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Utilising activity space concepts to sampling of alternatives for mode and destination choice modelling of discretionary activities

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Abstract

Choice models estimated on datasets with large numbers of alternatives present significant challenges leading to rapidly expanding computational cost, as well as potential behavioural realism issues. Sampling of alternatives has been a well-established method for overcoming the computational limitations, mostly applied to models of residential location. Nonetheless, destination choice models of discretionary activities require a different type of analysis, since the choice can be governed by time-space constraints and familiarity regarding the alternatives. Observing the general areas of travel for a period of days using high resolution GPS tracking can provide important information of the individuals' whereabouts. The present study, taking advantage of such a dataset, proposes a more behaviourally realistic sampling protocol to reduce the choice set utilising the geography-based concepts of activity spaces. Differential importance sampling rates are applied depending on the individual's activity space and trip chain making the resulting sampled choice set a function of person-specific spatial awareness and mode-specific time-space constraints. The performance of the sampling protocol developed is assessed using a model estimated with the full choice set and compared with random sampling and several other importance sampling protocols. The modelling outputs suggest that random sampling should be used with care, since it can result in highly biased estimates, but with low standard errors, as well. The proposed approach incorporates both time-space constraints and individual spatial awareness and is able to produce less biased estimates, achieve higher sampling stability and statistical efficiency, while also avoiding overfitting.

Keywords: activity spaces, time-space constraints, spatial awareness, mode-destination choice models, stratified importance sampling

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1. Introduction

Mathematical models capable of predicting the destinations of travellers are important for forecasting transport demand. First introduced by McFadden (1973) and later expanded by Daly (1982), discrete choice models have emerged as the prominent tool for modelling disaggregate level destination choices. The large number of potential alternatives, however, poses two issues, namely behavioural realism and computational complexity. On one hand, considering the full choice sets has the risk of leading to a behavioural misrepresentation of the individual-level decision making process, since in reality, the decision makers are highly unlikely to equally evaluate all the alternatives in the global choice set. On the other hand, estimating a model using a large number of alternatives in the choice set leads to high estimation times limiting their adoption in practical applications.

The problem of choice set specification and its significance is well documented in the literature (Thill, 1992; Pagliara and Timmermans, 2009). In fact, estimating a model using an inaccurate choice set can be considered a case of model misspecification leading to biased estimates (Swait and Ben-Akiva, 1987). *Probabilistic choice set generation* based on the theoretical foundations of Manski's model (Manski, 1977) has been proposed as an approach of decoupling the choice problem into choice set generation and alternative choice sub-problems (Thill, 1992; Horni et al., 2011). Manski's formulation requires an exhaustive enumeration of all possible non-empty choice sets, a process that quickly increases exponentially in complexity with the addition of more alternatives. Several variants based on the principles of Manski's model have been proposed over the years aiming to relax the computational complexity (Swait and Ben-Akiva, 1987; Ben-Akiva and Boccara, 1995; Thill and Horowitz, 1997a; Cascetta and Papola, 2001; Martinez et al., 2009; Haque et al., 2019). Nonetheless, in addition to being critiqued on whether these models are able to replicate Manski's principles (Bierlaire et al., 2010), in many cases they adversely impact the behavioural realism of choice set generation (e.g. independent availability of alternatives) negating the main purpose of this modelling approach, while the increased number of model parameters and the non-concavity of the log-likelihood function have also hindered their adoption in spatial choice models (Thill, 1992; Pagliara and Timmermans, 2009).

Despite the ongoing efforts to decouple choice set formation from the choice itself (Thill and Horowitz, 1997a), there is the counter-argument that the notion of choice set misspecification only has theoretical grounds (Lerman, 1985; Thill, 1992), since in an empirical setting, the choice probabilities of alternatives that are not in the actual choice set of an individual are likely to be negligible provided the utility function is correctly specified (Thill and Horowitz, 1997b). In that sense, the behaviourally accurate estimates from an unconstrained model using the full choice set could still be considered as a sufficient representation of reality.

Focusing this time on overcoming the computational limitations of models with large choice sets, *sampling of alternatives* has been proposed as a way to reduce the choice set size and in turn the estimation times, while still obtaining behaviourally realistic estimates. McFadden (1978) showed that constraining a choice set by sampling of alternatives still yields unbiased estimates, if the true model is an MNL, by adjusting the utility function with the inclusion of an additional term, called the sampling correction term (SC). The bias in the estimated parameters, defined as the difference between the sampled estimates and the estimates obtained using the full choice set, will decrease as the size of the sampled choice set keeps increasing (Guevara and Ben-Akiva, 2013b). The specific choice set size beyond which only marginal improvements are observed in the accuracy of the sampled estimates is to be determined as a result of the analysis. As mentioned in Guevara and Ben-Akiva (2013b), the process of identifying the minimum required choice set size to achieve estimation stability is equivalent to the process of finding the required number of draws for the same purpose in a simulated Maximum Likelihood estimation for a mixed Logit modelling framework. The issue of choice set specification is still relevant in the *sampling of alternatives* approach, since the inclusion of more relevant alternatives to the choice task/individual will lead to a lower bias with a smaller choice set size, hence in general to a more efficient sampling protocol.

The additional SC term has the purpose of adjusting the utility function to account for the sampling bias, since the spatial distribution of the sampled alternatives will now depend on the sampling protocol developed and it may differ substantially among individuals. The additional term is computed as $ln\pi(D_n|i, x_n)$, which is the logarithm of the probability of creating the choice set D_n given that alternative i was chosen for individual n. That can be also considered as a penalty added to the utility, since the $\pi(D_n|i, x_n)$ will always be between 0 and 1 and its logarithm will always be negative. In other words, the smaller the probability of sampling that choice set D_n given that alternative i is selected, the bigger the penalty applied. In that case the choice probabilities are modified as shown in *Equation 1* and the *SC* term for stratified importance sampling without replacement is defined in *Equation 2* (Ben-Akiva and Lerman, 1985; Guevara and Ben-Akiva, 2013a).

$$P(i \mid \beta, x_n, D_n) = \frac{e^{V(x_{in},\beta)+ln\pi(D_n|i,x_n)}}{\sum_{j\in D_n} e^{V(x_{jn},\beta)+ln\pi(D_n|j,x_n)}} \tag{1}$$

$$\pi(D_n \mid i, x_n) = \frac{J^*_{r(i)n}}{J_{r(i)n}} \tag{2}$$

where $J^*_{r(i)n}$ is the number of alternatives sampled from stratum r of alternative i and individual n and $J_{r(i)n}$ is the total number of alternatives in that stratum. The SC is calculated for each alternative i per choice task as if that alternative was chosen. It is clear to see that in cases of random sampling with a uniform probability from the global choice set, where $\pi(D_n \mid i, x_n) = \pi(D_n \mid j, x_n)$, the additional SC term remains the same across alternatives and hence it drops out (Nerella and Bhat, 2004). No correction is thus needed with random sampling, but that is not the case with importance sampling. Guevara and Ben-Akiva (2013a) and Guevara and Ben-Akiva (2013b) extended this theory for stratified importance sampling in GEV and mixed logit models, respectively.

Given the need for corrections when using importance sampling, random sampling provides an easier to implement sampling protocol compared to the former. The limitation of random sampling, however, is that it leads to more deterministic models, since the sampled alternatives can be topologically not relevant to the chosen alternative. Therefore, the model will assign higher choice probabilities to the chosen alternative compared to the rest diminishing the explanatory power of the model. The insufficient number of close substitute alternatives to the chosen one, for small choice set sizes, leads a random sampling protocol to require choice sets of generally larger sizes in order to achieve the same level of estimate accuracy compared to an importance sampling protocol, making the former a less efficient approach. Various importance sampling techniques have been proposed in the literature, as opposed to a pure random sampling, aiming to create a reduced choice set that would best represent the individual's trip-specific constraints (Li et al., 2005; Scott and He, 2012; Leite Mariante et al., 2018). Examples can be found in empirical studies of mainly residential location choice (McFadden, 1978; Farooq and Miller, 2012; Guevara and Ben-Akiva, 2013a; Guevara and Ben-Akiva, 2013b). The implementation of importance sampling in a destination choice of discretionary activities, however, will require a different type of handling from a residential location choice, since the chosen alternatives will be subject on some degree to travel impedance and time-space constraints (Daly et al., 2014). Evidence also shows that availability-consideration of alternatives depends not only on time-space constraints, but also on the familiarity/awareness of those destinations (Landau et al., 1982; Thill and Horowitz, 1997a).

The current paper focuses on the *sampling of alternatives* approach for the purpose of decreasing the computational cost of estimating a spatial choice model with a large number of alternatives. More specifically, the aim is to propose a sampling protocol that utilises concepts of Activity Spaces (AS) from the time-space and behavioural geography literature, namely (1) Potential Path Areas based on detour factors around a previous origin O and a following destination D; and (2) Ellipses incorporating a notion of the individuals' awareness/knowledge of their surrounding space. The geography-derived notion of Activity Spaces is a tool capable of capturing individual spatial awareness and time-space constraints, and we utilise them in order to create person- and trip-specific spaces, respectively, for importance sampling of mode-destination alternatives.

We rely on the notions of *Detour Ellipses (DEs)*, *Standard Deviational Ellipses (SDEs)* and *Familiarity Buffers (FBs)*, concepts that are looked at in detail in Section 2. To the best of our knowledge, SDEs and FBs have never been used before, on their own or in combination with DEs, for the purpose of delineating a choice set in a destination choice model, despite their extensive use in studies focusing on exploratory analysis of individual travel-activity behaviour. It is hypothesised that including an additional stratum delineated by SDEs and FBs would result in more accurate sampled choice set models (less biased estimates). That sampling protocol will result in constrained/sampled choice sets with most alternatives adhering to time-space constraints (within DEs) and also being familiar to the individual (within SDEs/FBs).

The remainder of the paper is as follows. In the following section, we give an overview of the relevant literature on time-space geography before expanding this to the context of sampling of destinations. In the third section, the modelling framework developed and the data utilised for the ensued practical application are presented. The results are presented next followed by a concluding section summarising the findings and setting the direction for future research.

2. Methodology

The present study aims to incorporate different forms of AS, namely DEs and SDEs/FBs in order to group the alternatives into three different spaces/strata for the purpose of stratified importance sampling. We will first review existing work on activity spaces in a general context, before extending this to destination sampling.

2.1. Activity spaces - general literature

Activity spaces (AS) originate from the work of time-space geography (Hagerstrand, 1970) and behavioural geography (Brown and Moore, 1970; Horton and Reynolds, 1970; Yuill, 1971) and they have been studied extensively since then for the purpose of understanding activity participation (Schönfelder and Axhausen, 2004; Schönfelder, 2006; Schönfelder and Axhausen, 2010; Kamruzzaman and Hine, 2012), trip chaining behaviour (Newsome et al., 1998) among others. They are mainly used as a measure of describing the spatial distribution of visited locations and they incorporate a notion of individual spatial awareness (Manley, 2016) by providing invaluable information about the exposure to specific locations and activities that individuals might perform based on their usual mobility patterns and their time-space constraints. Due to the vast range of studies and application domains, there are several different forms of AS proposed in the literature depending on the aspect under examination in each case and the level of analysis. In a systematic review, Smith et al. (2019) summarised the different AS forms, which, amongst others include the following:

- Ellipses formed around two fixed points of a specific trip or trip chain, labelled here as *Detour Ellipses (DEs)*
- Ellipses formed around the observed trips of an individual during a survey period, most commonly known as *Standard Deviational Ellipses (SDEs)*
- Circles/buffer zones around frequently visited locations, labelled here as *Familiarity Buffers (FBs)*

We will now look at these three in turn.

2.1.1. Detour Ellipse

DEs is a form of what is known as Potential Path Areas (PPAs). PPAs originate from the time-space geography literature (Hagerstrand, 1970) and have been used extensively as the two-dimensional form of time-space prisms (Miller, 1991; Miller, 2005; Demsar and Long, 2016). A PPA, as depicted in Figure 1, is formed as an ellipse around two fixed locations, the foci of the ellipse represented as P_i and P_{i+1}, where these are usually –but not limited to– the home and work locations, also referred to as *pegs* (Miller, 1991; Kamruzzaman and Hine, 2012). To complete the formation of the PPA, the available net time between the fixed activities performed in the two pegs is considered and an average travel speed or even real network travel speeds/times are taken into account to identify the maximum area of potential travel within that time frame, while still having sufficient time to perform the intermediate discretionary activity (Miller, 1991). The purpose of a PPA is to capture the reachable intermediate locations of discretionary activities between the foci based on the individual's time-space constraints, such as the chosen activity plan, activity duration and travel times.

Detour Ellipse -the specific type of *PPA* chosen for this research- is based on the notion of *detour factor (DF)*. A DF is defined as the ratio of the sum of the straight distances between O(previous origin)-S(shopping destination) and S(shopping destination)-D(next destination) and the straight distance between O-D, as defined in *Equation 3* (Justen et al., 2013). In other words, a DF measures the deviation that an individual is willing to make to reach an intermediate shopping location S between the O-D (Leite Mariante et al., 2018) and it serves as a measure of spatial dependence among destinations in a trip/activity chain. It is also clear that $DF \geq 1$ should always hold. A DE, therefore, explicitly accounts for time-space constraints, hence it is

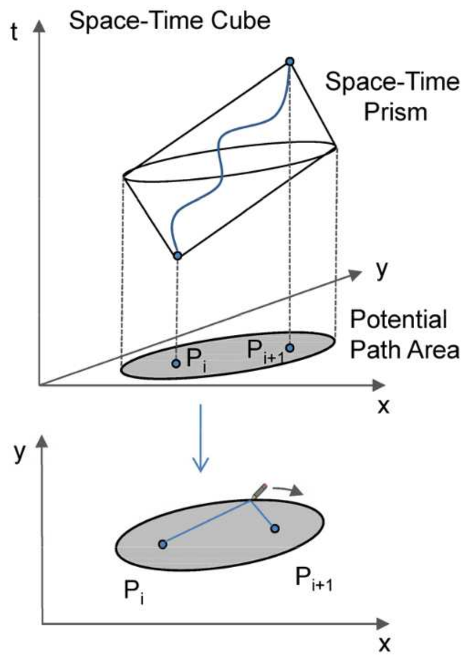


Figure 1: Two-dimensional projection of time-space prisms (Demsar and Long, 2016)

not susceptible to some of the limitations of traditional PPA formation, such as the preferred time spent in a shopping location or the departure/arrival time from previous/following fixed locations, outlined in Landau et al. (1982).

$$DF = \frac{l_{OS} + l_{SD}}{l_{OD}} \tag{3}$$

Previous studies have used fixed DFs for certain intermediate destinations to be considered along the path of observed *O-D* pairs (Cascetta and Papola, 2009). Newsome et al. (1998) created DEs based on the furthest visited intermediate location between home-work locations. Nonetheless, the DF would likely depend on the distance between O and D with longer OD distances resulting in smaller trip-specific DFs. That means that the individual would have reduced resources in terms of time and budget to deviate further away from the OD path. This relation between DF and OD distance has been taken into consideration in Justen et al. (2013), although their approach is limited by the fact that only average DF values per OD distance percentile are considered, while also factors that might further influence the DF, such as sociodemographic attributes and trip-specific characteristics, have not been taken into account.

2.1.2. Standard Deviational Ellipse

SDEs originate from behavioural geography (Brown and Moore, 1970; Horton and Reynolds, 1970; Yuill, 1971) and have been proposed as a measure of capturing the exposure of individuals to opportunities as a consequence of daily activities (Horton and Reynolds, 1971). ASs formed by SDEs are considered a subset of a larger latent *awareness space* (Brown and Moore, 1970; Patterson and Farber, 2015). In that sense, a SDE provides additional information on the individual awareness of certain destinations, that the DE/PPA is not able to provide.

SDEs have been mainly analysed in social geography for the purpose of understanding human mobility patterns with several measures that could be extracted, such as SDE's shape (minor to major axis ratio), size (area, number of polygons located within etc.), orientation and eccentricity (Yuill, 1971). Temporal factors can also be taken into account, such as examining weekday/weekend differences (Srivastava and Schoenfelder, 2003; Smith et al., 2019) and their evolution over decades (Axhausen, 2007). Survey duration also plays an

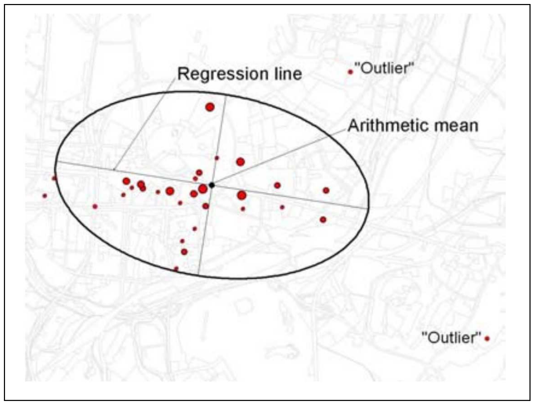


Figure 2: Weighted standard deviational ellipse around observed/visited destinations (Schönfelder, 2003)

important role in the SDE creation as shown by Schönfelder (2006) with surveys of longer durations required in order to observe a stability in the mobility/activity patterns and hence to create more representative SDEs.

Contrary to DEs/PPAs, SDEs are formed around all of the visited locations (observed latitude/longitude coordinates) of an individual during the survey period and it is considered the two-dimensional equivalent of a standard 95% confidence interval. Weighted SDEs can also be created based on trip frequency, activity duration etc. *(Figure 2)*. The major axis of the ellipse indicates the axis of major dispersion and it is the regression line of the latitude/longitude coordinates, while the orientation of the SDE depends on the correlation sign between them (Schönfelder, 2003). Destinations that are outside of a SDE are considered as *outliers*, since they are not part of the usual movement areas of an individual. Further details on how to create a SDE can be found in Yuill (1971).

2.1.3. Familiarity buffers

Buffer zones around frequently visited locations have been proposed as another form of AS used to capture the spatial awareness or the number and different types of services an individual is exposed to, similar to SDEs. Due to their ease of implementation, a large number of studies have implemented them with various buffer zones being proposed depending on their purpose ranging from 500 m to define *immediate home neighbourhoods* to 1.6 km to define broader areas (Larsen et al., 2009; van Heeswijck et al., 2015; Chaix et al., 2017). Weighted FBs have also been proposed based on the activity type performed, the visiting frequency or the time spent at those locations (Loebach and Gilliland, 2016). Finally, in a study more related to the current one, Horni et al. (2011) for their conceptual choice set formation framework, proposed adding a buffer zone, equivalent to 15 minutes of walking distance, around home and work locations in a PPA ellipse formed between home-based work trips.

2.2. Applying AS approaches to destination sampling

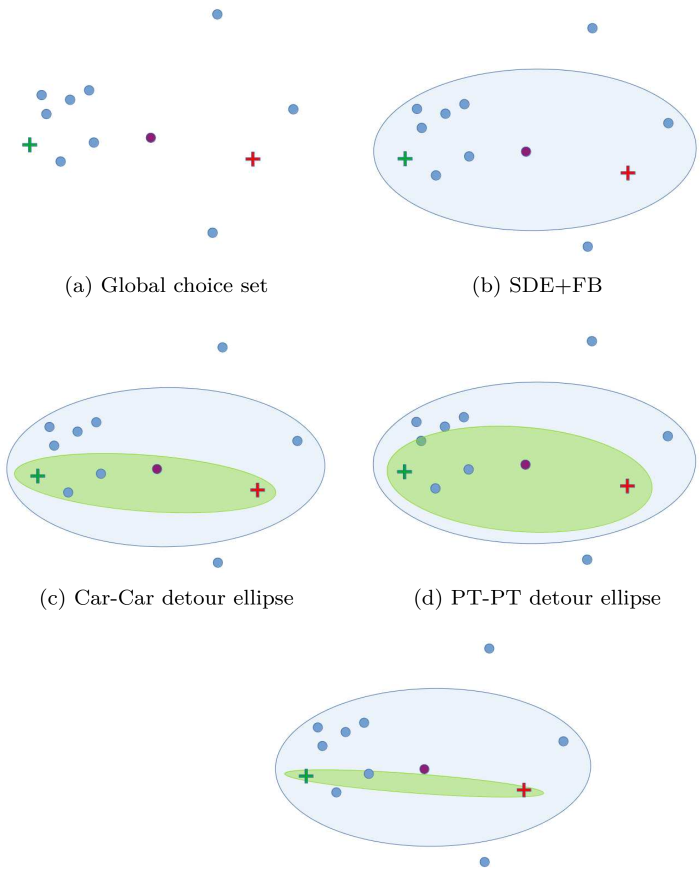
Only a handful of studies, at least to the authors' knowledge, have combined time-space constraints and sampling of alternatives in order to further reduce computational complexity. Scott and He (2012) analysed shopping trips using real network travel times to create PPAs and to identify the reachable shopping destinations with a positive net activity time. Random sampling of the identified locations was applied to construct the final constrained choice set. This approach is subject to the limitations described earlier (Landau et al., 1982). Excluding destinations with a negative net activity time, by considering the observed departure/arrival times as fixed, fails to take into account the trade-offs the individual is willing to make in order to reach a certain destination. Even excluding the possibility of measurement errors and even if the analyst considers the activity scheduling choice dimension to precede the choice of location, she cannot safely assume the same for the time allocation between those activity locations, such as departure-arrival time from/to different locations in a trip chain.

Leite Mariante et al. (2018) formed DEs (DF-based PPAs) for the purpose of sampling of alternatives for a destination choice model of different discretionary activity types. The DEs were defined based on the methodology described in Justen et al. (2013). The sampling protocol proposed involved selecting the chosen destination first and then sampling a number of alternatives from the space delineated by the DEs. In the case of not having enough sampled alternatives to reach the required choice set size, additional alternatives were sampled located outside the DEs. Mixed logit models were estimated utilising the methods proposed in Guevara and Ben-Akiva (2013a). The limitations of this study lie mainly on the sampling protocol developed and also on the DE formulation. Firstly, alternatives outside the DEs are sampled only in cases of an insufficient number of alternatives in the DEs. That means that many choice tasks will be estimated with choice sets containing alternatives only within DEs. That in turn can have significant implications on the estimation accuracy of parameters for spatial variables that generally lie in areas outside most of the DEs. Secondly, a problem could also arise in the case of small DEs. If we consider an example of a choice task/trip with a long distance between the previous O and the following D, then the chosen DF for the intermediate S would be small according to *Equation 3* resulting in a small DE. Let us assume now that the created space within the DE contains only 2 alternatives, the chosen and an additional non-chosen destination, and the required choice set size is 50 alternatives (i.e. the largest choice set size in this study). That means that 48 additional alternatives will be randomly sampled from the remaining universal choice set, making that choice task/trip a case of almost pure random sampling from the universal choice set, which will result in choice sets with a large number of spatially irrelevant alternatives to the chosen one. Therefore, a more balanced sampling protocol would be required to address both issues. Finally, the study is susceptible to the same limitations as in Justen et al. (2013) described earlier, such as average DFs per OD percentile and lack of sociodemographic and trip characteristics that might influence the DF.

The current study addresses the aforementioned limitations by formulating a range of stratified importance sampling protocols for shopping mode-destination alternatives and to provide a systematic comparison with random sampling. The main departure from the studies described so far, is to include SDEs and FBs alongside DEs and the corresponding activity spaces, to define strata for importance sampling. The space created within SDEs/FBs will provide an additional pool of alternatives to sample from and avoid the problems identified in Leite Mariante et al. (2018). In the case of small DEs, alternatives adhering to individual spatial awareness will be prioritised to be sampled in order to reach the required choice set size, instead of randomly sampling a large number of spatially irrelevant alternatives from the remaining global choice set. DEs for chosen/non-chosen alternatives are formed based on estimated DFs from an econometric model (linear regression), thus being based on a more accurate representation of individual behaviour. Furthermore, we purposely refrain from excluding alternatives outside DEs and SDEs/FBs, in an attempt to accommodate extreme cases, to account for possible measurement errors during the DE and SDE/FB formation and finally to ensure that all alternatives will have a positive probability of being included in the sampled choice set. Therefore, regardless of the choice set size, alternatives outside DEs and SDE/FBs can still be sampled, albeit with a lower probability. Accounting for the fact that DEs and SDEs/FBs are just *proxy* measures of space-time constraints and spatial awareness, respectively, these will be used simply as *soft* constraints to create strata per individual from which to sample alternatives with a higher probability (importance sampling) and not to exclude alternatives outside of them.

The stratum constrained by the DE, labelled as T, aims to identify the most likely reachable destinations per mode combination (mode for first/shopping trip-mode for following trip). The stratum constrained by the SDE/FB (excluding the alternatives already within T), labelled as A, has the purpose of acting as a proxy for the individual's spatial awareness/knowledge. That leads to the creation of a third stratum C, which is simply the remaining space outside T and A. The main assumption for the choice-set generation in this study is that alternatives that are more familiar and those that are in closer proximity to a specific trip chain between an O and D, are more likely to be considered and will contribute more in understanding individual behaviour than others. Therefore, the sampled choice set should include more alternatives from T, followed by alternatives from A and finally alternatives from C.

