

Estimating local car ownership models

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Abstract

Many studies in the transport demand literature have shown that income is an important factor in determining how many cars a household owns. When the models used to measure the strength of this relationship are estimated on cross-sectional data, they typically yield one overall value as the estimate. Local circumstances will, however, vary. This paper illustrates the use of the Geographically Weighted Regression technique to estimate the individual strength of this relationship for each of the United Kingdom electoral wards. Use of this type of model enables a wards' income elasticity to be based on both the local estimate of the strength of this relationship and the current local level of car ownership. How the use of this local elasticity changes future forecasts of the size of the vehicle fleet is illustrated.

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1. Introduction

The decision by a household to own a first or additional vehicle can be based on a variety of factors, with commonly cited reasons including household location, workplace location, lifestyle commitments and personal status (Dargay, 2002; Karlaftis and Golias, 2002). Coupled with these factors is whether the household has sufficient income to purchase, maintain and accommodate the vehicle. Given the importance of car ownership in determining individual and household travel behaviour, there are many published studies that attempt to assess the impact of these various factors on car ownership. Rather than attempt to review this vast range of studies, four recent or well maintained resources are mentioned here that provide an authoritative review of the relevant studies (on-line versions of these resources are also available, see the reference list).

The first resource is the Travel Demand Management Encyclopaedia maintained by the Victoria Transport Policy Institute—which has a section devoted to Transport

Elasticities. This section of the encyclopaedia begins with an introduction to the topic area followed by a few key mathematical definitions. The bulk of the section then contains a list of over 20 factors that impact on travel demand—using review information obtained from other studies. These travel demands include car ownership, car use and transit use, whilst the influential factors include price, income and provision of infrastructure and services. This resource is an ideal introduction to this area of research, and for off-line reading a pdf document version is available (Todd Litman, 2005).

The second study was produced by the Rand Europe Corporation (de Jong et al., 2004) as a prelude to the updating of the Dutch national car ownership prediction model. In their paper, the authors review a range of domestic Dutch and international studies on car ownership. The review is relatively contemporary, covering studies conducted since the early 1990s, and it outlines nine modelling methodologies used to model the relationship between car ownership and factors such as income, fixed/variable costs, quality of car stock and licence holding. Since the paper concentrates heavily on technical descriptions of modelling techniques, it is ideal for those who wish to gain a thorough understanding of the variety of work in this field of estimation from just

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one coherent, independent source. The paper does, however, contain little by way of quoted results from the models described in the paper. The interested reader is therefore required to refer to the individually cited papers for such information.

The third study, was conducted by the World Bank (Ingram and Liu, 1999) and is an international study of both motorization and road provision. Whilst the previous mentioned study by the Rand Corporation concentrated on the modelling methodologies, this study concentrates mainly on the outcomes from models—primarily the elasticities. From this study, it is clear that one of the most quoted determinants of car ownership is income—either at the national (GDP) or personal (household) level. In their Table 2, the authors provide a list of income elasticities estimated from cross-sectional, time series and panel type data. They suggest that elasticities estimated using cross-sectional data and at the national level are larger than those from time series data and for just urban areas. A discussion is then provided of other determinants quoted in the literature such as vehicle purchase costs, running costs (petrol, insurance and maintenance) and population density. The remaining parts of this report are primarily concerned with road space and transport provision (the ratio of vehicles to roads).

The final study comprises two similar reports commissioned by the United Kingdom Department for Transport (Goodwin et al., 2004; Graham and Glaister, 2004). The Goodwin paper only considers results based on United Kingdom (or similar countries) data, but even so they were able to gather evidence on the impact of price and income on car travel from 69 published studies—providing nearly 500 elasticity estimates. They also provide some assessment of the possible causes of and policy implications of different elasticity estimates. The review within the Graham paper initially covers similar ground to that in the Goodwin paper but devotes the bulk of its content to the consideration of freight elasticities.

Many of the models referred to so far use a regression model or a refinement of such a model to represent the relationship between car ownership and factors such as income. As outlined in the de Jong et al. (2004) paper, some of these models use cross-sectional data, where data are from a single period of time but from many locations, whilst some others use time series data, where the data are from many time periods but usually only one location. In addition, some models use highly disaggregate data, where detailed information is known about individuals or households, whilst some are based on information about the characteristics of an area in aggregate form. The model presented in this paper is a cross-sectional model on aggregate data.

2. Data source

The data that are used in this study are provided by the United Kingdom Office for National Statistics (ONS) and

are freely available in electronic format, either from the Internet or on CDs and DVDs that ONS are able supply on request.

2.1. Car ownership counts

The United Kingdom Government conducts a national census of its population every 10 years. The Census includes questions on household composition, housing stock, general health, education and, importantly for this study, car ownership and travel to work behaviour. This information is then used for policy and planning decisions at all levels of central and local government as well as by many bodies outside government.

ONS has now completed its release of tables of statistics from the 2001 Census. These data are provided at a range of geographical levels, from the small Census Output Area (COA) level (consisting on average of 150 households), through super output areas (500–1000 households), electoral wards, districts and on to the constituent nations of the UK.

The primary table used in this study is Key Statistic 17, residential car and van ownership, produced at the ward level. In this table, information is recorded on how many households do not own a car, own just one car, two cars, three cars and finally, four or more cars. The total number of households and cars in the ward is also provided and this enables an average car ownership level per household to be calculated for the ward.

Fig. 1 shows the geographical distribution of car ownership, expressed as the number of cars per household. Areas of the country that have good public transport provision and nearby access to services (shops, schools, medical, etc.) would be expected to have low levels of car ownership, whilst rural areas without this level of provision would be expected to have higher levels of car ownership. Looking at the map, it is clear that car ownership is lowest in the urban areas of northern England, south Wales, the central West Midlands and the centre of London. Elsewhere car ownership is high, particularly in the less urban parts of the South East and Eastern England.

2.2. Income estimation

One question that was not included in the 2001 Census was a question on the household's income. In April 1999, a trial Census was conducted and as part of this trial an income question was included on a number of the Census forms. Evidence from the response rate in those areas where an income question was included suggested that people were less likely to return a Census form if an income question was included. This, coupled with the difficulty in what to include as income, led the Government to drop the income question from the full Census.

