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Exploring the Effect of Local Transport Policies on the Adoption of Low Emission Vehicles: Evidence from the London Congestion Charge and Hybrid Electric Vehicles

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Abstract

The London Congestion Charge (LCC) is a transport policy with a precise spatial footprint. As such, its impact on the transport system can be expected to vary over space, providing an opportunity to explore the geographical reach of local transport interventions. This paper assesses whether the exemption of Hybrid Electric Vehicles (HEVs) from the LCC affected the registration rate of these vehicles in Greater London and the surrounding areas. The analysis uses official data on the number of HEVs registered across the local authorities of the United Kingdom. This dataset is assessed using [1] exploratory spatial analysis to determine the degree of spatial variation in HEV registrations, [2] area classifications to consider if HEV registrations diminish as nearness to the LCC recedes, and [3] spatial regression models to evaluate the association between distance to the LCC and HEV registrations, controlling for other area characteristics (i.e. socioeconomic, household, and transport system variables). The results clearly show that nearness to the LCC is positively associated with HEV registrations, implying that this form of transport policy is effective at promoting the adoption of low emission vehicles.

Highlights

- The demand for HEVs in the United Kingdom is spatially heterogeneous
- Spatial regression models are specified to explain the geographical variation in demand
- The exemption of HEVs from the LCC is significantly linked with HEV registrations

Key Words

Hybrid Electric Vehicle Demand; Congestion Charging; Local Transport Policy; Spatial Diffusion

Citation

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1. Introduction

Cities across the globe are facing a series of complex and interrelated challenges relating to the structure and operation of their urban transport systems (Banister, 2008; May, 2013). Of particular concern is traffic congestion and the resulting emission of global and local pollutants, which contribute to climate change and harm the health of citizens. Developing effective strategies which address these issues represents an important challenge for urban governance and public policy (Kennedy et al. 2005; Santos et al. 2010).

One strategy for addressing these issues involves restricting the entry of motorised road vehicles to certain areas within the city (Hensher and Puckett, 2007). Such strategies are referred to by Dotter (2016) as Urban Vehicle Access Regulations and can take on multiple forms. Congestion charging, which involves the levy of a fee on particular vehicles from entering marked zones during a specified time frame, has seen application in various urban settings including Stockholm, Milan, and Singapore and has been extensively evaluated. These evaluations cover issues including the effectiveness of the schemes in delivering improvements to relevant policy objectives (Goh, 2002; Olszewski and Xie, 2005; Santos and Fraser, 2006; Santos, 2008; Eliasson et al. 2009), the additional impacts of the schemes on ancillary issues such as social equity (Santos and Rojey, 2004; Eliasson and Mattsson, 2006; Levinson, 2010) and economic activity (Quddus, 2007) alongside the reactions of citizens to such schemes (Jones, 1998; Jakobsson et al. 2000; Schade and Baum, 2007; Schuitema et al. 2010; Jagers et al. 2017).

A somewhat underexplored issue relates to the potential effects of congestion charging on the composition of the vehicle fleet. With these schemes having the capacity to specify graduated fee levels for different types of vehicle, the opportunity exists for schemes employing such a strategy to promote vehicle variants which benefit from a reduced fee. The London Congestion Charge (LCC) scheme incorporates such a feature, offering a charge exemption to certain low emission vehicles. From the initial introduction of the LCC up until June 2013, new Hybrid Electric Vehicles (HEVs) purchased in the United Kingdom (UK) met the criteria for exemption. The purpose of this paper is to consider if this exemption is connected with the uptake of HEVs in the areas surrounding the LCC. Particular attention is paid to the hypothesis that the association between the LCC and HEV registrations diminishes as nearness to the charging zone decreases. This hypothesis is considered by analysing the spatial distribution of vehicle registrations from the Department for Transport's Vehicle Licensing Statistics database.

This paper proceeds by providing an overview of the LCC followed by a summary of the relevant literature on congestion charging policies as well as the research which examines the demand for HEVs. After this, the methodology section details the data utilised in the analysis and the statistical approaches employed to consider the research hypothesis. The results of the analysis are interpreted in the discussion and conclusions section with insights for policy offered.

2. Background

2.1 Overview of the London Congestion Charge

Introduced in February 2003, the LCC involves the application of a fee to qualifying vehicles that enter an area of 21.42 square kilometres in the centre of London (Santos and Shaffer, 2004; Leape, 2006). This area was later enlarged through a western extension in February 2007 and then subsequently removed in January 2011. Figure 1 illustrates the extent of the LCC in the context of the Greater London. The charging period for the scheme runs from 07:00 to 18:00 Monday to Friday with the charge initially set at £5 per day which has been iteratively increased to £11.50. Automatic Number Plate Recognition cameras are employed to track vehicles entering the charge area. The registered keepers of the vehicles are required to pay the charge either before or on the day of travel, with fines imposed for non-compliance.

The primary objectives of the LCC are to reduce congestion, improve journey time reliability, enhance the efficiency of goods and service distribution and to improve bus services through the redistribution of the revenue generated from the scheme to public transport projects (Santos and Fraser, 2006). These primary objectives were subsequently extended to include a series of ancillary goals covering improvements to road safety and enhancing the local environment (Transport for London, 2008). Increasing the market for HEVs is not an explicit objective of the LCC.

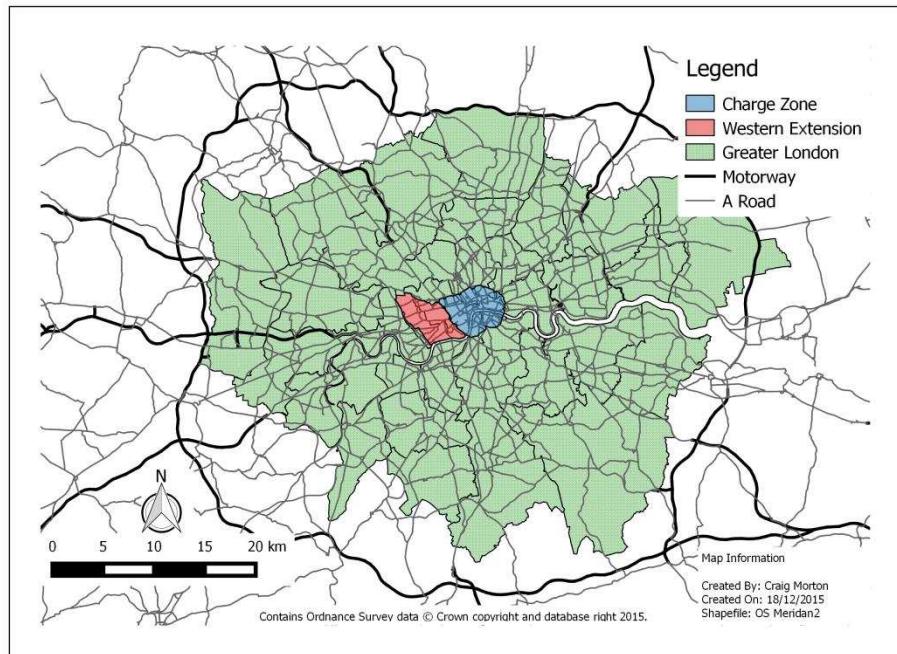


Figure 1: Map illustrating the area covered by the London Congestion Charge and the defunct Western Extension

A series of exemptions are in effect which exclude qualifying vehicles from having to pay the LCC's daily fee, one of which relates to the characteristics of car propulsion systems. From the introduction of the LCC up until December 2010, an Alternative Fuel Discount (AFV) applied to vehicles which operated wholly or partly from a fuel different to petrol and diesel. This discount was superseded in

2011 by the Greener Vehicle Discount (GVD), which required vehicles to emit 100 grams of carbon dioxide per kilometre or less to qualify. The GVD was replaced in July 2013 by the Ultra Low Emission Discount (ULED), which is presently in effect and requires vehicles to emit no more than 75 grams of carbon dioxide per kilometre. Thus, from the introduction of the LCC up until June 2013, all new HEVs sold within the UK would have been exempt from having to pay the LCC's daily fee. An overview of these different propulsion system exemptions is provided in Table 1.

