Transportmetrica A: Transport Science

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ttra21

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To cite this article: Panagiotis Tsoleridis, Stephane Hess & Charisma F. Choudhury (11 Sep 2024): Accounting for continuous correlations among alternatives in the context of spatial choice modelling using high resolution mobility data, Transportmetrica A: Transport Science, DOI: 10.1080/23249935.2024.2401425

To link to this article: https://doi.org/10.1080/23249935.2024.2401425

Published online: 11 Sep 2024.

TRANSPORTMETRICA A: TRANSPORT SCIENCE
https://doi.org/10.1080/23249935.2024.2401425

Accounting for continuous correlations among alternatives in the context of spatial choice modelling using high resolution mobility data

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ABSTRACT

Accounting for similarity among alternatives is important for having unbiased estimates and behaviourally reasonable substitutions. Capturing similarity in a spatial context is a challenging task and the common approach of discretising space into a number of disjoint nests generally leads to uncaptured spatial correlations. On the other hand, relying on more complex error structures quickly leads to computational issues. In the present paper, we propose an alternative approach, where a Cross-Nested Logit (CNL) modelling framework with a flexible correlation structure is used, where space is treated as continuous, while the allocation can be parameterised based on a range of similarity factors. The proposed structure is applied in the context of mode and destination choices of shopping trips using a smart-phone GPS panel survey from Leeds, UK. Results indicate that in addition to the improvements in model fit, the proposed CNL specification is able to uncover interesting findings about individual mobility behaviour.

ARTICLE HISTORY
Received 5 March 2023
Accepted 28 August 2024

KEYWORDS
GPS data; spatial correlation; mode-destination choice models; disaggregate shopping behaviour

1. Introduction

Individuals produce trips in order to participate in activities and fulfil their everyday needs (Bhat and Koppelman 2003). The location and accessibility of those activities play an important role in the trips that are produced. For example, individuals with car availability in their household could be more likely to choose a major suburban shopping centre with an abundance of parking spaces to cover their grocery shopping needs. On the other hand, individuals with no available car might choose a nearby shopping destination or a shopping destination in the city centre with good public transport accessibility. The activity locations and the modes available to access them could thus have important environmental, social and economic implications (Brundtland Commission 1987). Understanding the relative impacts of different factors on the mode and destination choices is therefore an important first step for formulating sustainable planning and policy measures – for instance devising targeted measures to improve accessibility and reduce car dependency.

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Destination choice models are of paramount importance for demand forecasting, as they provide insights on individual preferences for certain locations depending on the time of day, activity purpose, and mode availability, amongst others. Much of the work in destination choice modelling focuses on discretionary activities (shopping, leisure, etc.), since those activities give the individual the freedom to choose from a range of possible locations on a day-to-day basis. However, given the large numbers of available alternatives and high level of heterogeneity associated with choices, modelling the choice of destinations for discretionary activities presents a number of significant challenges for the transport system. The choice of transportation mode is also considered to play an important role in the choice of destination and vice versa. Transportation models used in practice often consider destination choice to precede mode choice, commonly referred to as steps 2 and 3 in a traditional 4-step demand model (Ortuzar and Willumsen 2011). There is empirical evidence, however, suggesting that the direction of causality between the two choice dimensions is less than clear and it could depend on trip characteristics, level of service variables and individual socio-demographics (Chakour and Eluru 2014; Keya et al. 2021). Since there is not a general consensus as to which choice dimension comes first, it would be safer to examine the two decision processes in a joint fashion acknowledging the complex interrelations between them (Ben-Akiva 1973; Ozonder and Miller 2019).

Mathematical travel behaviour models relating to questions of where (destination choice models) and how (mode choice models) individuals travel have been the primary tool for quantifying the relative impact of factors affecting individual behaviour and forecasting future demand for the transport system and related services. Early modelling applications in spatial contexts focused on the use of spatial interaction models, mainly aggregate Gravity models (Haynes and Fotheringham 1985), which draw analogies from Newton's law of gravity, assuming that, all else held equal, larger (in terms of population, employment opportunities, etc.) and closer (in terms of distance, travel time or cost) areas are going to attract more trips. Since its inception, the Gravity model has been extensively used in aggregate transport models (Ortuzar and Willumsen 2011) and studies of Regional/Urban Economics (Duranton, Henderson, and Strange 2015), in general. A non-parametric extension of the gravity model, called the radiation model, was proposed by Simini et al. (2012).

