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

3 Panagiotis Tsoleridis^{*,a}, Charisma F. Choudhury^a, Stephane Hess^a

4 ^aUniversity of Leeds, University road, Leeds, UK, LS2 9JT

5 **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.

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

*Corresponding Author

Email addresses: ts17pt@leeds.ac.uk (Panagiotis Tsoleridis), C.F.Choudhury@leeds.ac.uk (Charisma F. Choudhury), S.Hess@leeds.ac.uk (Stephane Hess)

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

1 probabilities are modified as shown in *Equation 1* and the *SC* term for stratified importance sampling without
 2 replacement is defined in *Equation 2* (Ben-Akiva and Lerman, 1985; Guevara and Ben-Akiva, 2013a).

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

$$\pi(D_n | i, x_n) = \frac{J_{r(i)n}^*}{J_{r(i)n}} \quad (2)$$

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

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

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

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

44 The remainder of the paper is as follows. In the following section, we give an overview of the relevant
 45 literature on time-space geography before expanding this to the context of sampling of destinations. In the

1 third section, the modelling framework developed and the data utilised for the ensued practical application
 2 are presented. The results are presented next followed by a concluding section summarising the findings and
 3 setting the direction for future research.

4 2. Methodology

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

9 2.1. Activity spaces - general literature

10 Activity spaces (AS) originate from the work of time-space geography (Hagerstrand, 1970) and behavioural
 11 geography (Brown and Moore, 1970; Horton and Reynolds, 1970; Yuill, 1971) and they have been studied
 12 extensively since then for the purpose of understanding activity participation (Schönfelder and Axhausen,
 13 2004; Schönfelder, 2006; Schönfelder and Axhausen, 2010; Kamruzzaman and Hine, 2012), trip chaining
 14 behaviour (Newsome et al., 1998) among others. They are mainly used as a measure of describing the spatial
 15 distribution of visited locations and they incorporate a notion of individual spatial awareness (Manley, 2016)
 16 by providing invaluable information about the exposure to specific locations and activities that individuals
 17 might perform based on their usual mobility patterns and their time-space constraints. Due to the vast
 18 range of studies and application domains, there are several different forms of AS proposed in the literature
 19 depending on the aspect under examination in each case and the level of analysis. In a systematic review,
 20 Smith et al. (2019) summarised the different AS forms, which, amongst others include the following:

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

26 We will now look at these three in turn.

27 2.1.1. Detour Ellipse

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

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

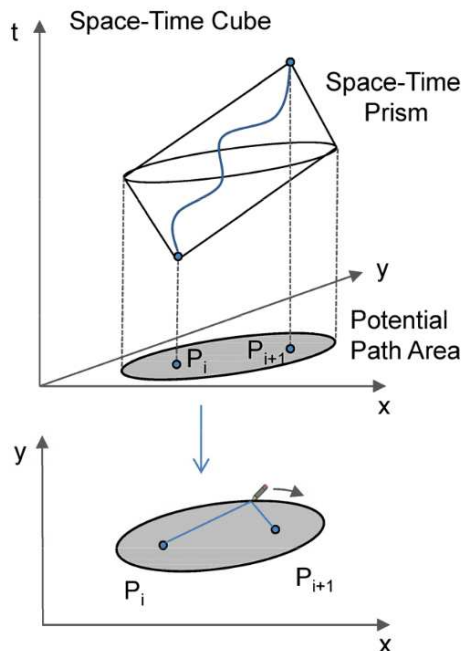


Figure 1: Two-dimensional projection of time-space prisms (Demsar and Long, 2016)

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

$$DF = \frac{l_{OS} + l_{SD}}{l_{OD}} \quad (3)$$

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

13 2.1.2. Standard Deviatonal Ellipse

14 SDEs originate from behavioural geography (Brown and Moore, 1970; Horton and Reynolds, 1970; Yuill,
 15 1971) and have been proposed as a measure of capturing the exposure of individuals to opportunities as a
 16 consequence of daily activities (Horton and Reynolds, 1971). ASs formed by SDEs are considered a subset of
 17 a larger latent *awareness space* (Brown and Moore, 1970; Patterson and Farber, 2015). In that sense, a SDE
 18 provides additional information on the individual awareness of certain destinations, that the DE/PPA is not
 19 able to provide.

20 SDEs have been mainly analysed in social geography for the purpose of understanding human mobility
 21 patterns with several measures that could be extracted, such as SDE's shape (minor to major axis ratio), size
 22 (area, number of polygons located within etc.), orientation and eccentricity (Yuill, 1971). Temporal factors
 23 can also be taken into account, such as examining weekday/weekend differences (Srivastava and Schoenfelder,
 24 2003; Smith et al., 2019) and their evolution over decades (Axhausen, 2007). Survey duration also plays an

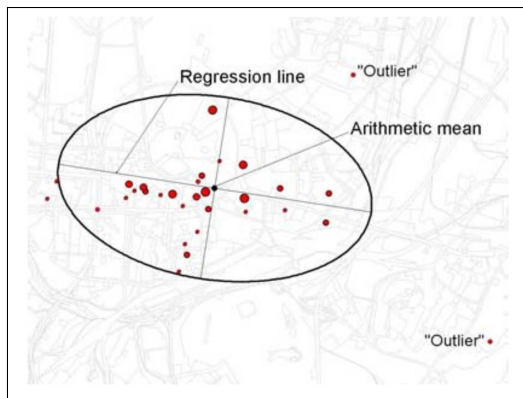


Figure 2: Weighted standard deviational ellipse around observed/visited destinations (Schönfelder, 2003)

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

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

11 2.1.3. Familiarity buffers

12 Buffer zones around frequently visited locations have been proposed as another form of AS used to capture
 13 the spatial awareness or the number and different types of services an individual is exposed to, similar to
 14 SDEs. Due to their ease of implementation, a large number of studies have implemented them with various
 15 buffer zones being proposed depending on their purpose ranging from 500 m to define *immediate home*
 16 *neighbourhoods* to 1.6 km to define broader areas (Larsen et al., 2009; van Heeswijck et al., 2015; Chaix et al.,
 17 2017). Weighted FBs have also been proposed based on the activity type performed, the visiting frequency
 18 or the time spent at those locations (Loebach and Gilliland, 2016). Finally, in a study more related to the
 19 current one, Horni et al. (2011) for their conceptual choice set formation framework, proposed adding a
 20 buffer zone, equivalent to 15 minutes of walking distance, around home and work locations in a PPA ellipse
 21 formed between home-based work trips.

22 2.2. Applying AS approaches to destination sampling

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

34 Leite Mariante et al. (2018) formed DEs (DF-based PPAs) for the purpose of sampling of alternatives
 35 for a destination choice model of different discretionary activity types. The DEs were defined based on the

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

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

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

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

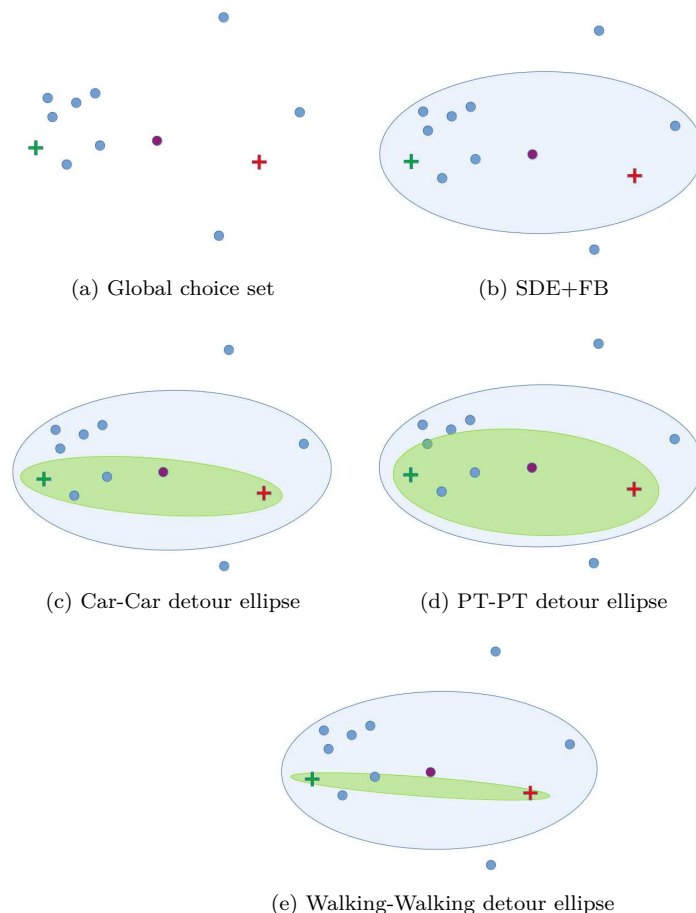


Figure 3: Example of sampled choice set specification (*SDE*: Standard Deviation Ellipse; *FB*: Familiarity Buffer)

1 and the following trip are *car-car*, *PT-PT* and *walking-walking*. Therefore, the global choice set consists of
 2 30 mode-destination alternatives. In the second subfigure, the combined SDE-FB area of the individual is
 3 defined based on the observed destinations she visited during the survey period. Finally, in the remaining 3
 4 subfigures, the estimated mode-specific DEs are defined for car-car, PT-PT and walking-walking, respectively,
 5 based on the modelling specification described in *Subsection 3.3.1*.

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

- 10
- *Random sampling* with a uniform probability from the full choice set
 - 11 • *AC* referring to sampling with a priority from A and then from C, such as $\pi(A) > \pi(C)$
 - 12 • *TC* referring to sampling with a priority from T and then from C, such as $\pi(T) > \pi(C)$
 - 13 • *TAC* referring to sampling with a priority from T, then from A and finally from C, such as $\pi(T) >$
 14 $\pi(A) > \pi(C)$

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

1 size, as shown in the following *Equation 4*:

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

2 where $\pi(r)$ is the sampling probability for stratum r and $nTrips_r$, $nTrips_{total}$ are the number of trips with
 3 chosen shopping destinations in stratum r and the total number of trips, respectively. Therefore, if on
 4 average 60%, 30% and 10% of the observed alternatives in the sample are within T, A and C, respectively,
 5 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
 6 alternatives is constructed by first selecting the chosen alternative and then performing importance sampling
 7 for the remaining $J - 1$ alternatives by sampling the desired number of alternatives from the respective
 8 stratum (Guevara and Ben-Akiva, 2013a; Guevara and Ben-Akiva, 2013b). In the case of not having enough
 9 alternatives to reach that desired number per stratum, alternatives from the next stratum in line, as defined
 10 per sampling protocol, are sampled. The inclusion of a properly calculated SC term in the utility function
 11 will guarantee the estimation of unbiased parameters for sufficient choice set sizes, even when not reaching
 12 the desired number of alternatives from the respective strata. It is also assumed that alternatives that are
 13 being sampled and included in the reduced choice set are all considered equally by the individuals, hence no
 14 further consideration thresholds have been applied in the utility function (see for example Martinez et al.
 15 (2009)). The developed framework is summarised below:

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

27 3. Empirical application: data and model specification

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

30 3.1. Data

31 3.1.1. Original GPS data

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

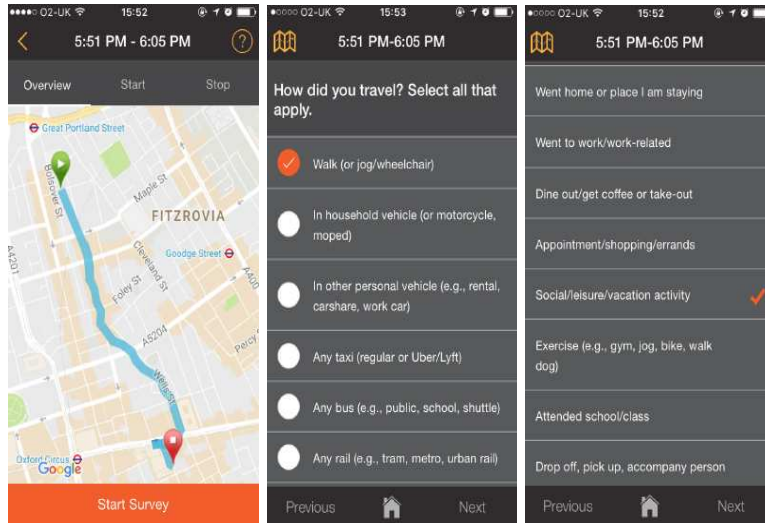


Figure 4: User interface of smartphone application used for the trip diary (Calastri et al., 2020)

1 The analysis presented in the current study is focused on a specific type of discretionary activity, namely
 2 shopping. The study area was defined as the region of Yorkshire. Only individuals residing in the local
 3 authority of Leeds were selected, assuming they will have a similar knowledge of their surrounding shopping
 4 destinations having to adhere to the same spatial constraints (Domencich and McFadden, 1975; Richards and
 5 Ben-Akiva, 1975; Adler and Ben-Akiva, M., 1976; Southworth, 1981; Miller and O’Kelly, 1983; Thill, 1992).
 6 The purpose of the analysis is to understand where the individuals are more likely to go for shopping with
 7 respect to the previous and the following activity locations. Therefore, from the initial dataset, the shopping
 8 trips and their following trips were chosen for the subsequent analysis. The final dataset used in the analysis
 9 contained 1541 shopping trips and an equal number of following trips performed by 270 unique individuals
 10 (5.7 trips per individual, on average). Regarding the sociodemographic information of the individuals included
 11 in the sample, 64.1% were female, 32.2% between 30-39 years old and most of them employed (77%). The
 12 vast majority possessed at least one car in their household, while 20% had either a bus or rail season ticket.

13 3.1.2. Processing of data into trip chains

14 The shopping and their following trips were combined to create trip chains, which formed the basis of the
 15 analysis performed. Most trip chains, 66%, were from an origin O to an intermediate shopping destination S
 16 and then to another destination D , which will be referred to as O - S - D trip chain. The remaining trip chains,
 17 34%, were from an origin O to a shopping destination S and then back to the origin O , which will be referred
 18 to as O - S - O trip chains. Shopping trips included three subcategories of shopping, namely grocery (82%),
 19 clothes (12.7%) and other types of shopping (5.3%), mainly for durables. The vast majority of following
 20 trips were trips going home (61.5%), while there was a small percentage (9.3%) of a consecutive shopping
 21 trip to a different shopping destination. From the remaining trips, 10.5% were for work/education, 11%
 22 for leisure/social and 7.7% were for other purposes. The present study is focused on a subset of modes of
 23 transports, namely car, public transport (PT) –as a combination of bus and rail– and walking. Most of
 24 the observed/chosen modes for the two legs of the trip chain were car-car (shopping-following trip) and
 25 walking-walking, namely 85.2%, while only 3% were PT-PT. Combinations of the three modes were also
 26 observed, such as car-PT, walking-car etc. and it was decided to include them in the analysis, despite their
 27 low mode share.

28 3.1.3. Definition of shopping areas

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

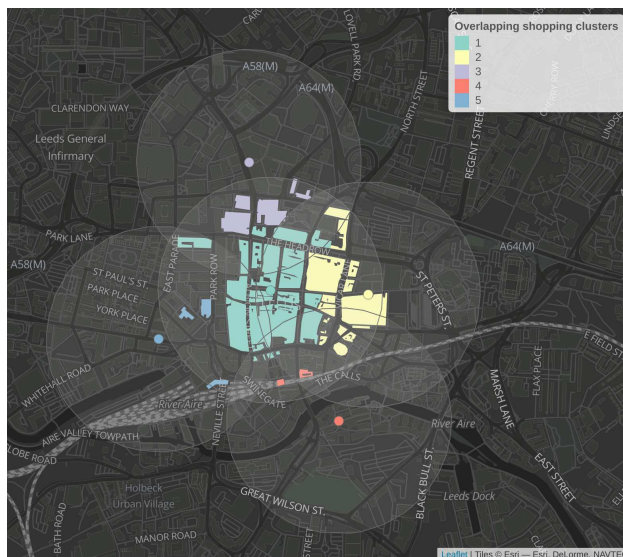


Figure 5: Allocation of retail polygons located within overlapping shopping clusters (OpenStreetMap contributors, 2021)

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

2 After defining the shopping clusters, their respective centroids were defined as the mean of the lati-
 3 tude/longitude coordinates of the elemental destinations in each cluster. The cluster centroids were then
 4 used to replace the original destination points of each shopping trip belonging to the cluster. The main
 5 goal of the clustering was to choose an appropriate distance threshold that would result in a small average
 6 distance difference between the original destination points of a cluster and its centroid. After trying different
 7 distance thresholds between 500m-1000m, a 800m distance threshold was selected resulting in an average
 8 distance difference of 112m, while the maximum distance difference was 338m, which equates to between
 9 4-5 minutes of walking (assuming a 5 km/h average walking speed). Larger distance thresholds resulted in
 10 distance differences of more than 5 minutes of walking distance, while smaller thresholds resulted in large
 11 shopping malls being split across two different clusters. In addition, visual inspection of the created clusters
 12 for different distance thresholds was performed in order to verify that distinct shopping areas were assigned to
 13 different clusters, with an emphasis on the main shopping areas of Leeds city centre. This procedure resulted
 14 in the creation of 176 general shopping clusters around the region of Yorkshire with most of them located
 15 around the city of Leeds. It is clear that shopping locations exist in other places within the study area, not
 16 captured by that process, mostly in areas outside the local authority of Leeds. Those shopping locations,
 17 which are never chosen by the individuals, are assumed to not having been considered by the individuals in
 18 the sample and hence are excluded from the subsequent analysis (Thill, 1992).

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

26 3.1.4. Data enrichment: level-of-service information and mode availability assumptions

27 In order to account for the fact that only travel times for chosen/observed alternatives were included
 28 in the dataset, travel times/distances were re-estimated both for chosen and non-chosen alternatives using
 29 the Bing Maps Routes API¹. The total number of queries passed on the API were 1,627,296 (1541 trips ×

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

1 176 shopping destinations \times 3 modes \times 2 legs). The small distance differences between the initial observed
 2 destinations and the cluster centroids, as previously described, ensured that there would not be any significant
 3 discrepancies between the API-derived travel times and the observed ones.