Table 1: Overview of the car propulsion system exemptions to the London Congestion Charge (expanded from Santos and Fraser (2006))

Exemption	Time Span	Requirement
Alternative Fuel Discount	February 2003 to December 2010	Vehicle must run wholly or partly from an alternative fuel (i.e. not Petrol or Diesel) and require emission savings of 40% over Euro IV standards
Greener Vehicle Discount	January 2011 to June 2013	Vehicle must emit 100 grams of carbon dioxide per kilometre or less
Ultra Low Emission Discount	July 2013 to present	Vehicle must emit 75 grams of carbon dioxide per kilometre or less

2.2 Impacts of Congestion Charging

The implementation of a congestion charging scheme has the potential to generate a multitude of impacts across the transport, social, environmental, and economic nexus. Research evaluating these potential impacts is important in both monitoring the effects of existing schemes and in considering the likely consequences of introducing new schemes. With the public acceptability of proposed schemes being of central importance to schemes reaching implementation (Kocak et al. 2005), evidence relating to different scheme aspects will likely reduce the level of perceived uncertainty and thus avoid situations where the public reject the introduction of schemes (Gaunt et al. 2007; Rye et al. 2008).

The direct impact of congestion charging schemes on the transport system represents a central issue in evaluating the realised and potential scheme effects. Transport for London conducted a series of annual impact monitoring studies for the LCC between 2003 and 2008, noting that the entrance of cars and minicabs to the central charge zone decreased from over 180,000 per day pre-implementation to around 120,000 per day post-implementation (Transport for London, 2008), with a concurrent 30% reduction in traffic congestion in the immediate post-implementation period. An analogous evaluation of Stockholm's six month congestion charge trial by Eliasson et al. (2009) found similar effects in terms of car entry to the charge zone and congestion levels as those observed in London. Examining Milan's congestion charge, Percoco (2014a) utilised a fifty day suspension in the scheme's operation to investigate changes in the composition of vehicles circulating within the charge zone. With drivers charged varying amounts to enter the zone depending on the emissions ratings of their vehicles, expectations are that the suspension will demonstrate the substitution effect which

occurs in car type when schemes with graduated charging levels are introduced. Their analysis shows that the suspension of the scheme coincided with a 17% reduction in bi-fuel and HEVs entering the charge zone (i.e. vehicles exempt from the charge) whilst the circulation of cars with Euro 0 to 3 emissions standards increased by 13% (i.e. vehicles paying the highest rate to enter the zone).

As a result of the decreased level of vehicles entering congestion charge zones and lower levels of congestion observed inside the zones, the general expectation is that emissions generated within the zone from road traffic should decrease. The estimation of cumulative emissions reductions is reasonably straightforward given accurate data on vehicle emission factors and anticipated reductions in vehicle kilometres travelled. Santos and Fraser (2006), for example, estimated a 12% decrease in carbon dioxide emissions resulting from the Western extension of the LCC. However, isolating the effect of congestion charges on the concentration of local air pollutants is more challenging. Carslaw and Beevers (2002) noted that decreases in ambient air pollution levels might not uniformly follow due to the non-linear chemistries of pollutant formation. These complexities are compounded by challenges associated with accurately measuring the effect of schemes on emissions levels both in terms of the appropriate site to locate measurement instruments and in separating the effects of the scheme from other policies aimed at reducing emissions (Atkinson et al. 2009). As a result of these complexities and challenges, a diverse array of results have been observed in terms of changes in emissions concentrations in the vicinity of congestion charge zones (Beevers and Carslaw, 2005; Atkinson et al. 2009).

Similarly, estimating the economic effect of such schemes can represent a complicated undertaking. Santos and Bhakar (2007) illustrate this through a demonstration of how alternative approaches to estimating the economic value of travel time savings can generate significantly different results. Whilst the direct costs and benefits of scheme introduction represent a focal point in the economic appraisal (Prud'homme and Bocarejo, 2005; Eliasson 2009; Rotaris et al. 2010), a range of additional economic effects may also emerge, with research attesting to the influence (or lack thereof) of congestion charging over retail business (Quddus et al. 2007; Daunfeldt et al. 2009) and house prices (Percoco, 2014b).

Congestion charging affects individuals in different ways depending on their income levels, travel behaviours, and their access to or capability with alternative forms of transport. Rajé (2003) outlines how the potential introduction of a congestion charge into the city of Bristol, UK, is perceived by citizen groups which are more at risk of social exclusion (i.e. ethnic minorities and the elderly). Bonsall and Kelly (2005) build on this by demonstrating an approach to geographically identifying groups at risk of social exclusion effects resulting from the introduction of different configurations of a congestion charge in the city of Leeds, UK. The general consensus seems to be that congestion charging has the potential to produce regressive impacts on certain groups, but these impacts can be addressed through solicitous scheme characteristics alongside mechanisms designed to appropriately incentivise travellers and allocate scheme revenues (Levinson, 2010).

Whilst existing research has generated useful insights across various issues, very little has been dedicated to the effects such schemes have over car fleet composition. Coming closest to this issue is the research of Ellison et al. (2013) who evaluated the effects of the introduction of the Low Emission Zone (LEZ) around London on the composition of the commercial fleet (i.e. light commercial vehicles

and heavy goods vehicles). Their results suggest the LEZ encouraged fleet renewal, with registrations of non-compliant commercial vehicles within the LEZ decreasing by 20% above the natural replacement rate. These findings are complemented by the analysis of Ozaki and Sevastyanova (2011) who found that the exemption of HEVs from the LCC represented a salient issue in private car driver's motivations to purchase a HEV. As the LCC represents a policy with a specific location, the effect of the LCC on HEV adoption will likely diminish as nearness to the LCC reduces. This is the particular issue investigated in this paper, which examines if the LCC is significantly associated with the registrations of HEVs and, if this is indeed the case, if this association tends to decay with distance.

2.3 Hybrid Electric Vehicle Demand

The body of research evaluating the impact of demographic characteristics, attitudes, and policy initiatives on the demand for HEVs is already extensive, providing insights concerning what conditions and approaches are effective at motivating the purchase of vehicles which embody advanced propulsion system technologies. The majority of this literature focuses on demographic correlates with HEV uptake, generally concluding that factors relating to age, education, income, and commuting patterns are useful explanatory factors (Caulfield et al. 2010; Saarenpää et al. 2013; Bansal et al. 2015; Pridmore and Anable, 2016; Dimatulac and Moah, 2017; Liu et al. 2017). However, several studies have also attempted to understand the impact of policy interventions although none of these, to our knowledge, specifically evaluate the role of congestion charging. This section summarises these policy-related studies as important context to the evaluation of the impact of the LCC on HEV adoption.

The impact of the preferential access for HEVs to high occupancy vehicle (HOV) lanes in the USA and Canada has been studied on several occasions, but with mixed results. Providing an initial evaluation of consumer response to policy incentives at a disaggregated scale, Sangkapichai and Saphores (2009) conducted a survey to elicit consumer interest in HEVs in California, USA, with their model integrating socioeconomic characteristics, attitudes, and proximity to counties which allow HEVs to access HOV lanes as explanatory variables. Whilst their results support the significant association of personal characteristics including age, education, and attitudes, their model also suggested that consumers who live in counties adjacent to those which allow HOV lane access appear more likely to display interest in HEV adoption. In contrast, Diamond (2009) utilised aggregated data of HEV sales between 2001 and 2006 across the states of the USA to examine the influence of fiscal incentives and HOV lane access over adoption patterns whilst controlling for socioeconomic variation and fuel price fluctuations. The results indicate that fuel prices are the most significant factor in explaining variation in HEV adoption, with vehicle miles travelled per capita also proving significant. The importance of income per capita as well as fiscal incentives and HOV lane access was more mixed, displaying significant yet small coefficients under some model conditions whilst holding insignificant coefficients in others.

Unlike Diamond (*ibid.*), Chandra et al. (2010)'s evaluation of the impact of different HEV sales rebate policies across the provinces of Canada identified rebates as having a substantial effect on HEV adoption, with 26% of sales being attributed to the presence of rebates. The disparity in the results observed by Diamond (*ibid.*) and Chandra et al. (*ibid.*) concerning the effectiveness of fiscal policies aimed at stimulating HEV adoption could be due to the diversity of fiscal policies which have been applied in the USA. To evaluate this diversity, Gallagher and Muehlegger (2011) considered the

effectiveness of sales tax waivers and income tax credits separately over sales of HEVs in the USA and found that sales tax waivers are significantly more effective at motivating HEV adoption. Furthermore, the analysis indicates that the effect of HOV lane access is inconsistent, with only the access scheme implemented in the state of Virginia positively associated with HEV sales. The findings of Gallagher and Muehlegger (*ibid.*) are generally supported by the analysis of Jenn et al. (2013) who found that HEV sales increased in the USA by 0.0046% for every dollar of incentive, though they note that this effect only becomes active once the incentive is in excess of \$1,000.

