Journal of Transport Geography 62 (2017) 30–37

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Temporal dynamics in local vehicle ownership for Great Britain

Stephen D. Clark[a,*], Sergio Rey[b]

[a] School of Geography and Leeds Institute for Data Analytics, University of Leeds, Leeds LS2 9JT, United Kingdom
[b] Center of Spatial Sciences, University of California, Riverside, United States

ARTICLE INFO

Keywords:
Vehicle ownership
Census
Temporal and spatial correlation
Spatial Markov chains

ABSTRACT

This article explores the stability of local vehicle ownership rates in Great Britain using the technique of spatial Markov chain analysis. Non-spatial Markov chain processes describe the transition of neighbourhoods through levels of ownership with no regard to their neighbourhood context. In reality however, how a neighbourhood transitions to different levels of ownership could be influenced by its neighbourhood context. A spatial Markov chain accounts for this context by estimating transition properties that are conditioned on the surrounding neighbourhood. These spatial Markov chain properties are estimated using a long run census time series from 1971 to 2011 of household vehicle ownership rates in Great Britain. These processes show that there is different behaviour in how neighbourhoods transition between levels of ownership depending on the context of their surrounding neighbours. The general finding is that the spatial Markov process will lead to a greater homogeneity in levels of ownership in each locality, with neighbourhoods surrounded by relatively low ownership neighbourhoods taking longer than a non-spatial Markov process would suggest to transition to higher levels, whilst neighbourhoods of high ownership surrounded by high ownership neighbourhoods take longer to transition to lower levels. This work corroborates Tobler's first law of geography "Everything is related to everything else, but near things are more related than distant things" but also provides practical guidance. Firstly, in modelling ownership, spatial effects need to be tested and when present, accounted for in the model formulation. Secondly, in a policy context, the surrounding neighbourhood situation is important, with neighbourhoods having a tendency towards homogeneity of ownership levels. This allows for the effective planning of transport provision for local services. Thirdly, vehicle ownership is often used as a proxy for the social and aspirational nature of an area and these results suggest that these properties will persist for a prolonged period, possibly perpetuating and exacerbating differentials in society.

1. Introduction

This study on vehicle ownership is set in the context of the island of Great Britain, which is part of the United Kingdom. Here vehicle ownership grew rapidly in the 20th century, as illustrated by the trends in Fig. 1 which show the shift in vehicle ownership levels since the early 1950s.

After previous rapid increases in vehicle ownership, the 21st century shows a more stable pattern, with one vehicle households accounting for around 45% of all households and two or more vehicle owning household accounting for a further 30%. The causes of this transition are well studied in the literature. Income is often cited, with households choosing to spend rising incomes on acquiring their first or subsequent vehicles. Household composition is also important, linked to life stage changes, e.g. the birth of the first or second child, a parent re-entering the work force, a late teenage child desiring independence and finally mobility and health issues in later life (Clifton, 2003; Hanly and Dargay, 2000; Prillwitz et al., 2006). In regards to wider factors, urban sprawl has tended to encourage vehicle ownership, although in Great Britain this has occurred to a lesser degree than in similar English speaking nations, particularly those outside Europe (Bramley et al., 2009). Environmentally, the UK's adoption of the recommendations of the Intergovernmental Panel on Climate Change in its Climate Change Act has necessitated policy interventions to try and mitigate the environmental impacts of vehicle use (Marsden and Rye, 2010). These have included a gradation in the amount of vehicle duty, now levied by engine size and fuel type, and the pricing mechanism of a fuel duty on petrol and diesel.

Having set the policy and historic context of vehicle ownership in Great Britain, the research question for this study is concerned with whether there is a spatial dimension to this changing pattern of ownership in Great Britain. In particular we ascertain if the likelihood of a neighbourhood to change its level of ownership relative to others is influenced by its surrounding neighbours and if so, how strong this

* Corresponding author.
E-mail addresses: tra6sdc@leeds.ac.uk (S.D. Clark), Sergio.Rey@ucr.edu (S. Rey).

http://dx.doi.org/10.1016/j.jtrangeo.2017.05.007
Received 20 April 2016; Received in revised form 21 May 2017; Accepted 22 May 2017

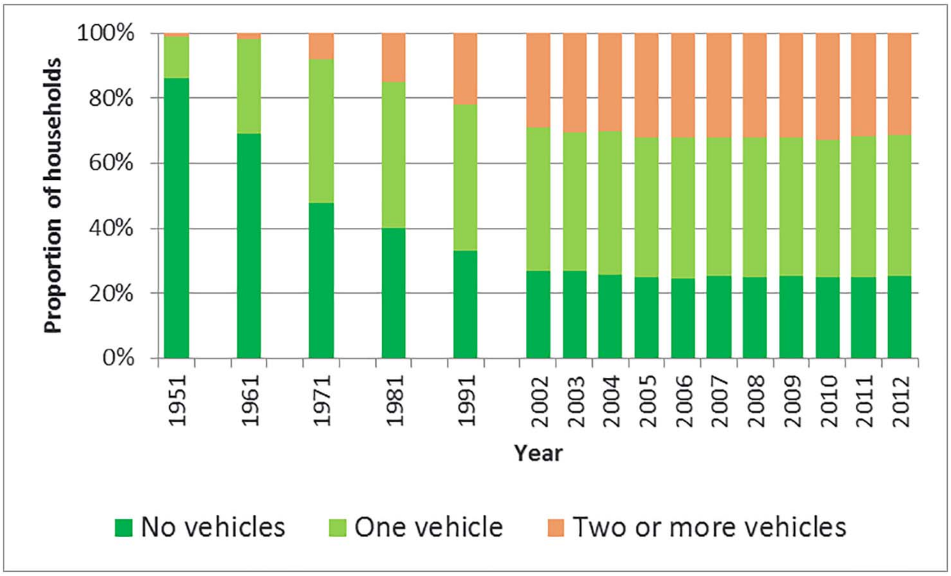

Fig. 1. Distribution of categories of vehicle ownership in Great Britain.

influence is. This is the first study to use the technique of spatial Markov chains to quantify the strength and duration of this relationship. Thus, whilst this study is not an attempt to model the determinates of vehicle ownership, it answers the question as to whether models that attempt to explain such ownership need to explicitly take account of neighbourhood effects in their specification (Paleti et al., 2013).

