The Spatial Pattern of Demand in the Early Market for Electric Vehicles: Evidence from the United Kingdom

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Abstract

This paper reports a spatial analysis of Electric Vehicle registrations across the local authorities of the United Kingdom during the early phase of market development. Spatial autocorrelation tests are applied in order to identify any spatial organisation in registrations rates and spatial regression models are specified to consider the effect of socioeconomic, household, and transport system characteristics over registrations. Specific attention is paid to the association between Electric Vehicle registrations and the presence of charging infrastructure to consider if registrations are affected by infrastructure in the immediate and intermediate vicinity.

The results of the analysis suggest Electric Vehicle demand exhibits a moderate degree of spatial clustering, which indicates the emergence of lead and laggard markets, and that the spatial variation in Electric Vehicle uptake can be partially explained through other characteristics of the local authorities. Characteristics relating to education level, employment status, income level, population density, dwelling type, household size, car availability, and the presence of Hybrid Electric Vehicles are significant factors in explaining the rate of Electric Vehicle registrations. Moreover, the level of charge point infrastructure installed within a local authority is positively associated with EV demand. From a policy perspective, the results reported in this paper indicate that local conditions are likely to be important in the rate of Electric Vehicle adoption, which may be of use when considering the development of geographically targeted interventions to accelerate Electric Vehicle demand.

Citation

1. Introduction

The dominant position of the car to service personal mobility needs in the majority of economically developed nations has been firmly embedded over the past half century. The desire of citizens for car mobility stems from the substantial affordances which cars offer (Dant, 2004), allowing their users to attain transport speeds, flexibilities, and seamless movements which alternative modes of transport usually cannot provide (Schwanen and Lucas, 2011). The car mobility system is remarkably resistant to subversion, meaning a transition away from their personalised service is unlikely to occur in the near future (Urry, 2007; Wells and Xenias, 2015). While car use will likely be sustained in the future, there is a general awareness of the harms the system generates inclusive of economic, social, and environmental issues (Banister, 2005). Geels (2012) refers to some of these harms as destabilising pressures, which have the potential to produce shifts in system configuration to allow for a sustainable transport future to be realised (Geerlings et al. 2012).

One such potential shift in the configuration of the transport system relates to the integration of new propulsion and fuel technologies in cars (Banister, 2008). Electric Vehicles (EVs), which partially or entirely replace the internal combustion engine with an electric motor powered by electricity stored in an on-board battery pack, represent the leading technology to motivate this shift. EVs have the potential to offer considerable benefits to society such as enhancing the energy efficiency of vehicles, diversifying the energy input to the transport system, improving local air quality, and reducing the greenhouse gas (GHG) emissions of car mobility (Faria et al. 2012; Ma et al. 2012; Sandy Thomas, 2012; Wu et al. 2015). In the United Kingdom (UK), EVs represent the primary mechanism through which substantial reductions in the GHG emissions inventory for the transport sector will be realised in order to meet the legislated carbon targets (Climate Change Act, 2008). This is apparent in the Committee on Climate Change's (2015) Fifth Carbon Budget which estimates that 9% of all new vehicle sales in the UK will need to be EVs by 2020, increasing to 60% by 2030.

Realising the preferred emissions reduction trajectory of the Committee on Climate Change for the transport sector is contingent on the appearance of high levels of demand for EVs. This anticipated emergence and subsequent rapid growth in EV demand has generated a large expansion in research investigating issues related to EV technical improvement (Dijk and Yarime, 2010; Tuttle and Kockelman, 2012), citizen reaction (Egbue and Long, 2012; Axsen et al. 2013; Graham-Rowe et al. 2011), energy system integration (Pasaoglu et al. 2014; Robinson et al. 2013), and identifying the characteristics of drivers likely to adopt EVs during their initial diffusion (Plötz et al. 2014; Shuitema et al. 2013; Nayum et al. 2015; Higgins et al. 2017). The diffusion of EVs through national vehicle fleets is often discussed temporally, with models designed in order to predict future rates of adoption and to construct potential uptake trajectories (Shepherd et al. 2012; Zubaryeva et al. 2012a; Tran et al. 2013). Comparatively less attention has been paid to the manner in which EVs are diffusing spatially and how the uptake of EVs differs across geographical areas. This paper contributes to this area of study by exploring how the early demand for EVs (i.e. plug-in hybrid and pure battery electric vehicles) has spatially manifested across the local authorities of the UK through the application of spatial econometric modelling. The analysis examines the spatial variation in the demand for EVs and determines if this variation displays signs of geographical organisation. Moreover, the analysis investigates the association which is present between EV demand and the environmental context covering the socioeconomic, household, and transport system characteristics of the local authorities.

Within this, the relationship between EV registrations and the installation of charging infrastructure is evaluated to consider if infrastructure investments are stimulating demand in the immediate and intermediate vicinity.

2. Existing Literature

The topic of EV demand has attracted a substantial degree of academic attention over the past decade, likely due to the degree of importance placed on EVs in transport policy (Al-Alwai and Bradley, 2013; Rezvani et al. 2015). Research has focused on how citizens will interpret the unique characteristics of EVs and their formation of preferences towards these vehicles. Applications of Discrete Choice Modelling (Train, 2009) have generally found that citizens are averse to the limited driving ranges and purchase price premiums of EVs, with the reduced environmental impact and improved operating costs of EVs unlikely to overcome these negative evaluations (Potoglou and Kanaroglou, 2007; Caulfield et al. 2010; Hidrue et al. 2011). Concentrating on the latent characteristics of individuals, research employing psychometric analysis has identified attitudes relating to environmental concerns (Ozaki and Sevatsyanova, 2011; Morton et al. 2016) and personal value structures (Jansson et al. 2011) as relevant issues in EV evaluations. The integration of Discrete Choice Modelling and psychometric analysis is an area which has been proposed (Ben-Akiva et al. 2002) and can lead to the specification of more realistic models (Bolduc et al. 2008). Model integration of this nature has been pursued by Daziano and Chiew (2012), who propose the combination of observable and latent attributes previously identified as holding explanatory power concerning preferences towards EVs into an integrated model of EV demand.