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

12 In some cases, the API returned only walking segments for PT due to a small trip distance or the
 13 unavailability of PT services. For those trips, PT was assigned as unavailable. For the car trips, the
 14 availability was based on logical checks. For example, if a person chooses *Car* for the shopping trip, the
 15 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),
 16 then only *Car* is assumed to be available for the following trip since the driver has the constraint to return
 17 the car back to *O*.

18 3.2. Full choice set model

19 In the current paper, it is assumed that a model estimated using the full choice set is considered the
 20 “true” model. Therefore, as a first step, a model using the full choice set is specified and estimated to act
 21 as the base for the assessment of the sampling protocols. Discrete choice modelling was used as the main
 22 methodological framework for the analysis (Ben-Akiva and Lerman, 1985). The analysis is performed at
 23 the level of the trip chain, which is defined as two consecutive trips, namely a shopping trip from an origin
 24 *O* to an intermediate shopping destination *S* with a mode *k* and a following trip to another destination *D*
 25 with a mode *j*. The behavioural model developed aims to understand the choices of modes *k* and *j* and of
 26 destination *S* for shopping trips in a joint fashion. In that context, the locations of *O* and *D* are considered
 27 as fixed for each choice task. Therefore, the full choice set consists of 3 modes for the first/shopping trip, 3
 28 modes for the following trip and 176 shopping destinations, for a total of 1584 combined mode-destination
 29 alternatives. The choice of activity (i.e. travelling for shopping), and the choice of trip-chain complexity, (i.e.
 30 including a shopping trip on the way to work *O-S-D* vs. performing a simple *O-S-O* trip chain) is assumed
 31 to precede the choice of mode-destination and is therefore considered exogenous (as described in Ye et al.
 32 (2007)).

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

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

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

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

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

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

9 3.3. Sampling strata formation

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

12 3.3.1. Creation of Detour Ellipses

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

27 3.3.2. Detour Factor modelling framework and outputs

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

32 For $O-S-D$ trip chains, the model specification has to guarantee that the estimated DFs will always be
 33 above 1.0. In addition, a logarithmic transformation was applied to the observed DFs, i.e. the dependent
 34 variable to guarantee that the transformed variable $\log(y-1)$ would follow a normal distribution $\log(y-1) \sim$
 35 $N(\mu_{\log(y-1)}, \sigma_{\log(y-1)})$. The predicted DFs are calculated for the chosen and non-chosen mode combinations
 36 per choice task and individual as follows:

$$\mu_y = 1 + \epsilon^{(\mu_{\log(y-1)} + 0.5\sigma_{\log(y-1)}^2)} \quad (7)$$

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

39 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
<i>Constant</i>	-0.8363	0.1734	-4.82
<i>Natural logarithm of O-D straight distance (km)</i>	-1.3253	0.0701	-18.92
<i>Car-Walking</i>	-1.8934	0.3206	-5.91
<i>PT-PT</i>	1.0609	0.3722	2.85
<i>Walking-Car</i>	-1.4617	0.3946	-3.70
<i>Walking-PT</i>	-0.6875	0.2904	-2.37
<i>Walking-Walking</i>	-1.6766	0.2425	-6.91
<i>Shopping: Clothes - Other</i>	0.6526	0.1895	3.44
<i>Household size: 3-4 members</i>	0.4733	0.1750	2.70
<i>Part time workers</i>	-0.3908	0.1726	-2.26
<i>Occupation: Students</i>	0.5936	0.3216	1.85
<i>Occupation: Other</i>	0.4199	0.2322	1.81
<i>Time of day: Weekend morning</i>	0.7590	0.2158	3.52
<i>Parking areas 400m around shopping cluster</i>	0.0182	0.0033	5.59
<i>Sigma</i>	2.0252	0.0613	33.03

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

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

22 For *O-S-O* trip chains, a different modelling approach had to be formulated, since for those cases the
23 $l_{OD,i}$ is 0, hence the DF cannot be defined. Consequently, the straight distance (in km) $l_{OS,i} = l_{SD,i}$ was
24 selected as the dependent variable for those trip chains, which again it was logarithmically transformed to
25 guarantee that it follows a normal distribution with $\log(y) \sim N(\mu_{\log(y)}, \sigma_{\log(y)})$. The predicted distances for
26 the chosen and non-chosen mode combinations per choice task were calculated as:

²It 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
<i>Constant</i>	0.3664	0.0951	3.85
<i>Walking-Walking</i>	-1.4375	0.0797	-18.76
<i>Shopping: Other</i>	0.5167	0.1667	3.32
<i>Time of day: Night</i>	-0.3542	0.1527	-2.41
<i>Following purpose: Social-Leisure</i>	-0.7769	0.1999	-4.01
<i>Age: 18-24</i>	-0.2366	0.0617	-3.71
<i>Parking areas (linear)</i>	0.0047	0.0016	2.89
<i>Retail areas (log)</i>	0.0821	0.0244	3.29
<i>Household Income: 40000-50000 GBP/year</i>	-0.2008	0.0894	-2.44
<i>Household Income: No reporting</i>	0.4776	0.1500	3.54
<i>Shopping activity duration</i>	0.2078	0.0537	4.30
<i>Sigma</i>	0.6526	0.0327	20.61

$$\mu_y = \epsilon^{(\mu_{\log(y)} + 0.5\sigma_{\log(y)}^2)} \quad (8)$$

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

3 A similar Bootstrap sampling approach was performed for *O-S-O* trip chains, as well, with 500 samples
4 resulting in a very small mean absolute percentage error of 0.025. The best-performing model, presented
5 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
6 the mode combination of walking-walking showed significant differences to car-car (base) indicating a lower
7 distance as expected for trips made by walking in both legs. Other types of shopping, i.e. durables, resulted
8 in a higher accepted distance, while smaller distances are accepted for trips chains where the following trip is
9 for social/leisure purposes. Finally, individuals who did not report their household income were found to
10 accept larger distances.

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

17 3.3.3. Creation of Standard Deviatonal Ellipses

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

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

1 2-week survey duration. It may be noted that the mobility patterns and hence the axes of the SDEs are
 2 expected to be functions of the sociodemographic characteristics of the person. For instance, the b/a ratio of
 3 workers is likely to be smaller than part-time workers or non workers due to their potentially non-flexible
 4 schedules.

5 3.3.4. Creation of Familiarity Buffers

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

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

$$r_{C_{j,i}} = \frac{nTrips_{C_{j,i}}}{nTrips_{C_{H,i}}} r_{C_{H,i}} \quad (9)$$

16 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
 17 to familiarity cluster j and to home-cluster H , respectively, and $r_{C_{H,i}}$ is the buffer radius of the home-cluster
 18 H which in the current study is fixed to 1200m.

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

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

33 3.4. Definition of sampling protocols

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

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

1 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
 2 individuals tend to confine themselves either within their time-space constraints or within their usual areas
 3 of movement (second column). A larger percentage of males tend to deviate from their time-space constraints
 4 than females, but still not outside their usual areas of movement. Starker differences are observed when it
 5 comes to income, with lower income individuals being more confined within T and A with 79.1% choosing
 6 their shopping destinations only within T or only within T and A. The opposite is true for individuals with
 7 a personal income of more than £20000, where 34.9% are able to be more flexible and choose shopping
 8 destinations from all strata. Similar findings can be observed for individuals with no season ticket ownership
 9 for PT, as well. Finally, younger individuals and those with no cars in their household are more constrained
 10 in regards to their shopping destinations with less than 20% of them venturing outside their respective T and
 11 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			
<i>Male</i>	12.2	58.6	29.2
<i>Female</i>	16.6	52.6	30.8
Personal income			
<i>Below £20000</i>	18.5	60.6	20.9
<i>Above £20000</i>	13.8	51.3	34.9
Age			
<i>Below 30 years</i>	23.5	58.1	18.4
<i>Above 30 years</i>	12.7	53.2	34.1
Season ticket ownership			
<i>No</i>	15.6	56.5	27.9
<i>Yes</i>	14.4	47.7	37.9
Car ownership			
<i>No car</i>	27.3	60.4	12.3
<i>At least one car</i>	11.7	52.5	35.8

12 For the *TAC* protocol, on average there are 76 alternatives located within *T*, 403 within *A* and 846 within
 13 *C* per choice task/trip. Using the *TAC* protocol, if there are not enough alternatives in *T* to account for the
 14 67% of the choice set, such as in the case of a long trip with a small estimated DF and resulting DE, then
 15 alternatives from *A* are sampled to reach that number, in addition to sampling the pre-specified number of
 16 alternatives from stratum A (i.e. 28.2%). The remaining number of alternatives required to reach the choice
 17 set size are always sampled from *C*.

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

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

30 For each sampling protocol examined, a set of increasing choice set sizes was tested, between 10 and 250
 31 alternatives, examining the rates of estimate improvements (*decreasing bias in the estimates and smaller*
 32 *standard errors*). Furthermore, for each choice set size per sampling protocol, five different choice set

1 realisations were sampled and used for model estimation to assess model stability in terms of sampling
 2 standard deviation of estimated parameters and to eliminate the possibility of a lucky/unlucky draw. The
 3 estimated parameters, the standard errors and the fit statistics of the models estimated with sampled choice
 4 sets are compared with those of the full choice set model. It is expected that the sampled choice set models
 5 will produce unbiased estimates after a sufficient choice set size, meaning that parameters with only negligible
 6 differences from those of the full choice set model are obtained. The full choice set model, however, is expected
 7 to produce more efficient estimates (lower standard errors), but at the expense of higher estimation times,
 8 which in many application cases can be prohibitive. It may be noted that the *true* model used as a base
 9 for the evaluation of the sampling protocols refers to an MNL model using the full choice set. It should be
 10 stated, however, that the full choice set model should not be considered as the most accurate representation
 11 of individual shopping behaviour, but only as a *sufficient* one, since the true choice set per individual will
 12 always remain latent in the context of a spatial choice model.

13 4. Results

14 4.1. Full choice set model outputs

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

18 4.1.1. Variable selection

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

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

32 Characteristics of the shopping clusters and their respective surrounding areas were also defined, in
 33 buffer zones of 400m (immediate area), 400-1000m (small distances), 1000-2000m (medium distances) and
 34 2000-5000m (large distances). Those characteristics, including parking areas and retail/commercial store
 35 areas extracted from OpenStreetMaps (OSM) and population and average residential price statistics during
 36 the years 2016-2017, were acquired from the Office for National Statistics (ONS). Specifically, the average
 37 residential prices were computed around shopping and home clusters (400m buffers - immediate area).
 38 Furthermore, the weighted price averages for home and shopping locations were discretised into quartiles to
 39 analyse whether e.g. people living in richer areas (fourth quartile of average residential prices) are willing to
 40 go shopping in poorer areas (first quartile of average residential prices) or vice versa. The rationale behind
 41 that variable specification is that the immediate environment around the home location will have an influence
 42 on the behaviour of the individual. The prior expectation was that individuals living in richer areas will have
 43 a lower probability of choosing shopping destinations located in poorer areas (Pellegrini et al., 1997).

44 Shopping store variability was captured using Shannon's entropy (H_k) (Equation 10) (Shannon, 1948;
 45 Whittaker, 1949) measuring the percentage of the area covered by specific store type $t \in T$ inside a shopping
 46 cluster k . Shannon's entropy has been widely used to quantify land-use variability mostly in studies related
 47 to walkability (Brown et al., 2009; Mavoia et al., 2018) and urban sprawl (Effat and Elshobaki, 2015). In
 48 the current study, it is used to see whether an increased variability in store types adds to the attraction
 49 of a shopping destination. A key thing to note here, is that n should refer to the total number of unique
 50 store types across all shopping clusters and not only in the cluster in question in order to ensure a proper

1 comparison among different locations (Hajna et al., 2014). In total, 101 unique shopping store types were
 2 included in the shopping clusters based on the OSM data. The H_k calculated for each cluster k ranges from 0
 3 to 1, with higher values denoting large store type variability and vice versa, while values around 0.5 indicate
 4 a more balanced distribution of store types within a shopping destination.

$$H_k = -\frac{\sum_{i=1}^T (p_i \ln(p_i))}{\ln n} \quad (10)$$

5 In addition to the above, the location of the most popular retailers in the UK market per shopping type,
 6 grocery-clothes-durables, was identified across the study area and matched with the shopping clusters. For
 7 grocery shopping, the focus was on the “*Big Four*” retailers, namely Tesco, Sainsbury, Asda and Morrisons,
 8 as referred to in Rhodes (2018) and also reported in Kantar world panel (2020) website for the end of 2017,
 9 holding 70.7% of the total market share in the UK. For clothes shopping, the analysis was focused on the top
 10 3 retailers for the year 2018/19 as reported in Retail Economics (2020) website, namely Marks & Spencer,
 11 Next and Primark. Finally, for durable shopping, the focus was on IKEA, as it is a well-established brand in
 12 that sector achieving a market share growth for the sixth consecutive year at 2017 and accounting for 8.1%
 13 market share according to their 2017 annual report (IKEA, 2017). A binary dummy variable was created for
 14 each one of the aforementioned stores based on whether they are located within a 400m buffer radius around
 15 a shopping cluster centroid.

16 4.1.2. Estimated parameters

17 The fit statistics of the full choice set model, together with the estimated parameters, their standard
 18 errors and the t-ratios are depicted in Table 4. Overall, the model achieves a high level of performance with
 19 an adjusted ρ^2 of 0.6162 and an average choice probability for correct predictions of 0.18 having a choice set
 20 of 1584 mode-destination alternatives. The main limitation that the sampling approach will aim to address is
 21 the high estimation time of more than 5 hours (using 6 cpu cores). Regarding the behavioural interpretation
 22 of the estimated parameters, it should be mentioned that, all else held equal, individuals with car ownership
 23 in their households have a positive inherent preference for car compared to PT and walking. Cost sensitivity,
 24 specified using a box-cox transformation, decreases as income increases with a sensitivity of -0.2435, which is
 25 close to the value (-0.3) proposed in Daly and Fox (2012) for non-work trips (cited in Sanko et al., 2014).
 26 Time (linear) and distance (box-cox) sensitivities of following trips are shown to be higher by 35.7% and
 27 25.2%, respectively, than for the first shopping trip. Furthermore, time and distance sensitivities tend to
 28 decrease with the increase of shopping duration, as captured by the respective shopping duration elasticities.

29 Individuals living in areas of high residential prices are less likely to go shopping in areas with low
 30 residential prices, all else held equal, a finding also discussed in Pellegrini et al. (1997). Retail areas per
 31 store type (clothes shopping, groceries and other types of shopping) act as significant attractions for trips of
 32 their respective shopping types. Moreover, the presence of major retailers per shopping category, also has
 33 a positive impact on the utility function. Finally, shopping store diversity captured using the Shannon’s
 34 entropy (Shannon, 1948; Whittaker, 1949) was found to be a significant attractor both in the immediate
 35 area of a shopping destination (400m buffer) and also in medium distances (1000-2000m buffer) for *O-S-D*
 36 trip chains with two consecutive shopping trips. It is acknowledged that there is an inherent uncertainty
 37 behind the reasons for making a subsequent shopping trip, since that could be a result of a pre-planned
 38 activity scheduling, of product unavailability in the first shopping destination, or simply a result of a random
 39 event (Kitamura, 1984). The final specification presented here shows that the attraction of neighbouring
 40 destinations, captured through shopping diversity, adds to the attraction of the visited destination only for
 41 cases where the individuals are going to make a subsequent shopping trip. The same was not true for cases
 42 where the following trip is for a different type of activity. That could serve as an additional indication that
 43 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		
<i>Log-likelihood (0)</i>	-11045.05		
<i>Log-likelihood (model)</i>	-4184.126		
<i>Adjusted ρ^2</i>	0.6162		
<i>AIC</i>	8478.25		
<i>BIC</i>	8771.96		
<i>Number of individuals</i>	270		
<i>Number of observations</i>	1541		
<i>Estimation time (min)</i>	322		
<i>Average choice probability of correct prediction</i>	0.18		
Parameter	Estimates	Rob. st. errors	Rob. t-ratios 0 (* t-ratios 1)
Locational constants			
<i>Constant rest Yorkshire</i>	0.5494	0.1457	3.77
Households with car ownership			
<i>Constant Car-Other (PT/walking)</i>	-2.7299	0.2727	-10.01
<i>Constant Other (PT/walking)-Car</i>	-0.8606	0.2333	-3.69
<i>Constant PT-PT</i>	-1.0775	0.4102	-2.63
<i>Constant PT-Walking</i>	-1.5518	0.4712	-3.29
<i>Constant Walking-PT</i>	-1.2089	0.4816	-2.51
<i>Constant Walking-Walking</i>	0.8418	0.3635	2.32
Mode shifts for households with no car ownership			
<i>Constant Car-Other (PT/walking)</i>	2.3264	0.6392	3.64
<i>Constant Other (PT/walking)-Car</i>	0.6329	0.5990	1.06
<i>Constant PT-PT</i>	4.2697	0.4906	8.70
<i>Constant PT-Walking</i>	3.3536	0.5753	5.83
<i>Constant Walking-PT</i>	2.7945	0.4704	5.94
<i>Constant Walking-Walking</i>	2.6604	0.4069	6.54
Mode shifts for central area destinations			
<i>PT-PT</i>	1.7449	0.3176	5.50
<i>PT-Walking</i>	1.8249	0.4225	4.32
<i>Walking-PT</i>	2.6880	0.4682	5.74
<i>Walking-Walking</i>	1.6469	0.2600	6.33
Mode shifts for individuals with season ticket ownership			
<i>Walking-Walking</i>	-0.5606	0.3189	-1.76
Mode shifts for trips with more than 1 passenger			
<i>PT first/shopping trip</i>	-1.8619	0.3411	-5.46
<i>PT following trip</i>	-0.8646	0.3552	-2.43
<i>Walking first/shopping trip</i>	-0.8007	0.2265	-3.53
<i>Walking following trip</i>	-0.3679	0.2462	-1.50
Mode shifts for students			
<i>Walking-Walking</i>	1.0751	0.3783	2.84
Mode shifts for married individuals			
<i>Walking-Walking</i>	-0.7828	0.2866	-2.73
Mode shifts for individuals living in 3-member households			
<i>Walking-Walking</i>	0.6899	0.3711	1.86
LOS variables			
<i>Travel time for first trip (base)</i>	-0.0912	0.0090	-10.10
<i>Travel time shift for clothes shopping</i>	0.0265	0.0095	2.78
<i>Travel time for O-S-O trip chains</i>	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)
<i>Travel time for HWH tours</i>	-0.0445	0.0093	-4.77
<i>Travel time multiplier for car</i>	1.0000	–	–
<i>Travel time multiplier for PT IVT</i>	0.5859	0.0646	-6.41
<i>Travel time multiplier for PT first access trip</i>	0.8196	0.2195	-0.82
<i>Travel time multiplier for PT last egress trip</i>	0.6089	0.1653	-2.37
<i>Travel time multiplier for PT remaining OVT</i>	0.3535	0.1608	-4.02
<i>Travel time multiplier for following trip</i>	1.3574	0.0963	3.71
<i>Travel time - Shopping duration elasticity</i>	-0.3157	0.0307	-10.30
<i>Travel walking distance for first trip (base)</i>	-1.6259	0.1222	-13.30
<i>Travel walking distance for O-S-O trip chains</i>	0.2691	0.1118	2.41
<i>Travel walking distance multiplier for following trip</i>	1.2515	0.0909	2.78
<i>Box-cox lambda for travel walking distance</i>	0.8051	0.0515	-3.79
<i>Travel walking distance - Shopping duration elasticity</i>	-0.1396	0.0333	-4.19
<i>Travel cost</i>	-0.6518	0.0795	-8.20
<i>Box-cox lambda for travel cost</i>	0.5362	0.0500	-9.27
<i>Travel cost - Personal income elasticity</i>	-0.2435	0.0963	-2.53
Locational variables			
<i>Living in rich areas-shopping in poor areas</i>	-0.8037	0.2721	-2.95
<i>Parking areas (400m buffer)</i>	0.0930	0.0263	3.54
<i>Box-cox lambda for parking areas (400m buffer)</i>	0.4218	0.0784	-7.38
<i>Presence of major clothes shopping retailers (400m buffer)</i>	1.9623	0.2046	9.59
<i>Presence of major grocery retailers (400m buffer)</i>	0.5334	0.0972	5.49
<i>Presence of major durables retailers (400m buffer)</i>	2.0478	0.8074	2.54
Size variables			
<i>Natural logarithm multiplier ϕ</i>	0.7298	0.0998	-2.71
<i>Population (400m buffer) (base)</i>	1.0000	–	–
<i>Retail areas for clothes shopping stores (400m buffer) (exp.)</i>	0.2185	0.5238	0.42
<i>Retail areas for grocery stores (400m buffer) (exp.)</i>	0.6728	0.3712	1.81
<i>Retail areas for durables/other stores (400m buffer) (exp.)</i>	0.5873	0.7312	0.80
<i>Shopping store variability (400m buffer) (exp.)</i>	1.2847	0.7525	1.71
<i>Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)</i>	2.7750	0.6896	4.02

