**Exploring the Effect of Local Transport Policies over the Adoption of Low Emission Vehicles: Evidence from the Exemption of Hybrid Electric Vehicles from the London Congestion Charge**

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**Word Count:** Body 5,945 Illustrations 1,500

**Submission Date**: August 1, 2016

**ABSTRACT**

The London Congestion Charge (LCC) represents a transport policy with a precise spatial footprint which will likely generate a certain area of effect in terms of the influence it has over the transport system. This paper focuses on the spatial features of the LCC and evaluates if the exemption of Hybrid Electric Vehicles (HEVs) from the LCC had an appreciable impact on the registration rates of these vehicles in Greater London and the surrounding areas. The evaluation utilises data which notes the quantity of HEVs registered across the lower tier local authorities of the United Kingdom. This data is assessed using exploratory spatial analysis to determine the degree of spatial variation in HEV registrations with relation to nearness to the LCC alongside spatial regression models in order to consider if nearness to the LCC has an appreciable impact on HEV registrations once the effect of other area characteristics are accounted for. The results of the analysis indicate that as nearness to and interaction with the LCC increases, so too does the level of HEV registrations. This effect remain having accounted for the impact of socioeconomic, household and transport system features.

**INTRODUCTION**

Cities across the globe are facing a series of complex challenges relating to the structure and operation of their urban transport systems (*1-2*). Of particular concern is motor traffic and resulting emissions, 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 (*3-5*).

One strategy for tacking these issues involves restricting the entry of motorised road vehicles to certain areas within the city (*6*). Such strategies are often referred to 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 (*7-9*); the additional impacts of the schemes on ancillary issues such as social equity (*10-12*); economic activity (*13-14*); and the reactions of citizens to such schemes (*15-16*).

A somewhat underexplored issue relates to the potential effects congestion charging may have 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 to promote vehicle variants which benefit from a reduced fee. The London Congestion Charge (LCC) 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 had an appreciable impact on the registrations of HEVs in the areas surrounding the LCC. Particular attention is paid to the hypothesis that the impact of the LCC on HEV ownership diminishes with distance from the charging zone. This hypothesis is explored by analysing the distribution of vehicle registrations from the Department for Transport’s Vehicle Licensing Statistics database.

**BACKGROUND**

**Overview of London Congestion Charge**

Introduced in February 2003, the LCC (*17*) involves the application of a fee to qualifying vehicles that enter an area of 21.42 square kilometres in the centre of London. Figure 1 [left image]illustrates the extent of the LCC in the context of the Greater London Area (GLA). A series of exemptions are in effect which exclude qualifying vehicles from having the pay the LCC’s daily fee. One of these exemptions 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 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. To summarise, 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.

**Impacts of Congestion Charging**

Existing research which examines the impacts of congestion charging have generated useful insights across various issues. However, little research 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. (*18*) who evaluated the effects of the introduction of the London Low Emission Zone (LEZ) with specific attention given to the impact on the composition of the commercial fleet (i.e. light commercial vehicles and heavy goods vehicles). The results of their analysis indicate that the LEZ encouraged commercial fleet renewal, with registrations of commercial vehicles within the LEZ which were non-compliant to the LEZ’s restrictions decreasing by 20% above the natural replacement rate. With Ozaki and Sevastyanova (*19*) having found that the exemption of HEVs from the LCC represented a salient issue in driver’s motivations to purchase a HEV, the expectation is that this issue will be observable in the composition of the car fleet.

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FIGURE 1: [left image] Map illustrating the area covered by the London Congestion Charge and the defunct Western Extension [right image] Illustration of the four area categories distinguishing level of contiguity of the local authorities to the London Congestion Charge zone.

**Hybrid Electric Vehicle Demand**

The body of research evaluating the impact of demographic characteristics (*20-21*), personal attitudes (*22*) and policy initiatives (*23-26*) 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. Often, these research studies consider the effects of these different factors in an integrated manner. A case in point is the analysis of Caulfield et al. (*24*) who applied a stated choice experiment to evaluate preferences towards cars operating different propulsion systems in Ireland, with their analysis indicating that increases to respondent age and income levels tended to increase the probability of a respondent preferring a HEV whilst male respondents are more likely to hold negative preferences for HEVs compared to females. Additionally, Caulfield et al. (*24*) evaluated the effect of introducing a graduated vehicle registration tax based on vehicle environmental impact across three different propulsion system categories of conventional vehicles (i.e. petrol and diesel cars), alternatively fuelled cars (i.e. liquefied petroleum gas cars) and HEVs. The findings of this part of their analysis indicate that the presence of a graduated registration tax has the least impact on HEV purchase intentions compared to the other propulsion system options.