With the market for EVs expected to grow substantially over the next 25 years, forecasting the demand for EVs represents an active area of inquiry. Current forecasts tend to present alternative adoption scenarios, demonstrating how alterations in the system parameters which are known to influence adoption (e.g. expectations concerning the reduction in EV purchase price premiums and expansions in EV driving range) can influence uptake trajectories. Musti and Kockelman (2011) simulate the evolution of household vehicle fleets in Austin, USA, over a 25 year period through the construction of alternative scenarios with their model indicating that two and three car households are most likely to integrate an EV into their household fleets while feebate[1] policies can discourage the adoption of vehicles with large footprints (e.g. Sports Utility Vehicles). Employing a conjoint adoption model, Eggers and Eggers (2011) produce a number of short-term (2009-2018) adoption scenarios for EVs and utilise a series of critical factors inclusive of purchase price, driving range, timing of EV market entry, and environmental evolution in their uptake trajectories. Modelling the demand for EVs to 2050, Shepherd et al. (2012) make use of a systems dynamics model to evaluate alternative market scenarios, with their results indicating that it is a combinations of different elements, that cover the configuration of market conditions, which are important, and that considering single factors in isolation may lead to suboptimal recommendations. Recently, Brand et al. (2013) evaluate the impact of different fiscal transport policy mixes through the UK Transport Carbon Model (Brand et al. 2012) with their findings supporting the importance of feebates by suggesting that policies which offer

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[1] Feebate policies generally include the provision of rebates for fuel efficient vehicles and surcharges for highly polluting vehicles

financial rewards for low carbon vehicle choices while penalising the purchase of heavily polluting vehicles will lead to the most rapid expansion in EV sales.

While research that explores the distribution of EV sales over time allows for considerations relating to the effect of government policy mix, initial market conditions, and anticipated technical improvements to be modelled, investigations of this nature tend to overlook the dispersal of EV sales across space. Spatial analysis of EV demand allows researchers to investigate issues relating to the role of infrastructure deployment, situational contexts, and varying demographic arrangements. Researchers have begun to address these issues with Campbell et al. (2012) constructing a spatial cluster model in an effort to identify the residential location of citizens who are most likely to adopt an EV in the city region of Birmingham, UK. Their model is built using UK census data with the results indicating that potential EV adopters tend to concentrate in suburban locations. Campbell et al.'s model is extended by Namdeo et al. (2014) who combine demographic data with travel patterns to identify optimal locations for the installation of public EV charging infrastructure in the Tyne and Wear metropolitan area of the UK. The results of their analysis suggest that latent demand for EVs relating to two citizen groups who tend to reside in the inner city could be promoted through the placement of proximate charging points.

A series of works have demonstrated the insights which can be generated when combining spatial and temporal aspects of EV demand forecasting in an integrated analysis. Zubaryeva et al. (2012b) develop adoption scenarios for the European Union based on the factors likely to influence early demand expressed by experts in a multi-criteria assessment (Zubaryeva et al. 2012a). They find that lead markets for EVs are likely to be sited in large, densely populated urban areas in the economically prosperous member states. These findings hold parallels to the work of Higgins et al. (2012), who spatially forecast EV demand out to 2030 across the metropolitan region of Melbourne, Australia, with geographical differences in uptake being primarily motivated by driving distances, employment status, and household income. Similarly, Kihm and Trommer (2014) model EV adoption trajectories to 2030 for the German market and find that EV registrations tend to concentrate in urban and suburban areas.

Recently, research has begun to examine the realised uptake of low emission vehicles, primarily through examinations of the geographic distribution of Hybrid Electric Vehicle (HEV) registrations. Saarenpää et al. (2013) conduct an analysis in which the spatial adoption of HEVs is compared to socioeconomic data in Finland. The analysis finds that HEVs have a higher propensity to be registered in areas which have populations that have a high degree of formal education, household income, and proportion of owner-occupied homes. Through the specification of a multinomial logit model of HEV demand across the census tracts of Windsor, Canada, Dimatulac and Maoh (2017) find that HEV uptake is associated with gender splits, employment type, education level, household size, and income. The demand for HEVs has also been examined using spatial econometric models, with the work of Liu et al. (2017) and Morton et al. (2017) finding that education level, car availability, household size, travel to work patterns, and personal incomes all have significant associations with uptake. Chen et al. (2015) build a Poisson log-normal conditional autoregressive model of non-hybrid EV adoption (i.e. plug-in hybrid and pure battery electric vehicles) across the census blocks of Pennsylvania, USA, with their findings suggesting that EV registrations tend to be lower in areas that have high densities of low income households and areas that have increased distance to the central

business district. Moreover, Chen et al. (ibid.) identify persisting spatial autocorrelation in their model of EV demand, implying that other issues which are spatially clustered and that are challenging to include in spatial models (e.g. parking availability and pricing) may also be associated with EV uptake.

To summarise, research which involves the spatial modelling of EV demand has so far fallen into two categories. Firstly, predictive models have been produced which aim to estimate the likelihood of areas to include early EV adopters (Campbell et al. 2012; Namdeo et al. 2014) and how this likelihood of adoption alters over time (Zubaryeva et al. 2012b; Higgins et al. 2012; Kihm and Trommer 2014). Secondly, explanatory models have been formatted with the goal of examining what area characteristics can be of use in accounting for the observed spatial variation in adoption (Saarenpää et al. 2013; Dimatulac and Maoh; 2017; Liu et al. 2017; Morton et al. 2017; Chen et al. 2015). The research presented in this paper sits within the second category and aims to extend current understanding regarding the spatial diffusion of EVs in the early market by determining the degree to which the socioeconomic, household, and transport characteristics of the areas as well as the presence of charging infrastructure in the immediate and intermediate vicinity can be of use in accounting for the spatial variation in EV adoption.

3. Methodology

This section of the paper first describes where the data utilised in the analysis has been sourced, how the data has been prepared for analysis, and some of the limitations of the data. Following this, the statistical methods applied to the data are briefly outlined.

3.1 Data Source

Georeferenced data covering the number of EVs registered in the UK has been tabulated from the Vehicle Licensing Statistics Database managed by the Department for Transport (Department for Transport, 2016). EVs are defined in this project as those vehicles registered by private households that have qualified for the UK Government's plug-in car grant which covers both plug-in hybrid electric vehicles (PHEVs) and pure battery electric vehicles (BEVs; Office of Low Emission Vehicles, 2015). In total, 36,444 EVs were registered to private households in the UK as of the end of 2016. Moreover, the number of Hybrid Electric Vehicles (HEVs) registered to private households has been recorded.

With the installation of charging infrastructure expected to play an important role in the diffusion of EVs, the number of charge points in each local authority has also been calculated using data sourced from the National Charge Point Registry (Department for Transport, 2015). In addition, data concerning the socioeconomic, household, and transport system profiles of the local authorities have been sourced from the UK's population census (Office of National Statistics, 2011; National Records for Scotland, 2011) and from Her Majesty's Revenue and Customs (2015). Descriptive statistics covering the data utilised in the analysis reported in this paper can be viewed in Table 1.

3.2 Spatial Resolution

The data is aggregated at what is generally referred to as lower-tier local authority level of UK administrative geography and is inclusive of the non-metropolitan districts of England, the

metropolitan districts of England, the unitary authorities of England, the London boroughs of England, the principal areas of Wales, and the council areas of Scotland. In total, 380 lower-tier local authorities cover England, Wales, and Scotland, and have a mean resident size of 161,503 (S.D. 5681) and a mean area of 60,250 (S.D. 8072) hectares. The lower-tier local authority spatial resolution is a common level of aggregation to report government statistics in the UK and is directly associated with local governance. In addition, it is an appropriate scale through which to consider spatial spillovers in EV infrastructure investment. As a journey to a neighbouring local authority generally represents an intermediate length trip, the availability of charging infrastructure in these nearby areas may hold more relevance to EV demand than availability in the immediate vicinity (i.e. charge points within the same local authority).

