Analysing parking search ('cruising') time using generalised multilevel structural equation modelling

Analysing parking search ('cruising') time using generalised multilevel structural equation modelling

Dr Sarah Brooke *(Corresponding Author)*
Research Fellow
Centre for Transport Research
School of Engineering
Fraser Noble Building
King's College
University of Aberdeen
Aberdeen
AB24 3UE
Scotland
United Kingdom

Tel: 01224 274087
Email: Sarah.Brooke@abdn.ac.uk

Professor Stephen Ison
Professor of Transport Policy
School of Civil and Building Engineering
Loughborough University
Leicestershire LE11 3TU
United Kingdom

Tel: 01509 222605
Email: S.G.Ison@lboro.ac.uk

Professor Mohammed Quddus
Professor of Intelligent Transport Systems
School of Civil and Building Engineering
Loughborough University
Leicestershire LE11 3TU
United Kingdom

Tel: 01509 228545
Email: M.A.Quddus@lboro.ac.uk

Date: 31st October 2017

Key words: parking search, cruising, on-street parking, generalised multilevel structural equation modelling, case study, factors affecting parking search

ABSTRACT

The aim of this paper is to identify factors influencing parking search (cruising) time. A revealed-preference on-street parking survey was undertaken with individual drivers in four UK cities to investigate the influence of personal, trip, socio-economic, physical, time-related, and price-related variables on parking search. In order to address the potential endogeneity problems between the factors (e.g. parking fee and parking search time) and hierarchical issues in the survey data, a generalised multilevel structural equation model was applied. It was revealed that cruising time could be reduced by seeking drivers to pay for parking as a way of improving social welfare.

1.0 INTRODUCTION

Parking search occurs when a motorist arrives at a destination, intends to park, and circulates in the vicinity of their destination in an attempt to locate a vacant on-street parking space that fulfils their particular requirements for that specific journey. Many factors have been identified that influence a driver's decision to search for on-street parking. These can be categorised as time-related, price-related, individual characteristics (personal, trip purpose, socio-economic), physical environment, and area-wide transport/parking policy. Influencing factors have previously been discussed elsewhere (Brooke et. al., 2014a; 2014b) hence only a brief review of the literature, focusing in particular on methodological and modelling research relating to parking search is presented here for completeness, while research on various factors affecting parking search are discussed within the Results and Discussion section.

Research investigating parking search influencing factors has been conducted utilising various methodological approaches including (Polak and Axhausen, 1990): unstructured/semi-structured driver interviewing; driver's log recording cruising behaviour;

revealed- and/or stated-preference driver surveys; computer-based laboratory simulation to investigate driver behaviour under various conditions; ‘park-and-visit’ surveys to record time taken to locate a vacant parking space; vehicle-following surveys; aerial observation of vehicles; tracking vehicles through registration-plate matching. The advantages and disadvantages of these approaches have been outlined in Brooke et. al. (2014a). It was noted the most frequently applied method for investigating parking search influencing factors was revealed- and/or stated-preference driver surveys. Revealed-preference surveys can be brief and hence short in duration, while establishing (subjective) estimates of cruising. However, subjective responses may create inaccurate and unreliable search times when compared to actual objectively-measured search. Revealed-preference surveys can be particularly helpful in eliciting detailed responses; thereby providing additional qualitative information that supports, adds context to, and enables a more complete understanding and interpretation of the quantitative data collected through the survey responses. Stated-preference surveys offer the capacity to predict drivers’ future parking search behaviour by requesting individuals to choose from alternative hypothetical scenarios characterised by relevant variables (influencing factors) (Thanos et.al., 2011). The difficulties with this approach are in presenting realistic hypothetical scenarios in which drivers are able to visualise themselves, which may create inconsistent responses compared to actual search behaviour (Thanos et.al., 2011). Additional research that has focused on potential parking technologies is that of Bulan et.al. (2013); Jermsurawong et.al. (2014); and Thornton et.al. (2014). Meanwhile, the SF*park* scheme (San Francisco) utilises technology to adjust on-street parking prices based on occupancy (Chatman and Manville, 2014; Millard-Ball et.al., 2014; Pierce and Shoup, 2013), including the utilisation of global positioning system (GPS) data to follow vehicle trips to understand congestion caused by parking search (Karlin-Resnick et.al., 2016).

Modelling approaches applied to parking behaviour research comprise (Polak and Vythoulkas, 1993): discrete choice; network; performance and design; and parking interaction and simulation. These each offer advantages and disadvantages (Brooke et.al., 2014a); discrete choice models enable inclusion of parking-related factors while investigating factors affecting travel choice decisions, but are less appropriate for forecasting or spatial sequential decision-making. Network models effectively represent different parking and driver types, but entail simplifying assumptions. Performance and design models provide information on individual parking facility performance but are less useful in examining wider-scale parking performance. Parking interaction and simulation models offer practical policy applications but lack coherence at a behavioural level. An important element missing from the models is the capacity to analyse parking data that has a hierarchical structure, such as the data used in this study which comprises individual drivers that are nested within streets where they are searching for a parking space.

Current modelling approaches have omitted to apply a multilevel mixed-effects model to analyse hierarchically structured data. Applying a multilevel modelling technique to the dataset in this study which comprises drivers nested within different streets allows similar issues relating to the same street on which drivers are cruising for parking to be considered. Furthermore, variations between drivers searching on different streets and additional variation according to individual personal characteristics are incorporated in the model. Thus a multilevel approach enables a more comprehensive analysis of parking search on multiple levels. The aim of this paper is to identify factors influencing parking search time using statistical models. This has been achieved through the use of a multilevel model to analyse revealed preference survey data. The remainder of the paper is organised as follows: Section 2 comprises Data Collection and Descriptive Statistics; Section 3 details the Multilevel

Modelling performed; Section 4 is devoted to the Results and Discussion; with Section 5 highlighting the Conclusions.

2.0 DATA COLLECTION AND DESCRIPTIVE STATISTICS

A revealed-preference on-street parking survey has been conducted with drivers in the East Midlands region of the UK (**Figure 1**). The aim of the survey was to identify the factors which influence drivers' decisions to search for parking. It comprised 33 structured questions, including socio-economic and vehicle-related factors. It was conducted utilising a face-to-face technique with the Interviewer asking questions of the respondent and was able to be completed in less than 5 minutes.