Daly (1982) formally extended the specification of the Gravity model by re-formulating it as a Multinomial Logit (MNL) model (McFadden 1973) and making it applicable for disaggregate analysis. In that specification, the utility function is split into variables of travel impedance and variables measuring the attraction of a destination, called size variables. Due to the vast number of elemental locations, e.g. specific stores in the context of shopping destinations, some form of aggregation usually needs to take place, such as at the level of traffic analysis zones. Size variables are used in order to best represent the utility of elemental alternatives within the aggregated destination alternatives (Kristoffersson, Daly, and Algers 2018). Since then, most studies focusing on destination choice have relied on structures belonging to the family of random utility maximisation (RUM) models, such as MNL, and have relied on Daly's specification with the inclusion of size variables.

One of the main principles governing the behaviour explained by an MNL model is the *IIA* (independent and irrelevant alternatives) principle. This postulates that no unobserved correlation exists among alternatives in the choice set, hence a change in the attributes of one alternative will proportionately affect the demand for the other alternatives in the choice set. As in many other areas of application, this assumption is unlikely to be valid in the context of destination choice, or indeed joint mode and destination choice. The key issue then relates to how to best capture the correlation among alternatives in an efficient way.

Capturing unobserved correlation among alternatives requires the use of further extensions of the MNL model. One approach involves the addition of the same multivariate random term in the utility function of alternatives that are assumed to share common unobserved characteristics. That model, known as the Error Components (EC) model, has the limitation of requiring simulation during estimation, thus significantly increasing the computational cost, while also often being subject to identification issues (Walker, Ben-Akiva, and Bolduc 2007). A different approach that has the advantage of having a closed form solution and not requiring simulation is the GEV family of models (McFadden 1978), which includes a wide range of models, such as the Nested Logit (NL) and the Cross Nested Logit (CNL) models (Small 1987; Vovsha 1997). The NL model (Daly et al. 1978; Williams 1977) has arguably been the most prominent GEV specification utilising a *tree* structure in which the choice set is partitioned into a finite set of *nests*, where each nest consists of similar/substitute alternatives.

Similarity among alternatives is highly dependent on the choice context itself, and this affects the decision on how to treat it. In a mode choice context, similarity among alternatives such as car, public transport and walking, can depend on the level of comfort, privacy and flexibility that each mode alternative can provide to the decision maker. In many cases, the use of a simple Nested Logit structure (Daly et al. 1978; McFadden 1973; Williams 1977) is then appropriate. A more complex topic of study when it comes to correlation between alternatives has been that of route choice, where similarity can occur with overlapping links between two different route alternatives with prominent examples including the C-Logit (Cascetta et al. 1996) and Path Size (Ben-Akiva and Bierlaire 1999) models. Similarities in a destination choice context, however, can be much more complex, since they can depend on public transport accessibility, availability of parking spots or other specific amenities, the existence of other competing neighbouring locations, etc. and a range of characteristics that the analyst might not be in a position to measure explicitly. Furthermore, there is not a clear consensus in the literature whether similar nearby locations would increase the utility of a destination, due to agglomeration effects, or decrease its utility due to spatial competition (Bernandin Jr, Koppelman, and Boyce 2009; Bhat, Govindarajan, and Pulugurta 1998; Schüssler and Axhausen 2007).