1

2 4.1.3. Value of Travel Time estimates and demand elasticities

3 Value of Travel Time (VTT) estimates and demand elasticities from the full choice set model were also
4 computed to assess the performance of the sampling protocols. In *Table 5*, the VTT estimates of the full
5 choice set model are presented in GBP/hour, namely the VTT for car, PT in-vehicle time, PT first access
6 and last egress time and the remaining PT out-of-vehicle time, both for the first/shopping and the following
7 trip. The VTTs were calculated as the ratio of the partial derivatives of the respective variable (i.e. car time,
8 PT in-vehicle time etc.) over the partial derivative of travel cost including all of the specified parameters
9 affecting them (i.e. shifts, elasticities etc.). Additionally, the standard errors of the VTT estimates, calculated
10 using the *delta* method (Daly et al., 2012) are presented. All of the VTT estimates are significant at the
11 95% confidence level. In addition, the VTT estimates are very close to the average value suggested by the
12 Transport Appraisal Guidance in the UK (WEBTag) for an average vehicle, namely 13.87 GBP/hour (using
13 2010 prices) (Department for Transport, 2014).

14 Demand elasticities were also calculated for the full choice set model with respect to a unit increase of
15 travel cost and travel time, made separately for car and PT. It is assumed that the change of cost will affect
16 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
<i>Car for first/shopping trip</i>	10.7728	0.0349
<i>PT IVT for first/shopping trip</i>	9.4761	0.0331
<i>PT first access trip for first/shopping trip</i>	13.2542	0.0741
<i>PT last egress trip for first/shopping trip</i>	9.8467	0.0566
<i>PT OVT remaining for first/shopping trip</i>	5.7177	0.0460
<i>Car for following trip</i>	13.7762	0.0440
<i>PT IVT for following trip</i>	8.7583	0.0298
<i>PT first access trip for following trip</i>	12.2501	0.0687
<i>PT last egress trip for following trip</i>	9.1007	0.0525
<i>PT OVT remaining for following trip</i>	5.2846	0.0431

1 on PT fare and season tickets. The increase of car travel time and PT in-vehicle time is assumed to affect
2 the accessibility to the shopping destination, hence the change is applied only on the shopping trip. Choice
3 forecasting was computed before and after the respective change using the estimated parameters and the
4 demand elasticities per mode and mode combination were calculated as $\frac{\log(demand_{after})}{\log(demand_{base})}/(\log(1.01))$, which
5 are presented in *Table 6*. The total elasticities for car, PT and walking were computed by aggregating the
6 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)
<i>Car</i>	-0.135	-0.158	0.061	0.037
<i>PT</i>	0.386	0.518	-0.567	-0.316
<i>Walking</i>	0.203	0.239	-0.019	-0.008
<i>Car - Car</i>	-0.163	-0.194	0.065	0.039
<i>Car-PT</i>	0.174	-0.427	-0.609	0.203
<i>Car-Walking</i>	0.103	-0.719	0.137	0.158
<i>PT-Car</i>	0.415	0.963	-0.742	-0.928
<i>PT-PT</i>	0.370	0.467	-0.847	-0.538
<i>PT-Walking</i>	0.401	0.602	-0.394	-0.768
<i>Walking-Car</i>	0.179	0.839	0.111	0.034
<i>Walking-PT</i>	0.401	0.530	-0.446	0.100
<i>Walking-Walking</i>	0.166	0.170	0.054	0.022

7 4.2. Sampling protocol evaluation/comparison

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

11 4.2.1. Fit statistics comparison

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

1 15.8% of the global choice set of 1584 alternatives, on average need almost 12% of the estimation time of the
 2 full choice set model (38 minutes compared to 322 minutes), which highlights the practical advantages of the
 3 sampling approach.

4 Out of all the sampling protocols examined, *Random sampling* leads to generally more deterministic models
 5 compared to the importance sampling protocols, as shown by the comparison of log-likelihood, adjusted
 6 ρ^2 and the average choice probability of correct prediction among models of the same choice set size. The
 7 main reason behind that is the fact that with the *Random sampling* protocol the choice set of size J includes
 8 the chosen alternative and $J - 1$ alternatives that are randomly sampled from the remaining global choice
 9 set. That leads to inevitably including many alternatives located further away from the chosen alternative
 10 and the space around the O and D of the specific choice task/trip. As a result, these alternatives will have
 11 an increased travel time/distance/cost compared to the chosen alternative and will not provide meaningful
 12 trade-offs for the model to properly evaluate the trade-offs the individuals would consider during the decision
 13 making process. On the other hand, all of the importance sampling protocols examined provide much more
 14 balanced choice sets leading to less deterministic models with the *TAC* protocol being the most balanced
 15 approach. That is also evident from the average choice probability of correct prediction, where for the *TAC*
 16 protocol with 250 alternatives that value, 0.229, is closer to the one of the full choice set model, namely
 17 0.18. In contrast, for the same choice set size, *TC* and *AC* achieve average choice probabilities of correct
 18 prediction of 0.266, 0.299, respectively, and the more deterministic *Random sampling* a much higher average
 19 choice probability of 0.464. Those findings serve as a first indication that importance sampling protocols
 20 and especially *TAC* will converge faster to the full choice set model compared to *Random sampling* that will
 21 require bigger choice sets.

Table 7: Fit statistics of sampling protocols

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

22 4.2.2. Sampled estimate comparison

23 In *Table 8*, an assessment of the accuracy, stability and statistical efficiency of the estimated parameters
 24 of the sampled choice set models is depicted, together with the average distance of the sampled alternatives

from the chosen one per sampling 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

1 better estimated parameters. Finally, *AC* leads to 48.4%-120.1% lower *AAPD* and 41-51 better estimated
 2 parameters. Sampling stability, as captured by the *ACoV*, provides similar conclusions with *TAC* showing
 3 the most significant improvements compared to *Random sampling*, followed by *TC* and *AC*.

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

21 Regarding the three importance sampling protocols, their differences are less stark, but clear trends can
 22 still be observed. Both *TAC* and *TC* outperform *AC* in all evaluation measures. On average, *TAC* is by
 23 34%-111.3% and by 75.2%-106.6% better than *AC* in terms of *AAPD* and *ACoV*, respectively, for choice sets
 24 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
 25 same evaluation measures and choice set sizes than *AC*. *TAC* models are generally more accurate and stable
 26 than their *TC* counterparts with an average 7.3%-33.9% lower *AAPD* and 0.6%-38.5% lower *ACoV* for choice
 27 sets with more than 10 alternatives. *TC* achieves its most comparable performance with *TAC* and significantly
 28 outperforms *AC* at a choice set size of 100 alternatives. A possible explanation is that, on average, there are
 29 76 alternatives in stratum *T* meaning that at a choice set size of 100, there are enough alternatives in stratum
 30 *T* to sample from in order to reach the required number of alternatives, i.e. $0.67 * 100 = 67$ alternatives from
 31 that stratum, without replenishing them from *C*. After that choice set size, however, there is the need to
 32 sample further alternatives from *C* reducing the performance of the estimated sampled models. That is also
 33 evident from the performance of the evaluation measures of *TC*, where for a choice set of 100 alternatives,
 34 *TC* models perform only marginally worse than *TAC*. After that point, however, *TAC* models manage to
 35 increase their performance gap from *TC*, going from an average of 7.3% to a 33.9% lower *AAPD*, for 250
 36 alternatives, and from 30 to 41 better estimated parameters. The increasing inclusion of worse alternatives in
 37 the choice set has an impact on stability, as well, with *TAC* models going from a mere 0.6% better *ACoV*, for
 38 100 alternatives, to a much higher 38.5%, for 250 alternatives. Furthermore, that is captured in the average
 39 improvement rates of *AAPD* and *ACoV*, where *TAC* shows higher decreasing rates than *TC*, meaning that
 40 it can still benefit more by increasing the choice set despite being already more accurate and stable than
 41 *TC*. Based on that finding, a reverse-engineering approach can be implemented, where the analyst can get a
 42 rough approximation of the optimal choice set size per sampling protocol by examining the average number
 43 of alternatives within the stratum that she wants to prioritise.

44 Regarding the choice set size, there is not any guideline as to which percentage of the full choice set is
 45 required to estimate stable parameters with insignificant bias. Therefore, the required choice set size should be
 46 viewed as case-specific and be carefully examined by the analyst. *Figure 6* provides a graphical representation
 47 of *Table 7* and can be used to identify the minimum required choice set to achieve estimate accuracy and
 48 stability. In the current study, it seems that even after a choice set of 50 alternatives, there are significant
 49 improvements in estimate accuracy and stability for the importance sampling protocols. *Random sampling*,
 50 however, needs at least 150 alternatives to show more consistently accurate estimates. The improvements on
 51 the four evaluation measures tend to slow down after 150 alternatives and for each subsequent choice set
 52 size for all sampling protocols. In the same *Figure*, a clear verdict can be made about the benefits of the
 53 proposed importance sampling protocols using AS concepts compared to *Random sampling*, which performs
 54 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							
<i>Average distance from chosen alternative (m)</i>	14908	14875.2	14888	14812.2	14819.8	14797.6	–
<i>Average AAB</i>	0.9691	0.3096	0.3593	0.1987	0.1910	0.1690	-0.1291
<i>Average AAPD</i>	1.0502	0.3658	0.3852	0.2328	0.2071	0.1888	-0.1401
<i>Average ACoV</i>	2.8367	0.3710	0.3384	0.2230	0.1660	0.1436	-0.4001
<i>Average st.errors</i>	0.9249	0.4663	0.3738	0.3443	0.3348	0.3154	-0.1311
AC sampling							
<i>Average distance from chosen alternative (m)</i>	8424.1	8457.4	9200.6	10014.6	10533.8	11023.2	–
<i>Average AAB</i>	0.4504	0.2035	0.1610	0.1231	0.1032	0.1000	-0.0598
<i>Average AAPD</i>	0.4984	0.2465	0.1750	0.1417	0.1187	0.1164	-0.0665
<i>Average ACoV</i>	0.5769	0.2001	0.1670	0.1337	0.1095	0.0879	-0.0767
<i>Average st.errors</i>	0.6106	0.3613	0.3405	0.3184	0.3110	0.3044	-0.0547
TC sampling							
<i>Average distance from chosen alternative (m)</i>	8495	11138.2	12642.2	13382	13842	14120.8	–
<i>Average AAB</i>	0.4058	0.1760	0.1183	0.0868	0.0774	0.0653	-0.0580
<i>Average AAPD</i>	0.4980	0.1974	0.1255	0.0996	0.0931	0.0738	-0.0703
<i>Average ACoV</i>	0.3491	0.1385	0.0871	0.0790	0.0845	0.0644	-0.0459
<i>Average st.errors</i>	0.4741	0.3382	0.3149	0.3056	0.2983	0.2917	-0.0345
TAC sampling							
<i>Average distance from chosen alternative (m)</i>	5124	7045.2	8164.6	8818.2	9527.8	10083	–
<i>Average AAB</i>	0.4012	0.1349	0.0955	0.0722	0.0597	0.0476	-0.0576
<i>Average AAPD</i>	0.5020	0.1839	0.1170	0.0874	0.0784	0.0551	-0.0740
<i>Average ACoV</i>	0.4399	0.1137	0.0876	0.0647	0.0625	0.0465	-0.0613
<i>Average st.errors</i>	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						
<i>Average AAB</i>	1.2% (31)	30.5% (35)	23.9% (30)	11.9% (35)	29.6% (37)	37.2% (41)
<i>Average AAPD</i>	-0.8% (31)	7.3% (35)	7.3% (30)	10.5% (35)	18.8% (37)	33.9% (41)
<i>Average ACoV</i>	-20.6% (27)	21.8% (35)	0.6% (33)	22.1% (27)	35.2% (30)	38.5% (33)
<i>Parameter scales</i>	-12.0 (30)	1.3% (21)	-3.5% (23)	1.0% (27)	0.5% (30)	-1.4% (21)
<i>Standard errors</i>	7.2% (41)	1.7% (34)	0.4% (27)	0.3% (26)	-0.9% (22)	-1.2% (25)
TAC-AC						
<i>Average AAB</i>	12.3% (36)	50.8% (45)	68.6% (42)	70.5% (44)	72.9% (45)	110.1% (51)
<i>Average AAPD</i>	-0.7% (36)	34.0% (45)	49.6% (42)	62.1% (44)	51.4% (45)	111.3% (51)
<i>Average ACoV</i>	31.1% (27)	76.0% (38)	90.6% (39)	106.6% (36)	75.2% (32)	89.0% (35)
<i>Parameter scales</i>	-19.7% (24)	-7.6% (27)	-5.5% (30)	-2.0% (31)	-1.0% (27)	-0.8% (25)
<i>Standard errors</i>	36.9% (51)	12.7% (48)	10.0% (51)	6.3% (46)	4.7% (48)	3.4% (48)
TAC-Random						
<i>Average AAB</i>	141.6% (53)	129.5% (51)	276.2% (54)	175.2% (51)	219.9% (51)	255.0% (55)
<i>Average AAPD</i>	109.2% (53)	98.9% (51)	229.2% (54)	166.4% (51)	164.2% (51)	242.6% (55)
<i>Average ACoV</i>	544.9% (29)	226.3% (32)	286.3% (32)	244.7% (33)	165.6% (33)	208.8% (36)
<i>Parameter scales</i>	97.2% (26)	-3.5% (23)	2.9% (28)	-3.5% (28)	-6.2% (27)	-8.2% (27)
<i>Standard errors</i>	93.5% (53)	40.5% (51)	22.2% (49)	15.6% (49)	12.4% (47)	7.6% (43)
TC-AC						
<i>Average AAB</i>	11.0% (35)	15.6% (35)	36.1% (44)	41.8% (39)	33.3% (37)	53.1% (43)
<i>Average AAPD</i>	0.1% (35)	24.9% (35)	39.4% (44)	42.3% (39)	27.5% (37)	57.7% (43)
<i>Average ACoV</i>	65.3% (27)	44.5% (35)	91.7% (34)	69.2% (31)	29.6% (32)	36.5% (34)
<i>Average RMSE</i>	28.8% (51)	6.8% (47)	8.4% (48)	4.6% (46)	4.2% (46)	4.5% (45)
<i>Parameter scales</i>	-16.0% (26)	-20.0% (32)	-2.7% (33)	-3.7% (28)	-2.0% (25)	-1.4% (28)
<i>Standard errors</i>	29.1% (51)	12.2% (47)	10.4% (48)	6.5% (46)	5.9% (46)	5.0% (45)
TC-Random						
<i>Average AAB</i>	138.8% (49)	75.9% (48)	203.7% (52)	128.9% (49)	146.8% (51)	158.8% (52)
<i>Average AAPD</i>	110.9% (49)	85.3% (48)	206.9% (52)	133.7% (49)	122.4% (51)	155.8% (52)
<i>Average ACoV</i>	712.6% (28)	167.9% (30)	288.5% (33)	182.3% (33)	96.4% (32)	123.0% (35)
<i>Parameter scales</i>	-34.9% (28)	-13.3% (27)	6.0% (28)	4.3% (32)	-7.3% (26)	-6.7% (29)
<i>Standard errors</i>	87.0% (53)	39.6% (52)	22.5% (49)	15.6% (50)	13.7% (49)	8.9% (45)
AC-Random						
<i>Average AAB</i>	115.2% (51)	52.1% (47)	123.2% (46)	61.4% (41)	85.1% (49)	69.0% (45)
<i>Average AAPD</i>	110.7% (51)	48.4% (47)	120.1% (46)	64.3% (41)	74.5% (49)	62.2% (45)
<i>Average ACoV</i>	391.7% (29)	85.4% (23)	102.6% (28)	66.8% (34)	51.6% (32)	63.4% (26)
<i>Parameter scales</i>	51.7% (25)	4.4% (23)	15.3% (23)	-0.6% (27)	-5.4% (29)	-6.7% (31)
<i>Standard errors</i>	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