The following section provides a brief summary of the existing literature in the area of vehicle ownership modelling. Section 3 introduces the analysis technique of spatial Markov chains. Section 4 describes the data used in this study, the United Kingdom decennial censuses from 1971 to 2011. Section 5 presents the results of the analysis and is followed by Section 6 which provides a discussion of the results.

2. Literature review

Vehicle ownership is commonly examined using either individual disaggregate data or summary aggregate data (de Jong et al., 2004; Anowar et al., 2014). Access to disaggregate individual data, particularly if it is of a panel or longitudinal nature, allows the vehicle owning decisions of the individuals or households to be placed in the historic and contemporary context of their circumstances, e.g. the acquisition or disposal of a motor vehicle can be related to changes in household characteristics. Such data is however expensive to collect, has issues associated with being potentially disclosive of the individual's identify and, since it is ‘merely’ a sample of the population, cannot provide a complete picture. Most importantly here, the geographic coverage of such surveys is patchy, making local variations in any relationship difficult to identify. Recognising this shortcoming, adaptations of traditional econometric models to incorporate a spatial component into panel type data are beginning to be discussed and reported (Frazier and Kockelman, 2005; Paleti et al., 2013).

Alternative aggregate data has the advantages that it is not generally disclosive; it may also be constructed from a number of sources, e.g. governmental; commercial; or administrative (Redfern, 2004) and has the potential to provide a complete picture of a population under study. Periodic population censuses are common sources for such aggregate data and with the comprehensive coverage of such data, it becomes possible to examine local variations in aspects such as transport, travel and vehicle ownership. It is this aggregate form of vehicle ownership data that is used in this study.

Whilst this study is not concerned with the underlying mechanisms motivating vehicle ownership, merely with their outcome in a spatial context, it is worth highlighting some of the relevant spatial mechanisms so that it is possible to better understand these results. Firstly vehicle ownership has a utility in its own right; it confers the ability of individuals to travel to a destination of their choice, at a time of their choice, to receive a service. There are, however, impedances associated with this choice, primarily time, cost and congestion which need to be judged against alternatives (public transport, conducting business online or not making the journey). The availability and quality of public transport varies by place. In urban areas alternative public transport in the form of metro, trams, trains or buses are available. In sub-urban areas sustainable modes become more attractive, such as walking or cycling. In rural areas alternatives become less attractive, public transport is poor and distances to the nearest workplaces, schools, shops or health clinics may be large (Dargay, 2002).

Vehicle ownership is also used as a proxy for other things. The most common is its use in some facet of area classification or the calculation of a deprivation measure (Haase and Pratschke, 2005) where it is acting as a proxy for income. However this relationship between vehicle ownership and income is not straight forward. Typically these two are positively related but, as highlighted already, in rural areas a vehicle becomes almost an essential item, the encumbrance of which may cause strains on household budgets (Johnson et al., 2010). Conversely, in affluent urban areas with good quality public transport infrastructure, such as central London, the need for a private vehicle becomes almost unnecessary and potentially burdensome.

Whilst the above studies have identified how individual characteristics and ideas influence car ownership, there is also a case to be made to consider place and it is this aspect that is the most germane to this study. Pioneering work by Schelling (1969) showed that only subtle tendencies towards a desire to live with people of a similar background could, over time, produce dramatic segregation effects. Since neighbourhood are largely shaped by their inhabitants, if you live in a neighbourhood with high car ownership then you may be more likely to purchase a car or if you are re-locating and have a desire to remain or become a car owner then neighbourhoods with high car ownership will be more attractive (Pinjari et al., 2007). Looking beyond the immediate neighbourhood, if Tobler's law of geography is to be believed (Tobler, 1970), the influence is not just from the immediate neighbourhood but also surrounding neighbourhoods. Historically, aggregate models of vehicle ownership fail to explicitly take account of this influence and do not adopt a specification that accounts for spatial autocorrelation - although more recently a greater number of models that incorporate spatial relationships have begun to appear in the literature (Brunsdon et al., 1996; Clark and Finley, 2010). If the importance and significance of place could be established, then there would a strong case for such models to recognise this influence. It is the strength of this place influence that this study is aimed at establishing.

3. Spatial Markov chains

To explore the local dynamics of vehicle ownership, recent methods of spatial distribution dynamics are employed. The ownership rate is viewed from the lens of discrete Markov chains and the transitions of neighbourhoods across levels of ownership over time.

3.1. Markov chains

The point of departure is the classic discrete Markov chain framework where $r_{i,t}$, the ownership rate in area i at time period t, is discretised into one of K states. More specifically, state boundaries are taken as the quintiles of ownership over all spatial units in a given time period such that $x_{i,t} = j \Leftrightarrow Q_{j-1,t} < r_{i,t} \le Q_{j,t}$, with $Q_{j,t}$ the jth quintile threshold for period t, denoted as q_j.

The central focus in discrete Markov chain modelling is to map the distribution of ownership rates in one period onto that of a subsequent period, thus tracing out the evolution of the distribution over time. To do so, estimates of the probability transition matrix are obtained using maximum likelihood estimation:

$$\hat{p}_{j,l} = \frac{\sum_t n_{j,l,t}}{\sum_t \sum_{m=1}^{K} n_{j,m,t}} \tag{1}$$

where $n_{j,l,t}$ is the observed number of units that transitioned from ownership state j to state l over the time interval $(t, t+1)$ obtained as:

$$n_{j,l,t} = \sum_r \Upsilon_{r,j,l,t} \tag{2}$$

where:

$$\Upsilon_{r,j,l,t} = \begin{cases} 1 & \text{if } x_{i,t} = j \text{ and } x_{i,t+1} = l \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Here, we assume the chain is temporally homogeneous, meaning the transition probabilities are time invariant.