A pilot study took place in one city (Lincoln) with the survey being subsequently conducted across the 4 main cities in the East Midlands, namely, Nottingham, Leicester, Derby and Lincoln during the period March-June 2014. It was decided to conduct the surveys at various on-street parking areas which represented 7 different area types and usage by drivers with various trip purposes within each city. A total of 97 streets across the 4 cities were surveyed. Each street contained a number of on-street parking spaces that ranged in quantity from <6 bays up to 90 bays according to factors such as: the total length of the street; whether parking was permitted on one or both sides of the carriageway; and the type of area in terms of primary use (for instance, residential areas required access to property driveways be kept clear of parking). Schedules were devised in order to target different streets within each area according to the time of day and day of the week so as to capture a representative sample of drivers with various trip purposes using on-street parking. This sampling technique had a further advantage of maximising potential responses. The number of responses totalled 1,002 across the 4 cities with average response rate of 78.6 per cent. As to whether the sample is representative of the survey area, the income distribution of the respondents was compared with that of the overall population by using a discrete probability distribution. According to the UK Office for National Statistics (ONS), the average salary in Leicester is £20,300/year (2013), whereas our survey data from Leicester indicates an average salary of £19,020/year; £21,124 for Nottingham (ONS) with our sample indicating £19,560/year; while for Derby £22,667 (ONS) with £18,600 for our sample. In terms of Lincoln our sample data indicates £16,000 but ONS implies £18,770 in 2015. While the sample data for Leicester and Nottingham would appear to be representative in terms of average income, this is not the case for the other two cities, suggesting that selection bias might exist. As a result, findings from the survey may need to be interpreted carefully.

Table 1 indicates the main influencing factors included as variables within the statistical multilevel model. 'WalkTime' was coded as a continuous variable; all other variables were categorical. The variable 'AreaType' was used to categorise the streets in which the driver survey was undertaken by classifying streets according to the primary function they fulfilled in terms of location and user ends. Descriptive statistics in terms of mean and standard deviation for continuous variables and frequency percentages for categorical variables are outlined.

Descriptive statistics indicated a low mean 'SearchTime' (1.7 minutes), with slightly higher 'WalkTime' (4.391 minutes). This would be expected as many drivers stated 0 minutes search time, whereas very few had the equivalent walk time. Findings indicated 93.51 per cent of drivers searched for ≤5 minutes; while 99.10 per cent searched and located a parking space in ≤10 minutes. These percentages indicate short search time was the experience for most drivers. 'CityName' frequency analysis indicated the highest number of respondents from 'Nottingham' (33.13 per cent), followed by 'Leicester' (24.85 per cent), 'Derby' (21.66 per cent), and 'Lincoln' (20.36 per cent). There was a relatively consistent

'AreaType' split, notably for 'AreaType 1, 2, 3, 6, 7', with slightly fewer respondents for 'AreaType 4, 5'. The variable 'Purpose' indicated two trip purposes namely 'shopping' and 'work' were undertaken by the most respondents. '. 'ParkCharge' showed the greatest number of drivers paying 'no fee', '<£1.00-£1.99', or '£2.00-£2.99'. 'Weather' was fairly evenly split between 'Warm/sunny' and 'Cool/light rain', experiencing 48.00 per cent and 40.62 per cent of weather types respectively. 'TripTime' findings indicated 90.21 per cent of drivers travelling for ≤40 minutes to a parking place; with <10 per cent travelling longer. The most frequent times of parking arrival were 08:00-12:59 which showed consistent values ranging from 13.37 per cent to 11.88 per cent. The least frequent parking time was 15:00-15:59. In terms of parking habit, most drivers parked 'frequently' or 'sometimes' at the same parking place. There was a fairly consistent split between two vehicle types; 'small hatchback' and 'medium hatchback/saloon', with fewer vehicles comprising the four other categories.

3.0 MULTILEVEL MODELLING

As indicated earlier, the main purpose of this study is to identify factors influencing cruising for parking. This can be achieved through the development of a statistical model that can explain the relationship between parking search time and the factors affecting search time. Since survey data are inherently nested, a multilevel model would be more appropriate. In order to develop a multilevel model, the first step is to cluster the survey data from the four UK cities into homogeneous groups. Respondents can be clustered at three different spatial units: (i) city-level (i.e. Leicester, Nottingham, Derby and Lincoln) (ii) land-use (area) type (i.e. core shopping, shopping, tourist, events, hospital/train station/university, industrial and residential), and (iii) street-level (i.e. 97 different streets from four cities).. The spatial units at the city- and area-levels are quite large and drivers searching for parking within a large geographical unit are exposed to heterogeneous supply-side variables (e.g. enforcement, parking fee and other regulatory policies and, therefore, their parking behaviours may not be correlated. In the case of street-level clustering, drivers travelling to a specific street may perceive a similar level of issues relating to parking search as they share the same road geometry, traffic characteristics, charging mechanism, level of parking demand/supply and other street characteristics. In addition, they are likely to be exposed to the same regulatory agency. Therefore, within-cluster correlations at street level are expected to be significant (Pearson and Hartley, 1966). Furthermore, drivers cruising within the same streets may share similar characteristics among factors such as trip purpose and time of arrival, and attitudes towards walk time and parking charges, for example. Drivers from different clusters (in other words, streets) may also perceive different types of parking search issues due to the fact that their personal circumstances and attitudes towards parking are different and there are variations in street characteristics in terms of parking charge, time restrictions for free-of-charge on-street parking and demand/supply of parking. This is known as between-cluster variations (Pearson and Hartley, 1966). In order to take into account a wide range of driver characteristics and attitudes towards parking-related aspects, it was decided to apply the multilevel model to drivers nested within streets, as opposed to clustering drivers according to city or area types, for example. This hierarchical data structure is depicted in **Figure 2**.

Consequently, a statistical model needs to be chosen in such a way that the model is capable of jointly controlling both within- and between-cluster variations. One such statistical model is a multilevel linear regression model that can allow for dependency of parking search time within streets and can examine the extent of between-city variation in the perception of parking. For a single independent variable, the model is shown in the following equation:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij} \qquad (1)$$

Where Y_{ij} is the dependent variable representing the amount of parking search time of driver i in street j, X is a driver-level independent variable, e is the driver-level residual that is independent across observations and follows a normal distribution with a zero mean and a constant variance i.e. $e \sim N(0, \sigma_e^2)$.

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z + u_{oj} \qquad u_0 \sim N(0, \sigma_{u_0}^2) \qquad (2)$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} \mathrm{Z} + u_{1j} \qquad u_1 \sim N(0, \sigma_{u_1}^2) \qquad (3)$$

$$\binom{u_{0j}}{u_{1j}} \sim MVN(\mathbf{0}, \boldsymbol{\Omega}_u), \qquad \mathbf{0} = \binom{0}{0}, \boldsymbol{\Omega}_u = \begin{pmatrix} \sigma_{u_0}^2 & \sigma_{u_{01}} \\ \sigma_{u_{10}} & \sigma_{u_1}^2 \end{pmatrix}$$

Where: γ_{00} the overall mean parking search time (per driver) across cities; u_{0j} is the effect of city j on the parking search time (i.e. a city-specific effect or city-level residual that follows a normal distribution with mean zero and variance $\sigma_{u_0}^2$; γ_{01} is the coefficient for the city-level variable; Z is a city-level independent variable; u_{1j} is the city-specific random slope for the driver-level variable and this is also assumed to follow a normal distribution with mean zero; and variance $\sigma_{u_1}^2$, $\sigma_{u_{10}} = \sigma_{u_{01}}$ indicates the covariance between u_{0j} and u_{1j}. Using equations (2) and (3) into equation (1) yields the following model:

$$Y_{ij} = \gamma_{00} + \gamma_{01} Z + \gamma_{10} X + \gamma_{11} XZ + u_{oj} + u_{1j} X + e_{ij} \qquad (4)$$

Where γ_{11} is the coefficient for the cross-level interaction term. If it is thought that equation (3) should not include any upper-level covariates (i.e. Z), then equation (4) would not have any cross-level interaction terms.

