# An analysis of parking behaviour using discrete choice models calibrated on SP datasets

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## ABSTRACT

Parking policy is an important component of contemporary travel demand management policies. The effectiveness of many parking policy measures depends on influencing parking type choice, so that understanding the factors affecting these choices is of considerable practical importance. Yet, academic interest in this issue has been, at best, intermittent. This paper reports the results of an analysis of parking choice behaviour, based on a stated preference (SP) dataset, collected in various city centre locations in the UK. The analysis advances the state of the art in the analysis of parking choice behaviour by using a mixed multinomial logit (MMNL) model, capable of accommodating random heterogeneity in travellers' tastes and potential correlation structure induced by repeated observations being made of the same individuals. The results of the analysis indicate that taste heterogeneity is a major factor in parking type choice. Accommodating this heterogeneity leads to significantly different conclusions regarding the influence of substantive factors such as access, search and egress time and on the treatment of potential fines for illegal parking. It also has important effects on the implied willingness to pay for timesavings and on the distribution of this willingness in the population. Our analysis also reveals important differences in parking behaviour across different journey purposes, and the models reveal an important locational effect, in such that the results of the analysis vary substantively across the three locations used in the SP surveys. Finally, the paper also discusses a number of technical issues related to the specification of taste heterogeneity that are of wider significance in the application of the MMNL model.

## 1. INTRODUCTION

The development of an efficient parking policy is an important component of urban transport planning, as it can help ease congestion and improve the competitiveness of city centres as well as the quality of life in residential areas. As the aim of many parking policy measures is to

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influence choices made during the parking process, it is important to gain an understanding of the factors affecting parking behaviour.

One important aspect of the study of travellers' parking behaviour is the modelling of the choice of parking type. In this paper, we conduct a disaggregate modelling analysis of this choice process, using an SP dataset collected in three separate locations in the United Kingdom in 1989. It should be expected that, like in many other areas of choice-making behaviour, there are important differences across decision-makers in their reaction to changes in various attributes of a given alternative; in this case a specific type of parking. Such differences in choice-making behaviour are known as taste variation, and their existence signals a departure from a purely homogeneous population of decision-makers. While it is possible to explain some part of this variation in a deterministic way, by a segmentation of the population into mutually exclusive subsets, there is, in many situations, an additional, purely random variation in tastes within groups of decision-makers (as opposed to the between-groups variation). So far, the literature on parking-behaviour has ignored the possibility of such a random variation in tastes. Given the potential bias that can be caused by ignoring such variation, in addition to the poorer model fit, this omission seems to be a major gap in the present area of research. The aim of our analysis is thus to test for the presence of random as well as deterministic taste variation, and to quantify the impacts of incorporating such random variations in tastes, in terms of coefficient-values as well as model performance. For this, we employ a Mixed Multinomial Logit model that allows for both types of taste heterogeneity, and which furthermore explicitly accounts for the repeated choice nature of the dataset. In our attempts to explain the deterministic differences in choice behaviour across locations and journeys purposes, the data is split into subsets and a separate model is estimated for each subset.

The remainder of this paper is organised as follows. In the next section, we give a brief review of existing studies of parking choice. The third section describes the data used in the present analysis, and the fourth section describes the modelling approach used. Finally, the fifth section presents and discusses the findings of the modelling analysis for the different datasets used.

## 2. REVIEW OF PARKING TYPE CHOICE LITERATURE

The SP data used in the present analysis has previously been used in the modelling of choice of parking type by Axhausen and Polak (1991). As part of their research, Axhausen and Polak reviewed previous studies of the choice of parking type, noting that, while the effects of parking costs and times on mode choice had been investigated in great detail, few applications had, up to that point, investigated the choice between different types of parking, a situation that has not changed greatly since.

Past research that is of special importance in the current analysis is that based on the use of discrete choice models; a brief overview of such studies is given in section 4.2. In terms of the actual parking-type choice process modelled in the present paper, only a small number of past studies are of importance. One such example is the application given by Van der Goot (1982), who groups the different parking options not just by location, but also by type of parking. Another example is given by Hunt (1988), who conducts an analysis that is similar to our analysis not just in terms of using logit-type models, but also in terms of the different types of parking considered. Aside from these two studies, most other existing research has looked at more general transport issues that have some parking component; for a more detailed review of such studies, see for example Axhausen and Polak (1991) or Polak and Vythoulkas (1993).

## 3. DATA

### 3.1. Description of Data and SP survey

The SP data used in this paper was collected for an analysis of parking behaviour in the West Midlands region of the United Kingdom (c.f. Polak et al., 1990). SP surveys were conducted in 1989 in the central business districts of the cities of Birmingham and Coventry and in a suburban centre, Sutton Coldfield. Although the data are now somewhat dated, the main aim of the paper is to explore the relevance of simulation-based models in the modelling of parking type choice (rather than to undertake policy analysis per se), so this is not regarded as a significant drawback.

Respondents were selected at street-level on the basis of certain screening criteria and target quotas, concerned with socio-economic as well as journey related factors; for more details, see Polak and Axhausen (1989).

Five different types of parking options were considered:

- Free-on-street
- Charged-on-street
- Charged-off-street
- Multi-storey car parking
- Illegal parking

The different types of parking were described by a set of four attributes; access time (to the parking area), search time (for a parking space), egress time (walking time to final destination) and parking cost. The cost attribute was set to zero for the free-on-street alternative and was replaced by the expected fine for the illegal parking alternative, where this expected fine was calculated by multiplying the probability of receiving a ticket with the level of fine currently in use (where the probability of the fine actually being enforced was treated as an unknown factor).

Respondents were asked to provide details about their current type of parking along with two possible alternative parking options for their current journey, such that the set of three alternatives contained illegal parking and two different legal parking options. Using this information, along with the attributes for the three alternatives, 81 different choice situations were constructed, each including the three given parking options, but with the attributes of the alternatives being varied according to an orthogonal SP design (c.f. Polak and Axhausen, 1989). Four different journey purposes, or activities, were identified in the SP survey; these were full-time and part-time work trips, shopping trips, and errand trips. In the ensuing SP experiment, each respondent was presented with a fractional factorial block (of varied size) of different SP choice situations (for the original journey-type used), drawn at random from the 81 possible choice situations. For more details on the actual SP survey, see Polak and Axhausen (1989).

In the present analysis, two divisions of the dataset were used, grouping respondents by location (3 groups) as well as by activity, where, due to the low number of part-time work and errand trips, only two groups were used, defined as *work trips* (full-time and part-time), and *shopping and errand trips*. The resulting distribution of attribute values across alternatives is summarised in table 1, giving the minimum, mean and maximum values for each attribute in the different groups. In this paper, data from a total of 1,335 choice situations were used, collected from a sample of 298 respondents. The data are summarised in table 2, giving the number of observations by location and activity as well as the number of times that each alternative was included in the SP choice situations.