There was still, however, recognition that estimates of household incomes for small geographical areas were required. To this end, a project was established to produce

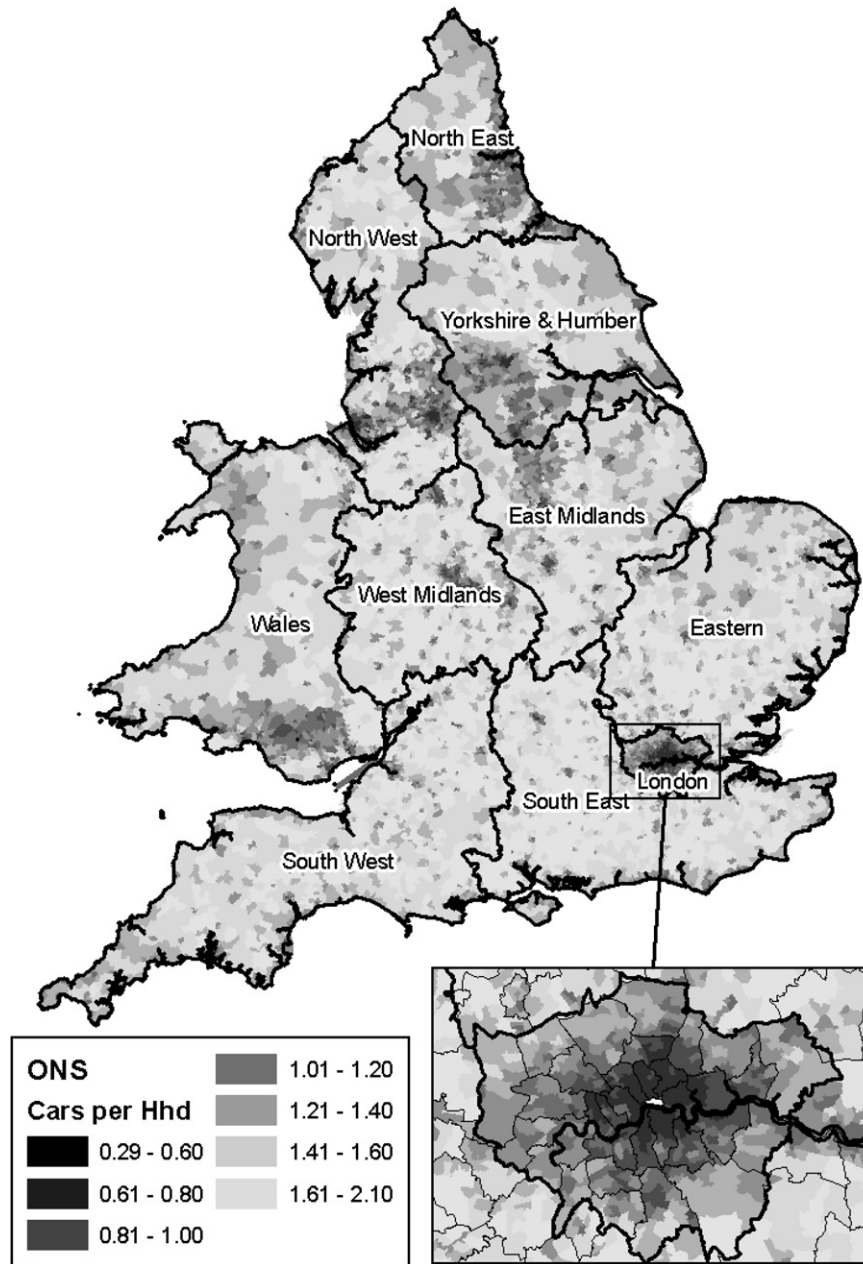


Fig. 1. Residential car and van ownership (cars and vans per household).

income estimates at a level of geography as low as the local authority ward (Williams, 2000). A brief summary of the methodology is presented here.

Information on household income is regularly collected as part of the Government's Family Resource Survey (FRS) (Department for Work and Pensions, 2005). The clustered coverage of this survey is not, however, sufficient to provide reliable estimates of household income for every UK ward. For those wards that have sufficiently reliable estimates of income from the FRS, a relationship was established between the income and a range of nationally available covariates. For the study, covariate data were taken from a number of sources: 2001 Census data; the Department of Works and Pensions claimant count; the

Land Registry dwelling price data; Local Authority Council Tax data and regional indicators. Once this relationship was calibrated and validated for the subset of wards, it was then applied to the nationally available covariate data to provide income estimates for all wards. Whilst car ownership was included in this process as a candidate national covariate, it was not selected for inclusion in the final model (Goldring et al., 2005) thereby eliminating a possible "feedback" effect. This is important since car ownership is commonly used as a proxy for incomes, e.g. in Longley and Tobón (2004), an attempt is made to explain the variability in household incomes in Bristol, UK, using a basket of socio-demographic indicators, one of which is the number of households owning two or more cars.

Returning to the ONS study, estimates (and the associated 95% confidence intervals) for four types of household weekly income were produced: Gross (unequivalised); Net (unequivalised); Net before housing costs (equivalised) and Net after housing costs (equivalised). The process of equivalisation adjusts the income to take account of the composition of households in the area. Thus, three households with the same unequivalised weekly income of £200 could translate to £264 for a single person household, £200 for a couple and just £172 for a couple with two children.

There are 31 wards with unusually small resident populations (mainly in the City of London) and to protect the confidentiality of these residents' incomes no estimates are provided. This leaves 8837 wards with an income esti-

mate. Fig. 2 shows how the Net (unequivalised) income measure varies across England and Wales. Whilst it was perhaps once the case that incomes in the UK tended to be fairly homogenous, trends in the gap between the poorest and richest in society have been dynamic in the past 20 years and this has resulted in some wide income disparities. Effects that widen this gap include higher annual pay rises for skilled as opposed to unskilled labour, increases in both two earner and no-earner households and income tax cuts. On the opposite side, the increase in indirect taxation and the introduction of means-tested benefits tend to reduce this income gap. The result of these dynamics has tended to concentrate high income households in the South East and Eastern England along with some pockets in the rural