It is noticeable that equation (4) contains both fixed-effects ($\gamma_{00} + \gamma_{01} Z + \gamma_{10} X + \gamma_{11} XZ$) and random-effects ($u_{oj} + u_{1j} X$) therefore, this can be termed as a multilevel mixed-effect (random-intercept and random-coefficient) linear regression model. Equation (4) can easily be generalised into the case in which multiple driver-level and city-level independent variables can be incorporated as follows:

$$Y_{ij} = \boldsymbol{\vartheta W} + \boldsymbol{\delta V} + \boldsymbol{\varepsilon} \qquad (5)$$

in which: $\boldsymbol{W}$ is a matrix containing the fixed effects independent variables; $\boldsymbol{\vartheta}$ is a vector of fixed effects parameters; $\boldsymbol{V}$ is a matrix containing the random effects; $\boldsymbol{\vartheta}$ is the vector of random effects; and $\boldsymbol{\varepsilon}$ is the vector of errors**.** A model without the inclusion of $\boldsymbol{V}$ can be termed as random-intercept linear regression model and a model without $\boldsymbol{W}$ can be termed as random-coefficient linear regression model. Equation (5) can be estimated using the maximum likelihood (ML) estimation method (Heck and Thomas, 2009).

It is however envisaged that variables to be employed in modelling parking search time may suffer from the problem of endogeneity. For instance, there may be an endogenous relationship between parking charge and parking search time. In addition, vehicle occupancy rates may affect both search time and parking fee. Therefore, an in-depth investigation of endogeneity should be carried out in order to obtain credible estimates. For example, the commonly employed Durbin-Wu-Hausman test (also known as the Hausman specification test) (Hausman, 1978) for endogeneity could reveal potential endogeneity issues with the set of variables. If endogeneity is detected, one should address this problem by utilising an appropriate modelling strategy. One way to develop a model with the presence of endogeneity is to use a simultaneous equation model and to estimate the modelling parameters through the three-stage least squares (3SLS) estimator. However, such an estimator may not fully address the hierarchical data structure (i.e multilevel data), especially if a random-slope is considered. In order to concurrently address both endogeneity and data hierarchy, researchers develop a generalised multilevel structural equation model (Rabe-

Hesketh et al., 2004). For instance, if endogeneity is apparent between parking fee and search time, then the following simultaneous equation model should be considered:

$$ParkingCharge_{ij} = \beta_{0j} + \beta_{1j}SearchTime_{ij} + \beta_{2j}Duration_{ij} + \cdots \ldots + e_{1ij}$$

$$SearchTime_{ij} = \theta_{0j} + \theta_{1j}ParkingCharge_{ij} + \theta_{2j}Duration_{ij} + \cdots \ldots + e_{2ij}$$

This modelling framework is diagrammatically represented in **Figure 3**. In this path diagram, the variable (i.e. street identification number) within the double rings indicates a latent variable at the street level that is constant within a street and varies across the streets (i.e. a random effect). Parking charge (average parking fee per hour) and parking search time are the observed endogenous variables and other variables are the observed exogenous variables. The path from the latent variable is pointing to a box and also to another path, meaning that this modelling framework supports both a random intercept and a random slope. The curved path connecting the two double rings specifies that these variables are allowed to be correlated.

Insert Figure 3 here

The statistical package STATA supports the estimation of a generalised (multilevel) structural equation model by employing a numerical integration – the *mean–variance adaptive Gauss–Hermite quadrature* (StataCorp, 2015).

4.0 RESULTS AND DISCUSSION

The focus was to develop a statistical model for parking search time with the aim of identifying important factors so as to formulate reliable parking policies. As stated in the previous section, there may be an issue of endogeneity with the factors utilised in the modelling exercise. This is especially true for the case of two of the most important variables, namely parking fee and search time. Therefore, the Durbin-Wu-Hausman test was applied to check whether there was an endogenous relationship between these variables. The test result confirmed an endogeneity problem at the 95% confidence level indicating that a statistical model capable of accounting for endogeneity should be employed. Consequently, a generalised multilevel structural equation model was applied to our survey data.

A separate analysis of the intra-class correlation coefficients at the three spatial units (i.e. city, area and street) revealed within-correlations of parking search time among the respondents, while clustering at the city-level or area-level is not correlated. As expected, there are significant correlations among drivers searching for spaces at the street level. More specifically, the intra-class correlation coefficient for clustering at the street level was found to be 0.154 suggesting that 15.4 per cent of the variation in parking search time is attributed to street-wide differences in issues related to parking search. It could be argued however that drivers parking on the same street may not necessarily be exposed to the same supply-side variables as their relevant search area might be different due to distinct final destinations. More specifically, a driver's final destination could be situated some distance to the left of the intended parking space, and another could be some distance to the right. Although they might be exposed to the same supply-side factors within a given street, this might not necessarily be true for their planned search area, as parking supply and regulation varies by enforcing agencies. Therefore, clustering at a small area may be more preferable. However, such data are not available to the authors and, therefore, our analysis was based on clustering at the street level.

Utilising the modelling framework presented in **Figure 3**, a generalised multilevel structural equation model (GSEM) was developed. Both random-intercept and random-slope models (i.e. mixed-effects models) in the context of multilevel (2-level) models were considered. Two-level survey data are recorded in long-form; that is, there are repeated observations within a given street. In the repeated observations for a street, some variables (e.g. search time) vary as they are at the observation- (i.e. driver-) level and other variables (e.g. road characteristics) do not vary as they are at the street-level. It is also worthwhile reporting that there are no observations with missing values for which GSEM is reactive.