Table 1: Descriptive statistics of the variables related to the socioeconomic, household, and transport system characteristics of the local authorities of the United Kingdom included in the analysis (n = 374)

Variable	Mean	S.D.	Min	Max
Socioeconomics				
Median Age (years) [A]	40.54	4.27	29.00	51.00
No Qualifications (%) [A]	22.80	5.14	6.72	36.04
High School Qualification (GCSE grades D-G) (%) [A]	14.30	3.43	4.30	28.26
High School Qualification (GCSE grades A*-C) (%) [A]	15.55	1.98	6.58	18.55
College/Pre-University (A-Levels) (%) [A]	12.08	2.03	7.16	32.59
University Degree (%) [A]	26.93	7.71	1.42	68.36
Median Personal Income (000's GBP) [B]	22.89	3.69	17.50	61.10
Full Time Employment (%) [A]	38.83	3.97	26.41	51.45
Part Time Employment (%) [A]	14.03	1.60	5.71	17.08
Self-Employed (%) [A]	10.01	2.76	4.77	17.45
Unemployed (%) [A]	4.06	1.23	2.01	8.02
Retired (%) [A]	14.79	3.51	4.71	24.06
Household				
Detached House (%) [A]	25.91	12.68	0.39	60.52
Semi-Detached House (%) [A]	30.22	8.27	0.21	48.85
Terraced House (%) [A]	23.40	8.81	1.45	56.13
Flats/Apartments (%) [A]	15.91	12.16	3.20	86.34
Population Density (per hectare) [A]	15.02	22.52	0.09	138.70
Own Home Outright (%) [A]	32.44	7.07	8.45	47.96
Own Home Mortgage (%) [A]	33.47	5.19	12.83	44.16
Rent (social) (%) [A]	16.64	6.61	5.35	43.72
Rent (private) (%) [A]	15.27	5.52	4.89	39.66
Mean Residents [A]	2.33	0.13	1.64	2.99
Transport System				
Travel to Work: Light Rail [A]	2.43	7.23	0.01	39.84
Travel to Work: Train [A]	4.61	5.23	0.26	30.83

Travel to Work: Bus (%) [A]	5.97	4.63	1.09	26.66
Travel to Work: Car Driver (%) [A]	60.11	12.78	3.05	75.48
Travel to Work: Car Passenger (%) [A]	5.31	1.76	0.25	11.55
Travel to Work: Bicycle (%) [A]	2.67	2.44	0.27	29.87
Travel to Work: Foot (%) [A]	10.76	3.91	3.52	48.39
No Car in Household (%) [A]	23.06	10.48	8.04	69.40
One Car in Household (%) [A]	42.27	2.93	25.09	50.20
Two Cars in Household (%) [A]	26.45	7.14	3.95	42.09
Three Cars or more in Household (%) [A]	6.03	2.20	0.51	11.19
Electric Vehicles per 1,000 cars [C]	1.39	1.16	0.16	11.39
Hybrid Electric Vehicles per 1,000 cars [C]	7.61	5.98	1.24	46.54
Charge points [D]	9.92	21.89	0	252

A: data sourced from the UK census (England and Wales: Office of National Statistics,2011; Scotland: National Records for Scotland, 2011)

B: data sourced from Her Majesty's Revenue and Customs (2015)

C: data sourced from the Department for Transport (2016)

D: data sourced from the Department for Transport (2015)

3.3 Data Preparation

The data from the sources outlined in the previous section has been integrated into a unified spreadsheet in order to link the observations of EV registrations with the socioeconomic, household, and transport system characteristics of the local authorities. Following this step, the unified spreadsheet has been spatially joined to a shapefile covering the relevant boundaries of the administrative geography sourced from the Office of National Statistics (2013). Non-contiguous areas of the UK have been removed from the analysis covering Northern Ireland and the islands which have lower-tier local authority status inclusive of Anglesey, Na h-Eileanan an Iar, Orkney, Scilly, Shetland, and Wight. After the removal of non-contiguous areas, the number of cases included in the analysis covers 374 lower-tier local authorities. To ensure that the analysis is not unduly affected by the differing population sizes of the local authorities, a number of the variables associated with the transport system features have been standardised. Specifically, the numbers of EVs and HEVs in each local authority have been divided by the number of thousand cars registered in each local authority.

3.4 Data Limitations

There are a number of limitations with the dataset utilised in this analysis which need to be considered when interpreting the results. First, while the spatial resolution across all the data is constant, a degree of variation exists relating to the time the data was collected. For instance, the data corresponding to personal income was collected during 2012 while the remaining socioeconomic characteristics are sourced from the UK census which was collected in 2011. This temporal divergence has the potential to lead to bias in the analysis if significant changes in the characteristics of the areas have occurred in the intervening time periods.

Second, the administrative geography of the UK is a complex arrangement of local governance structures which have undergone a series of partial restructurings over the last half century. Use of data aggregated at this spatial resolution can generate a number of potential biases. One of these

biases is the Ecological Fallacy Problem (Anselin, 2002), which reasons against making inferences to micro relationships from macro observations. As such, conclusions to individual consumer behaviour from the results presented here should be avoided. Another relevant bias is the Modifiable Areal Unit Problem (Fotheringham and Wong, 1991), which concerns the sensitivity of findings to alterations in the spatial resolution of the geographical units. As such, the results presented here could prove susceptible to changes in spatial boundaries. These biases are clearly described in the context of transport studies by Wang et al. (2012) who propose a series of strategies to improve model quality which could be pursued in reference to EV registrations when more data becomes available at different levels of spatial resolution.

3.5 Spatial Analysis

The acquisition of georeferenced data concerning the registrations of EVs throughout the local authorities of the UK allows for the application of spatial statistics which offer insights relating to how the early demand for EVs has manifested across space. Spatial analysis methodologies are becoming more popular in transport as an increasing amount of spatial data is being released. Examples include, Quddus (2008) exploring spatial correlation in traffic collisions in London, Vandenbulcke et al. (2011) examining spatial determinants of cycle commuting in Belgium, Yu et al. (2013) identifying spatial spillovers in economic growth resulting from transportation infrastructure investments while Adjemian et al. (2010) investigate spatial dependence in vehicle type choice in San Francisco.

The methods utilised in this paper are summarised in the following sections with interested readers directed to the contributions of LeSage and Pace (2009) and Arbia (2014) for thorough definitions and descriptions. To produce the statistical outputs, a series of software packages have been used inclusive of Quantum GIS for the spatial variance analysis, GeoDa for the spatial weight construction and spatial autocorrelation analysis (Anselin et al. 2006), and the MatLab routines developed by Elhorst (2014) for the spatial regression analysis.