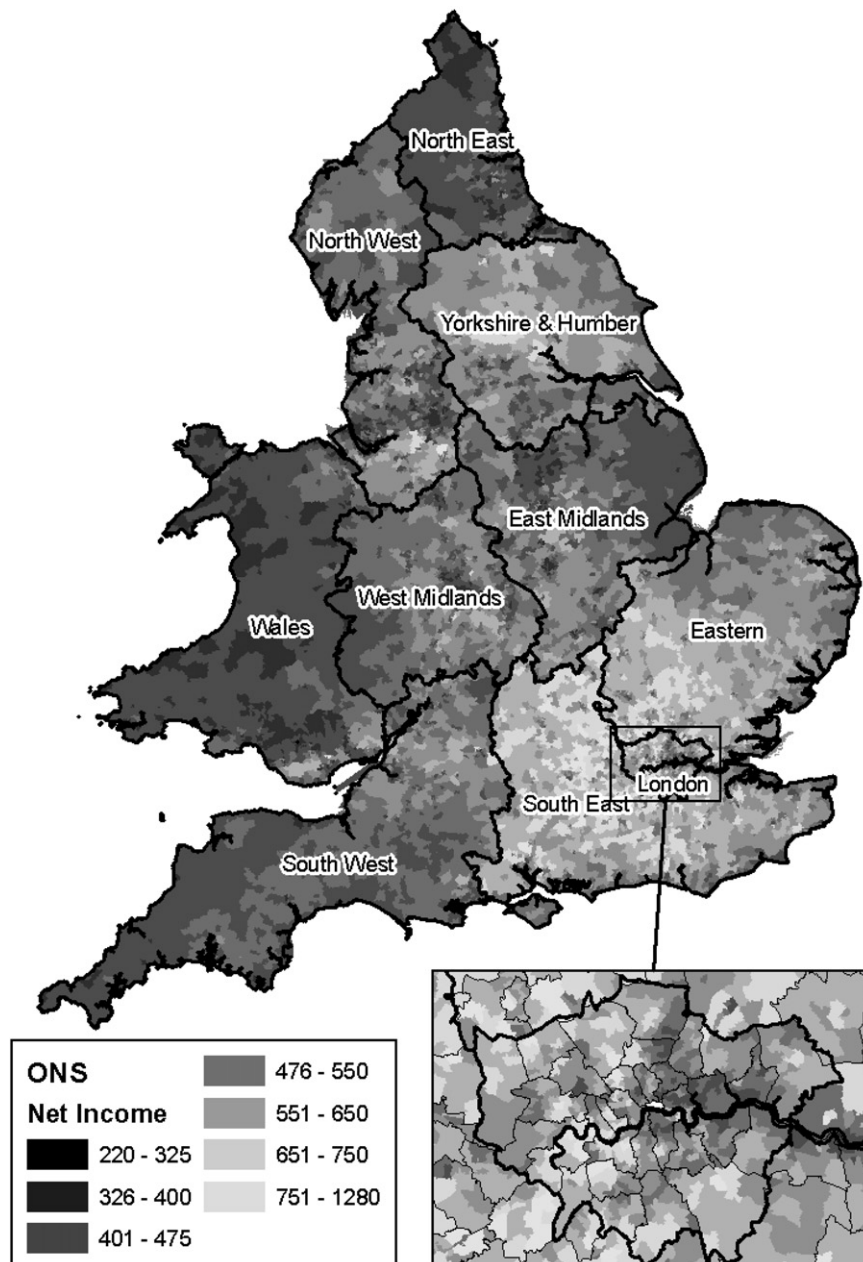


Fig. 2. Distribution of household net income (£ per week).

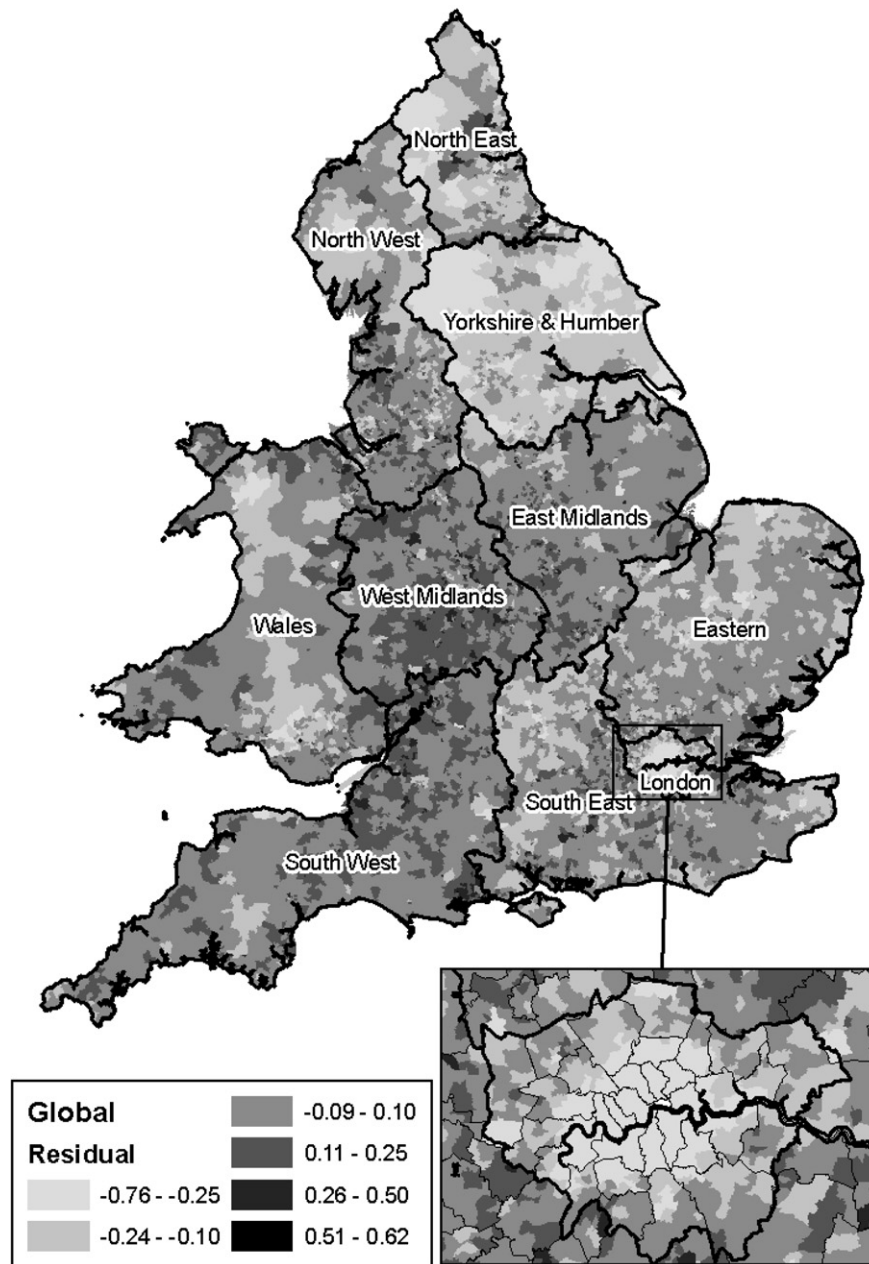


Fig. 3. Residuals from the global regression model.

The presence of such correlations is of concern for two reasons. Firstly, it violates the assumption of randomly distributed and independent error terms in regression modelling. Any significance tests arising from the interpretation of this model are therefore suspect. Secondly, the residuals clearly contain some geographic information which the global model is unable to incorporate in its formulation and is therefore lost.

A possible model enhancement is the use of Spatial Error Models (SEM), which extend the traditional regression formulation to include an explicit term to take account of the spatial structure in the regression's error term. Whilst this change deals with the statistical concern over the nature of the error term, it does not provide a measure

of the strength of the relationship between variables at a local level. To see an illustration of the application of a SEM with these data, see [Appendix 1](#).