Collecting all cell estimates, gives:

$$\hat{P} = \begin{pmatrix} \hat{p}_{1,1} & \cdots & \hat{p}_{1,K} \\ \square & \ddots & \square \\ \hat{p}_{K,1} & \cdots & \hat{p}_{K,K} \end{pmatrix} \tag{4}$$

The transition probability matrix provides a wealth of information regarding the transitional dynamics of a Markov chain, as a number of useful summary measures can then be derived. Subject to the conditions that the chain: [1] is irreducible, meaning every state is reachable from every other state over time; [2] has all states positive recurrent; and [3] is temporally homogeneous, so the long run, or steady state, distribution of the chain can be estimated:

$$\hat{\pi}_*' = \hat{\pi}_*' \hat{P} \tag{5}$$

such that:

$$\hat{\Pi}_* = \hat{P}^{v}_{v\to\infty} \tag{6}$$

and:

$$\hat{\Pi}_{i,j} = \hat{\Pi}_{i+1,j} = \ldots = \hat{\Pi}_{k,j} \;\; \forall\, j \tag{7}$$

which implies that any row represents the transpose of the ergodic distribution $\hat{\pi}_*$.

Additionally, the first mean passage time required for the chain to pass from level j to level m is given as:

$$\hat{F} = (I - \hat{Z} + E\hat{Z})\hat{D} \tag{8}$$

where:

$$\hat{Z} = (I - \hat{P} + \hat{\Pi})^{-1} \tag{9}$$

$E = \iota\iota'$ where ι is a vector of ones, and ι' is its transpose, $\hat{D} = (\hat{\Pi})^{-1}$. When $i = j$ the first mean passage time is referred to as the recurrence time.

3.2. Spatial Markov chains

Whilst the classic discrete Markov chain is a flexible framework for modelling transitional dynamics, it has some potential limitations when applied in a spatial context. A key assumption is that the time series of transitions for each spatial unit provides independent information on the dynamics of change. However, this independence assumption rules out any interdependencies between the changes in one area and those in the surrounding area. To the extent that such interactions are at work, the classic discrete Markov chain would obscure the role of spatial spill overs in the dynamics.

One approach to extend the classic discrete Markov chain framework to incorporate a spatial dimension is the so called spatial Markov chain. Originally suggested by Rey (2001), the spatial Markov chain provides a mechanism to allow the transition probabilities to be conditioned upon the spatial context of an area. This is done by estimating conditional transition probability matrices with elements:

$$\hat{p}(s)_{j,l} = \frac{\sum_t n(s)_{j,l,t}}{\sum_t \sum_{m=1}^{K} n(s)_{j,m,t}} \tag{10}$$

where $n(s)_{j,l,t}$ is the observed number of areas that transitioned from state j to l in over period $(t, t+1)$ and whose neighbours had ownership rates in state s in period t. The latter is determined by first using the spatial lag of ownership rates defined as: $\tilde{r}_{i,t} = \sum_b w_{i,b} r_{b,t}$, where $w_{i,b}$ is a spatial weight indicating the potential interaction between area i and b. Here we use a row standardised contiguity matrix such that $w_{i,b} = \frac{c_{i,b}}{\sum_b c_{i,b}}$ where $c_{i,b} = 1$ if areas i and b are contiguous, 0 otherwise.

In a similar fashion to the discretisation of the original ownership rates, we have $\tilde{x}_{i,t} = j \Leftrightarrow Q_{j-1,t} < \tilde{r}_{i,t} \le Q_{j,t}$. From this we obtain:

$$n(s)_{j,l,t} = \sum_r \Upsilon(s)_{r,j,l,t} \tag{11}$$

where:

$$\Upsilon(s)_{r,j,l,t} = \begin{cases} 1 \text{ if } \tilde{x}_{r,t} = j,\ \tilde{x}_{r,t+1} = l \text{ and } L_{r,t} = s \\ \quad 0 \text{ otherwise} \end{cases} \tag{12}$$

and L is the lag operator.

The spatial Markov chain results in the estimation of K, $(K \times K)$ transition probability matrices, one for each state of the spatial lag. Tests of whether the probability transition matrices are different across these levels can be carried out to examine if there are spatial spill overs in the evolution of ownership rates. More formally:

$$H_0\colon p(1)_{j,l} = p(2)_{j,l} = \ldots = p(K)_{j,l} = p_{j,l} \;\; \forall\, j, l \tag{13}$$

$$H_a\colon \exists\, a\colon p(a)_{j,l} \ne p_{j,l}\ (k = 1, \ldots, K) \tag{14}$$

The specific tests to employ include a likelihood ratio test and a χ^2 test which have asymptotic chi-square distribution under the null hypothesis (Bickenbach and Bode, 2003) (These are provided in Section 5.2 below).

Rejection of the null hypothesis in favour of the alternative, that the transition probabilities are different, leads to the question of how the long run dynamics of vehicle ownership rates may be impacted by neighbourhood context. To answer this, estimates of the steady state distributions as well as the first mean passage times can be obtained for each of the conditional chains by substituting the estimated conditional probability transition matrix into Eqs. (6) and (9), respectively.

4. Processing of census data

This study uses data from the 1971, 1981, 1991, 2001 and 2011 United Kingdom censuses. The measurement of interest is the level of vehicle ownership, expressed as the mean number of vehicles per household, which is a continuous measure bounded below by zero. Data published in the National Travel Survey shows that nationally over the past 20 years this values has remained fairly stable at around 1.50 cars or vans per household, although with some regional variations; for example it is much lower in London, at around 0.80 cars or vans per household (Department for Transport, 2015). The advantage of studying the island of Great Britain is that there are no unknown edge effects, where information on neighbours is missing (since the edges are all water!) so $w_{i,b}$ is complete. The significant challenge associated with using these five censuses however is that there is little consistency in the output geography, making the comparison of how ownership levels change in a neighbourhood over time problematic. This inconsistency is understandable; over time, as places change (through administrative or population changes) the geography also needs to change to remain relevant. What is therefore required is a way to impose a consistent and meaningful geography on all five censuses.