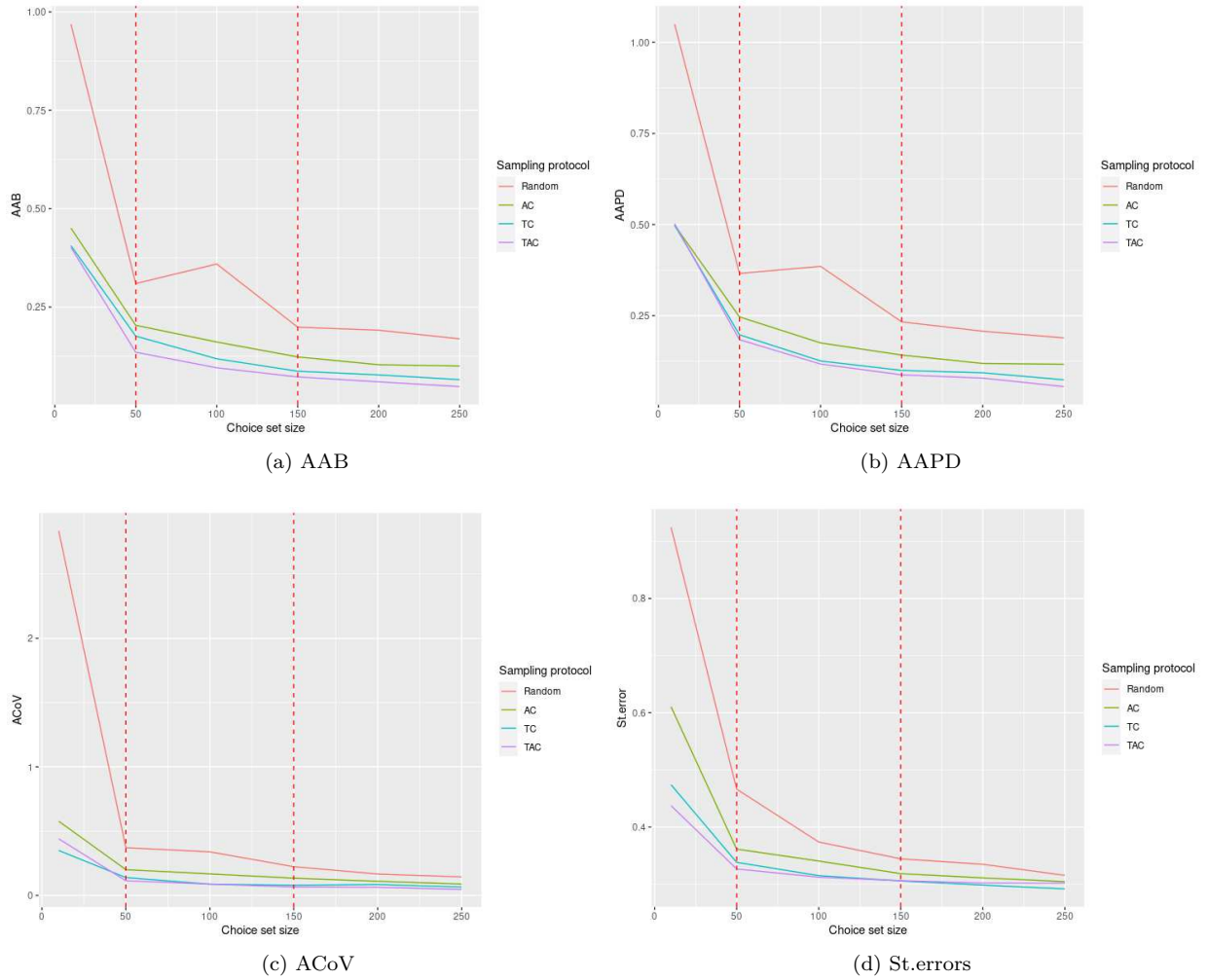


Figure 6: Improvements of evaluation measures across sampling protocols and choice set sizes (*AAB*: Average Absolute Bias; *AAPD*: Average Absolute Percentage Difference; *ACoV*: Absolute Coefficient of Variation)

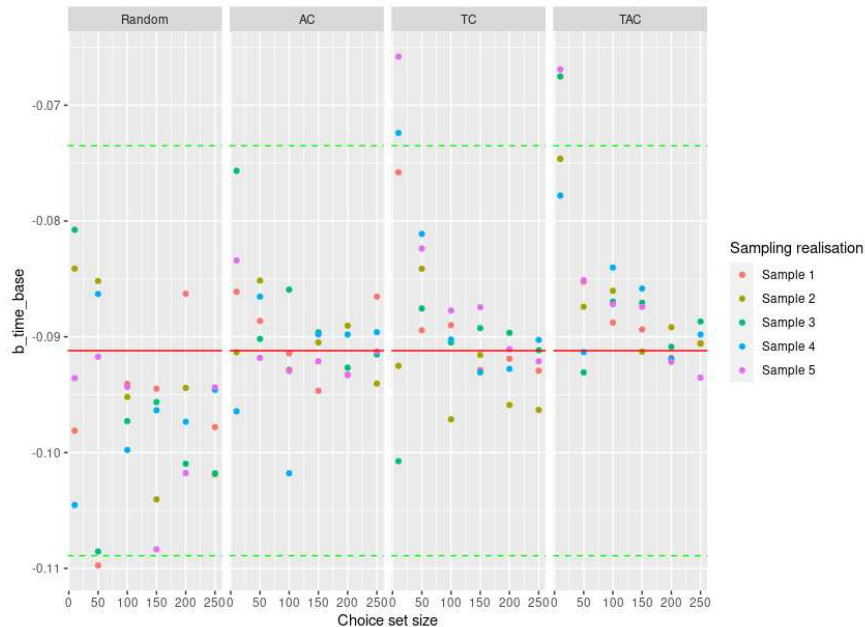


Figure 7: Plots for β_{time}^{base} estimates for each sampling realisation across sampling protocols

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

8 4.2.3. Evaluation of sampled VTT estimates and demand elasticities

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

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

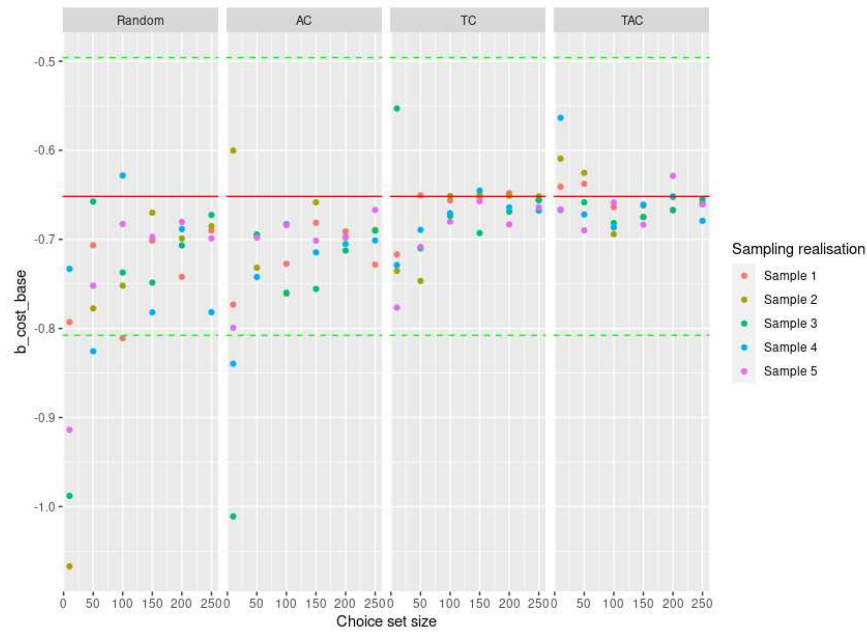
Figure 8: Plots for β_{cost}^{base} estimates for each sampling realisation across sampling protocols

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

1 take part during their calculation and not just the time and cost-related parameters. As already mentioned,
 2 *TC* achieves its best performance for a choice set of 100 alternatives, but even in that case, *TAC* achieves a
 3 16.8% lower *AAB*, a 20.3% lower *AAPD* and 33 out of 48 better estimated elasticities, but also less stable
 4 estimates with 4.5% higher *ACoV*. As the choice set size increases, however, the performance gap for *TAC*
 5 shoes gradual improvements reaching a 47.3% lower *AAB*, a 64.2% lower *AAPD*, 39 out of 48 better estimated
 6 elasticities and a 18% lower *ACoV*, for a choice set of 250 alternatives. *AC* performs worse than the other two
 7 importance sampling protocols, but still better than *Random sampling*. *TAC* shows the largest performance
 8 improvements compared to *Random sampling*, almost 1.5 times more than *TC* and 2.5 times more than *AC*.
 9 The overall better forecasting ability of *TAC* is indicative of the less deterministic models derived from that
 10 sampling protocol (see *Table 7*). The impact that this might have in a practical application presents a clear
 11 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 of improvement
	10	50	100	150	200	250	
Random sampling							
<i>Average AAB</i>	0.2455	0.1589	0.1133	0.0885	0.0740	0.0615	-0.0343
<i>Average AAPD</i>	0.7593	0.5032	0.3911	0.2968	0.2647	0.2257	-0.0994
<i>Average ACoV</i>	0.5224	0.1962	0.1414	0.1055	0.1042	0.0936	-0.0702
AC sampling							
<i>Average AAB</i>	0.2208	0.1077	0.0703	0.0507	0.0367	0.0316	-0.0337
<i>Average AAPD</i>	0.6794	0.3386	0.2335	0.1607	0.1277	0.1028	-0.1025
<i>Average ACoV</i>	0.3542	0.1113	0.1190	0.0807	0.0589	0.0532	-0.0486
TC sampling							
<i>Average AAB</i>	0.1890	0.0888	0.0480	0.0367	0.0275	0.0249	-0.0290
<i>Average AAPD</i>	0.5716	0.2631	0.1530	0.1140	0.0914	0.0852	-0.0853
<i>Average ACoV</i>	0.2219	0.1003	0.0617	0.0606	0.0528	0.0406	-0.0300
TAC sampling							
<i>Average AAB</i>	0.1850	0.0716	0.0411	0.0280	0.0189	0.0169	-0.0289
<i>Average AAPD</i>	0.5614	0.2157	0.1272	0.0873	0.0651	0.0519	-0.0868
<i>Average ACoV</i>	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

12 5. Conclusions

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

24 A general recommendation regarding the choice set size, relative to the full choice set, in order to achieve
 25 stable and sufficiently accurate estimates cannot be made, since this is generally case-specific, but also specific
 26 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						
<i>Average AAB</i>	2.2% (33)	24.0% (35)	16.8% (33)	31.1% (38)	45.5% (36)	47.3% (39)
<i>Average AAPD</i>	1.8% (33)	22.0% (35)	20.3% (33)	30.6% (38)	40.4% (36)	64.2% (39)
<i>Average ACoV</i>	-9.4% (26)	37.0% (40)	-4.5% (18)	52.3% (37)	29.1% (37)	18.0% (30)
TAC-AC						
<i>Average AAB</i>	19.4% (42)	50.4% (44)	71.0% (40)	81.1% (43)	94.2% (44)	87.0% (42)
<i>Average AAPD</i>	21.0% (42)	57.0% (44)	83.6% (40)	84.1% (43)	96.2% (44)	98.1% (42)
<i>Average ACoV</i>	44.6% (34)	52.0% (38)	84.2% (42)	102.8% (43)	44.0% (38)	54.7% (37)
TAC-Random						
<i>Average AAB</i>	32.7% (42)	121.9% (46)	175.7% (46)	216.1% (47)	291.5% (45)	263.9% (46)
<i>Average AAPD</i>	35.3% (42)	133.3% (46)	207.5% (46)	240.0% (47)	306.6% (45)	334.9% (46)
<i>Average ACoV</i>	113.3% (39)	168.0% (44)	118.9% (45)	165.1% (46)	154.8% (42)	172.1% (42)
TC-AC						
<i>Average AAB</i>	16.8% (45)	21.3% (36)	46.5% (41)	38.1% (39)	33.5% (30)	26.9% (33)
<i>Average AAPD</i>	18.9% (45)	28.7% (36)	52.6% (41)	41.0% (39)	39.7% (30)	20.7% (33)
<i>Average ACoV</i>	59.6% (33)	11.0% (24)	92.9% (44)	33.2% (33)	11.6% (23)	31.0% (36)
TC-Random						
<i>Average AAB</i>	29.9% (46)	78.9% (45)	136.0% (48)	141.1% (47)	169.1% (44)	147.0% (47)
<i>Average AAPD</i>	32.8% (46)	91.3% (45)	155.6% (48)	160.4% (47)	189.6% (44)	164.9% (47)
<i>Average ACoV</i>	135.4% (43)	95.6% (39)	129.2% (42)	74.1% (45)	97.3% (38)	130.5% (43)
AC-Random						
<i>Average AAB</i>	11.2% (43)	47.5% (46)	61.2% (45)	74.6% (45)	101.6% (46)	94.6% (44)
<i>Average AAPD</i>	11.8% (43)	48.6% (46)	67.5% (45)	84.7% (45)	107.3% (46)	119.6% (44)
<i>Average ACoV</i>	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

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

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

15 The benefit of the dataset used in the current study is that it presents a combination of a traditional
 16 household survey and GPS tracking providing a wealth of observed behaviour to the researcher. Nonetheless,
 17 one of its limitations is arguably its small survey duration (2 weeks) that could have an impact on the
 18 accurate calculation of the SDE/FB. Therefore, future studies on datasets of longer duration, such as the
 19 6-week Mobidrive dataset (Axhausen et al., 2002) and the more recent 2-month Mobis survey (Molloy et
 20 al., 2021), are essential in order to assess the impact of survey duration on the SDE/FB formation and the
 21 proposed sampling protocols.

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

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

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Table 14: Glossary of terms in alphabetical order