The modelling results are presented in Table 2. Two models were simultaneously estimated for: (i) parking fee and (ii) parking search time. Only statistically significant variables at the 90% confidence level were retained in the final model that was chosen based on the goodness-of-fit statistics. Random intercepts for both models were found to have sufficient variances, indicating that a multilevel model is more appropriate. None of the variables were found to have a random slope, indicating that the impact of an explanatory variable on an endogenous variable is uniform. Interpretation of the significant variables are discussed below:

Modelling results for parking fee:

Based on the survey data, average parking charge per hour for each of the 1,002 parking events was calculated and employed in the model as an endogenous variable. Only three variables, such as parking search time, planned parking duration and searching for a parking space at another location, were found to be statistically significant at the 90% confidence level. As expected, parking search time was negatively associated with parking fee, indicating that if a driver spends more time searching for a parking space s/he would pay less for parking. More specifically, if parking search time increases by 1% then the average parking fee would reduce by 0.1%, *ceteris paribus*. This is likely to result from drivers extending their search time until a space is found that is subjectively considered as being acceptable in terms of cost but that also meets their other requirements (e.g. factors such as walk time to a destination). If drivers did not continue to search, this could result in their paying a slightly higher parking fee, since the first parking spaces encountered might be at higher cost. Intended parking duration has the highest influence on parking fee. If parking duration increases by 1% then parking payment decreases by 1.25%. This is likely due to long-duration parking being charged at a lower price than more in-demand short-stay parking, which typically tends to be in more desirable locations close to significant destinations (e.g. central shopping areas) where high turnover of parking is encouraged. High turnover of parking spaces benefits shops and other small businesses, by enabling greater numbers of potential customers to access parking nearby; thereby, providing economic benefits to the local area. In contrast, long-duration parking tends to be located on the peripheral areas of cities, away from core shopping areas, and is less in demand by individuals seeking to park for shorter duration. Such parking has lower turnover and is typically used by commuters who park all day, rather than by visitors or shoppers, who may require parking for only a few hours, for example. In addition, a driver pays £0.20/hour more for a parking without searching at another location. These are all expected results. Since the primary focus is on the parking search time, the parking fee model is considered to be a ‘control’ model.

It might initially appear as surprising that the occupancy rate of the vehicle was found to be statistically insignificant, since it is envisaged that parking fee changes in response to occupancy levels that may also affect parking search time. Some researchers, however, suggest that such a link may not exist, as parking fees in most cities are not demand-responsive (performance-based parking) but respond to political decisions (e.g. Madsen, Mulalic & Pilegaard, 2013).

Modelling results for parking search time:

In comparison with the parking fee model, more variables were found to be statistically significant at the 95% confidence level in the model for parking search time (see Table 2).

Parking charge: this variable has a significant negative impact on parking search time. The result indicates that if a commuter is willing to pay for a parking space, the parking search time would reduce by about 42 seconds. This is significant given that the average parking search time in the sample data is only 93 seconds. This finding is consistent with other research where the influence of price has been investigated through parking charge increases and the effect of these on parking preference. Drivers were more likely to search for on-street parking if it was priced lower than off-street alternatives (Gragera and Albalate, 2016; Kobus et.al., 2013). Roth (1965) observed certain driver's preference would be to pay to park to avoid extended search. Parking price was considered by drivers to be the most important parking choice influencing factor (Golias et.al., 2002). A model was developed that varied tariffs and time limits as a means of predicting parking behaviour (Simicevic et.al., 2013). On-street parking time limits to reduce parking search were examined (Arnott and Rowse, 2013). The price paid by drivers varies according to factors such as parking location (city core/periphery) and duration (how long a driver intends to park). Parking duration influences search since parking that fulfils duration requirements must be located. Longer durations increased search times for on-street parking (Shoup, 2006; Van Ommeren et.al., 2012). This has not been confirmed in this study as parking duration was found to be statistically insignificant. Various alternative specifications were tested. This includes the interaction of parking charge with intended parking duration and disposable household income. However, the findings were not statistically significant.

The cost that an additional on-street parked vehicle enforces other vehicles to search for parking, known as the external cruising costs for parking (Arnott et.al., 2015). If on-street parking is completely free or under-priced, then demand may exceed supply resulting in a high external cruising cost for parking. Therefore, any reduction in external cruising costs for parking through the introduction of a parking charge or even increasing the parking price would be considered as an improvement in social welfare with respect to a reduction in delays and vehicle emissions as well as better air quality. This argument has also been supported by Arnott and Inci (2006, p.418) who stated that "it is efficient to raise the on-street parking fee to the point where cruising for parking is eliminated without parking being unsaturated".

The finding of increased search time as 'WalkTime' increased was unexpected, as one would typically find more search around key destinations with shorter walking time, due to higher demand for those parking spaces, as shown in earlier research. The influence of walk time (from parking to destination) on search time has been investigated (Axhausen and Polak, 1991; Hess and Polak, 2004). Drivers evaluated time and price; selecting shorter egress (walk) times and higher parking tariffs, or longer egress times with lower fees (Yun et.al., 2008). Parking fees and egress distances were highly negatively significant (Harmatuck, 2007). In contrast, increased walk time implies drivers choosing to park further from destinations where one would expect lesser demand and lower search time. A possible explanation could be high demand for longer duration parking, which is located further from key destinations and hence creates longer walk times and more cruising if provision of long-stay parking spaces is limited. In the multilevel model, 'Walk Time' was found to have a random effect on cruising for parking, with significance being indicated in both the mean value of the coefficient and the standard deviation of the coefficient values that was based upon variation between the individual survey respondents. It was assumed that the coefficients were normally distributed and that the mean of ‘WalkTime’ was in the middle of the distribution.

‘TripTime’ showed positive significant coefficients; the highest values being for the linear model. These results indicated that as ‘TripTime’ increased, more cruising occurred. This was expected as it would be unlikely for a driver travelling a short distance to spend a long time searching for parking given the high percentage of total trip time that search would contribute. Meanwhile, search time would consist of a far smaller percentage of whole trip time if the distance from origin to parking was greater. ‘TripTime’ from journey origin to parking place noted positive coefficients for trip times compared to ‘<10 minutes’, indicating that as trip time increased, more cruising occurred. Significant positive coefficient values were obtained for ‘41-50 minutes’ and ‘>60 minutes’; the highest level of search time indicated for ‘>60 minutes’.

‘ParkTime’ revealed consistent positive significant values for all categories; indicating more cruising time generated by later parking arrival times compared to the reference case ‘07:00-07:59’. For some categories the linear model produced higher values, while the multilevel model gave higher coefficients for other categories. It would be expected that the period ‘07:00-07:59’ would experience lower parking demand, and hence search time, since it is prior to the time when commuter and other traffic arrives at a destination to park. Findings indicated search time increased as mornings progressed, through lunchtimes when there was consistency in both models indicating the highest value between ‘12:00-12:59’, before decreasing slightly but maintaining a high coefficient between ‘13:00-13:59’. High lunchtime search times would be expected due to high demand for short-duration spaces from individuals shopping or meeting friends. Time of arrival at a parking place indicated significant positive coefficients for all park times, compared to ‘07:00-07:59’, with more search occurring after this time. Most cruising time occurred during ‘17:00-17:59’, indicating a coefficient of +3.002; followed by ‘12:00-12:59’ with a coefficient of +2.88.