Of particular importance to the direction of the research presented in this paper, a number of authors have already evaluated the demand for HEVs through a spatial lens. Conducting a geodemographic analysis of HEV ownership in Finland, Saarenpää et al. (*20*)found that certain population characteristics covering income levels, education levels, number of children and residence size coincide spatially with the adoption of HEVs in Finland. A similar piece of research is presented by Bansal et al. (*21*), who applied a Poisson-lognormal conditional autoregressive model of HEV registrations across census tracts of four different conurbations in Texas, USA. The results of their analysis indicate that a set of demographic characteristics are significant in explaining variance in HEV adoption, with the mean age of the populace, the proportion of the populace with a university degree and the proportion of the populace commuting to work by car significantly increasing HEV registrations whilst the average size of the household and the population density of the tract significant decrease registrations.

**METHODS**

**Data Sources**

The Department for Transport’s Vehicle Licensing Statistics Database (VLSD) represents the source of the registration numbers for HEVs utilised in the analysis reported in this paper (*27*). The data pertaining to HEV registrations, total number of cars registered and total number of cars registered as company cars has been extracted from the VLSD and aggregated to lower-tier local authority level of administrative geography 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 (*28*) as well as Her Majesty’s Revenues and Customs (*29*) at the same geographical level. Descriptive statistics regarding the data utilised in the analysis are reported in Table 1.

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| **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** | **Std. Dev.** | **Min** | **Max** |
| *Socioeconomics* | | | | |
| Mean Age (years) | 40.27 | 2.82 | 30.9 | 47.7 |
| No Qualifications (%) | 22.80 | 5.14 | 6.72 | 36.04 |
| Level 1 Qualification (GCSE grades D-G) (%) | 14.30 | 3.43 | 4.30 | 28.26 |
| Level 2 Qualification (GCSE grades A\*-C) (%) | 15.55 | 1.98 | 6.58 | 18.55 |
| Level 3 Qualification (A-Levels) (%) | 12.08 | 2.03 | 7.16 | 32.59 |
| Level 4 Qualification (University Degree) (%) | 26.93 | 7.71 | 1.42 | 68.36 |
| Mean Personal Income (000’s GBP) | 29.73 | 10.58 | 20.20 | 131.00 |
| Full Time Employment (%) | 38.83 | 3.97 | 26.41 | 51.45 |
| Part Time Employment (%) | 14.03 | 1.60 | 5.71 | 17.08 |
| Self Employed (%) | 10.01 | 2.76 | 4.77 | 17.45 |
| Unemployed (%) | 4.06 | 1.23 | 2.01 | 8.02 |
| Retired (%) | 14.79 | 3.51 | 4.71 | 24.06 |
| Disabled (%) | 3.99 | 1.60 | 1.35 | 9.64 |
| *Household* | | | | |
| Population Density (per hectare) | 15.02 | 22.52 | 0.09 | 138.70 |
| No Car in Household (%) | 23.06 | 10.48 | 8.04 | 69.40 |
| One Car in Household (%) | 42.27 | 2.93 | 25.09 | 50.20 |
| Two Cars in Household (%) | 26.45 | 7.14 | 3.95 | 42.09 |
| Three or More Cars in Household (%) | 6.03 | 2.20 | 0.51 | 11.19 |
| Mean Household Size (residents) | 2.33 | 0.13 | 1.64 | 2.99 |
| *Transport System* | | | | |
| Hybrid Electric Vehicles per 1000 cars | 6.25 | 6.54 | .83 | 60.59 |
| Company Cars per 1000 cars | 77.68 | 143.12 | 24.66 | 1620.43 |
| Private Mode of Transport to Work (%) | 66.68 | 13.82 | 4.76 | 83.33 |
| Public Mode of Transport to Work (%) | 13.01 | 12.80 | 1.80 | 65.51 |
| Active Mode of Transport to Work (%) | 13.42 | 5.26 | 4.31 | 53.70 |

**Area Classification**

Given the nature of the data which is available, three alternative approaches to considering the effect of the LCC over registrations of HEVs are feasible. These approaches provide different perspectives on how the association between the local authorities and the LCC can be conceptualised.