The reporting geographies with the smallest populations are enumeration districts (EDs) in the 1971, 1981 and 1991 censuses and Output Areas (OAs) in 2001 and 2011. The EDs are an operational geography, defined as an area allocated to an enumerator to hand out and collect census forms, and also the EDs used in 1971 are not necessarily the same as those used in 1981 or 1991. The more recent OAs are a statistical geography designed using detailed census outputs to create homogeneous areas for the dissemination of census counts. Again, the EDs and OAs are not a consistent geography across the five censuses; this is illustrated in Fig. 2 which shows the 1981 census ED and 2011 census OA boundaries and population centroids (PWC) for the same geographic area in northern England (see Supplemental material for maps of the same area with 1971, 1991 and 2011 boundaries).

To carry out this analysis what is needed is a consistent geography so that the level of vehicle ownership in the exact same area can be measured between two censuses. Additionally the areas need to be: [1] able to provide reliable estimates; [2] of a size to reveal the potential neighbourhood effects that are under investigation; [3] conceptually robust and [4] capable of being estimated for all the censuses. The geography adopted for this purpose is the 2011 Middle layer Super Output Areas (MSOA) in England and Wales and the Intermediate Zones (IZ) in Scotland (Office for National Statistics, 2015) (these are shown as thick grey outlines in Fig. 2).

Taking point [1], the techniques used to provide estimates of household vehicle ownership involves the creation of a look-up of a small population geography (here EDs or OAs) to a larger population geography (here MSOAs\IZs). The typical number of EDs or OAs allocated to each MSOA\IZ in this lookup varies by time and space but is typically 15 to 25, which means that the estimate of ownership is based on a reasonable number of observations. Whilst being large enough to capture a reasonable number of EDs or OAs, the MSOA/IZs are still of a suitable size to embody a neighbourhood as required by point [2] (the average number of households in each MSOA\IZ in 1971 is 2222, rising to 3014 in 2011). In regards to point [3], the MSOAs\IZs are a statistical geography designed to cover an area which has a degree of homogeneity and are largely consistent for the latter 2001 and 2011 censuses. There are no equivalent middle layer geographies for the earlier three censes. The final point [4] is trivial given the availably of GIS files that define the PWC of the OAs and EDs and the boundaries of the MSOAs\IZs. The count of households and vehicles in each ED or OA are allocated to the MSO\IZ that its PWC falls within (Clark, 2015).

There are 8480 MSOAs and IZs in Great Britain and after the geo-conversion process, the distribution of the size of these MSOAs/IZs (in hectares) and number of households is shown in Table 1.

This approach provides us with a consistent temporal and spatial representation of vehicle ownership in Great Britain for the five decennial census years. Fig. 4 shows the map for the level of vehicle ownership rates, $r_{i,t}$, for the census years 1971, 1991, 2001 and 2001 (Supplemental material contains these same maps for all five censuses and an animated GIF file).

Before the spatial Markov matrices are estimated for these data, it would be useful to assess what the degree of spatial correlation there is present in these cross sectional data sets. This is done by calculating Moran's I statistic for each data set and Fig. 3 shows how this varies over a spatial range in each census (Sawada, 1999).

There is a clear pattern for the spatial correlation to diminish as the distance increases and also there is greater spatial correlation in the more recent census data. This suggests that there is a greater spatial polarisation in rates of vehicle ownership in more recent years.

5. Non-spatial and spatial results

The rates of vehicle ownership in each census are discretised into quintiles with the thresholds derived separately for each census year and the boundaries between these quintiles (Q_n) are shown in Table 2. This approach allows the rate of ownership for an area to be put in a national context and the relative change in ownership levels between censuses to be captured, rather than just change in the rate of ownership.

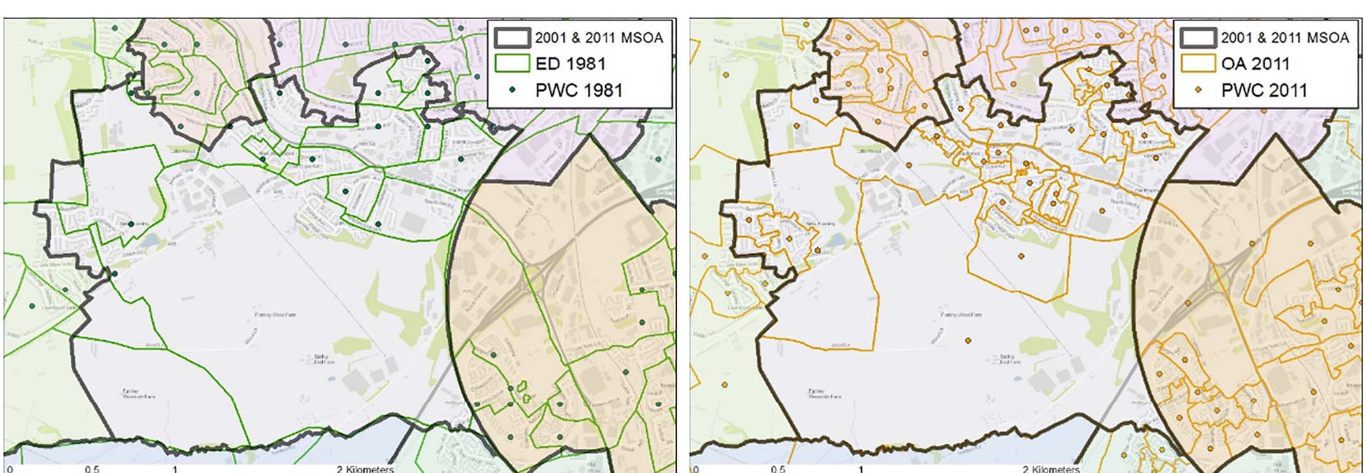

Fig. 2. Example geo-conversion data from EDs or OAs to MSOA E02002412.

Table 1
: Quintiles of MSOA\IZ area and number of households.