Analysis of individual factors found significance in a negative direction for ‘Purpose’, with ‘shopping’ indicating a -0.3526 coefficient value compared to the category ‘work’. Earlier research found that trip purpose affects cruising for parking through differing constraints upon drivers’ time; search was found to be more likely among drivers engaged in retail/leisure activities than for employment/business (Van Ommeren et.al., 2012). Shoppers and part-time employees undertook longer searches than full-time workers (Bradley and Layzell, 1986). Utilisation of Parking Guidance Information (PGI) varied by trip purpose (Thompson et.al., 1998); tourists being most likely to use PGI to assist parking choice (Thompson and Bonsall, 1997).

Parking habits become established after repeated visits to parking places; reducing/replacing initially important influencing factors. Rather than thinking rationally about utility/disutility of parking places or trip decisions, drivers act automatically and habitually from earlier behaviour (Aarts et.al., 1997; Verplanken et.al., 1998). At ‘Driver Level’, the variable ‘Habit’ revealed positive significance for two categories, with slightly higher values for the multilevel model. More search occurred for ‘I rarely park here’ and ‘This is my first visit’ compared to ‘I always park here’. Since a driver who always parks in the same place would be familiar with the area and know the best time to arrive in order to find a vacant space, this finding would be expected. Significant coefficients of 0.3188 for ‘First visit’ and 0.9670 for ‘Rarely’ were found; thereby indicating more search time compared to ‘Always’. That drivers avoided searching for parking by selecting to park in previously-used car-parks was found by Bonsall and Palmer (2004). Drivers’ parking habits were investigated by Van der Waerden et.al. (2014), who found drivers regularly or often used the same parking facility on each occasion when travelling to a central business area.

The finding that 'Light Goods Vehicle' drivers searched more may arise due to LGVs being used by trades-people and containing valuable tools/equipment, which influence drivers to park close to a destination for greater security hence increasing cruising time in high demand destinations. Furthermore, trades-people typically work at specific addresses for each particular job which requires a parking space close to the address which, at peak parking times, involve increased search. Looking at the type of vehicle being driven, only 'Light Goods Vehicle' showed a significant coefficient (+0.6746), indicating more search time'.
While this paper introduced a new strategy of simultaneously modelling the on-street parking fee and parking search time, some limitations with respect to data should be highlighted. Although existing studies revealed that parking occupancy level affect parking search time (for example, Madsen et.al., 2013; Arnott et.al., 2015), our survey data does not contain information on this variable. In addition, there may be an issue with our sample as the average annual income of the survey respondents is slightly lower than that of the overall population.

5.0 CONCLUSIONS

To examine the issue of endogeneity with the factors associated in the modelling exercise, the Durbin-Wu-Hausman test was applied to check whether there was an endogenous relationship between the variables parking fee and parking search time. The test results confirmed existence of an endogeneity problem; therefore a statistical model capable of accounting for endogeneity (the generalised multilevel structural equation model) was applied to the survey data. Two models were simultaneously estimated: i) for parking fee and ii) for parking search time; which resulted in more logical findings than employing a modelling approach that did not take into account potential endogeneity. Random intercepts for both models were found to have sufficient variances, indicating that a multilevel model is more appropriate. None of the variables were found to have a random slope, indicating that the impact of an explanatory variable on an endogenous variable is uniform. A separate analysis of the intra-class correlation coefficients at the three spatial units (i.e. city, area and street) revealed within-correlations of parking search time among drivers, while clustering at the city-level or area-level is not correlated. Significant factors included: arrival time at a parking place (for which every time period after the 07:00-07:59 reference case indicated increased search time); trip time from origin to parking place; and walking time from a parking place to a destination. Several factors related to driver trip and personal characteristics; the influence of which varied according to the individual and would be difficult for government transport policy-makers to affect.

A new methodological approach to the analysis of cruising time that has merit from a policy decision perspective has been offered. The proposed methodology is transferable in that it can be can be applied to any city irrespective of their data gathering capabilities and parking regulation system. It can also offer an alternative to be taken into account by garage parkers; whose transaction data will be extremely rare to be made available by private operators. Additionally, it might well complement other transaction data approaches that fail in reflecting trip and drivers' characteristics. The results are useful to inform policy makers on the best tools to address the parking market distortions (cruising), but also to the development of broader parking guidance information technologies targeting such an issue.

Parking search research would be enhanced by the undertaking of a much larger-scale national study in the UK that encompassed urban areas of various sizes, ranging from market towns through to cities and large conurbations. Ideally, research examining cruising for parking would additionally include drivers who had utilised off-street parking facilities, in order to investigate those individuals who had initially searched for an on-street parking space but had subsequently chosen to abandon their search and instead to park off-street. A larger scale national study that encompassed drivers within off-street parking facilities would greatly extend the knowledge and understanding of significant factors that potentially influence parking search time. A further important area of research is concerned with new technological developments that have the potential to significantly influence the amount of cruising time engaged in by drivers. Research in this area would quantify the impact on parking search time of traveller parking information systems such as Internet websites and smartphone applications that assist drivers in locating, reserving and paying for vacant parking spaces in advance of arrival at a destination. Urban areas in which local authorities have chosen to install such measures have the potential to see significantly reduced search times; research is needed to quantify the impact on cruising that such technological advances might have. Future statistical analysis could extend the current research in the four cities in the UK by applying a multilevel model utilising individual drivers nested within parking area types and, as a separate analysis, around different time periods. This would enable the effect of other clusters (area type; time period) to be studied.

ACKNOWLEDGEMENTS

The authors are indebted to two anonymous referees for their detailed comments on earlier drafts of the paper. They certainly made for a much improved and focused paper. We would also like to thank Nicolette Formosa for drafting Figure 3.