A simplified example is presented in *Figure 3* focusing on the context of the empirical application used later in the paper, which looks at destination choice for shopping activities. In the first subfigure, a choice task is presented, in which the individual starts from an origin (green cross) and during her trip to a destination (red cross), she chooses an intermediate shopping destination (purple circle) out of a set of available shopping destinations (blue circles). In total, there are 10 available destinations in the global choice set. The available transport modes for those two trips are combinations of car, public transport (PT) and walking. For simplicity, we assume that for that specific choice task, the only available mode combinations for the first/shopping



(a) Global choice set

(b) SDE+FB

(c) Car-Car detour ellipse

(d) PT-PT detour ellipse

(e) Walking-Walking detour ellipse

Figure 3: Example of sampled choice set specification *(SDE: Standard Deviation Ellipse; FB: Familiarity Buffer)*

and the following trip are *car-car*, *PT-PT* and *walking-walking*. Therefore, the global choice set consists of 30 mode-destination alternatives. In the second subfigure, the combined SDE-FB area of the individual is defined based on the observed destinations she visited during the survey period. Finally, in the remaining 3 subfigures, the estimated mode-specific DEs are defined for car-car, PT-PT and walking-walking, respectively, based on the modelling specification described in *Subsection 3.3.1*.

After the creation of the three strata *(T, A, C)* and the identification of the stratum of each mode-destination alternative, the following four different sampling protocols (without replacement) were compared with the model using the full choice set and were assessed in terms of parameter bias, sampling stability and forecasting performance:

- *Random sampling* with a uniform probability from the full choice set
- *AC* referring to sampling with a priority from A and then from C, such as $\pi(A) > \pi(C)$
- *TC* referring to sampling with a priority from T and then from C, such as $\pi(T) > \pi(C)$
- *TAC* referring to sampling with a priority from T, then from A and finally from C, such as $\pi(T) > \pi(A) > \pi(C)$

In the case of stratified importance sampling, a fixed number of alternatives is sampled per stratum with that number adhering to some notion of *importance* for a specific stratum relative to the rest. For that purpose and in order to avoid setting an arbitrary number of alternatives to be sampled per stratum, the stratum of each chosen alternative was identified by performing a *"spatial join"* operation between the strata and the observed mode-destination alternatives. The identified frequencies per stratum were then used as the *desired* share of alternatives from each stratum, $\pi(T)$, $\pi(A)$, $\pi(C)$, to be included in a choice set of a certain size, as shown in the following *Equation 4*:

$$\pi(r) = \frac{nTrips_r}{nTrips_{total}} \tag{4}$$

where $\pi(r)$ is the sampling probability for stratum r and $nTrips_r$, $nTrips_{total}$ are the number of trips with chosen shopping destinations in stratum r and the total number of trips, respectively. Therefore, if on average 60%, 30% and 10% of the observed alternatives in the sample are within T, A and C, respectively, the sampling probabilities are assigned as $\pi(T)$=0.6, $\pi(A)$=0.3 and $\pi(C)$=0.1. A sampled choice set with J alternatives is constructed by first selecting the chosen alternative and then performing importance sampling for the remaining $J-1$ alternatives by sampling the desired number of alternatives from the respective stratum (Guevara and Ben-Akiva, 2013a; Guevara and Ben-Akiva, 2013b). In the case of not having enough alternatives to reach that desired number per stratum, alternatives from the next stratum in line, as defined per sampling protocol, are sampled. The inclusion of a properly calculated SC term in the utility function will guarantee the estimation of unbiased parameters for sufficient choice set sizes, even when not reaching the desired number of alternatives from the respective strata. It is also assumed that alternatives that are being sampled and included in the reduced choice set are all considered equally by the individuals, hence no further consideration thresholds have been applied in the utility function (see for example Martinez et al. (2009)). The developed framework is summarised below:

1. Estimate a model using the full choice set to use as the base for evaluation of the sampling protocols developed
2. Create DEs based on estimated values derived from a linear regression econometric model
3. Create SDEs and FBs per individual using the observed destinations
4. Define the strata per choice task and individual
5. Define the sampling protocols to be compared
6. Perform sampling of alternatives from the respective strata for each sampling protocol and for different choice set sizes
7. Estimate models on the sampled choice sets using the same specification as in the full choice set model
8. Assess the performance of the sampled choice set models per sampling protocol and choice set size based on specific evaluation criteria proposed

3. Empirical application: data and model specification

This section discusses the data and its processing, before looking at model specification and the settings used for the AS approach to sampling of alternatives.

3.1. Data

3.1.1. Original GPS data

The dataset used in the current study was collected as part of the research project “DECISIONS” carried out by the Choice Modelling Centre at the University of Leeds, during November 2016 and March 2017. The project aimed at observing individual decisions over a range of choice dimensions with an emphasis on travel, activities performed, both in-home and out-home, social networks and energy consumption over a period of 2 weeks. A detailed description of the survey and all of its different submodules (e.g. household survey, trip diary, energy consumption etc.) is presented in Calastri et al. (2020). For the purpose of the current study, only the trip diary and the household survey submodules were used. The trip diary includes all the trips that a participant made during the survey period. The trip diary was collected using a smartphone application that would record the GPS coordinates of each trip. The participants had to provide information regarding the chosen mode and the purpose of the activity performed at the end of each trip (*Figure 4*). In total, out of the 47,161 trips performed by 713 individuals, almost 75% of those were tagged with mode-purpose information. The majority of trips was within the region of Yorkshire and specifically around the city of Leeds. The household survey provided important sociodemographic information on the participants, such as gender, age, income, car ownership etc. which can be important explanatory variables in a behavioural model.

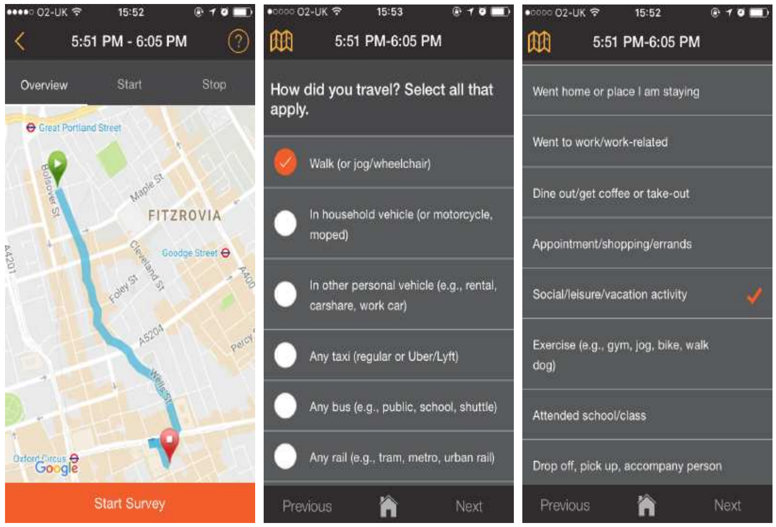


Figure 4: User interface of smartphone application used for the trip diary (Calastri et al., 2020)

The analysis presented in the current study is focused on a specific type of discretionary activity, namely shopping. The study area was defined as the region of Yorkshire. Only individuals residing in the local authority of Leeds were selected, assuming they will have a similar knowledge of their surrounding shopping destinations having to adhere to the same spatial constraints (Domencich and McFadden, 1975; Richards and Ben-Akiva, 1975; Adler and Ben-Akiva, M., 1976; Southworth, 1981; Miller and O'Kelly, 1983; Thill, 1992). The purpose of the analysis is to understand where the individuals are more likely to go for shopping with respect to the previous and the following activity locations. Therefore, from the initial dataset, the shopping trips and their following trips were chosen for the subsequent analysis. The final dataset used in the analysis contained 1541 shopping trips and an equal number of following trips performed by 270 unique individuals (5.7 trips per individual, on average). Regarding the sociodemographic information of the individuals included in the sample, 64.1% were female, 32.2% between 30-39 years old and most of them employed (77%). The vast majority possessed at least one car in their household, while 20% had either a bus or rail season ticket.

3.1.2. Processing of data into trip chains

The shopping and their following trips were combined to create trip chains, which formed the basis of the analysis performed. Most trip chains, 66%, were from an origin O to an intermediate shopping destination S and then to another destination D, which will be referred to as O-S-D trip chain. The remaining trip chains, 34%, were from an origin O to a shopping destination S and then back to the origin O, which will be referred to as O-S-O trip chains. Shopping trips included three subcategories of shopping, namely grocery (82%), clothes (12.7%) and other types of shopping (5.3%), mainly for durables. The vast majority of following trips were trips going home (61.5%), while there was a small percentage (9.3%) of a consecutive shopping trip to a different shopping destination. From the remaining trips, 10.5% were for work/education, 11% for leisure/social and 7.7% were for other purposes. The present study is focused on a subset of modes of transports, namely car, public transport (PT) –as a combination of bus and rail– and walking. Most of the observed/chosen modes for the two legs of the trip chain were car-car (shopping-following trip) and walking-walking, namely 85.2%, while only 3% were PT-PT. Combinations of the three modes were also observed, such as car-PT, walking-car etc. and it was decided to include them in the analysis, despite their low mode share.

3.1.3. Definition of shopping areas

The shopping destinations for the study area were defined by clustering the elemental observed shopping trip destinations. Hierarchical Agglomerative Clustering was implemented with a 800m distance threshold between the shopping trip destinations. The purpose of clustering the shopping destinations was to define general *shopping areas* and take advantage of the higher GPS data resolution, instead of limiting the analysis

Figure 5: Allocation of retail polygons located within overlapping shopping clusters (OpenStreetMap contributors, 2021)

to the general geographical units in the UK (e.g. Middle or Lower Super Output Areas).

After defining the shopping clusters, their respective centroids were defined as the mean of the latitude/longitude coordinates of the elemental destinations in each cluster. The cluster centroids were then used to replace the original destination points of each shopping trip belonging to the cluster. The main goal of the clustering was to choose an appropriate distance threshold that would result in a small average distance difference between the original destination points of a cluster and its centroid. After trying different distance thresholds between 500m-1000m, a 800m distance threshold was selected resulting in an average distance difference of 112m, while the maximum distance difference was 338m, which equates to between 4-5 minutes of walking (assuming a 5 km/h average walking speed). Larger distance thresholds resulted in distance differences of more than 5 minutes of walking distance, while smaller thresholds resulted in large shopping malls being split across two different clusters. In addition, visual inspection of the created clusters for different distance thresholds was performed in order to verify that distinct shopping areas were assigned to different clusters, with an emphasis on the main shopping areas of Leeds city centre. This procedure resulted in the creation of 176 general shopping clusters around the region of Yorkshire with most of them located around the city of Leeds. It is clear that shopping locations exist in other places within the study area, not captured by that process, mostly in areas outside the local authority of Leeds. Those shopping locations, which are never chosen by the individuals, are assumed to not having been considered by the individuals in the sample and hence are excluded from the subsequent analysis (Thill, 1992).

As a final step, a 400m buffer was created around the centroid of each shopping cluster to define the shopping areas. Therefore, a shopping area is defined as the space equivalent to 5 minutes of walking time around the cluster centroid. That high resolution of shopping area definition translates into having unique shopping malls, shopping districts etc. as separate destination alternatives. In the case of overlapping buffers, especially in Leeds city centre, the polygons within them were assigned to their closest cluster centroid (*Figure 5*). This ensured that each elemental shopping destination (in the form of polygons/individual stores) would belong to a single defined shopping area.

3.1.4. Data enrichment: level-of-service information and mode availability assumptions

In order to account for the fact that only travel times for chosen/observed alternatives were included in the dataset, travel times/distances were re-estimated both for chosen and non-chosen alternatives using the Bing Maps Routes API[1]. The total number of queries passed on the API were 1,627,296 (1541 trips ×

[1]Details can be found here: https://docs.microsoft.com/en-us/bingmaps/rest-services/routes/

176 shopping destinations $\times$ 3 modes $\times$ 2 legs). The small distance differences between the initial observed destinations and the cluster centroids, as previously described, ensured that there would not be any significant discrepancies between the API-derived travel times and the observed ones.

For car travel cost, separate calculations for fuel and operating costs were performed using the UK's Transport Appraisal Guidance (WEBTag) specifications (Department for Transport, 2014). Parking cost was also calculated for trips with destinations in central areas/high streets across the region of Yorkshire based on information on hourly or fixed parking costs provided by the respective Local Authorities. Fuel, operating and parking costs were then added together to calculate the final car travel cost per trip. For PT, an average distance-based fare was used for bus and rail and a total PT cost was calculated per trip based on the information provided from the API regarding which leg was performed with bus or rail and what was its distance. Furthermore, a discount was applied for trips made by season ticket holders.

In some cases, the API returned only walking segments for PT due to a small trip distance or the unavailability of PT services. For those trips, PT was assigned as unavailable. For the car trips, the availability was based on logical checks. For example, if a person chooses *Car* for the shopping trip, the group size is 1 (i.e. the person is the sole driver) and the following trip returns back to O (O-S-O trip chain), then only *Car* is assumed to be available for the following trip since the driver has the constraint to return the car back to O.

3.2. Full choice set model

In the current paper, it is assumed that a model estimated using the full choice set is considered the *"true"* model. Therefore, as a first step, a model using the full choice set is specified and estimated to act as the base for the assessment of the sampling protocols. Discrete choice modelling was used as the main methodological framework for the analysis (Ben-Akiva and Lerman, 1985). The analysis is performed at the level of the trip chain, which is defined as two consecutive trips, namely a shopping trip from an origin O to an intermediate shopping destination S with a mode k and a following trip to another destination D with a mode j. The behavioural model developed aims to understand the choices of modes k and j and of destination S for shopping trips in a joint fashion. In that context, the locations of O and D are considered as fixed for each choice task. Therefore, the full choice set consists of 3 modes for the first/shopping trip, 3 modes for the following trip and 176 shopping destinations, for a total of 1584 combined mode-destination alternatives. The choice of activity (i.e. travelling for shopping), and the choice of trip-chain complexity, (i.e. including a shopping trip on the way to work O-S-D vs. performing a simple O-S-O trip chain) is assumed to precede the choice of mode-destination and is therefore considered exogenous (as described in Ye et al. (2007)).

The specification proposed by Daly (1982) was utilised with the presence of level-of-service (LOS) variables, quality locational variables and lastly a number of size variables specified inside a composite log term *(Equation 5)*. Deterministic taste heterogeneity is captured through the interaction of Alternative Specific Constants (ASCs) and LOS variables with sociodemographic covariates. Random heterogeneity has not been included (with the specification of mixed MNL models) due to the high estimation times of the full choice set model. The *sampling of alternatives* approach can provide a well-performing model using a reduced choice set with significantly lower estimation times. That model, if needed, could be further used as the base for more advanced modelling specifications, such as incorporating random heterogeneity –either continuous (e.g. mixed Logit) or discrete (e.g. latent class choice models)– although this is out of the scope of the current study. Interactions with categorical sociodemographic variables were specified as shifts from the base level of the ASC, while non-linear interactions were specified for continuous sociodemographic variables, namely personal income interacted with travel cost and shopping duration interacted with travel time and walking distance.

$$V_{kj,S} = \sum_{r \in L} \beta_r x_{r,kj,S} + \sum_{r \in D} \beta_r y_{rS} + \phi \log(A_S) \tag{5}$$

where $x_{r,kj,S}$ is the r^{th} element of a vector L of LOS attributes for mode combination kj and shopping destination S, y_{rS} is the r^{th} element of a vector D of quality locational attributes for destination S and A_S is the composite size measure capturing the attraction of destination S defined as:

$$A_S = a_{1S} + \sum_{r>1} exp(\gamma_r) a_{rS} \tag{6}$$

where a_{1S} is the attraction attribute used as a base with a γ parameter normalised to 1.0, a_{rS} are the additional attraction attributes of destination S relative to the base attribute and γ_r are the parameters to be estimated to capture the effect of those attributes on the attraction of that destination. Using the exponential form ensures the effects of γ_r are always positive.

The attraction of neighbouring destinations, at various distances away of the visited destination, has also been included in the size of the visited destination to capture the effects of trip chaining behaviour (Kitamura, 1984; Kristoffersson et al., 2018). It is believed that a destination with more surrounding shopping destinations will be perceived as more attractive compared to a more isolated destination, all else held equal.

3.3. Sampling strata formation

In the current subsection, we focus on the steps taken in order to form the different strata used for the subsequent practical application.

3.3.1. Creation of Detour Ellipses

For the DE creation, the limitation to overcome was having information only for the observed DFs referring to the chosen mode combination and shopping destination. Different mode combinations, however, would likely result in different space-time constraints and hence lead to different DFs. For instance, a mode combination of walking-walking is expected to result in a smaller DF compared to car-car, all else held equal. Furthermore, sociodemographic and trip-specific attributes could also influence the deviation an individual is willing or able to make in order to reach an intermediate shopping destination. Because of those reasons, the observed DFs and a number of trip-related, locational and sociodemographic explanatory variables were used to estimate a continuous model for DFs. The purpose of the estimated linear regression based DF model was to produce predicted values for the DFs for all of the 9 mode combinations per trip, both chosen and non-chosen, thus overcoming the limitation of having DFs only for the observed mode combinations while ensuring consistency. The estimated DFs were then used to produce DEs that are based on mode-specific, trip-specific and individual-specific time-space constraints of the participants in the sample and not simply on the observed/visited intermediate shopping locations. The DF modelling framework is described in further detail in *Subsection 3.3.2*.

3.3.2. Detour Factor modelling framework and outputs

Prior to the DF model specification, the trip chains were grouped into those starting-finishing at the same location, i.e. *O-S-O*, like a simple *Home-Shop-Home* tour, and those starting-finishing at different locations, i.e. *O-S-D*, such as a typical *Home-Shop-Work* trip chain. Therefore, two different continuous models were estimated for each case using Maximum Likelihood estimation (MLE).

For *O-S-D* trip chains, the model specification has to guarantee that the estimated DFs will always be above 1.0. In addition, a logarithmic transformation was applied to the observed DFs, i.e. the dependent variable to guarantee that the transformed variable $log(y-1)$ would follow a normal distribution $log(y-1) \sim N(\mu_{log(y-1)}, \sigma_{log(y-1)})$. The predicted DFs are calculated for the chosen and non-chosen mode combinations per choice task and individual as follows:

$$\mu_y = 1 + \epsilon^{(\mu_{log(y-1)} + 0.5\sigma^2_{log(y-1)})} \tag{7}$$

where $\mu_{log(y-1)} = \Sigma\beta_{x_i} x_i$ and x_i and β_{x_i} are the explanatory variables and the respective estimated parameters for choice task i.

Since the aim was to produce as accurate predictions as possible for the DFs, Bootstrap sampling (Daly

Table 1: Modelling outputs of the DF model for *O-S-D* trip chains

Parameters	MLE Estimates	Bootstrap sampling st.dev.	t-ratios
Constant	-0.8363	0.1734	-4.82
Natural logarithm of O-D straigth distance (km)	-1.3253	0.0701	-18.92
Car-Walking	-1.8934	0.3206	-5.91
PT-PT	1.0609	0.3722	2.85
Walking-Car	-1.4617	0.3946	-3.70
Walking-PT	-0.6875	0.2904	-2.37
Walking-Walking	-1.6766	0.2425	-6.91
Shopping: Clothes - Other	0.6526	0.1895	3.44
Household size: 3-4 members	0.4733	0.1750	2.70
Part time workers	-0.3908	0.1726	-2.26
Occupation: Students	0.5936	0.3216	1.85
Occupation: Other	0.4199	0.2322	1.81
Time of day: Weekend morning	0.7590	0.2158	3.52
Parking areas 400m around shopping cluster	0.0182	0.0033	5.59
Sigma	2.0252	0.0613	33.03

et al., 2020) was used in addition to MLE for a more robust assessment of the standard errors.[2] After trying different numbers of Bootstrap samples and checking the differences between the mean of the Bootstrap estimates and the MLE estimates, it was decided to use 500 samples for the *OSD* model, since at that number of samples the average of the Bootstrap estimates showed only negligible average absolute percentage differences from the MLE estimates, namely 0.018. The t-ratios were then calculated as the ratio of the MLE estimate and the Bootstrap sampling standard deviation.

The estimated parameters and the standard errors, presented in Table 1, refer to the Maximum Likelihood estimates and the standard deviation of the respective Bootstrap parameters. The best-performing model resulted in a Root Mean Square Error (rmse) of 4.35, a mean absolute error of 1.09 and a correlation between predicted and observed DFs of 0.69. Regarding the estimated parameters, the larger the *OD* distance (log) the smaller the DF, as expected due to the time limitations to reach those destinations and participate in the respective activities. All of the mode combinations would result in a smaller DF compared to the base mode combination of car-car. The only exception is PT-PT that results in a larger DF than car-car, all else held equal. Worth-noting is also the finding that individuals going for clothes shopping or for other types of durable shopping are willing to deviate more from the direct OD route compared to travelling for groceries. That is in accordance with prior expectation, since clothes shopping is an activity generally performed in more *"relaxed"* days of the week and times of day, hence there is more freedom to roam around the urban environment. Likewise shopping for durables usually requires going to specialised stores (e.g.IKEA), hence the individuals are willing to choose larger DFs to reach those destinations. On the other hand, grocery shopping is considered mostly a necessity and the individuals are usually trying to fit that in their everyday or weekly schedule with smaller deviations from their routing plan.

For *O-S-O* trip chains, a different modelling approach had to be formulated, since for those cases the $l_{OD,i}$ is 0, hence the DF cannot be defined. Consequently, the straight distance (in km) $l_{OS,i} = l_{SD,i}$ was selected as the dependent variable for those trip chains, which again it was logarithmically transformed to guarantee that it follows a normal distribution with $log(y) \sim N(\mu_{log(y)}, \sigma_{log(y)})$. The predicted distances for the chosen and non-chosen mode combinations per choice task were calculated as:

[2]It should be noted that Bootstrap sampling is not strictly required, since the analyst can simply rely on the standard errors obtained from the MLE. Having said that, for the current study, the standard errors obtained from Bootstrap sampling were more strict than those obtained from MLE resulting in a lower number of statistically significant parameters and finally in a more accurate fit (lower rmse) between observed-predicted DFs.

Table 2: Modelling outputs of the travel distance model for *O-S-O* trip chains

Parameters	MLE Estimates	Bootstrap sampling st.dev.	t-ratios
Constant	0.3664	0.0951	3.85
Walking-Walking	-1.4375	0.0797	-18.76
Shopping: Other	0.5167	0.1667	3.32
Time of day: Night	-0.3542	0.1527	-2.41
Following purpose: Social-Leisure	-0.7769	0.1999	-4.01
Age: 18-24	-0.2366	0.0617	-3.71
Parking areas (linear)	0.0047	0.0016	2.89
Retail areas (log)	0.0821	0.0244	3.29
Household Income: 40000-50000 GBP/year	-0.2008	0.0894	-2.44
Household Income: No reporting	0.4776	0.1500	3.54
Shopping activity duration	0.2078	0.0537	4.30
Sigma	0.6526	0.0327	20.61

$$\mu_y = \epsilon^{(\mu_{log(y)} + 0.5\sigma^2_{log(y)})} \tag{8}$$

where $\mu_{log(y)} = \Sigma\beta_{x_i}x_i$ and x_i and β_{x_i} are the explanatory variables and the respective estimated parameters for choice task i.

A similar Bootstrap sampling approach was performed for *O-S-O* trip chains, as well, with 500 samples resulting in a very small mean absolute percentage error of 0.025. The best-performing model, presented in Table 2, resulted in an rmse of 1.99, a mean absolute error of 1.13 km and a correlation of 0.68. Only the mode combination of walking-walking showed significant differences to car-car (base) indicating a lower distance as expected for trips made by walking in both legs. Other types of shopping, i.e. durables, resulted in a higher accepted distance, while smaller distances are accepted for trips chains where the following trip is for social/leisure purposes. Finally, individuals who did not report their household income were found to accept larger distances.

The mode-specific predicted DFs and straight distances produced from the aforementioned procedure, were used to construct the DEs (detour ellipses and circles), representing the boundaries of potentially reachable areas or PPAs for a specific trip and mode combination with fixed *Os* and *Ds*. For *O-S-D* trip chains, the predicted DFs were used to create DEs following the procedure described in Justen et al. (2013). For *O-S-O* trip chains, the predicted distance was simply used as the radius of a circle with its centre being the location of *O*.

3.3.3. Creation of Standard Deviational Ellipses

As mentioned before, SDEs were defined for the purpose of capturing spatial familiarity or awareness of the individual's surrounding space. The SDEs were constructed using all of the observed destinations during the 2-week survey period. To achieve the most accurate representation of the AS of a participant, the untagged trips were used, as well, in addition to the tagged ones. As each trip between the same O-D is considered as a unique observation in the calculation, the created SDEs are shifted towards destinations that are more frequently visited, similar to a weighted SDE based on trip frequency.

After the SDE creation per individual, various metrics can be derived describing their mobility patterns during the survey period with the most important being the ratio between the minor/major ellipse axis (b/a). A ratio close to 1.0, i.e. $b = a$, would lead to an ellipse closely resembling a circle indicating that either an individual tends to roam more randomly around space or that the survey duration was probably not enough to capture the regularity of her travel. On the other hand, a small ratio, leading to an ellipse resembling a straight line, would indicate that this person has a quite tight schedule or limited resources to deviate from her usual axis of travel. It would be useful to note that on average the b/a ratio is 0.39 indicating that well-balanced spatial distributions of individual mobility patterns were captured even in the arguably limited

2-week survey duration. It may be noted that the mobility patterns and hence the axes of the SDEs are expected to be functions of the sociodemographic characteristics of the person. For instance, the b/a ratio of workers is likely to be smaller than part-time workers or non workers due to their potentially non-flexible schedules.