## 4. METHODOLOGY

### 4.1. Data rearrangement

Given the differences in scale and interpretation, it seems inappropriate to treat the cost for legal parking and the expected fine for illegal parking in the same way. Also, as respondents were presented with the overall fine level along with the probability of being caught (rather than the expected fine), the differences across respondents in their evaluation of this information can almost be guaranteed to be more important than is the case with the fixed parking fee attribute, given the differences in evaluations of risk. It was thus decided to treat the two attributes separately, by using a cost parameter for legal forms of parking and a penalty parameter for illegal parking. This is not only more consistent with the real-world meaning of the two attributes, but is also helpful in the interpretation of the estimated values for the coefficients associated with the two parameters.

### 4.2. Choice of model

The use of discrete choice models in transportation research has increased rapidly over the past three decades. These models are designed for the analysis of the choice between discrete alternatives, where the choice probability of an alternative is a function of the relative utility of that alternative (compared to that of all other available alternatives), calculated as a function of the attributes of the alternatives and the tastes of the decision-maker. For various reasons, including modelling uncertainty and the presence of non-measurable attributes, only part of an alternative's utility is observed, and the distributional assumptions regarding the unobserved part determine the structure and behaviour of the resulting model (c.f. Train, 2003).

Originally, most applications were based on the use of the Multinomial Logit (MNL) model (c.f. McFadden, 1974), which, although it has important advantages in terms of ease of estimation, has certain disadvantages, notably in the form of inflexible substitution patterns. Several alternative model forms have been proposed to address these problems, with the most prominent choice being the Nested Logit (NL) model (Daly and Zachary, 1978, McFadden, 1978 and Williams, 1977), which improves flexibility by nesting similar alternatives together. Recently, the use of an even more flexible model form, the Mixed Multinomial Logit (MMNL) model, has increased dramatically, mainly thanks to improvements in the efficiency of simulation-based estimation processes, which are required when using this model form. The crucial advantage of this model over other logit-type models is that it allows for random taste variation across decision-makers (differences across otherwise *identical* agents in their evaluation of an alternative's attributes) as well as deterministic taste variation across groups of decision-makers (e.g. different journey purposes), and deterministic continuous differences across respondents (e.g. cost elasticity as a function of income). This enables the MMNL model to give a more accurate representation of real-world behaviour than its fixed-coefficients counterparts (which are limited to explaining taste heterogeneity in a deterministic way). Furthermore, the MMNL structure allows researchers to explicitly account for the serial correlations arising between repeated choice observations in the case of panel data.

The number of applications using the MMNL model has increased steadily over the past few years. For some recent examples, see Algers et al. (1998), Train (1998), Revelt and Train (1998, 2000), Brownstone and Train (1999) and Hess et al. (2004). For a more detailed discussion of the power and flexibility of the MMNL model, and comparisons with other model forms, see for example McFadden and Train (2000), or Munizaga and Alvarez-Daziano (2001). For a discussion of the use of SP data in MMNL models, see for example Brownstone et al. (2000).

To the authors' knowledge, the MMNL structure has not yet been exploited in the modelling of parking type choice. There have however been a number of studies using basic, non-simulation-based discrete choice models in this area of research. For example, logit-type models have been used by Ergün (1971) in the modelling of the choice of parking location and by Spiess (1996) in the modelling of parking lot choice in a park and ride context. Another application using the MNL model for the modelling of parking location is given by Teknomo and Hokao (1997), while Hunt (1988) uses NL models in the modelling of parking type as well as location. Finally, Bradley et al. (1993) use an NL model to predict changes in mode and parking type choice resulting from changes in parking policies in major cities. Other applications have focused on the effects of parking availability on more general travel behaviour. For example, Hess (2001) uses an MNL model to assess the impact of the availability of free parking on mode choice and parking demand for work related travel, while Hensher and King (2001) use an NL model to analyse the effects of parking cost and availability (by location) on the choice between car and public transport for journeys to the central business district.

The above discussion has shown that there have been a number of applications using basic discrete choice models in the analysis of parking behaviour; however, there has been a distinct lack of applications using more advanced model forms, such as the MMNL model. While the attributes of parking options have been used as explanatory variables in MMNL models (e.g. Bhat and Castelar, 2002), an important avenue of research thus remains unexplored in the actual MMNL modelling of parking behaviour, with parking type choice being but one example. Indeed, the extra flexibility of allowing for random taste variation can potentially offer great benefits in this area of research, given for example the differences across travellers in their sensitivity to search time or egress time. An even more likely source for taste variation is the attitude of decision-makers towards illegal parking and their appraisal of the risks involved.

### 4.3. Model specification and estimation

The MMNL model uses integration of the MNL probabilities over the (assumed) distribution of the random parameters included in the model (see for example Train, 2003). Formally, the probability of decision-maker n choosing alternative i is given by:

$$P(n,i) = \int L_i(\beta, z_n) f(\beta|\theta) d\beta \,, \qquad \ldots(1)$$

where $z_n$ is a matrix of the attributes of the different alternatives as faced by decision-maker n, and where the function $L_i(\beta, z_n)$ represents the conditional (on β) MNL choice probability, given by:

$$L_i(\beta, z_n) = \frac{e^{\beta' z_{ni}}}{\sum_{j=1}^{I} e^{\beta' z_{nj}}} \,, \qquad \ldots(2)$$

where I gives the total number of alternatives in the choice set, and where $z_{ni}$ is the vector of attributes of alternative i as faced by decision-maker n. The vector β varies over decision-makers and reflects the idiosyncratic aspects of decision-maker n's preferences; these terms are distributed in the population with density f(β|θ), where θ is a vector of parameters to be estimated that comprises, for example, the population mean and standard deviation of the single coefficients contained in vector β. In general, two parameters are associated with each randomly distributed coefficient, representing the mean and spread in the coefficient's values across the population.

The aim is to find optimal values of $\theta$ for the population used in the sample. For this, the likelihood function of the observed choices is maximised with respect to $\theta$. Formally, with $i_{(n)}$ giving the alterative chosen by decision-maker *n*, the likelihood function with *N* decision-makers is given by:

$$L_N = \prod_{n=1}^{N} P(n, i(n)) = \prod_{n=1}^{N} \left( \int L_{i(n)}(\beta, z_n) f(\beta|\theta) d\beta \right). \qquad \ldots(3)$$

In the case of stated preference data (where we have multiple hypothetical choice-situations per individual), the above formula needs to be adapted. Notably, for each respondent, the integral of the conditional choice probability $L_{i(n)}(\beta, z_n)$ over the distribution of $\beta$ is replaced by an integral of the conditional choice probability of the sequence of observed choices for this individual, where the conditional choice probability of this sequence is given by the product of the conditional choice probabilities of the individual choices. Formally, with $T_{(n)}$ giving the number of choices observed for respondent $n$, and $i_{n(t)}$ representing respondent $n$'s choice in the $t^{th}$ choice situation (with a corresponding explanation for $z_{n(t)}$), we have:

$$L_N = \prod_{n=1}^{N} \left( \int \left( \prod_{t=1}^{T_{(n)}} L_{i_{n(t)}} \left(\beta, z_{n(t)}\right) f\left(\beta | \theta\right) \right) d\beta \right) \qquad \ldots(4)$$

The MMNL model specification can also be adapted to accommodate serial correlation across SP replications. For this purpose, additional error components are specified, where the structure imposed for these error components can be used to induce correlation across alternatives, replications, or individuals. These error-components can for example be used to identify learning and fatigue factors, allowing researchers to accommodate changes in behaviour across choice situations. These extensions are beyond the scope of this paper, and the modelling of these effects in the context of the present application is the topic of ongoing research. For the current analysis, the simple specification shown in equation (4) is used, allowing for a random variation in tastes across agents, while maintaining the assumption of constant tastes across replications for a given individual.