3.5.1 Spatial Weights

The specification of a spatial weights matrix (Haining, 2009) allows for the space for which georeferenced data is available (e.g. the UK) to be classified in order to express the arrangement of geographical units (e.g. local authorities). This expression of arrangement can generally be determined either by a measurement of distance or a measurement of contiguity. In this paper, a contiguity approach is employed based on the geometric layout of the local authorities of the UK to determine spatial connectivity. The structural form of the spatial weights matrix is reported in Equation 1 which follows a binary contiguity configuration with w_{ij} representing the contiguity between geographical units i and j while n notes the total number of geographical units. A queen contiguity criterion is followed here which defines geographical units as neighbours if they share a common line or point border.

$$W = \begin{vmatrix} W_{11} & \cdots & & W_{n1} \\ \cdots & & & \\ & & W_{ij} & \\ W_{1n} & & & W_{nn} \end{vmatrix} \qquad (1)$$

$$W_{ij} = \begin{cases} 1 & \text{if spatial unit } j \text{ and } i \text{ are neighbours} \\ 0 & \text{if spatial unit } j \text{ and } i \text{ are not neighbours} \end{cases}$$

3.5.2 Spatial Autocorrelation

Georeferenced data allows for the application of spatial analysis to examine if the values of a variable observed across the geographical units are associated with the observed values in neighbouring geographical units. This type of examination is generally referred to as spatial autocorrelation analysis (Cliff and Ord, 1973; Getis, 2009) and is often categorised by those methods which focus on global or local effects. Global approaches to spatial autocorrelation take into account all of the geographical units which exist within a given area whereas local approaches explore spatial autocorrelation for singular geographical units.

For global spatial autocorrelation, Moran's I represents a commonly applied approach to determining if the observed values of a variable are spatially associated (Moran, 1948; Rogerson, 2010). Moran's I is similar in structure to Pearson's product moment correlation analysis with the structural form of the equation modified through the inclusion of a spatial weights matrix. The structural form of Moran's I is summarised in Equation 2 where y_i and y_j represent the observed values of the variable of interest (e.g. EV registrations per 1,000 cars) in geographical units i and j while $\bar{y}$ represents the mean of the variable of interest.

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\,(y_i - \bar{y}) - (y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (2)$$

Local indicators of spatial association (LISAs) have been developed which decompose global statistics (e.g. Moran's I) to allow for the identification of local patterns to occur (Anselin, 1995). The application of LISAs can be useful in identifying spatial regimes, whereby geographic sub-regions display distinct values of a variable thus indicating the presence of spatial heterogeneity, and in identifying spatial clusters, whereby values of a variable appear to gravitate around a single geographical unit. A local version of Moran's I can be specified which allows for the presence of spatial regimes and clusters to be identified with the structural form reported in Equation 3.

$$I_i = n\,(y_i - \bar{y}) \sum_{j} W_{ij}\,(y_j - \bar{y}) \qquad (3)$$

3.5.3 Spatial Regression

A benchmark ordinary least squares (OLS) regression model can be extended through the integration of spatial interaction effects to investigate if observations of a variable across geographical units can be explained by observations of a variable in neighbouring geographical units (LeSage and Pace, 2009; Arbia, 2014). Spatial interaction effects generally relate to the inclusion of spatially-lagged variables, which can be integrated into the OLS regression model to account for local or global spatial spillovers (LeSage, 2014). The calculation of the robust Lagrange Multiplier provides guidance on whether extending for local or global spillovers is optimal (Anselin et al. 1996). In this paper, global spillovers are modelled through the specification of the Spatial Durbin Model using Maximum Likelihood estimation (Elhorst, 2010; Elhorst, 2014). The Spatial Durbin Model introduces an endogenous spatial interaction effect through the spatial lag of the model's dependent variable, while also estimating direct, indirect, and total effects for each independent variable. The endogenous spatial interaction effect allows the analysis to consider whether the uptake of EVs in a particular local authority is associated with the level of demand for EVs observed in neighbouring local authorities. The estimation of direct effects allows the model to consider the association between an independent variable and the dependent variable within a local authority, indirect effects to assess the association between an independent variable and the dependent variable in neighbouring local authorities, with total effects being the combination of direct and indirect effects. The structural form of the Spatial Durbin Model is reported in Equation 4, where y is a vector of observations of the dependent variable, α is a constant parameter, β is a vector of coefficients for the model independent variables, x is a vector set of observations of the model independent variables, p is the endogenous spatial interaction coefficient, Wy is a vector of observations of a spatially lagged model dependent variable, Θ is a vector of coefficients of the spatially lagged model independent variables, Wx is a vector set of observations of the spatially lagged model independent variables, and ε is the model residual.

$$y = \alpha + \beta x + pWy + \theta Wx + \varepsilon \qquad (4)$$

4. Results

The results of the analysis are presented in four stages. First, the spatial variation of EV registrations across the local authorities of the UK is illustrated. Second, the spatial variation is examined using spatial autocorrelation analysis to investigate if spatial clustering in registrations can be observed. Third, correlation analysis is utilised to identify relationships that exist between the registrations of EVs and area characteristics covering socioeconomic, household, and transport system variables. Fourth, a series of regression models are specified in an effort to explain the variation in EV registrations using area characteristics.