3.3.4. Creation of Familiarity Buffers

In addition to the SDE, FBs are also defined around each destination, mainly inspired by the previous work of Horni et al. (2011), described in *Subsection 2.1.3*. FBs had to be defined around each unique destination. For that purpose, the initial GPS destinations had to be clustered to define unique visited locations per individual. Different thresholds for Hierarchical Agglomerative Clustering were tested between 50m-300m, with 200m resulting in the most accurate results following a visual inspection of the clusters created in each case. From that process, home-work clusters/locations were identified based on the purpose of trips assigned to those clusters.

In the current study, a buffer equivalent to 15 minutes of walking distance (1200 m) was created around the home location of each individual. Following that, buffers around the remaining visited destination clusters were created with a radius relative to the one of their home-cluster as per the following *Equation 9*:

$$r_{C_{j,i}} = \frac{nTrips_{C_{j,i}}}{nTrips_{C_{H,i}}} r_{C_{H,i}} \tag{9}$$

where $r_{C_{j,i}}$ is the buffer radius of familiarity cluster j for individual i, $nTrips_{C_{j,i}}$ and $nTrips_{C_{H,i}}$ are the trips to familiarity cluster j and to home-cluster H, respectively, and $r_{C_{H,i}}$ is the buffer radius of the home-cluster H which in the current study is fixed to 1200m.

It was assumed that the home cluster should have the majority of trips, therefore the largest buffer radius. As a result, in cases where other non-home clusters attracted more trips, those familiarity buffers were fixed to have the same radius as the buffer of the home cluster. The rationale for that, was that the home-cluster should always attract the highest number of trips and the cases where that was not observed could be attributed to the limited survey duration of 2 weeks and/or missing observations.

Contrary to Horni et al. (2011), in the current study the created FBs were subsequently merged with the previously defined SDEs, instead of the DE/PPA. That was decided since the FBs carry a notion of spatial awareness similar to the SDE and are not a result of trip-specific time-space constraints as the DE/PPA. The merged SDE/FB resulted in a common space of places, where the individual is likely to possess a better knowledge/awareness of the surrounding shopping opportunities compared to the rest of the study area. Furthermore, the addition of FBs into the previously created SDEs ensures that *outlier* locations outside of the SDE would still contribute to the spatial awareness of the individual. Those locations, even if they are not part of the usual movement patterns of the individual, they are still visited, hence the individual would likely possess some knowledge of their surrounding space.

3.4. Definition of sampling protocols

After the creation of DEs and SDEs/FBs, the different sampling strata, T, A and C, were empirically defined. On average, 67% of the chosen shopping destinations are located within T, 28.2% are located within A and the remaining 4.8% within C[3]. Not all alternatives within DEs are also within SDEs/FBs and vice versa, since there can be cases of trips performed outside the usual movement spaces captured by SDEs/FBs. The aforementioned percentages, calculated using *Equation 4*, were used to define the sampling probabilities for each stratum and they conform to our initial objective of having $\pi(T) > \pi(A) > \pi(C)$. That way, regardless of the total number of alternatives in the choice set, there will be more alternatives sampled from T, compared to the other 2 strata, provided there are enough alternatives within that space to sample from. In order to better understand the constraints faced by the individuals, descriptive statistics are presented in *Table 3* showing what types of individuals choose shopping destinations located only within T,

[3]These values are unlikely to be spatially transferable, but should be easy to calculate from the data collected from the location of application.

both within T and A and within the global choice set, i.e. T, A and C. From that table, we can see that most individuals tend to consine themselves either within their time-space constraints or within their usual areas of movement (second column). A larger percentage of males tend to deviate from their time-space constraints than females, but still not outside their usual areas of movement. Starker differences are observed when it comes to income, with lower income individuals being more confined within T and A with 79.1% choosing their shopping destinations only within T or only within T and A. The opposite is true for individuals with a personal income of more than £20000, where 34.9% are able to be more flexible and choose shopping destinations from all strata. Similar findings can be observed for individuals with no season ticket ownership for PT, as well. Finally, younger individuals and those with no cars in their household are more constrained in regards to their shopping destinations with less than 20% of them venturing outside their respective T and A strata.

Table 3: Sociodemographic descriptive statistics for chosen strata of shopping destinations

Sociodemographic characteristic	**Only within T (%)**	**Only within T, A (%)**	**Within T, A, C (%)**
Gender			
Male	12.2	58.6	29.2
Female	16.6	52.6	30.8
Personal income			
Below £20000	18.5	60.6	20.9
Above £20000	13.8	51.3	34.9
Age			
Below 30 years	23.5	58.1	18.4
Above 30 years	12.7	53.2	34.1
Season ticket ownership			
No	15.6	56.5	27.9
Yes	14.4	47.7	37.9
Car ownership			
No car	27.3	60.4	12.3
At least one car	11.7	52.5	35.8

For the *TAC* protocol, on average there are 76 alternatives located within T, 403 within A and 846 within C per choice task/trip. Using the *TAC* protocol, if there are not enough alternatives in T to account for the 67% of the choice set, such as in the case of a long trip with a small estimated DF and resulting DE, then alternatives from A are sampled to reach that number, in addition to sampling the pre-specified number of alternatives from stratum A (i.e. 28.2%). The remaining number of alternatives required to reach the choice set size are always sampled from C.

The sampling probabilities for the *TC* protocol are 67% from T and 33% from C, since in that case C contains all alternatives outside T. On average, there are 76 alternatives located within T and 1249 within C per choice task/trip. Contrary to *TAC*, in cases of an insufficient number of alternatives in T, the remaining alternatives are sampled from C resulting in a higher probability of including alternatives in the choice set that are not relevant to the time-space constraints of the trip and to the individual's awareness, since the *TC* protocol lacks that notion of spatial awareness ingrained in *TAC*.

The sampling probabilities for the *AC* protocol are 91.5% from A and 8.5% from C. On average, there are 468 alternatives within A and 859 alternatives within C. That sampling protocol is used to illustrate the fact that by prioritising only the spatial awareness of the individual and neglecting the time-space constraints is still not as efficient as *TAC* that incorporates both. Finally, *Random sampling* is used for comparison reasons illustrating the evident limitations of that approach and the clear advantages of importance sampling protocols using AS concepts.

For each sampling protocol examined, a set of increasing choice set sizes was tested, between 10 and 250 alternatives, examining the rates of estimate improvements *(decreasing bias in the estimates and smaller standard errors)*. Furthermore, for each choice set size per sampling protocol, five different choice set realisations were sampled and used for model estimation to assess model stability in terms of sampling standard deviation of estimated parameters and to eliminate the possibility of a lucky/unlucky draw. The estimated parameters, the standard errors and the fit statistics of the models estimated with sampled choice sets are compared with those of the full choice set model. It is expected that the sampled choice set models will produce unbiased estimates after a sufficient choice set size, meaning that parameters with only negligible differences from those of the full choice set model are obtained. The full choice set model, however, is expected to produce more efficient estimates (lower standard errors), but at the expense of higher estimation times, which in many application cases can be prohibitive. It may be noted that the *true* model used as a base for the evaluation of the sampling protocols refers to an MNL model using the full choice set. It should be stated, however, that the full choice set model should not be considered as the most accurate representation of individual shopping behaviour, but only as a *sufficient* one, since the true choice set per individual will always remain latent in the context of a spatial choice model.

4. Results

4.1. Full choice set model outputs

The MNL model using the full choice set in this case produced reasonable estimated parameters, VTT estimates and demand elasticities in accordance with official specifications as described in the following paragraphs.

4.1.1. Variable selection

The variables used in the subsequent modelling analysis can be categorised into level-of-service (LOS) and locational variables. The former capture the travel impedance to a specific destination with a specific mode of transport, while the latter aim to capture the attraction of certain characteristics of the shopping destinations. These are described in the following paragraphs.

Regarding LOS variables, travel time for car and PT and travel distance for walking were selected. For PT, travel time was segmented into in-vehicle time (IVT), first access time, last egress time and the remaining out-of-vehicle time (OVT) containing waiting time and time between transfers. The parameter for travel time was specified having the travel time for car for the shopping trip as the base and then having multipliers for the sensitivities of PT travel time components and for the travel time of the following trip in order to capture their difference with respect to the base (car time for shopping trip). A similar approach was implemented for walking distance, as well, by having the travel distance for the shopping trip as the base and then having a multiplier capturing the sensitivity difference for the following trip. For travel cost, a generic parameter was specified across modes (car/PT) and trip legs (shopping/following trip).

Characteristics of the shopping clusters and their respective surrounding areas were also defined, in buffer zones of 400m (immediate area), 400-1000m (small distances), 1000-2000m (medium distances) and 2000-5000m (large distances). Those characteristics, including parking areas and retail/commercial store areas extracted from OpenStreetMaps (OSM) and population and average residential price statistics during the years 2016-2017, were acquired from the Office for National Statistics (ONS). Specifically, the average residential prices were computed around shopping and home clusters (400m buffers - immediate area). Furthermore, the weighted price averages for home and shopping locations were discretised into quartiles to analyse whether e.g. people living in richer areas (fourth quartile of average residential prices) are willing to go shopping in poorer areas (first quartile of average residential prices) or vice versa. The rationale behind that variable specification is that the immediate environment around the home location will have an influence on the behaviour of the individual. The prior expectation was that individuals living in richer areas will have a lower probability of choosing shopping destinations located in poorer areas (Pellegrini et al., 1997).

Shopping store variability was captured using Shannon's entropy (H_k) *(Equation 10)* (Shannon, 1948; Whittaker, 1949) measuring the percentage of the area covered by specific store type $t \in T$ inside a shopping cluster k. Shannon's entropy has been widely used to quantify land-use variability mostly in studies related to walkability (Brown et al., 2009; Mavoa et al., 2018) and urban sprawl (Effat and Elshobaki, 2015). In the current study, it is used to see whether an increased variability in store types adds to the attraction of a shopping destination. A key thing to note here, is that n should refer to the total number of unique store types across all shopping clusters and not only in the cluster in question in order to ensure a proper comparison among different locations (Hajna et al., 2014). In total, 101 unique shopping store types were included in the shopping clusters based on the OSM data. The H_k calculated for each cluster k ranges from 0 to 1, with higher values denoting large store type variability and vice versa, while values around 0.5 indicate a more balanced distribution of store types within a shopping destination.

$$H_k = -\frac{\sum_{t=1}^{T}\left(p_t \ln\left(p_t\right)\right)}{\ln n} \tag{10}$$

In addition to the above, the location of the most popular retailers in the UK market per shopping type, grocery-clothes-durables, was identified across the study area and matched with the shopping clusters. For grocery shopping, the focus was on the *"Big Four"* retailers, namely Tesco, Sainsbury, Asda and Morrisons, as referred to in Rhodes (2018) and also reported in Kantar world panel (2020) website for the end of 2017, holding 70.7% of the total market share in the UK. For clothes shopping, the analysis was focused on the top 3 retailers for the year 2018/19 as reported in Retail Economics (2020) website, namely Marks & Spencer, Next and Primark. Finally, for durable shopping, the focus was on IKEA, as it is a well-established brand in that sector achieving a market share growth for the sixth consecutive year at 2017 and accounting for 8.1% market share according to their 2017 annual report (IKEA, 2017). A binary dummy variable was created for each one of the aforementioned stores based on whether they are located within a 400m buffer radius around a shopping cluster centroid.

4.1.2. Estimated parameters

The fit statistics of the full choice set model, together with the estimated parameters, their standard errors and the t-ratios are depicted in Table 4. Overall, the model achieves a high level of performance with an adjusted ρ^2 of 0.6162 and an average choice probability for correct predictions of 0.18 having a choice set of 1584 mode-destination alternatives. The main limitation that the sampling approach will aim to address is the high estimation time of more than 5 hours (using 6 cpu cores). Regarding the behavioural interpretation of the estimated parameters, it should be mentioned that, all else held equal, individuals with car ownership in their households have a positive inherent preference for car compared to PT and walking. Cost sensitivity, specified using a box-cox transformation, decreases as income increases with a sensitivity of -0.2435, which is close to the value (-0.3) proposed in Daly and Fox (2012) for non-work trips (cited in Sanko et al., 2014). Time (linear) and distance (box-cox) sensitivities of following trips are shown to be higher by 35.7% and 25.2%, respectively, than for the first shopping trip. Furthermore, time and distance sensitivities tend to decrease with the increase of shopping duration, as captured by the respective shopping duration elasticities.

Individuals living in areas of high residential prices are less likely to go shopping in areas with low residential prices, all else held equal, a finding also discussed in Pellegrini et al. (1997). Retail areas per store type (clothes shopping, groceries and other types of shopping) act as significant attractions for trips of their respective shopping types. Moreover, the presence of major retailers per shopping category, also has a positive impact on the utility function. Finally, shopping store diversity captured using the Shannon's entropy (Shannon, 1948; Whittaker, 1949) was found to be a significant attractor both in the immediate area of a shopping destination (400m buffer) and also in medium distances (1000-2000m buffer) for *O-S-D* trip chains with two consecutive shopping trips. It is acknowledged that there is an inherent uncertainty behind the reasons for making a subsequent shopping trip, since that could be a result of a pre-planned activity scheduling, of product unavailability in the first shopping destination, or simply a result of a random event (Kitamura, 1984). The final specification presented here shows that the attraction of neighbouring destinations, captured through shopping diversity, adds to the attraction of the visited destination only for cases where the individuals are going to make a subsequent shopping trip. The same was not true for cases where the following trip is for a different type of activity. That could serve as an additional indication that the choice of a daily activity plan generally precedes the mode-destination choice.

Table 4: Modelling outputs of the full choice set model

Fit statistics	**Value**		
Log-likelihood (0)	-11045.05		
Log-likelihood (model)	-4184.126		
Adjusted ρ^2	0.6162		
AIC	8478.25		
BIC	8771.96		
Number of individuals	270		
Number of observations	1541		
Estimation time (min)	322		
Average choice probability of correct prediction	0.18		
Parameter	**Estimates**	**Rob. st. errors**	**Rob. t-ratios 0** *(* t-ratios 1)*
Locational constants			
Constant rest Yorkshire	0.5494	0.1457	3.77
Households with car ownership			
Constant Car-Other (PT/walking)	-2.7299	0.2727	-10.01
Constant Other (PT/walking)-Car	-0.8606	0.2333	-3.69
Constant PT-PT	-1.0775	0.4102	-2.63
Constant PT-Walking	-1.5518	0.4712	-3.29
Constant Walking-PT	-1.2089	0.4816	-2.51
Constant Walking-Walking	0.8418	0.3635	2.32
Mode shifts for households with no car ownership			
Constant Car-Other (PT/walking)	2.3264	0.6392	3.64
Constant Other (PT/walking)-Car	0.6329	0.5990	1.06
Constant PT-PT	4.2697	0.4906	8.70
Constant PT-Walking	3.3536	0.5753	5.83
Constant Walking-PT	2.7945	0.4704	5.94
Constant Walking-Walking	2.6604	0.4069	6.54
Mode shifts for central area destinations			
PT-PT	1.7449	0.3176	5.50
PT-Walking	1.8249	0.4225	4.32
Walking-PT	2.6880	0.4682	5.74
Walking-Walking	1.6469	0.2600	6.33
Mode shifts for individuals with season ticket ownership			
Walking-Walking	-0.5606	0.3189	-1.76
Mode shifts for trips with more than 1 passenger			
PT first/shopping trip	-1.8619	0.3411	-5.46
PT following trip	-0.8646	0.3552	-2.43
Walking first/shopping trip	-0.8007	0.2265	-3.53
Walking following trip	-0.3679	0.2462	-1.50
Mode shifts for students			
Walking-Walking	1.0751	0.3783	2.84
Mode shifts for married individuals			
Walking-Walking	-0.7828	0.2866	-2.73
Mode shifts for individuals living in 3-member households			
Walking-Walking	0.6899	0.3711	1.86
LOS variables			
Travel time for first trip (base)	-0.0912	0.0090	-10.10
Travel time shift for clothes shopping	0.0265	0.0095	2.78
Travel time for O-S-O trip chains	0.0152	0.0061	2.49

Continued on next page

Table 4 – continued from previous page

Parameter	**Estimates**	**Rob. st. errors**	**Rob. t-ratios 0** *(* t-ratios 1)*
Travel time for HWH tours	-0.0445	0.0093	-4.77
Travel time multiplier for car	1.0000	–	–
Travel time multiplier for PT IVT	0.5859	0.0646	*-6.41*
Travel time multiplier for PT first access trip	0.8196	0.2195	*-0.82*
Travel time multiplier for PT last egress trip	0.6089	0.1653	*-2.37*
Travel time multiplier for PT remaining OVT	0.3535	0.1608	*-4.02*
Travel time multiplier for following trip	1.3574	0.0963	*3.71*
Travel time - Shopping duration elasticity	-0.3157	0.0307	-10.30
Travel walking distance for first trip (base)	-1.6259	0.1222	-13.30
Travel walking distance for O-S-O trip chains	0.2691	0.1118	2.41
Travel walking distance multiplier for following trip	1.2515	0.0909	*2.78*
Box-cox lambda for travel walking distance	0.8051	0.0515	*-3.79*
Travel walking distance - Shopping duration elasticity	-0.1396	0.0333	-4.19
Travel cost	-0.6518	0.0795	-8.20
Box-cox lambda for travel cost	0.5362	0.0500	*-9.27*
Travel cost - Personal income elasticity	-0.2435	0.0963	-2.53
Locational variables			
Living in rich areas-shopping in poor areas	-0.8037	0.2721	-2.95
Parking areas (400m buffer))	0.0930	0.0263	3.54
Box-cox lambda for parking areas (400m buffer)	0.4218	0.0784	*-7.38*
Presence of major clothes shopping retailers (400m buffer)	1.9623	0.2046	9.59
Presence of major grocery retailers (400m buffer)	0.5334	0.0972	5.49
Presence of major durables retailers (400m buffer)	2.0478	0.8074	2.54
Size variables			
Natural logarithm multiplier ϕ	0.7298	0.0998	*-2.71*
Population (400m buffer) (base)	1.0000	–	–
Retail areas for clothes shopping stores (400m buffer) (exp.)	0.2185	0.5238	0.42
Retail areas for grocery stores (400m buffer) (exp.)	0.6728	0.3712	1.81
Retail areas for durables/other stores (400m buffer) (exp.)	0.5873	0.7312	0.80
Shopping store variability (400m buffer) (exp.)	1.2847	0.7525	1.71
Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)	2.7750	0.6896	4.02

4.1.3. Value of Travel Time estimates and demand elasticities

Value of Travel Time (VTT) estimates and demand elasticities from the full choice set model were also computed to assess the performance of the sampling protocols. In *Table 5*, the VTT estimates of the full choice set model are presented in GBP/hour, namely the VTT for car, PT in-vehicle time, PT first access and last egress time and the remaining PT out-of-vehicle time, both for the first/shopping and the following trip. The VTTs were calculated as the ratio of the partial derivatives of the respective variable (i.e. car time, PT in-vehicle time etc.) over the partial derivative of travel cost including all of the specified parameters affecting them (i.e. shifts, elasticities etc.). Additionally, the standard errors of the VTT estimates, calculated using the *delta* method (Daly et al., 2012) are presented. All of the VTT estimates are significant at the 95% confidence level. In addition, the VTT estimates are very close to the average value suggested by the Transport Appraisal Guidance in the UK (WEBTag) for an average vehicle, namely 13.87 GBP/hour (using 2010 prices) (Department for Transport, 2014).

Demand elasticities were also calculated for the full choice set model with respect to a unit increase of travel cost and travel time, made separately for car and PT. It is assumed that the change of cost will affect both trips, i.e. shopping and following trip, since it will be an increase of fuel cost for car or a general increase

Table 5: Value of Travel Time estimates of full choice set model

VTT measure	Estimate (£/hour)	Robust st. errors
Car for first/shopping trip	10.7728	0.0349
PT IVT for first/shopping trip	9.4761	0.0331
PT first access trip for first/shopping trip	13.2542	0.0741
PT last egress trip for first/shopping trip	9.8467	0.0566
PT OVT remaining for first/shopping trip	5.7177	0.0460
Car for following trip	13.7762	0.0440
PT IVT for following trip	8.7583	0.0298
PT first access trip for following trip	12.2501	0.0687
PT last egress trip for following trip	9.1007	0.0525
PT OVT remaining for following trip	5.2846	0.0431

on PT fare and season tickets. The increase of car travel time and PT in-vehicle time is assumed to affect the accessibility to the shopping destination, hence the change is applied only on the shopping trip. Choice forecasting was computed before and after the respective change using the estimated parameters and the demand elasticities per mode and mode combination were calculated as $\frac{\log(demand_{after})}{\log(demand_{base})}/(\log(1.01))$, which are presented in *Table 6*. The total elasticities for car, PT and walking were computed by aggregating the elasticities of all the mode combinations affecting each one of those three modes.

Table 6: Demand elasticities of full choice set model

Demand elasticities	Increase of car cost (both trips)	Increase of car time (shopping trip)	Increase of PT cost (both trips)	Increase of PT IVT (shopping trip)
Car	-0.135	-0.158	0.061	0.037
PT	0.386	0.518	-0.567	-0.316
Walking	0.203	0.239	-0.019	-0.008
Car -Car	-0.163	-0.194	0.065	0.039
Car-PT	0.174	-0.427	-0.609	0.203
Car-Walking	0.103	-0.719	0.137	0.158
PT-Car	0.415	0.963	-0.742	-0.928
PT-PT	0.370	0.467	-0.847	-0.538
PT-Walking	0.401	0.602	-0.394	-0.768
Walking-Car	0.179	0.839	0.111	0.034
Walking-PT	0.401	0.530	-0.446	0.100
Walking-Walking	0.166	0.170	0.054	0.022

4.2. Sampling protocol evaluation/comparison

The evaluation of the sampling protocols is performed with regard to the fit statistics, the estimation times and the estimated parameters of the respective sampled choice set models, i.e. beta estimates, VTT estimates and demand elasticities, as described in the following paragraphs.

4.2.1. Fit statistics comparison

As a first step, the fit statistics, the estimation times of the sampled choice set models and the average choice probabilities of correct predictions are presented in *Table 7* and are compared with those of the full choice set model. In that table, it is clearly shown how estimation times increase linearly as the size of the choice set increases. The models estimated using the largest choice set size examined of 250 alternatives, i.e.

15.8% of the global choice set of 1584 alternatives, on average need almost 12% of the estimation time of the full choice set model (38 minutes compared to 322 minutes), which highlights the practical advantages of the sampling approach.

Out of all the sampling protocols examined, *Random sampling* leads to generally more deterministic models compared to the importance sampling protocols, as shown by the comparison of log-likelihood, adjusted ρ^2 and the average choice probability of correct prediction among models of the same choice set size. The main reason behind that is the fact that with the *Random sampling* protocol the choice set of size J includes the chosen alternative and $J-1$ alternatives that are randomly sampled from the remaining global choice set. That leads to inevitably including many alternatives located further away from the chosen alternative and the space around the O and D of the specific choice task/trip. As a result, these alternatives will have an increased travel time/distance/cost compared to the chosen alternative and will not provide meaningful trade-offs for the model to properly evaluate the trade-offs the individuals would consider during the decision making process. On the other hand, all of the importance sampling protocols examined provide much more balanced choice sets leading to less deterministic models with the *TAC* protocol being the most balanced approach. That is also evident from the average choice probability of correct prediction, where for the *TAC* protocol with 250 alternatives that value, 0.229, is closer to the one of the full choice set model, namely 0.18. In contrast, for the same choice set size, *TC* and *AC* achieve average choice probabilities of correct prediction of 0.266, 0.299, respectively, and the more deterministic *Random sampling* a much higher average choice probability of 0.464. Those findings serve as a first indication that importance sampling protocols and especially *TAC* will converge faster to the full choice set model compared to *Random sampling* that will require bigger choice sets.