Acronym	Explanation
<i>A</i>	Stratum delineated by the standard deviation ellipse per individual excluding the alternatives in A
<i>AAB</i>	Average Absolute Bias
<i>AAPD</i>	Average Absolute Percentage Difference
<i>AC</i>	Sampling protocol incorporating strata A and C
<i>ACoV</i>	Absolute Coefficient of Variation
<i>API</i>	Application Programming Interface
<i>AS</i>	Activity Space
<i>C</i>	Stratum including the remaining alternatives from the global choice set after excluding the ones within T and A
<i>DE</i>	Detour Ellipse
<i>DF</i>	Detour Factor
<i>GEV</i>	Generalised Extreme Value distribution
<i>GPS</i>	Global Positioning System
<i>HWH</i>	Home-Work-Home tour including a commuting trip to primary workplace
<i>IVT</i>	In Vehicle Time for Public Transport
<i>LCCM</i>	Latent Class Choice Model
<i>LOS</i>	Level Of Service variables
<i>MLE</i>	Maximum Likelihood Estimation
<i>MNL</i>	Multinomial Logit model
<i>OD</i>	Origin-Destination
<i>ONS</i>	Office for National Statistics
<i>O-S-D</i>	Trip chain of Origin-Shopping-Destination
<i>O-S-O</i>	Simple trip chain of Origin-Shopping-Origin
<i>OSM</i>	OpenStreetMaps
<i>OVT</i>	Out of Vehicle Time for Public Transport
<i>PPA</i>	Potential Path Area
<i>PT</i>	Public Transport
<i>rmse</i>	Root Mean Square Error
<i>SC</i>	Sampling Correction term
<i>SDE</i>	Standard Deviatonal Ellipse
<i>T</i>	Stratum delineated by the estimated detour ellipses
<i>TAC</i>	Sampling protocol incorporating strata T, A and C
<i>TC</i>	Sampling protocol incorporating strata T and C
<i>VTT</i>	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												
<i>Constant rest Yorkshire</i>	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												
<i>Constant Car-Other (PT/walking)</i>	-3.0689	0.3531	0.4242	0.8341	-2.7741	0.0864	0.1138	0.4461	-2.7962	0.0643	0.0829	0.4032
<i>Constant Other (PT/walking)-Car</i>	-0.6713	0.6203	0.9823	0.6997	-0.6444	0.3574	0.4431	0.4122	-0.7890	0.2336	0.2971	0.3319
<i>Constant PT-PT</i>	-0.3663	1.0848	3.2898	1.0643	-0.5703	0.4707	0.3812	0.5082	-1.0525	0.2141	0.2530	0.5157
<i>Constant PT-Walking</i>	-0.7595	0.8553	1.8626	1.2554	-1.1786	0.2405	0.2984	0.7171	-1.3964	0.2154	0.3083	0.6652
<i>Constant Walking-PT</i>	0.5371	1.5386	2.3525	1.0882	-0.5867	0.5183	0.8407	0.6598	-0.9462	0.2739	0.3842	0.5809
<i>Constant Walking-Walking</i>	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												
<i>Constant Car-Other (PT/walking)</i>	1.3638	0.4329	0.6994	1.0602	1.7655	0.2411	0.3025	0.8250	1.8533	0.2033	0.1265	0.6139
<i>Constant Other (PT/walking)-Car</i>	1.8766	2.0283	0.4480	1.1878	1.3023	1.0578	0.1820	0.8232	1.1631	0.8378	0.1824	0.6588
<i>Constant PT-PT</i>	5.5908	0.3094	0.1589	1.2148	4.7587	0.1145	0.0578	0.6654	4.8897	0.1452	0.0881	0.5933
<i>Constant PT-Walking</i>	4.0594	0.3066	0.2533	1.2563	3.9395	0.2352	0.2023	0.8527	4.1286	0.2311	0.0894	0.7449
<i>Constant Walking-PT</i>	3.5896	0.3591	0.2252	1.3848	2.9944	0.1609	0.1622	0.7405	3.1180	0.1186	0.1328	0.6106
<i>Constant Walking-Walking</i>	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												
<i>PT-PT</i>	2.1532	0.5586	0.5132	0.8852	2.0115	0.1528	0.0143	0.4901	1.8707	0.1465	0.2128	0.4108
<i>PT-Walking</i>	2.2721	0.7801	0.7267	1.0657	1.7930	0.1765	0.2131	0.7964	1.6911	0.2954	0.3991	0.6362
<i>Walking-PT</i>	2.5118	0.2276	0.2923	1.0694	3.1858	0.2242	0.1616	0.6646	2.7802	0.0832	0.0981	0.5863
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>PT first/shopping trip</i>	-2.3461	0.4225	0.4878	0.8458	-2.0975	0.1265	0.0647	0.5165	-2.2493	0.2081	0.1078	0.4630
<i>PT following trip</i>	-0.5191	1.2082	2.2718	0.8537	-0.7681	0.1844	0.1886	0.5121	-0.6703	0.2469	0.2753	0.4384
<i>Walking first/shopping trip</i>	-1.3286	0.8049	0.5477	0.7973	-1.0196	0.2756	0.2333	0.4030	-1.0792	0.3478	0.1200	0.3310
<i>Walking following trip</i>	-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												
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>Walking-Walking</i>	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												
<i>Travel time for first trip (base level)</i>	-0.0922	0.0879	0.1064	0.0203	-0.0963	0.1037	0.1245	0.0137	-0.0961	0.0537	0.0249	0.0120
<i>Travel time shift for clothes shopping</i>	-0.0610	3.2992	1.0287	0.0335	-0.0055	1.2074	4.1777	0.0162	0.0144	0.4587	0.3322	0.0123
<i>Travel time for O-S-O trip chains</i>	0.0118	1.0243	1.5322	0.0186	0.0231	0.7009	0.5493	0.0095	0.0213	0.4025	0.1588	0.0077
<i>Travel time for HWH tours</i>	-0.0528	0.4264	0.4220	0.0202	-0.0420	0.2539	0.3180	0.0124	-0.0462	0.0523	0.0709	0.0114
<i>Travel time multiplier for car</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Travel time multiplier for PT IVT</i>	0.5984	0.0995	0.1648	0.1358	0.5840	0.0234	0.0303	0.0904	0.5836	0.0601	0.0740	0.0848
<i>Travel time multiplier for PT first access trip</i>	1.2979	0.6771	0.4044	0.4737	0.8818	0.1610	0.1617	0.3109	0.7801	0.0771	0.1163	0.2751
<i>Travel time multiplier for PT last egress trip</i>	0.8746	0.4365	0.3591	0.4432	0.7761	0.2747	0.1669	0.2606	0.6338	0.1508	0.1674	0.2035
<i>Travel time multiplier for PT remaining OVT</i>	0.4532	0.9455	0.9127	0.4097	0.3437	0.4582	0.6304	0.2779	0.2558	0.3510	0.4893	0.2346
<i>Travel time multiplier for following trip</i>	1.2880	0.1299	0.1672	0.1839	1.2649	0.0710	0.0704	0.1208	1.2969	0.0446	0.0410	0.1142
<i>Travel time - Shopping duration elasticity</i>	-0.3769	0.3337	0.3203	0.0905	-0.3368	0.0895	0.0986	0.0516	-0.3277	0.0767	0.1018	0.0428
<i>Travel walking distance (base)</i>	-2.1274	0.3084	0.1390	0.3806	-1.9060	0.1723	0.0501	0.2209	-1.8504	0.1381	0.0430	0.1859
<i>Travel walking distance for O-S-O trip chains</i>	0.5248	1.1663	0.5786	0.3164	0.4030	0.5392	0.3635	0.2102	0.3971	0.4756	0.0914	0.1732
<i>Travel walking distance multiplier for following trip</i>	1.0838	0.1340	0.0357	0.1752	1.1269	0.0996	0.0432	0.1175	1.1482	0.0826	0.0509	0.1009
<i>Box-cox lambda for travel walking distance</i>	0.6191	0.2310	0.0838	0.1403	0.6831	0.1515	0.0722	0.0797	0.6776	0.1584	0.0266	0.0656
<i>Travel walking distance - Shopping duration elasticity</i>	-0.2442	0.7659	0.3461	0.0831	-0.1761	0.2611	0.1963	0.0483	-0.1820	0.3037	0.1282	0.0459
<i>Travel cost</i>	-0.8989	0.3792	0.1525	0.1994	-0.7438	0.1412	0.0869	0.1101	-0.7222	0.1225	0.0963	0.1003
<i>Box-cox lambda for travel cost</i>	0.3580	0.3322	0.3391	0.1792	0.3428	0.3607	0.1601	0.0853	0.3861	0.2800	0.1222	0.0746
<i>Travel cost - Personal income elasticity</i>	-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												
<i>Living in rich areas-shopping in poor areas</i>	-1.4764	1.0070	0.6788	0.6873	-1.1477	0.4281	0.1539	0.3894	-1.1507	0.4319	0.1882	0.3458
<i>Parking areas (400m buffer)</i>	0.0979	0.3886	0.4832	0.0522	0.1098	0.2254	0.2112	0.0345	0.0985	0.1185	0.1246	0.0293
<i>Box-cox lambda for parking areas (400m buffer)</i>	0.4979	0.3017	0.2632	0.1890	0.4715	0.1277	0.1097	0.1042	0.4864	0.1543	0.1098	0.0898
<i>Presence of major clothes shopping retailers (400m buffer)</i>	3.2163	0.6585	0.3566	1.0994	2.3616	0.2562	0.1888	0.4642	2.1641	0.1028	0.0846	0.3514
<i>Presence of major grocery retailers (400m buffer)</i>	0.3718	0.4327	0.6763	0.2696	0.3888	0.2712	0.2753	0.1448	0.4755	0.1085	0.0808	0.1232
<i>Presence of major durables retailers (400m buffer)</i>	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												
<i>Natural logarithm multiplier ϕ</i>	1.1449	0.6398	0.3166	0.3958	0.7984	0.0940	0.0641	0.1583	0.7851	0.0758	0.0426	0.1219
<i>Population (400m buffer)</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Retail areas for clothes stores (400m buffer) (exp.)</i>	-0.3754	2.9033	2.0190	0.8163	0.5708	1.6734	0.5045	0.5899	0.3098	1.2985	1.1233	0.5293
<i>Retail areas for grocery stores (400m buffer) (exp.)</i>	-0.0092	1.5287	107.8340	0.9790	0.6230	0.1909	0.2738	0.5442	0.6312	0.2278	0.3280	0.4406
<i>Retail areas for dur./other stores (400m buffer) (exp.)</i>	-4.6136	8.9172	1.8808	1.2844	-0.3459	1.5889	1.4782	0.9318	-2.7486	5.6801	2.2035	1.2648
<i>Shopping store variability (400m buffer) (exp.)</i>	-1.3641	2.4067	3.5162	12.6872	1.5184	1.8322	0.1066	0.8112	1.6491	0.2963	0.2054	0.6449
<i>Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)</i>	-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												
<i>Constant rest Yorkshire</i>	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												
<i>Constant Car-Other (PT/walking)</i>	-2.8979	0.0753	0.0665	0.3668	-2.8382	0.0514	0.0471	0.3376	-2.9225	0.0705	0.0492	0.3178
<i>Constant Other (PT/walking)-Car</i>	-0.7514	0.1625	0.2066	0.3062	-0.8617	0.0946	0.1258	0.2766	-0.8853	0.0848	0.0907	0.2670
<i>Constant PT-PT</i>	-0.9947	0.1780	0.2303	0.4568	-1.0786	0.0369	0.0540	0.4331	-1.0919	0.0527	0.0696	0.4260
<i>Constant PT-Walking</i>	-1.5281	0.1057	0.1479	0.6085	-1.6367	0.1239	0.1482	0.5720	-1.8196	0.1756	0.1386	0.5848
<i>Constant Walking-PT</i>	-0.8996	0.3044	0.3098	0.5709	-1.1721	0.2566	0.3082	0.5788	-1.3627	0.1454	0.1562	0.5784
<i>Constant Walking-Walking</i>	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												
<i>Constant Car-Other (PT/walking)</i>	2.1800	0.0756	0.1153	0.6624	1.9896	0.1455	0.1363	0.5996	2.1791	0.0633	0.0311	0.5973
<i>Constant Other (PT/walking)-Car</i>	0.8598	0.4231	0.3415	0.7298	0.9739	0.5389	0.2840	0.6720	0.8056	0.4972	0.4706	0.6873
<i>Constant PT-PT</i>	4.7370	0.1094	0.0430	0.5461	4.5458	0.0647	0.0298	0.5350	4.6773	0.0955	0.0254	0.5209
<i>Constant PT-Walking</i>	3.9023	0.1636	0.0693	0.7409	3.9530	0.1802	0.0991	0.6701	3.9240	0.1701	0.0737	0.6640
<i>Constant Walking-PT</i>	2.8793	0.1183	0.1425	0.5754	3.1324	0.1209	0.0298	0.5720	3.0857	0.1042	0.0450	0.5643
<i>Constant Walking-Walking</i>	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												
<i>PT-PT</i>	1.9325	0.1075	0.0479	0.3685	1.8878	0.0819	0.0612	0.3421	1.8275	0.0807	0.0721	0.3555
<i>PT-Walking</i>	1.6806	0.0790	0.0554	0.6056	1.6828	0.1109	0.1344	0.5531	2.1363	0.1706	0.0811	0.5609
<i>Walking-PT</i>	2.6370	0.0210	0.0208	0.5655	2.6701	0.0917	0.1155	0.5877	2.9235	0.0876	0.0643	0.5868
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>PT first/shopping trip</i>	-2.0881	0.1247	0.0890	0.4234	-1.9753	0.0768	0.0614	0.3888	-1.9546	0.0654	0.0701	0.3942
<i>PT following trip</i>	-0.7380	0.1946	0.2532	0.4124	-0.7446	0.2222	0.2606	0.4016	-0.7707	0.1672	0.2060	0.3974
<i>Walking first/shopping trip</i>	-0.8791	0.1021	0.1207	0.3088	-0.9424	0.2125	0.1953	0.2896	-0.9575	0.1958	0.1313	0.2784
<i>Walking following trip</i>	-0.4411	0.2305	0.1792	0.3343	-0.4882	0.3473	0.1314	0.3075	-0.4656	0.2657	0.1586	0.2962
Mode shifts for students												
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>Walking-Walking</i>	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												
<i>Travel time for first trip (base level)</i>	-0.0998	0.0936	0.0611	0.0109	-0.0962	0.0756	0.0650	0.0102	-0.0981	0.0751	0.0376	0.0097
<i>Travel time shift for clothes shopping</i>	0.0193	0.2717	0.2482	0.0116	0.0170	0.3598	0.3677	0.0107	0.0201	0.2408	0.1561	0.0106
<i>Travel time for O-S-O trip chains</i>	0.0246	0.6161	0.1133	0.0071	0.0200	0.3127	0.1261	0.0066	0.0201	0.3219	0.1245	0.0065
<i>Travel time for HWH tours</i>	-0.0404	0.0924	0.0624	0.0110	-0.0408	0.0836	0.0438	0.0104	-0.0447	0.1093	0.1521	0.0099
<i>Travel time multiplier for car</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Travel time multiplier for PT IVT</i>	0.5965	0.0450	0.0629	0.0734	0.5587	0.0562	0.0622	0.0732	0.5753	0.0363	0.0398	0.0655
<i>Travel time multiplier for PT first access trip</i>	0.7998	0.0653	0.0886	0.2657	0.8283	0.0277	0.0373	0.2765	0.7656	0.1122	0.1315	0.2357
<i>Travel time multiplier for PT last egress trip</i>	0.6225	0.1357	0.1869	0.2002	0.6358	0.1834	0.2205	0.1830	0.6475	0.0756	0.0704	0.1786
<i>Travel time multiplier for PT remaining OVT</i>	0.2498	0.2979	0.3694	0.2089	0.4198	0.1874	0.0643	0.2171	0.3556	0.2344	0.2749	0.1760
<i>Travel time multiplier for following trip</i>	1.3066	0.0437	0.0337	0.1072	1.2890	0.0504	0.0278	0.0975	1.2917	0.0484	0.0270	0.0931
<i>Travel time - Shopping duration elasticity</i>	-0.3125	0.0150	0.0181	0.0370	-0.3320	0.0630	0.0602	0.0354	-0.3248	0.0450	0.0410	0.0324
<i>Travel walking distance (base)</i>	-1.8316	0.1265	0.0210	0.1722	-1.7974	0.1055	0.0760	0.1661	-1.7705	0.0889	0.0309	0.1518
<i>Travel walking distance for O-S-O trip chains</i>	0.4258	0.5823	0.1712	0.1610	0.3635	0.3621	0.2889	0.1488	0.3392	0.2627	0.1316	0.1428
<i>Travel walking distance multiplier for following trip</i>	1.1450	0.0851	0.0481	0.0976	1.1808	0.0591	0.0581	0.0947	1.1838	0.0541	0.0198	0.0964
<i>Boz-car lambda for travel walking distance</i>	0.7131	0.1142	0.0252	0.0621	0.7285	0.1037	0.0896	0.0554	0.7438	0.0762	0.0330	0.0563
<i>Travel walking distance - Shopping duration elasticity</i>	-0.1504	0.0822	0.0665	0.0409	-0.1504	0.1438	0.1601	0.0385	-0.1546	0.1630	0.1635	0.0378
<i>Travel cost</i>	-0.7198	0.1043	0.0622	0.0845	-0.7033	0.0791	0.0339	0.0845	-0.7056	0.0826	0.0617	0.0810
<i>Boz-car lambda for travel cost</i>	0.3975	0.2587	0.0771	0.0660	0.4100	0.2353	0.0636	0.0640	0.4421	0.1755	0.0666	0.0581
<i>Travel cost - Personal income elasticity</i>	-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												
<i>Living in rich areas-shopping in poor areas</i>	-1.0836	0.3483	0.1258	0.3136	-1.0661	0.3265	0.1472	0.2923	-0.9644	0.2000	0.0758	0.2627
<i>Parking areas (400m buffer)</i>	0.0915	0.0851	0.1119	0.0273	0.0900	0.0507	0.0581	0.0271	0.0986	0.0767	0.0610	0.0270
<i>Boz-car lambda for parking areas (400m buffer)</i>	0.5130	0.2162	0.0742	0.0879	0.4846	0.1489	0.0452	0.0898	0.4307	0.0562	0.0632	0.0794
<i>Presence of major clothes shopping retailers (400m buffer)</i>	1.9151	0.0486	0.0584	0.2995	2.2829	0.1634	0.0662	0.2857	2.0313	0.0606	0.0636	0.2574