One way to incorporate this geographical information at the local level is to introduce region specific dummy variables or regional interaction terms into the regression equation. Whilst this will go some way towards addressing the geographical issues, the discrete nature of this approach is a little arbitrary. It does erroneously assume, for instance, that a ward in the North West, but on the border with the West Midlands, will have more in common with a ward to the far north of the North West, some 250 km away, than a neighbouring West Midlands ward. A series of more local or overlapping dummy variables can help

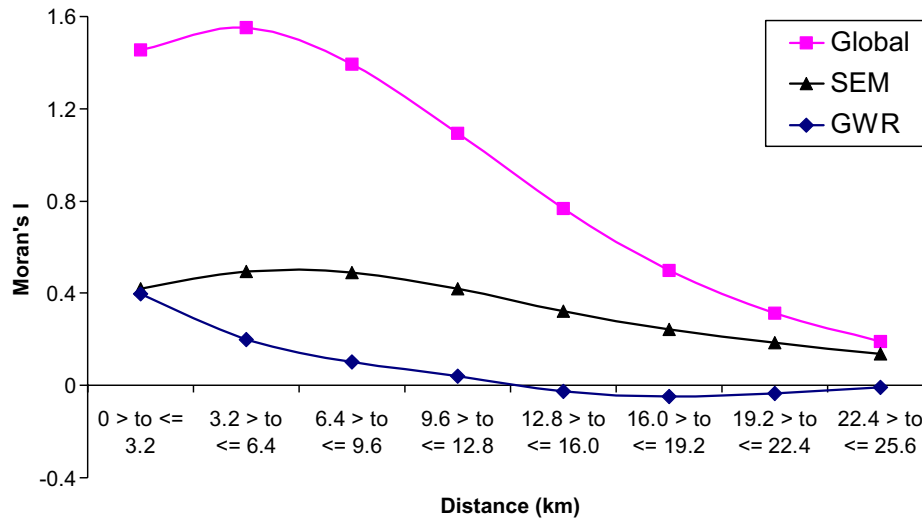


Fig. 4. Moran's I statistic for the residuals from the global, SEM and GWR models.

to minimise this impact but the question then arises as to how to define these areas.

4. Geographically Weighted Regression

In the global model reported above, each observation is taken as an independent observation, contributing the same amount of information to the relationship at each data point. These data do, however, have a geographical context and this information is not used. In particular, there is no reason to believe that the strength of the income relationship will be the same across the whole of England and Wales. The global model is therefore a compromise that may not actually be appropriate for ANY area of England and Wales.

The technique of Geographical Weighted Regression (GWR) (Brunsdon et al., 1998) attempts to incorporate this geographical information into a regression model using a series of distance related weights. In effect, when estimating the local relationship between car ownership and income for a particular ward the corresponding information from neighbouring wards is given a higher weight than information from more distant wards. The outcome of this process is that rather than just having one estimate for the income parameter, each ward has its own estimate based on a specific set of observation weights. The model is summarised in the following equation:

$$y_i = \alpha_{(u_i, v_i)} + \sum_{j=1}^k \beta_{j, (u_i, v_i)} x_{j, i} + \varepsilon_i,$$

where y_i is the estimated car ownership in ward i ; $x_{j, i}$ is the value of explanatory parameter j for ward i ; $\alpha_{(u_i, v_i)}$ is the estimated intercept for ward i located at point (u_i, v_i) ; $\beta_{j, (u_i, v_i)}$ is the estimated value for parameter j for ward i located at point (u_i, v_i) ; k is the number of explanatory variables in the model; and ε_i is a randomly distributed error term, $\varepsilon_i \sim N(0, \sigma^2)$.

In order to estimate the parameters in this model, the following calculations are performed for each ward. Firstly, the distances from the current ward to all the other wards are calculated and a decay function is applied to convert these distances into regression weights. This produces a 8837 by 8837 diagonal matrix. The regression equation is then estimated using these weights. The parameter estimates and ancillary statistics from this regression are taken to be those for the current ward. The process then moves on by considering the next ward.

Initially, such GWR models were used in a purely exploratory manner but recently attempts have been made to put the formulation, validation and interpretation of the models on a more robust statistical footing (Brunsdon et al., 2000).

An initial scoping study along the lines of the national study reported here was conducted by the author (Clark, 2004). In this study, only a limited geographical data set consisting of 220 wards was used in a GWR model but some interesting insights into local car ownership patterns were apparent. Other researchers have also used GWR techniques in a transport context. Two studies have attempted to estimate the increase in local land values as a result of enhanced or differing transport accessibility, either by calculating land value up-lifts as a result of a new tram system in Croydon, south London (ARW, 2003) or by examining how the different patterns of accessibility in an urban area of northern England affect house prices (Du and Mulley, 2006). Two further studies have investigated how travel volumes and distances vary across an area and if the use of GWR can provide additional insight—the first by modelling the relationship between commuting distance and socio-economic variables in Northern Ireland (Lloyd and Shuttleworth, 2005) and a second which attempts to discern patterns in a national Origin–Destination matrix for Japan (Nakaya, 2001). Other transportation studies using GWR include estimating the accident risk at traffic network locations in

Toronto, Canada (Hadayeghi et al., 2003) and explaining the demand for public transit ridership in Broward County, Florida, USA (Chow et al., 2006).

4.1. Fitting the GWR model

The GWR model is fitted to these data using the bespoke package, GWR3, produced at the National University of Ireland (2005). The package allows the use of a variety of calibration techniques to specify how quickly the regression weight diminishes as the distance from the estimation point increases and how to optimise a bandwidth parameter. For the model results reported below,

the adaptive kernel weighting function, where a constant number of neighbouring wards are used in the estimation process, is used in preference to the fixed distance kernel (which uses all wards within a constant distance). The rationale behind this choice is that for rural wards the fixed approach would include too few neighbouring wards leading to an ill-defined estimation problem and for dense urban areas it would include too many wards and would potentially dilute the local nature of the relationship. The Akaike Information Criterion (corrected) (AIC_c) is used for selecting the optimal kernel size so that account is taken of the changes in the model specification—typically the number of effective parameters in the model.