Table 7: Fit statistics of sampling protocols

Fit statistics	**Choice set sizes**					
	10	**50**	**100**	**150**	**200**	**250**
Log-likelihood (0)	-3548.284	-6028.427	-7096.567	-7721.389	-8164.707	-8508.093
Average estimation time (min)	1.75	8.50	16.75	26.00	33.25	38.00
Random sampling						
Average Log-likelihood (model)	-194.5996	-799.467	-1268.742	-1608.966	-1877.833	-2082.2
Average adjusted ρ^2	0.9296	0.8583	0.8135	0.7845	0.7633	0.7488
Average choice probability of correct prediction	0.932	0.761	0.632	0.564	0.505	0.464
AC sampling						
Average Log-likelihood (model)	-435.7331	-1484.0916	-2091.9002	-2528.5710	-2860.0574	-3088.101
Average adjusted ρ^2	0.8617	0.7447	0.6975	0.6654	0.6475	0.6346
Average choice probability of correct prediction	0.851	0.582	0.456	0.378	0.333	0.299
TC sampling						
Average Log-likelihood (model)	-806.2441	-2021.0204	-2565.6798	-2906.7886	-3090.3342	-3236.4498
Average adjusted ρ^2	0.7573	0.6557	0.6307	0.6164	0.6148	0.6132
Average choice probability of correct prediction	0.739	0.468	0.369	0.311	0.282	0.266
TAC sampling						
Average Log-likelihood (model)	-929.5913	-2299.664	-2903.2052	-3219.2278	-3406.7728	-3555.7114
Average adjusted ρ^2	0.7225	0.6094	0.5831	0.5760	0.5759	0.5756
Average choice probability of correct prediction	0.698	0.402	0.307	0.265	0.245	0.229

4.2.2. Sampled estimate comparison

In *Table 8*, an assessment of the accuracy, stability and statistical efficiency of the estimated parameters of the sampled choice set models is depicted, together with the average distance of the sampled alternatives from the chosen one per sapling protocol. Furthermore, in *Table 9*, a comparison between the sampling protocols is presented with regard to how much better the performance on each evaluation measure is for the protocol in focus compared to the remaining three protocols. As an example, the numbers presented for *TAC-TC* comparison with regard to *AAPD* are calculated as $(AAPD_{TC} - AAPD_{TAC})/AAPD_{TAC}$. In the same Table, the number of parameters where each sampling protocol performs better is also included. In addition, the number of parameters where the average scale and the average standard error of each parameter across the sampling realisations are larger and smaller, respectively, is also presented. The assessment and the comparison of the sampling protocols is performed based on the following evaluation measures:

- *Average Absolute Bias (AAB)*, measuring the absolute difference between the *true* and sampled estimates and taking the average across the r number of sampling realisations.
- *Average Absolute Percentage Difference (AAPD)*, measuring the absolute percentage difference between the *true* and the sampled estimates and taking the average across the r number of sampling realisations. *AAPD* offers a normalised equivalent to *AAB*, which can be important when there are significant scale differences among the estimates.
- *Absolute Coefficient of Variation (ACoV)*, offering a normalised measure for capturing the stability or the lack thereof of sampling realisations per choice set size. *ACoV* is defined as the absolute value of the ratio of the sampling standard deviation over the average sampled estimate across the r number of sampling realisations. A small *ACoV* would provide the analyst the certainty that a following sampling realisation would still result in similar estimates.
- *Average Standard Error*, calculated as the average of the robust standard errors across the r number of sampling realisations per parameter with the purpose of assessing the statistical efficiency of the sampling protocols.
- *Improvement rates*, calculated from linear regressions per parameter and for each of the four previously-defined evaluation measures across the six choice set sizes examined. A higher improvement rate (more negative) indicates that the sampling protocol will benefit more by further increasing the size of the choice set.

With regard to the average straight distance between the sampled and the chosen alternatives, *Random sampling* results in sampled alternatives with similar average distances from the chosen alternatives regardless of the choice set size, since the alternatives are sampled with a uniform probability from the global choice set. The sampled alternatives in the *AC* protocol have a smaller average distance from the chosen alternative compared to the *TC* protocol due to the bigger size of the SDEs/FBs offering a sufficient pool of alternatives to sample from without the need of further sampling from C. The higher average distance of alternatives in the *TC* protocol is in accordance with our initial hypotheses that this specific protocol will result in having an increased number of spatially irrelevant alternatives to the chosen one. On the other hand, the *TAC* protocol, with the addition of SDE/FB spaces, manages to provide choice sets with a smaller average distance between sampled and chosen alternatives leading to less deterministic models and to average probabilities for the chosen alternatives that are closer to those of the *true* model (0.18), as shown in *Table 7*. That finding supports the idea of the current study, that an additional space is required around the DEs in order to sample more spatially relevant alternatives for the respective choice task. The role of the additional stratum A in the *TAC* protocol is to provide a further structure of sampling for the remaining alternatives and to minimise the inclusion of spatially irrelevant alternatives that will not provide a meaningful trade-off comparison for the model.

In general, the three stratified importance sampling protocols, namely *AC*, *TC* and *TAC*, perform significantly better than *Random sampling* given the choice set size. The average rates of improvement for all evaluation measures for the *Random sampling* are higher compared to those of the importance sampling protocols meaning that the performance of *Random sampling* models would benefit more with increased choice set sizes. That is a further indication that using *Random sampling* would require a higher choice set size to achieve the same level of accuracy compared to an importance sampling approach. On average, *TAC* leads to 98.9%-242.6% lower *AAPD* and more than 51 out of 55 better estimated parameters than *Random sampling*. *TC* leads to slightly less improvements with 85.3%-206.9% lower *AAPD*, and 48-52 better estimated parameters. Finally, AC leads to 48.4%-120.1% lower $AAPD$ and 41-51 better estimated parameters. Sampling stability, as captured by the $ACoV$, provides similar conclusions with TAC showing the most significant improvements compared to *Random sampling*, followed by TC and AC.

An interesting finding can be discerned by examining the *average standard errors* across sampling protocols. Importance sampling protocols generally achieve lower standard errors for their estimated parameters, while *Random sampling* protocol generally leads to larger parameter scales, as shown in *Table 9*, which is indicative of its more deterministic nature. As the choice set sizes keep increasing, the standard errors in Random sampling models decrease, but their bias compared to the estimates of the full choice set model still remain high. As a result, at a choice set of 10 alternatives, only 25 out of 55 of the estimated parameters from *Random sampling* are statistically significant at the 95% confidence level, while at a choice set size of 250 alternatives 45 out of 55 parameters are statistically significant, which are as many as in TAC. The bias, however, for *Random sampling* with 250 alternatives still remains almost three times higher than TAC. A possible explanation could be that as the number of alternatives in the choice set of *Random sampling* models increases, the estimated parameters get closer to the true statistical value of the *Random sampling* models and with lower standard errors. That true statistical value of those models, however, is different from the parameter value of the full choice set model, as shown by the high bias still remaining even for the largest choice set size tested in that study. In a practical setting with the absence of a full choice set model to properly evaluate the performance of the chosen sampling protocol, the analyst can potentially make a false assessment of the behavioural model, which in turn can have severe policy implications both during interpretation and application.

Regarding the three importance sampling protocols, their differences are less stark, but clear trends can still be observed. Both TAC and TC outperform AC in all evaluation measures. On average, TAC is by 34%-111.3% and by 75.2%-106.6% better than AC in terms of $AAPD$ and $ACoV$, respectively, for choice sets with more than 10 alternatives. In a similar notion, TC is by 24.9%-57.7% and by 29.6%-91.7% better for the same evaluation measures and choice set sizes than AC.TAC models are generally more accurate and stable than their TC counterparts with an average 7.3%-33.9% lower $AAPD$ and 0.6%-38.5& lower $ACoV$ for choice sets with more than 10 alternatives. TC achieves its most comparable performance with TAC and significantly outperforms AC at a choice set size of 100 alternatives. A possible explanation is that, on average, there are 76 alternatives in stratum T meaning that at a choice set size of 100, there are enough alternatives in stratum T to sample from in order to reach the required number of alternatives, i.e. $0.67 * 100 = 67$ alternatives from that stratum, without replenishing them from C. After that choice set size, however, there is the need to sample further alternatives from C reducing the performance of the estimated sampled models. That is also evident from the performance of the evaluation measures of TC, where for a choice set of 100 alternatives, TC models perform only marginally worse than TAC. After that point, however, TAC models manage to increase their performance gap from TC, going from an average of 7.3% to a 33.9% lower $AAPD$, for 250 alternatives, and from 30 to 41 better estimated parameters. The increasing inclusion of worse alternatives in the choice set has an impact on stability, as well, with TAC models going from a mere 0.6% better $ACoV$, for 100 alternatives, to a much higher 38.5%, for 250 alternatives. Furthermore, that is captured in the average improvement rates of $AAPD$ and $ACoV$, where TAC shows higher decreasing rates than TC, meaning that it can still benefit more by increasing the choice set despite being already more accurate and stable than TC. Based on that finding, a reverse-engineering approach can be implemented, where the analyst can get a rough approximation of the optimal choice set size per sampling protocol by examining the average number of alternatives within the stratum that she wants to prioritise.

Regarding the choice set size, there is not any guideline as to which percentage of the full choice set is required to estimate stable parameters with insignificant bias. Therefore, the required choice set size should be viewed as case-specific and be carefully examined by the analyst. *Figure 6* provides a graphical representation of *Table 7* and can be used to identify the minimum required choice set to achieve estimate accuracy and stability. In the current study, it seems that even after a choice set of 50 alternatives, there are significant improvements in estimate accuracy and stability for the importance sampling protocols. *Random sampling*, however, needs at least 150 alternatives to show more consistently accurate estimates. The improvements on the four evaluation measures tend to slow down after 150 alternatives and for each subsequent choice set size for all sampling protocols. In the same Figure, a clear verdict can be made about the benefits of the proposed importance sampling protocols using AS concepts compared to *Random sampling*, which performs significantly worse across all four evaluation measures.

Table 8: Estimate evaluation of sampling protocols

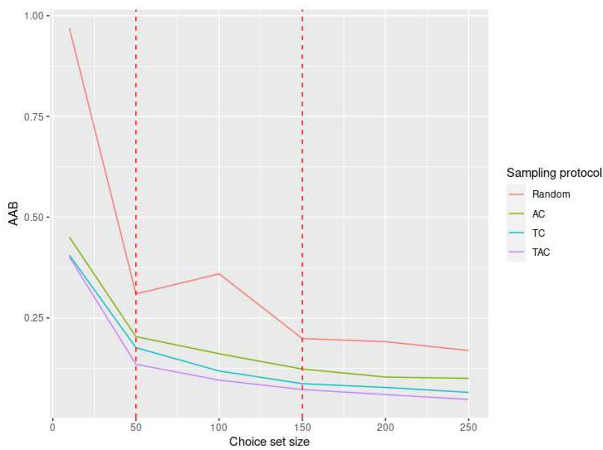
Evaluation measure	**Choice set sizes**						**Average rate of improvement**
	10	**50**	**100**	**150**	**200**	**250**	
Random sampling							
Average distance from chosen alternative (m)	14908	14875.2	14888	14812.2	14819.8	14797.6	–
Average AAB	0.9691	0.3096	0.3593	0.1987	0.1910	0.1690	-0.1291
Average AAPD	1.0502	0.3658	0.3852	0.2328	0.2071	0.1888	-0.1401
Average ACoV	2.8367	0.3710	0.3384	0.2230	0.1660	0.1436	-0.4001
Average st.errors	0.9249	0.4663	0.3738	0.3443	0.3348	0.3154	-0.1311
AC sampling							
Average distance chosen alternative (m)	8424.1	8457.4	9200.6	10014.6	10533.8	11023.2	–
Average AAB	0.4504	0.2035	0.1610	0.1231	0.1032	0.1000	-0.0598
Average AAPD	0.4984	0.2465	0.1750	0.1417	0.1187	0.1164	-0.0665
Average ACoV	0.5769	0.2001	0.1670	0.1337	0.1095	0.0879	-0.0767
Average st.errors	0.6106	0.3613	0.3405	0.3184	0.3110	0.3044	-0.0547
TC sampling							
Average distance from chosen alternative (m)	8495	11138.2	12642.2	13382	13842	14120.8	–
Average AAB	0.4058	0.1760	0.1183	0.0868	0.0774	0.0653	-0.0580
Average AAPD	**0.4980**	0.1974	0.1255	0.0996	0.0931	0.0738	-0.0703
Average ACoV	**0.3491**	0.1385	**0.0871**	0.0790	0.0845	0.0644	-0.0459
Average st.errors	0.4741	0.3382	0.3149	**0.3056**	**0.2983**	**0.2917**	-0.0345
TAC sampling							
Average distance from chosen alternative (m)	**5124**	**7045.2**	**8164.6**	**8818.2**	**9527.8**	**10083**	–
Average AAB	**0.4012**	**0.1349**	**0.0955**	**0.0722**	**0.0597**	**0.0476**	-0.0576
Average AAPD	0.5020	**0.1839**	**0.1170**	**0.0874**	**0.0784**	**0.0551**	-0.0740
Average ACoV	0.4399	**0.1137**	0.0876	**0.0647**	**0.0625**	**0.0465**	-0.0613
Average st.errors	**0.4374**	**0.3266**	**0.3122**	0.3061	0.3020	0.3017	-0.0245

The best-performing sampling protocol per choice set size and evaluation measure is highlighted
Notation: AAB: Average Absolute Bias; AAPD: Average Absolute Percentage Difference;
ACoV: Absolute Coefficient of Variation

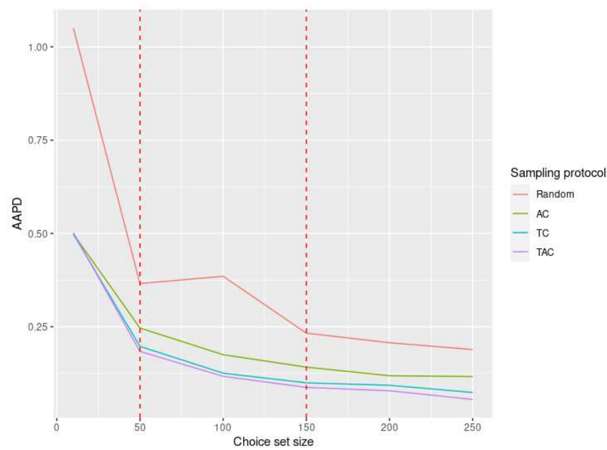
Table 9: Comparison of sampling protocols

Protocols compared	Choice set sizes 10	50	100	150	200	250
TAC-TC						
Average AAB	1.2% (31)	30.5% (35)	23.9% (30)	11.9% (35)	29.6% (37)	37.2% (41)
Average AAPD	-0.8% (31)	7.3% (35)	7.3% (30)	10.5% (35)	18.8% (37)	33.9% (41)
Average ACoV	-20.6% (27)	21.8% (35)	0.6% (33)	22.1% (27)	35.2% (30)	38.5% (33)
Parameter scales	-12.0 (30)	1.3% (21)	-3.5% (23)	1.0% (27)	0.5% (30)	-1.4% (21)
Standard errors	7.2% (41)	1.7% (34)	0.4% (27)	0.3% (26)	-0.9% (22)	-1.2% (25)
TAC-AC						
Average AAB	12.3% (36)	50.8% (45)	68.6% (42)	70.5% (44)	72.9% (45)	110.1% (51)
Average AAPD	-0.7% (36)	34.0% (45)	49.6% (42)	62.1% (44)	51.4% (45)	111.3% (51)
Average ACoV	31.1% (27)	76.0% (38)	90.6% (39)	106.6% (36)	75.2% (32)	89.0% (35)
Parameter scales	-19.7% (24)	-7.6% (27)	-5.5% (30)	-2.0% (31)	-1.0% (27)	-0.8% (25)
Standard errors	36.9% (51)	12.7% (48)	10.0% (51)	6.3% (46)	4.7% (48)	3.4% (48)
TAC-Random						
Average AAB	141.6% (53)	129.5% (51)	276.2% (54)	175.2% (51)	219.9% (51)	255.0% (55)
Average AAPD	109.2% (53)	98.9% (51)	229.2% (54)	166.4% (51)	164.2% (51)	242.6% (55)
Average ACoV	544.9% (29)	226.3% (32)	286.3% (32)	244.7% (33)	165.6% (33)	208.8% (36)
Parameter scales	97.2% (26)	-3.5% (23)	2.9% (28)	-3.5% (28)	-6.2% (27)	-8.2% (27)
Standard errors	93.5% (53)	40.5% (51)	22.2% (49)	15.6% (49)	12.4% (47)	7.6% (43)
TC-AC						
Average AAB	11.0% (35)	15.6% (35)	36.1% (44)	41.8% (39)	33.3% (37)	53.1% (43)
Average AAPD	0.1% (35)	24.9% (35)	39.4% (44)	42.3% (39)	27.5% (37)	57.7% (43)
Average ACoV	65.3% (27)	44.5% (35)	91.7% (34)	69.2% (31)	29.6% (32)	36.5% (34)
Average RMSE	28.8% (51)	6.8% (47)	8.4% (48)	4.6% (46)	4.2% (46)	4.5% (45)
Parameter scales	-16.0% (26)	-20.0% (32)	-2.7% (33)	-3.7% (28)	-2.0% (25)	-1.4% (28)
Standard errors	29.1% (51)	12.2% (47)	10.4% (48)	6.5% (46)	5.9% (46)	5.0% (45)
TC-Random						
Average AAB	138.8% (49)	75.9% (48)	203.7% (52)	128.9% (49)	146.8% (51)	158.8% (52)
Average AAPD	110.9% (49)	85.3% (48)	206.9% (52)	133.7% (49)	122.4% (51)	155.8% (52)
Average ACoV	712.6% (28)	167.9% (30)	288.5% (33)	182.3% (33)	96.4% (32)	123.0% (35)
Parameter scales	-34.9% (28)	-13.3% (27)	6.0% (28)	4.3% (32)	-7.3% (26)	-6.7% (29)
Standard errors	87.0% (53)	39.6% (52)	22.5% (49)	15.6% (50)	13.7% (49)	8.9% (45)
AC-Random						
Average AAB	115.2% (51)	52.1% (47)	123.2% (46)	61.4% (41)	85.1% (49)	69.0% (45)
Average AAPD	110.7% (51)	48.4% (47)	120.1% (46)	64.3% (41)	74.5% (49)	62.2% (45)
Average ACoV	391.7% (29)	85.4% (23)	102.6% (28)	66.8% (34)	51.6% (32)	63.4% (26)
Parameter scales	51.7% (25)	4.4% (23)	15.3% (23)	-0.6% (27)	-5.4% (29)	-6.7% (31)
Standard errors	64.4% (50)	23.1% (50)	11.0% (46)	8.4% (46)	7.0% (44)	3.9% (39)

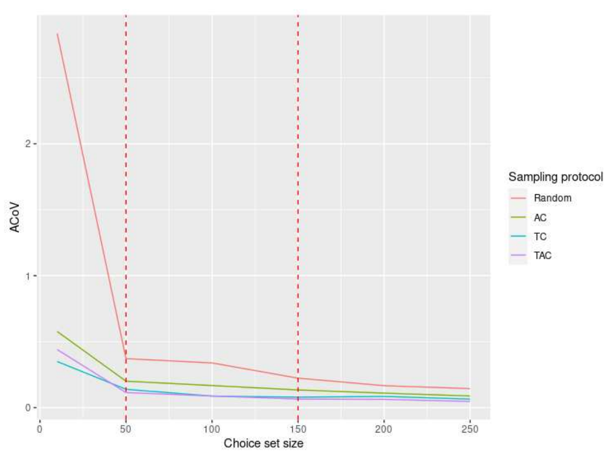
The number in parenthesis denotes the number of parameters with lower evaluation measure for the sampling protocol in focus out of a total of 55 parameters
Notation: AAB: Average Absolute Bias; AAPD: Average Absolute Percentage Difference; ACoV: Absolute Coefficient of Variation



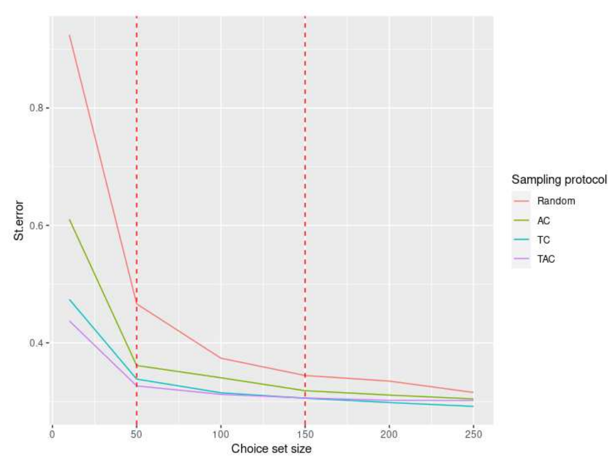
(a) AAB



(b) AAPD



(c) ACoV



(d) St.errors

Figure 6: Improvements of evaluation measures across sampling protocols and choice set sizes *(AAB: Average Absolute Bias; AAPD: Average Absolute Percentage Difference; ACoV: Absolute Coefficient of Variation)*

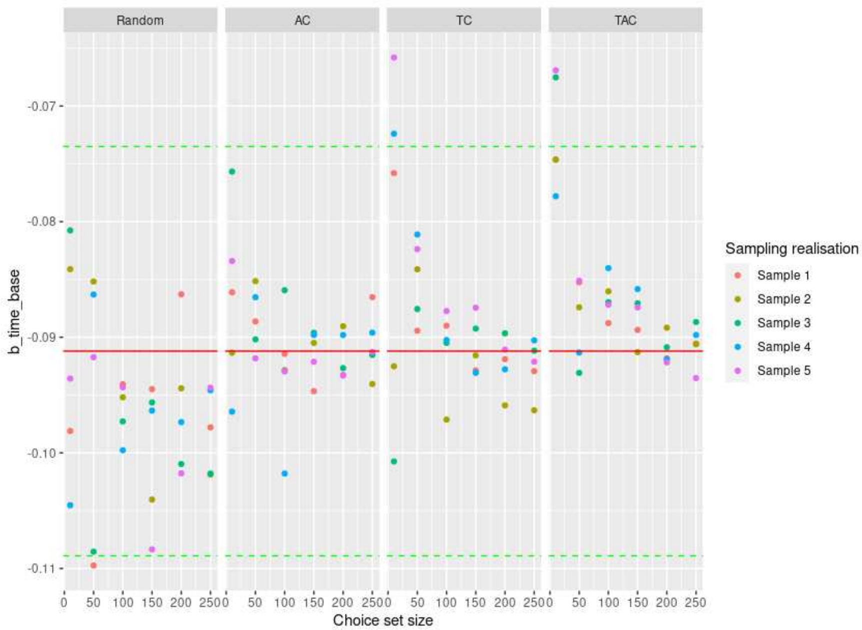


Figure 7: Plots for β_{time}^{base} estimates for each sampling realisation across sampling protocols

A visual representation of the sampled estimates and how they improve with the increase of the choice set is depicted in *Figures 7 and 8* focusing on two of the most important parameters from a policy perspective, namely β_{time}^{base} and β_{cost}^{base}, respectively. In those Figures, it can be seen how the sampled estimates across the five realisations tend to concentrate around the *true* value (red horizontal line) as the choice set size increases (green dashed lines represent the 95% confidence interval of the *true* value). Detailed tables depicting the average estimates and the evaluation measures per parameter across the five realisations per sampling protocol and choice set size can be found in the supplementary material provided in the *Appendix*.

4.2.3. Evaluation of sampled VTT estimates and demand elasticities

In *Table 10*, a comparison is performed with the VTT estimates of the full choice set model by calculating the *AAB*, *AAPD*, *ACoV* and *average standard errors*, as defined earlier, while *Table 11* depicts a comparison between sampling protocols. The three importance sampling protocols, on average, have a less than 1£/hour difference from the *true* VTTs for choice sets with more than 100 alternatives, while VTTs derived from *Random sampling* are significantly more biased. *TC* manages to outperform the remaining protocols and achieves the best performance with 100 alternatives. For that choice set size, it performs significantly better even than *TAC* by having more than 30% lower *AAB* and *AAPD*, 28.5% lower *ACoV* and 9 out of 10 better estimated VTTs. The performance of *TC*, however, deteriorates as the choice set size increases and inevitably more spatially irrelevant alternatives are included, reaching the point of an almost equal performance with *TAC* for 250 alternatives. Time and cost-related parameters that influence the VTT estimation show an equal performance between *TAC* and *TC*, in contrast to the remaining parameters where *TAC* excels, and that is the reason behind the good overall performance of *TC* for VTTs. The previous finding regarding the decrease of standard errors for *Random sampling* models with the gradual increase of the choice set size, is evident here, as well. More specifically, at a choice set of 10 alternatives, only 4 out 10 VTT estimates are statistically significant at the 95% confidence level. At a choice set size of 250 alternatives, however, due to the decrease of the standard errors, that number increases to 8 out of 10 VTTs, while their difference from the VTTs of the full choice set model still remains noticeably higher than the remaining sampling protocols and more than twice as high than *TAC*.