REFERENCES

Aarts,H., Verplanken,B., and van Knippenberg,A. (1997) ‘Habit and information use in travel mode choices’, *Acta Psychologica*, **96**, 1-14

Arnott,R. and Inci,E. (2006) An integrated model of downtown parking and traffic congestion, *Journal of Urban Economics* **60**(3), 418-422

Arnott,R., Inci,E. and Rowse,J., (2015) ‘Downtown curbside parking capacity’, *Journal of Urban Economics* **86**, 83-97

Arnott,R. and Rowse,J. (2013) ‘Curbside parking time limits’, *Transportation Research Part A* **55**, 89-110

Axhausen,K.W. and Polak,J.W. (1991) ‘Choice of parking: Stated-preference approach’, *Transportation*, **18**(1), 59-81

Bonsall,P. and Palmer,I. (2004) ‘Modelling drivers car-parking behaviour using data from a travel-choice simulator’, *Transportation Research Part C: Emerging Technologies*, **12**(5), 321-347

Bradley,M. and Layzell, A. (1986) *Parking Behaviour in a Suburban Town-Centre: An Analysis of Town Surveys in Kingston-upon-Thames, Report No.354*, Transport Studies Unit, Oxford University, Oxford, UK

Brooke,S.L., Ison,S.G., and Quddus,M.A. (2014a) ‘On-Street Parking Search: a review and future research direction’, *Transportation Research Board 93rd Annual Meeting,* Washington, D.C., USA

Brooke,S.L., Ison,S.G., and Quddus,M.A., (2014b) 'Parking Choice'. In Ison.S.G., and Mulley,C. (Eds.), *Parking: Issues and Policies,* Transport and Sustainability, Vol.5, Emerald Group Publishing, Bingley, UK

Bulan,O., Loce,R.P., Wu,W., Wang,YR., Bernal,E.A., and Fan,Z., (2013) 'Video-based real-time on-street parking occupancy detection system', *Journal of Electronic Imaging* **22**(4), 1-14

Chatman,D.G. and Manville,M. (2014) 'Theory versus implementation in congestion-priced parking: An evaluation of SF*park'*, *Research in Transportation Economics* (2014) http://dx.doi.org/10.1016/j.retrec.2014.04.005

Golias,J., Yannis,G., and Harvatis,M. (2002) 'Off-street parking choice sensitivity', *Transportation Planning and Technology*, **25**(4), 333-348

Gragera,A. and Albalate,D. (2016) 'The impact of curbside parking regulation on garage demand', *Transport Policy*, **47**, 160-168

Harmatuck,D.J. (2007) 'Revealed-Parking Choices and the Value of Time', *Transportation Research Board 86th Annual Meeting*, Washington, D.C., USA.

Hausman, J.A. (1978) Specification tests in econometrics. *Econometrica* **46**, 1251–1271

Heck,R.H. and Thomas,S.L. (2009) *An introduction to multilevel modelling techniques*, Second Edition, Routledge, New York, USA

Hess,S. and Polak,J.W. (2004) 'Mixed-Logit estimation of parking-type choice', *Transportation Research Board 83rd Annual Meeting*, Washington, D.C., USA

Jermsurawong,J., Ahsan,U., Haidar,A., Dong,H., and Mavridis,N. (2014) ‘One-Day Long Statistical Analysis of Parking Demand by Using Single-Camera Vacancy Detection’, *Journal of Transportation Systems Engineering and Information Technology*, **14**(2), 33-44

Karlin-Resnick,J., Weinberger, R.R., Millard-Ball,A., Hampshire,R.C., Dykstra,T., and Lucas,K. (2016) ‘Parking Search Caused Congestion: What We Learn from a Controlled GPS Example with Applications to Big Data’, *Transportation Research Board 95th Annual Meeting*, Washington, D.C., USA

Kobus,M., Puigarnau,E.G., Rietveld,P., and van Ommeren,J.N. (2013) ‘The On-Street Parking Premium and Car Drivers' Choice between Street and Garage Parking’, *Regional Science and Urban Economics*, **43**(2), 395-403

Madsen, E., Mulalic, I., and Pilegaard, N. (2013) A model for estimation of the demand for on-street parking, MPRA Working Paper, Item 52361, https://mpra.ub.uni-muenchen.de/id/eprint/52361

Millard-Ball, A., Weinberger, R.R., and Hampshire,R.C. (2014) ‘Is the curb 80% full or 20% empty? Assessing the impacts of San Francisco’s parking pricing experiment’, *Transportation Research Part A*, **63**, 76-92

Office for National Statistics (2017) Online. https://www.ons.gov.uk/search?q=average+salary [Accessed 30th October 2017]

Pearson,E.S. and Hartley,H.O., (Eds.) (1966) *Biometrika Tables for Statisticians*, Volume 1, 3rd Ed., Table 12, Cambridge University Press, New York, USA

Pierce,G. and Shoup,D. (2013) ‘Getting the Prices Right: An Evaluation of Pricing Parking by Demand in San Francisco’, *Journal of the American Planning Association*, **79**(1), 67-81

Polak,J.W. and Axhausen,K.W. (1990) *Parking-Search Behaviour: A Review of Current and Future Prospects*, Report No.540, Transport Studies Unit, Oxford University, Oxford, UK

Polak,J.W. and Vythoulkas,P. (1993) *An Assessment of the State-of-the-Art in the Modelling of Parking Behaviour*, Report No.752, Transport Studies Unit, Oxford University, Oxford, UK

Rabe-Hesketh,S., Skrondal,A., and Pickles,A. (2004) Generalized multilevel structural equation modelling, *Psychometrika* **69**(2), 167-190

Roth,G. J. (1965) *Paying for Parking*, Hobart Paper 33, The Institute of Economic Affairs Ltd, London, UK

Shoup,D.C. (2006) ‘Cruising for parking’, *Transport Policy*, **13**(6), 479-486

Simicevic,J., Vukanovic,S., and Milosavljevic,N. (2013) ‘The effect of parking charges and time limit to car usage and parking behaviour’, *Transport Policy* **30**, 125-131

StataCorp (2015) Stata: Release 14. Statistical Software. College Station, TX: StataCorp LP

Thanos,S., Wardman,M., and Bristow,A.L. (2011) ‘Valuing Aircraft Noise: Stated-Choice Experiments Reflecting Inter-Temporal Noise Changes From Airport Relocation’, *Environmental and Resource Economics*, **50**(4), 559-583

Thompson,R.G., Takada,K., and Kobayakawa,S. (1998) ‘Understanding the demand for access information’, *Transportation Research Part C*, **6**(4), 231-245

Thompson,R.G. and Bonsall,P. (1997) ‘Drivers response to parking guidance and information systems’, *Transport Reviews*, **17**(2), 89-104