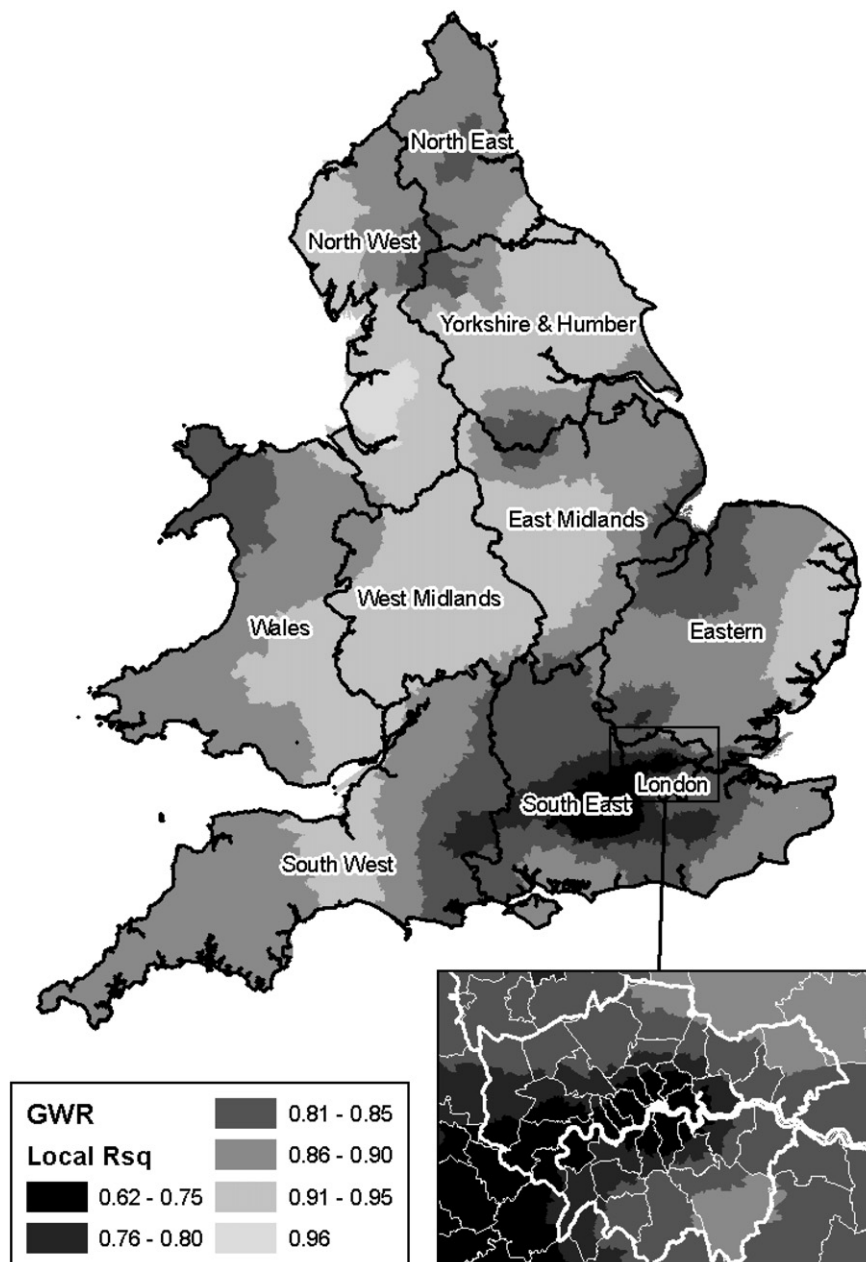


Fig. 5. Local goodness of fit statistics (R^2_{adj}).

4.2. Results

The GWR software package confirms the global model estimates provided in Eq. (1) and also calculates the global AIC_c as -7088 with three parameters. The GWR model is fitted to these data, adapting the bandwidth of the Kernel to ensure that 454 observations (this is 5% of the total number of wards) are included in all the regression estimates. The AIC_c for the GWR model is -15054 on 154.1 effective parameters which represents a large improvement in fit, even when the increase in the number of parameters is taken into account (the estimation of a fractional number of parameters is an unusual feature of GWR models—for

an explanation of how this value is derived, see Appendix 2). The global R^2_{adj} value has also increased from 75.3% to 90.1%. All the estimates for the income and population density parameters are significant at the 5% level and none of the standardised residuals are beyond ± 3.0 . Examination of the statistical distribution of the GWR parameter estimates and the results of a Monte–Carlo significance test suggest that there is spatial distribution in all three parameters. There is a strong linear correlation between the constant term and the income parameter, a not uncommon feature of GWR type models.

Fig. 5 maps how the local R^2_{adj} value varies over England and Wales. The model fit is particularly good in the West

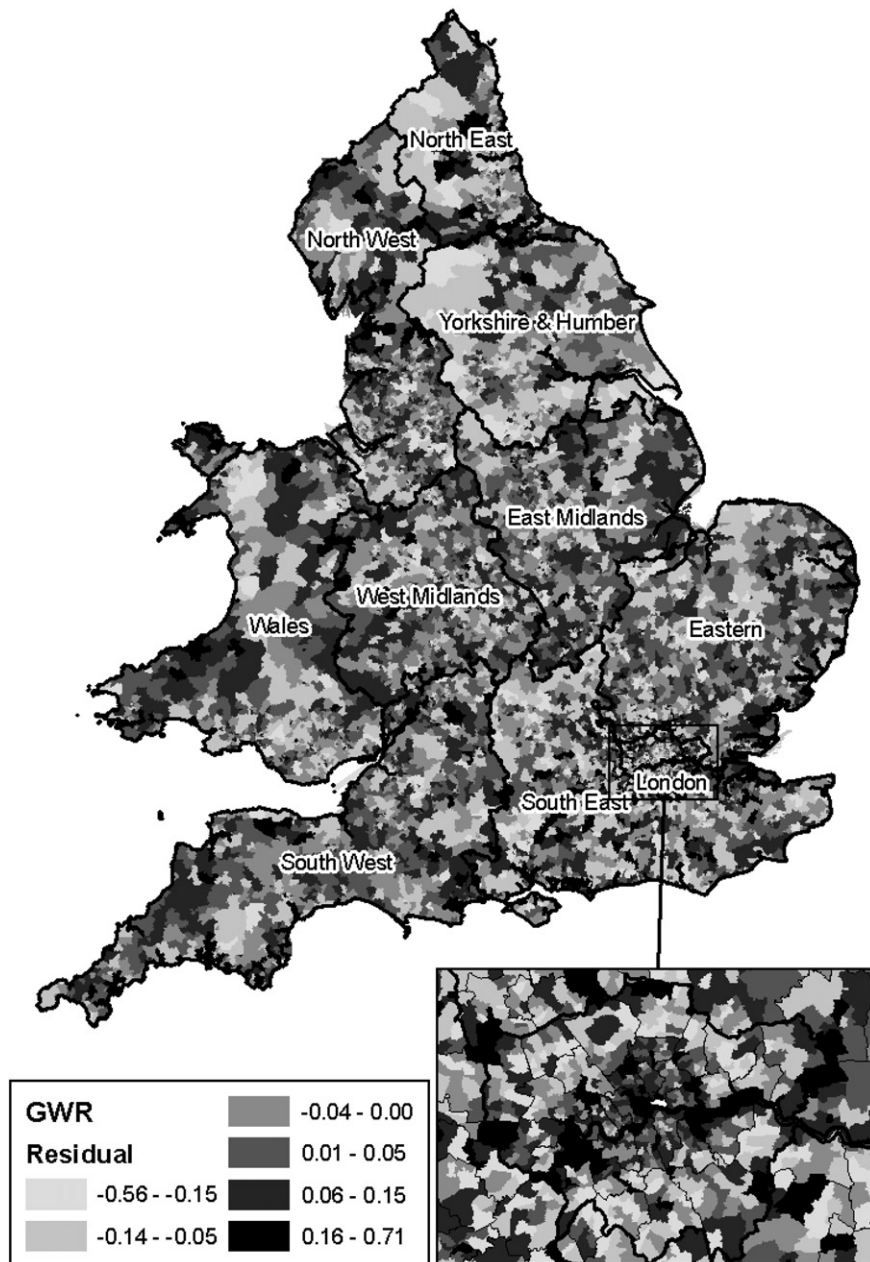


Fig. 6. Residuals from the GWR model.