Demand elasticities estimated from sampled models are assessed in *Table 12* and a performance comparison between sampling protocols is presented in *Table 13*. Contrary to the VTT estimates, the estimation of demand elasticities with *TAC* is much more accurate than *TC*, since in that context all of the 55 parameters

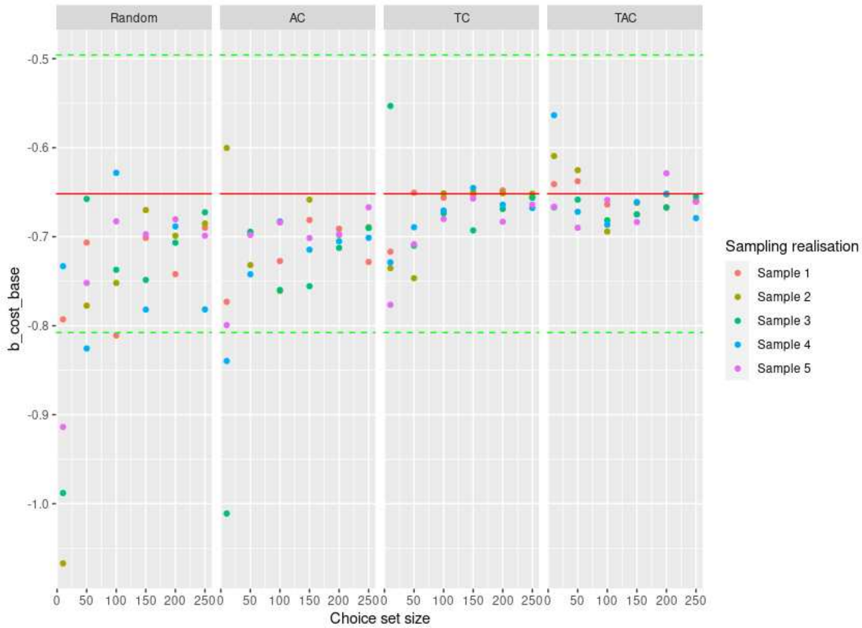


Figure 8: Plots for β_{cost}^{base} estimates for each sampling realisation across sampling protocols

Table 10: Evaluation of VTT estimates of sampling protocols

Evaluation measure	**Choice set sizes**						**Average rate of improvement**
	10	**50**	**100**	**150**	**200**	**250**	
Random sampling							
Average AAB (£/hour)	4.5384	2.0949	1.7056	1.2674	1.1843	1.0772	-0.5850
Average AAPD	0.5108	0.2318	0.1979	0.1498	0.1286	0.1222	-0.0657
Average ACoV	0.4905	0.2392	0.2490	0.1756	0.0929	0.1314	-0.0660
Average st.error	0.1144	0.0697	0.0596	0.0535	0.0545	0.0492	-0.0117
AC sampling							
Average AAB (£/hour)	3.4104	1.4050	1.2356	0.9829	0.8192	0.8003	-0.4303
Average AAPD	0.3544	0.1728	0.1391	0.1048	0.0880	0.0878	-0.0463
Average ACoV	0.4004	0.2063	0.1536	0.1164	0.0840	0.0695	-0.0588
Average st.error	0.0876	0.0558	0.0515	0.0505	**0.0488**	**0.0479**	-0.0067
TC sampling							
Average AAB (£/hour)	2.2496	1.1970	**0.7061**	**0.5570**	**0.4921**	**0.3972**	-0.3293
Average AAPD	0.2475	0.1261	**0.0781**	**0.0623**	**0.0559**	**0.0435**	-0.0356
Average ACoV	**0.2224**	**0.0885**	**0.0862**	**0.0658**	**0.0697**	0.0492	-0.0269
Average st.error	**0.0697**	**0.0518**	0.0516	0.0522	0.0491	0.0489	-0.0033
TAC sampling							
Average AAB (£/hour)	**1.5254**	**1.0395**	1.0281	0.7506	0.5209	0.4458	-0.2066
Average AAPD	**0.1754**	**0.1239**	0.1267	0.0826	0.0650	0.0501	-0.0242
Average ACoV	0.2351	0.1381	0.1205	0.0882	0.0754	**0.0386**	-0.0344
Average st.error	0.0711	0.0558	**0.0496**	**0.0498**	0.0505	0.0486	-0.0039

The best-performing sampling protocol per choice set size and evaluation measure is highlighted
Notation: AAB: Average Absolute Bias; AAPD: Average Absolute Percentage Difference;
ACoV: Absolute Coefficient of Variation

Table 11: VTT comparison of sampling protocols

Protocols compared	**Choice set sizes**					
	10	**50**	**100**	**150**	**200**	**250**
TAC-TC						
Average AAB	47.5% (9)	15.2% (6)	-31.3% (1)	-25.8% (3)	-5.5% (7)	-10.9% (5)
Average AAPD	41.1% (9)	1.8% (6)	-38.4% (1)	-24.6% (3)	-14.0% (7)	-13.2% (5)
Average ACoV	-5.4% (5)	-35.9% (4)	-28.5% (3)	-25.4% (4)	-7.6% (3)	27.5% (6)
Average st.error	-2.8% (3)	-7.1% (0)	4.0% (8)	4.6% (8)	-13.7% (2)	0.6% (7)
TAC-AC						
Average AAB	123.6% (10)	35.2% (8)	20.2% (5)	30.9% (7)	57.3% (8) (9)	79.5% (7)
Average AAPD	102.1% (10)	39.5% (8)	9.8% (5)	26.9% (7)	35.4% (8) (9)	75.2% (7)
Average ACoV	70.3% (9)	49.4% (8)	27.5% (7)	32.0% (9)	11.4% (7) (8)	80.1% (10)
Average st.error	24.9% (10)	0.2% (4)	3.8% (5)	1.4% (5)	-14.2% (2) (6)	-1.2% (4)
TAC-Random						
Average AAB	197.5% (10)	101.5% (10)	65.9% (10)	68.9% (9)	127.4% (9)	141.6% (10)
Average AAPD	191.2% (10)	87.1% (10)	56.2% (10)	81.4% (9)	97.8% (9)	143.9% (10)
Average ACoV	108.6% (10)	73.2% (8)	106.6% (10)	99.1% (8)	23.2% (8)	240.4% (10)
Average st.error	67.0% (10)	25.4% (9)	21.1% (10)	7.6% (6)	-4.2% (6)	1.6% (4)
TC-AC						
Average AAB	51.6% (8)	17.4% (6)	75.0% (8)	76.5% (9)	66.5% (9)	101.5% (9)
Average AAPD	43.2% (8)	37.0% (6)	78.1% (8)	68.2% (9)	57.4% (9)	101.8% (9)
Average ACoV	80.0% (8)	133.1% (7)	78.2% (6)	76.9% (8)	20.5% (7)	41.3% (9)
Average st.error	28.4% (10)	7.9% (8)	-0.2% (4)	-3.1% (4)	-0.6% (4)	-1.8% (4)
TC-Random						
Average AAB	101.7% (9)	75.0% (9)	141.6% (10)	127.5% (9)	140.7% (9)	171.2% (10)
Average AAPD	106.4% (9)	83.8% (9)	153.4% (10)	140.4% (9)	130.1% (9)	180.9% (10)
Average ACoV	120.5% (10)	170.3% (10)	188.9% (10)	166.9% (10)	33.3% (8)	167.1% (9)
Average st.error	71.7% (10)	35.0% (10)	16.4% (10)	2.9% (5)	11.0% (7)	1.0% (4)
AC-Random						
Average AAB	33.1% (9)	49.1% (8)	38.0% (10)	28.9% (8)	44.6% (6)	34.6% (8)
Average AAPD	44.1% (9)	34.1% (8)	42.3% (10)	42.9% (8)	46.1% (6)	39.2% (8)
Average ACoV	22.5% (9)	15.9% (6)	62.1% (10)	50.9% (8)	10.6% (6)	89.1% (9)
Average st.error	33.7% (10)	25.1% (10)	16.7% (10)	6.1% (7)	11.7% (9)	2.9% (6)

The number in parenthesis denotes the number of estimated VTTs with lower evaluation measure for the sampling protocol in focus out of a total of 10 VTT estimates
Notation: AAB: Average Absolute Bias; AAPD: Average Absolute Percentage Difference; ACoV: Absolute Coefficient of Variation

take part during their calculation and not just the time and cost-related parameters. As already mentioned, *TC* achieves its best performance for a choice set of 100 alternatives, but even in that case, *TAC* achieves a 16.8% lower *AAB*, a 20.3% lower *AAPD* and 33 out of 48 better estimated elasticities, but also less stable estimates with 4.5% higher *ACoV*. As the choice set size increases, however, the performance gap for *TAC* shoes gradual improvements reaching a 47.3% lower *AAB*, a 64.2% lower *AAPD*, 39 out of 48 better estimated elasticities and a 18% lower *ACoV*, for a choice set of 250 alternatives. *AC* performs worse than the other two importance sampling protocols, but still better than *Random sampling*. *TAC* shows the largest performance improvements compared to *Random sampling*, almost 1.5 times more than *TC* and 2.5 times more than *AC*. The overall better forecasting ability of *TAC* is indicative of the less deterministic models derived from that sampling protocol (see *Table 7*). The impact that this might have in a practical application presents a clear verdict in favour of combining DEs and SDEs/FBs for importance sampling and not neglecting the latter.

Table 12: Evaluation of demand elasticities of sampling protocols

Evaluation measure	**Choice set sizes**						**Average rate**
	10	**50**	**100**	**150**	**200**	**250**	**of improvement**
Random sampling							
Average AAB	0.2455	0.1589	0.1133	0.0885	0.0740	0.0615	-0.0343
Average AAPD	0.7593	0.5032	0.3911	0.2968	0.2647	0.2257	-0.0994
Average ACoV	0.5224	0.1962	0.1414	0.1055	0.1042	0.0936	-0.0702
AC sampling							
Average AAB	0.2208	0.1077	0.0703	0.0507	0.0367	0.0316	-0.0337
Average AAPD	0.6794	0.3386	0.2335	0.1607	0.1277	0.1028	-0.1025
Average ACoV	0.3542	0.1113	0.1190	0.0807	0.0589	0.0532	-0.0486
TC sampling							
Average AAB	0.1890	0.0888	0.0480	0.0367	0.0275	0.0249	-0.0290
Average AAPD	0.5716	0.2631	0.1530	0.1140	0.0914	0.0852	-0.0853
Average ACoV	**0.2219**	0.1003	**0.0617**	0.0606	0.0528	0.0406	-0.0300
TAC sampling							
Average AAB	**0.1850**	**0.0716**	**0.0411**	**0.0280**	**0.0189**	**0.0169**	-0.0289
Average AAPD	**0.5614**	**0.2157**	**0.1272**	**0.0873**	**0.0651**	**0.0519**	-0.0868
Average ACoV	0.2449	**0.0732**	0.0646	**0.0398**	**0.0409**	**0.0344**	-0.0335

The best-performing sampling protocol per choice set size and evaluation measure is highlighted
Notation: AAB: Average Absolute Bias; AAPD: Average Absolute Percentage Difference;
ACoV: Absolute Coefficient of Variation

5. Conclusions

The paper proposes a novel stratified importance sampling protocol based on concepts from the activity space literature to overcome the computational challenges associated with the estimation of a joint mode-destination choice model in a behaviourally realistic manner. The results indicate that the proposed importance sampling protocol, *TAC*, combining both DEs and SDEs/FBs, is capable of achieving a better balance between estimate accuracy, sampling stability and statistical efficiency compared to the other importance sampling protocols examined and especially compared to *Random sampling*, also leading to improvements in VTT estimation and demand forecasting. Furthermore, *TAC*-derived models avoid overfitting by more closely matching the average choice probabilities for correct predictions of the *true* model. The results hint to the fact that *Random sampling* will benefit more by an increased choice set size compared to the importance sampling protocols, since more spatially relevant alternatives would be required to achieve the same level of accuracy and stability.

A general recommendation regarding the choice set size, relative to the full choice set, in order to achieve stable and sufficiently accurate estimates cannot be made, since this is generally case-specific, but also specific to the sampling protocol employed, as showed in the current study with the performance of *TC*. As a general

Table 13: Demand elasticity comparison of sampling protocols

Protocols compared	**Choice set sizes**					
	10	**50**	**100**	**150**	**200**	**250**
TAC-TC						
Average AAB	2.2% (33)	24.0% (35)	16.8% (33)	31.1% (38)	45.5% (36)	47.3% (39)
Average AAPD	1.8% (33)	22.0% (35)	20.3% (33)	30.6% (38)	40.4% (36)	64.2% (39)
Average ACoV	-9.4% (26)	37.0% (40)	-4.5% (18)	52.3% (37)	29.1% (37)	18.0% (30)
TAC-AC						
Average AAB	19.4% (42)	50.4% (44)	71.0% (40)	81.1% (43)	94.2% (44)	87.0% (42)
Average AAPD	21.0% (42)	57.0% (44)	83.6% (40)	84.1% (43)	96.2% (44)	98.1% (42)
Average ACoV	44.6% (34)	52.0% (38)	84.2% (42)	102.8% (43)	44.0% (38)	54.7% (37)
TAC-Random						
Average AAB	32.7% (42)	121.9% (46)	175.7% (46)	216.1% (47)	291.5% (45)	263.9% (46)
Average AAPD	35.3% (42)	133.3% (46)	207.5% (46)	240.0% (47)	306.6% (45)	334.9% (46)
Average ACoV	113.3% (39)	168.0% (44)	118.9% (45)	165.1% (46)	154.8% (42)	172.1% (42)
TC-AC						
Average AAB	16.8% (45)	21.3% (36)	46.5% (41)	38.1% (39)	33.5% (30)	26.9% (33)
Average AAPD	18.9% (45)	28.7% (36)	52.6% (41)	41.0% (39)	39.7% (30)	20.7% (33)
Average ACoV	59.6% (33)	11.0% (24)	92.9% (44)	33.2% (33)	11.6% (23)	31.0% (36)
TC-Random						
Average AAB	29.9% (46)	78.9% (45)	136.0% (48)	141.1% (47)	169.1% (44)	147.0% (47)
Average AAPD	32.8% (46)	91.3% (45)	155.6% (48)	160.4% (47)	189.6% (44)	164.9% (47)
Average ACoV	135.4% (43)	95.6% (39)	129.2% (42)	74.1% (45)	97.3% (38)	130.5% (43)
AC-Random						
Average AAB	11.2% (43)	47.5% (46)	61.2% (45)	74.6% (45)	101.6% (46)	94.6% (44)
Average AAPD	11.8% (43)	48.6% (46)	67.5% (45)	84.7% (45)	107.3% (46)	119.6% (44)
Average ACoV	47.5% (41)	76.3% (39)	18.8% (31)	30.7% (29)	76.9% (41)	75.9% (36)

The number in parenthesis denotes the number of demand elasticities with lower evaluation measure for the sampling protocol in focus out of a total of 48 estimates
Notation: AAB: Average Absolute Bias; AAPD: Average Absolute Percentage Difference;
ACoV: Absolute Coefficient of Variation

rule of thumb, though, it could be suggested that having only gradual improvements in estimate accuracy and stability can serve as a sufficient indication of reaching the optimal choice set size. In a practical setting, however, with the absence of a full choice set model to properly assess sampled model accuracy, sampling stability can be considered as a more appropriate evaluation measure.

The current study does not claim that the proposed AS-based importance sampling protocols are the most effective ones, since the main focus was simply to address the limitations identified in the relevant literature. In future research, the problem of finding the most effective sampling protocol for reducing the choice set size in a destination choice problem of discretionary activities can be formalised as an optimisation problem analysing to what extend the three importance sampling protocols might be more suitable for specific trips/choice tasks or for specific individuals based on their observed behaviour. Future studies should also acknowledge the intricate complications of destination choice of discretionary activities (time-space constraints and travel impedance) that differentiates it from a residential location problem. It will be also interesting to compare the predictive performance of the models with approaches that are independent of the spatial form, such as the *"location repertoire"* approach suggested by Ordonez-Medina (2015).

The benefit of the dataset used in the current study is that it presents a combination of a traditional household survey and GPS tracking providing a wealth of observed behaviour to the researcher. Nonetheless, one of its limitations is arguably its small survey duration (2 weeks) that could have an impact on the accurate calculation of the SDE/FB. Therefore, future studies on datasets of longer duration, such as the 6-week Mobidrive dataset (Axhausen et al., 2002) and the more recent 2-month Mobis survey (Molloy et al., 2021), are essential in order to assess the impact of survey duration on the SDE/FB formation and the proposed sampling protocols.

Furthermore, the current paper focused on reducing the computational complexity of the full choice set model. Future studies should also try to incorporate the described notions of Activity Spaces in modelling frameworks focusing this time on the other approach of choice set specification, i.e. that of understanding the underlying choice mechanisms and decomposing the problem into the choice of a consideration set and the choice of a mode-destination alternative. Inspired by the study of Thill and Horowitz (1997a) utilising a simplification of the Manski model, a latent class choice model (LCCM) can be specified by allocating probabilistically individuals into latent strata defined by T, A and C, while sampling of alternatives could also be performed for the aforementioned LCCM framework as a further extension.

Finally, the current study showcases that emerging data sources, such as GPS, can be effectively used for the specification-estimation of behavioural models. The increased spatial and temporal resolution of new emerging data sources can help researchers to overcome the data limitations of the past and holds the promise of providing a better understanding of the constraints the individuals face during their daily mobility that could be leveraged to further enhance current modelling specifications or even spur the need for developing new ones.

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Appendix

Table 14: Glossary of terms in alphabetical order

Acronym	**Explanation**
A	Stratum delineated by the standard deviation ellipse per individual excluding the alterantives in A
AAB	Average Absolute Bias
AAPD	Average Asbolute Percentage Difference
AC	Sampling protocol incorporating strata A and C
ACoV	Absolute Coefficient of Variation
API	Application Programming Interface
AS	Activity Space
C	Stratum including the remaining alterantives from the global choice set after excluding the ones within T and A
DE	Detour Ellipse
DF	Detour Factor
GEV	Generalised Extreme Value distribution
GPS	Global Positioning System
HWH	Home-Work-Home tour including a commuting trip to primary workplace
IVT	In Vehicle Time for Public Transport
LCCM	Latent Class Choice Model
LOS	Level Of Service variables
MLE	Maximum Likelihood Estimation
MNL	Multinomial Logit model
OD	Origin-Destination
ONS	Office for National Statistics
O-S-D	Trip chain of Origin-Shopping-Destination
O-S-O	Simple trip chain of Origin-Shopping-Origin
OSM	OpenStreetMaps
OVT	Out of Vehicle Time for Public Transport
PPA	Potential Path Area
PT	Public Transport
rmse	Root Mean Square Error
SC	Sampling Correction term
SDE	Standard Deviational Ellipse
T	Stratum delineated by the estimated detour ellipses
TAC	Sampling protocol incorporating strata T, A and C
TC	Sampling protocol incorporating strata T and C
VTT	Values of Travel Time estimates

Table 15: Evaluation of Random sampling protocol for choice sets of 10, 50 and 100 alts

Parameter	10 alts				50 alts				100 alts			
	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.
Locational constants												
Constant rest Yorkshire	1.4167	1.5786	0.3390	0.4765	1.0374	0.8881	0.1121	0.2229	0.8557	0.5574	0.1413	0.1779
Households with car ownership												
Constant Car-Other (PT/walking)	-3.0689	0.3531	0.4242	0.8341	-2.7741	0.0864	0.1138	0.4461	-2.7962	0.0643	0.0829	0.4032
Constant Other (PT/walking)-Car	-0.6713	0.6203	0.9823	0.6997	-0.6444	0.3574	0.4431	0.4122	-0.7890	0.2336	0.2971	0.3319
Constant PT-PT	-0.3663	1.0848	3.2898	1.0643	-0.5703	0.4707	0.3812	0.5082	-1.0525	0.2141	0.2530	0.5157
Constant PT-Walking	-0.7595	0.8553	1.8626	1.2554	-1.1786	0.2405	0.2984	0.7171	-1.3964	0.2154	0.3083	0.6652
Constant Walking-PT	0.5371	1.5386	2.3525	1.0882	-0.5867	0.5183	0.8407	0.6598	-0.9462	0.2739	0.3842	0.5809
Constant Walking-Walking	1.2292	1.1858	1.0773	1.1487	1.0729	0.2745	0.1941	0.6349	0.9753	0.2216	0.1668	0.5199
Mode shifts for households with no car ownership												
Constant Car-Other (PT/walking)	1.3638	0.4329	0.6994	1.0602	1.7655	0.2411	0.3025	0.8250	1.8533	0.2033	0.1265	0.6139
Constant Other (PT/walking)-Car	1.8766	2.0283	0.4480	1.1878	1.3023	1.0578	0.1820	0.8232	1.1631	0.8378	0.1824	0.6588
Constant PT-PT	5.5908	0.3094	0.1589	1.2148	4.7587	0.1145	0.0578	0.6654	4.8897	0.1452	0.0881	0.5933
Constant PT-Walking	4.0594	0.3066	0.2533	1.2563	3.9395	0.2352	0.2023	0.8527	4.1286	0.2311	0.0894	0.7449
Constant Walking-PT	3.5896	0.3591	0.2252	1.3848	2.9944	0.1609	0.1622	0.7405	3.1180	0.1186	0.1328	0.6106
Constant Walking-Walking	3.8626	0.4580	0.3218	1.0969	3.3905	0.3008	0.1505	0.6246	3.2720	0.2299	0.1159	0.5087
Mode shifts for central area destinations												
PT-PT	2.1532	0.5586	0.5132	0.8852	2.0115	0.1528	0.0143	0.4901	1.8707	0.1465	0.2128	0.4108
PT-Walking	2.2721	0.7801	0.7267	1.0657	1.7930	0.1765	0.2131	0.7964	1.6911	0.2954	0.3991	0.6362
Walking-PT	2.5118	0.2276	0.2923	1.0694	3.1858	0.2242	0.1616	0.6646	2.7802	0.0832	0.0981	0.5863
Walking-Walking	1.9471	0.6174	0.6415	0.7923	2.0594	0.2505	0.1512	0.4502	1.7975	0.1101	0.0909	0.3332
Mode shifts for individuals with season ticket ownership												
Walking-Walking	-0.6761	1.7066	1.7172	0.8494	-0.7865	0.4549	0.3104	0.4860	-0.9489	0.8172	0.3653	0.4051
Mode shifts for trips with more than 1 passenger												
PT first/shopping trip	-2.3461	0.4225	0.4878	0.8458	-2.0975	0.1265	0.0647	0.5165	-2.2493	0.2081	0.1078	0.4630
PT following trip	-0.5191	1.2082	2.2718	0.8537	-0.7681	0.1844	0.1886	0.5121	-0.6703	0.2469	0.2753	0.4384
Walking first/shopping trip	-1.3286	0.8049	0.5477	0.7973	-1.0196	0.2756	0.2333	0.4030	-1.0792	0.3478	0.1200	0.3310
Walking following trip	-0.1618	1.2944	4.7519	0.8493	-0.0985	0.7408	1.8696	0.4568	-0.1908	0.4813	0.8911	0.3725
Mode shifts for students												
Walking-Walking	1.6425	1.2062	0.8518	1.0099	1.1274	0.3659	0.4934	0.6204	1.2227	0.2596	0.2518	0.5423
Mode shifts for married individuals												
Walking-Walking	-1.0603	1.1118	0.8998	0.9067	-0.7735	0.2886	0.3788	0.4731	-0.5672	0.3963	0.7648	0.3900
Mode shifts for individuals living in 3-member households												
Walking-Walking	1.1107	1.3608	0.9690	1.0093	1.1281	0.6660	0.3349	0.6584	0.9556	0.4020	0.3232	0.4924
LOS variables												
Travel time for first trip (base level)	-0.0922	0.0879	0.1064	0.0203	-0.0963	0.1037	0.1245	0.0137	-0.0961	0.0537	0.0249	0.0120
Travel time shift for clothes shopping	-0.0610	3.2992	1.0287	0.0335	-0.0055	1.2074	4.1777	0.0162	0.0144	0.4587	0.3322	0.0123
Travel time for O-S-O trip chains	0.0118	1.0243	1.5322	0.0186	0.0231	0.7009	0.5493	0.0095	0.0213	0.4025	0.1588	0.0077
Travel time for HWH tours	-0.0528	0.4264	0.4220	0.0202	-0.0420	0.2539	0.3180	0.0124	-0.0462	0.0523	0.0709	0.0114
Travel time multiplier for car	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Travel time multiplier for PT IVT	0.5984	0.0995	0.1648	0.1358	0.5840	0.0234	0.0303	0.0904	0.5836	0.0601	0.0740	0.0848
Travel time multiplier for PT first access trip	1.2979	0.6771	0.4044	0.4737	0.8818	0.1610	0.1617	0.3109	0.7801	0.0771	0.1163	0.2751
Travel time multiplier for PT last egress trip	0.8746	0.4365	0.3591	0.4432	0.7761	0.2747	0.1669	0.2606	0.6338	0.1508	0.1674	0.2035
Travel time multiplier for PT remaining OVT	0.4532	0.9455	0.9127	0.4097	0.3437	0.4582	0.6304	0.2779	0.2558	0.3510	0.4893	0.2346
Travel time multiplier for following trip	1.2880	0.1299	0.1672	0.1839	1.2649	0.0710	0.0704	0.1208	1.2969	0.0446	0.0410	0.1142
Travel time - Shopping duration elasticity	-0.3769	0.3337	0.3203	0.0905	-0.3368	0.0895	0.0986	0.0516	-0.3277	0.0767	0.1018	0.0428
Travel walking distance (base)	-2.1274	0.3084	0.1390	0.3806	-1.9060	0.1723	0.0501	0.2209	-1.8504	0.1381	0.0430	0.1859
Travel walking distance for O-S-O trip chains	0.5248	1.1663	0.5786	0.3164	0.4030	0.5392	0.3635	0.2102	0.3971	0.4756	0.0914	0.1732
Travel walking distance multiplier for following trip	1.0838	0.1340	0.0357	0.1752	1.1269	0.0996	0.0432	0.1175	1.1482	0.0826	0.0509	0.1009
Box-cox lambda for travel walking distance	0.6191	0.2310	0.0838	0.1403	0.6831	0.1515	0.0722	0.0797	0.6776	0.1584	0.0266	0.0656
Travel walking distance - Shopping duration elasticity	-0.2442	0.7659	0.3461	0.0831	-0.1761	0.2611	0.1963	0.0483	-0.1820	0.3037	0.1282	0.0459
Travel cost	-0.8989	0.3792	0.1525	0.1994	-0.7438	0.1412	0.0869	0.1101	-0.7222	0.1225	0.0963	0.1003
Box-cox lambda for travel cost	0.3580	0.3322	0.3391	0.1792	0.3428	0.3607	0.1601	0.0853	0.3861	0.2800	0.1222	0.0746
Travel cost - Personal income elasticity	-0.2669	0.6026	0.7081	0.2038	-0.2476	0.2922	0.4000	0.1049	-0.2830	0.2263	0.2357	0.0954
Locational variables												
Living in rich areas-shopping in poor areas	-1.4764	1.0070	0.6788	0.6873	-1.1477	0.4281	0.1539	0.3894	-1.1507	0.4319	0.1882	0.3458
Parking areas (400m buffer))	0.0979	0.3886	0.4832	0.0522	0.1098	0.2254	0.2112	0.0345	0.0985	0.1185	0.1246	0.0293
Box-cox lambda for parking areas (400m buffer)	0.4979	0.3017	0.2632	0.1890	0.4715	0.1277	0.1097	0.1042	0.4864	0.1543	0.1098	0.0898
Presence of major clothes shopping retailers (400m buffer)	3.2163	0.6585	0.3566	1.0994	2.3616	0.2562	0.1888	0.4642	2.1641	0.1028	0.0846	0.3514
Presence of major grocery retailers (400m buffer)	0.3718	0.4327	0.6763	0.2696	0.3888	0.2712	0.2753	0.1448	0.4755	0.1085	0.0808	0.1232
Presence of major durables retailers (400m buffer)	7.3593	2.7997	0.7790	1.8094	2.5897	0.3350	0.2795	0.9656	2.6262	0.3398	0.2316	0.9241
Size variables												
Natural logarithm multiplier ϕ	1.1449	0.6398	0.3166	0.3958	0.7984	0.0940	0.0641	0.1583	0.7851	0.0758	0.0426	0.1219
Population (400m buffer)	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Retail areas for clothes stores (400m buffer) (exp.)	-0.3754	2.9033	2.0190	0.8163	0.5708	1.6734	0.5045	0.5899	0.3098	1.2985	1.1233	0.5293
Retail areas for grocery stores (400m buffer) (exp.)	-0.0092	1.5287	107.8340	0.9790	0.6230	0.1909	0.2738	0.5442	0.6312	0.2278	0.3280	0.4406
Retail areas for dur./other stores (400m buffer) (exp.)	-4.6136	8.9172	1.8808	1.2844	-0.3459	1.5889	1.4782	0.9318	-2.7486	5.6801	2.2035	1.2648
Shopping store variability (400m buffer) (exp.)	-1.3641	2.4067	3.5162	12.6872	1.5184	0.1832	0.1066	0.8112	1.6491	0.2963	0.2054	0.6449
Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)	-2.6509	1.9874	2.3104	2.3920	1.3105	0.5277	1.2041	3.7093	-1.3732	1.4948	5.2516	1.5274