4.1 Spatial Variation Assessment

Figure 1 illustrates the number of EV registrations per 1,000 cars across the local authorities of the UK up to the end of 2016. A substantial degree of spatial variation is clearly apparent, with some local authorities displaying relatively high levels of EV adoption while other local authorities are less advanced in EV uptake.
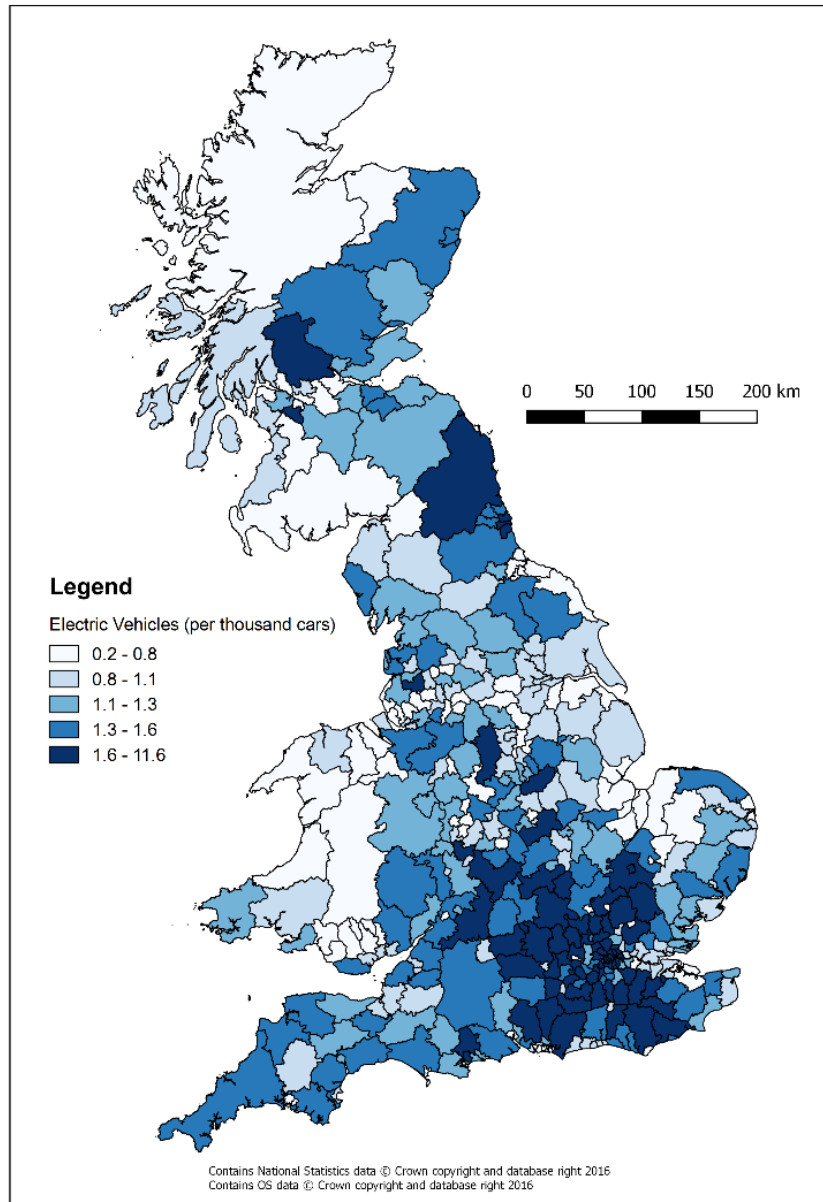
Figure 1: Choropleth map of Electric Vehicle registrations per 1,000 cars across the local authorities of the United Kingdom up to December 2016

4.2 Spatial Autocorrelation Analysis

While a substantial degree of spatial variation in EV registrations is visible in Figure 1, it is not clear from a visual inspection of this map if this variation is random or if some degree of spatial organisation is present. To examine if the registrations of EVs across the local authorities of the UK are related to the number of registrations observed in neighbouring local authorities, a Moran's I test of spatial autocorrelation has been conducted (detailed in section 3.6). The analysis returns a result of 0.551 (p-value < 0.01), indicating that registrations of EVs are moderately spatially correlated. To investigate if spatial autocorrelation of EV registrations is clustered in specific regions of the UK, a LISA analysis has been conducted with the results presented in Figure 2. Regions highlighted in deep blue represent clusters of local authorities which display low levels of EV registrations, suggesting these areas are

cold-spots of EV adoption. These cold-spot clusters appear to cover some of the large cities in the north of England (i.e. Manchester and Liverpool), much of central and northern Wales, and also the Humber region to the mid-east of the UK. Comparatively few regions are identified as hot-spots of adoption (highlighted in deep red), with central London found to represent a cluster of local authorities with relatively high levels of EV registrations.
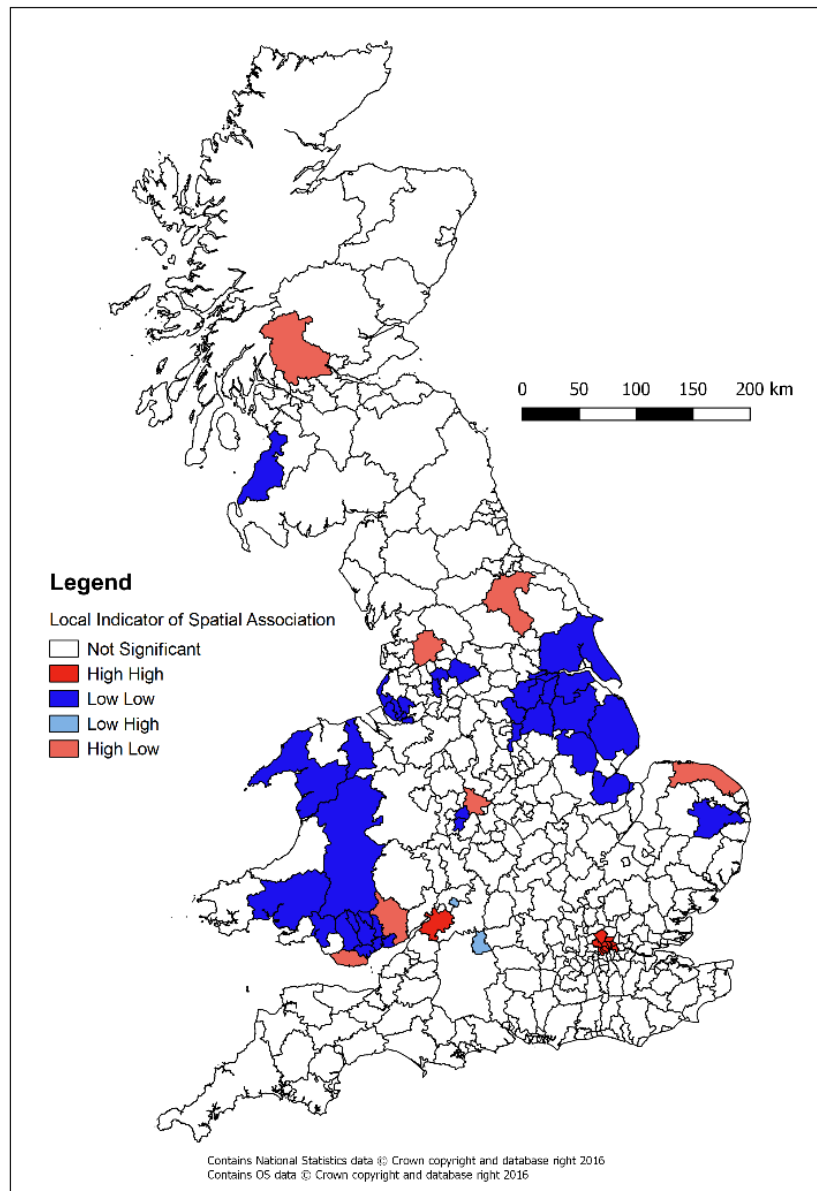
Figure 2: Local spatial autocorrelation analysis of Electric Vehicle registrations across the local authorities of the UK

4.3 Correlation Analysis

A series of correlation analyses have been conducted to investigate if the registrations of EVs in local authorities are related to other characteristics of these areas. As the variables included in the analysis do not conform to the assumptions of parametric statistics, the correlation analyses follow Spearman's rank-order approach. Three different groups of characteristics are considered covering

the socioeconomic characteristics, household attributes, and transport system features of the areas (detailed in Table 1).