The MMNL model is calibrated by maximising equation (4) (respectively equation (3) in the case of cross-sectional data) for $\theta$, thus finding the optimal values for representing the behaviour observed in the sample; for optimisation reasons, working with the log-likelihood is generally preferable (c.f. Train, 2003). The maximisation of this log-likelihood function clearly requires the calculation of the individual choice probabilities, respectively the choice probabilities of the observed sequences of choices for the different respondents. However, in the case of the MMNL model, the integrals representing these choice probabilities do not in general have a closed-form solution, and need to be approximated, for example by simulation. For this, the value of a given integrand is calculated for a high number of draws from the relevant random distributions, and the average of these values over the set of draws is used as an approximation, where the precision of this approximation increases with the number of draws used. For more details on the consistency and efficiency of this simulation approach, see Train (2003).

Classically, Monte-Carlo integration was used for this simulation process. However, the underlying randomness of the pseudo-random (PMC) draws used in this process leads to an uneven distribution of draws across the area of integration. This means that, in order to achieve a certain degree of precision in the simulation process, a relatively high number of PMC draws needs to be used, leading to high computational cost in estimation and application, especially so for models with a high number of randomly distributed parameters. Although recent advances in computer technology have led to important reductions in computation time, researchers have for a long time tried to devise ways of making the simulation process more efficient. One such improvement comes in the use of alternatives to PMC draws, known as quasi-random (QMC) draws, which, through giving a more uniform distribution of draws across the area of integration, enable the use of a lower number of draws, leading to lower computational costs. One popular choice of quasi-random number sequence is the Halton sequence (Halton, 1960), introduced to the field of transportation by Bhat (1999). The use of these sequentially constructed sequences has been observed to lead to important gains in simulation and estimation performance (e.g. Bhat, 1999, Train, 1999) and has been used successfully in the field of transportation research (e.g. Bhat, 2000), as well as in many other areas of economics (e.g. Train, 1999). While Halton sequences can offer important savings when used in low-dimensional integration exercises, problems with correlation occur when using Halton sequences in high-dimensional problems; these problems leads to poor coverage and can results in decreases in simulation performance (see for example Bhat, 2002, Hess and Polak, 2003a, 2003b). Several approaches have been proposed to address the problems of high correlation, for a discussion of these approaches, see for example Bhat (2002), Hess and Polak (2003a, 2003b) and Hess et al. (2003, 2004). A separate analysis showed that, given the relatively low number of dimensions used ($\leq 9$), there were no significant problems with correlation when using Halton sequences in the present application. Furthermore, the low number of dimensions enabled us to use a relatively high number of draws (1,000) per respondent and per dimension, leading to very stable estimation results.

In the present analysis, a total of 10 coefficients could be used; these are the coefficients associated with the five attributes of the different alternatives (access time, search time, egress time, parking fee and expected fine for illegal parking) and five alternative-specific constants (ASC) for the five different parking options. For reasons of identification, one of the ASCs needs to be normalised to a value of 0. To minimise any loss of information (which would increase the error term in the model) in an MMNL model, the ASC with the least amount of variability across decision-makers should be selected for normalisation (c.f. Hensher and Greene, 2001). In the present context, this was (for all subsamples) found to be the ASC for the free-on-street alternative; this ASC was thus set to 0, such that the estimated values for the four remaining ASCs capture the net impact of unmeasured variables (including general attitude) on the respective alternatives' utilities relative to the free-on-street option.. A total of 9 coefficients were thus used in the model. Given that two parameters are associated with each random coefficient, a maximum of 18 parameters would thus need to be estimated.

### 4.4. Choice of random distributions

When using the MMNL model, an important question arises as to what distributions should be used for the different coefficients. While the commonly used Normal distribution is a valid choice for a large selection of coefficients, the absence of constraints on the sign of the random variates makes it an inappropriate choice in the presence of an a priori assumption about the sign of a coefficient (e.g. negative cost coefficients). The most commonly used distribution for such coefficients is the Lognormal distribution; this leads to positive coefficients, such that the sign of any undesirable attributes needs to be reversed to guarantee that increases in attribute values lead to decreases in utility.

While the *Lognormal* distribution has been used successfully in some MMNL applications (e.g. Bhat, 1998, Hess et al, 2004), it can occasionally lead to poor convergence and problems with unreasonably large parameter values, especially for the measure of spread (c.f. Train, 2003). A solution to the latter problem is to use distributions that are bounded on both sides. Such distributions include the uniform and triangular distributions (see for example Hensher and Greene, 2001) as well as the more advanced $S_B$ distribution (c.f. Train and Sonnier, 2003). For a more detailed discussion of existing approaches and past experience, see Train (2003).

It seems crucial to point out the importance of this issue of choice of distribution, due to the potential effects of wrong distributional assumptions on modelling results and policy decisions. While the issue has been discussed in detail by some authors (e.g. Train, 2003, Hensher and Greene, 2001), it is still ignored by many authors, putting them at risk of producing seriously misleading results. In the current analysis, the *Normal* distribution could safely be used for the ASCs associated with the different types of parking. In fact, the *Normal* distribution is the perfect choice for these coefficients, as it allows for positive and negative values, thus reflecting the very different attitudes, notably to illegal parking, observed across decision-makers (where these attitudes form part of the unobserved variables whose impact is captured by the ASCs). For the remaining five coefficients, which reflect the sensitivity to costs in terms of time and money, the use of the *Normal* distribution cannot in general be justified, as strictly negative values would normally be expected for these coefficients. A non-signed distribution can thus lead to misleading results and potentially wrong policy implications, so that, in the presence of significant taste variation, a bounded distribution should ideally be used.

Good results were obtained with the use of *lognormally* distributed values for the coefficients associated with access time, search time, egress time and parking fee. However, problems with significant overestimating of the standard deviation arose when using the *Lognormal* distribution for the coefficient associated with the expected fine for illegal parking (in one example, this distribution produced a mean of 5, and a standard deviation of 500). Except for the three smaller datasets (Sutton Coldfield, Coventry, and work trips), the use of a fixed coefficient however resulted in seriously underestimated coefficients and poor model fit, signalling the existence of significant levels of taste variation across decision-makers. Experiments using distributions bounded on either side however led to various problems, including slow convergence and poor model fit. On the other hand, very good model fit, along with realistic parameter values (very low probability of wrongly signed coefficient), was obtained when using normally distributed coefficients. Although this is not fully consistent with the recommendations made above regarding the use of the Normal distribution for coefficients for which assumptions exist about the sign, it was decided to forego these recommendations in those cases where the probability of a wrongly signed coefficient is at an acceptably low level. Any problems resulting from this were deemed to be less important than the poor model fit resulting from the assumption of no taste variation or the problems of poor estimates when using alternative bounded distributions.