To summarise, research has already started to consider the effect of policies which have clear spatial boundaries, such as the work which explores the impact of HOV lane access on HEV demand in the USA. Such policies can have lasting implications for the structure of the car fleet, as the promotion of certain vehicle variants will likely persist until the cars are scrapped, with the average lifetime of a car in the UK being around 13 years. The research reported in this paper will extend insight into the role of local policies targeted at accelerating the introduction of alternatively fuelled vehicles by using vehicle registration data to evaluate the association between HEV exemptions from the LCC over ownership rates of these vehicles. By investigating the impact of this policy at a fine spatial scale around the charge zone, it will offer a unique perspective on the reach of such a policy on HEV demand alongside the link with socioeconomic, household, and transport system characteristics.

3. Methods

3.1 Data Sources

The Department for Transport's Vehicle Licensing Statistics Database (VLSD) is the source of the registration numbers for HEVs utilised in the analysis (Department for Transport, 2015). The VLSD holds an individual record for each vehicle registered for use on the roads of the UK, with vehicle level characteristics such as make, model, age, propulsion system, and the location of the registered keeper. The data pertaining to HEV registrations, total number of cars registered, and total number of cars registered as company cars (i.e. cars owned and operated by a corporate or public sector fleet) has been extracted from the VLSD up to the end of 2012 to correspond to the removal of the HEV exemption from the LCC. Demographic data has been sourced from the UK population census (Office of National Statistics, 2011; National Records for Scotland, 2011) as well as Her Majesty's Revenues and Customs (2015). Descriptive statistics regarding the data utilised in the analysis are summarised in Table 2.

Table 2: 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	Std. Dev.	Min	Max
<i>Socioeconomics</i>				
Mean Age (years) ^A	40.27	2.82	30.9	47.7
No Qualifications (%) ^A	22.80	5.14	6.72	36.04
Level 1 Qualification (GCSE grades D-G) (%) ^A	14.30	3.43	4.30	28.26
Level 2 Qualification (GCSE grades A*-C) (%) ^A	15.55	1.98	6.58	18.55
Level 3 Qualification (A-Levels) (%) ^A	12.08	2.03	7.16	32.59
Level 4 Qualification (University Degree) (%) ^A	26.93	7.71	1.42	68.36
Mean Personal Income (000's GBP) ^B	29.73	10.58	20.20	131.00
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
Disabled (%) ^A	3.99	1.60	1.35	9.64
<i>Household</i>				
Population Density (per hectare) ^A	15.02	22.52	0.09	138.70
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 or More Cars in Household (%) ^A	6.03	2.20	0.51	11.19
Mean Household Size (residents) ^A	2.33	0.13	1.64	2.99
<i>Transport System</i>				
Hybrid Electric Vehicles per 1000 cars ^C	6.25	6.54	.83	60.59
Company Cars per 1000 cars ^C	77.68	143.12	24.66	1620.43
Private Mode of Transport to Work (%) ^A	66.68	13.82	4.76	83.33
Public Mode of Transport to Work (%) ^A	13.01	12.80	1.80	65.51
Active Mode of Transport to Work (%) ^A	13.42	5.26	4.31	53.70

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 (2015)

3.2 Geographical Resolution

The data used in the analysis is aggregated at the lower-tier local authority level of UK administrative geography. This directly relates to the primary layout of local government in the UK and represents a common means through which to consider spatial variation in government statistics. There are 391 geographical units covering the unitary authorities of England, the non-metropolitan districts of

England, the metropolitan districts of England, the boroughs of London, the council areas of Scotland, the unitary authorities of Wales, and the districts of Northern Ireland.

3.3 Data Preparation

The dataset has been prepared in the following ways to make it suitable for analysis. First, non-contiguous geographical units which relate to the six island local authorities of Great Britain and the eleven districts of Northern Ireland have been removed. Second, variables utilised in the analysis have been standardised to ensure the varying sizes of the local authority populations do not unduly influence the results. For instance, HEV registrations are considered in terms of registrations per thousand cars, whilst education levels are considered in terms of the percentage of the population that have attained certain levels of qualification. The dataset has been spatially joined to a shapefile (Office on National Statistics, 2013) which records the geometric configuration of the local authority polygons relating to the lower-tier local authority geographical resolution.

3.4 Research Limitations

The data has been derived from an official source and represents the total population of people and vehicles, ensuring comprehensive coverage of the vehicle fleet. However, the interpretation of the results should take into account the following limitations. First, the geographical units of analysis are quite large, potentially masking intra-local authority variation. Second, there is a slight temporal disparity in the collection of the data which comprise the dataset. For example, the characteristics of the population were observed in 2011 whilst the registrations of HEVs were observed in 2012.

Second, the analysis is cross-sectional in nature, exploring the variation in HEV ownership at the end of 2012 without examining how the adoption of these vehicles varied temporally. This means that the identification of causation between HEV demand and the LCC cannot be substantiated by the evidence that is presented. Moreover, the analysis considers the total level of HEV ownership in 2012 and does not distinguish between new and existing registrations, meaning that the dynamics of the used car market cannot be accounted for.

Third, the analysis is only applied at the lower-tier local authority level of geographical resolution. This limitation prohibits the analysis from considering if the results can be observed across different geographical resolutions and thus the degree of spatial transference of the results cannot be evaluated. Fourth, the possibility exists that other issues that are not accounted for by the model and which are local to London could be stimulating the adoption of HEVs. For instance, some London boroughs have previously provided free parking permits (i.e. domestic parking) for HEVs, though information concerning this is fragmented. However, as the monetary value of these parking permits is around £100 annually, it is arguable if they would have represented an effective stimulus to demand.

3.5 Area Classification

Three alternative approaches for exploring the association between the LCC and the registrations of HEVs are implemented. These approaches provide different perspectives on how the nearness of a

local authority to the LCC can be conceptualised. In the analysis, all three approaches are employed to assess whether the association is persistent.

1. Contiguity Approach: the first method considers the geometric layout of the local authority geographical units and how they relate to the boundary of the LCC. Geographical units are categorised in accordance with their degree of separation from the LCC. Four categories are proposed, covering [1] the local authorities which represent boroughs of London and constitute Greater London ($n = 32$), [2] the local authorities which are first order neighbours to Greater London ($n = 16$), [3] the local authorities which are second order neighbours to the Greater London ($n = 23$), and [4] the local authorities which represent the rest of the UK ($n = 303$). This classification system is illustrated in Figure 2. The hypothesis here is that as contiguity to the LCC recedes, the registration rates of HEVs will tend to decrease.
2. Proximity Approach: the second method considers the Euclidean distance between the geometric centroids of the local authorities and the LCC polygon. Each local authority is assigned a value which measures their spatial proximity to the centre of the LCC in kilometres. The hypothesis here is that as proximity to the LCC decreases, the registration rates of HEVs will tend to decrease.
3. Interaction Approach: the third method considers the degree of interaction which exists between the local authorities and the LCC. This is applied by evaluating the number of residents (per thousand) that drive a car to work to the City of London local authority (which represents the only local authority entirely encapsulated by the LCC). This is achieved through the specification of an origin destination matrix concerning commuting patterns recorded by the 2011 UK population census. The hypothesis here is that as interaction with the LCC increases, the registration rates of HEVs will tend to increase.