A simple NL model can still be used of course, where, in the context of shopping store choice, Suarez, Rodriguez-Poo, and Moral (2004) utilised an NL specification grouping location alternatives into nests of hypermarkets that resulted in a better model fit than a base MNL model and in significant substitution patterns among alternatives belonging within the same nest. Nonetheless, the required division of destinations into mutually exclusive nests is arbitrary, and can be counter-intuitive, with for example heightened correlation between two destinations at opposite sides of a hypermarket cluster and with no correlation between two adjacent destinations that are in different clusters. Ideally, an analyst would thus want to capture the correlation between each pair of destinations, as in a Paired Combinatorial Logit (PCL) model (Chu 1989; Koppelman and Wen 2000; Pravinvongvuth and Chen 2005), which is a simplified specification of a CNL model in which the unobserved

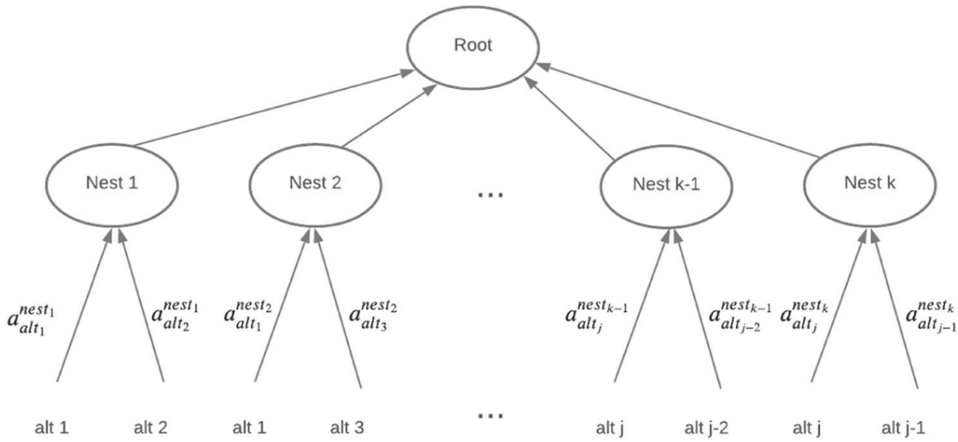


Figure 1. Nesting structure of a PCL specification.

correlation among alternatives is captured by specifying nests for each pair of alternatives in the choice set Figure 1. An alternative *i* can belong to every nest by a certain percentage to be estimated, called the allocation parameter $\alpha_{i,ij}$, measuring the allocation probability of alternative *i* into the nest with alternative *j*. The αs should be between 0 and 1 and they should add up to 1.0 for every target alternative *i*. The Spatially Correlated Logit (SCL) model of Bhat and Guo (2004) adapts the allocation parameters of the PCL specification to account for similarities among adjacent traffic analysis zones (zones sharing a common boundary) in a residential location choice context. A similar SCL-based specification was also proposed in Bekhor and Prashker (2008) in the context of shopping destination choice. An important limitation of those approaches is that the spatial correlations among non-adjacent zones are assumed to be zero. The alternative of working with each possible pair of alternatives of course quickly becomes difficult in terms of the number of parameters to estimate.

All of the aforementioned specifications share a common characteristic; they present some form of space discretisation either in the form of hypermarkets or based on adjacency. Discretising space, however, can quickly lead to a wide range of different potential nesting structures to be examined, such as nests based on administrative area or geographical location relative to the city centre etc. More importantly, it fails to treat space as continuous, which would be more behaviourally plausible, since setting arbitrary borders on a map would hardly have any real behavioural meaning, especially in the context of discretionary activity location choice. In fact, *Tobler's first law of geography* (Tobler 1970) postulates that in a spatial context 'everything relates to everything else, but near things are more related than distant things '. The study of Sener, Pendyala, and Bhat (2011) based their proposed methodology around that principle by addressing the main limitation of Bhat and Guo (2004) and relaxing the allocation parameters to account for spatial correlation across all alternatives in the choice set. Their proposed SCL specification, however, failed to provide any significant improvements in terms of model fit compared to a base MNL model in their empirical application. In addition to that, the main limitation of the specification in Sener, Pendyala, and Bhat (2011) is the large number of nests that had to be specified, which has to be equal to the number of all possible combinations of two alternatives in the same nest, hence $\frac{J!}{(J-2)!(2)!}$, where J is the total number of alternatives in the choice set. In a more recent study, Weiss and Habib (2017), moving away from GEV models, proposed an EC model to account for spatial unobserved correlation among alternatives in a park & ride location choice model. They based their methodology on Tobler's principle, however, due to the high computational cost, the choice set was constrained to include only the five closest alternatives from the origin of each trip, a simplification that is fair to assume in the context of park & ride location choice, but not behaviourally reasonable in the context of shopping destination choice. Therefore, the first limitation that the current study will aim to address is to propose a more efficient nesting structure suitable for uncovering unobserved correlations among destinations without imposing an analyst-specified grouping of alternatives, while being flexible enough to treat space as continuous.