*Connectivity Approach*

The first method considers the geometric layout of the local authority geographical units and how they relate to the boundary of the LCC. Local authorities are categorised in accordance with their degree of separation from the LCC. Four categories are proposed, covering the local authorities which represent [1] boroughs of London and constitute the GLA (n = 32), [2] the local authorities which are first order neighbours to the GLA (n = 16), [3] the local authorities which are second order neighbours to the GLA (n = 23) and [4] the local authorities which represent the rest of the UK (n = 303). This classification system is illustrated in Figure 1 [right image]. The hypothesis here is that as contiguity to the LCC recedes, the registration rates of HEVs will tend to decrease.

*Proximity Approach*

The second method considers the Euclidean distance between the geometric centroids of the local authorities and the LCC. 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 reduces, the registration rates of HEVs will tend to decrease.

*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) who 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.

**Statistical Analysis**

The analysis progresses through a series of four stages. These 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 (*30*) and the MatLab scripts prepared by Elhorst (*31*).

*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 spatial 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 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 (categorical and continuous), alternative statistical approaches are required to evaluate this association. Firstly, descriptive statistics are specified for the connectivity approach, whereby the range, dispersion and central tendency of HEV registrations across the four area categories are detailed. 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] proportion of 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 (*32*) 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 (*33*).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. In the analysis reported in this paper, a binary contiguity spatial weights matrix is specified which follows a queen contiguity approach. Spatial autocorrelation analysis can generally be conducted in two different approaches. Firstly, the global approach (here specified as Moran’s I (*34*)) to spatial autocorrelation determines the degree to which a variable is related to its spatial lag for the entire dataset. Secondly, the local approach to spatial autocorrelation evaluates the occurrence of spatial patterns by noting the presence of regional groups of geographical units which either share similar or divergent values for a variable. Often referred to as Local Indicators of Spatial Association (LISAs), 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 (*35*).

*Stage Four*

In the fourth stage of the analysis, two varieties of regression models are specified which utilise HEV registrations (per thousand cars) at the end of 2012 across the local authorities as the dependent variable. The purpose of these models is to consider the significance of the LCC over 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 (expect for the dummy variables associated with the local authority area categories) are transformed to their natural logarithms to allow the coefficients calculated by the model to be interpreted as elasticity estimates. A series of benchmark ordinary least squares (OLS) log-log 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. The structural form of OLS Model 1 is reported in Equation 1, where represents a vector of dependent variable observations, represents a constant term coefficient, represents a vector of coefficients associated with the area characteristics, represents a vector set containing observations of the area characteristic variables and represents the model residual.

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| --- | --- | --- |
|  |  | ((1) |

OLS Model 2: incorporates the area characteristics of OLS Model 1 as well as dummy variables covering the area categories outlined in the connectivity approach. The structural form of OLS Model 2 is reported in Equation 2 where represents a vector of coefficients associated with the area category dummy variables and represents a vector set of observations of the area category dummy variables.

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|  |  | ((2) |

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

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|  |  | ((3) |

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 4 where represents a coefficient for the variable measuring the proportion of residents driving a car to work in the City of London and represents a vector of observations of the proportion of residents driving a car to work in the City of London.

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|  |  | ((4) |

The selection of area characteristics, which cover socioeconomic, household and transport system attributes, to include in the models as independent variables has been based on the results of past research. Specifically, the work of (*21-26*)suggest that age, education, income, household size, journey to work and population density are characteristics which are useful in explaining variance in HEV registrations and preferences.

A series of spatial regression models (*36-37*) are specified 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 5 where represents the spatial interaction coefficient for the spatially lagged dependent variable and represents a vector of spatially lagged observations of the dependent variable.

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| --- | --- | --- |
|  |  | ((5) |

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 6 and 7 where represents a spatial interaction coefficient associated with the spatial lag of the OLS model’s residuals and represents a vector of observations of spatially lagged OLS model residuals.

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| --- | --- | --- |
|  |  | (6) |
|  |  | (7) |

**RESULTS**

**Exploratory Spatial Analysis**

The registrations of HEVs across the UK at the end of 2012 have been spatially located across the UK’s local authorities and standardised by considering the number of registrations per thousand cars. Figure 2 [left image] illustrates the spatial variation in the registration of HEVs. A significant degree of spatial variation is observed, with the local authority of Blaenau Gwent 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).