<i>Presence of major grocery retailers (400m buffer)</i>	0.5166	0.0513	0.0757	0.1156	0.4945	0.0767	0.0725	0.1115	0.5082	0.0548	0.0554	0.1043
<i>Presence of major durables retailers (400m buffer)</i>	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												
<i>Natural logarithm multiplier ϕ</i>	0.7713	0.0881	0.0818	0.1183	0.7253	0.0656	0.0845	0.1112	0.7490	0.0504	0.0509	0.1088
<i>Population (400m buffer)</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Retail areas for clothes stores (400m buffer) (exp.)</i>	0.2841	1.3004	1.2744	0.5625	0.4234	0.9589	0.5156	0.5723	0.4279	1.3007	0.6631	0.5419
<i>Retail areas for grocery stores (400m buffer) (exp.)</i>	0.6258	0.4163	0.6023	0.4405	0.8671	0.2889	0.1557	0.4601	0.8265	0.2534	0.1436	0.4119
<i>Retail areas for dur./other stores (400m buffer) (exp.)</i>	-0.0224	1.0382	18.2843	0.8689	0.2944	0.7021	1.2029	0.8762	0.1552	0.7357	0.4078	0.7667
<i>Shopping store variability (400m buffer) (exp.)</i>	1.6700	0.3606	0.2231	0.6576	1.7679	0.3761	0.1098	0.6371	1.5989	0.2801	0.1659	0.6421
<i>Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)</i>	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												
<i>Constant rest Yorkshire</i>	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												
<i>Constant Car-Other (PT/walking)</i>	-2.7630	0.1091	0.1415	0.5933	-2.8108	0.0475	0.0567	0.3691	-2.8736	0.0526	0.0484	0.3312
<i>Constant Other (PT/walking)-Car</i>	-0.8126	0.4196	0.5225	0.5306	-0.7615	0.1317	0.1643	0.3040	-0.8626	0.2360	0.3091	0.2767
<i>Constant PT-PT</i>	-0.9213	0.3800	0.5193	0.7122	-1.1338	0.1335	0.1614	0.4839	-1.2381	0.1490	0.0772	0.4634
<i>Constant PT-Walking</i>	-1.3146	0.3793	0.5855	1.0210	-1.4213	0.1740	0.2223	0.5953	-1.7795	0.1877	0.1661	0.6390
<i>Constant Walking-PT</i>	-0.5743	0.5250	0.2354	0.8972	-1.2640	0.0856	0.0934	0.5781	-1.1244	0.1713	0.2363	0.5105
<i>Constant Walking-Walking</i>	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												
<i>Constant Car-Other (PT/walking)</i>	1.2589	0.4589	0.3962	0.9732	1.9530	0.1605	0.0744	0.6367	2.1790	0.1054	0.1471	0.6892
<i>Constant Other (PT/walking)-Car</i>	1.7809	1.8141	0.1583	0.8752	0.9967	0.5749	0.2037	0.6958	0.8680	0.3716	0.1420	0.6890
<i>Constant PT-PT</i>	5.5339	0.2961	0.1414	0.8913	4.6813	0.0964	0.0648	0.5696	4.7026	0.1014	0.0353	0.5490
<i>Constant PT-Walking</i>	3.9305	0.1720	0.1114	0.9674	3.4049	0.0974	0.1348	0.6683	3.8796	0.1569	0.0328	0.7103
<i>Constant Walking-PT</i>	2.9049	0.0643	0.0679	0.8173	3.1943	0.1431	0.0366	0.5749	3.0983	0.1087	0.0582	0.5348
<i>Constant Walking-Walking</i>	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												
<i>PT-PT</i>	1.8072	0.1919	0.2364	0.6243	1.8418	0.1032	0.1217	0.4181	1.8431	0.0801	0.0926	0.3981
<i>PT-Walking</i>	1.7459	0.3341	0.4748	0.8157	2.0025	0.1367	0.1152	0.5388	1.8852	0.1251	0.1464	0.5529
<i>Walking-PT</i>	2.7491	0.1091	0.1449	0.7602	2.8434	0.0618	0.0695	0.5505	2.7293	0.0530	0.0724	0.4977
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>PT first/shopping trip</i>	-2.3933	0.3116	0.2372	0.5725	-2.2622	0.2150	0.0257	0.4219	-2.0000	0.0878	0.1128	0.3972
<i>PT following trip</i>	-1.0317	0.3903	0.3720	0.6112	-0.7952	0.1529	0.1796	0.4231	-0.8403	0.2126	0.2695	0.3902
<i>Walking first/shopping trip</i>	-0.7289	0.5103	0.6676	0.4897	-0.7906	0.0488	0.0625	0.3051	-0.8959	0.1912	0.1876	0.2739
<i>Walking following trip</i>	-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												
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>Walking-Walking</i>	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												
<i>Travel time for first trip (base level)</i>	-0.0866	0.0741	0.0911	0.0182	-0.0885	0.0329	0.0304	0.0119	-0.0930	0.0425	0.0612	0.0105
<i>Travel time shift for clothes shopping</i>	0.0020	0.9253	6.8277	0.0215	0.0085	0.7061	1.6917	0.0140	0.0175	0.3420	0.2892	0.0122
<i>Travel time for O-S-O trip chains</i>	0.0147	0.3103	0.4398	0.0116	0.0175	0.2087	0.1737	0.0070	0.0175	0.2494	0.2651	0.0068
<i>Travel time for HWH tours</i>	-0.0340	0.2802	0.3418	0.0144	-0.0455	0.0676	0.0823	0.0112	-0.0493	0.1069	0.0314	0.0107
<i>Travel time multiplier for car</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Travel time multiplier for PT IVT</i>	0.5449	0.1598	0.2007	0.1155	0.5731	0.0354	0.0450	0.0807	0.5788	0.0251	0.0290	0.0717
<i>Travel time multiplier for PT first access trip</i>	1.2339	0.5056	0.1843	0.4703	0.8582	0.1113	0.1449	0.2868	0.7498	0.0952	0.0917	0.2676
<i>Travel time multiplier for PT last egress trip</i>	0.5858	0.2968	0.3961	0.3194	0.5444	0.1915	0.2231	0.1701	0.5451	0.1047	0.0704	0.1924
<i>Travel time multiplier for PT remaining OVT</i>	0.2416	0.4719	0.6751	0.3913	0.2262	0.4048	0.5520	0.2106	0.3244	0.2460	0.4603	0.2085
<i>Travel time multiplier for following trip</i>	1.4495	0.0679	0.0447	0.2276	1.3872	0.0499	0.0538	0.1374	1.3242	0.0393	0.0409	0.1115
<i>Travel time - Shopping duration elasticity</i>	-0.3399	0.1324	0.1654	0.0646	-0.3375	0.0691	0.0532	0.0392	-0.3219	0.0201	0.0277	0.0350
<i>Travel walking distance (base)</i>	-1.8748	0.1805	0.1445	0.2396	-1.7064	0.0589	0.0619	0.1646	-1.6516	0.0253	0.0228	0.1527
<i>Travel walking distance for O-S-O trip chains</i>	0.4892	1.0733	0.5400	0.2086	0.3763	0.3982	0.2705	0.1467	0.3188	0.2155	0.1446	0.1345
<i>Travel walking distance multiplier for following trip</i>	1.2206	0.0527	0.0633	0.1484	1.2036	0.0507	0.0575	0.1071	1.2510	0.0179	0.0217	0.1085
<i>Box-coz lambda for travel walking distance</i>	0.6855	0.1835	0.1802	0.0863	0.7604	0.0555	0.0476	0.0613	0.7975	0.0214	0.0314	0.0606
<i>Travel walking distance - Shopping duration elasticity</i>	-0.1568	0.1879	0.2303	0.0548	-0.1703	0.2198	0.0681	0.0387	-0.1565	0.1213	0.0557	0.0360
<i>Travel cost</i>	-0.8047	0.2661	0.1828	0.1443	-0.7125	0.0932	0.0319	0.0944	-0.7230	0.1092	0.0533	0.0859
<i>Box-coz lambda for travel cost</i>	0.3244	0.3950	0.3799	0.1251	0.4182	0.2200	0.0529	0.0757	0.4651	0.1326	0.0920	0.0639
<i>Travel cost - Personal income elasticity</i>	-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												
<i>Living in rich areas-shopping in poor areas</i>	-0.8565	0.4590	0.5836	0.5884	-1.0699	0.3312	0.0519	0.3812	-0.9716	0.2227	0.1246	0.3223
<i>Parking areas (400m buffer)</i>	0.0755	0.2917	0.3769	0.0410	0.0877	0.0731	0.0762	0.0297	0.0942	0.0731	0.0954	0.0288
<i>Box-coz lambda for parking areas (400m buffer)</i>	0.6697	0.5877	0.2224	0.1771	0.5103	0.2098	0.0453	0.0971	0.4678	0.1090	0.0848	0.0893
<i>Presence of major clothes shopping retailers (400m buffer)</i>	1.7913	0.1500	0.1994	0.6610	2.3460	0.1955	0.1017	0.3629	2.2923	0.1681	0.0626	0.2873
<i>Presence of major grocery retailers (400m buffer)</i>	0.6901	0.3942	0.2676	0.2023	0.6139	0.1510	0.1362	0.1227	0.5967	0.1187	0.0569	0.1113
<i>Presence of major durables retailers (400m buffer)</i>	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												
<i>Natural logarithm multiplier ϕ</i>	1.0431	0.4293	0.1594	0.3196	0.7114	0.0535	0.0745	0.1567	0.7826	0.0979	0.0983	0.1364
<i>Population (400m buffer)</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Retail areas for clothes stores (400m buffer) (exp.)</i>	0.3701	1.9494	1.2811	0.9365	0.3854	1.6010	1.1433	0.7451	0.2720	1.0427	1.2265	0.6364
<i>Retail areas for grocery stores (400m buffer) (exp.)</i>	0.2170	0.9064	3.2420	0.9911	0.8034	0.3940	0.4298	0.6676	0.6636	0.2521	0.3352	0.4854
<i>Retail areas for dur./other stores (400m buffer) (exp.)</i>	-0.5344	2.0462	2.9334	2.8434	0.7488	0.6850	0.8303	0.8870	0.4043	0.5342	0.7774	0.7719
<i>Shopping store variability (400m buffer) (exp.)</i>	2.3098	0.7978	0.2051	0.7121	1.9304	0.5026	0.2025	0.6438	1.5502	0.2077	0.1408	0.6492
<i>Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)</i>	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												
<i>Constant rest Yorkshire</i>	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												
<i>Constant Car-Other (PT/walking)</i>	-2.8399	0.0403	0.0118	0.3086	-2.8568	0.0465	0.0179	0.3126	-2.7969	0.0290	0.0229	0.2929
<i>Constant Other (PT/walking)-Car</i>	-0.8700	0.0399	0.0549	0.2616	-0.7957	0.0858	0.0884	0.2502	-0.8663	0.0610	0.0857	0.2648
<i>Constant PT-PT</i>	-1.1307	0.1303	0.1402	0.4481	-1.1034	0.0562	0.0989	0.4382	-1.0367	0.1159	0.1471	0.4252
<i>Constant PT-Walking</i>	-1.5744	0.0971	0.1447	0.5367	-1.6048	0.0524	0.0627	0.5378	-1.4630	0.0688	0.0692	0.5003
<i>Constant Walking-PT</i>	-1.0361	0.1471	0.1373	0.5160	-1.1859	0.0898	0.1177	0.5332	-1.0723	0.1252	0.1189	0.4892
<i>Constant Walking-Walking</i>	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												
<i>Constant Car-Other (PT/walking)</i>	2.2870	0.0598	0.0765	0.6462	2.3535	0.0338	0.0397	0.6904	2.4160	0.0385	0.0386	0.6673
<i>Constant Other (PT/walking)-Car</i>	0.8151	0.2879	0.1476	0.6492	0.7254	0.1659	0.1384	0.6661	0.8818	0.3934	0.1109	0.6409
<i>Constant PT-PT</i>	4.4775	0.0487	0.0228	0.5311	4.4940	0.0525	0.0160	0.5183	4.3979	0.0336	0.0220	0.5202
<i>Constant PT-Walking</i>	3.6771	0.0965	0.0475	0.6317	3.8020	0.1337	0.0279	0.6096	3.6108	0.0767	0.0360	0.6126
<i>Constant Walking-PT</i>	2.8438	0.0290	0.0342	0.5328	2.9108	0.0485	0.0394	0.5214	2.8151	0.0268	0.0349	0.5005
<i>Constant Walking-Walking</i>	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												
<i>PT-PT</i>	1.7538	0.0153	0.0210	0.3628	1.7820	0.0522	0.0640	0.3390	1.7435	0.0339	0.0395	0.3390
<i>PT-Walking</i>	1.7227	0.0791	0.0829	0.4552	1.8413	0.0562	0.0648	0.4478	1.8393	0.0612	0.0775	0.4462
<i>Walking-PT</i>	2.6121	0.0419	0.0566	0.5164	2.7768	0.0438	0.0456	0.5256	2.6977	0.0298	0.0436	0.4782
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>PT first/shopping trip</i>	-1.9958	0.0757	0.0769	0.3747	-1.9414	0.0706	0.0762	0.3650	-1.9869	0.0701	0.0591	0.3611
<i>PT following trip</i>	-0.8189	0.1850	0.2640	0.3786	-0.7385	0.1458	0.1345	0.3801	-0.7322	0.1531	0.0833	0.3683
<i>Walking first/shopping trip</i>	-0.8786	0.1794	0.1641	0.2602	-0.8798	0.1642	0.1522	0.2508	-0.8292	0.0536	0.0626	0.2517
<i>Walking following trip</i>	-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												
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>Walking-Walking</i>	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												
<i>Travel time for first trip (base level)</i>	-0.0913	0.0178	0.0231	0.0100	-0.0916	0.0201	0.0222	0.0098	-0.0906	0.0208	0.0306	0.0097
<i>Travel time shift for clothes shopping</i>	0.0168	0.3665	0.1841	0.0120	0.0208	0.2171	0.1494	0.0105	0.0199	0.2498	0.1785	0.0102
<i>Travel time for O-S-O trip chains</i>	0.0178	0.1770	0.1302	0.0064	0.0178	0.1732	0.1282	0.0062	0.0169	0.1675	0.1587	0.0062
<i>Travel time for HWH tours</i>	-0.0435	0.0938	0.1164	0.0097	-0.0436	0.0621	0.0694	0.0094	-0.0449	0.0416	0.0528	0.0095
<i>Travel time multiplier for car</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Travel time multiplier for PT IVT</i>	0.5806	0.0278	0.0319	0.0714	0.5914	0.0341	0.0432	0.0683	0.5833	0.0225	0.0379	0.0661
<i>Travel time multiplier for PT first access trip</i>	0.7964	0.1011	0.1280	0.2591	0.7830	0.0778	0.0882	0.2546	0.8601	0.0752	0.0703	0.2539
<i>Travel time multiplier for PT last egress trip</i>	0.6135	0.0729	0.0873	0.1818	0.6067	0.0560	0.0782	0.1710	0.5523	0.0929	0.0881	0.1671
<i>Travel time multiplier for PT remaining OVT</i>	0.3344	0.1403	0.1808	0.1971	0.3412	0.1442	0.1690	0.2046	0.3395	0.0885	0.1046	0.1818
<i>Travel time multiplier for following trip</i>	1.3683	0.0137	0.0199	0.1106	1.3440	0.0117	0.0118	0.1090	1.3558	0.0137	0.0169	0.1114
<i>Travel time - Shopping duration elasticity</i>	-0.3207	0.0441	0.0563	0.0341	-0.3270	0.0365	0.0261	0.0324	-0.3165	0.0187	0.0250	0.0324
<i>Travel walking distance (base)</i>	-1.6665	0.0304	0.0260	0.1432	-1.6255	0.0165	0.0234	0.1365	-1.6177	0.0138	0.0171	0.1327
<i>Travel walking distance for O-S-O trip chains</i>	0.3218	0.1957	0.0622	0.1293	0.2591	0.0871	0.1166	0.1260	0.2507	0.1271	0.1425	0.1220
<i>Travel walking distance multiplier for following trip</i>	1.2304	0.0198	0.0239	0.0997	1.2390	0.0218	0.0301	0.0964	1.2544	0.0190	0.0252	0.0955
<i>Box-coz lambda for travel walking distance</i>	0.8167	0.0162	0.0173	0.0575	0.8165	0.0194	0.0228	0.0553	0.8133	0.0190	0.0259	0.0540
<i>Travel walking distance - Shopping duration elasticity</i>	-0.1473	0.0905	0.1057	0.0334	-0.1597	0.1440	0.0442	0.0337	-0.1478	0.0758	0.0682	0.0337
<i>Travel cost</i>	-0.7023	0.0774	0.0521	0.0828	-0.7008	0.0751	0.0118	0.0792	-0.6953	0.0667	0.0321	0.0798
<i>Box-coz lambda for travel cost</i>	0.4908	0.0873	0.0749	0.0607	0.5216	0.0411	0.0423	0.0574	0.4953	0.0763	0.0370	0.0558
<i>Travel cost - Personal income elasticity</i>	-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												
<i>Living in rich areas-shopping in poor areas</i>	-0.9014	0.1216	0.0673	0.3004	-0.9441	0.1747	0.0782	0.3070	-0.8970	0.1283	0.1107	0.3052
<i>Parking areas (400m buffer)</i>	0.0900	0.0613	0.0789	0.0267	0.0987	0.0610	0.0361	0.0273	0.0962	0.0583	0.0641	0.0274
<i>Box-coz lambda for parking areas (400m buffer)</i>	0.4593	0.0925	0.1070	0.0807	0.4253	0.0299	0.0382	0.0767	0.4462	0.0697	0.0917	0.0801
<i>Presence of major clothes shopping retailers (400m buffer)</i>	2.1805	0.1112	0.0908	0.2546	2.1209	0.0808	0.0398	0.2507	2.1794	0.1106	0.0563	0.2388
<i>Presence of major grocery retailers (400m buffer)</i>	0.5857	0.0981	0.0598	0.1043	0.5686	0.0660	0.0568	0.1031	0.5703	0.0692	0.0388	0.1016
<i>Presence of major durables retailers (400m buffer)</i>	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												
<i>Natural logarithm multiplier ϕ</i>	0.7570	0.0449	0.0555	0.1242	0.7507	0.0444	0.0447	0.1188	0.7472	0.0303	0.0414	0.1158