The results of the correlation analyses between EV registrations and socioeconomic characteristics are presented in Table 2. A substantial degree of interaction is present, with EV registrations displaying significant relationships with most of the socioeconomic variables included in the analysis. Notably, EV registrations hold moderate-to-strong[2] positive correlations with the proportion of residents that hold a university degree (r_s: 0.753), that are classified as self-employed (r_s: 0.593), and median personal incomes (r_s: 0.666). A series of moderate-to-strong negative correlations are also identified with the proportion of residents that have no formal qualifications (r_s: -0.709), low-level secondary school qualifications (r_s: -0.456), and that are classified as unemployed (r_s: -0.500).

The results of the correlation analyses between EV registrations and household features are presented in Table 3. In this instance, a lower degree of interaction is observed, with correlations between EV registrations and household features tending to be weak or absent. Three moderate negative correlations are identified between EV registrations and the proportion of semi-detached households (r_s: -0.216), terraced households (r_s: -0.366), and the proportion of households that are rented socially (r_s: -0.254).

The last set of characteristics examined concerns the relationships between EV uptake and the features of the transport system. These results are presented in Table 4 and indicate that weak-to-moderate associations between these variables tend to be present. In terms of positive correlations, EV uptake is significantly connected with the proportion of households that have two cars (r_s: 0.355), three or more cars (r_s: 0.336), that use light-rail (r_s: 0.448) and train (r_s: 0.351) to travel to work as well as the number of HEVs per thousand cars (r_s: 0.506). Additionally, a significant positive relationship is identified between EV registrations and the number of charge points (r_s: 0.252). In terms of the negative correlations, the rate of EV registrations is significantly linked to the proportion of households that own no cars (r_s: -0.356), have one car (r_s: -0.376), and the proportion of residents that are car passengers on their commute (r_s: -0.693).

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[2] For the purpose of this analysis, weak correlations are considered as those which are between 0.2 and 0.4, moderate correlations those which are between 0.4 and 0.6, and strong correlations those which are greater than 0.6

Table 2: Correlation analysis between Electric Vehicle registrations and socioeconomic characteristics of the population across the local authorities of the United Kingdom

	A	B	C	D	E	F	G	H	I	J	K	L
EV (A)	1											
Median Age (B)	.061	1										
No Qualification (C)	-.709**	.163**	1									
GCSE D-G (D)	-.456**	.125*	.607**	1								
GCSE C-A* (E)	-.167**	.424**	.154**	.465**	1							
A Level (F)	-0.043	-.057	-.206**	-.299**	.175**	1						
University Degree (G)	.753**	-.068	-.914**	-.692**	-.361**	.067	1					
Part Time (H)	-.213**	.658**	.275**	.244**	.539**	.168**	-.301**	1				
Full Time (I)	.274**	-.317**	-.431**	.113*	.039	-.024	.268**	-.223**	1			
Self-Employed (J)	.593**	.425**	-.587**	-.416**	.111*	-.121*	.608**	.105*	-.015	1		
Unemployed (K)	-.500**	-.520**	.589**	.329**	-.212**	-.254**	-.550**	-.286**	-.195**	-.685**	1	
Retired (L)	-.165**	.925**	.408**	.209**	.410**	-.032	-.302**	.673**	-.455**	.166**	-.289**	1
Income (M)	.666**	-.142**	-.796**	-.358**	-.145**	-.024	.754**	-.320**	.547**	.483**	-.464**	-.379**

*: p-value < .05
**: p-value < .01

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Table 3: Correlation analysis between Electric Vehicle registrations and household attributes across the local authorities of the United Kingdom

	A	B	C	D	E	F	G	H	I	J
EV (A)	1									
Detached (B)	.179**	1								
Semi-Detached (C)	-.216**	.070	1							
Terrace (D)	-.366**	-.594**	-.013	1						
Flat (E)	.178**	-.651**	-.476**	.134**	1					
Owned Outright (F)	.104*	.800**	.132*	-.459**	-.608**	1				
Owned Mortgage (G)	.077	.188**	.390**	-.034	-.250**	.044	1			
Rent Social (H)	-.254**	-.645**	-.082	.420**	.410**	-.760**	-.305**	1		
Rent Private (I)	.015	-.409**	-.349**	.204**	.446**	-.379**	-.563**	.088	1	
Mean Residents (J)	.147**	-.055	.190**	.100	-.027	-.216**	.489**	-.032	-.095	1
Pop Density (K)	-.069	-.802**	-.025	.313**	.621**	-.705**	-.035	.420**	.382**	.255**

*: p-value < .05
**: p-value < .01

Table 4: Correlation analysis between Electric Vehicle registrations and transport system features across the local authorities of the UK

	A	B	C	D	E	F	G	H	I	J	K	L	M
EV (A)	1												
No Car (B)	-.356**	1											
One Car (C)	-.376**	.275**	1										
Two Car (D)	.355**	-.978**	-.383**	1									
Three+ Car (E)	.336**	-.968**	-.348**	.954**	1								
Light Rail (F)	.448**	.077	-.216**	-.094	-.059	1							
Train (G)	.351**	.027	-.224**	-.006	-.009	.605**	1						
Bus (H)	-.195**	.847**	.175**	-.808**	-.859**	.178**	.097	1					
Car Drive (I)	-.160**	-.535**	-.210**	.601**	.538**	-.464**	-.410**	-.528**	1				
Car Pass(J)	-.693**	.332**	.263**	-.284**	-.302**	-.621**	-.531**	.147**	.354**	1			
Bicycle (K)	.114*	.064	.155**	-.116*	-.151**	.137**	-.058	0.09	-.230**	-.222**	1		
Foot (L)	-.137**	.205**	.269**	-.264**	-.206**	-.150**	-.336**	-.009	-.304**	.147**	.376**	1	
HEV (M)	.506**	.019	-.165**	0.007	-.052	.656**	.576**	.194**	-.386**	-.641**	.201**	-.161**	1
Charge Points (N)	.252**	.322**	-.093	-.304**	-.329**	.332**	.278**	.395**	-.419**	-.226**	.091	-.092	.346**

*: p-value < .05
**: p-value < .01

4.4 Regression Analysis

To investigate if the socioeconomic characteristics, household attributes, and transport system features of the local authorities can be useful in explaining EV registrations, a series of regression models have been specified. The dependent variable utilised in the analysis is the natural log of EV registrations per thousand cars in a local authority. The independent variables included in the analysis have also been transformed into their natural logs[3] and have been selected based on the findings of past research, the results of the correlation analysis, and specific issues under investigation in this paper. Due to the high degree of interaction between the different groups of independent variables, the specification of models which are not biased by multicollinearity can be challenging. To ensure this condition does not unduly affect the outputs of the analysis specified here, the variance inflation factor (VIF) has been calculated for each of the specified models with the highest VIF observed being 7.52 with a mean VIF of 4.31, which are within the threshold tolerance level of 10 (Field, 2009).