Our discussion so far has focused on the treatment of correlation between destinations alone. However, as discussed earlier, destination choices are often made jointly with mode choices, and the simultaneous modelling of the two raises additional issues in the treatment of the correlation between alternatives. In the context of a joint mode and destination choice modelling, while most of the early applications revolved around the use of MNL models (Adler and Ben-Akiva 1976; Richards and Ben-Akiva 1974; Southworth 1981), in recent years more advanced modelling specifications have been put forward, mainly NL models. Two main approaches have been used for the specification of the nesting tree, one with mode at the upper level and destination at the lower, known as *Mode-over-Destination* (*MoD*), and another structure where destination is at the upper level and mode at the lower level, known as *Destination-over-Mode* (*DoM*) Figure 2. An *MoD* nesting structure implies that the errors in destination choice are smaller than in mode choice, hence the choice of destination is more deterministic than the choice of mode, while the opposite is true for *DoM*. Those NL specifications are simply a way of representing the error distribution across the choice dimensions and do not imply a sequential decision making process, as was emphasised in Daly et al. (1978). Each one of the two aforementioned nesting structures has to be tested for a specific application context (Ozonder and Miller 2019) and there

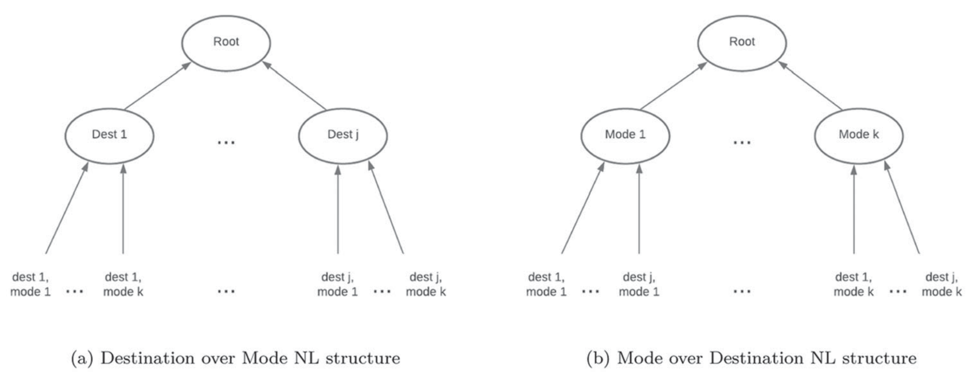


Figure 2. NL structures for joint mode and destination choice model. (a) Destination over Mode NL structure and (b) Mode over Destination NL structure.

is empirical evidence suggesting that it could be influenced by the socio-cultural characteristics of the sample (Kristoffersson, Daly, and Algers 2018; Newman 2010), while it could also change through the years due to network and administration changes (Fox 2015; Fox et al. 2014).