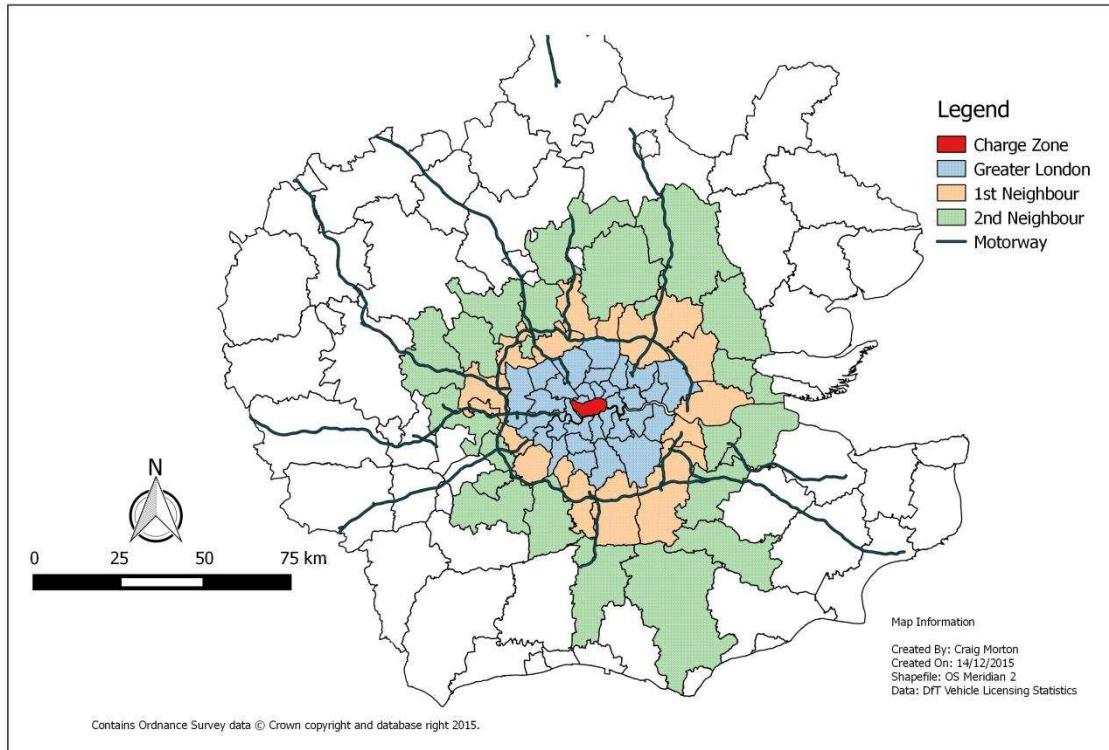


Figure 2: Illustration of the four area categories distinguishing level of contiguity of the local authorities to the London Congestion Charge zone

3.6 Statistical Analysis

The analysis of the dataset progresses through a series of five stages. The stages comprise a mixture of spatial and non-spatial statistics which are detailed in the following paragraphs. In terms of the spatial statistics, the analysis primarily relies upon the GeoDa software (Anselin et al. 2006) and the MatLab scripts prepared by Elhorst (2014).

Stage One

In the first stage, exploratory spatial statistics are applied by locating HEV registrations at local authority level in order to visualise the data and consider its geographical variation. A choropleth map is produced with equal bin counts to separate the data into intensity categories.

Stage Two

In the second stage, the area classifications (detailed in section 3.5) are evaluated to determine if HEV registrations are associated with the LCC. As the data pertaining to the area classifications is in two distinct forms (i.e. categorical and continuous), alternative statistical approaches are required to evaluate this association. Firstly, descriptive statistics are specified for the contiguity approach, whereby the range, dispersion, and central tendency of HEV registrations across the four area categories are illustrated. In order to determine if HEV registration levels are statistically different across these four categories, the Kruskal-Wallis test is applied. Secondly, scatterplots are formatted for the proximity and interaction approaches, with HEV registrations charted alongside [1] distance to

the LCC and [2] drivers commuting to the City of London. To determine if these variables are related to one another, Spearman's rank order correlation analysis is applied.

Stage Three

In the third stage, spatial autocorrelation analysis (Getis, 2009) is applied in order to evaluate if observations of HEV registrations in particular local authorities are related to observations of HEV registrations in neighbouring local authorities. This type of analysis is contingent on the specification of a spatial weights matrix which classifies the space for which the georeferenced data pertains according to the configuration of the geographical units (Haining, 2009). Specifically, the spatial weights matrix measures the contiguity between the geographical units by noting those which share common borders and are thus spatial neighbours. This allows for spatial lags of variables to be calculated, which measure the mean value of a variable in neighbouring geographical units. In the analysis reported in this paper, a binary spatial weights matrix is specified which follows a first order queen contiguity approach that classifies geographical units which share either point or line segment borders as neighbours. The structure of the spatial weights matrix is reported in Equation 1 in which W_{ij} represents the contiguity between geographical units i and j and n represents the total number of geographical units within the dataset.

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

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

Spatial autocorrelation analysis can generally be conducted in two different ways. Firstly, the global approach to spatial autocorrelation determines the degree to which a variable is related to its spatial lag for the entire dataset. A common variant of global spatial autocorrelation is Moran's I test (Moran, 1948) which extends Pearson's product moment correlation analysis through the integration of a spatial weights matrix. The structure of Moran's I is reported in Equation 2 where y_i and y_j represents the observed value of the variable in the geographical unit i and j while \bar{y} represents the mean of the variable.

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

Secondly, the local approach to spatial autocorrelation evaluates the occurrence of spatial patterns by noting the presence of groups of geographical units which either share similar or divergent values for a variable. Often referred to as Local Indicators of Spatial Association (LISA), this approach assists in identifying spatial clusters which either tend to gravitate around relatively low (cold-spots) or high

(hot-spots) values for a variable (Anselin, 1995). Additionally, this approach assists in the identification of geographical units which are spatial outliers that exhibit values for a variable which are distinctly different from their neighbours. The structural form of the LISA is reported in Equation 3 where I_i represents the degree of spatial autocorrelation in geographical unit i .

$$I_i = n (y_i - \bar{y}) \sum_j W_{ij} (y_j - \bar{y}) \quad (3)$$

Stage Four

In the fourth stage of the analysis, registrations of HEVs are compared with other area characteristics covering the socioeconomic and household characteristics of the population as well as characteristics of the transport system. The purpose of this stage is to provide insights concerning which other area characteristics can act as valid indicators of HEV registrations and should be considered as independent variables in the regression models (stage five). The comparison is conducted through the application of Spearman's rank order correlation analysis in order to assess how these variables are related to one another. The analysis is arranged in two different batches with the first batch evaluating the correlations between HEV registrations and socioeconomic characteristics whilst the second batch assesses the correlations between HEV registrations and household and transport system characteristics.

Stage Five

In the fifth stage of the analysis, two varieties of regression models are specified which utilise HEV registrations (per thousand cars) as the dependent variable. The purpose of these models is to explore the association between the LCC and HEV registrations having controlled for the effect of socioeconomic, household, and transport system variables. These models take a log-log approach, whereby both the dependent and independent variables (except for the dummy variables associated with the local authority area categories) are transformed into their natural logarithms.

A series of benchmark ordinary least squares (OLS) regression models are specified which have the following independent variable configurations:

OLS Model 1: incorporates area characteristics covering socioeconomic, household, and transport system attributes as independent variables (i.e. omitting a measurement of nearness to the LCC). The structural form of OLS Model 1 is reported in Equation 4, where y represents a vector of dependent variable observations, α represents a constant term coefficient, β_a represents a vector of coefficients associated with the area characteristics, x_a represents a vector set containing observations of the area characteristic variables and ε represents the model residual.

$$y = \alpha + \beta_a x_a + \varepsilon \quad (4)$$

OLS Model 2: incorporates the area characteristics of OLS Model 1 as well as dummy variables covering the local authority categories outlined in the contiguity approach. The structural form of OLS Model 2 is reported in Equation 5 where β_c represents a vector of coefficients associated with the local

authority category dummy variables and x_c represents a vector set of observations of the local authority category dummy variables.

$$y = \alpha + \beta_a x_a + \beta_c x_c + \varepsilon \quad (5)$$

OLS Model 3: incorporates the area characteristics of OLS Model 1 as well as the distance to the LCC centroid as outlined in the proximity approach. The structural form of OLS Model 3 is reported in Equation 6 whereby β_p represents a coefficient for the variable measuring distance to the LCC and x_p represents a vector of observations of distance to the LCC.

$$y = \alpha + \beta_a x_a + \beta_p x_p + \varepsilon \quad (6)$$

OLS Model 4: incorporates the area characteristics of OLS Model 1 as well as the proportion of residents driving a car to work in the City of London outlined in the interaction approach. The structural form of OLS Model 4 is reported in Equation 7 where β_i represents a coefficient for the variable measuring the proportion of residents driving a car to work in the City of London and x_i represents a vector of observations of the proportion of residents driving a car to work in the City of London.

$$y = \alpha + \beta_a x_a + \beta_i x_i + \varepsilon \quad (7)$$

The selection of area characteristics, which cover socioeconomic, household, and transport system attributes, to include in the model as independent variables is based on two rationales. First, the results of past research provide insights concerning which particular characteristics represent valid indicators of HEV demand. The work of Sangkapichai and Saphores (2009), Caulfield et al. (2010), Saarenpää et al. (2013), Bansal et al. (2015), Pridmore and Anable (2016), Dimatulac and Moah (2017), and Liu et al. (2017) suggest that age, education, income, journey to work, population density, and household size are characteristics which are useful in explaining variance in HEV registrations and preferences. Secondly, the results of the correlation analysis (stage four of the analysis) are inspected to identify significant and strong relationships between HEV registrations and socioeconomic, household, and transport system characteristics to consider if any additional variables might be useful as indicators of HEV registrations.