## 5. RESULTS

In this section, we present the results produced by the models estimated on the different datasets. The results are summarised in tables 3-5, giving, for each dataset, the results from the best fitting MMNL model alongside the results produced by an MNL model. This allows us to quantify the advantages offered by the MMNL model, and shows the effect that the assumption of fixed coefficients (MNL) has on the values of coefficients (when compared to the mean values of their randomly distributed counterparts).

At this point, it seems worthwhile to point out a convention that was used in the presentation of the results for *lognormally* distributed coefficients. Indeed, for these coefficients, the estimated parameters are the mean *c* and standard deviation *s* of the log of the coefficient. For ease of interpretation, the values presented in tables 3-5 are in fact the actual mean and standard deviation of the *lognormally* distributed coefficients, given by

$$\mu = \exp\left(c + \frac{s^2}{2}\right) \qquad \ldots(5)$$

and

$$\sigma = \mu\sqrt{\exp\left(s^2\right) - 1}\,. \qquad \ldots(6)$$

As the t-test values generated in the estimation are for the original parameters of the distribution, they do not relate directly to the values reported in the tables. As both mean and standard deviation are functions of *c* and *s*, it is thus important that both reported t-values are statistically significant. This differs from the case of normally distributed parameters, where the t-test value of the standard deviation is of higher importance in the search for random taste heterogeneity. Also, for ease of interpretation, the sign of the mean values of *lognormally* distributed coefficients was reversed in the tables, to reflect the negative impact of the associated attributes on the utility of an alternative.

Aside from the implied values of time, the tables also show the ratio of the parking fee coefficient against the expected fine coefficient. With one exception, this ratio is strictly greater than 1, suggesting that a single £ paid in parking fee carries a higher disutility than a single £ in expected fine for illegal parking. This in turn suggests that when faced with the uncertain prospect of a parking fine, drivers behave as risk-prone decision-makers.

### 5.1. Overall Dataset

The first part of the analysis (table 3) consisted of fitting a model to a dataset containing information on all 298 respondents (1335 observations). In the MMNL model, a Normal distribution was used for all four identified ASCs; the highly significant standard deviations for these coefficients show the extent of taste variation in these coefficients, at least partly reflecting the differences in terms of respondents' attitudes towards the different types of parking. It should be noted that in a model using SP data, the ASCs capture a range of effects, including both substantive effects relating to actual preferences, and effects relating to the design of the SP survey. This should always be kept in mind when trying to infer information on actual agent behaviour based on the estimates for these coefficients. Even so, the large negative value for the ASC associated with illegal parking can be seen to at least partly reflect the general law-abiding nature of the majority of the population. The fact that there is a 7.9% probability of the coefficient being positive further illustrates the extent of taste variation for this coefficient.

In terms of sensitivity to time, there is significant taste variation only for search time and egress time, leading to a fixed coefficient for access time, and *lognormally* distributed coefficients for search time and egress time. A lognormal distribution was also used for the cost coefficient, while, given the reasons mentioned in the earlier discussion, a Normal distribution had to be used for the expected fine coefficient. Although this does imply a probability of ~0.7% of a positive coefficient, this risk is a necessary evil in this case, as very poor results were obtained with all of the alternative distributions.

The implied mean values of time show that access time is the least negatively valued factor, while search time is valued more negatively than egress time. Also, the ratio between the mean coefficients for parking fee and expected fine shows that, as expected, the coefficient for parking fee is higher (in absolute value) than that for expected fine.

A comparison with the MNL model shows very important differences in model fit; with 8 additional parameters, the MMNL model has increased the log-likelihood by 246.16, where the 99.9% $\chi^2_8$ significance limit for such a change is only 26.12. The effects of not allowing for random taste variation become most obvious in the negative coefficients associated with the ASCs for the charged-off-street and multi-storey car park options (where the mean values in the MMNL model were positive). Finally, while the ratio of fee against expected fine is comparable, there are significant differences between the models in terms of implied values of search time and egress time, with egress time being in fact valued more negatively than search time in the MNL model. Also, the differences in scale observed when comparing the implied values of search time and egress time to the value of access time seem a bit high when compared to those observed in the MMNL model (e.g. VET/VAT gives 2.74 compared to 1.58).

### 5.2. Grouping by location

The next step consisted of fitting separate models for the three different locations considered (table 4). For all three datasets, the use of the MMNL model again leads to highly significant increases in the log-likelihood when compared to the MNL model.

There are significant differences in the number of observations across locations, and the number of observations in Sutton Coldfield and Coventry are so low (366 and 294 respectively), that significant taste variation could only be identified for a handful of coefficients. Indeed, the three time coefficients as well as the parking fee and expected fine coefficients had to be assumed to take on fixed values in these two models. Furthermore, while sufficient taste variation was identified in the Sutton Coldfield dataset to allow the use of a Normal distribution for all four ASCs, in the Coventry dataset, this was only possible for the ASCs for charged-off-street and illegal parking. The fact that the Coventry model thus uses only two randomly distributed coefficients makes the increase in the log-likelihood by 59.39 even more remarkable, given the 99.9% $\chi_2^2$ significance limit of just 13.82.

The dataset for Birmingham contained a sufficiently high number of observations (675) to reveal significant taste variation for the coefficients associated with search time (lognormal), parking fee (lognormal) and expected fine (Normal) as well as the coefficients associated with the ASCs for the charged-on-street, charged-off-street and illegal parking options (all normally distributed). For the same reasons given in the previous section, a Normal distribution again had to be assumed for the expected fine coefficient. With the estimated parameters, there is a probability of a positive coefficient of ~0.4%, which is again acceptable given the circumstances. Even though the associated standard deviation is significant only at the 89% level, the use of a randomly distributed coefficient was justified by the fact that it leads to important gains in model fit over the use of a fixed penalty coefficient.

The implied values of time in the different MMNL models reveal significant differences across locations. The Birmingham model repeats the findings from the previous section showing that search time is valued the most negative, with access time being valued the least negative.