Independent of whether mode is nested above destination or destination above mode, additional levels of nesting could be introduced to capture differential levels of correlation between different groups of destinations, just as in a NL model for destination choice alone. The limitations of this have already been made clear in our discussion of destination choice models. A further limitation arises in NL models of multiple choice dimensions, such as a joint mode and destination model. In such models, the NL nesting structure imposes constraints on the captured correlation. For example, in a *MoD* NL specification, full correlation is only explained along the mode dimension and two alternatives sharing similar unobserved characteristics based on their location will not be nested together leading to uncaptured correlation and hence to biased estimates. Similarly, in a *DoM* NL specification, only correlation among alternatives sharing the same location can be explained. Hess and Polak (2006) demonstrated the benefits of a CNL structure for such multi-dimensional choice processes in a joint model of airport, airline and access mode choice for the Greater London Area, where a joint alternative is allowed to belong to all three nests of the different choice dimensions at the same time. The $\alpha_{j,m}$s in that study were fixed to 1/3 assuming an equal proportion of each alternative falling within each nest. That study was later extending to a multi-regional context covering multiple metropolitan areas in the East Coast of the United States (Hess et al. 2006). A CNL specification allows for a simultaneous capturing of correlation across all choice dimensions and for all alternatives, where, as in a PCL model, the degree of membership of an alternative j to a specific nest m in CNL is captured by specifying an additional allocation parameter $\alpha_{j,m}$, with $0 \leq \alpha_{j,m} \leq 1$ and $\Sigma_{m=1}^{M}\alpha_{j,m} = 1$. The advantage of CNL over PCL is that it provides a much simpler nesting structure without the need of specifying nests for each pair combination of alternatives. CNL models have, however, not gained much attention in destination and joint mode and destination choice modelling, with Schüssler and Axhausen (2009) going as far as arguing that CNL models are not suitable to be used in spatial choice modelling that usually includes a large number of alternatives, mainly due to the increased estimation time forcing the analyst to work with only a subset of the initial dataset. To the best of the authors' knowledge, the study of Ding et al. (2014) and more recently the study of Fox, Patrunu, and Daly (2019) are the only examples presenting a CNL application for joint mode and destination choices, with a nesting structure inspired by the study of Hess and Polak (2006), where an alternative is allowed to belong to one destination and one mode nest at the same time with α_{dest} and α_{mode}, respectively, Figure 3. In the study of Ding et al. (2014), the authors followed an approach similar to the study of Hess and Polak (2006) keeping the $\alpha_{j,m}$s fixed to 0.5 to avoid numerical issues during estimation. Nonetheless, their proposed CNL specification failed to outperform a base MNL and a *DoM* NL model in terms of model fit. In the study of Fox, Patrunu, and Daly (2019), a grid search approach was employed for finding the best combination of $\alpha_{j,m}$s, but still their CNL model was not able to outperform a simpler NL model.

The aforementioned CNL specifications are still susceptible to behavioural limitations that could be a potential cause for their low performance. Specifically, they do not take into

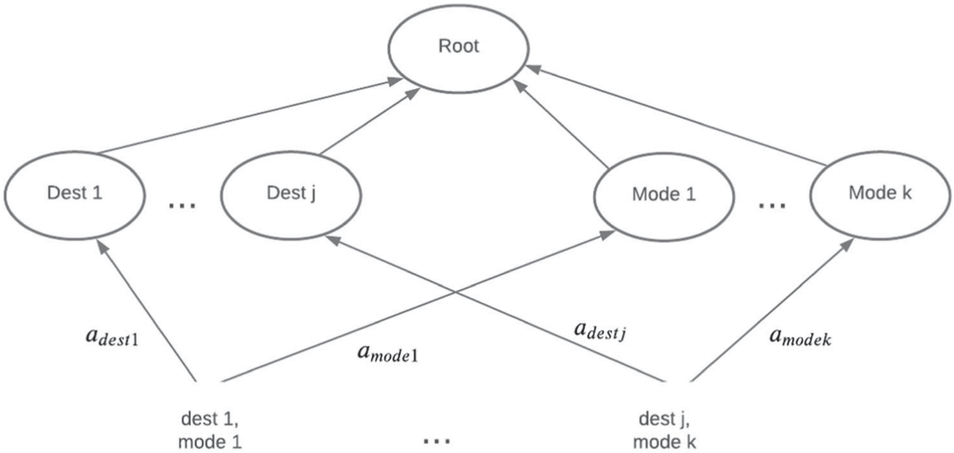


Figure 3. Existing CNL nesting structure for a joint mode and destination choice model (Ding et al. 2014).

account how the existence of neighbouring destinations might affect the allocation parameter to a specific destination nest. Therefore, the second limitation that the current study will aim to address is to propose a CNL structure in which a joint mode and destination alternative, instead of belonging to a mode nest and a single destination nest, belongs with a non-zero probability to every destination nest, but still with a higher probability to its *own* nest. Spatial proximity, measured as the geographical distance among destinations, can be utilised as a means of understanding if and how the remaining destination nests might impact the allocation parameters. In addition to that, however, several measures of proximity can also be used, such as land use similarity, as two non-neighbouring destinations with similar land use profiles can also share common unobserved characteristics.