The occurrence of spatial autocorrelation in the model dependent variable can indicate the presence of spatial dependence regarding the phenomenon being evaluated. If this spatial autocorrelation is not accounted for through the inclusion of the independent variables, the possibility exists for the models specified to produce biased estimates. Anselin et al. (1996) advises the calculation of the robust Lagrange Multipliers in order to identify model misspecification resulting from the omissions of a spatially lagged dependent variable or a spatial lag of the model residual. If these tests return significant results, the implication is that extending the model through the inclusion of spatial interaction effects could improve model performance. Such extensions are generally referred to as spatial regression models (LeSage and Pace, 2009; Arbia, 2014), which allow the model to consider if

observations of the model's dependent variable in particular geographical units are associated with observations of variables in neighbouring geographical units.

A series of spatial regression models are specified using Maximum Likelihood estimation which include two different spatial interaction effects. Firstly, the Spatial Lag Model (SLM) is specified which incorporates a spatially lagged variant of the model dependent variable as an independent variable. The structural form of the SLM is reported in Equation 8 where p represents the spatial interaction coefficient for the spatially lagged dependent variable and Wy represents a vector of spatially lagged observations of the dependent variable.

$$y = \alpha + \beta_a x_a + \beta_i x_i + pWy + \varepsilon \quad (8)$$

Secondly, the Spatial Error Model (SEM) is specified which integrates a spatial lag of the benchmark OLS model's residual as an independent variable. The structural form of the SEM is reported in Equations 9 and 10 where λ represents a spatial interaction coefficient associated with the spatial lag of the OLS model's residuals and Wu represents a vector of observations of spatially lagged OLS model residuals.

$$y = \alpha + \beta_a x_a + \beta_i x_i + u \quad (9)$$

$$u = \lambda Wu + \varepsilon \quad (10)$$

4. Results

4.1 Exploratory Spatial Analysis

The registrations of HEVs across the UK at the end of 2012 have been spatially located across the local authorities and standardised by considering the number of registrations per thousand cars. Figure 3 depicts a choropleth map which illustrates the spatial variation in the registration of HEVs. A substantial degree of spatial variation is observed, with the local authority of Blaenau Gwent (central Wales) representing the geographical unit with the lowest level of registrations (0.43 HEV registrations per thousand cars) whilst the local authority of City of London is the geographical unit with the highest registration level (55.55 HEV registrations per thousand cars).

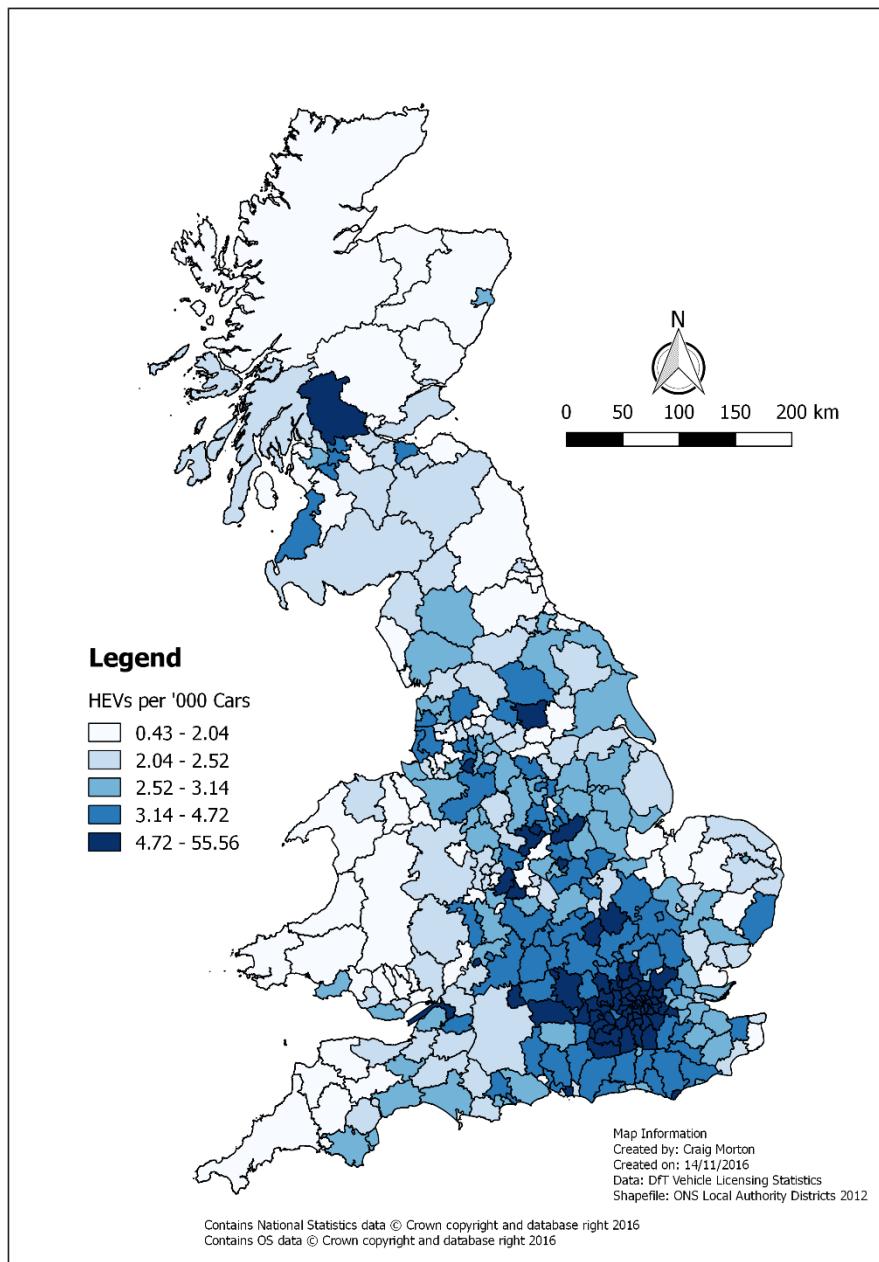


Figure 3: Choropleth map illustrating the spatial variation in Hybrid Electric Vehicle registrations (per thousand cars) across the local authorities of the United Kingdom

4.2 Area Classification Analysis

Table 3 reports the descriptive statistics concerning the observed levels of HEV registrations across the different categories of local authorities (i.e. the contiguity approach detailed in section 3.5). The Kruskal-Wallis test returns a significant result ($\chi^2 = 110.52$, $p\text{-value} < 0.01$), which indicates that the observed levels of HEV registrations are distinct across these different categories of local authorities. Inspecting the mean values of HEV registrations across the different categories, the descriptive statistics indicate that as contiguity to the LCC diminishes, registrations of HEVs tend to decrease.

Table 3: Descriptive statistics of Hybrid Electric Vehicle registrations (per thousand cars) across the four local authority categories

Local Authority Category	Mean	Std. Dev.	Min.	Max.
London Boroughs (n = 32)	10.58	6.81	2.00	30.98
First Order Neighbours to Greater London (n = 16)	8.34	8.88	2.61	38.96
Second Order Neighbours to Greater London (n = 23)	4.31	1.33	2.27	6.90
Rest of the United Kingdom (n = 303)	3.22	4.00	0.43	55.56

Figure 4 (a) illustrates the association between HEV registrations and the distance between the LCC and the local authority (i.e. the proximity approach). The scatterplot indicates that these two variables are divergent, which is supported by the observation of a significant negative correlation ($r_s: -0.621$; $p\text{-value} < .001$). Thus, as proximity to the LCC reduces, registrations of HEVs tend to decrease. Similarly, Figure 4 (b) displays the association between HEV registrations and the proportion of local authority residents that drive a car to the City of London local authority for work (i.e. the interaction approach). In this instance, the scatterplot suggests that these two variables are concurrent, which is substantiated through the presence of a significant positive correlation ($r_s: 0.634$; $p\text{-value} < .001$). Thus, as interaction with the LCC increases, registrations of HEVs tend to increase.