Midlands Region (in excess of 90%) and poorest in central and south west London and the South East (as low as 62%).

The residuals from the GWR model are displayed in Fig. 6. Here, the appearance is much more “dappled” than in Fig. 3 with no blocks of neighbouring wards showing a similar rendering. The values of Moran’s I statistic for these GWR residuals are shown in Fig. 4 and this shows that there is much less evidence of spatial correlation in the GWR model than for the global model and the SEM.

The values for the estimated income parameter vary across England and Wales and are shown in Fig. 7. The parameter is lowest in central and west London but highest

in the West Midlands and areas in the North West and the North East. In central London the model outputs suggest that a high level of income is required to own a vehicle whilst in the West Midlands and the North West, high car ownership happens at much lower levels of income.

Fig. 8 shows the variation in the implied elasticity of car ownership with respect to income. The median elasticity is 0.71 and the 95% interval is (0.345 1.872). The elasticity is highest in the city centres of northern England, the West Midlands and south Wales. In these high elasticity areas car ownership levels are traditionally low (see Fig. 2), so this effect may be a desire to increase car ownership levels using a large proportion of available income. The elasticity is low

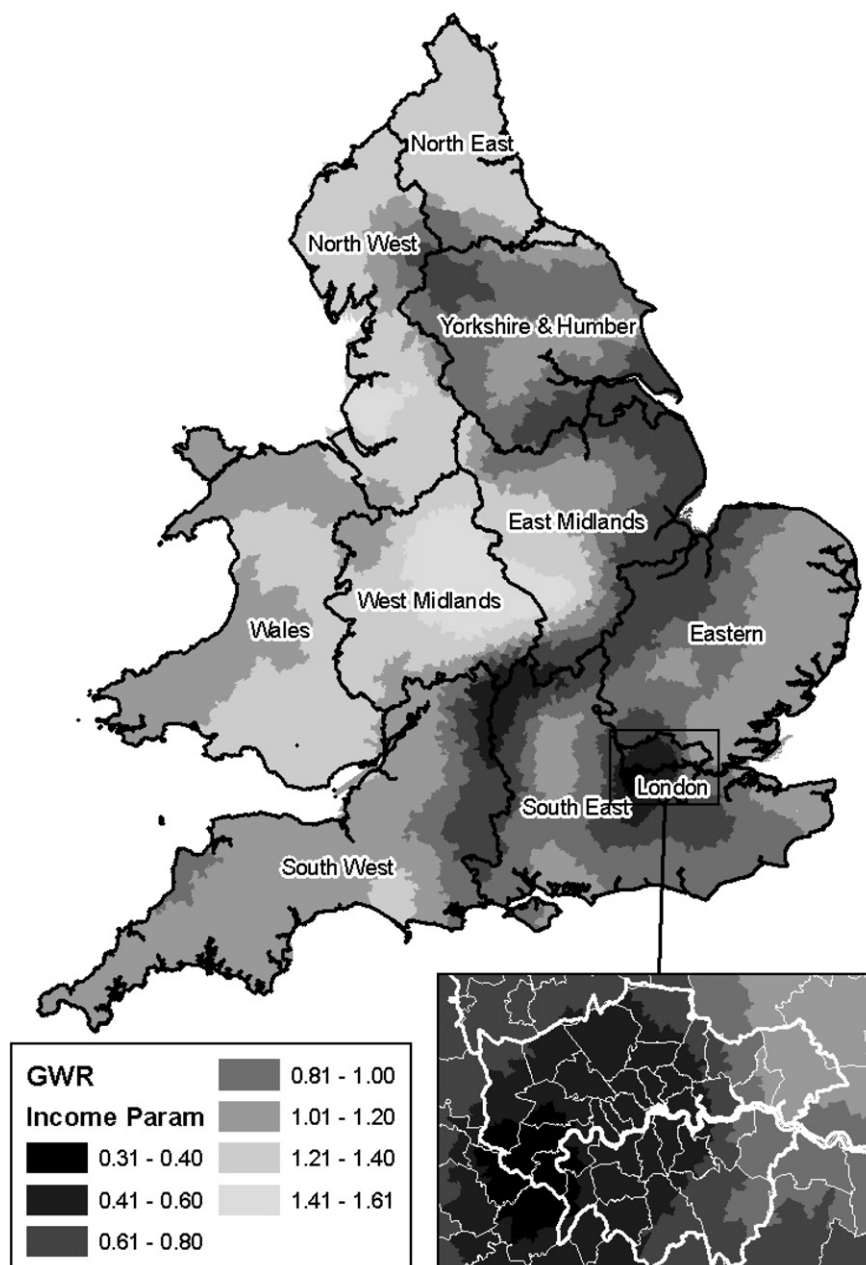


Fig. 7. Local model estimates for the income parameter.