Table 16: Evaluation of Random sampling protocol for choice sets of 150, 200 and 250 alts

Parameter	150 alts				200 alts				250 alts			
	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.
Locational constants												
Constant rest Yorkshire	0.7577	0.3790	0.0988	0.1683	0.7260	0.3214	0.1705	0.1554	0.7647	0.3919	0.0702	0.1551
Households with car ownership												
Constant Car-Other (PT/walking)	-2.8979	0.0753	0.0665	0.3668	-2.8382	0.0514	0.0471	0.3376	-2.9225	0.0705	0.0492	0.3178
Constant Other (PT/walking)-Car	-0.7514	0.1625	0.2066	0.3062	-0.8617	0.0946	0.1258	0.2766	-0.8853	0.0848	0.0907	0.2670
Constant PT-PT	-0.9947	0.1780	0.2303	0.4568	-1.0786	0.0369	0.0540	0.4331	-1.0919	0.0527	0.0696	0.4260
Constant PT-Walking	-1.5281	0.1057	0.1479	0.6085	-1.6367	0.1239	0.1482	0.5720	-1.8196	0.1756	0.1386	0.5848
Constant Walking-PT	-0.8996	0.3044	0.3098	0.5709	-1.1721	0.2566	0.3082	0.5788	-1.3627	0.1454	0.1562	0.5784
Constant Walking-Walking	1.2612	0.4982	0.1588	0.4815	1.1927	0.4168	0.1077	0.4589	1.0403	0.2847	0.1657	0.4318
Mode shifts for households with no car ownership												
Constant Car-Other (PT/walking)	2.1800	0.0756	0.1153	0.6624	1.9896	0.1455	0.1363	0.5996	2.1791	0.0633	0.0311	0.5973
Constant Other (PT/walking)-Car	0.8598	0.4231	0.3415	0.7298	0.9739	0.5389	0.2840	0.6720	0.8056	0.4972	0.4706	0.6873
Constant PT-PT	4.7370	0.1094	0.0430	0.5461	4.5458	0.0647	0.0298	0.5350	4.6773	0.0955	0.0254	0.5209
Constant PT-Walking	3.9023	0.1636	0.0693	0.7409	3.9530	0.1802	0.0991	0.6701	3.9240	0.1701	0.0737	0.6640
Constant Walking-PT	2.8793	0.1183	0.1425	0.5754	3.1324	0.1209	0.0298	0.5720	3.0857	0.1042	0.0450	0.5643
Constant Walking-Walking	2.9753	0.1313	0.0947	0.5019	3.0446	0.1444	0.0782	0.4604	3.1301	0.1766	0.0599	0.4671
Mode shifts for central area destinations												
PT-PT	1.9325	0.1075	0.0479	0.3685	1.8878	0.0819	0.0612	0.3421	1.8275	0.0807	0.0721	0.3555
PT-Walking	1.6806	0.0790	0.0554	0.6056	1.6828	0.1109	0.1344	0.5531	2.1363	0.1706	0.0811	0.5609
Walking-PT	2.6370	0.0210	0.0208	0.5655	2.6701	0.0917	0.1155	0.5877	2.9235	0.0876	0.0643	0.5868
Walking-Walking	1.7122	0.0943	0.1099	0.3172	1.7493	0.0918	0.1253	0.3198	1.8282	0.1290	0.0937	0.2974
Mode shifts for individuals with season ticket ownership												
Walking-Walking	-0.7760	0.5816	0.4644	0.3713	-0.8637	0.5468	0.3062	0.3550	-0.7280	0.3084	0.2321	0.3473
Mode shifts for trips with more than 1 passenger												
PT first/shopping trip	-2.0881	0.1247	0.0890	0.4234	-1.9753	0.0768	0.0614	0.3888	-1.9546	0.0654	0.0701	0.3942
PT following trip	-0.7380	0.1946	0.2532	0.4124	-0.7446	0.2222	0.2606	0.4016	-0.7707	0.1672	0.2060	0.3974
Walking first/shopping trip	-0.8791	0.1021	0.1207	0.3088	-0.9424	0.2125	0.1953	0.2896	-0.9575	0.1958	0.1313	0.2784
Walking following trip	-0.4411	0.2305	0.1792	0.3343	-0.4882	0.3473	0.3214	0.3075	-0.4656	0.2657	0.1586	0.2962
Mode shifts for students												
Walking-Walking	0.9004	0.1943	0.2761	0.4925	0.9109	0.2247	0.3481	0.4555	0.8569	0.2029	0.1990	0.4379
Mode shifts for married individuals												
Walking-Walking	-0.8595	0.1053	0.0836	0.3805	-0.7988	0.1397	0.1676	0.3605	-0.7854	0.2240	0.2632	0.3456
Mode shifts for individuals living in 3-member households												
Walking-Walking	0.8440	0.2786	0.3694	0.4455	0.8133	0.3924	0.4126	0.4028	0.8573	0.3384	0.3462	0.4484
LOS variables												
Travel time for first trip (base level)	-0.0998	0.0936	0.0611	0.0109	-0.0962	0.0756	0.0650	0.0102	-0.0981	0.0751	0.0376	0.0097
Travel time shift for clothes shopping	0.0193	0.2717	0.2482	0.0116	0.0170	0.3598	0.3677	0.0107	0.0201	0.2408	0.1561	0.0106
Travel time for O-S-O trip chains	0.0246	0.6161	0.1133	0.0071	0.0200	0.3127	0.1261	0.0066	0.0201	0.3219	0.1245	0.0065
Travel time for HWH tours	-0.0404	0.0924	0.0624	0.0110	-0.0408	0.0836	0.0438	0.0104	-0.0447	0.1093	0.1521	0.0099
Travel time multiplier for car	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Travel time multiplier for PT IVT	0.5965	0.0450	0.0629	0.0734	0.5587	0.0562	0.0622	0.0732	0.5753	0.0363	0.0398	0.0655
Travel time multiplier for PT first access trip	0.7998	0.0653	0.0886	0.2657	0.8283	0.0277	0.0373	0.2765	0.7656	0.1122	0.1315	0.2357
Travel time multiplier for PT last egress trip	0.6225	0.1357	0.1869	0.2002	0.6358	0.1834	0.2205	0.1830	0.6475	0.0756	0.0704	0.1786
Travel time multiplier for PT remaining OVT	0.2498	0.2979	0.3694	0.2089	0.4198	0.1874	0.0643	0.2171	0.3556	0.2344	0.2749	0.1760
Travel time multiplier for following trip	1.3066	0.0437	0.0337	0.1072	1.2890	0.0504	0.0278	0.0975	1.2917	0.0484	0.0270	0.0931
Travel time - Shopping duration elasticity	-0.3125	0.0150	0.0181	0.0370	-0.3320	0.0630	0.0602	0.0354	-0.3248	0.0450	0.0410	0.0324
Travel walking distance (base)	-1.8316	0.1265	0.0210	0.1722	-1.7974	0.1055	0.0760	0.1661	-1.7705	0.0889	0.0309	0.1518
Travel walking distance for O-S-O trip chains	0.4258	0.5823	0.1712	0.1610	0.3635	0.3621	0.2889	0.1488	0.3392	0.2627	0.1316	0.1428
Travel walking distance multiplier for following trip	1.1450	0.0851	0.0481	0.0976	1.1808	0.0591	0.0581	0.0947	1.1838	0.0541	0.0198	0.0964
Box-cox lambda for travel walking distance	0.7131	0.1142	0.0252	0.0621	0.7285	0.1037	0.0896	0.0554	0.7438	0.0762	0.0330	0.0563
Travel walking distance - Shopping duration elasticity	-0.1504	0.0822	0.0665	0.0409	-0.1504	0.1438	0.1601	0.0385	-0.1546	0.1630	0.1635	0.0378
Travel cost	-0.7198	0.1043	0.0622	0.0845	-0.7033	0.0791	0.0339	0.0845	-0.7056	0.0826	0.0617	0.0810
Box-cox lambda for travel cost	0.3975	0.2587	0.0771	0.0660	0.4100	0.2353	0.0636	0.0640	0.4421	0.1755	0.0666	0.0581
Travel cost - Personal income elasticity	-0.2394	0.2391	0.3166	0.0878	-0.2435	0.0609	0.0910	0.0920	-0.2461	0.0492	0.0655	0.0889
Locational variables												
Living in rich areas-shopping in poor areas	-1.0836	0.3483	0.1258	0.3136	-1.0661	0.3265	0.1472	0.2923	-0.9644	0.2000	0.0758	0.2627
Parking areas (400m buffer))	0.0915	0.0851	0.1119	0.0273	0.0900	0.0507	0.0581	0.0271	0.0986	0.0767	0.0610	0.0270
Box-cox lambda for parking areas (400m buffer)	0.5130	0.2162	0.0742	0.0879	0.4846	0.1489	0.0452	0.0898	0.4307	0.0562	0.0632	0.0794
Presence of major clothes shopping retailers (400m buffer)	1.9151	0.0486	0.0584	0.2995	2.2829	0.1634	0.0662	0.2857	2.0313	0.0606	0.0636	0.2574
Presence of major grocery retailers (400m buffer)	0.5166	0.0513	0.0757	0.1156	0.4945	0.0767	0.0725	0.1115	0.5082	0.0548	0.0554	0.1043
Presence of major durables retailers (400m buffer)	2.8624	0.3978	0.1209	0.7178	2.6322	0.2854	0.1060	0.7648	2.8184	0.3763	0.1518	0.6725
Size variables												
Natural logarithm multiplier ϕ	0.7713	0.0881	0.0818	0.1183	0.7253	0.0656	0.0845	0.1112	0.7490	0.0504	0.0509	0.1088
Population (400m buffer)	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Retail areas for clothes stores (400m buffer) (exp.)	0.2841	1.3004	1.2744	0.5625	0.4234	0.9589	0.5156	0.5723	0.4279	1.3007	0.6631	0.5419
Retail areas for grocery stores (400m buffer) (exp.)	0.6258	0.4163	0.6023	0.4405	0.8671	0.2889	0.1557	0.4601	0.8265	0.2534	0.1436	0.4119
Retail areas for dur./other stores (400m buffer) (exp.)	-0.0224	1.0382	18.2843	0.8689	0.2944	0.7021	1.2029	0.8762	0.1552	0.7357	0.4078	0.7667
Shopping store variability (400m buffer) (exp.)	1.6700	0.3606	0.2231	0.6576	1.7679	0.3761	0.1098	0.6371	1.5989	0.2801	0.1659	0.6421
Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)	1.8200	0.3441	0.1356	1.2832	1.9151	0.3662	0.5019	1.4347	2.3921	0.1380	0.1102	0.9343

Table 17: Evaluation of AC sampling protocol for choice sets of 10, 50 and 100 alts

Parameter	10 alts				50 alts				100 alts			
	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.
Locational constants												
Constant rest Yorkshire	1.3580	1.4717	0.2369	0.3652	0.9906	0.8030	0.1524	0.2280	0.7494	0.3640	0.1829	0.2000
Households with car ownership												
Constant Car-Other (PT/walking)	-2.7630	0.1091	0.1415	0.5933	-2.8108	0.0475	0.0567	0.3691	-2.8736	0.0526	0.0484	0.3312
Constant Other (PT/walking)-Car	-0.8126	0.4196	0.5225	0.5306	-0.7615	0.1317	0.1643	0.3040	-0.8626	0.2360	0.3091	0.2767
Constant PT-PT	-0.9213	0.3800	0.5193	0.7122	-1.1338	0.1335	0.1614	0.4839	-1.2381	0.1490	0.0772	0.4634
Constant PT-Walking	-1.3146	0.3793	0.5855	1.0210	-1.4213	0.1740	0.2223	0.5953	-1.7795	0.1877	0.1661	0.6390
Constant Walking-PT	-0.5743	0.5250	0.2354	0.8972	-1.2640	0.0856	0.0934	0.5781	-1.1244	0.1713	0.2363	0.5105
Constant Walking-Walking	1.4737	0.7506	0.3232	0.8226	1.1590	0.3767	0.0690	0.4831	1.1199	0.3303	0.1703	0.4353
Mode shifts for households with no car ownership												
Constant Car-Other (PT/walking)	1.2589	0.4589	0.3962	0.9732	1.9530	0.1605	0.0744	0.6367	2.1790	0.1054	0.1471	0.6892
Constant Other (PT/walking)-Car	1.7809	1.8141	0.1583	0.8752	0.9967	0.5749	0.2037	0.6958	0.8680	0.3716	0.1420	0.6890
Constant PT-PT	5.5339	0.2961	0.1414	0.8913	4.6813	0.0964	0.0648	0.5696	4.7026	0.1014	0.0353	0.5490
Constant PT-Walking	3.9305	0.1720	0.1114	0.9674	3.4049	0.0974	0.1348	0.6683	3.8796	0.1569	0.0328	0.7103
Constant Walking-PT	2.9049	0.0643	0.0679	0.8173	3.1943	0.1431	0.0366	0.5749	3.0983	0.1087	0.0582	0.5348
Constant Walking-Walking	3.4497	0.2967	0.0934	0.6626	2.9998	0.1276	0.0532	0.4712	3.0482	0.1458	0.0853	0.4531
Mode shifts for central area destinations												
PT-PT	1.8072	0.1919	0.2364	0.6243	1.8418	0.1032	0.1217	0.4181	1.8431	0.0801	0.0926	0.3981
PT-Walking	1.7459	0.3341	0.4748	0.8157	2.0025	0.1367	0.1152	0.5388	1.8852	0.1251	0.1464	0.5529
Walking-PT	2.7491	0.1091	0.1449	0.7602	2.8434	0.0618	0.0695	0.5505	2.7293	0.0530	0.0724	0.4977
Walking-Walking	1.4996	0.1233	0.1382	0.3951	1.4513	0.1187	0.1020	0.3206	1.5539	0.0704	0.0606	0.3153
Mode shifts for individuals with season ticket ownership												
Walking-Walking	-0.5680	0.2232	0.2749	0.4929	-0.8398	0.4980	0.2730	0.3888	-0.6791	0.2289	0.2464	0.3686
Mode shifts for trips with more than 1 passenger												
PT first/shopping trip	-2.3933	0.3116	0.2372	0.5725	-2.2622	0.2150	0.0257	0.4219	-2.0000	0.0878	0.1128	0.3972
PT following trip	-1.0317	0.3903	0.3720	0.6112	-0.7952	0.1529	0.1796	0.4231	-0.8403	0.2126	0.2695	0.3902
Walking first/shopping trip	-0.7289	0.5103	0.6676	0.4897	-0.7906	0.0488	0.0625	0.3051	-0.8959	0.1912	0.1876	0.2739
Walking following trip	-0.5509	0.9468	0.8140	0.5382	-0.5608	0.5637	0.3092	0.3364	-0.4150	0.2852	0.2861	0.3009
Mode shifts for students												
Walking-Walking	1.5656	0.5310	0.4064	0.6161	1.0471	0.0500	0.0685	0.4440	1.0021	0.0743	0.0807	0.4212
Mode shifts for married individuals												
Walking-Walking	-0.5557	0.5215	0.8849	0.5677	-0.6452	0.2037	0.2273	0.3637	-0.7598	0.1377	0.1763	0.3343
Mode shifts for individuals living in 3-member households												
Walking-Walking	0.8155	0.1819	0.1457	0.6533	0.9943	0.4411	0.1207	0.4442	0.7435	0.2214	0.2640	0.4280
LOS variables												
Travel time for first trip (base level)	-0.0866	0.0741	0.0911	0.0182	-0.0885	0.0329	0.0304	0.0119	-0.0930	0.0425	0.0612	0.0105
Travel time shift for clothes shopping	0.0020	0.9253	6.8277	0.0215	0.0085	0.7061	1.6917	0.0140	0.0175	0.3420	0.2892	0.0122
Travel time for O-S-O trip chains	0.0147	0.3103	0.4398	0.0116	0.0175	0.2087	0.1737	0.0070	0.0175	0.2494	0.2651	0.0068
Travel time for HWH tours	-0.0340	0.2802	0.3418	0.0144	-0.0455	0.0676	0.0823	0.0112	-0.0493	0.1069	0.0314	0.0107
Travel time multiplier for car	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Travel time multiplier for PT IVT	0.5449	0.1598	0.2007	0.1155	0.5731	0.0354	0.0450	0.0807	0.5788	0.0251	0.0290	0.0717
Travel time multiplier for PT first access trip	1.2339	0.5056	0.1843	0.4703	0.8582	0.1113	0.1449	0.2868	0.7498	0.0952	0.0917	0.2676
Travel time multiplier for PT last egress trip	0.5858	0.2968	0.3961	0.3194	0.5444	0.1915	0.2231	0.1701	0.5451	0.1047	0.0704	0.1924
Travel time multiplier for PT remaining OVT	0.2416	0.4719	0.6751	0.3913	0.2262	0.4048	0.5520	0.2106	0.3244	0.2460	0.4603	0.2085
Travel time multiplier for following trip	1.4495	0.0679	0.0447	0.2276	1.3872	0.0499	0.0538	0.1374	1.3242	0.0393	0.0409	0.1115
Travel time - Shopping duration elasticity	-0.3399	0.1324	0.1654	0.0646	-0.3375	0.0691	0.0532	0.0392	-0.3219	0.0201	0.0277	0.0350
Travel walking distance (base)	-1.8748	0.1805	0.1445	0.2396	-1.7064	0.0589	0.0619	0.1646	-1.6516	0.0253	0.0228	0.1527
Travel walking distance for O-S-O trip chains	0.4892	1.0733	0.5400	0.2086	0.3763	0.3982	0.2705	0.1467	0.3188	0.2155	0.1446	0.1345
Travel walking distance multiplier for following trip	1.2206	0.0527	0.0633	0.1484	1.2036	0.0507	0.0575	0.1071	1.2510	0.0179	0.0217	0.1085
Box-cox lambda for travel walking distance	0.6855	0.1835	0.1802	0.0863	0.7604	0.0555	0.0476	0.0613	0.7975	0.0214	0.0314	0.0606
Travel walking distance - Shopping duration elasticity	-0.1568	0.1879	0.2303	0.0548	-0.1703	0.2198	0.0681	0.0387	-0.1565	0.1213	0.0557	0.0360
Travel cost	-0.8047	0.2661	0.1828	0.1443	-0.7125	0.0932	0.0319	0.0944	-0.7230	0.1092	0.0533	0.0859
Box-cox lambda for travel cost	0.3244	0.3950	0.3799	0.1251	0.4182	0.2200	0.0529	0.0757	0.4651	0.1326	0.0920	0.0639
Travel cost - Personal income elasticity	-0.2904	0.3000	0.3098	0.1244	-0.2419	0.1504	0.2141	0.0983	-0.2168	0.1097	0.0672	0.0924
Locational variables												
Living in rich areas-shopping in poor areas	-0.8565	0.4590	0.5836	0.5884	-1.0699	0.3312	0.0519	0.3812	-0.9716	0.2227	0.1246	0.3223
Parking areas (400m buffer))	0.0755	0.2917	0.3769	0.0410	0.0877	0.0731	0.0762	0.0297	0.0942	0.0731	0.0954	0.0288
Box-cox lambda for parking areas (400m buffer)	0.6697	0.5877	0.2224	0.1771	0.5103	0.2098	0.0453	0.0971	0.4678	0.1090	0.0848	0.0893
Presence of major clothes shopping retailers (400m buffer)	1.7913	0.1500	0.1994	0.6610	2.3460	0.1955	0.1017	0.3629	2.2923	0.1681	0.0626	0.2873
Presence of major grocery retailers (400m buffer)	0.6901	0.3942	0.2676	0.2023	0.6139	0.1510	0.1362	0.1227	0.5967	0.1187	0.0569	0.1113
Presence of major durables retailers (400m buffer)	3.3681	1.3595	1.1242	1.6821	1.6180	0.5389	0.7255	1.0431	2.1408	0.3428	0.4076	1.4676
Size variables												
Natural logarithm multiplier ϕ	1.0431	0.4293	0.1594	0.3196	0.7114	0.0535	0.0745	0.1567	0.7826	0.0979	0.0983	0.1364
Population (400m buffer)	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Retail areas for clothes stores (400m buffer) (exp.)	0.3701	1.9494	1.2811	0.9365	0.3854	1.6010	1.1433	0.7451	0.2720	1.0427	1.2265	0.6364
Retail areas for grocery stores (400m buffer) (exp.)	0.2170	0.9064	3.2420	0.9911	0.8034	0.3940	0.4298	0.6676	0.6636	0.2521	0.3352	0.4854
Retail areas for dur./other stores (400m buffer) (exp.)	-0.5344	2.0462	2.9334	2.8434	0.7488	0.6850	0.8303	0.8870	0.4043	0.5342	0.7774	0.7719
Shopping store variability (400m buffer) (exp.)	2.3098	0.7978	0.2051	0.7121	1.9304	0.5026	0.2025	0.6438	1.5502	0.2077	0.1408	0.6492
Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)	0.9303	0.6648	1.4059	4.3766	2.3578	0.1504	0.1733	1.3635	2.6676	0.1842	0.2350	0.9185

Table 18: Evaluation of AC sampling protocol for choice sets of 150, 200 and 250 alts