To begin, a batch of benchmark OLS models have been specified. A staged-entry procedure for the independent variables is utilised to construct the benchmark OLS models to allow for the different groups of independent variables to be considered separately. In the first stage (Model 1), variables covering socioeconomic characteristics are included as independent variables. In the second stage (Model 2), variables covering household attributes are included as independent variables. In the third stage (Model 3), variables relating to the features of the transport system are included as independent variables. In the final stage (Model 4), the independent variables incorporated in the preceding models are combined into an integrated model.

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[3] Except for the variable measuring the number of charge points which remains untransformed due to the occurrence of zero observations (i.e. local authorities with no charge points)

Table 5: Benchmark log-log ordinary least squares regression models with Electric Vehicle registrations per thousand cars as the dependent variable

	OLS: M1		OLS: M2		OLS: M3		OLS: M4	
	Beta	**Std. Err.**	**Beta**	**Std. Err.**	**Beta**	**Std. Err.**	**Beta**	**Std. Err.**
Intercept	-15.039**	1.736	0.878**	0.338	8.148**	0.992	-5.101*	2.251
Socioeconomics								
Median Age (years)	0.109	0.176					0.488	0.290
University Degree (%)	0.698**	0.101					0.426**	0.097
Self-Employed (%)	0.298**	0.081					0.353**	0.092
Median Income (GBP)	1.184**	0.173					0.740**	0.168
Household								
Population Density (per hectare)			-0.041*	0.016			0.003	0.017
Semi-Detached (%)			-0.564**	0.051			0.193**	0.065
Mean Residents			1.491**	0.442			-1.878**	0.425
Transport								
One Car Household (%)					-2.323**	0.276	-1.440**	0.238
Car Driver to Work (%)					-0.006	0.072	-0.085	0.098
HEVs per 1,000 cars					0.397**	0.045	0.274**	0.055
Charge Points					0.002	0.001	0.003**	0.001
Model Fit								
Adjusted R^2	0.631		0.246		0.467		0.72	
AIC	148.098		414.506		286.026		48.070	
Model Diagnostics								
Robust LM (lag)	5.801*		56.435**		17.019**		15.124**	
Robust LM (error)	28.886**		9.203**		0.146		0.335	

*: p-value < .05
**: p-value < .01

The results of the benchmark OLS models are presented in Table 5. In terms of the different groups of independent variables considered, it is apparent that socioeconomic characteristics offer relatively high explanatory power over EV registrations (Model 1 R^2: 0.631) whereas household attributes are comparatively less successful (Model 2 R^2: 0.246). Unsurprisingly, the model which integrates all of the groups of independent variables (Model 4) displays the highest degree of explanatory power, accounting for almost three quarters of the variance observed in EV registrations. For each benchmark OLS model specified, the robust Lagrange Multiplier (LM) tests have been calculated following the recommendations of Anselin et al. (1996) to identify model misspecification due to the omission of a spatially lagged dependent variable or spatial autocorrelation in the model error. For the integrated model (Model 4), the results of the diagnostics suggest that extending the benchmark OLS through the inclusion of a spatially lagged dependent variable would improve model fit. To this end, the Spatial Durbin Model is specified with the results being summarised in Table 6.

Table 6: Spatial Durbin Model with Electric Vehicle registrations per thousand cars as the dependent variable

	Direct		Indirect		Total	
	Mean	**Z-Value**	**Mean**	**Z-Value**	**Mean**	**Z-Value**
Socioeconomics						
Median Age (years)	0.224	0.624	-0.036	0.048	0.188	0.144
University Degree (%)	0.452**	3.940	-0.022	-0.148	0.430	1.439
Self-Employed (%)	0.273*	2.551	0.225	0.894	0.498*	2.025
Median Income (GBP)	0.653**	3.949	0.206	0.437	0.859	1.786
Household						
Population Density (per hectare)	-0.043	-1.810	0.103*	2.241	0.061	1.353
Semi-Detached (%)	0.224**	3.176	-0.083	-0.551	0.141	0.857
Mean Residents	-1.930**	-3.980	-1.620	-1.253	-3.550*	-2.551
Transport						
One Car Household (%)	-1.049**	-4.082	-0.528	-1.007	-1.578**	-2.771
Car Driver to Work (%)	-0.043	-0.310	0.202	0.671	0.159	0.589
HEVs per 1,000 cars	0.211**	3.086	0.027	0.264	0.238	1.820
Charge Points	0.003**	4.551	0.004	1.932	0.007**	2.917
Spatial Interaction						
Spatial lag of EVs per 1,000 cars	0.417**	6.861				
Model Fit						
AIC	16.663					

*: p-value < .05
**: p-value < .01

In terms of the independent variables included in the Spatial Durbin Model, the occurrence of direct effects is most apparent. The proportion of residents with a university qualification holds a direct positive effect (β: 0.452), suggesting that EVs are more popular in areas which have high levels of education. The rate of self-employed workers in an area holds a direct positive effect (β: 0.273), indicating that entrepreneurial activity within an area is associated with higher rates of EV uptake. Median personal income displays a direct positive effect (β: 0.653), implying that EV registrations tend to increase as the wealth of the population increases. The proportion of households that are semi-detached exhibits a direct positive effect (β: 0.224), indicating that EV uptake tends to be higher in sub-urban locations. The number of HEVs per thousand cars has a direct positive effect (β: 0.211), which suggest that areas that were receptive to the introduction of HEVs also tend to be lead markets for EVs. The final direct positive effect observed is for the number of charge points (β: 0.003), implying that the availability of EV infrastructure in the immediate vicinity tends to be associated with higher levels of EV uptake.

Two direct negative effects are also identified in the model. The first of these relates to the mean number of residents (β: -1.930), indicating that areas with larger households tend to have reduced demand for EVs. This result could be due to the types of EVs available in the early market, with hatchbacks being more prominent. As EVs with larger chassis become available, this observation may no longer hold true. The second covers the proportion of households with access to one car (β: -1.049), implying that areas in which the population relies on one car to meet mobility needs, EVs tend to be less popular.

One indirect effect is observed in the model, with population density positively associated (θ: 0.103) with the rate of EV registrations. This result signifies that EVs are more popular in areas that are surrounded by populated regions. The variable measuring the number of charge points displays a positive indirect effect which is on the threshold of significance (p-value: 0.053), which may indicate that the availability of charge points in the intermediate vicinity of an area (i.e. in the surrounding local authorities) is associated with increased rates of adoption, though further investigation would be necessary to substantiate this observation. The spatial autocorrelation coefficient in the model displays a significant positive effect (ρ: 0.417), meaning that the rate of EV adoption in a particular local authority is positively associated with the rates observed in neighbouring local authorities. This finding is potentially indicative of an imitation effect, whereby citizens in nearby locations have a tendency to mimic the taste for EVs displayed by their neighbours (Mau et al. 2008).