The actual implied values of time are also very similar to those reported in table 3, reflecting the fact that the Birmingham data accounts for 46% of total respondents and just over 50% of total observations (this suggests that the overall results are somewhat skewed by the results from Birmingham). Again, the MNL model seems to significantly overestimate the value of egress time, which is ranked higher than search time. For Sutton Coldfield, the results from the MMNL model show that surprisingly, access time is valued more highly than search time, which is valued higher than egress time. Again, the values of time produced by the MNL model seem very high for search time and egress time, and the ranking is also the opposite of that produced by the MMNL model. The differences in valuations of time are even more significant in Coventry, where egress time is ranked as the most negative, ahead of search time and access time. The fact that the estimated coefficient for egress time is more than four times as important as that for search time shows an inherent dislike by respondents for the foot journey between the parking space and the final destination. This can at least be partly explained by noting that, at the time of the SP survey, foot journeys to Coventry city centre often involved walks through unattractive neighbourhoods and the use of a large number of subways, making walking a very unpleasant activity. Although the MNL model does in this case manage to retrieve the correct ordering of the values of time, it seems to overestimate the value of search time. This means that the model underestimates the ratio between the egress time and search time coefficients, which is all the more surprising as both coefficients were similarly kept fixed in the MMNL model. The reasons for this problem can be traced to the fact that the MNL model ignores the presence of taste variation in the charged-off-street and illegal parking ASCs; this leads to high residual error in the model, which then leads to poor estimation of some of the remaining coefficients. This is especially important in the case of the ASC for charged-off-street parking; here, the parameters estimated by the MMNL model lead to a high probability of a positive value for the associated coefficient, while, in the MNL model, the sign of the coefficients is assumed to remain constant (negative) across the population.

Another observation that can be made from table 4 is that there are significant differences across locations in the ratio of the parking fee coefficient against the expected fine coefficient. Respondents in Birmingham treat the parking fee coefficient in a very similar way to the expected fine coefficient; given the differences in scale of the two associated attributes, this should lead to low utility for illegal parking. The high standard deviation of the ASC for illegal parking however leads to a significant probability of a positive impact by unmeasured variables on the utility of illegal parking; such a positive value of the ASC for illegal parking would lessen the negative impact of the coefficient associated with the expected fine. Again, special care must be taken in the interpretation of the values of the ASCs, given the likely impact of the SP survey design on these estimates. Even so, the possibility of a positive ASC for illegal parking in the Birmingham model can at least be partly explained by the fact that, at the time of the SP survey, fine enforcement in Birmingham was very poor (poor court admin), making the risk of actual prosecution very low. While respondents thus react negatively to high expected fines, their general attitude towards illegal parking is less negative, given their knowledge about the lax enforcement. Finally, the high ratio of fee against expected fine in Sutton Coldfield shows low sensitivity of people towards expected fines, which is partly explainable by very high average wages in that area. It should also be noted that in the case of Sutton Coldfield and Coventry, the MNL estimates lead to an underestimation of the ratio between the parking fee and expected fine coefficients, which is a result of the underestimated parking fee coefficient, which also led to overestimated values of time in these models.

### 5.3. Grouping by activity

The final part of the analysis was concerned with grouping the data by activity (table 5), leading to two datasets, one for full-time and part-time work (51 respondents, 233 observations) and one for shopping and errand trips (247 respondents, 1102 observations). Given the low number of observations in the dataset for work trips, it came as no surprise that significant taste variation was only observed for three coefficients, namely those associated with search time, egress time, and parking fee, all of which were assigned a lognormal distribution. It is interesting to note that, while in the models used for the smaller datasets in the grouping by location, significant taste variation was only observed for the ASCs, in the model for work trips, such taste variation is only observed for time and cost coefficients. This could signal homogeneity in the working population in terms of the general attitude towards different parking options (reflected by the overall impact of unmeasured attributes), but significant heterogeneity with regards to values of time (e.g. different sensitivity to lateness). With only three randomly distributed coefficients, the MMNL model still manages to increase the log-likelihood by 26.55, which compares well to the 99.9% $\chi_3^2$ limit of 16.27. The t-value of the $s$ parameter associated with the lognormal distribution of the egress time coefficient shows significance only at the 91% level, which is however still acceptable. The implied values of time show that workers are most sensitive to egress time; this can be explained by various factors, including for example the monotony of the walk from the parking space to the final destination, a return journey that most workers will have to embark on five times per week. While the implied values of time in the MNL model are identical in terms of ranking and broadly similar in terms of ratios, the value of egress time especially seems a bit high in the MNL model.

In the model for shopping and errand trips, a Normal distribution was used for all four ASCs and for the expected fine coefficient, along with a fixed access time coefficient and lognormal distributions for the search time, egress time and parking fee coefficients, showing significant taste variation for all but one coefficient. The use of the Normal distribution for the expected fine coefficient does in this case lead to a slightly high probability of a positive value (~1.8%); this can however again be seen as a necessary evil, given the very poor performance when using a bounded distribution. The effects of using a fixed penalty coefficient are illustrated in the MNL model, which shows a ratio of fee against expected fine of 1.96, whereas, in the MMNL model, this ratio is 0.8, showing for the first time a higher sensitivity to expected fines than to parking fees. This should lead to low levels of illegal parking, and is consistent with the notion that many shoppers do not mind using expensive parking, as long as it is conveniently located. In this case, the MNL model thus significantly underestimates the negative impact of the expected fine level on the utility of illegal parking.

The MMNL model also shows that shoppers are more sensitive to search time than to egress time and access time. This can be partly explained by the low availability of parking spots during main shopping rush hours, resulting in a stressful search process that has a very negative impact on the perceived overall quality of the shopping trip. As with all other datasets, the MNL model again assigns the highest valuation of time to egress time, followed by search time and access time. Finally, with this dataset, the MMNL model manages to increase the likelihood by 202.63 with 8 additional parameters, with a corresponding 99.9% $\chi_8^2$ significance limit of only 26.12.

### 5.4. Implied distributions of value of time savings

While the use of randomly distributed coefficients in an MMNL model gives some indication of the variation in the coefficients across decision-makers, the actual distributions matter most when looking at the distribution of ratios of coefficients, such as the values of time (willingness to pay). The results presented thus far (sections 5.1 to 5.3) have ignored this variation and have simply looked at the ratios of the coefficient mean values. We now extend this analysis, by incorporating the entire distribution of the coefficients into the calculation of the implied distributions of the values of time. For a detailed discussion of different approaches that can be used in such an analysis, see for example Hensher and Greene (2001).

In the present analysis, there were no significant levels of correlation between the individual coefficients used in the model, such that a rather straightforward approach could be used in the calculation of the distribution of the values of time (no requirement to use a Choleski factor transformation). The approach starts by producing a high number of draws (100,000) for the different coefficients, using the distributional assumptions resulting from the model fitting exercise. For a given value of time statistic (access time, search time and egress time), the required ratio was then calculated for each of the 100,000 pairs of draws used. As expected, the resulting statistics were all observed to follow a roughly lognormal distribution. Special care was required at this stage as the long tail of this distribution can lead to a very high estimate of the mean and standard deviation of the value of time measures when based on the full sample of 100,000 draws. Therefore, it was decided to remove the upper two percentiles of the produced measures, and to calculate the mean and standard deviations on the resulting sample of 98,000 measures (c.f. Hensher and Greene, 2001). This method was used for the three different measures of value time used, and for the four datasets in which at least one of the relevant coefficients follows a random distribution. The results are summarised in table 6.