<i>Population (400m buffer)</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Retail areas for clothes stores (400m buffer) (exp.)</i>	0.1975	0.8504	1.1849	0.6278	0.2150	0.7121	1.0978	0.5904	0.2270	0.7681	0.8917	0.5877
<i>Retail areas for grocery stores (400m buffer) (exp.)</i>	0.6719	0.1730	0.2304	0.4519	0.6376	0.1851	0.2284	0.4250	0.6348	0.1320	0.2134	0.4235
<i>Retail areas for dur./other stores (400m buffer) (exp.)</i>	0.5681	0.3305	0.4331	0.7428	0.5246	0.3458	0.4548	0.7599	0.6207	0.2764	0.3808	0.6825
<i>Shopping store variability (400m buffer) (exp.)</i>	1.5794	0.2294	0.1104	0.6179	1.3800	0.1411	0.1325	0.6873	1.4553	0.1328	0.1337	0.6815
<i>Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)</i>	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												
<i>Constant rest Yorkshire</i>	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												
<i>Constant Car-Other (PT/walking)</i>	-3.1171	0.1418	0.0722	0.4717	-2.8785	0.0725	0.0747	0.3309	-2.8640	0.0618	0.0530	0.2981
<i>Constant Other (PT/walking)-Car</i>	-1.0399	0.2083	0.1500	0.3595	-0.8199	0.0891	0.1066	0.2694	-0.8422	0.0381	0.0493	0.2454
<i>Constant PT-PT</i>	-1.7143	0.5979	0.2318	0.6904	-1.1798	0.1221	0.1057	0.4855	-1.1893	0.1158	0.0688	0.4440
<i>Constant PT-Walking</i>	-2.6159	0.6857	0.1352	0.7059	-1.8802	0.2116	0.0507	0.5340	-1.7389	0.1206	0.0672	0.4942
<i>Constant Walking-PT</i>	-1.1054	0.3284	0.4547	0.6723	-1.1300	0.0951	0.1162	0.5371	-1.2565	0.0804	0.1015	0.5142
<i>Constant Walking-Walking</i>	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												
<i>Constant Car-Other (PT/walking)</i>	2.2010	0.0700	0.0937	0.8087	2.3893	0.0591	0.0735	0.7582	2.3109	0.0389	0.0597	0.7266
<i>Constant Other (PT/walking)-Car</i>	0.9220	0.6870	0.6206	0.8788	0.7340	0.2666	0.2251	0.6893	0.7433	0.2008	0.1606	0.6505
<i>Constant PT-PT</i>	5.2949	0.2401	0.0891	0.7017	4.7821	0.1200	0.0427	0.5543	4.6175	0.0815	0.0091	0.5121
<i>Constant PT-Walking</i>	4.6488	0.3862	0.1030	0.7341	4.0846	0.2180	0.0586	0.6081	3.5963	0.0724	0.0341	0.6150
<i>Constant Walking-PT</i>	2.9984	0.1453	0.1657	0.7399	2.8510	0.0531	0.0867	0.5211	2.8774	0.0387	0.0497	0.4900
<i>Constant Walking-Walking</i>	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												
<i>PT-PT</i>	1.8752	0.1795	0.2446	0.5381	1.8029	0.0905	0.1101	0.3676	1.7526	0.0541	0.0641	0.3450
<i>PT-Walking</i>	2.5330	0.3881	0.0810	0.6219	2.0626	0.1303	0.1019	0.4719	1.9792	0.0936	0.0804	0.4617
<i>Walking-PT</i>	2.8119	0.0958	0.1062	0.6440	2.9960	0.1146	0.0537	0.5091	3.0025	0.1170	0.0423	0.4930
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>PT first/shopping trip</i>	-2.2999	0.2352	0.1039	0.4935	-2.0229	0.0947	0.0587	0.3764	-1.9338	0.0628	0.0616	0.3509
<i>PT following trip</i>	-1.1375	0.3372	0.3138	0.5201	-0.8703	0.1376	0.1797	0.3740	-0.9071	0.1279	0.1448	0.3597
<i>Walking first/shopping trip</i>	-0.9896	0.2705	0.2209	0.3592	-0.8970	0.1203	0.0527	0.2597	-0.8447	0.1101	0.1291	0.2334
<i>Walking following trip</i>	-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												
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>Walking-Walking</i>	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												
<i>Travel time for first trip (base level)</i>	-0.0815	0.1545	0.1793	0.0124	-0.0849	0.0692	0.0412	0.0108	-0.0909	0.0293	0.0400	0.0096
<i>Travel time shift for clothes shopping</i>	-0.0088	1.3330	2.3067	0.0186	0.0172	0.3504	0.2385	0.0106	0.0232	0.1697	0.2052	0.0092
<i>Travel time for O-S-O trip chains</i>	0.0040	0.8035	2.1592	0.0094	0.0085	0.4425	0.1213	0.0064	0.0130	0.1434	0.1425	0.0060
<i>Travel time for HWH tours</i>	-0.0408	0.1535	0.2041	0.0122	-0.0405	0.0993	0.1304	0.0090	-0.0436	0.0346	0.0455	0.0089
<i>Travel time multiplier for car</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Travel time multiplier for PT IVT</i>	0.5455	0.1087	0.1725	0.0949	0.5944	0.0402	0.0532	0.0780	0.5914	0.0257	0.0343	0.0706
<i>Travel time multiplier for PT first access trip</i>	0.8595	0.2134	0.3491	0.3671	0.7604	0.0730	0.0784	0.2804	0.7798	0.0593	0.0755	0.2453
<i>Travel time multiplier for PT last egress trip</i>	0.5363	0.1192	0.0890	0.2802	0.6305	0.0634	0.0788	0.2114	0.6022	0.0984	0.1161	0.1941
<i>Travel time multiplier for PT remaining OVT</i>	0.5524	0.5626	0.2538	0.3437	0.3308	0.1439	0.1736	0.2144	0.3701	0.1413	0.1573	0.2008
<i>Travel time multiplier for following trip</i>	1.4065	0.0571	0.0777	0.1526	1.4173	0.0532	0.0484	0.1210	1.3923	0.0368	0.0339	0.1063
<i>Travel time - Shopping duration elasticity</i>	-0.3261	0.0616	0.0745	0.0475	-0.3238	0.0259	0.0268	0.0332	-0.3139	0.0141	0.0165	0.0301
<i>Travel walking distance (base)</i>	-1.8091	0.1126	0.0662	0.1793	-1.7025	0.0471	0.0419	0.1431	-1.6829	0.0350	0.0124	0.1340
<i>Travel walking distance for O-S-O trip chains</i>	0.2582	0.1136	0.1577	0.2017	0.2414	0.2417	0.2965	0.1321	0.2837	0.0565	0.0432	0.1255
<i>Travel walking distance multiplier for following trip</i>	1.0823	0.1352	0.0534	0.1099	1.1591	0.0738	0.0329	0.0945	1.1744	0.0616	0.0154	0.0914
<i>Boz-coz lambda for travel walking distance</i>	0.7333	0.0892	0.0386	0.0646	0.7718	0.0413	0.0203	0.0565	0.8035	0.0195	0.0232	0.0558
<i>Travel walking distance - Shopping duration elasticity</i>	-0.1499	0.0740	0.0606	0.0438	-0.1578	0.1473	0.1021	0.0381	-0.1522	0.0902	0.0883	0.0370
<i>Travel cost</i>	-0.7021	0.1378	0.1229	0.1106	-0.7010	0.0763	0.0499	0.0877	-0.6664	0.0226	0.0182	0.0816
<i>Boz-coz lambda for travel cost</i>	0.6385	0.1908	0.1520	0.0765	0.6204	0.1571	0.0351	0.0592	0.6049	0.1282	0.0279	0.0542
<i>Travel cost - Personal income elasticity</i>	-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												
<i>Living in rich areas-shopping in poor areas</i>	-0.8624	0.2805	0.2964	0.5233	-0.9391	0.2087	0.2062	0.3474	-0.9458	0.1769	0.1320	0.3034
<i>Parking areas (400m buffer)</i>	0.0959	0.1181	0.1407	0.0396	0.1067	0.1474	0.0434	0.0310	0.0983	0.0593	0.0457	0.0300
<i>Boz-coz lambda for parking areas (400m buffer)</i>	0.4144	0.0845	0.1037	0.1276	0.4150	0.0306	0.0508	0.0870	0.4393	0.0490	0.0644	0.0910
<i>Presence of major clothes shopping retailers (400m buffer)</i>	2.7210	0.4009	0.3650	0.6385	2.1301	0.0999	0.0807	0.2993	2.0977	0.0690	0.0339	0.2571
<i>Presence of major grocery retailers (400m buffer)</i>	0.3981	0.2537	0.1653	0.1596	0.5156	0.0710	0.1003	0.1165	0.4838	0.1081	0.0939	0.1040
<i>Presence of major durables retailers (400m buffer)</i>	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												
<i>Natural logarithm multiplier ϕ</i>	0.7023	0.0840	0.1101	0.1705	0.7319	0.0400	0.0521	0.1056	0.7069	0.0314	0.0247	0.0981
<i>Population (400m buffer)</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Retail areas for clothes stores (400m buffer) (exp.)</i>	1.0362	3.7422	0.4033	0.8377	0.4524	1.2408	0.4998	0.5754	0.4018	0.8628	0.2841	0.5651
<i>Retail areas for grocery stores (400m buffer) (exp.)</i>	0.9698	0.4414	0.2639	0.7281	0.8163	0.2375	0.1665	0.4098	0.9827	0.4606	0.0523	0.4054
<i>Retail areas for dur./other stores (400m buffer) (exp.)</i>	-3.0410	6.1781	2.0427	3.0768	0.4134	0.4103	0.6864	0.8018	0.6645	0.1865	0.1864	0.7552
<i>Shopping store variability (400m buffer) (exp.)</i>	1.4551	0.2133	0.2093	1.1505	0.7252	0.5514	0.8753	1.4662	0.9511	0.2673	0.3773	1.2001
<i>Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)</i>	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												
<i>Constant rest Yorkshire</i>	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												
<i>Constant Car-Other (PT/walking)</i>	-2.8518	0.0447	0.0274	0.2941	-2.8163	0.0316	0.0400	0.2848	-2.7157	0.0174	0.0218	0.2834
<i>Constant Other (PT/walking)-Car</i>	-0.7938	0.0776	0.0499	0.2466	-0.8739	0.0562	0.0680	0.2420	-0.8270	0.0548	0.0633	0.2398
<i>Constant PT-PT</i>	-1.0516	0.0888	0.1154	0.4295	-1.1333	0.0588	0.0767	0.4317	-1.1568	0.0736	0.0434	0.4299
<i>Constant PT-Walking</i>	-1.6699	0.0761	0.0342	0.4865	-1.6764	0.0803	0.0284	0.4743	-1.6308	0.0509	0.0340	0.4785
<i>Constant Walking-PT</i>	-1.1246	0.0843	0.0767	0.4856	-1.2377	0.0503	0.0651	0.4780	-1.1385	0.0892	0.0824	0.4822
<i>Constant Walking-Walking</i>	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												
<i>Constant Car-Other (PT/walking)</i>	2.2521	0.0319	0.0283	0.6893	2.2940	0.0380	0.0486	0.6842	2.2569	0.0356	0.0372	0.6724
<i>Constant Other (PT/walking)-Car</i>	0.6393	0.0749	0.0987	0.6365	0.5573	0.1208	0.1572	0.6282	0.5509	0.1295	0.0622	0.6246
<i>Constant PT-PT</i>	4.4315	0.0379	0.0264	0.4986	4.3992	0.0303	0.0117	0.4888	4.4607	0.0447	0.0195	0.4923
<i>Constant PT-Walking</i>	3.4854	0.0393	0.0227	0.5959	3.4196	0.0229	0.0164	0.5751	3.4613	0.0321	0.0146	0.5762
<i>Constant Walking-PT</i>	2.6895	0.0376	0.0285	0.4882	2.7851	0.0177	0.0197	0.4694	2.7201	0.0278	0.0340	0.4610
<i>Constant Walking-Walking</i>	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												
<i>PT-PT</i>	1.6915	0.0492	0.0610	0.3315	1.6597	0.0552	0.0400	0.3365	1.7714	0.0454	0.0573	0.3272
<i>PT-Walking</i>	1.9909	0.0947	0.0561	0.4526	1.8451	0.0499	0.0595	0.4527	1.9059	0.0505	0.0586	0.4492
<i>Walking-PT</i>	2.8235	0.0504	0.0329	0.4832	2.8449	0.0584	0.0225	0.4717	2.8088	0.0516	0.0504	0.4808
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>PT first/shopping trip</i>	-1.9022	0.0367	0.0417	0.3486	-1.8623	0.0395	0.0482	0.3439	-1.8639	0.0252	0.0329	0.3463
<i>PT following trip</i>	-0.7985	0.1180	0.1272	0.3619	-0.8274	0.1024	0.1426	0.3473	-0.8805	0.0261	0.0287	0.3491
<i>Walking first/shopping trip</i>	-0.8395	0.0485	0.0394	0.2324	-0.8302	0.0523	0.0654	0.2312	-0.7919	0.0153	0.0165	0.2265
<i>Walking following trip</i>	-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												
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>Walking-Walking</i>	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												
<i>Travel time for first trip (base level)</i>	-0.0908	0.0210	0.0268	0.0096	-0.0923	0.0188	0.0253	0.0092	-0.0926	0.0191	0.0251	0.0094
<i>Travel time shift for clothes shopping</i>	0.0245	0.1111	0.1130	0.0090	0.0271	0.0520	0.0846	0.0088	0.0249	0.0600	0.0735	0.0090
<i>Travel time for O-S-O trip chains</i>	0.0128	0.1593	0.1089	0.0059	0.0130	0.1463	0.0904	0.0059	0.0154	0.0714	0.0908	0.0059
<i>Travel time for HWH tours</i>	-0.0422	0.0831	0.0807	0.0091	-0.0453	0.0261	0.0305	0.0093	-0.0443	0.0315	0.0387	0.0091
<i>Travel time multiplier for car</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Travel time multiplier for PT IVT</i>	0.5966	0.0268	0.0329	0.0712	0.5780	0.0136	0.0140	0.0670	0.5818	0.0138	0.0175	0.0652
<i>Travel time multiplier for PT first access trip</i>	0.8066	0.0330	0.0521	0.2550	0.7985	0.0416	0.0459	0.2380	0.8174	0.0410	0.0540	0.2407
<i>Travel time multiplier for PT last egress trip</i>	0.6458	0.0721	0.0657	0.1911	0.6095	0.0712	0.0937	0.1832	0.5973	0.0543	0.0679	0.1654
<i>Travel time multiplier for PT remaining OVT</i>	0.3429	0.0851	0.0937	0.1765	0.3811	0.1162	0.1613	0.1638	0.3463	0.0643	0.0730	0.1651
<i>Travel time multiplier for following trip</i>	1.4032	0.0337	0.0241	0.1043	1.3615	0.0145	0.0190	0.0958	1.3779	0.0173	0.0177	0.1024
<i>Travel time - Shopping duration elasticity</i>	-0.3158	0.0162	0.0241	0.0304	-0.3160	0.0168	0.0198	0.0295	-0.3135	0.0143	0.0200	0.0290
<i>Travel walking distance (base)</i>	-1.6614	0.0247	0.0170	0.1326	-1.6590	0.0203	0.0144	0.1277	-1.6338	0.0105	0.0138	0.1248
<i>Travel walking distance for O-S-O trip chains</i>	0.2808	0.1498	0.1630	0.1209	0.2876	0.1057	0.1013	0.1174	0.2797	0.0684	0.0858	0.1149
<i>Travel walking distance multiplier for following trip</i>	1.1929	0.0468	0.0158	0.0915	1.2213	0.0241	0.0076	0.0906	1.2312	0.0179	0.0226	0.0906
<i>Boz-coz lambda for travel walking distance</i>	0.7999	0.0182	0.0227	0.0540	0.7844	0.0257	0.0085	0.0505	0.8097	0.0079	0.0095	0.0526
<i>Travel walking distance - Shopping duration elasticity</i>	-0.1500	0.0743	0.0500	0.0365	-0.1423	0.0740	0.0860	0.0356	-0.1504	0.0771	0.0488	0.0355
<i>Travel cost</i>	-0.6597	0.0174	0.0290	0.0820	-0.6630	0.0200	0.0214	0.0776	-0.6590	0.0111	0.0101	0.0777
<i>Boz-coz lambda for travel cost</i>	0.5834	0.0881	0.0359	0.0527	0.5812	0.0840	0.0167	0.0520	0.5709	0.0648	0.0274	0.0509
<i>Travel cost - Personal income elasticity</i>	-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												
<i>Living in rich areas-shopping in poor areas</i>	-0.9315	0.1590	0.0603	0.2979	-0.9197	0.1444	0.1342	0.2861	-0.9201	0.1449	0.0852	0.2899
<i>Parking areas (400m buffer)</i>	0.0998	0.0750	0.0435	0.0295	0.0962	0.0339	0.0250	0.0287	0.0975	0.0499	0.0474	0.0281
<i>Boz-coz lambda for parking areas (400m buffer)</i>	0.4470	0.0597	0.0365	0.0860	0.4460	0.0595	0.0481	0.0867	0.4430	0.0591	0.0513	0.0833
<i>Presence of major clothes shopping retailers (400m buffer)</i>	2.0226	0.0583	0.0775	0.2477	2.0447	0.0420	0.0528	0.2363	2.0153	0.0270	0.0208	0.2285
<i>Presence of major grocery retailers (400m buffer)</i>	0.5026	0.0621	0.0625	0.1038	0.5233	0.0394	0.0551	0.1006	0.5231	0.0323	0.0367	0.1009
<i>Presence of major durables retailers (400m buffer)</i>	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												
<i>Natural logarithm multiplier ϕ</i>	0.7244	0.0283	0.0339	0.1000	0.7206	0.0425	0.0565	0.0977	0.7140	0.0455	0.0495	0.0970
<i>Population (400m buffer)</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Retail areas for clothes stores (400m buffer) (exp.)</i>	0.3643	0.6672	0.3652	0.5235	0.3255	1.0320	0.7678	0.5242	0.2821	0.4467	0.3880	0.5269
<i>Retail areas for grocery stores (400m buffer) (exp.)</i>	0.8070	0.2131	0.1509	0.3859	0.8015	0.2139	0.1454	0.3864	0.8132	0.2088	0.1306	0.3809
<i>Retail areas for dur./other stores (400m buffer) (exp.)</i>	0.5259	0.2685	0.3698	0.7105	0.5223	0.2303	0.3733	0.7189	0.5798	0.2709	0.3723	0.7350