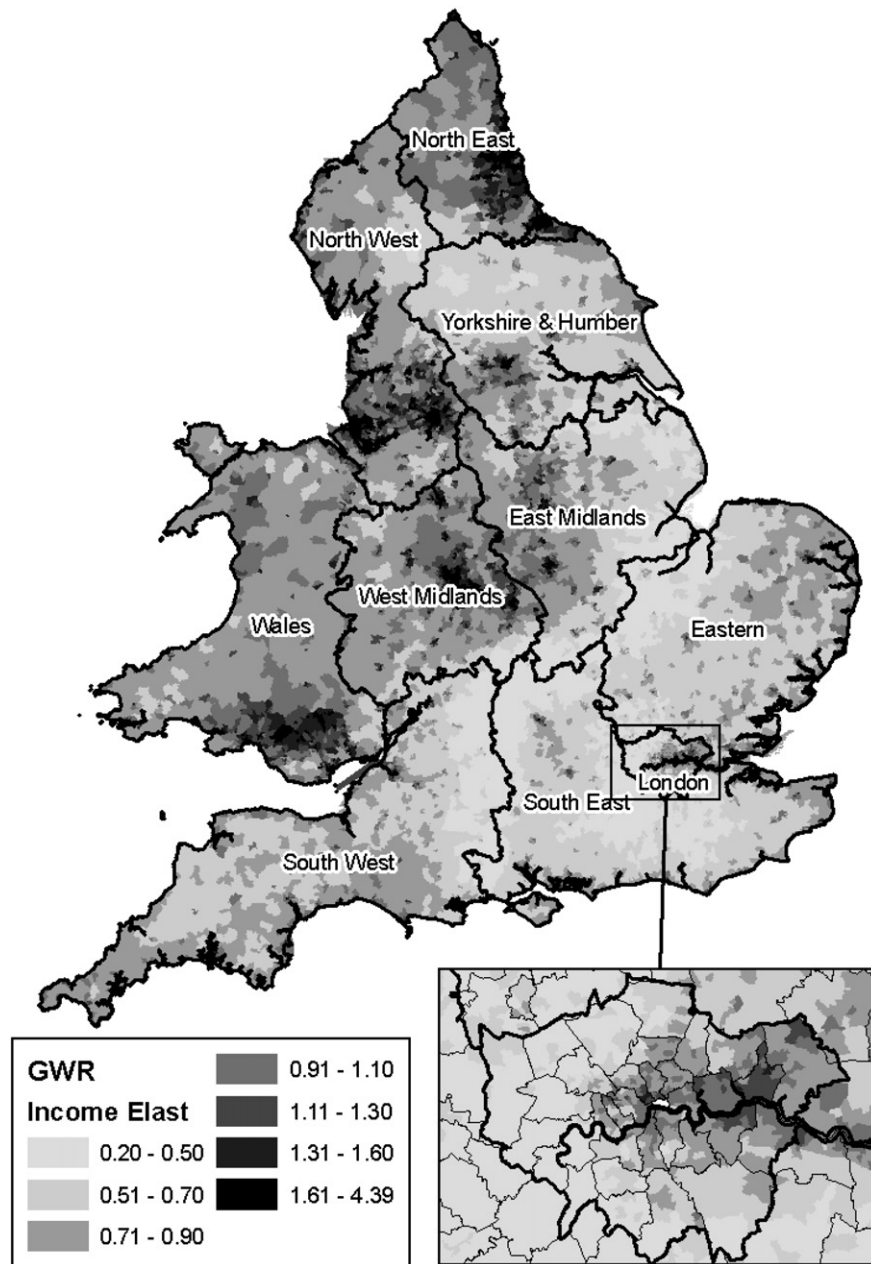


Fig. 8. Implied values for the elasticity of car ownership with respect to income.

in the South East of England, suggesting that car ownership aspirations here are already largely satisfied (note that the car ownership levels are high here in Fig. 2) and that income is used for other household purposes.

To demonstrate the impact of using different elasticity estimates, the change in national and local car ownership of a 10% rise in real incomes is estimated. One scenario is to assume a constant global elasticity of $\eta_{co} = 0.608$; this assumes that the car ownership behaviour is uniform across the whole of England and Wales. The second scenario is to assume ward specific elasticities from $\eta_{co} = 0.744/y_i$, which takes account of local circumstances but still assumes a uniformly estimated value for the strength

of the relationship between car ownership and incomes. The third scenario is the most flexible, it uses the locally estimated GWR income parameters when estimating the elasticity, $\eta_{co} = \beta_{income(u_i, v_i)}/y_i$. The predicted size of the national and London car and van fleet under these three scenarios is shown in Table 1. On a total 2001 vehicle stock of 24 million cars and vans, the increase derived from the ward specific GWR elasticities is 781 k more cars than that from the global elasticity. For London, a different pattern emerges: the car ownership level estimated in scenario three is lower than that in scenario two. Clearly the estimated national parameter value of 0.744 is too high for the London situation.

Table 1
Estimated number of cars and vans under three elasticity scenarios

Scenario		England and Wales	London (excluding the City of London)
Number of cars and vans (2001 Census)		23 933 690	2 614 387
Car and van fleet size after a 10% increase in real incomes	$\eta_{co} = 0.608$	25 388 858 (+6.1%)	2 773 341 (+6.1%)
	$\eta_{co} = 0.744/y_i$	25 544 841 (+6.7%)	2 838 454 (+8.6%)
	$\eta_{co} = \beta_{income(u,v)}/y_i$	26 169 943 (+9.3%)	2 784 299 (+6.5%)

5. Discussion

Other similar studies of the relationship between incomes and car ownership have only provided a rudimentary allowance for the possibility that the strength of the relationship will vary over such a wide and diverse area as the UK. The attempts to allow for some spatial variation have included introducing covariate data such as population density (as this study has) or area specific dummy variables. These models will produce a reliable estimate for the income elasticity (in that the income term is freed from having to represent other features in the data), but they still produce a single income parameter and elasticity estimate. This GWR model has allowed for a truly spatially varying estimate of the income parameter and hence the calculation of a local income elasticity.

One potential concern is whether the GWR model is over-fitting these data. The increase in the effective number of parameters from just three in the global model to 155 in the GWR model does appear large. This increase needs to be placed in the context of the size of the whole data set consisting of nearly 8900 observations, and there is therefore a 1 to 50 ratio between parameters and data. Even if the alternative (and arguably less appropriate) approach of using an additional dummy variable for each local authority district so as to modify just the intercept term in a regression is used, there would initially be more than 370 additional dummy variables in the global model. The analyst would then have the task of eliminating insignificant and combining together similar dummy variables. Even if the number of dummy variables were halved, there would still be more parameters than in the GWR model.

Another concern is that the variability in the parameters is really “picking-up” the existence of another important variable which has been omitted from the model. The strength of the relationship in the global model suggests that there is little need for additional variables in the model. Also, the range of GWR income parameter estimates is roughly what one might expect from such regression type models, suggesting that no “outside influence” has caused them to be modified in some unreasonable manner.

Artificial edge effects were a concern in the scoping study for this paper (Clark, 2004). Unlike the region studied in this earlier article, England and Wales is a highly segregated landmass, largely bounded by coastlines, thereby enabling an effective and natural border to be drawn

around the area of study. The only locations used in the model which are likely to be affected by artificial edge effects are those which border Scotland in the north. These bordering wards should technically use income and car ownership values from neighbouring Scottish wards but these have not been included in this model. This border, is however, quite short in relation to the entire England and Wales coastline.

In terms of further analysis, the approach outlined in this study could easily be applied to the other travel-related question asked in the 2001 Census, “Method of Travel to Work”. The mode share of each of the various modes (Key Statistic 15) or the distance travelled (Standard Table S121) could be related to income and other explanatory variables and any variability in this relationship mapped across England and Wales. Since travel to work is an individual response (rather than a household response), an equivalised income measure may be more appropriate than the net income used here. Initial explorations suggest that equivalised income has a negative exponential relationship with the proportion of people who travel to work as a passenger in a car or van. Beyond the subject area of transport, similar analysis could be conducted against the other question domains within the Census such as health, educational attainment and living conditions.

6. Summary

In establishing that incomes are a significant and influential factor in explaining levels of car ownership, this study is in line with the body of previously published evidence in this field. The estimated global value for the elasticity of car ownership with respect to income is, maybe, on the low side, but is within the range found in other studies.