	Area (ha)	Households 1971	Households 1981	Households 1991	Households 2001	Households 2011
Q_0 (min)	15.2	0	14	28	58	734
Q_1	137.2	1449	1691	1995	2279	2401
Q_2	224.7	1950	2125	2402	2619	2810
Q_3	449.1	2381	2487	2758	3006	3205
Q_4	2112.5	2899	2926	3185	3396	3690
Q_5 (max)	320,695.0	7584	6414	6057	5758	6100

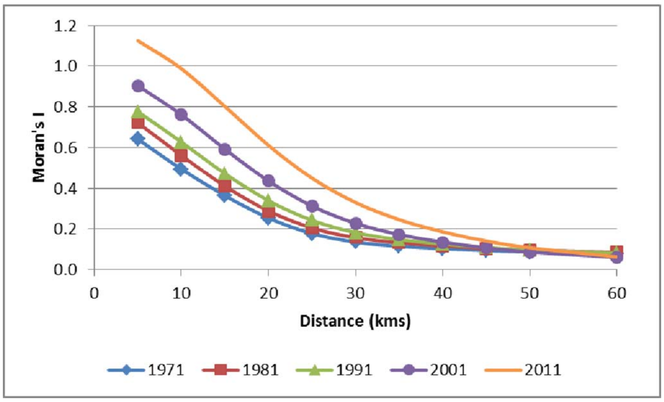

Fig. 3. Spatial auto-correlation in vehicle ownership.

5.1. Classic Markov chain

The PySAL Spatial Markov extensions are used to provide initial comparative estimates from a non-spatial classic Markov chain (Rey and Anselin, 2009). The transition matrix M1 shows the transition counts in levels of ownership, $n_{j,1}$. The sum of this matrix is 33,920, the number of transitions that 8480 areas can make between pairs of five successive censuses. As expected, the matrix is strongly diagonal with the number of transitions diminishing the further from the diagonal.

	(q_1)	(q_2)	(q_3)	(q_4)	(q_5)
Lowest quintile (q_1)	5936	750	38	23	37
Second lowest (q_2)	837	5061	872	11	3
Middle quintile (q_3)	9	964	4953	850	8
Second highest (q_4)	1	6	904	5106	767
Highest quintile (q_5)	1	3	17	794	5969

(M1)

These counts translate into the probabilities $(\hat{p}_{j,1})$ in matrix M2. As indicated by the counts, for each level of vehicle ownership the most likely outcome is that the MSOA\IZ will remain in the same quintile between censuses.

	(q_1)	(q_2)	(q_3)	(q_4)	(q_5)
(q_1)	0.8750	0.1106	0.0056	0.0034	0.0055
(q_2)	0.1234	0.7460	0.1285	0.0016	0.0004
(q_3)	0.0013	0.1421	0.7301	0.1253	0.0012
(q_4)	0.0001	0.0009	0.1333	0.7527	0.1131
(q_5)	0.0001	0.0004	0.0025	0.1170	0.8799

(M2)

By design, the steady state probabilities $(\hat{\pi}_*')$ are all 0.2000. The ergodic values estimate the passage of time between ownership levels $(\hat{F})$ and are given in matrix M3.

	(q_1)	(q_2)	(q_3)	(q_4)	(q_5)
(q_1)	5	11.6	22.7	40.0	67.5
(q_2)	28.5	5	15.1	34.6	63.6
(q_3)	47.5	19.4	5	22.1	52.7
(q_4)	61.4	33.4	14.3	5	32.7
(q_5)	69.2	41.3	22.4	9.0	5

(M3)

Recall that these values represent ten year inter census periods, so an MSOA\IZ in the lowest quintile will take, on average 116 years to transition to the second lowest quintile and 675 years to transition to the highest level of ownership. An MSOA\IZ in the highest quintile will take 90 years to transition to the second highest quintile. These are long time spans.

5.2. Test of spatial transitions

In section 3.2 a pair of statistics was referenced that tests whether the probability transition matrices are different amongst the levels of ownership. The results of these tests of are shown in Table 3. Both the likelihood ratio (LR) and the χ^2 (Q) tests are significant at the 0.1% level which provides supporting evidence to conclude that the transition probabilities are different for each quintile of ownership. This justifies the estimation of the transition matrices and ergodic values for the spatial Markov chains.

5.3. Spatial Markov chain

The PySAL spatial Markov extensions are now used to estimate the spatial equivalents of the classic Markov chain results shown above. (The spatial equivalents of the transition probabilities, M4, are given in Supplementary material.) Matrix M5 shows the estimated steady state probabilities for each quintile (these are all 0.2000 in the non-spatial case).

Surrounding neighbours	(q_1)	(q_2)	(q_3)	(q_4)	(q_5)
Lowest quintile (q_1)	0.5240	0.2236	0.1390	0.0866	0.0269
Second lowest (q_2)	0.2191	0.2574	0.2375	0.1859	0.1001
Middle quintile (q_3)	0.1205	0.2241	0.2298	0.2461	0.1794
Second highest (q_4)	0.0753	0.1950	0.2261	0.2344	0.2692
Highest quintile (q_5)	0.0361	0.1071	0.1876	0.2646	0.4047

(M5)

The long-run distribution for MSOAs\IZs with surrounding neighbours that have levels of ownership in the lowest quintile is for 52.40% to also be in the lowest quintile, 22.36% in the second lowest quintile and just 2.69% in the highest quintile. For those MSOAs\IZs with neighbours in the highest quintile, just 3.61% are in the lowest quintile whilst 40.47% are in the highest quintile. The spatial ergodic estimates are shown in matrix M6 (and may be compared with non-spatial equivalents in matrix M3).