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FIGURE 2: [left image] Choropleth map illustrating the spatial variation in Hybrid Electric Vehicle registrations (per thousand cars) across the local authorities of the United Kingdom [right image] Local Indicator of Spatial Association map of Hybrid Electric Vehicle registrations (per thousand cars) across the local authorities of the United Kingdom.

**Area Classification Analysis**

Table 2 reports the descriptive statistics concerning the observed levels of HEV registrations across the different categories of local authorities. The Kruskal-Wallis test returns a significant result (χ2 = 110.52, p-value < 0.01), which indicates that the observed levels of HEV registrations are distinct across these different categories. Inspecting the mean values of HEV registrations across the different categories, the descriptive statistics indicate that as contiguity to the LCC diminishes, the registrations of HEVs tends to decrease.

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| **TABLE 2:** Descriptive statistics of Hybrid Electric Vehicle registrations (per thousand vehicles) 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 United Kingdom (n = 303) | 3.22 | 4.00 | 0.43 | 55.56 |

Figure 3 [left image] illustrates the association between HEV registrations and the distance between the LCC and the local authorities. The scatterplot indicates that these two variables are divergent, which is supported by the observation of a significant negative correlation between these two variables (rs: -.621; p-value < .001). Thus, as distance from the LCC increases, registrations of HEVs tend to decrease. Similarly, Figure 3 [right image] displays the association between HEV registrations and the proportion of local authority residents who drive a car to the City of London local authority for work. In this instance, the scatterplot suggests that these two variables are concurrent, which is substantiated through the presence of a significant positive correlation between these two variables (rs: .634; p-value < .001). Thus, as interaction with the LCC increases, registration rates of HEVs tend to increase.

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| **FIGURE 3:** **Scatterplots of Hybrid Electric Vehicle registrations (per thousand cars) against [left image] distance to London Congestion Charge and [right image] residents who drive a car to work to the City of London (per thousand).** | |

**Spatial Autocorrelation Analysis**

The global Moran’s-I spatial autocorrelation analysis returns a significant result (I = 0.62, p-value < 0.001), 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 2 [right image] illustrates the results of the LISA analysis, with the output indicating that regional clusters 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 shaded deep red represent a hot-spot region where local authorities display relatively high values in terms of HEV registrations. In this instance, the region is centred on the GLA.

**Regression Analysis**

The series of regression models aimed at explaining the observed spatial variation in HEV registrations is reported in Table 3. The results of OLS Model 1 indicate that just less than three quarters of the observed variation in HEV registrations can be explained through a small set of independent variables.

The Results of OLS Models 2-4 illustrate the effect of expanding OLS Model 1 through the integration of the area classifications which account for the effect of the LCC. Indeed, the variables associated with the three different approaches to evaluating the effect of the LCC over HEV registrations all display significant coefficients. These results provides support to the view that nearness to the LCC has had a significant effect over registrations of HEVs even after accounting for the influence of socioeconomic, household and transport system characteristics.