The main purpose of the study is to present a framework to capture the unobserved correlations in the context of spatial choices in a computationally tractable manner for contexts where it is challenging to define the choice set. More specifically, it aims to propose a novel, efficient and operational CNL structure for a destination and a joint mode and destination choice model of shopping trips. That is achieved by proposing an approach based on spatial similarity for parameterising the allocation parameters and by treating space as continuous, which is a novel addition to spatial CNL models. A general term of similarity between two destinations is being used in the current study, not limited just to geographical distance. A flexible correlation structure is thus being proposed able to accommodate several similarity measures at the same time, based on different attributes of the location alternatives.

The proposed specifications are empirically tested on trips captured through smartphone GPS tracking and performed across the region of Yorkshire, UK. More specifically, the purpose of the destination model is to analyse the individual behaviour for choosing an intermediate shopping destination *S* between a previous origin *O* and a next destination *D*, while the joint model aims to capture both the location of that intermediate shopping destination, as well as the modes used to travel to that and to the following location.

The remainder of the paper is as follows. In the second section, the methodological frameworks of the proposed model specifications are thoroughly explained, while in the following section, the data used in the practical application is described. In the fourth section, the modelling outputs and their interpretations are highlighted. Finally, in the last section the conclusions of the study are summarised and recommendations for future research are suggested.

2. Methodology

We start our model description by looking at the destination choice scenario alone, i.e. without mode choice. Let us consider a situation where an individual faces a finite set of D independent and mutually exclusive destinations with specific attributes x_d for destination d in a specific journey. The utility for a destination is a latent construct comprised by a deterministic utility V_d and a disturbance term ϵ_d. The deterministic part of the utility is a combination of individual- and alternative-specific attributes as shown in Equation (1).

$$U_d = V_d + \epsilon_d = f(\beta, x_d) + \epsilon_d \tag{1}$$

Assumptions regarding the disturbance term can yield different specifications. In a CNL model, we make use of a Generalised Extreme Value (GEV) distribution for the error term, allowing us to capture flexible correlation structures between the errors. Specifically, an alternative can now belong to multiple nests, and the unconditional choice probability for alternative d is given by a sum over all S nests, each time using the product of the probability of choosing an alternative within nest s and the conditional probability of choosing alternative d within nest s as shown in Equation (2). The choice probability of nest s and the choice probability of alternative d conditional on choosing nest s are shown in Equations (3) and (4) (Train 2009):

$$P(d) = \sum_{s=1}^{S} P(s)\, P(d \mid s) \tag{2}$$

$$P(s) = \frac{\left(\Sigma_{j \in A_s} (\alpha_{sj}\, e^{V_j})^{\frac{1}{\lambda_s}}\right)^{\lambda_s}}{\Sigma_{k=1}^{S} \left(\Sigma_{j \in A_k} (\alpha_{kj}\, e^{V_j})^{\frac{1}{\lambda_k}}\right)^{\lambda_k}} \tag{3}$$

$$P(d \mid s) = \frac{(\alpha_{sd}\, e^{V_d})^{\frac{1}{\lambda_s}}}{\Sigma_{j \in A_s} (\alpha_{sj}\, e^{V_j})^{\frac{1}{\lambda_s}}} \tag{4}$$

where A_s is the set of alternatives in nest s, $P(d)$ is the unconditional choice probability of alternative d, $P(s)$ is the probability of choosing nest s, $P(d \mid s)$ is the conditional probability of choosing destination d in nest s, λ_s is the structure parameter for nest s, and α_{sd} is the allocation parameter of alternative d for nest s. We have that $0 < \lambda_s \leq 1\, \forall s$, $0 \leq \alpha_{sd} \leq 1\, \forall d, s$, and $\sum_{s=1}^{S} \alpha_{sd} = 1\, \forall d$.