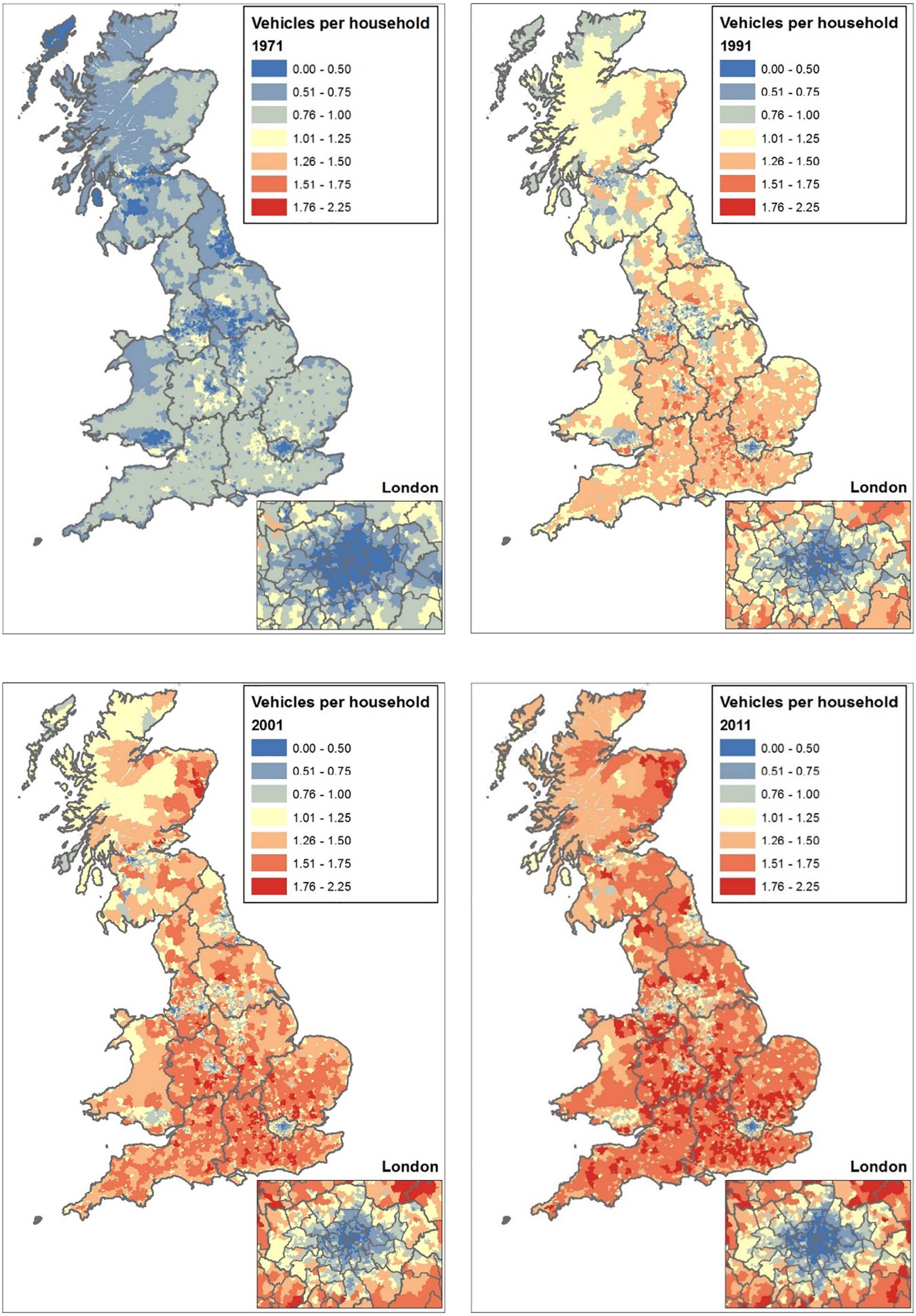

Fig. 4. Spatial distribution of vehicles per household rates, $r_{i,t}$, by MSOA\IZ, 1971, 1991, 2001 and 2011 (Orkney and Shetland omitted from this map).

Table 2
: Quintiles of vehicle ownership (vehicles per household).

Threshold	1971	1981	1991	2001	2011
Q_0 (min)	0.00	0.08	0.11	0.21	0.19
Q_1	0.41	0.55	0.67	0.79	0.85
Q_2	0.55	0.72	0.86	1.00	1.09
Q_3	0.69	0.88	1.05	1.20	1.28
Q_4	0.83	1.06	1.24	1.41	1.49
Q_5 (max)	1.47	1.66	1.83	1.94	2.02

Table 3
: Statistical test of probability transition matrices being different across levels.

Test	LR	Q
Statistic	589.958	695.691
dof	80	80
p-Value	0.000	0.000

Surrounding neighbours in the lowest quintile (q_1)

	(q_1)	(q_2)	(q_3)	(q_4)	(q_5)
(q_1)	1.9	14.1	43.2	91.1	227.8
(q_2)	11.3	4.5	31.6	80.5	218.7
(q_3)	21.2	10.4	7.2	52.3	193.8
(q_4)	27.5	16.8	7.1	11.6	148.4
(q_5)	31.0	20.2	11.2	9.7	37.2

Surrounding neighbours in the second lowest quintile (q_2)

	(q_1)	(q_2)	(q_3)	(q_4)	(q_5)
(q_1)	4.6	8.0	18.1	41.6	81.2
(q_2)	22.7	3.9	12.0	36.4	76.3
(q_3)	34.8	12.6	4.2	25.6	65.9
(q_4)	44.5	22.5	10.7	5.4	41.5
(q_5)	48.8	26.7	15.1	5.8	10.0

Surrounding neighbours in the middle quintile (q_3)

	(q_1)	(q_2)	(q_3)	(q_4)	(q_5)
(q_1)	8.3	8.0	16.4	30.1	55.3
(q_2)	31.9	4.5	11.6	27.1	54.3
(q_3)	50.7	19.3	4.4	17.2	45.9
(q_4)	62.8	31.4	12.2	4.1	30.7
(q_5)	69.3	37.9	18.9	7.1	5.6

Surrounding neighbours in the second highest quintile (q_4)

	(q_1)	(q_2)	(q_3)	(q_4)	(q_5)
(q_1)	13.3	15.4	17.7	24.1	39.5
(q_2)	49.0	5.1	11.2	24.0	42.5
(q_3)	69.8	21.0	4.4	16.7	37.2
(q_4)	84.9	36.4	15.7	4.3	23.2
(q_5)	92.8	44.6	24.0	9.2	3.7

Surrounding neighbours in the highest quintile (q_5)

	(q_1)	(q_2)	(q_3)	(q_4)	(q_5)
(q_1)	27.7	25.7	19.0	18.0	26.9
(q_2)	79.8	9.3	12.0	17.7	30.1
(q_3)	119.6	39.8	5.3	11.1	25.8
(q_4)	140.1	60.3	20.4	3.8	16.4
(q_5)	151.1	71.3	31.4	11.3	2.5

(M6)

Inspecting those MSOAs\IZs in the lowest quintile with surrounding neighbours also in the lowest quintile, it is seen that they will take on average 141 years to move to the second lowest quintile (the non-spatial equivalent is 116 years) and 432 years (227) to move to the middle quintile. Those in the lowest quintile but with surrounding neighbours who are in the middle quintile move to the second quintile after just 80 years (116) and to the middle quintile after 164 years (227). Looking at movements down the levels of ownership, those with surrounding neighbours in the highest quintile who are in the highest level of ownership take 113 years to move down to the second highest level (just 90 years in the non-spatial case) and 313 to move down to the middle level (224).