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| **TABLE 3:** **Ordinary least squares and spatial regression log-log models with Hybrid Electric Vehicle registrations (per thousand cars) as the dependent variable** | | | | | | |
| **Variable** | **OLS: M1**  Beta  (Std. Err.) | **OLS: M2**  Beta  (Std. Err.) | **OLS: M3**  Beta  (Std. Err.) | **OLS: M4**  Beta  (Std. Err.) | **SLM**  Beta  (Std. Err.) | **SEM**  Beta  (Std. Err.) |
| Constant | -17.073\*\*  (2.007) | -14.620\*\*  (2.121) | -13.917\*\*  (2.180) | -13.677\*\*  (2.119) | -12.755\*\*  (1.956) | -12.358\*\*  (2.064) |
| *Area Characteristics* | | | | | | |
| Mean Age (ln) | 2.336\*\*  (0.482) | 1.975\*\*  (0.491) | 1.819\*\*  (0.498) | 1.873\*\*  (0.483) | 1.594\*\*  (0.449) | 1.982\*\*  (0.474) |
| % University Degree (ln) | 0.657\*\*  (0.095) | 0.701\*\*  (0.096) | 0.724\*\*  (0.096) | 0.685\*\*  (0.093) | 0.651\*\*  (0.087) | 0.822\*\*  (0.094) |
| % Employed Part Time (ln) | -0.236  (0.254) | -0.139  (0.253) | -0.218  (0.250) | -0.239  (0.248) | -0.117  (0.232) | -0.375\*\*  (0.257) |
| Mean Personal Income (ln) | 0.853\*\*  (0.126) | 0.753\*\*  (0.140) | 0.659\*\*  (0.136) | 0.635\*\*  (0.133) | 0.461\*\*  (0.123) | 0.384\*\*  (0.131) |
| % One Car Households (ln) | 0.566\*  (0.266) | 0.248  (0.280) | 0.597\*  (0.262) | 0.473  (0.260) | 0.518\*  (0.241) | 0.157  (0.273) |
| % Private Transport to Work (ln) | -0.403\*\*  (0.086) | -0.215  (0.111) | -0.223\*  (0.010) | -0.337  (0.086) | -0.212\*\*  (0.080) | -0.292\*\*  (0.108) |
| Population Density (ln) | 0.123\*\*  (0.017) | 0.112\*\*  (0.017) | 0.104\*\*  (0.017) | 0.105\*\*  (0.017) | 0.070\*\*  (0.016) | 0.092\*\*  (0.019) |
| Mean Household Size (ln) | 3.550\*\*  (0.409) | 2.558\*\*  (0.512) | 2.75\*\*  (0.466) | 2.43  (0.479) | 1.771\*\*  (0.455) | 2.425\*\*  (0.467) |
| Company Cars per ‘000 (ln) | 0.384\*\*  (0.027) | 0.400\*\*  (0.028) | 0.382\*\*  (0.027) | 0.397\*\*  (0.027) | 0.403\*\*  (0.025) | 0.410\*\*  (0.024) |
| *Area Classifications* | | | | | | |
| London Borough A |  | 0.309\*\*  (0.108) |  |  |  |  |
| First Order Neighbour A |  | 0.224\*  (0.089) |  |  |  |  |
| Second Order Neighbour A |  | 0.068  (0.074) |  |  |  |  |
| Distance to City of London in km (ln) |  |  | -0.084\*\*  (0.025) |  |  |  |
| Drive to City of London per ‘000 (ln) |  |  |  | 0.069\*\*  (0.016) | 0.041\*\*  (0.015) | 0.061\*\*  (0.017) |
| *Spatial Interaction Effects* |  |  |  |  |  |  |
| Spatial lag of HEV registrations () |  |  |  |  | 0.335\*\*  (0.051) |  |
| Spatial lag of OLS model residual () |  |  |  |  |  | 0.458\*\*  (0.061) |
| *Model Fit* |  |  |  |  |  |  |
| R2 | 0.774 | 0.779 | 0.780 | 0.784 | 0.816 | 0.821 |
| Log Likelihood | -72.705 | -67.024 | -66.705 | -63.672 | -42.9931 | -42.230 |
| AIC | 165.410 | 160.048 | 155.409 | 149.344 | 109.986 | 106.461 |
| SC | 204.653 | 211.063 | 198.576 | 192.511 | 157.077 | 149.627 |
| *Spatial Diagnostics* |  |  |  |  |  |  |
| Robust LM (lag) | 14.023\*\* | 6.278\* | 8.561\*\* | 6.815\*\* | - | - |
| Robust LM (error) | 4.438\*\* | 8.316\*\* | 6.292\* | 7.311\*\* | - | - |
| \*\*: p-value < .01; \*: p-value < 0.05  A: dummy variable with [1] to signify the local authority represents the specified category and [2] to signify the local authority does not represent the specified category | | | | | | |

The observation of a significant degree of spatial autocorrelation in the registrations of HEVs indicates that spatial dependence is present. To ascertain whether the inclusion of the independent variables specified in the OLS log-log regression models has corrected for this spatial dependence, the results of the robust Lagrange Multiplier spatial diagnostics prove useful (reported at the bottom of Table 3, (*38*)). 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 3.