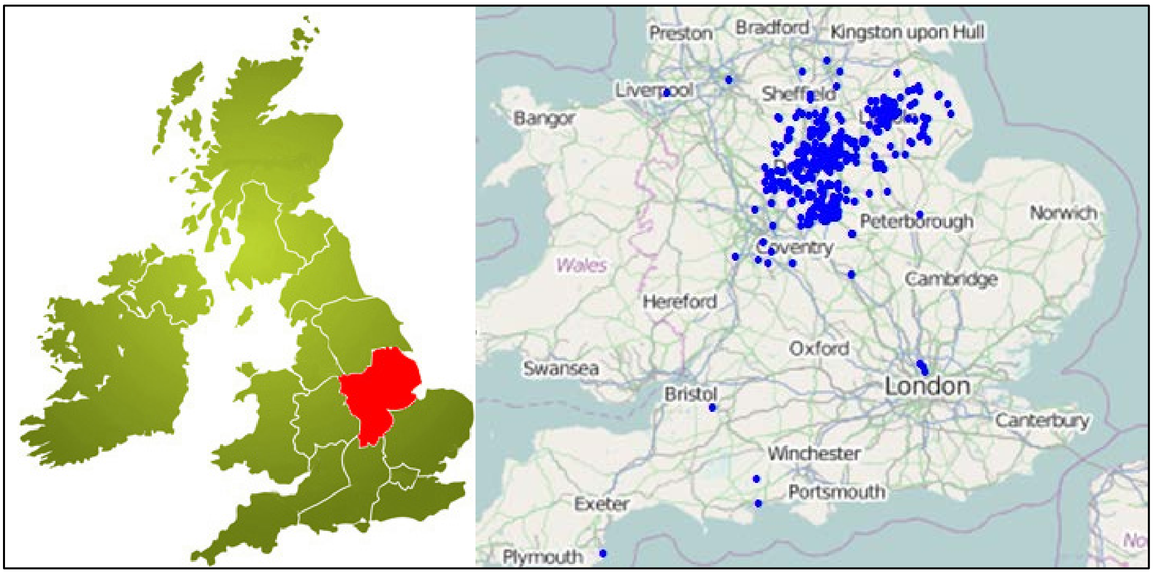
Thornton,D.A., Redmill,K., and Coifman,B. (2014) ‘Automated parking surveys from a LIDAR equipped vehicle’, *Transportation Research Part C* **39**, 23-35

Van der Waerden,P., Timmermans,H., and da Silva,A.N.R. (2014) ‘The Influence of Personal and Trip Characteristics on Habitual Parking Behavior’, *Case Studies on Transport Policy*, http://dx.doi.org/10.1016/j.cstp.2010.04.001

Van Ommeren,J.N., Wentink,D., and Rietveld,P. (2012) ‘Empirical evidence on cruising for parking’, *Transportation Research Part A: Policy and Practice*, **46**(1), 123-130

Verplanken,B., Aarts,H., van Knippenberg,A., and Moonen,A. (1998) ‘Habit versus planned behaviour: A field study’, *British Journal of Social Psychology*, **37**(1), 111-128

Yun,M., Lao,Y., Ma,Y., and Yang,X. (2008) ‘Optimization Model on Scale of Public Parking-Lot Considering Parking Behavior’, *International Conference on Intelligent Computation Technology and Automation*



1(a): the case study area **1(b): spatial distribution of respondents' home postcodes**

FIGURE 1: Case study location and home postcodes plots: East Midlands region, UK

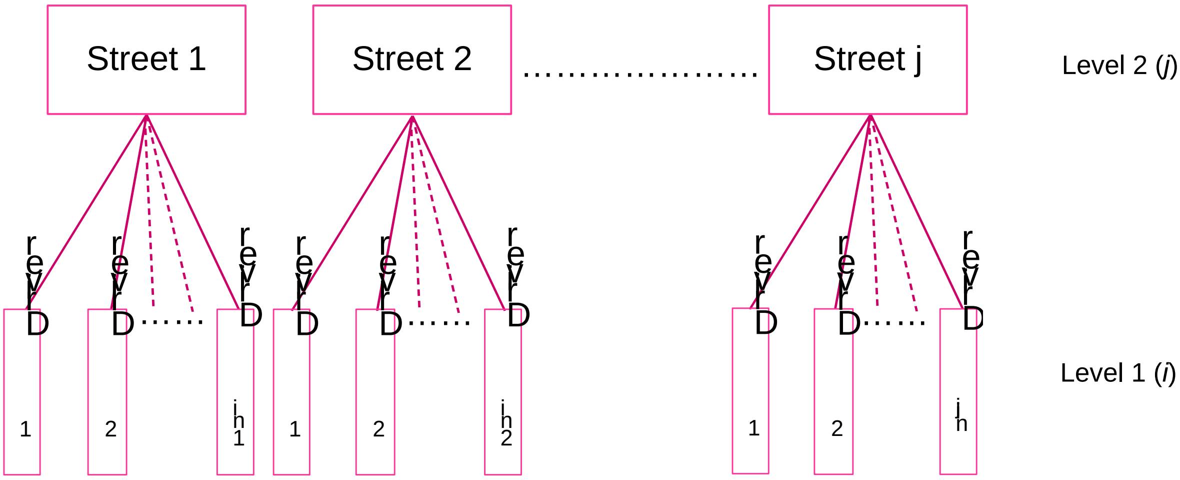


FIGURE 2: A two-level hierarchical data structure on parking search time

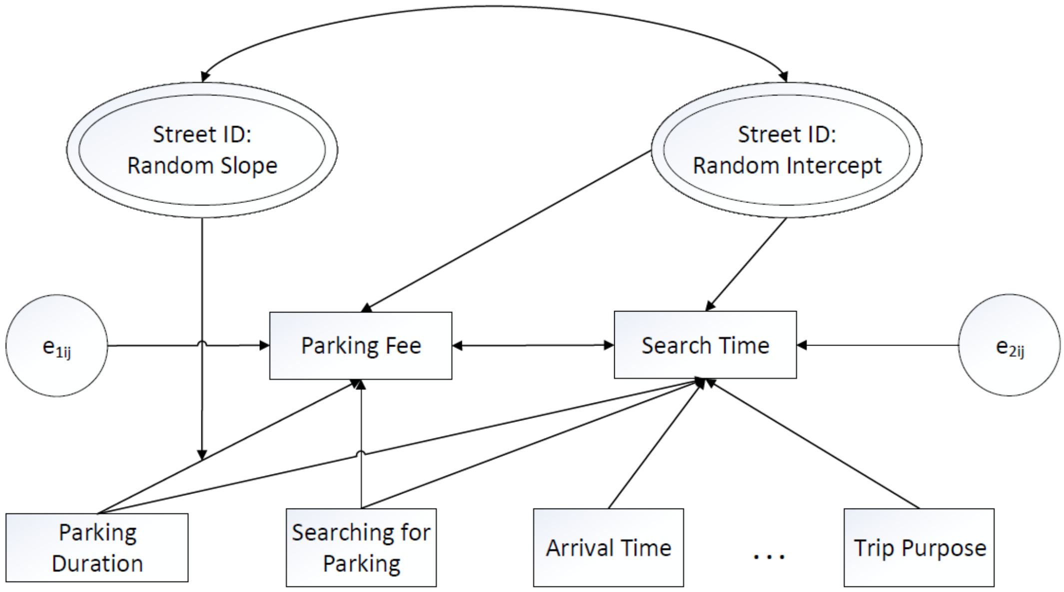


FIGURE 3: Modelling framework: a path diagram

TABLE 1: Variables Included Within Multilevel Model and Associated Descriptive Statistics