<i>Shopping store variability (400m buffer) (exp.)</i>	0.9835	0.2345	0.2067	1.0151	1.0034	0.2549	0.2876	0.9861	1.1556	0.1141	0.0893	0.8725
<i>Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)</i>	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												
<i>Constant rest Yorkshire</i>	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												
<i>Constant Car-Other (PT/walking)</i>	-3.2345	0.1848	0.1013	0.4147	-2.9922	0.0961	0.0421	0.3197	-2.9136	0.0673	0.0259	0.2893
<i>Constant Other (PT/walking)-Car</i>	-1.0579	0.2292	0.1921	0.3301	-0.9305	0.1186	0.1205	0.2567	-0.8186	0.0669	0.0708	0.2423
<i>Constant PT-PT</i>	-1.7943	0.6652	0.1944	0.5990	-1.2637	0.1787	0.1064	0.4679	-1.2740	0.1824	0.0775	0.4367
<i>Constant PT-Walking</i>	-2.4047	0.5497	0.0561	0.6353	-1.7935	0.1558	0.0888	0.5132	-1.6566	0.0849	0.0696	0.5016
<i>Constant Walking-PT</i>	-1.6604	0.3735	0.1400	0.6011	-1.3519	0.1183	0.0946	0.5007	-1.2231	0.0596	0.0697	0.4795
<i>Constant Walking-Walking</i>	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												
<i>Constant Car-Other (PT/walking)</i>	2.3091	0.2056	0.2600	0.8292	2.4397	0.0487	0.0453	0.7213	2.3924	0.0604	0.0636	0.6602
<i>Constant Other (PT/walking)-Car</i>	0.4816	0.4263	0.8205	0.7237	0.6134	0.2143	0.2619	0.6271	0.6606	0.1801	0.2123	0.6262
<i>Constant PT-PT</i>	4.8408	0.1338	0.0560	0.6605	4.5934	0.0758	0.0514	0.5305	4.5721	0.0708	0.0291	0.5166
<i>Constant PT-Walking</i>	4.0774	0.2158	0.0897	0.7404	3.7291	0.1120	0.0665	0.6141	3.4815	0.0399	0.0317	0.6034
<i>Constant Walking-PT</i>	2.7831	0.1335	0.1925	0.6582	2.8766	0.0353	0.0423	0.5127	2.7306	0.0385	0.0425	0.4980
<i>Constant Walking-Walking</i>	3.3167	0.2467	0.0981	0.5641	2.7734	0.0473	0.0443	0.4282	2.7075	0.0236	0.0225	0.4170
Mode shifts for central area destinations												
<i>PT-PT</i>	1.8844	0.1084	0.1082	0.4832	1.6922	0.0412	0.0361	0.3846	1.7356	0.0378	0.0591	0.3514
<i>PT-Walking</i>	2.5269	0.3847	0.2223	0.6495	1.8289	0.0839	0.1063	0.4643	1.8540	0.0375	0.0516	0.4617
<i>Walking-PT</i>	3.2592	0.2125	0.0640	0.5762	2.8427	0.0576	0.0426	0.4858	2.8259	0.0513	0.0312	0.4762
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>PT first/shopping trip</i>	-2.2572	0.2123	0.0982	0.4787	-2.0993	0.1275	0.0858	0.3769	-1.9648	0.0808	0.0791	0.3525
<i>PT following trip</i>	-0.8831	0.2436	0.3406	0.4622	-0.7520	0.1769	0.1817	0.3624	-0.7767	0.1072	0.0845	0.3613
<i>Walking first/shopping trip</i>	-0.9184	0.2638	0.2794	0.3357	-0.8673	0.1115	0.0828	0.2459	-0.8816	0.1120	0.0754	0.2386
<i>Walking following trip</i>	-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												
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>Walking-Walking</i>	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												
<i>Travel time for first trip (base level)</i>	-0.0723	0.2075	0.0667	0.0115	-0.0884	0.0392	0.0409	0.0101	-0.0866	0.0509	0.0202	0.0095
<i>Travel time shift for clothes shopping</i>	-0.0019	1.0714	5.7320	0.0154	0.0130	0.5112	0.4340	0.0121	0.0200	0.2471	0.1130	0.0106
<i>Travel time for O-S-O trip chains</i>	0.0066	0.5677	0.6542	0.0088	0.0124	0.2217	0.2646	0.0064	0.0111	0.2678	0.0526	0.0063
<i>Travel time for HWH tours</i>	-0.0483	0.1071	0.0869	0.0122	-0.0442	0.0297	0.0360	0.0099	-0.0453	0.0347	0.0502	0.0093
<i>Travel time multiplier for car</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Travel time multiplier for PT IVT</i>	0.5548	0.0901	0.1383	0.0903	0.5790	0.0223	0.0269	0.0754	0.5904	0.0253	0.0300	0.0680
<i>Travel time multiplier for PT first access trip</i>	0.8013	0.1132	0.1870	0.3393	0.7586	0.0823	0.0943	0.2648	0.7911	0.0347	0.0285	0.2656
<i>Travel time multiplier for PT last egress trip</i>	0.6293	0.2045	0.2567	0.2432	0.5551	0.1369	0.1334	0.2055	0.5742	0.0872	0.0944	0.1810
<i>Travel time multiplier for PT remaining OVT</i>	0.3848	0.4166	0.4593	0.2977	0.3061	0.2628	0.3050	0.2017	0.2595	0.3011	0.3739	0.1882
<i>Travel time multiplier for following trip</i>	1.4072	0.0656	0.0814	0.1610	1.3628	0.0258	0.0337	0.1076	1.3836	0.0202	0.0228	0.1053
<i>Travel time - Shopping duration elasticity</i>	-0.3462	0.0968	0.0797	0.0418	-0.3346	0.0602	0.0216	0.0336	-0.3253	0.0305	0.0212	0.0330
<i>Travel walking distance (base)</i>	-1.6664	0.0684	0.0774	0.1619	-1.6477	0.0147	0.0109	0.1377	-1.5886	0.0267	0.0245	0.1259
<i>Travel walking distance for O-S-O trip chains</i>	0.2191	0.2131	0.1989	0.1693	0.2325	0.1613	0.1635	0.1274	0.2332	0.1526	0.1588	0.1171
<i>Travel walking distance multiplier for following trip</i>	1.1807	0.0813	0.0882	0.1108	1.1921	0.0475	0.0207	0.0989	1.2532	0.0109	0.0145	0.0990
<i>Box-cox lambda for travel walking distance</i>	0.7399	0.0810	0.0644	0.0606	0.7771	0.0348	0.0195	0.0531	0.8083	0.0092	0.0110	0.0527
<i>Travel walking distance - Shopping duration elasticity</i>	-0.1651	0.1824	0.2165	0.0419	-0.1518	0.0885	0.0565	0.0362	-0.1480	0.0804	0.0834	0.0339
<i>Travel cost</i>	-0.6295	0.0525	0.0695	0.1040	-0.6566	0.0324	0.0395	0.0894	-0.6769	0.0386	0.0224	0.0822
<i>Box-cox lambda for travel cost</i>	0.5464	0.1448	0.1755	0.0915	0.5949	0.1094	0.0246	0.0580	0.5971	0.1136	0.0253	0.0536
<i>Travel cost - Personal income elasticity</i>	-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												
<i>Living in rich areas-shopping in poor areas</i>	-1.2773	0.7024	0.3139	0.5073	-0.9951	0.2382	0.0398	0.3979	-0.9590	0.1933	0.1270	0.3649
<i>Parking areas (400m buffer)</i>	0.0756	0.1870	0.0584	0.0333	0.0995	0.0696	0.0280	0.0302	0.1023	0.0992	0.0480	0.0286
<i>Box-cox lambda for parking areas (400m buffer)</i>	0.4932	0.1693	0.0353	0.1250	0.4198	0.0159	0.0200	0.0875	0.4005	0.0521	0.0406	0.0820
<i>Presence of major clothes shopping retailers (400m buffer)</i>	2.1518	0.2299	0.2246	0.5199	2.0857	0.0629	0.0427	0.2890	2.0458	0.0425	0.0391	0.2418
<i>Presence of major grocery retailers (400m buffer)</i>	0.4562	0.1447	0.1111	0.1495	0.5432	0.0483	0.0555	0.1076	0.5687	0.0661	0.0455	0.1037
<i>Presence of major durables retailers (400m buffer)</i>	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												
<i>Natural logarithm multiplier ϕ</i>	0.6628	0.1316	0.1456	0.1423	0.6968	0.0485	0.0468	0.1111	0.7138	0.0305	0.0298	0.1044
<i>Population (400m buffer)</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Retail areas for clothes stores (400m buffer) (exp.)</i>	0.9429	4.2951	0.8612	0.9882	0.7796	2.5675	0.2748	0.6304	0.4749	1.1732	0.3343	0.5996
<i>Retail areas for grocery stores (400m buffer) (exp.)</i>	1.5007	1.2306	0.3058	0.7292	0.9297	0.3819	0.1434	0.4728	0.8020	0.1920	0.1246	0.4232
<i>Retail areas for dur./other stores (400m buffer) (exp.)</i>	-2.0882	5.8491	3.1765	1.7849	0.8669	0.4947	0.3969	0.8789	0.7113	0.4126	0.3943	0.7856
<i>Shopping store variability (400m buffer) (exp.)</i>	1.7527	0.7496	0.6904	1.5115	1.3553	0.1288	0.1407	0.8763	1.2372	0.0892	0.1021	0.8673
<i>Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)</i>	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												
<i>Constant rest Yorkshire</i>	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												
<i>Constant Car-Other (PT/walking)</i>	-2.8391	0.0419	0.0276	0.2918	-2.8645	0.0493	0.0130	0.2840	-2.7983	0.0251	0.0149	0.2812
<i>Constant Other (PT/walking)-Car</i>	-0.8208	0.0462	0.0159	0.2380	-0.8709	0.0622	0.0866	0.2402	-0.8622	0.0424	0.0545	0.2386
<i>Constant PT-PT</i>	-1.2350	0.1461	0.0511	0.4398	-1.2034	0.1533	0.1326	0.4212	-1.1201	0.0406	0.0395	0.4185
<i>Constant PT-Walking</i>	-1.6200	0.0472	0.0385	0.4910	-1.6316	0.0575	0.0492	0.4839	-1.5801	0.0376	0.0481	0.4819
<i>Constant Walking-PT</i>	-1.1634	0.0486	0.0426	0.4828	-1.2912	0.0845	0.0615	0.4850	-1.2025	0.0279	0.0452	0.4805
<i>Constant Walking-Walking</i>	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												
<i>Constant Car-Other (PT/walking)</i>	2.4436	0.0504	0.0254	0.6723	2.4353	0.0468	0.0207	0.6467	2.3976	0.0306	0.0109	0.6516
<i>Constant Other (PT/walking)-Car</i>	0.5800	0.1676	0.2098	0.6107	0.6451	0.1034	0.1187	0.6103	0.6383	0.0407	0.0574	0.6171
<i>Constant PT-PT</i>	4.4777	0.0487	0.0138	0.5012	4.3713	0.0285	0.0273	0.4949	4.3784	0.0255	0.0130	0.5065
<i>Constant PT-Walking</i>	3.4181	0.0330	0.0322	0.6024	3.3968	0.0168	0.0218	0.5810	3.4530	0.0296	0.0242	0.5872
<i>Constant Walking-PT</i>	2.7217	0.0291	0.0338	0.4750	2.8306	0.0154	0.0131	0.4667	2.7867	0.0059	0.0073	0.4761
<i>Constant Walking-Walking</i>	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												
<i>PT-PT</i>	1.8123	0.0466	0.0499	0.3376	1.7869	0.0351	0.0432	0.3368	1.7084	0.0472	0.0584	0.3281
<i>PT-Walking</i>	1.8937	0.0556	0.0537	0.4579	1.8765	0.0341	0.0360	0.4434	1.7769	0.0333	0.0306	0.4392
<i>Walking-PT</i>	2.8277	0.0520	0.0149	0.4769	2.7540	0.0246	0.0072	0.4754	2.7517	0.0269	0.0230	0.4727
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>PT first/shopping trip</i>	-1.8738	0.0124	0.0159	0.3563	-1.9288	0.0435	0.0345	0.3464	-1.9111	0.0391	0.0450	0.3492
<i>PT following trip</i>	-0.8106	0.1083	0.1375	0.3500	-0.7481	0.1347	0.1005	0.3521	-0.7952	0.0802	0.0803	0.3531
<i>Walking first/shopping trip</i>	-0.8712	0.0881	0.0558	0.2332	-0.8545	0.0733	0.0690	0.2344	-0.8460	0.0566	0.0408	0.2322
<i>Walking following trip</i>	-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												
<i>Walking-Walking</i>	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												
<i>Walking-Walking</i>	-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												
<i>Walking-Walking</i>	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												
<i>Travel time for first trip (base level)</i>	-0.0882	0.0335	0.0243	0.0092	-0.0912	0.0102	0.0135	0.0092	-0.0906	0.0166	0.0198	0.0093
<i>Travel time shift for clothes shopping</i>	0.0248	0.1249	0.1372	0.0097	0.0249	0.0920	0.1824	0.0100	0.0248	0.1224	0.1382	0.0100
<i>Travel time for O-S-O trip chains</i>	0.0133	0.1270	0.0960	0.0061	0.0144	0.0893	0.1242	0.0061	0.0142	0.0763	0.0821	0.0061
<i>Travel time for HWH tours</i>	-0.0436	0.0462	0.0621	0.0092	-0.0449	0.0195	0.0331	0.0093	-0.0447	0.0238	0.0264	0.0093
<i>Travel time multiplier for car</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Travel time multiplier for PT IVT</i>	0.5952	0.0169	0.0250	0.0653	0.5817	0.0094	0.0085	0.0636	0.5843	0.0077	0.0100	0.0631
<i>Travel time multiplier for PT first access trip</i>	0.7945	0.0811	0.0965	0.2649	0.8096	0.0460	0.0554	0.2420	0.7909	0.0349	0.0141	0.2361
<i>Travel time multiplier for PT last egress trip</i>	0.5885	0.0569	0.0739	0.1746	0.5880	0.0487	0.0604	0.1768	0.5959	0.0320	0.0346	0.1696
<i>Travel time multiplier for PT remaining OVT</i>	0.3358	0.1364	0.1858	0.1938	0.2943	0.1786	0.2271	0.1813	0.3352	0.0780	0.0964	0.1819
<i>Travel time multiplier for following trip</i>	1.3847	0.0211	0.0188	0.1051	1.3744	0.0152	0.0134	0.0987	1.3647	0.0163	0.0186	0.1000
<i>Travel time - Shopping duration elasticity</i>	-0.3243	0.0274	0.0184	0.0328	-0.3192	0.0159	0.0148	0.0314	-0.3172	0.0124	0.0212	0.0316
<i>Travel walking distance (base)</i>	-1.5921	0.0208	0.0101	0.1226	-1.6070	0.0117	0.0092	0.1229	-1.6117	0.0088	0.0056	0.1227
<i>Travel walking distance for O-S-O trip chains</i>	0.2497	0.0744	0.0593	0.1150	0.2495	0.0731	0.0423	0.1143	0.2435	0.0951	0.0564	0.1143
<i>Travel walking distance multiplier for following trip</i>	1.2529	0.0065	0.0078	0.0952	1.2501	0.0084	0.0105	0.0932	1.2497	0.0083	0.0119	0.0932
<i>Box-coz lambda for travel walking distance</i>	0.8105	0.0118	0.0133	0.0530	0.8067	0.0031	0.0053	0.0525	0.8072	0.0030	0.0037	0.0519
<i>Travel walking distance - Shopping duration elasticity</i>	-0.1470	0.0585	0.0485	0.0329	-0.1441	0.0330	0.0265	0.0331	-0.1400	0.0250	0.0312	0.0329
<i>Travel cost</i>	-0.6713	0.0298	0.0143	0.0796	-0.6534	0.0166	0.0240	0.0784	-0.6630	0.0171	0.0141	0.0784
<i>Box-coz lambda for travel cost</i>	0.5798	0.0814	0.0349	0.0538	0.5722	0.0671	0.0222	0.0538	0.5697	0.0625	0.0172	0.0518
<i>Travel cost - Personal income elasticity</i>	-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												
<i>Living in rich areas-shopping in poor areas</i>	-0.8054	0.1039	0.1421	0.3174	-0.8504	0.0701	0.0779	0.3179	-0.8184	0.0655	0.0804	0.3020
<i>Parking areas (400m buffer)</i>	0.0961	0.0372	0.0436	0.0273	0.0948	0.0448	0.0585	0.0277	0.0978	0.0509	0.0112	0.0278
<i>Box-coz lambda for parking areas (400m buffer)</i>	0.4278	0.0374	0.0426	0.0795	0.4331	0.0410	0.0475	0.0835	0.4147	0.0168	0.0125	0.0811
<i>Presence of major clothes shopping retailers (400m buffer)</i>	2.0760	0.0650	0.0575	0.2340	2.0318	0.0354	0.0131	0.2232	2.0139	0.0263	0.0046	0.2165
<i>Presence of major grocery retailers (400m buffer)</i>	0.5491	0.0323	0.0270	0.1008	0.5631	0.0556	0.0286	0.0990	0.5498	0.0416	0.0352	0.0992
<i>Presence of major durables retailers (400m buffer)</i>	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												
<i>Natural logarithm multiplier ϕ</i>	0.7276	0.0112	0.0138	0.1056	0.7220	0.0279	0.0340	0.1025	0.7467	0.0240	0.0247	0.1040
<i>Population (400m buffer)</i>	1.0000	-	-	-	1.0000	-	-	-	1.0000	-	-	-
<i>Retail areas for clothes stores (400m buffer) (exp.)</i>	0.3792	0.7351	0.2813	0.5615	0.4392	1.0099	0.2900	0.5625	0.2789	0.3235	0.2595	0.5543
<i>Retail areas for grocery stores (400m buffer) (exp.)</i>	0.7512	0.1311	0.1220	0.4033	0.7687	0.1605	0.1275	0.4051	0.6600	0.0758	0.0924	0.3810
<i>Retail areas for dur./other stores (400m buffer) (exp.)</i>	0.7906	0.3462	0.1223	0.7536	0.6542	0.1139	0.0529	0.7568	0.6826	0.1623	0.0791	0.7249
<i>Shopping store variability (400m buffer) (exp.)</i>	1.2536	0.0606	0.0748	0.7959	1.2522	0.0555	0.0837	0.8243	1.2250	0.0589	0.0605	0.7873
<i>Shopping store variability when following trip purpose is shopping (1000-2000m buffer) (exp.)</i>	2.9791	0.0736	0.0534	0.7052	2.9645	0.0683	0.0435	0.6957	2.7594	0.0406	0.0487	0.7083