The results produced with the parameters estimated on the overall dataset show the effects of random taste variation on the implied values of time, with high standard deviations for all three measures. The results also show the differences in the mean values of time when incorporating the full distribution of the relevant coefficients in the calculation of the values of time, with all three values being significantly higher than the corresponding mean values in table 3. While this moves the values closer to those produced by the MNL model (and thus adds some credibility to the results produced by the latter model), the ranking obtained with the present approach is the same as that obtained by the MMNL model in table 3 (VST>VET>VAT), and different from that obtained with the MNL model. This again illustrates the bias in the results when not allowing for random taste variation. Also, the ratios of the different values of time (e.g.

VET/VAT) are much closer to those produced for the MMNL model in table 3 than the respective ratios for the MNL model. This further increases confidence in the MMNL model.

The conclusions for the Birmingham dataset are much the same; the use of the full distribution of the values of time results in higher mean values, along with high standard deviations, while the same ranking and similar differences in scale between values are observed as for the MMNL model in table 4. Again, the ranking and differences in scale are different from those produced by the MNL model, which overestimates the value of egress time. The results produced on the dataset for full-time and part-time work again show an increase in the mean values when accommodating the full distribution, along with high standard deviations for the different values of time. In the case of the dataset for work-trips, the use of the MNL model does lead to the correct ranking (highest values of time for egress), but again slightly overestimates the value of egress time when compared to the MMNL model. The results produced with the dataset for shopping and errand trips stand out, as the use of the actual distributions of the values of time results in the biggest changes from the values observed when simply using the mean values of time. This is due to the much higher standard deviations of the coefficients in this dataset, which, for the search time, egress time and parking fee coefficients are more important than the coefficients themselves (c.f. table 5). This leads directly to larger standard deviations in the implied distributions of the value of time measures. Again, the ranking of values of time stays the same as with the other method, whereas the MNL model overestimates the value of egress time.

In general, the mean values obtained when accounting for the distribution of the values of time are higher than when simply using the mean values of the coefficients, illustrating the limitation of the latter approach. The fact that the standard deviations of the values of time are very high, especially for the shopping and errand trips dataset, shows the importance of incorporating the distribution of the values of time. Again, this would not be possible with the MNL model, reflecting the restrictions of that model, and illustrating the gains that can be made when using the MMNL model in the modelling of parking type choice.

Little further gains could be made when using the same approach in the calculation of the distribution of the ratio of fee against expected fine; this resulted in an excessively high standard deviation, even after removing the upper two percentile points. The resulting mean values were however roughly similar to those observed when simply using the mean values, with the shopping and errand trips dataset again being the only case where the mean value of the ratio is inferior to 1.

## 6. SUMMARY AND CONCLUSIONS

Our analysis has revealed the presence of significant taste variation in respondents' evaluation of parking options, in terms of differences in valuation of the components of travel time, as well as in the impact of unmeasured variables, and in terms of willingness to take risks when contemplating to park illegally. The extent of this random taste variation in the population was such that, for all datasets considered, the use of the Mixed Logit model resulted in important gains in model fit over the use of a simple Multinomial Logit model. This suggests that the use of the MMNL model can lead to important gains in accuracy in the modelling of parking behaviour.

We have also highlighted some important issues in the specification of the MMNL model, especially with regards to the choice of distribution in the case where an a priori assumption exists about the sign of some or all of the coefficients. Our analysis has reinforced earlier results with regards to occasional overestimation of the standard deviation of the coefficients when using a lognormal distribution. The analysis has also shown the importance of incorporating the full distribution of coefficients in the calculation of willingness to pay measures, rather than simply using the mean values of the coefficients, which can lead to biased measures.

The analysis has shown important differences in the valuation of the components of travel time across different locations and across different journey purposes. Indeed, while access time was valued the lowest in Birmingham and Coventry, it was valued higher than search time and egress time in Sutton Coldfield. Also, while egress time is valued second highest in Birmingham and lowest in Sutton Coldfield, it is valued higher than access time and search time in Coventry, to such an extent that the estimated value of egress time in Coventry is actually more than four times larger than the value of search time and more than five times larger than the value of access time. As for the differences across journey-types, it was observed that workers value egress time the highest, while shoppers place more importance on search time, rating it over three times as highly as workers do (when taking into account the full distribution of the value of time).

Except for Sutton Coldfield, the results produced in the present analysis are broadly consistent with previous results, rating walk egress time higher than access time, although the ratio between the two is generally below the lower limit of 2 suggested by Axhausen and Polak (1991) for this ratio. Again, with the exception of Sutton Coldfield, our analysis also confirms earlier findings rating search time higher than access time, although the resulting ratio occasionally falls outside the interval suggested by Axhausen and Polak (1991), which ranges from 1.2 to 2.

As mentioned before, it should be stressed that the data used in this research are rather dated, so that the results are not necessarily reflective of current parking behaviour. Indeed, it can be assumed that the values of time would have been higher had a more up-to-date dataset been used. Similarly, agents' attitudes towards illegal parking may well have changed over time; the same observation could be made with regards to the perception of the relative levels of safety of the different parking types. An important step for further research is thus to use a flexible MMNL framework with a more up-to-date dataset. It has also been suggested that other qualitative factors could be included in the evaluation of (especially off-street) parking options, such as the perceived risk of being mugged or hassled on the walk segment to and from the parking area. Also, as mentioned in section 4.3., an important avenue for further research with this dataset is the explicit modelling of correlation between SP replications.

However, as we have emphasised, the value of this work in the current context lies not mainly in the additional insight it provides into the processes of parking type choice but the insight into the prevalence of heterogeneity in tastes. Although the latter may to some degree reflect heterogeneity in the incidence of SP specific errors, rather than in underlying tastes *per se*, the overall magnitude of observed taste heterogeneity suggests that these effects do indeed play a significant role in parking choice and that analysts should account for them through suitable model specifications, such as MMNL. Finally, it should be noted that some of the heterogeneity in tastes identified by the MMNL models could potentially also be explained as a function of socio-demographic attributes, such as income. Nevertheless, ongoing research has shown that the segmentation used in the present analysis (purpose and region) accounts for the majority of such deterministic taste variation, and that a significant remaining portion of heterogeneity can only be explained in a non-deterministic manner.