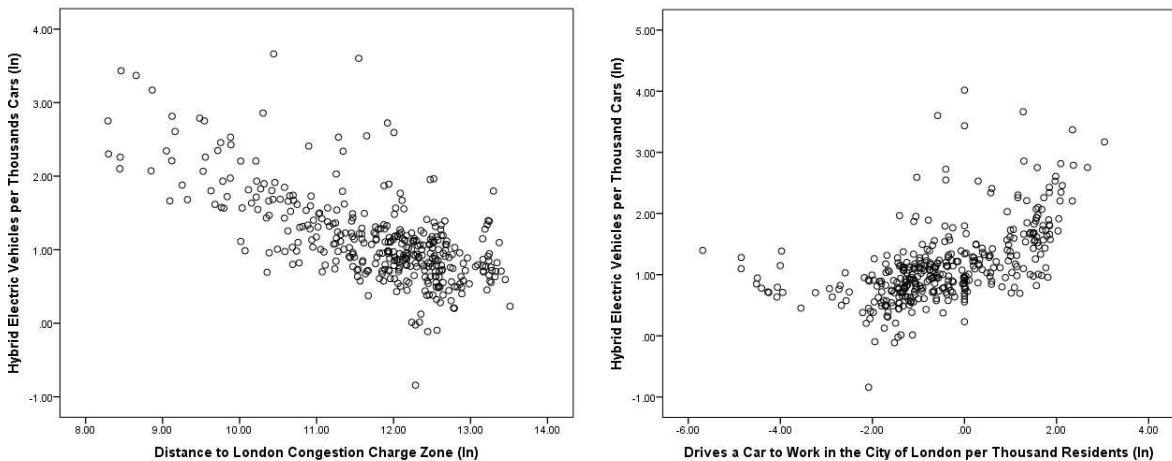


Figure 4: Scatterplots of Hybrid Electric Vehicle registrations (per thousand cars) against (a) distance to London Congestion Charge and (b) residents that drive a car to work in the City of London (per thousand residents)

4.3 Spatial Autocorrelation Analysis

The global Moran's-I spatial autocorrelation analysis returns a significant result ($I = 0.62$, $p\text{-value} < 0.01$), which implies that the observations of HEV registrations in local authorities tend to be related to the mean observations of HEV registrations in neighbouring local authorities. Figure 5 illustrates the results of the LISA analysis, with the output indicating that clusters of local authorities with similar rates of HEV registrations are present across the UK. The local authorities shaded deep blue represent cold-spot regions, where local authorities display relatively low values in terms of HEV registrations. These regions cover the South-West of England, Wales, parts of East Anglia, parts of the North of

England, and parts of Scotland. Conversely, the local authorities in and around London shaded deep red represent a hot-spot region with high levels of HEV registrations

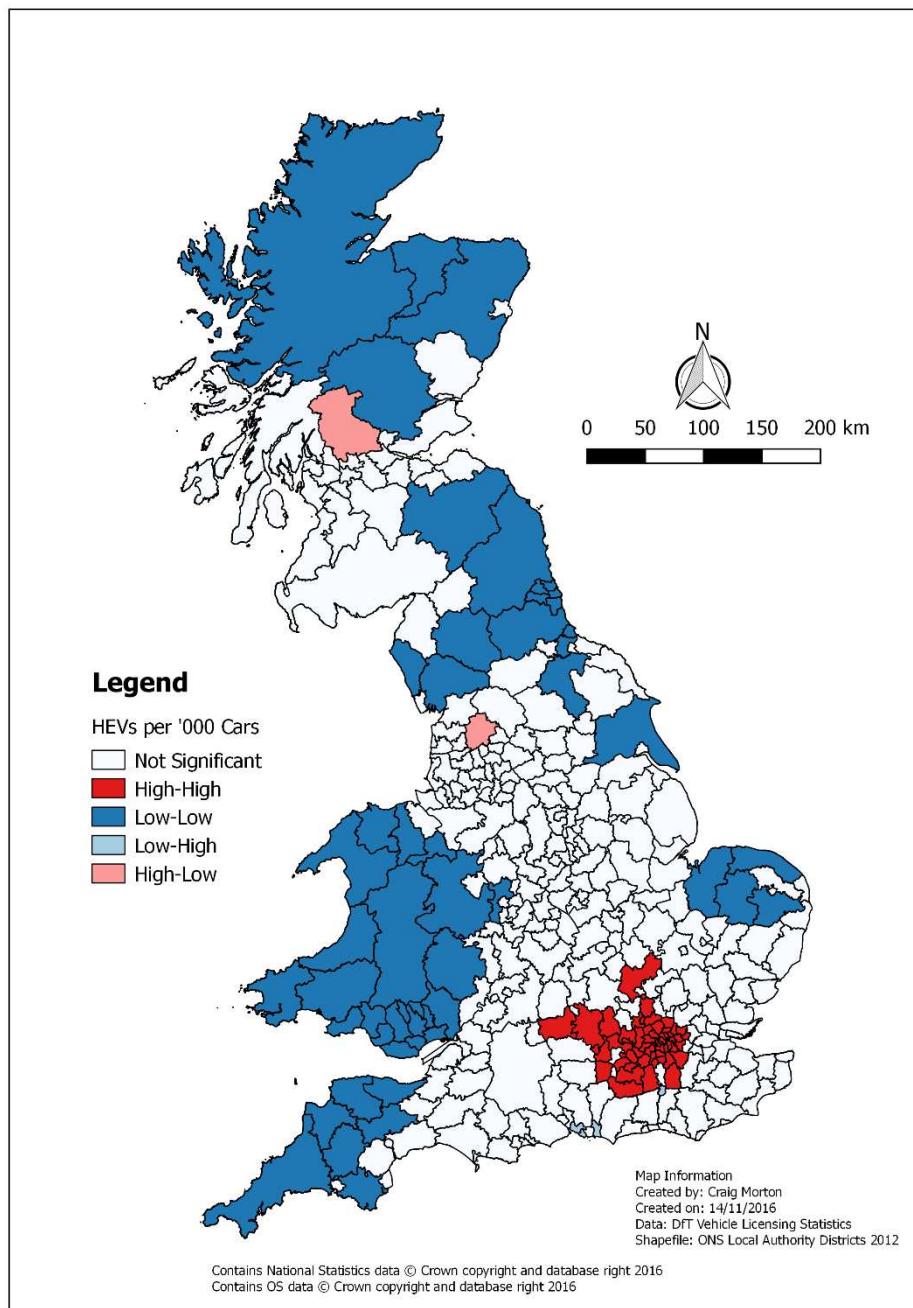


Figure 5: Local Indicator of Spatial Association map of Hybrid Electric Vehicle registrations (per thousand private cars) across the local authorities of the United Kingdom

The occurrence of spatial outliers is less common. For instance, one local authority in central Scotland (Stirling) is categorised as a high-low area (light red shading), implying that it has relatively high levels of HEV registrations but that the local authorities in its vicinity tend to display relatively low levels of HEV adoption. Three local authorities (Fareham, Gosport, and Havant) which surround the city of Portsmouth on the south coast of the UK represent low-high areas and are shaded in light blue. This indicates that these local authorities have comparatively low levels of HEV adoption though they are in close vicinity to local authorities which tend to display high values of HEV adoption.

Greater London not only represents a hotspot of HEV uptake, but is also a distinct area in terms of the structure of the population that reside in its vicinity (e.g. levels of income and education) and its transport system (e.g. travel to work patterns and levels of car availability). As such, it can be challenging to isolate the association of one particular issue (i.e. the LCC's exemption policy) over HEV demand, as the demand is likely to be motivated by a series of factors which are themselves spatially connected. As such, a multivariate analysis which simultaneously estimates the association between HEV registrations and area characteristics seems appropriate to evaluate if nearness to the LCC is linked with higher rates of HEV uptake.