Parameter	150 alts				200 alts				250 alts			
	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.
Locational constants												
Constant rest Yorkshire	0.7803	0.4202	0.1203	0.1864	0.6641	0.2087	0.0984	0.1748	0.6977	0.2699	0.0744	0.1799
Households with car ownership												
Constant Car-Other (PT/walking)	-2.8399	0.0403	0.0118	0.3086	-2.8568	0.0465	0.0179	0.3126	-2.7969	0.0290	0.0229	0.2929
Constant Other (PT/walking)-Car	-0.8700	0.0399	0.0549	0.2616	-0.7957	0.0858	0.0884	0.2502	-0.8663	0.0610	0.0857	0.2648
Constant PT-PT	-1.1307	0.1303	0.1402	0.4481	-1.1034	0.0562	0.0989	0.4382	-1.0367	0.1159	0.1471	0.4252
Constant PT-Walking	-1.5744	0.0971	0.1447	0.5367	-1.6048	0.0524	0.0627	0.5378	-1.4630	0.0688	0.0692	0.5003
Constant Walking-PT	-1.0361	0.1471	0.1373	0.5160	-1.1859	0.0898	0.1177	0.5332	-1.0723	0.1252	0.1189	0.4892
Constant Walking-Walking	1.1012	0.3082	0.1173	0.4154	1.1492	0.3651	0.0991	0.3953	1.1272	0.3390	0.1007	0.3865
Mode shifts for households with no car ownership												
Constant Car-Other (PT/walking)	2.2870	0.0598	0.0765	0.6462	2.3535	0.0338	0.0397	0.6904	2.4160	0.0385	0.0386	0.6673
Constant Other (PT/walking)-Car	0.8151	0.2879	0.1476	0.6492	0.7254	0.1659	0.1384	0.6661	0.8818	0.3934	0.1109	0.6409
Constant PT-PT	4.4775	0.0487	0.0228	0.5311	4.4940	0.0525	0.0160	0.5183	4.3979	0.0336	0.0220	0.5202
Constant PT-Walking	3.6771	0.0965	0.0475	0.6317	3.8020	0.1337	0.0279	0.6096	3.6108	0.0767	0.0360	0.6126
Constant Walking-PT	2.8438	0.0290	0.0342	0.5328	2.9108	0.0485	0.0394	0.5214	2.8151	0.0268	0.0349	0.5005
Constant Walking-Walking	2.8470	0.0701	0.0278	0.4502	2.7004	0.0201	0.0204	0.4319	2.6801	0.0172	0.0202	0.4311
Mode shifts for central area destinations												
PT-PT	1.7538	0.0153	0.0210	0.3628	1.7820	0.0522	0.0640	0.3390	1.7435	0.0339	0.0395	0.3390
PT-Walking	1.7227	0.0791	0.0829	0.4552	1.8413	0.0562	0.0648	0.4478	1.8393	0.0612	0.0775	0.4462
Walking-PT	2.6121	0.0419	0.0566	0.5164	2.7768	0.0438	0.0456	0.5256	2.6977	0.0298	0.0436	0.4782
Walking-Walking	1.5325	0.0747	0.0732	0.2886	1.5940	0.0321	0.0185	0.2897	1.6185	0.0298	0.0335	0.2820
Mode shifts for individuals with season ticket ownership												
Walking-Walking	-0.7041	0.2560	0.1577	0.3638	-0.7074	0.2785	0.1568	0.3475	-0.6929	0.2359	0.0768	0.3411
Mode shifts for trips with more than 1 passenger												
PT first/shopping trip	-1.9958	0.0757	0.0769	0.3747	-1.9414	0.0706	0.0762	0.3650	-1.9869	0.0701	0.0591	0.3611
PT following trip	-0.8189	0.1850	0.2640	0.3786	-0.7385	0.1458	0.1345	0.3801	-0.7322	0.1531	0.0833	0.3683
Walking first/shopping trip	-0.8786	0.1794	0.1641	0.2602	-0.8798	0.1642	0.1522	0.2508	-0.8292	0.0536	0.0626	0.2517
Walking following trip	-0.3889	0.2422	0.3509	0.2874	-0.3944	0.1867	0.2151	0.2723	-0.4391	0.2074	0.1248	0.2684
Mode shifts for students												
Walking-Walking	1.0249	0.1015	0.1349	0.4097	0.9415	0.1243	0.0782	0.3867	1.0107	0.0734	0.0906	0.3872
Mode shifts for married individuals												
Walking-Walking	-0.8194	0.0816	0.1038	0.3284	-0.8049	0.1486	0.1825	0.3138	-0.8412	0.0887	0.0778	0.3105
Mode shifts for individuals living in 3-member households												
Walking-Walking	0.8940	0.2958	0.1851	0.4264	0.8476	0.3418	0.2527	0.3974	0.8001	0.1801	0.1086	0.3942
LOS variables												
Travel time for first trip (base level)	-0.0913	0.0178	0.0231	0.0100	-0.0916	0.0201	0.0222	0.0098	-0.0906	0.0208	0.0306	0.0097
Travel time shift for clothes shopping	0.0168	0.3665	0.1841	0.0120	0.0208	0.2171	0.1494	0.0105	0.0199	0.2498	0.1785	0.0102
Travel time for O-S-O trip chains	0.0178	0.1770	0.1302	0.0064	0.0178	0.1732	0.1282	0.0062	0.0169	0.1675	0.1587	0.0062
Travel time for HWH tours	-0.0435	0.0938	0.1164	0.0097	-0.0436	0.0621	0.0694	0.0094	-0.0449	0.0416	0.0528	0.0095
Travel time multiplier for car	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Travel time multiplier for PT IVT	0.5806	0.0278	0.0319	0.0714	0.5914	0.0341	0.0432	0.0683	0.5833	0.0225	0.0379	0.0661
Travel time multiplier for PT first access trip	0.7964	0.1011	0.1280	0.2591	0.7830	0.0778	0.0882	0.2546	0.8601	0.0752	0.0703	0.2539
Travel time multiplier for PT last egress trip	0.6135	0.0729	0.0873	0.1818	0.6067	0.0560	0.0782	0.1710	0.5523	0.0929	0.0881	0.1671
Travel time multiplier for PT remaining OVT	0.3344	0.1403	0.1808	0.1971	0.3412	0.1442	0.1690	0.2046	0.3395	0.0885	0.1046	0.1818
Travel time multiplier for following trip	1.3683	0.0137	0.0199	0.1106	1.3440	0.0117	0.0118	0.1090	1.3558	0.0137	0.0169	0.1114
Travel time - Shopping duration elasticity	-0.3207	0.0441	0.0563	0.0341	-0.3270	0.0365	0.0261	0.0324	-0.3165	0.0187	0.0250	0.0324
Travel walking distance (base)	-1.6665	0.0304	0.0260	0.1432	-1.6255	0.0165	0.0234	0.1365	-1.6177	0.0138	0.0171	0.1327
Travel walking distance for O-S-O trip chains	0.3218	0.1957	0.0622	0.1293	0.2591	0.0871	0.1166	0.1260	0.2507	0.1271	0.1425	0.1220
Travel walking distance multiplier for following trip	1.2304	0.0198	0.0239	0.0997	1.2390	0.0218	0.0301	0.0964	1.2544	0.0190	0.0252	0.0955
Box-cox lambda for travel walking distance	0.8167	0.0162	0.0173	0.0575	0.8165	0.0194	0.0228	0.0553	0.8133	0.0190	0.0259	0.0540
Travel walking distance - Shopping duration elasticity	-0.1473	0.0905	0.1057	0.0334	-0.1597	0.1440	0.0442	0.0337	-0.1478	0.0758	0.0682	0.0337
Travel cost	-0.7023	0.0774	0.0521	0.0828	-0.7008	0.0751	0.0118	0.0792	-0.6953	0.0667	0.0321	0.0798
Box-cox lambda for travel cost	0.4908	0.0873	0.0749	0.0607	0.5216	0.0411	0.0423	0.0574	0.4953	0.0763	0.0370	0.0558
Travel cost - Personal income elasticity	-0.2290	0.1178	0.1753	0.0907	-0.2242	0.0993	0.1124	0.0907	-0.2241	0.0796	0.0349	0.0887
Locational variables												
Living in rich areas-shopping in poor areas	-0.9014	0.1216	0.0673	0.3004	-0.9441	0.1747	0.0782	0.3070	-0.8970	0.1283	0.1107	0.3052
Parking areas (400m buffer))	0.0900	0.0613	0.0789	0.0267	0.0987	0.0610	0.0361	0.0273	0.0962	0.0583	0.0641	0.0274
Box-cox lambda for parking areas (400m buffer)	0.4593	0.0925	0.1070	0.0807	0.4253	0.0299	0.0382	0.0767	0.4462	0.0697	0.0917	0.0801
Presence of major clothes shopping retailers (400m buffer)	2.1805	0.1112	0.0908	0.2546	2.1209	0.0808	0.0398	0.2507	2.1794	0.1106	0.0563	0.2388
Presence of major grocery retailers (400m buffer)	0.5857	0.0981	0.0598	0.1043	0.5686	0.0660	0.0568	0.1031	0.5703	0.0692	0.0388	0.1016
Presence of major durables retailers (400m buffer)	1.9430	0.4170	0.5454	1.0719	1.8601	0.1871	0.2305	0.9334	1.3167	0.4492	0.5295	1.0468
Size variables												
Natural logarithm multiplier ϕ	0.7570	0.0449	0.0555	0.1242	0.7507	0.0444	0.0447	0.1188	0.7472	0.0303	0.0414	0.1158
Population (400m buffer)	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Retail areas for clothes stores (400m buffer) (exp.)	0.1975	0.8504	1.1849	0.6278	0.2150	0.7121	1.0978	0.5904	0.2270	0.7681	0.8917	0.5877
Retail areas for grocery stores (400m buffer) (exp.)	0.6719	0.1730	0.2304	0.4519	0.6376	0.1851	0.2284	0.4250	0.6348	0.1320	0.2134	0.4235
Retail areas for dur./other stores (400m buffer) (exp.)	0.5681	0.3305	0.4331	0.7428	0.5246	0.3458	0.4548	0.7599	0.6207	0.2764	0.3808	0.6825
Shopping store variability (400m buffer) (exp.)	1.5794	0.2294	0.1104	0.6179	1.3800	0.1411	0.1325	0.6873	1.4553	0.1328	0.1337	0.6815
Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)	2.3054	0.1692	0.1429	0.9547	2.3328	0.1593	0.0889	0.8808	2.5941	0.0973	0.0987	0.8036

Table 19: Evaluation of TC sampling protocol for choice sets of 10, 50 and 100 alts

Parameter	10 alts				50 alts				100 alts			
	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.
Locational constants												
Constant rest Yorkshire	0.9534	0.7354	0.2063	0.2731	0.7769	0.4140	0.0813	0.1796	0.7560	0.3760	0.0760	0.1632
Households with car ownership												
Constant Car-Other (PT/walking)	-3.1171	0.1418	0.0722	0.4717	-2.8785	0.0725	0.0747	0.3309	-2.8640	0.0618	0.0530	0.2981
Constant Other (PT/walking)-Car	-1.0399	0.2083	0.1500	0.3595	-0.8199	0.0891	0.1066	0.2694	-0.8422	0.0381	0.0493	0.2454
Constant PT-PT	-1.7143	0.5979	0.2318	0.6904	-1.1798	0.1221	0.1057	0.4855	-1.1893	0.1158	0.0688	0.4440
Constant PT-Walking	-2.6159	0.6857	0.1352	0.7059	-1.8802	0.2116	0.0507	0.5340	-1.7389	0.1206	0.0672	0.4942
Constant Walking-PT	-1.1054	0.3284	0.4547	0.6723	-1.1300	0.0951	0.1162	0.5371	-1.2565	0.0804	0.1015	0.5142
Constant Walking-Walking	0.5746	0.3511	0.5857	0.5429	0.7838	0.1045	0.1189	0.3977	0.7024	0.1656	0.1532	0.3876
Mode shifts for households with no car ownership												
Constant Car-Other (PT/walking)	2.2010	0.0700	0.0937	0.8087	2.3893	0.0591	0.0735	0.7582	2.3109	0.0389	0.0597	0.7266
Constant Other (PT/walking)-Car	0.9220	0.6870	0.6206	0.8788	0.7340	0.2666	0.2251	0.6893	0.7433	0.2008	0.1606	0.6505
Constant PT-PT	5.2949	0.2401	0.0891	0.7017	4.7821	0.1200	0.0427	0.5543	4.6175	0.0815	0.0091	0.5121
Constant PT-Walking	4.6488	0.3862	0.1030	0.7341	4.0846	0.2180	0.0586	0.6081	3.5963	0.0724	0.0341	0.6150
Constant Walking-PT	2.9984	0.1453	0.1657	0.7399	2.8510	0.0531	0.0867	0.5211	2.8774	0.0387	0.0497	0.4900
Constant Walking-Walking	3.1511	0.2442	0.1651	0.5907	2.7860	0.0780	0.0738	0.4307	2.7063	0.0407	0.0450	0.4153
Mode shifts for central area destinations												
PT-PT	1.8752	0.1795	0.2446	0.5381	1.8029	0.0905	0.1101	0.3676	1.7526	0.0541	0.0641	0.3450
PT-Walking	2.5330	0.3881	0.0810	0.6219	2.0626	0.1303	0.1019	0.4719	1.9792	0.0936	0.0804	0.4617
Walking-PT	2.8119	0.0958	0.1062	0.6440	2.9960	0.1146	0.0537	0.5091	3.0025	0.1170	0.0423	0.4930
Walking-Walking	2.6844	0.6300	0.1978	0.5155	2.2885	0.3896	0.0683	0.3215	2.1182	0.2862	0.0322	0.3071
Mode shifts for individuals with season ticket ownership												
Walking-Walking	-0.2209	0.6059	0.9346	0.4511	-0.1236	0.7795	0.1920	0.3387	-0.4712	0.2043	0.2003	0.3245
Mode shifts for trips with more than 1 passenger												
PT first/shopping trip	-2.2999	0.2352	0.1039	0.4935	-2.0229	0.0947	0.0587	0.3764	-1.9338	0.0628	0.0616	0.3509
PT following trip	-1.1375	0.3372	0.3138	0.5201	-0.8703	0.1376	0.1797	0.3740	-0.9071	0.1279	0.1448	0.3597
Walking first/shopping trip	-0.9896	0.2705	0.2209	0.3592	-0.8970	0.1203	0.0527	0.2597	-0.8447	0.1101	0.1291	0.2334
Walking following trip	-0.3221	0.3700	0.5067	0.4026	-0.4085	0.1971	0.1969	0.2722	-0.3722	0.0178	0.0206	0.2502
Mode shifts for students												
Walking-Walking	2.0155	0.8748	0.2071	0.5306	1.4538	0.3522	0.1753	0.3795	1.3304	0.2375	0.0964	0.3803
Mode shifts for married individuals												
Walking-Walking	-1.2282	0.5690	0.2073	0.4140	-1.0899	0.3923	0.0610	0.3180	-0.7987	0.0410	0.0631	0.3078
Mode shifts for individuals living in 3-member households												
Walking-Walking	0.1531	0.7780	1.5811	0.5016	0.3176	0.5396	0.3562	0.3902	0.4710	0.3174	0.1555	0.3810
LOS variables												
Travel time for first trip (base level)	-0.0815	0.1545	0.1793	0.0124	-0.0849	0.0692	0.0412	0.0108	-0.0909	0.0293	0.0400	0.0096
Travel time shift for clothes shopping	-0.0088	1.3330	2.3067	0.0186	0.0172	0.3504	0.2385	0.0106	0.0232	0.1697	0.2052	0.0092
Travel time for O-S-O trip chains	0.0040	0.8035	2.1592	0.0094	0.0085	0.4425	0.1213	0.0064	0.0130	0.1434	0.1425	0.0060
Travel time for HWH tours	-0.0408	0.1535	0.2041	0.0122	-0.0405	0.0993	0.1304	0.0090	-0.0436	0.0346	0.0455	0.0089
Travel time multiplier for car	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Travel time multiplier for PT IVT	0.5455	0.1087	0.1725	0.0949	0.5944	0.0402	0.0532	0.0780	0.5914	0.0257	0.0343	0.0706
Travel time multiplier for PT first access trip	0.8595	0.2134	0.3491	0.3671	0.7604	0.0730	0.0784	0.2804	0.7798	0.0593	0.0755	0.2453
Travel time multiplier for PT last egress trip	0.5363	0.1192	0.0890	0.2802	0.6305	0.0634	0.0788	0.2114	0.6022	0.0984	0.1161	0.1941
Travel time multiplier for PT remaining OVT	0.5524	0.5626	0.2538	0.3437	0.3308	0.1439	0.1736	0.2144	0.3701	0.1413	0.1573	0.2008
Travel time multiplier for following trip	1.4065	0.0571	0.0777	0.1526	1.4173	0.0532	0.0484	0.1210	1.3923	0.0368	0.0339	0.1063
Travel time - Shopping duration elasticity	-0.3261	0.0616	0.0745	0.0475	-0.3238	0.0259	0.0268	0.0332	-0.3139	0.0141	0.0165	0.0301
Travel walking distance (base)	-1.8091	0.1126	0.0662	0.1793	-1.7025	0.0471	0.0419	0.1431	-1.6829	0.0350	0.0124	0.1340
Travel walking distance for O-S-O trip chains	0.2582	0.1136	0.1577	0.2017	0.2414	0.2417	0.2965	0.1321	0.2837	0.0565	0.0432	0.1255
Travel walking distance multiplier for following trip	1.0823	0.1352	0.0534	0.1099	1.1591	0.0738	0.0329	0.0945	1.1744	0.0616	0.0154	0.0914
Box-cox lambda for travel walking distance	0.7333	0.0892	0.0386	0.0646	0.7718	0.0413	0.0203	0.0565	0.8035	0.0195	0.0232	0.0558
Travel walking distance - Shopping duration elasticity	-0.1499	0.0740	0.0606	0.0438	-0.1578	0.1473	0.1021	0.0381	-0.1522	0.0902	0.0883	0.0370
Travel cost	-0.7021	0.1378	0.1229	0.1106	-0.7010	0.0763	0.0499	0.0877	-0.6664	0.0226	0.0182	0.0816
Box-cox lambda for travel cost	0.6385	0.1908	0.1520	0.0765	0.6204	0.1571	0.0351	0.0592	0.6049	0.1282	0.0279	0.0542
Travel cost - Personal income elasticity	-0.1988	0.3074	0.4771	0.1227	-0.2179	0.1174	0.0886	0.0946	-0.2455	0.0641	0.0769	0.0914
Locational variables												
Living in rich areas-shopping in poor areas	-0.8624	0.2805	0.2964	0.5233	-0.9391	0.2087	0.2062	0.3474	-0.9458	0.1769	0.1320	0.3034
Parking areas (400m buffer))	0.0959	0.1181	0.1407	0.0396	0.1067	0.1474	0.0434	0.0310	0.0983	0.0593	0.0457	0.0300
Box-cox lambda for parking areas (400m buffer)	0.4144	0.0845	0.1037	0.1276	0.4150	0.0306	0.0508	0.0870	0.4393	0.0490	0.0644	0.0910
Presence of major clothes shopping retailers (400m buffer)	2.7210	0.4009	0.3650	0.6385	2.1301	0.0999	0.0807	0.2993	2.0977	0.0690	0.0339	0.2571
Presence of major grocery retailers (400m buffer)	0.3981	0.2537	0.1653	0.1596	0.5156	0.0710	0.1003	0.1165	0.4838	0.1081	0.0939	0.1040
Presence of major durables retailers (400m buffer)	1.1167	0.4547	0.1443	1.1296	1.9632	0.2028	0.2488	1.3149	1.8444	0.2116	0.2477	1.1689
Size variables												
Natural logarithm multiplier ϕ	0.7023	0.0840	0.1101	0.1705	0.7319	0.0400	0.0521	0.1056	0.7069	0.0314	0.0247	0.0981
Population (400m buffer)	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Retail areas for clothes stores (400m buffer) (exp.)	1.0362	3.7422	0.4033	0.8377	0.4524	1.2408	0.4998	0.5754	0.4018	0.8628	0.2841	0.5651
Retail areas for grocery stores (400m buffer) (exp.)	0.9698	0.4414	0.2639	0.7281	0.8163	0.2375	0.1665	0.4098	0.9827	0.4606	0.0523	0.4054
Retail areas for dur./other stores (400m buffer) (exp.)	-3.0410	6.1781	2.0427	3.0768	0.4134	0.4103	0.6864	0.8018	0.6645	0.1865	0.1864	0.7552
Shopping store variability (400m buffer) (exp.)	1.4551	0.2133	0.2093	1.1505	0.7252	0.5514	0.8753	1.4662	0.9511	0.2673	0.3773	1.2001
Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)	3.3670	0.2535	0.1840	1.0827	2.8766	0.1137	0.1283	0.6905	3.0200	0.0883	0.0563	0.6406

Table 20: Evaluation of TC sampling protocol for choice sets of 150, 200 and 250 alts

Parameter	150 alts				200 alts				250 alts			
	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.
Locational constants												
Constant rest Yorkshire	0.6933	0.2620	0.0628	0.1571	0.6323	0.1509	0.0887	0.1564	0.6870	0.2504	0.0458	0.1495
Households with car ownership												
Constant Car-Other (PT/walking)	-2.8518	0.0447	0.0274	0.2941	-2.8163	0.0316	0.0400	0.2848	-2.7157	0.0174	0.0218	0.2834
Constant Other (PT/walking)-Car	-0.7938	0.0776	0.0499	0.2466	-0.8739	0.0562	0.0680	0.2420	-0.8270	0.0548	0.0633	0.2398
Constant PT-PT	-1.0516	0.0888	0.1154	0.4295	-1.1333	0.0588	0.0767	0.4317	-1.1568	0.0736	0.0434	0.4299
Constant PT-Walking	-1.6699	0.0761	0.0342	0.4865	-1.6764	0.0803	0.0284	0.4743	-1.6308	0.0509	0.0340	0.4785
Constant Walking-PT	-1.1246	0.0843	0.0767	0.4856	-1.2377	0.0503	0.0651	0.4780	-1.1385	0.0892	0.0824	0.4822
Constant Walking-Walking	0.6986	0.1702	0.0322	0.3777	0.7007	0.1676	0.0522	0.3665	0.7662	0.1098	0.1144	0.3678
Mode shifts for households with no car ownership												
Constant Car-Other (PT/walking)	2.2521	0.0319	0.0283	0.6893	2.2940	0.0380	0.0486	0.6842	2.2569	0.0356	0.0372	0.6724
Constant Other (PT/walking)-Car	0.6393	0.0749	0.0987	0.6365	0.5573	0.1208	0.1572	0.6282	0.5509	0.1295	0.0622	0.6246
Constant PT-PT	4.4315	0.0379	0.0264	0.4986	4.3992	0.0303	0.0117	0.4888	4.4607	0.0447	0.0195	0.4923
Constant PT-Walking	3.4854	0.0393	0.0227	0.5959	3.4196	0.0229	0.0164	0.5751	3.4613	0.0321	0.0146	0.5762
Constant Walking-PT	2.6895	0.0376	0.0285	0.4882	2.7851	0.0177	0.0197	0.4694	2.7201	0.0278	0.0340	0.4610
Constant Walking-Walking	2.6663	0.0152	0.0200	0.4099	2.6921	0.0307	0.0389	0.4039	2.6978	0.0206	0.0171	0.3977
Mode shifts for central area destinations												
PT-PT	1.6915	0.0492	0.0610	0.3315	1.6597	0.0552	0.0400	0.3365	1.7714	0.0454	0.0573	0.3272
PT-Walking	1.9909	0.0947	0.0561	0.4526	1.8451	0.0499	0.0595	0.4527	1.9059	0.0505	0.0586	0.4492
Walking-PT	2.8235	0.0504	0.0329	0.4832	2.8449	0.0584	0.0225	0.4717	2.8088	0.0516	0.0504	0.4808
Walking-Walking	1.9489	0.1834	0.0565	0.2916	2.0378	0.2374	0.0506	0.2784	1.8508	0.1238	0.0320	0.2795
Mode shifts for individuals with season ticket ownership												
Walking-Walking	-0.4666	0.1677	0.2064	0.3127	-0.5125	0.1382	0.1553	0.3149	-0.4735	0.1554	0.1220	0.3050
Mode shifts for trips with more than 1 passenger												
PT first/shopping trip	-1.9022	0.0367	0.0417	0.3486	-1.8623	0.0395	0.0482	0.3439	-1.8639	0.0252	0.0329	0.3463
PT following trip	-0.7985	0.1180	0.1272	0.3619	-0.8274	0.1024	0.1426	0.3473	-0.8805	0.0261	0.0287	0.3491
Walking first/shopping trip	-0.8395	0.0485	0.0394	0.2324	-0.8302	0.0523	0.0654	0.2312	-0.7919	0.0153	0.0165	0.2265
Walking following trip	-0.3163	0.1749	0.1990	0.2485	-0.3331	0.0991	0.1350	0.2492	-0.4051	0.1291	0.1069	0.2449
Mode shifts for students												
Walking-Walking	1.1574	0.0898	0.0756	0.3872	1.1219	0.0758	0.0739	0.3906	1.0842	0.0390	0.0606	0.3815
Mode shifts for married individuals												
Walking-Walking	-0.8320	0.0629	0.0601	0.2967	-0.8403	0.0957	0.0687	0.2951	-0.8218	0.0915	0.1005	0.2910
Mode shifts for individuals living in 3-member households												
Walking-Walking	0.5828	0.1553	0.1134	0.3767	0.6402	0.0748	0.0692	0.3781	0.6344	0.0805	0.0656	0.3804
LOS variables												
Travel time for first trip (base level)	-0.0908	0.0210	0.0268	0.0096	-0.0923	0.0188	0.0253	0.0092	-0.0926	0.0191	0.0251	0.0094
Travel time shift for clothes shopping	0.0245	0.1111	0.1130	0.0090	0.0271	0.0520	0.0846	0.0088	0.0249	0.0600	0.0735	0.0090
Travel time for O-S-O trip chains	0.0128	0.1593	0.1089	0.0059	0.0130	0.1463	0.0904	0.0059	0.0154	0.0714	0.0908	0.0059
Travel time for HWH tours	-0.0422	0.0831	0.0807	0.0091	-0.0453	0.0261	0.0305	0.0093	-0.0443	0.0315	0.0387	0.0091
Travel time multiplier for car	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Travel time multiplier for PT IVT	0.5966	0.0268	0.0329	0.0712	0.5780	0.0136	0.0140	0.0670	0.5818	0.0138	0.0175	0.0652
Travel time multiplier for PT first access trip	0.8066	0.0330	0.0521	0.2550	0.7985	0.0416	0.0459	0.2380	0.8174	0.0410	0.0540	0.2407
Travel time multiplier for PT last egress trip	0.6458	0.0721	0.0657	0.1911	0.6095	0.0712	0.0937	0.1832	0.5973	0.0543	0.0679	0.1654
Travel time multiplier for PT remaining OVT	0.3429	0.0851	0.0937	0.1765	0.3811	0.1162	0.1613	0.1638	0.3463	0.0643	0.0730	0.1651
Travel time multiplier for following trip	1.4032	0.0337	0.0241	0.1043	1.3615	0.0145	0.0190	0.0958	1.3779	0.0173	0.0177	0.1024
Travel time - Shopping duration elasticity	-0.3158	0.0162	0.0241	0.0304	-0.3160	0.0168	0.0198	0.0295	-0.3135	0.0143	0.0200	0.0290
Travel walking distance (base)	-1.6614	0.0247	0.0170	0.1326	-1.6590	0.0203	0.0144	0.1277	-1.6338	0.0105	0.0138	0.1248
Travel walking distance for O-S-O trip chains	0.2808	0.1498	0.1630	0.1209	0.2876	0.1057	0.1013	0.1174	0.2797	0.0684	0.0858	0.1149
Travel walking distance multiplier for following trip	1.1929	0.0468	0.0158	0.0915	1.2213	0.0241	0.0076	0.0906	1.2312	0.0179	0.0226	0.0906
Box-cox lambda for travel walking distance	0.7999	0.0182	0.0227	0.0540	0.7844	0.0257	0.0085	0.0505	0.8097	0.0079	0.0095	0.0526
Travel walking distance - Shopping duration elasticity	-0.1500	0.0743	0.0500	0.0365	-0.1423	0.0740	0.0860	0.0356	-0.1504	0.0771	0.0488	0.0355
Travel cost	-0.6597	0.0174	0.0290	0.0820	-0.6630	0.0200	0.0214	0.0776	-0.6590	0.0111	0.0101	0.0777
Box-cox lambda for travel cost	0.5834	0.0881	0.0359	0.0527	0.5812	0.0840	0.0167	0.0520	0.5709	0.0648	0.0274	0.0509
Travel cost - Personal income elasticity	-0.2389	0.0518	0.0682	0.0924	-0.2458	0.0516	0.0656	0.0915	-0.2526	0.0524	0.0559	0.0948
Locational variables												
Living in rich areas-shopping in poor areas	-0.9315	0.1590	0.0603	0.2979	-0.9197	0.1444	0.1342	0.2861	-0.9201	0.1449	0.0852	0.2899
Parking areas (400m buffer))	0.0998	0.0750	0.0435	0.0295	0.0962	0.0339	0.0250	0.0287	0.0975	0.0499	0.0474	0.0281
Box-cox lambda for parking areas (400m buffer)	0.4470	0.0597	0.0365	0.0860	0.4460	0.0595	0.0481	0.0867	0.4430	0.0591	0.0513	0.0833
Presence of major clothes shopping retailers (400m buffer)	2.0226	0.0583	0.0775	0.2477	2.0447	0.0420	0.0528	0.2363	2.0153	0.0270	0.0208	0.2285
Presence of major grocery retailers (400m buffer)	0.5026	0.0621	0.0625	0.1038	0.5233	0.0394	0.0551	0.1006	0.5231	0.0323	0.0367	0.1009
Presence of major durables retailers (400m buffer)	2.2204	0.1737	0.1890	1.2152	2.1477	0.0734	0.0847	1.0707	1.8223	0.1125	0.1397	0.8535
Size variables												
Natural logarithm multiplier ϕ	0.7244	0.0283	0.0339	0.1000	0.7206	0.0425	0.0565	0.0977	0.7140	0.0455	0.0495	0.0970
Population (400m buffer)	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Retail areas for clothes stores (400m buffer) (exp.)	0.3643	0.6672	0.3652	0.5235	0.3255	1.0320	0.7678	0.5242	0.2821	0.4467	0.3880	0.5269
Retail areas for grocery stores (400m buffer) (exp.)	0.8070	0.2131	0.1509	0.3859	0.8015	0.2139	0.1454	0.3864	0.8132	0.2088	0.1306	0.3809
Retail areas for dur./other stores (400m buffer) (exp.)	0.5259	0.2685	0.3698	0.7105	0.5223	0.2303	0.3733	0.7189	0.5798	0.2709	0.3723	0.7350
Shopping store variability (400m buffer) (exp.)	0.9835	0.2345	0.2067	1.0151	1.0034	0.2549	0.2876	0.9861	1.1556	0.1141	0.0893	0.8725
Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)	3.0318	0.0925	0.0335	0.6508	3.0076	0.0988	0.0668	0.6580	2.9711	0.0794	0.0610	0.6871