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**Table 1. Attributes of different parking options across locations and journey purposes[1]**

| | Location | | | | | | | | | Activity | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Birmingham | | | Sutton Coldfield | | | Coventry | | | Work (FT & PT) | | | Shopping and Errands | | |
| | min | mean | max | min | mean | max | min | mean | max | min | mean | max | min | mean | max |
| ***Free-on-street*** | | | | | | | | | | | | | | | |
| Access time | 1 | 23.3 | 54 | 1 | 11 | 50 | 4 | 13.8 | 36 | 8 | 26.7 | 54 | 1 | 15 | 54 |
| Search time | 1 | 17.1 | 90 | 0 | 5 | 38 | 0 | 8 | 30 | 1 | 18 | 90 | 0 | 9.8 | 90 |
| Egress time | 1 | 10.1 | 68 | 1 | 5.2 | 23 | 1 | 8 | 30 | 1 | 7 | 23 | 1 | 8.7 | 68 |
| ***Charged-on-street*** | | | | | | | | | | | | | | | |
| Access time | 1 | 22.3 | 50 | 10 | 16.7 | 35 | 5 | 8.3 | 15 | 10 | 28.6 | 50 | 1 | 17.1 | 45 |
| Search time | 0 | 13.1 | 90 | 1 | 7.4 | 23 | 0 | 11.8 | 30 | 0 | 13.6 | 90 | 0 | 11.6 | 68 |
| Egress time | 1 | 9.9 | 93 | 1 | 5.9 | 15 | 1 | 7.5 | 15 | 1 | 6.9 | 30 | 1 | 9.5 | 93 |
| Fee | 0 | 1 | 8 | 0.1 | 0.5 | 2.7 | 0.2 | 0.7 | 2 | 0.3 | 1.6 | 8 | 0 | 0.7 | 5.3 |
| ***Charged-off-street*** | | | | | | | | | | | | | | | |
| Access time | 3 | 24.2 | 54 | 0 | 10.6 | 36 | 2 | 14.9 | 48 | 3 | 23.8 | 54 | 0 | 17.1 | 54 |
| Search time | 0 | 8.1 | 60 | 0 | 2.9 | 20 | 0 | 7.2 | 45 | 0 | 7.2 | 20 | 0 | 6.2 | 60 |
| Egress time | 0 | 9.6 | 62 | 0 | 4.9 | 36 | 1 | 6.1 | 25 | 1 | 8.6 | 23 | 0 | 7.2 | 62 |
| Fee | 0 | 1.1 | 5.3 | 0 | 0.6 | 6.7 | 0 | 0.8 | 4 | 0.3 | 1.4 | 4 | 0 | 0.8 | 6.7 |
| ***Multi-storey*** | | | | | | | | | | | | | | | |
| Access time | 1 | 23.4 | 50 | 0 | 12.2 | 35 | 3 | 15 | 30 | 1 | 24.8 | 50 | 0 | 16.9 | 50 |
| Search time | 0 | 7 | 60 | 0 | 5 | 20 | 0 | 7.7 | 30 | 0 | 5.3 | 30 | 0 | 6.9 | 60 |
| Egress time | 1 | 6.9 | 30 | 0 | 4.2 | 30 | 1 | 4.6 | 15 | 1 | 6.6 | 30 | 0 | 5.4 | 30 |
| Fee | 0.2 | 1.9 | 10 | 0 | 0.7 | 5 | 0.2 | 0.9 | 2.5 | 0.2 | 2.6 | 10 | 0 | 1 | 5 |
| ***Illegal*** | | | | | | | | | | | | | | | |
| Access time | 1 | 22.9 | 54 | 0 | 10.9 | 50 | 2 | 14.4 | 48 | 1 | 24.9 | 54 | 0 | 16.2 | 54 |
| Search time | 0 | 3 | 5 | 3 | 3 | 3 | 1 | 2.9 | 3 | 0 | 2.9 | 5 | 1 | 2.9 | 3 |
| Egress time | 1 | 3.2 | 5 | 2 | 3.5 | 5 | 1 | 3.2 | 5 | 1 | 3.3 | 5 | 1 | 3.3 | 5 |
| Expected fine | 0 | 9.9 | 100 | 0 | 9.4 | 50 | 0 | 8 | 36 | 0 | 9.3 | 50 | 0 | 9.4 | 100 |

1. times in minutes, fees in £/hr and expected fines in £

**Table 2. Description of SP datasets**

| | | Overall | Location | | | Activity | |
|---|---|---|---|---|---|---|---|
| | | | Birmingham | Sutton Coldfield | Coventry | Work (FT & PT) | Shopping and Errands |
| | Number of respondents | 298 | 137 | 89 | 72 | 51 | 247 |
| | Number of observations | 1335 | 675 | 366 | 294 | 233 | 1102 |
| Number of times available | Free-on-street | 498 | 254 | 130 | 114 | 124 | 374 |
| | Charged-on-street | 283 | 199 | 48 | 36 | 59 | 224 |
| | Charged-off-street | 964 | 448 | 286 | 230 | 128 | 836 |
| | Multi-storey | 925 | 449 | 268 | 208 | 155 | 770 |
| | Illegal | 1335 | 675 | 366 | 294 | 233 | 1102 |

**Table 3. Modelling results on overall dataset**

| Coefficient | | Dist. | MMNL model | MNL model |
|---|---|---|---|---|
| ***Time*** | | | | |
| Access | mean | F | -0.1174 (3.9) | -0.0311 (2.1) |
| | std.dev. | | - | - |
| Search | mean | LN | -0.2159 (7.9) | -0.0575 (5.2) |
| | std.dev. | | 0.1604 (7.2) | - |
| Egress | mean | LN | -0.1855 (8.7) | -0.0850 (5.2) |
| | std.dev. | | 0.1961 (5.1) | - |
| Parking fee | mean | LN | -3.3069 (6.2) | -0.6306 (4.1) |
| | std.dev. | | 2.6249 (12.9) | - |
| Expected fine | mean | N | -2.2931 (4.9) | -0.3965 (4.4) |
| | std.dev. | | 0.9405 (5.0) | - |
| ***ASCs*** | | | | |
| Charged-on-street | mean | N | -3.1645 (3.1) | -1.0006 (3.2) |
| | std.dev. | | 3.9765 (5.1) | - |
| Charged-off-street | mean | N | 0.5975 (1.3) | -0.0373 (0.2) |
| | std.dev. | | 2.3408 (6.6) | - |
| Multi-storey | mean | N | 0.6633 (1.2) | -0.0425 (0.2) |
| | std.dev. | | 3.5897 (7.0) | - |
| Illegal | mean | N | -6.4912 (4.6) | -2.2544 (5.7) |
| | std.dev. | | 4.5956 (4.5) | - |
| ***Mean values of time (£/h)*** | | | | |
| Access | | | 2.13 | 2.95 |
| Search | | | 3.92 | 5.47 |
| Egress | | | 3.37 | 8.09 |
| Ratio of fee against expected fine | | | 1.44 | 1.59 |
| LL at convergence | | | -636.49 | -882.65 |
| Parameters estimated | | | 17 | 9 |