The overall pattern in matrix M6 is that transitions to higher levels of ownership are slower when neighbours of the MSOAs\IZs have low ownership levels but quicker when the neighbours have higher levels. Also transitions down from high levels take longer when the neighbours are also in the higher levels, but quicker when the neighbours are in the lowest levels. Thus neighbours can be seen to exert a 'drag effect' that inhibits the movement of an MSOA\IZ away from the surrounding neighbourhood level of ownership. Whilst the time spans for the non-spatial Markov chains was seen to be long, these spatial time spans are very long and attest to how stable the relative level of ownership in neighbourhoods is likely to remain in the future.

6. Discussion

Econometric models examining vehicle ownership do not always account for the potential influence of surrounding neighbourhoods. If this neighbourhood influence is real and neglected, such models will be ill-specified and any parameters estimated will be unreliable, biased or non-transferable. This study has applied a novel method to gauge not just the repeated cross-sectional extent of this influence from such neighbourhoods but also capture the temporal strength over a 40 year time span. The key findings and contributions of this study are that: (i) a comparison of the steady state probabilities and transition times in the non-spatial and spatial cases clearly demonstrates that neighbourhood context influences the transition of neighbourhoods through the levels of vehicle ownership; (iii) the duration to transition between the extreme levels of ownership is seen to be long (in the order of centuries) when the neighbourhood context is different to that at the end of the transition; and (ii) the incorporation of spatial effects into models of behaviour are therefore likely to produce substantially different estimates and conclusions.

In the context of the existing literature, this is one of the few studies that has estimated the strength of the spatial relationships in vehicle ownership over time using aggregate data. The aggregate nature of the data provides a comprehensive picture of area level vehicle ownership rather than the partial picture obtained from sparser dis-aggregate data. The time span of this study is also long, covering 40 years and during this time the UK economy has experienced periods of economic stability; rapid growth; and deep recession, allowing us to provide estimates that are not influenced by the short-term economic cycles that some individual panel type data may capture. Whilst there are no directly comparative studies to put these GB results in context, it is possible to replicate this study in other geographic contexts, given access to spatially consistent counts or estimates of vehicle ownership over time. This would provide some context for the dynamics described here for GB.

As highlighted in the introduction, a potential criticism is that this is a descriptive assessment of the spatio-temporal dynamics of vehicle ownership and not an attempt to model the determinants of vehicle ownership. It has, however, quantified how the dynamics in local vehicle ownership are influenced by both neighbourhood and the passage of time in one estimation consistent framework. These estimates have been obtained without the reliance on any statistical assumptions regarding the form of the data or model. This knowledge on the importance of spatial dependence provides an encouragement to those who are advancing the area of spatio-temporal modelling (e.g. Cressie and Wikle, 2011). Whilst the time span of the data used in this study is long, it is rather course, relying on the decennial nature of the UK censuses. More frequent observations within this time span would allow a more dynamic relationship to be captured, e.g. the example of Australia which has had quintennial censuses since 1961 (Australian

Bureau of Statistics, 2017). Also the technique relies on the usual Markov assumptions in regards to the Markov process and the time homogeneous nature of the process.

In terms of policy relevance, the finding of this study are also important for those who are interested in setting policies or making long term investment plans where such decisions are influenced by likely vehicle ownership rates. A neighbourhood with relatively low levels of ownership situated in the context of surrounding neighbourhoods with low ownership is likely to remain low. Thus when developing retail, health or community services to serve such communities, car parking provision is not so critical. But a neighbourhood of low ownership whose surrounding neighbours have middle or high levels of ownership will not stay at this level long and will transition to higher levels, meaning the demand for vehicle parking on local centres and local traffic is likely to increase. Planning guidelines in England require that planners take into account 'local car ownership' in setting guidelines for parking standards for both non-residential and residential developments (Department for Communities and Local Government, 2012; Transport for London, 2012; Institute of Highway Engineers, 2017). Studies have also demonstrated how local residential car ownership influences neighbourhood design and travel patterns, either through the desire for car-free environments (Morris et al., 2009) or environments with constrained parking provision (Weinberger et al., 2009; Guo, 2013a, 2013b).

Finally, aside from these practical aspects, there are instances where vehicle ownership is used as a proxy for the nature of society, e.g. through the calculation of deprivation measures, here then neighbourhoods will tend to homogeneity too. This presents important challenges, both practically (how to reduce deprivation if society moves to perpetuating or enhancing segregation?) and methodologically (is vehicle ownership dynamic enough to accurately capture an aspect of deprivation or changes in deprivation?) (Norman, 2016). This is important since such deprivation measures often influence the apportionment of resources aimed at tackling dis-advantage.

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jtrangeo.2017.05.007.

Acknowledgements

The data sets referred or used in the article were supplied by the Office for National Statistics and National Records Scotland under the terms of the Open Government Licence and UK Government Licensing Framework and are Crown Copyright. The authors would like to thank the reviewers who provided constructive comments on an earlier drafts of this article. This work was supported by the Consumer Data Research Centre, Economic and Social Research Council (grant number ES/L011891/1).

References

Anowar, S., Eluru, N., Miranda-Moreno, L.F., 2014. Alternative modeling approaches used for examining automobile ownership: a comprehensive review. Transp. Rev. 34 (4), 441–473.

Australian Bureau of Statistics, 2017. Historical reference and information. http://abs.gov.au/websitedbs/censushome.nsf/home/historicalinformation?opendocument&navpos=320.

Bickenbach, F., Bode, E., 2003. Evaluating the Markov property in studies of economic convergence. Int. Reg. Sci. Rev. 26 (3), 363–392.