4.4 Correlation Analysis

The relationships which exist between HEV registrations and other characteristics of the local authorities are considered in two batches. The first batch evaluates the relationships between HEV registrations and the socioeconomic characteristics of the population with the results of the analysis reported in Table 4 (appendix). A strong positive relationship is observed with the mean income of the population (r_s : 0.656), implying that wealth is an effective indicator of HEV demand. A similar magnitude of association is observed with level of education, with the proportion of the population that has no formal qualification (r_s : -0.667) and a university degree (r_s : 0.656) both displaying significant correlation coefficients. The economic status of the population also appears to be connected with HEV registrations, with the proportion of the population that are classified as employed part-time (r_s : -0.426) and retired (r_s : -0.522) displaying significant negative correlations whilst the proportion of the population categorised as employed full-time (r_s : 0.322) and self-employed (r_s : 0.327) hold significant positive correlations. The mean age of the population is negatively associated with HEV registrations (r_s : -0.350).

In the second batch, the level of HEV registrations across the local authorities is compared with a number of characteristics relating to local authority household structure and transport system. The results of the analysis are reported in Table 5 (appendix) and imply that certain characteristics are significantly correlated with HEV registrations. HEV registrations appear to be negatively related to the proportion of one car households (r_s : -0.233) and the proportion of the population that use a private mode to travel to work (r_s : -0.428). Conversely, significant positive correlations are observed with population density (r_s : 0.379), mean household size (r_s : 0.381) and the proportion of the population that use a public mode to travel to work (r_s : 0.477)

4.5 Regression Analysis

The series of benchmark OLS regression models aimed at explaining the observed variation in HEV registrations is reported in Table 6. The highest Variance Inflation Factor (VIF) observed is 4.4, with a mean VIF of 2.8, indicating that the models are not unduly biased by multicollinearity. The results of OLS Model 1 indicate that around three quarters of the observed variation in HEV registrations can be explained through a small set of independent variables.

The Results of OLS Models 2 through 4 indicate that the expansion of OLS Model 1 through the integration of the area classifications which measure nearness to the LCC produces a slight

improvement to model fit. The variables associated with the three different approaches to measuring nearness to the LCC all display significant coefficients. There has also been a reduction in the size of the coefficients of a number of the area characteristics, notably mean age and mean household size. These findings indicate that the results of OLS Model 1 are biased by the omission of the nearness measurement.

Table 6: Ordinary least squares log-log regression models with Hybrid Electric Vehicle registrations (per thousand cars) as the dependent variable

Variable	OLS Model 1	OLS Model 2	OLS Model 3	OLS Model 4
	Beta (Std. Err.)	Beta (Std. Err.)	Beta (Std. Err.)	Beta (Std. Err.)
Constant	-16.942** (2.002)	-14.504** (2.108)	-13.780** (2.174)	-13.547** (2.115)
<i>Area Characteristics</i>				
Mean Age (ln)	2.157** (0.441)	1.863** (0.446)	1.650** (0.458)	1.691** (0.445)
% University Degree (ln)	0.656** (0.095)	0.701** (0.096)	0.724** (0.010)	0.685** (0.093)
Mean Personal Income (ln)	0.894** (0.118)	0.777** (0.132)	0.696** (0.130)	0.677** (0.126)
% One Car Households (ln)	0.565* (0.266)	0.241 (0.280)	0.595* (0.262)	0.471 (0.261)
% Private Transport to Work (ln)	-0.440** (0.077)	-0.231* (0.107)	-0.256** (0.093)	-0.374** (0.077)
Population Density (ln)	0.123** (0.017)	0.112** (0.017)	0.104** (0.017)	0.105** (0.017)
Mean Household Size (ln)	3.461** (0.397)	2.487** (0.495)	2.661** (0.454)	2.341** (0.470)
Company Cars per '000 (ln)	0.385** (0.027)	0.401** (0.028)	0.384** (0.027)	0.398** (0.027)
<i>Area Classifications</i>				
London Borough ^A		0.316** (0.107)		
First Order Neighbour ^A		0.227* (0.089)		
Second Order Neighbour ^A		0.067 (0.074)		
Distance to City of London in km (ln)			-0.084** (0.024)	
Drive to City of London per '000 (ln)				0.068** (0.016)
<i>Model Fit</i>				
R ²	0.774	0.779	0.781	0.784
Log Likelihood	-73.150	-67.179	-67.097	-64.151

AIC	164.300	158.358	154.194	148.301
SC	199.618	205.449	193.436	187.544
<i>Spatial Diagnostics</i>				
Robust Lagrange Multiplier (lag)	15.174**	6.761**	9.371**	7.797**
Robust Lagrange Multiplier (error)	3.904*	7.906**	5.742**	6.495**

**: p-value < .01; *: p-value < 0.05

A: dummy variable with [1] to signify the local authority represents the specified category and [0] to signify the local authority does not represent the specified category

To ascertain whether the inclusion of the independent variables specified in the OLS log-log regression has corrected for the observed spatial dependence, the results of the robust Lagrange Multiplier spatial diagnostics prove useful (reported at the bottom of Table 6). Across all 4 of the specified models, the results of the diagnostics indicate that spatial autocorrelation in both the model dependent variable and model residual remains. In order to account for this persisting spatial autocorrelation, the SLM and SEM have been specified using the variable structure of OLS Model 4 which includes the interaction approach to accounting for the effect of the LCC. The reason for selecting OLS Model 4 to be extended is that it outperforms the other OLS models in terms of its model fit. The results of the spatial regression models are reported in Table 7.

In the SLM, the spatial interaction coefficient (p) associated with the spatial lag of the model dependent variable proves to be significant. This result indicates that observations of the registration rates of HEVs in particular local authorities are associated with the observations of HEV registrations in neighbouring local authorities. In the SEM, the spatial interaction coefficient (λ) which is measured through the spatial lag of the residual of OLS Model 4 is also significant. This finding implies that spatial autocorrelation remains an issue in the variables which are omitted from the analysis.

Out of all of the regression models specified (OLS log-log models 1 through 4, SLM, and SEM) the SEM model provides the best model fit. Exploring the variables which are included in the SEM and their association with HEV registrations, a number of notable findings can be discerned. The variable measuring the mean age of the population holds a significant positive coefficient in the model (Beta: 1.729), which is in agreement to the findings of Caulfield et al. (2010) though is counter to the results of Saarenpää et al. (2013) and Bansal et al. (2015) who identified a negative association between mean age and HEV registrations. The variable measuring the proportion of the population that have attained a university degree holds a significant positive coefficient in the model (Beta: 0.822), which is in agreement with the findings of past research (Sangkapichai and Saphores 2009; Caulfield et al. 2010; Saarenpää et al. 2013; Bansal et al. 2015; Pridmore and Anable, 2016). The average income of the population has a significant positive coefficient in the model (Beta: 0.441), which is in agreement to the findings of Caulfield et al. (2010) and Saarenpää et al. (2013) though Sangkapichai and Saphores (2009) observed a non-linear income effect. Whilst Bansal et al. (2015) found that the proportion of individuals driving a car to work to be positively associated with HEV registrations, the opposite is observed in the SEM reported in this paper (B: -0.360). A similar situation is also present regarding population density, with Bansal et al. (2015) reporting a significant negative association whilst the SEM reports a significant positive coefficient (B: 0.092). The mean size of the household (in terms of residents) holds a significant positive coefficient in the model (Beta: 2.425), which agrees with the

results of Saarenpää et al. (2013) though is counter to the results of Bansal et al. (2015) whose model indicates that this variable has a negative association with HEV registration rates.