The residuals from this global model were, however, found to contain spatial correlation which raised a number of concerns. Primary among these was that the local information or variability in the relationship was being ignored by the global regression model. This led to the development of a geographically weighted regression model that was able to capture the spatially varying nature of the relationship. An illustration of the use of the spatially varying elasticity estimates was demonstrated with a scenario of a 10% rise in real incomes.

This prediction exercise demonstrated that the use of global estimates is unlikely to predict local changes very well. In areas of the country where the elasticity is low,

e.g. the South East of England and parts of London, the ownership levels calculated using the global estimate of the strength of the relationship will tend to be over predictions. Similarly in areas where the elasticity is high, such as the urban areas of northern England, use of the global estimate will under predict car ownership. Even in aggregate, at a national level of England and Wales, these under and over estimates do not cancel out. For local planners who need to predict future car ownership levels, for example to plan future road and parking provision or forecast the use of public transport, the local GWR estimates will be more appropriate.

Acknowledgements

Any views expressed in this paper are those of the author only and should not be taken to be those of Leeds City Council or its Agencies. The author would like to thank the anonymous referees for their comments and observations on an earlier draft of this paper.

Appendix 1. Fitting a spatial error model

Spatial error models (SEM) are an intermediate type of model, in that they retain the global nature of the parameter estimates associated with the explanatory variable but extend the model form to explicitly account for the spatial structure in the residuals (LeSage, 1998). The model form is

$$Y = X\beta + u \tag{A.1a}$$

$$u = \lambda Wu + \varepsilon, \tag{A.1b}$$

where **Y** is a $n \times 1$ vector of dependant data; **X** is a $n \times k$ matrix of explanatory data; β is a $k \times 1$ vector of parameter estimates; **u** is a $n \times 1$ vector of spatially correlated disturbances; λ is a scalar parameter measuring the spatial correlation; **W** is a $n \times n$ matrix which captures the spatial congruity in the data; and ε is a $n \times 1$ vector such that $\varepsilon \sim N(0, \sigma^2 I_{n \times n})$. The λ parameter is analogous to the moving average parameters typically used in autoregressive and moving average (ARMA) time series models.

The estimation of the parameters in this model is done using the public domain *R* package (R Development Core Team, 2005) and the spatial dependence add in package *spdep*. As a preliminary to the fitting of the model, the *tri2nb()* function is used to create a triangulation grid from the wards' centroid co-ordinates. This grid essentially provides the structure of the **W** matrix in Eq. (A1b).

The actual SEM model is fitted using the *Gmerrorsar()* function.

$$\text{cars per household} = \underset{(0.051)}{-4.804} + \underset{(0.008)}{1.016} \ln(\text{net income}) - \underset{(0.001)}{0.077} \ln(\text{population density})$$

with the spatial correlation parameter $\lambda = 0.747$. The likelihood ratio test from this model is highly significant

Table A1
Estimated number of cars and vans using SEM estimates

Scenario		England and Wales
Number of cars and vans (2001 Census)		23933690
Car and van fleet size after a 10% increase in real incomes	$\eta_{co} = 0.831$ $\eta_{co} = 1.016/y_i$	25921967 (+8.3%) 26133864 (+9.2%)

(p -value $< 2.22e-16$), thereby rejecting the null hypothesis that there is no spatial correlation in the global model (confirming the conclusions from the global line in Fig. 4). Also looking at Fig. 4, it is apparent that the values of Moran's I statistic are lower for the residuals from a SEM than from the global model. This suggests that a revised estimate of the car ownership elasticity is now $\eta_{co} = (1.016/1.223) = 0.831$, a higher value than with the global model, where $\eta_{co} = 0.608$. The AIC value for this SEM model is -15101 with five parameters. This compares well with the AIC_c value of -15054 with 154.1 parameters from the GWR model.

Table A1 provides estimates of the total UK car ownership under two scenarios consistent with those in Table 1 but using SEM estimated parameters. The estimate derived from using the second scenario of a global SEM parameter estimate with ward car ownership levels (26.13 m) is very close to that of the third scenario in Table 1, which uses both ward specific GWR parameter estimates and car ownership (26.17 m). Whilst this similarity at a national level is remarkable, the SEM model still does not provide the best estimate of car ownership growth at the local ward level since it fails to estimate the strength of the relationship at a local level.

Appendix 2. Estimating the number of parameters in a GWR model

The goodness of fit of a statistical model should always be put in the context of the number of parameters used in its estimation. With GWR models each data point has its own estimate of each of the parameters in the model, so in theory the number of parameters could be $n(k + 1)$, where n is the number of observations—a highly over-parameterised model. There is, however, a relationship between neighbouring parameters (clearly visible in Fig. 7) reducing the freedom that the model has to estimate these parameters. In Brunsdon et al. (2000), an argument is proposed that allows an estimate to be made of the effective number of parameters in a GWR model. This argument is summarised here.

In the global regression model, the expression for the expected values of the residual sum of squares (RSS) is given by

$$E[\text{RSS}] = (n - \text{DoF})\sigma^2, \tag{A.2a}$$

where DoF is the degrees of freedom within the model, equal to $(k + 1)$ (that is, k variables plus an intercept); and σ^2 is the variance of the error term.

In their paper, Brunsdon proposes the existence of an $(n + 1)$ by $(n + 1)$ transformation matrix, \mathbf{S} , that transforms the observed y_i 's to the fitted \tilde{y}_i 's

$$\tilde{\mathbf{y}} = \mathbf{S}\mathbf{y}.$$

The fitted residuals are thus $(\mathbf{I} - \mathbf{S})\mathbf{y}$, and $\text{RSS} = \mathbf{y}'(\mathbf{I} - \mathbf{S})(\mathbf{I} - \mathbf{S})\mathbf{y}$.

Using published results and assumptions with regard to the small size of a bias term when we have a large sample, the expectation of the RSS in the case of GWR equates to

$$E[\text{RSS}] = (n - (2\text{tr}(\mathbf{S}) - \text{tr}(\mathbf{S}'\mathbf{S})))\sigma^2.$$

In many cases, $\text{tr}(\mathbf{S}'\mathbf{S})$ is close to $\text{tr}(\mathbf{S})$, thereby reducing the expected residual sum of squares to

$$E[\text{RSS}] = (n - \text{tr}(\mathbf{S}))\sigma^2. \quad (\text{A.2b})$$

A comparison of (A.2b) and (A.2a) suggests that the degrees of freedom, and hence the number of effective parameters in a GWR model are given by the trace of the \mathbf{S} matrix. This can clearly be an unorthodox, non-integer, value but it does give an indication of how heavily parameterised the model is.

This value of $\text{tr}(\mathbf{S})$ is also used in the calculation of a GWR version of the AIC statistic:

$$\text{AIC}_c = 2n \log(\tilde{\sigma}) + \frac{n + \text{tr}(\mathbf{S})}{n + 2 - \text{tr}(\mathbf{S})}.$$

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