Influencing Factor	**Variable Name**	**Descriptive Statistics**				
		Mean	**Std. dev.**	**Search Time (minutes)**	**Freq. (%)**	**Cum. (%)**
Search Time (minutes)	'SearchTime'	1.700	2.598	0	47.60	47.60
				1	15.17	62.77
				2	15.27	78.04
				3	5.29	83.33
				4	2.10	85.43
				5	8.08	93.51
				10	2.00	99.10
Walk Time (minutes)	'WalkTime'	4.391	4.004	-		
				Variable Category	**Category Definition**	**Freq. (%)**
Trip Purpose	'Purpose'	-	-	Purpose1	Work	26.15
		-	-	Purpose2	Business - Trade	4.59
		-	-	Purpose3	Education	5.49
		-	-	Purpose4	Shopping	36.03
		-	-	Purpose5	Personal Business	13.77
		-	-	Purpose6	Social or Entertainment	6.89
		-	-	Purpose7	Other	7.09
Parking Charge	'ParkCharge'	-	-	ParkCharge1	No fee	30.74
		-	-	ParkCharge2	<£1.00-£1.99	25.45
		-	-	ParkCharge3	£2.00-£2.99	33.03
		-	-	ParkCharge4	≥£3.00	10.78
Weather	'Weather'	-	-	Weather1	Warm / Sunny	48.00
		-	-	Weather2	Cool / Light Rain	40.62
		-	-	Weather3	Heavy Rain	1.60
		-	-	Weather4	Cool / Sunny	6.79
		-	-	Weather5	Warm / Light Rain	2.99
Trip Duration from Origin to Parking Place	'TripTime'	-	-	TripTime1	<10 minutes	18.56
		-	-	TripTime2	11-20 minutes	34.03
		-	-	TripTime3	21-30 minutes	24.25
		-	-	TripTime4	31-40 minutes	13.37
		-	-	TripTime5	41-50 minutes	4.29
		-	-	TripTime6	51-60 minutes	2.69
		-	-	TripTime7	>60 minutes	2.79
Time of Arrival at Parking Place	'ParkTime'	-	-	ParkTime1	07:00-07:59	6.89
		-	-	ParkTime2	08:00-08:59	13.37

		-	-	ParkTime3	09:00-09:59	15.47
		-	-	ParkTime4	10:00-10:59	15.27
		-	-	ParkTime5	11:00-11:59	14.67
		-	-	ParkTime6	12:00-12:59	11.88
		-	-	ParkTime7	13:00-13:59	7.78
		-	-	ParkTime8	14:00-14:59	2.99
		-	-	ParkTime9	15:00-15:59	1.80
		-	-	ParkTime10	16:00-16:59	3.69
		-	-	ParkTime11	17:00-17:59	4.09
		-	-	ParkTime12	18:00-19:00	2.10
Parking Habit	'Habit'	-	-	Habit1	Always	12.67
		-	-	Habit2	Frequently	39.62
		-	-	Habit3	Sometimes	31.24
		-	-	Habit4	Rarely	12.08
		-	-	Habit5	Never	2.40
		-	-	Habit6	First Visit	2.00
Number of Parking Places Visited	'NumVisit'	-	-	NumVisit1	0 places visited	65.37
		-	-	NumVisit2	1 place visited	24.95
		-	-	NumVisit3	≥2 places visited	9.68
Vehicle Type	'VehType'	-	-	VehType1	Small hatchback	35.23
		-	-	VehType2	Medium hatchback / Saloon	31.44
		-	-	VehType3	Executive saloon	15.07
		-	-	VehType4	4x4 / Sports Utility Vehicle (SUV)	10.78
		-	-	VehType5	Light Goods Vehicle (LGV)	6.39
		-	-	VehType6	Sports car	1.10
Area Type	'AreaType'	-	-	AreaType1	Core; shopping	16.97
		-	-	AreaType2	Tourist	18.26
		-	-	AreaType3	Events	14.97
		-	-	AreaType4	Non-core; shopping	8.78
		-	-	AreaType5	Peripheral; industrial (used by commuters)	7.19
		-	-	AreaType6	Peripheral; university, hospital, train station	15.77
		-	-	AreaType7	Residential (used by commuters)	18.06
City	'CityName'	-	-	CityName1	Lincoln	20.36
		-	-	CityName2	Nottingham	33.13

		-	-	CityName3	Leicester	24.85
		-	-	CityName4	Derby	21.66

TABLE 2: Modelling results for parking fee and search time: Generalised (multilevel: random-intercept) structural equation modelling

Dependent variables (Endogeneous): Parking fee and parking search time	**Coefficient**	**p-value**
Parking fee model:		
Endogeneous variable: Average parking fee (£/hour)		
Parking Search time (minutes)	-0.0699	0.01
Parking duration (minutes)	-0.7668	0.00
Parking without searching at another location (Yes=1; No=0)	0.1933	0.08
Intercept	3.5101	0.00
Variance at street level (Random intercept)	1.3553	0.00
Estimated error variance for parking fee	1.9937	0.00
Parking search time model:		
Endogeneous variable: Parking search time (minutes)		
Paid for parking (Yes = 1; No = 0)	- 0.7277	0.00
Walking time to the final destination (minutes)	0.0738	0.00
Parking purpose: shopping (Yes = 1; No=0)	-0.3526	0.03
Visiting the parking place for the first time (Yes=1; No=0)	0.9670	0.06
Rarely parking here ((Yes=1; No=0)	0.3188	0.14
Trip time (Categorical):		
≤ 10 minutes (Reference case)		
41-60 minutes	0.7594	0.02
>60 minutes	1.2527	0.00
Number of parking places visited on this trip (Categorical):		
Zero-parking places (Reference case)		
One parking place	1.3143	0.00
Two or more parking places	3.5012	0.00
Arrival time at a parking place:		
07:00-07:59 (Reference case)		
08:00-08:59	0.6698	0.03
09:00-09:59	2.1096	0.00
10:00-10:59	2.2256	0.00
11:00-11:59	2.0742	0.00
12:00-12:59	2.4204	0.00
13:00-13:59	2.2733	0.00
14:00-14:59	1.3519	0.00
15:00-15:59	1.1570	0.04
16:00-16:59	1.8672	0.00
17:00-17:59	1.3380	0.00
18:00-19:00	0.7868	0.14
Light Goods Vehicle (Yes = 1; No=0)	0.6746	0.02
Intercept	-0.9521	0.00
Variance at street level (Random intercept)	0.4439	0.00
Estimated error variance for parking search time	4.2901	0.00
Model goodness-of-fit and other statistics		
Intra-class correlation coefficient	0.154	
Log-likelihood at convergence	-3997.1	
Log-likelihood ratio index	0.0800	
Number of observations	1002 Drivers & 97 Streets	