Table 7: Spatial log-log regression models with Hybrid Electric Vehicle registrations (per thousand cars) as the dependent variable

Variable	SLM		SEM	
	Beta	Std. Err.	Beta	Std. Err.
Constant	-12.687**	1.951	-12.208**	2.067
<i>Area Characteristics</i>				
Mean age (ln)	1.504**	0.411	1.729**	0.442
% University Degree (ln)	0.651**	0.087	0.822**	0.094
Mean Personal Income (ln)	0.481**	0.117	0.441**	0.125
% One Car Households (ln)	0.518*	0.241	0.161	0.273
% Private Transport to Work (ln)	-0.229**	0.073	-0.360**	0.097
Population Density (ln)	0.070**	0.016	0.091**	0.019
Mean Household Size (ln)	1.724**	0.444	2.271**	0.456
Company Cars per '000 (ln)	0.404**	0.025	0.408**	0.024
<i>Area Classifications</i>				
Drive to City of London per '000 (ln)	0.041**	0.015	0.061**	0.017
<i>Spatial Interaction Effects</i>				
Spatial lag of HEV registrations (p)	0.336**	0.050		
Spatial lag of OLS model residual (λ)			0.455	0.061
<i>Model Fit</i>				
R ²	0.816		0.820	
Log Likelihood	-43.123		-43.292	
AIC	108.247		106.584	
SC	151.414		145.826	

**: p-value < .01; *: p-value < 0.01

In addition to evaluating the level of agreement between the results of the SEM to observations of past research, the SEM also includes a number of additional area characteristics to consider their effect over HEV registrations. First, the proportion of households with access to one car appears to be insignificant in the SEM, indicating that the level of car availability may not affect HEV registrations. Second, the number of company cars registered (per thousand cars) has a significant positive coefficient in the model (Beta: 0.397), implying that the presence of company car fleets in an area is associated with registration rates of HEVs.

5. Discussion and Conclusions

The adoption of HEVs across the local authorities of the UK has occurred in a spatially heterogeneous manner. This fact is clearly visible in Figure 3, which illustrates that HEVs have been assimilated into the car fleets of some local authorities to a much greater degree than others. This process of spatially locating the registrations of HEVs and comparing them across different areas (stage one of the

analysis) represents the first step in understanding the geographical issues that might be generating the spatial variation which is apparent.

A result that stands out from the exploratory spatial analysis is that the City of London has the highest level of HEV registrations (55.55 HEVs per thousand private cars). A number of reasons could explain this. First, the population of the City of London is, on average, the wealthiest in the UK, meaning they would have the resources to afford the price premium associated with the purchase of a HEV. Second, as the City of London sits entirely within the LCC, its residents are provided with a 90% discount on their first car from having to pay the daily fee associated with the LCC. With this in mind, the high levels of HEV registrations observed within the City of London could be the result of households in this area purchasing HEVs to act as second cars, as these would not be granted an exemption from the LCC unless they were HEVs. Third, residents of the City of London will likely be exposed to HEVs at a much higher rate compared to residents of other local authorities, which could lead to HEVs being more salient in their minds when considering their next vehicle purchase. Mau et al. (2008) has already demonstrated the presence of a neighbour effect in vehicle purchasing decisions, meaning individuals are more likely to purchase an alternatively fuelled vehicle if these vehicles are visible in their vicinity. Thus, the high degree of HEV registrations within the City of London could be due to residents imitating the vehicle preferences of drivers circulating within the LCC. This explanation is further supported by the significance of the spatial lag of HEV registrations included in the SLM, which implies that the registration rates of these vehicles in a particular local authority are positively associated with the rates observed in neighbouring local authorities, which could signify the presence of an imitation effect. Indeed, such an effect has already been identified in a mixed-methods analysis of HEV uptake within London (Pridmore and Anable, 2016), whereby social influence is found to be an important motivator of adoption. Fourth, the discount to the LCC for zone residents does not extend to firms and companies which are located within the LCC. Thus, it is possible that the LCC has influenced firms and companies within the LCC to purchase HEVs in order to reduce the total cost of ownership of their vehicle fleets. All of these reasons could apply, to varying degrees, although demonstrating causation would require additional research.

The three approaches to considering the effect of the LCC over HEV registrations all indicate an association between the LCC and HEV registrations. As local authorities recede in contiguity and proximity to the boundary of the LCC, registration rates of HEVs tends to decrease. This is further supported by the interaction approach, which indicates that registrations of HEVs are significantly related to the proportion of local authority residents that drive a car to work in the City of London. The results of the spatial autocorrelation analysis add support to the view that an association exists between nearness to the LCC and HEV registrations. This is apparent in the LISA analysis which clearly demonstrates that London and the South East of England represent a hot-spot for adoption.

Whilst the results of stage two and three of the analysis indicate that nearness to the LCC corresponds to increased registration rates of HEVs, there is the possibility that other factors are at play in and around London which are effecting registration rates. The results of past research highlight the role that demographic characteristics can play in HEV registrations (Sangkapichai and Saphores 2009; Caulfield et al. 2010; Saarenpää et al. 2013; Bansal et al. 2015; Pridmore and Anable, 2016; Dimatulac and Moah, 2017; Liu et al. 2017). Thus it could be that it is the characteristics of the population which reside in and around London which are affecting HEV registrations and not the presence of the LCC.

Indeed, stage four of the analysis clearly demonstrates that registration levels of HEVs are significantly correlated with a variety of different area characteristics, with a number of large correlation coefficients being observed with the variables measuring such characteristics as income and level of education. To evaluate if nearness to the LCC has a significant association with registration rates of HEVs having controlled for the effect of socioeconomic, household, and transport system characteristics, the results of the regression models (stage five of the analysis) are of interest. Across the OLS log-log regression models which include variables that aim to evaluate the association of nearness to of the LCC over HEV registrations (Models 2-4), the results of the analysis imply that as contiguity, proximity and interaction with the LCC diminishes, so too do registrations of HEVs. This is a robust result, having controlled for the area characteristics which are likely to be effecting HEV demand. Moreover, the significance of the variable measuring the proportion of population that drive a car to the City of London (i.e. the interaction approach) remains having accounted for the effect of spatial interaction of the model dependent variable (SLM) and the effect of the spatial interaction in the model error term (SEM). Taken as a whole, the results of the analysis support the view that the LCC and the rate of HEV registrations are connected issues.

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Appendix

Table 4: Spearman's correlation analysis between Hybrid Electric Vehicle registrations (per thousand cars) and socioeconomic characteristics of the population

Variable	A	B	C	D	E	F	G	H	I	J	K	L	M
HEVs (A)	1.000												
Mean Age (B)	-.350**	1.000											
No Qualification (C)	-.667**	.157**	1.000										
Level1 Qualification (D)	-.425**	.080	.607**	1.000									
Level2 Qualification (E)	-.267**	.393**	.154**	.465**	1.000								
Level3 Qualification (F)	-.016	-.031	-.206**	-.299**	.175**	1.000							
Level4 Qualification (G)	.644**	-.060	-.914**	-.692**	-.360**	.068	1.000						
Part Time Employment (H)	-.426**	.651**	.275**	.244**	.539**	.168**	-.301**	1.000					
Full Time Employment (I)	.322**	-.349**	-.431**	.113*	.039	-.024	.268**	-.223**	1.000				
Self Employment (J)	.327**	.418**	-.587**	-.416**	.111*	-.121*	.607**	.105*	-.016	1.000			
Unemployed (K)	-.176**	-.527**	.589**	.329**	-.212**	-.253**	-.550**	-.286**	-.195**	-.685**	1.000		
Retired (L)	-.522**	.925**	.408**	.208**	.410**	-.032	-.302**	.673**	-.456**	.166**	-.289**	1.000	
Mean Personal Income (M)	.656**	-.032	-.819**	-.391**	-.119*	-.037	.813**	-.250**	.483**	.598**	-.556**	-.282**	1.000

**: p-value < .01; *: p-value < 0.05

Table 5: Spearman's correlation analysis between Hybrid Electric Vehicle registrations (per thousand cars) and characteristics of the transport system and households

Variable	A	B	C	D	E	F	G	H	I	J	K
HEVs (A)	1.000										
No Car (B)	-.059	1.000									
One Car (C)	-.233**	.275**	1.000								
Two Cars (D)	.078	-.978**	-.383**	1.000							
Three or More Cars (E)	.022	-.968**	-.348**	.954**	1.000						
Private Mode (F)	-.428**	-.389**	-.129*	.457**	.397**	1.000					
Public Mode (G)	.477**	.536**	-.076	-.507**	-.531**	-.676**	1.000				
Active Mode (H)	-.040	.185**	.282**	-.259**	-.220**	-.328**	-.196**	1.000			
Population Density (I)	.379**	.655**	.055	-.620**	-.667**	-.387**	.746**	-.020	1.000		
Household Size (J)	.381**	-.217**	-.279**	.270**	.237**	.024	.312**	-.440**	.254**	1.000	
Company Cars (K)	.055	.510**	.050	-.464**	-.507**	-.044	.215**	.055	.315**	-.047	1.000

**: p-value < .01; *: p-value < 0.05