5. Discussion

Exploring the ways in which the adoption of EVs is related to characteristics of the areas in which they are registered allows for an appreciation of how local conditions can signify lead and laggard markets for EV adoption. The correlation analysis reported in Section 4.3 indicates that EV registrations display a number of interactions with socioeconomic, household, and transport system characteristics. The variables measuring educational attainment, median personal incomes, and the employment status of residents display relatively strong correlation coefficients, suggesting that these variables are useful indicators for detecting lead markets for EV adoption. These results generally support the findings of existing research on the spatial adoption of Hybrid Electric Vehicles (Saarenpää et al. 2013; Dimatulac and Maoh, 2017; Liu et al. 2017; Morton et al. 2017), where registration levels have been found to be connected with these area characteristics. Indeed, with the results of the analysis indicating that EV registrations are tending to occur in the same areas which have existing HEV registrations, it appears as if the spatial diffusion of these advanced propulsion systems is concurrent. With this in mind, the possibility exists for the findings of this analysis to be of use when considering the emerging market for future propulsion system innovations, such as the introduction of Hydrogen Fuel Cell Electric Vehicles into the mainstream automotive market.

The application of regression analysis allows for the association of particular independent variables with EV registrations to be determined while controlling for the effect of other independent variables, thus allowing for *ceteris paribus* considerations to be made. The regression models reported in Section 4.4 illustrate the ways in which EV registrations can be explained through other area characteristics. The results of the benchmark OLS models indicate that socioeconomic, household, and transport system characteristics display significant explanatory power over EV registrations. The model which examines the utility of socioeconomic characteristics (OLS Model 1) is relatively successful in

explaining EV registrations, accounting for over 60% of the variance. This finding implies that the construction of quite modest regression models which incorporate population characteristics are reasonably effective at describing the spatial variation in EV registrations. The application of spatial diagnostics indicates that the extension of the benchmark OLS models through the introduction of spatial interaction effects would lead to the specification of an improved model. The extension of the benchmark OLS model to a Spatial Durbin Model indicates that direct effects for the model independent variables predominate, though population density does display an indirect effect over EV uptake. The mean size of residences and level of car availability display the largest direct effects in the model and generally agree with the findings of past research on HEV uptake whereby the proportion of small households has been found to negatively affect adoption (Dimatulac and Moah, 2017) as well as the incidence of one car households (Liu et al. 2017). The presence of HEVs appears to be a valid indicator of EV uptake, which supports the argument of Saarenpää et al. (2013) who propose that the spatial diffusion of plug-in EVs is likely to partially mimic that of HEVs. Additionally, the spatial autocorrelation coefficient proves to be significant in the model, which is in agreement to the findings of Chen et al. (2015), who identified residual spatial autocorrelation in their model of EV registrations. This could indicate either the presence of a neighbour effect, whereby consumers observe preferences for vehicles in their vicinity and incorporate this information in their choices, or that other issues which cross spatial boundaries (such as road networks and parking regulations) and that are not accounted for in the model might also be having an impact on EV demand.

Of particular importance in the analysis is the interaction which exists between the rate of EV registrations and the presence of charging infrastructure. The results of the correlation analysis indicate that these two variables are significantly related, tending to increase and decrease together. This result is in agreement with the finding of Bailey et al. (2015), who identified a significant relationship between awareness of EV charging points and interest in EVs amongst individual consumers. Moreover, the results of the regression analysis imply that, once the effect of other area characteristics is accounted for, the level of installed charging infrastructure within a local authority is significantly positively associated with the rate of EV registrations. However, the number of charge points does not hold a significant indirect effect in the model, implying that the availability of charging infrastructure in neighbouring local authorities is not associated with higher EV uptake. One interpretation of this result is that investment in charging infrastructure is not spilling over and generating EV registrations in neighbouring local authorities. However, this indirect effect between EV uptake and installed charge points is on the boundary of significance (p-value: 0.053), suggesting that the potential spillover effect between infrastructure investment and EV demand warrants further attention.

6. Conclusions

The attainment of data regarding the locations of EV registrations in the UK allows for a number of insights to be generated concerning the manner in which the early demand for EVs is manifesting spatially. Mapping EV registrations to the local authorities of the UK illustrates that the transition towards EVs is occurring in a spatially heterogeneous manner, with certain areas further ahead in their EV adoption than others. Whilst on the surface this may seem like an obvious finding, it can have a number of important implications. For instance, there is growing awareness of the need to extend the structure of socio-technical transition theory to account for geographical issues such as the formation

of spatial niches and the uneven rate of innovation diffusion in different locations (Coenen et al, 2012; Geels, 2012; Whitmarsh, 2012; Balta-Ozkan et al. 2015; Schwanen, 2015). Research which focuses on these issues has the potential to contribute towards understanding the environmental conditions and contexts which promote sustainability transitions.

The identification of pioneering local markets for the diffusion of sustainable technologies through the application of LISA analysis allows for insights to be generated concerning the ways in which these areas establish as front runners. Equally, LISA analysis can be of use in detecting spatial clusters which are lagging in their adoption of sustainable technologies. This detection allows research to investigate the local circumstances that might be restricting EV adoption, which would be of use when considering the ways in which any identified barriers can be reduced. Barriers to the transition towards EVs are often discussed in terms of consumer perceptions (Egbue and Long, 2012), technical deficiencies (Axsen et al. 2010; Offer et al. 2010) and market conditions (Steinhilber et al. 2013). Providing specific attention to the ways in which local barriers are restricting EV demand could potentially improve the understanding of how transitions can be facilitated (Anderton et al. 2015). Put another way, the research presented in this paper sheds light on how different areas may have different EV transition capacities, with local conditions involving the socioeconomic characteristics of the population, the attributes of the households, and the features of the transport system likely having an effect on EV adoption. For instance, the results of the LISA analysis indicate that the largest cities of England represent both adoption hot-spots (i.e. London) and cold-spots (i.e. Manchester and Liverpool), suggesting that cities may not be universal early adopters of advanced automotive technology and that a more spatially nuanced perspective on this issue is required.

The spatial patterns observed here are indicative of adoption behaviour in the early market for EVs. The degree to which these patterns are temporally dynamic as the market transitions from niche to mainstream represents an area which could benefit from focused attention. Brown (1981, p. 12) notes that '*every spatial pattern of diffusion has its temporal expression, and every temporal pattern its spatial expression*', highlighting the interconnected nature of these aspects. Research which integrates the spatial and temporal aspects of EV diffusion would likely offer insights regarding the stability of adoption patterns, determining if early front-runners tend to maintain their advantage or are overtaken.

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