**Table 4. Modelling results on dataset using grouping by location**

| Coefficient | | Birmingham | | | Sutton Coldfield | | | Coventry | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | MMNL model | | MNL model | MMNL model | | MNL model | MMNL model | | MNL model |
| ***Time*** | | Dist. | | | Dist. | | | Dist. | | |
| Access | mean | F | -0.1099 (3.6) | -0.0461 (2.8) | F | -0.2977 (2.3) | -0.0590 (0.9) | F | -0.0413 (0.8) | 0.0483 (1.7) |
| | std.dev. | | - | - | | - | - | | - | - |
| Search | mean | LN | -0.1621 (7.3) | -0.0500 (4.1) | F | -0.2842 (3.1) | -0.1148 (2.9) | F | -0.0514 (1.1) | -0.0700 (2.2) |
| | std.dev. | | 0.1206 (2.7) | - | | - | - | | - | - |
| Egress | mean | F | -0.1470 (4.6) | -0.0888 (4.8) | F | -0.2367 (2.2) | -0.1228 (1.7) | F | -0.2149 (3.4) | -0.0825 (1.7) |
| | std.dev. | | - | - | | - | - | | - | - |
| Parking fee | mean | LN | -2.6405 (4.8) | -0.8348 (3.9) | F | -4.5197 (2.0) | -1.1065 (2.3) | F | -1.4677 (1.9) | -0.4181 (0.9) |
| | std.dev. | | 1.3663 (4.7) | - | | - | - | | - | - |
| Expected fine | mean | N | -2.0081 (1.8) | -0.6374 (4.0) | F | -0.5318 (1.7) | -0.2665 (1.6) | F | -0.5409 (2.8) | -0.3875 (2.2) |
| | std.dev. | | 0.7547 (1.6) | - | | - | - | | - | - |
| ***ASCs*** | | | | | | | | | | |
| Charged-on-street | mean | N | -2.3387 (1.7) | -0.3999 (1.1) | N | -2.2543 (0.9) | -1.5265 (1.9) | F | -2.5016 (1.4) | -1.5475 (1.7) |
| | std.dev. | | 4.3671 (2.3) | - | | 3.2032 (2.0) | - | | - | - |
| Charged-off-street | mean | N | 1.4107 (2.4) | 0.4436 (1.5) | N | -0.1194 (0.1) | -0.0673 (0.2) | N | -0.6110 (0.6) | -0.6868 (1.4) |
| | std.dev. | | 2.0128 (4.4) | - | | 2.4714 (2.9) | - | | 5.5897 (4.0) | - |
| Multi-storey | mean | F | 2.4515 (3.5) | 0.8587 (2.4) | N | -1.4049 (1.1) | -0.4494 (0.9) | F | -0.6854 (0.9) | -0.6696 (1.3) |
| | std.dev. | | - | - | | 6.8436 (3.9) | - | | - | - |
| Illegal | mean | N | -5.0345 (2.7) | -1.8627 (3.4) | N | -11.876 (3.0) | -2.9469 (4.1) | N | -4.2277 (2.7) | -1.9558 (2.6) |
| | std.dev. | | 4.4304 (2.7) | - | | 6.9021 (2.6) | - | | 2.6371 (2.5) | - |
| ***Mean values of time (£/h)*** | | | | | | | | | | |
| Access | | | 2.5 | 3.31 | | 3.95 | 3.2 | | 1.69 | 6.93 |
| Search | | | 3.68 | 3.59 | | 3.77 | 6.23 | | 2.1 | 10.05 |
| Egress | | | 3.34 | 6.38 | | 3.14 | 6.66 | | 8.79 | 11.84 |
| Ratio of fee against expected fine | | | 1.32 | 1.31 | | 8.5 | 4.15 | | 2.71 | 1.08 |
| LL at convergence | | | -319.65 | -414.24 | | -157.47 | -219.30 | | -148.15 | -207.54 |
| Parameters estimated | | | 15 | 9 | | 13 | 9 | | 11 | 9 |

**Table 5. Modelling results on dataset using grouping by activity**

| Coefficient | | Full-time and Part-time work | | | Shopping and Errand trips | | |
|---|---|---|---|---|---|---|---|
| | | MMNL model | | MNL model | MMNL model | | MNL model |
| ***Time*** | | Dist. | | | Dist. | | |
| Access | mean | F | -0.1563 (3.5) | -0.0513 (1.1) | F | -0.1004 (2.7) | -0.0283 (1.7) |
| | std.dev. | | - | - | | - | - |
| Search | mean | LN | -0.1674 (6.1) | -0.0632 (2.9) | LN | -0.4809 (3.7) | -0.0589 (4.5) |
| | std.dev. | | 0.1062 (2.0) | - | | 1.5974 (8.3) | - |
| Egress | mean | LN | -0.2338 (3.7) | -0.0925 (2.2) | LN | -0.2173 (5.9) | -0.0924 (5.0) |
| | std.dev. | | 0.1656 (1.7) | - | | 0.2370 (3.6) | - |
| Parking fee | mean | LN | -3.8206 (4.8) | -0.9727 (2.0) | LN | -4.5945 (3.4) | -0.5701 (3.5) |
| | std.dev. | | 2.4664 (4.9) | - | | 6.4869 (13.2) | - |
| Expected fine | mean | F | -1.8351 (3.2) | -0.8515 (5.2) | N | -5.7450 (4.1) | -0.2916 (3.2) |
| | std.dev. | | - | - | | 2.7353 (3.9) | - |
| ***ASCs*** | | | | | | | |
| Charged-on-street | mean | F | -2.6823 (1.0) | -2.7628 (2.1) | N | -1.5882 (1.6) | -0.8126 (2.5) |
| | std.dev. | | - | - | | 2.2736 (2.5) | - |
| Charged-off-street | mean | F | 2.7228 (1.8) | 0.2830 (0.5) | N | 0.6057 (1.1) | -0.0913 (0.4) |
| | std.dev. | | - | - | | 1.9604 (4.1) | - |
| Multi-storey | mean | F | 4.1859 (2.6) | 1.0614 (1.4) | N | 0.8140 (1.2) | -0.2140 (0.9) |
| | std.dev. | | - | - | | 4.4146 (5.4) | - |
| Illegal | mean | F | -1.8723 (2.4) | -0.8833 (1.3) | N | -8.7620 (2.7) | -2.8972 (5.5) |
| | std.dev. | | - | - | | 5.0492 (2.6) | - |
| ***Mean values of time (£/h)*** | | | | | | | |
| Access | | | 2.46 | 3.16 | | 1.31 | 2.98 |
| Search | | | 2.63 | 3.90 | | 6.28 | 6.20 |
| Egress | | | 3.67 | 5.71 | | 2.84 | 9.73 |
| Ratio of fee against expected fine | | | 2.08 | 1.14 | | 0.80 | 1.96 |
| LL at convergence | | | -96.84 | -123.39 | | -528.59 | -731.22 |
| Parameters estimated | | | 12 | 9 | | 17 | 9 |

**Table 6. Implied distributions of value of time savings**

| | | Overall | Birmingham | FT & PT work trips | Shopping & errand trips |
|---|---|---|---|---|---|
| ***Values of time (£/h)*** | | | | | |
| Access | mean | 3.2272 | 3.0543 | 3.3053 | 3.3658 |
| | std.dev. | 2.1104 | 1.3708 | 1.8166 | 3.3507 |
| Search | mean | 5.5835 | 4.4247 | 3.3927 | 10.8249 |
| | std.dev. | 5.0829 | 3.3710 | 2.6447 | 20.5549 |
| Egress | mean | 4.6129 | 4.0854 | 4.6725 | 6.5464 |
| | std.dev. | 4.9040 | 1.8335 | 3.8057 | 8.7584 |