Table 21: Evaluation of TAC sampling protocol for choice sets of 10, 50 and 100 alts

Parameter	10 alts				50 alts				100 alts			
	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.
Locational constants												
Constant rest Yorkshire	1.1660	1.1223	0.0825	0.2827	0.7311	0.3308	0.1141	0.2076	0.7121	0.2961	0.1069	0.1767
Households with car ownership												
Constant Car-Other (PT/walking)	-3.2345	0.1848	0.1013	0.4147	-2.9922	0.0961	0.0421	0.3197	-2.9136	0.0673	0.0259	0.2893
Constant Other (PT/walking)-Car	-1.0579	0.2292	0.1921	0.3301	-0.9305	0.1186	0.1205	0.2567	-0.8186	0.0669	0.0708	0.2423
Constant PT-PT	-1.7943	0.6652	0.1944	0.5990	-1.2637	0.1787	0.1064	0.4679	-1.2740	0.1824	0.0775	0.4367
Constant PT-Walking	-2.4047	0.5497	0.0561	0.6353	-1.7935	0.1558	0.0888	0.5132	-1.6566	0.0849	0.0696	0.5016
Constant Walking-PT	-1.6604	0.3735	0.1400	0.6011	-1.3519	0.1183	0.0946	0.5007	-1.2231	0.0596	0.0697	0.4795
Constant Walking-Walking	0.6818	0.2803	0.4283	0.5398	0.6945	0.1772	0.1764	0.4070	0.8118	0.0741	0.1172 0.3831	
Mode shifts for households with no car ownership												
Constant Car-Other (PT/walking)	2.3091	0.2056	0.2600	0.8292	2.4397	0.0487	0.0453	0.7213	2.3924	0.0604	0.0636	0.6602
Constant Other (PT/walking)-Car	0.4816	0.4263	0.8205	0.7237	0.6134	0.2143	0.2619	0.6271	0.6606	0.1801	0.2123	0.6262
Constant PT-PT	4.8408	0.1338	0.0560	0.6605	4.5934	0.0758	0.0514	0.5305	4.5721	0.0708	0.0291	0.5166
Constant PT-Walking	4.0774	0.2158	0.0897	0.7404	3.7291	0.1120	0.0665	0.6141	3.4815	0.0399	0.0317	0.6034
Constant Walking-PT	2.7831	0.1335	0.1925	0.6582	2.8766	0.0353	0.0423	0.5127	2.7306	0.0385	0.0425	0.4980
Constant Walking-Walking	3.3167	0.2467	0.0981	0.5641	2.7734	0.0473	0.0441	0.4282	2.7075	0.0236	0.0225	0.4170
Mode shifts for central area destinations												
PT-PT	1.8844	0.1084	0.1082	0.4832	1.6922	0.0412	0.0361	0.3846	1.7356	0.0378	0.0591	0.3514
PT-Walking	2.5269	0.3847	0.2223	0.6495	1.8289	0.0839	0.1063	0.4643	1.8540	0.0375	0.0516	0.4617
Walking-PT	3.2592	0.2125	0.0640	0.5762	2.8427	0.0576	0.0426	0.4858	2.8259	0.0513	0.0312	0.4762
Walking-Walking	1.8465	0.1457	0.1028	0.4080	1.7924	0.0884	0.0344	0.3150	1.7308	0.0518	0.0356	0.2967
Mode shifts for individuals with season ticket ownership												
Walking-Walking	-0.3608	0.3565	0.4409	0.4503	-0.3209	0.4275	0.4189	0.3391	-0.3951	0.2951	0.1802	0.3343
Mode shifts for trips with more than 1 passenger												
PT first/shopping trip	-2.2572	0.2123	0.0982	0.4787	-2.0993	0.1275	0.0858	0.3769	-1.9648	0.0808	0.0791	0.3525
PT following trip	-0.8831	0.2436	0.3406	0.4622	-0.7520	0.1769	0.1817	0.3624	-0.7767	0.1072	0.0845	0.3613
Walking first/shopping trip	-0.9184	0.2638	0.2794	0.3357	-0.8673	0.1115	0.0828	0.2459	-0.8816	0.1120	0.0754	0.2386
Walking following trip	-0.2420	0.5529	1.3431	0.3717	-0.3314	0.2575	0.3721	0.2683	-0.2468	0.3472	0.3600	0.2569
Mode shifts for students												
Walking-Walking	1.3938	0.3337	0.2078	0.4853	1.3746	0.2786	0.0862	0.3840	1.1138	0.0360	0.0297	0.3768
Mode shifts for married individuals												
Walking-Walking	-1.0906	0.3933	0.1494	0.4218	-0.8657	0.1059	0.0667	0.3108	-0.9143	0.1681	0.0847	0.2948
Mode shifts for individuals living in 3-member households												
Walking-Walking	0.2072	0.6996	1.3627	0.4892	0.5067	0.2655	0.1626	0.3768	0.6557	0.1083	0.1283	0.3822
LOS variables												
Travel time for first trip (base level)	-0.0723	0.2075	0.0667	0.0115	-0.0884	0.0392	0.0409	0.0101	-0.0866	0.0509	0.0202	0.0095
Travel time shift for clothes shopping	-0.0019	1.0714	5.7320	0.0154	0.0130	0.5112	0.4340	0.0121	0.0200	0.2471	0.1130	0.0106
Travel time for O-S-O trip chains	0.0066	0.5677	0.6542	0.0088	0.0124	0.2217	0.2646	0.0064	0.0111	0.2678	0.0526	0.0063
Travel time for HWH tours	-0.0483	0.1071	0.0869	0.0122	-0.0442	0.0297	0.0360	0.0099	-0.0453	0.0347	0.0502	0.0093
Travel time multiplier for car	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Travel time multiplier for PT IVT	0.5548	0.0901	0.1383	0.0903	0.5790	0.0223	0.0269	0.0754	0.5904	0.0253	0.0300	0.0680
Travel time multiplier for PT first access trip	0.8013	0.1132	0.1870	0.3393	0.7586	0.0823	0.0943	0.2648	0.7911	0.0347	0.0285	0.2656
Travel time multiplier for PT last egress trip	0.6293	0.2045	0.2567	0.2432	0.5551	0.1369	0.1334	0.2055	0.5742	0.0872	0.0944	0.1810
Travel time multiplier for PT remaining OVT	0.3848	0.4166	0.4593	0.2977	0.3061	0.2628	0.3050	0.2017	0.2595	0.3011	0.3739	0.1882
Travel time multiplier for following trip	1.4072	0.0656	0.0814	0.1610	1.3628	0.0258	0.0337	0.1076	1.3836	0.0202	0.0228	0.1053
Travel time - Shopping duration elasticity	-0.3462	0.0968	0.0797	0.0418	-0.3346	0.0602	0.0216	0.0336	-0.3253	0.0305	0.0212	0.0330
Travel walking distance (base)	-1.6664	0.0684	0.0774	0.1619	-1.6477	0.0147	0.0109	0.1377	-1.5886	0.0267	0.0245	0.1259
Travel walking distance for O-S-O trip chains	0.2191	0.2131	0.1989	0.1693	0.2325	0.1613	0.1635	0.1274	0.2332	0.1526	0.1588	0.1171
Travel walking distance multiplier for following trip	1.1807	0.0813	0.0882	0.1108	1.1921	0.0475	0.0207	0.0989	1.2532	0.0109	0.0145	0.0990
Box-cox lambda for travel walking distance	0.7399	0.0810	0.0644	0.0606	0.7771	0.0348	0.0195	0.0531	0.8083	0.0092	0.0110	0.0527
Travel walking distance - Shopping duration elasticity	-0.1651	0.1824	0.2165	0.0419	-0.1518	0.0885	0.0565	0.0362	-0.1480	0.0804	0.0834	0.0339
Travel cost	-0.6295	0.0525	0.0695	0.1040	-0.6566	0.0324	0.0395	0.0894	-0.6769	0.0386	0.0224	0.0822
Box-cox lambda for travel cost	0.5464	0.1448	0.1755	0.0915	0.5949	0.1094	0.0246	0.0580	0.5971	0.1136	0.0253	0.0536
Travel cost - Personal income elasticity	-0.1960	0.2851	0.4207	0.1371	-0.2357	0.0983	0.1206	0.1044	-0.2437	0.0680	0.1020	0.0959
Locational variables												
Living in rich areas-shopping in poor areas	-1.2773	0.7024	0.3139	0.5073	-0.9951	0.2382	0.0398	0.3979	-0.9590	0.1933	0.1270	0.3649
Parking areas (400m buffer))	0.0756	0.1870	0.0584	0.0333	0.0995	0.0696	0.0280	0.0302	0.1023	0.0992	0.0480	0.0286
Box-cox lambda for parking areas (400m buffer)	0.4932	0.1693	0.0353	0.1250	0.4198	0.0159	0.0200	0.0875	0.4005	0.0521	0.0406	0.0820
Presence of major clothes shopping retailers (400m buffer)	2.1518	0.2299	0.2246	0.5199	2.0857	0.0629	0.0427	0.2890	2.0458	0.0425	0.0391	0.2418
Presence of major grocery retailers (400m buffer)	0.4562	0.1447	0.1111	0.1495	0.5432	0.0483	0.0555	0.1076	0.5687	0.0661	0.0455	0.1037
Presence of major durables retailers (400m buffer)	0.4675	0.7717	1.5566	1.0567	1.5932	0.2220	0.1861	1.2884	1.6379	0.2211	0.2207	1.2813
Size variables												
Natural logarithm multiplier ϕ	0.6628	0.1316	0.1456	0.1423	0.6968	0.0485	0.0468	0.1111	0.7138	0.0305	0.0298	0.1044
Population (400m buffer)	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Retail areas for clothes stores (400m buffer) (exp.)	0.9429	4.2951	0.8612	0.9882	0.7796	2.5675	0.2748	0.6304	0.4749	1.1732	0.3343	0.5996
Retail areas for grocery stores (400m buffer) (exp.)	1.5007	1.2306	0.3058	0.7292	0.9297	0.3819	0.1434	0.4728	0.8020	0.1920	0.1246	0.4232
Retail areas for dur./other stores (400m buffer) (exp.)	-2.0882	5.8491	3.1765	1.7849	0.8669	0.4947	0.3969	0.8789	0.7113	0.4126	0.3943	0.7856
Shopping store variability (400m buffer) (exp.)	1.7527	0.7496	0.6904	1.5115	1.3553	0.1288	0.1407	0.8763	1.2372	0.0892	0.1021	0.8673
Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)	3.8221	0.4258	0.2294	1.2216	3.1041	0.1261	0.1022	0.7390	2.9727	0.1064	0.0983	0.7347

Table 22: Evaluation of TAC sampling protocol for choice sets of 150, 200 and 250 alts

Parameter	150 alts				200 alts				250 alts			
	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.	Av.est.	AAPD	ACoV	Av.st.err.
Locational constants												
Constant rest Yorkshire	0.7301	0.3290	0.1091	0.1707	0.6680	0.2159	0.0996	0.1668	0.6527	0.1880	0.0620	0.1581
Households with car ownership												
Constant Car-Other (PT/walking)	-2.8391	0.0419	0.0276	0.2918	-2.8645	0.0493	0.0130	0.2840	-2.7983	0.0251	0.0149	0.2812
Constant Other (PT/walking)-Car	-0.8208	0.0462	0.0159	0.2380	-0.8709	0.0622	0.0866	0.2402	-0.8622	0.0424	0.0545	0.2386
Constant PT-PT	-1.2350	0.1461	0.0511	0.4398	-1.2034	0.1533	0.1326	0.4212	-1.1201	0.0406	0.0395	0.4185
Constant PT-Walking	-1.6200	0.0472	0.0385	0.4910	-1.6316	0.0575	0.0492	0.4839	-1.5801	0.0376	0.0481	0.4819
Constant Walking-PT	-1.1634	0.0486	0.0426	0.4828	-1.2912	0.0845	0.0615	0.4850	-1.2025	0.0279	0.0452	0.4805
Constant Walking-Walking	0.8634	0.0768	0.0845	0.3736	0.7677	0.0881	0.0815	0.3713	0.8275	0.0287	0.0393	0.3673
Mode shifts for households with no car ownership												
Constant Car-Other (PT/walking)	2.4436	0.0504	0.0254	0.6723	2.4353	0.0468	0.0207	0.6467	2.3976	0.0306	0.0109	0.6516
Constant Other (PT/walking)-Car	0.5800	0.1676	0.2098	0.6107	0.6451	0.1034	0.1187	0.6103	0.6383	0.0407	0.0574	0.6171
Constant PT-PT	4.4777	0.0487	0.0138	0.5012	4.3713	0.0285	0.0273	0.4949	4.3784	0.0255	0.0130	0.5065
Constant PT-Walking	3.4181	0.0330	0.0322	0.6024	3.3968	0.0168	0.0218	0.5810	3.4530	0.0296	0.0242	0.5872
Constant Walking-PT	2.7217	0.0291	0.0338	0.4750	2.8306	0.0154	0.0131	0.4667	2.7867	0.0059	0.0073	0.4761
Constant Walking-Walking	2.6366	0.0158	0.0218	0.4063	2.6616	0.0072	0.0108	0.4026	2.6935	0.0198	0.0200	0.4111
Mode shifts for central area destinations												
PT-PT	1.8123	0.0466	0.0499	0.3376	1.7869	0.0351	0.0432	0.3368	1.7084	0.0472	0.0584	0.3281
PT-Walking	1.8937	0.0556	0.0537	0.4579	1.8765	0.0341	0.0360	0.4434	1.7769	0.0333	0.0306	0.4392
Walking-PT	2.8277	0.0520	0.0149	0.4769	2.7540	0.0246	0.0072	0.4754	2.7517	0.0269	0.0230	0.4727
Walking-Walking	1.7114	0.0392	0.0197	0.2810	1.6796	0.0199	0.0140	0.2738	1.6577	0.0247	0.0268	0.2705
Mode shifts for individuals with season ticket ownership												
Walking-Walking	-0.4440	0.2080	0.0696	0.3228	-0.5205	0.0894	0.1108	0.3245	-0.5130	0.0921	0.0728	0.3221
Mode shifts for trips with more than 1 passenger												
PT first/shopping trip	-1.8738	0.0124	0.0159	0.3563	-1.9288	0.0435	0.0345	0.3464	-1.9111	0.0391	0.0450	0.3492
PT following trip	-0.8106	0.1083	0.1375	0.3500	-0.7481	0.1347	0.1005	0.3521	-0.7952	0.0802	0.0803	0.3531
Walking first/shopping trip	-0.8712	0.0881	0.0558	0.2332	-0.8545	0.0733	0.0690	0.2344	-0.8460	0.0566	0.0408	0.2322
Walking following trip	-0.3314	0.1208	0.1591	0.2537	-0.3144	0.1454	0.0853	0.2538	-0.3134	0.1481	0.0707	0.2515
Mode shifts for students												
Walking-Walking	1.1118	0.0347	0.0487	0.3750	1.1027	0.0414	0.0578	0.3693	1.0831	0.0357	0.0507	0.3788
Mode shifts for married individuals												
Walking-Walking	-0.8603	0.0991	0.0420	0.2932	-0.8149	0.0411	0.0400	0.2917	-0.8355	0.0674	0.0271	0.2911
Mode shifts for individuals living in 3-member households												
Walking-Walking	0.6591	0.0447	0.0255	0.3871	0.7295	0.0573	0.0567	0.3845	0.7057	0.0627	0.0676	0.3854
LOS variables												
Travel time for first trip (base level)	-0.0882	0.0335	0.0243	0.0092	-0.0912	0.0102	0.0135	0.0092	-0.0906	0.0166	0.0198	0.0093
Travel time shift for clothes shopping	0.0248	0.1249	0.1372	0.0097	0.0249	0.0920	0.1824	0.0100	0.0248	0.1224	0.1382	0.0100
Travel time for O-S-O trip chains	0.0133	0.1270	0.0960	0.0061	0.0144	0.0893	0.1242	0.0061	0.0142	0.0763	0.0821	0.0061
Travel time for HWH tours	-0.0436	0.0462	0.0621	0.0092	-0.0449	0.0195	0.0331	0.0093	-0.0447	0.0238	0.0264	0.0093
Travel time multiplier for car	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Travel time multiplier for PT IVT	0.5952	0.0169	0.0250	0.0653	0.5817	0.0094	0.0085	0.0636	0.5843	0.0077	0.0100	0.0631
Travel time multiplier for PT first access trip	0.7945	0.0811	0.0965	0.2649	0.8096	0.0460	0.0554	0.2420	0.7909	0.0349	0.0141	0.2361
Travel time multiplier for PT last egress trip	0.5885	0.0569	0.0739	0.1746	0.5880	0.0487	0.0604	0.1768	0.5959	0.0320	0.0346	0.1696
Travel time multiplier for PT remaining OVT	0.3358	0.1364	0.1858	0.1938	0.2943	0.1786	0.2271	0.1813	0.3352	0.0780	0.0964	0.1819
Travel time multiplier for following trip	1.3847	0.0211	0.0188	0.1051	1.3744	0.0152	0.0134	0.0987	1.3647	0.0163	0.0186	0.1000
Travel time - Shopping duration elasticity	-0.3243	0.0274	0.0184	0.0328	-0.3192	0.0159	0.0148	0.0314	-0.3172	0.0124	0.0212	0.0316
Travel walking distance (base)	-1.5921	0.0208	0.0101	0.1226	-1.6070	0.0117	0.0092	0.1229	-1.6117	0.0088	0.0056	0.1227
Travel walking distance for O-S-O trip chains	0.2497	0.0744	0.0593	0.1150	0.2495	0.0731	0.0423	0.1143	0.2435	0.0951	0.0564	0.1143
Travel walking distance multiplier for following trip	1.2529	0.0065	0.0078	0.0952	1.2501	0.0084	0.0105	0.0932	1.2497	0.0083	0.0119	0.0932
Box-cox lambda for travel walking distance	0.8105	0.0118	0.0133	0.0530	0.8067	0.0031	0.0053	0.0525	0.8072	0.0030	0.0037	0.0519
Travel walking distance - Shopping duration elasticity	-0.1470	0.0585	0.0485	0.0329	-0.1441	0.0330	0.0265	0.0331	-0.1400	0.0250	0.0312	0.0329
Travel cost	-0.6713	0.0298	0.0143	0.0796	-0.6534	0.0166	0.0240	0.0784	-0.6630	0.0171	0.0141	0.0784
Box-cox lambda for travel cost	0.5798	0.0814	0.0349	0.0538	0.5722	0.0671	0.0222	0.0538	0.5697	0.0625	0.0172	0.0518
Travel cost - Personal income elasticity	-0.2364	0.0426	0.0412	0.0978	-0.2403	0.0826	0.1153	0.0964	-0.2522	0.0483	0.0468	0.0960
Locational variables												
Living in rich areas-shopping in poor areas	-0.8054	0.1039	0.1421	0.3174	-0.8504	0.0701	0.0779	0.3179	-0.8184	0.0655	0.0804	0.3020
Parking areas (400m buffer))	0.0961	0.0372	0.0436	0.0273	0.0948	0.0448	0.0585	0.0277	0.0978	0.0509	0.0112	0.0278
Box-cox lambda for parking areas (400m buffer)	0.4278	0.0374	0.0426	0.0795	0.4331	0.0410	0.0475	0.0835	0.4147	0.0168	0.0125	0.0811
Presence of major clothes shopping retailers (400m buffer)	2.0760	0.0650	0.0575	0.2340	2.0318	0.0354	0.0131	0.2232	2.0139	0.0263	0.0046	0.2165
Presence of major grocery retailers (400m buffer)	0.5491	0.0323	0.0270	0.1008	0.5631	0.0556	0.0286	0.0990	0.5498	0.0416	0.0352	0.0992
Presence of major durables retailers (400m buffer)	2.1292	0.1872	0.2127	1.3533	2.0369	0.1396	0.1979	1.3000	1.6899	0.1977	0.1719	1.3995
Size variables												
Natural logarithm multiplier ϕ	0.7276	0.0112	0.0138	0.1056	0.7220	0.0279	0.0340	0.1025	0.7467	0.0240	0.0247	0.1040
Population (400m buffer)	1.0000	–	–	–	1.0000	–	–	–	1.0000	–	–	–
Retail areas for clothes stores (400m buffer) (exp.)	0.3792	0.7351	0.2813	0.5615	0.4392	1.0099	0.2900	0.5625	0.2789	0.3235	0.2595	0.5543
Retail areas for grocery stores (400m buffer) (exp.)	0.7512	0.1311	0.1220	0.4033	0.7687	0.1605	0.1275	0.4051	0.6600	0.0758	0.0924	0.3810
Retail areas for dur./other stores (400m buffer) (exp.)	0.7906	0.3462	0.1223	0.7536	0.6542	0.1139	0.0529	0.7568	0.6826	0.1623	0.0791	0.7249
Shopping store variability (400m buffer) (exp.)	1.2536	0.0606	0.0748	0.7959	1.2522	0.0555	0.0837	0.8243	1.2250	0.0589	0.0605	0.7873
Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)	2.9791	0.0736	0.0534	0.7052	2.9645	0.0683	0.0435	0.6957	2.7594	0.0406	0.0487	0.7083