Bramley, G., Dempsey, N., Power, S., Brown, C., Watkins, D., 2009. Social sustainability and urban form: evidence from five British cities. Environ. Plan. A 41 (9), 2125–2142. http://dx.doi.org/10.1068/a4184.

Brunsdon, C., Fotheringham, A.S., Charlton, M.E., 1996. Geographically weighted regression: a method for exploring spatial nonstationarity. Geogr. Anal. 28 (4), 281–298.

Clark, S.D., 2015. Mapping car ownership in Great Britain over four decades. J. Maps 11 (2), 354–360. http://dx.doi.org/10.1080/17445647.2014.960484.

Clark, S., Finley, A.O., 2010. Spatial modelling of car ownership data: a case study from the United Kingdom. Appl. Spat. Anal. Policy 3 (1), 45–65.

Clifton, K., 2003. Independent mobility among teenagers: exploration of travel to after-school activities. Transp. Res. Rec. 1854, 74–80.

Cressie, N., Wikle, C.K., 2011. Statistics for Spatio-temporal Data. John Wiley & Sons.

Dargay, J.M., 2002. Determinants of car ownership in rural and urban areas: a pseudo-panel analysis. Transp. Res. E: Logist. Transportation Rev. 38 (5), 351–366. http://dx.doi.org/10.1016/S1366-5545(01)00019-9.

Department for Communities and Local Government, 2012. National Planning Policy Framework. Available at: https://www.gov.uk/government/publications/national-planning-policy-framework–2.

Department for Transport, 2015. National Travel Survey: 2014 report. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/457752/nts2014-01.pdf.

Frazier, C., Kockelman, K., 2005. Spatial econometric models for panel data: incorporating spatial and temporal data. Transp. Res. Rec. 1902, 80–90.

Guo, Z., 2013a. Does residential parking supply affect household car ownership? The case of New York City. J. Transp. Geogr. 26, 18–28.

Guo, Z., 2013b. Home parking convenience, household car usage, and implications to residential parking policies. Transp. Policy 29, 97–106.

Haase, T., Pratschke, J., 2005. Deprivation and Its Spatial Articulation in the Republic of Ireland – New Measures of Deprivation Based on the Census of Population, 1991, 1996 and 2002. Pobal, Dublin The full report is available at: http://trutzhaase.eu/publications/deprivation-and-its-spatial-articulation-in-the-republic-of-ireland/.

Hanly, M., Dargay, J., 2000. Car ownership in Great Britain: panel data analysis. Transp. Res. Rec. 1718, 83–89.

Institute of Highway Engineers, 2017. Guidance note: residential parking. http://www.ciht.org.uk/en/knowledge/standards-advice/residential-parking-guidance-note.cfm.

Johnson, V., Currie, G., Stanley, J., 2010. Measures of disadvantage: is car ownership a good indicator? Soc. Indic. Res. 97 (3), 439–450. http://dx.doi.org/10.1007/s11205-009-9510-1.

de Jong, G., Fox, J., Daly, A., Pieters, M., Smit, R., 2004. Comparison of car ownership models. Transp. Rev. 24 (4), 379–408. http://dx.doi.org/10.1080/0144164032000138733.

Marsden, G., Rye, T., 2010. The governance of transport and climate change. J. Transp. Geogr. 18 (6), 669–678. http://dx.doi.org/10.1016/j.jtrangeo.2009.09.014.

Morris, D., Enoch, M., Pitfield, D., Ison, S., 2009. Car-free development through UK community travel plans. Proc. Inst. Civ. Eng.-Urban Des. Plann. 162 (1), 19–27.

Norman, P.D., 2016. The changing geography of deprivation in Britain, 1971 to 2011 and beyond. In: Champion, T., Falkingham, J. (Eds.), Population Change in the United Kingdom. Rowman and Little, London.

Office for National Statistics, 2015. Super output areas. http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/census/super-output-areas–soas-/index.html.

Paleti, R., Bhat, C., Pendyala, R., Goulias, K., 2013. Modeling of household vehicle type choice accommodating spatial dependence effects. Transp. Res. Rec. 2343, 86–94.

Pinjari, A.R., Pendyala, R.M., Bhat, C.R., Waddell, P.A., 2007. Modelling residential sorting effects to understand the impact of the built environment on commute mode choice. Transportation 34 (5), 557–573. http://dx.doi.org/10.1007/s11116-007-9127-7.

Prillwitz, J., Harms, S., Lanzendorf, M., 2006. Impact of life-course events on car ownership. Transp. Res. Rec. 1985, 71–77.

Redfern, P., 2004. An alternative view of the 2001 census and future census taking. J. R. Stat. Soc. A. Stat. Soc. 167 (2), 209–228. http://dx.doi.org/10.1046/j.1467-985X.2003.02041.x.

Rey, S.J., 2001. Spatial empirics for economic growth and convergence. Geogr. Anal. 33 (3), 195–214. http://dx.doi.org/10.1111/j.1538-4632.2001.tb00444.x.

Rey, S.J., Anselin, L., 2009. PySAL: a Python library of spatial analytical methods. In: Handbook of Applied Spatial Analysis, pp. 175–193. http://dx.doi.org/10.1007/978-3-642-03647-7_11.

Sawada, M., 1999. ROOKCASE: an Excel 97/2000 visual basic (VB) add-in for exploring global and local spatial autocorrelation. Bull. Ecol. Soc. Am. 80 (4), 231–234.

Schelling, T.C., 1969. Models of segregation. Am. Econ. Rev. 59 (2), 488–493.

Tobler, W., 1970. A computer movie simulating urban growth in the Detroit region. Econ. Geogr. 46 (2), 234–240. http://dx.doi.org/10.2307/143141.

Transport for London, 2012. Residential Parking provision in new developments travel in London research report. http://content.tfl.gov.uk/residential-parking-provision-new-development.pdf.

Weinberger, R., Seaman, M., Johnson, C., 2009. Residential off-street parking impacts on car ownership, vehicle miles traveled, and related carbon emissions: New York City case study. Transp. Res. Rec. 2118, 24–30.