\beta_{LSOAmediannc ome(ui,vi)}/y_i$	29,068,809 (+6.5%)	2,795,858 (+5.0%)
Scenario 6: The sixth scenario is the most flexible at Ward level, it uses the locally (Ward) estimated GWR median income parameters when estimating the elasticity, $\beta_{Wardmediannc ome(ui,vi)}/y_i$	27,594,897 (+1.1%)	2,713,314 (+1.9%)

Table 1: Estimated number of cars and vans under six elasticity scenarios (3 scenarios x 2 spatial resolutions)

4. Discussion and conclusion

This study is in line with previous car ownership studies establishing income as a significant predictor, but different results were achieved using two levels of geographies (LSOA and Ward) when household median income was considered. GWR based approach was used to examine the relationship between household median income and car ownership along with population density at both Lower Layer Super Output and Ward geographies. We found similar values when Clark's results were re-computed for the three elasticity scenarios (only Ward levels) except small changes in the estimates for London scenarios; $0.744/y_i$ and β_{income}/y_i were 9.4% and 7% respectively (Clark study estimated 8.6% and 6.5% respectively). Despite the increase in parameters in GWR compared to global regression models, GWR model allows for a true estimation of the local parameter spatially (Clark, 2007b). Although Clark (2007a) suggested that his methodological approach could be used to understand other variables in 2001 Census and their relationship to income and other explanatory variables to map the outcome across England and Wales, we used the approach along with new datasets (particularly 2011 Census and 2011 Experian median income) to explain how car ownership relates to household median income using 2011 population density as a covariate data. MAUP was found to have varying effect on the derived elasticity scenarios as shown when the scenarios are compared (i.e. 1 & 2, 3 & 4, and 5 & 6); the differences in the case of London are bigger compare to the rest of England and Wales. It is suggested that future work should incorporate road worthiness tests data, at LLSOA and Ward geographies, from MOT as a proxy for car ownership and use to deepen our understanding of car ownership (and use) trends to inform transport policy in England and Wales. This is because the current MOT data released only contain postcode area information for Vehicle Test Stations (VTS) which is considered too coarse (Chatterton et al., 2014); and, therefore inappropriate for a comparative analysis in this paper. Having registered keepers information together with pass/fail MOT tests at LSOA geography, for example, will provide alternative to derived car ownership measure from the Census for understanding car ownership from a different perspective.

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6. Biography

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