In the SLM, the spatial interaction coefficient () 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 is particular local authorities are affected by the observations of HEV registrations in neighbouring local authorities. In the SEM, the spatial interaction coefficient () which is associated with 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 Models 1-4, SLM and SEM) the SEM model provides the best model fit. Exploring the variables which are included in the SEM and their effect on HEV registrations, a number of notable findings can be discerned. The variable measuring the mean age of the populace holds a significant positive effect in the model (Beta: 1.982), which is in agreement to the findings of Caulfield et al. (*24*) though is counter to the results of Saarenpää et al. (*20*) and Bansal et al. (*21*). The variable measuring the proportion of the populace who have attained a university degree holds a significant positive effect in the model (Beta: 0.822), which is in agreement with the findings of past research (*21-22, 24*). The average income of the populace has a significant positive effect in the model (Beta: 0.384), which is in agreement to the findings of Caulfield et al. (*24*) and Saarenpää et al. (*20*) though Sangkapichai and Saphores (*22*) observed a non-linear income effect. Whilst Bansal et al. (*21*) found that the proportion of individuals driving a car to work to positively affect HEV registrations, the opposite is observed in the SEM (B: -0.292). A similar situation is also present regarding population density, with Bansal et al. (*21*) reporting a significant negative effect whilst the SEM displays a significant positive effect (B: 0.092). The mean size of the household (in terms of residents) holds a significant positive effect in the SEM (Beta: 2.425), which agrees with the results of Saarenpää et al. (*20*) though is counter to the results of Bansal et al. (*21*).

In addition to evaluating the level of agreement between the results of the SEM to the observations of past research, the SEM also includes a number of additional area characteristics to consider their effect over HEV registrations. Firstly, the variable measuring the proportion of the populace classified as employed part-time holds a significant negative effect (Beta: -0.375). However, this variable proves to be insignificant in all of the other regression models specified in the paper. With this lack of stability in mind, the interpretation of this finding should be made with caution. Secondly, 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. Thirdly, the number of company cars registered (per thousand) has a positive significant effect in the model (Beta: 0.397), implying that the presence of corporate car fleets in an area increases registration rates of HEVs.

**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 2 [left image], 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 represents the first step in understanding the geographical issues which might be generating the spatial variation which is apparent.

One particularly interesting result stands out from this stage of the analysis. The City of London represents the local authority with the highest level of HEV registrations (55.55 HEVs per thousand cars). This is a surprising observation, as the City of London sits entirely within the LCC, meaning City of London residents are exempt from having to pay the daily fee associated with the LCC. With this in mind, the expectation is that the LCC should have had no effect over HEV registrations within the City of London, yet this is where the highest degree of HEV adoption is observed. On the surface, this seems to be a counterintuitive finding, but it might be explained by two reasons. Firstly, 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. Indeed, Mau et al. (*39*)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. Secondly, the exemption to the LCC for 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. Both of these reasons seem plausible but would require additional research in order to substantiate.

The three approaches to considering the effect of the LCC over HEV registrations all appear to indicate that there is an association between the LCC and HEV registrations. As local authorities recede in contiguity and proximity to the LCC, there 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 who drive a car to work in the City of London. The results of the spatial autocorrelation analysis add support to the view that the LCC is exerting an influence over 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. Indeed, the results of this stage of the research assist in not only considering where HEV registrations have been relatively high but also in identifying regions which seem to be orientated around low levels of HEV adoption. However, these cold-spots should be interpreted with some caution as the analysis might be overly affected by London and the South East of England producing quite a prominent positive skew (long right tail) in the distribution of HEV registrations per thousand cars. Thus, if the analysis was to be re-specified with the local authorities which comprise the GLA being omitted from the analysis, different hot-spots and cold-spots might be identified.

Whilst the results of stage two and three of the analysis indicate that nearness to and interaction with the LCC corresponds to increased registration rates of HEVs, there is the possibility that other issues are at play in and around London which are effecting registration rates. The results of past research highlight the significant role that demographic characteristics of the populace play in HEV registrations (*21-26*). Thus the possibility exists 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. In order to evaluate if nearness to and interaction with the LCC has a significant effect over registration rates of HEVs having controlled for the effect of socioeconomic, household and transport system characteristics, the results of the regression models (stage four of the analysis) are of interest. Across the OLS log-log regression models which include variables that aim to evaluate the effect of the LCC over HEV registrations (OLS Models 2-4), the results of the analysis imply that as contiguity, proximity and interaction with the LCC increases, so too do registrations of HEVs. Moreover, the significance of the variable measuring the proportion of populace who drive a car to the City of London 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 imply that the exemption of HEVs from the LCC has had a significant positive effect over registrations of these vehicles in the vicinity of London.

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