We seek to allow differential patterns of substitution between destination alternatives. The ‘traditional’ way of doing this would be to specify a PCL model, such as the one proposed in Sener, Pendyala, and Bhat (2011), which uses one nest for each possible pair of alternatives, making the model computationally challenging with even moderate numbers of alternatives (see Figure 1). In our proposed CNL specification for the destination choice model, we instead define as many nests as there are destinations, such that $S = D$ and as a result the number of nests just grows linearly with the number of alternatives. The key question now relates to the specification of the allocation parameters in a way that would allow us to capture correlation between more than two alternatives at a time, as potentially all J alternatives have a non-zero allocation to a given nest, adding flexibility over the PCL model. Rather than freely estimating these parameters, or fixing them to a specific value, we define the allocation parameters to be a function of a range of C spatial similarity measures among the destinations, such as the euclidean distance, the difference between land-use attributes etc., here denoted as a range of symmetrical similarity matrices $\mathbf{D_c}$. By parameterising the allocation parameters as a function of observed characteristics, we are further able to put a structure on the correlation that drives the model, linking it to observed facts about the alternatives.

A similarity matrix $\mathbf{D_c}$ contains cells, r_{sd} capturing the similarity between destinations that now corresponds to nests s (rows) and all the other destinations d (columns). The diagonal elements denote the similarities of destinations with their own nest, labelled here as the *home nest*. The allocation is thus a function of a range of similarity factors along with their estimated parameters with each destination alternative belonging to every nest with a non-zero probability, captured by the estimated $\alpha_{\mathrm{sd}} \in \mathbf{A}$, where $\mathbf{A}$ is the matrix of allocation parameters Figure 4. In order to achieve that, the product of $r^c_{\mathrm{sd}} \in \mathbf{D_c}$ and the respective γ_c parameter was normalised using a logit transformation as defined in Equation (5).

$$\alpha_{\mathrm{sd}} = \frac{e^{\sum_{c=1}^{C} \gamma_c r^c_{\mathrm{sd}}}}{\sum_{j \in D} e^{\sum_{c=1}^{C} \gamma_c r^c_{sj}}} \tag{5}$$

where the additional γ_c parameter captures the impact of similarity factor c from its respective similarity matrix $\mathbf{D_c}$. If all $\gamma_c = 0$, each alternative falls into each nest with the same proportion.

A simplified example is presented in the following where a matrix of straight distances $\mathbf{D}_{\mathrm{dist}}$ among five destinations is computed, where the $r^{\mathrm{dist}}_{\mathrm{sd}}$ are measured in km. The distance matrix $\mathbf{D}_{\mathrm{dist}}$ is then multiplied by the γ_{dist} parameter. Assuming that $\gamma_{\mathrm{dist}} = -1$, the logit transformation of the product yields the matrix $\mathbf{A}$ of the allocation probabilities α_{sd}. In $\mathbf{A}$, the columns represent the destination alternatives d, while the rows represent the nests s. The sum of each column is equal to 1.0 and the diagonal elements have the highest α_{sd} per column. Furthermore, the most isolated destination, namely alternative 3, which has a mean distance of 4 km from the remaining destinations, has the highest diagonal element, $\alpha_{3,3}$, in $\mathbf{A}$. In contrast, alternative 5 has the lowest mean distance from the remaining destinations of 2.1 km and $\alpha_{5,5}$ is the lowest diagonal element in $\mathbf{A}$.

$$\mathbf{D}_{\mathrm{dist}}\gamma_{\mathrm{dist}} = \begin{pmatrix} 0 & 2 & 6 & 3 & 0.5 \\ 2 & 0 & 7 & 5 & 2 \\ 6 & 7 & 0 & 2 & 5 \\ 3 & 5 & 2 & 0 & 3 \\ 0.5 & 2 & 5 & 3 & 0 \end{pmatrix} \gamma_{\mathrm{dist}} \xrightarrow[\text{trans.}]{\text{logit}}$$

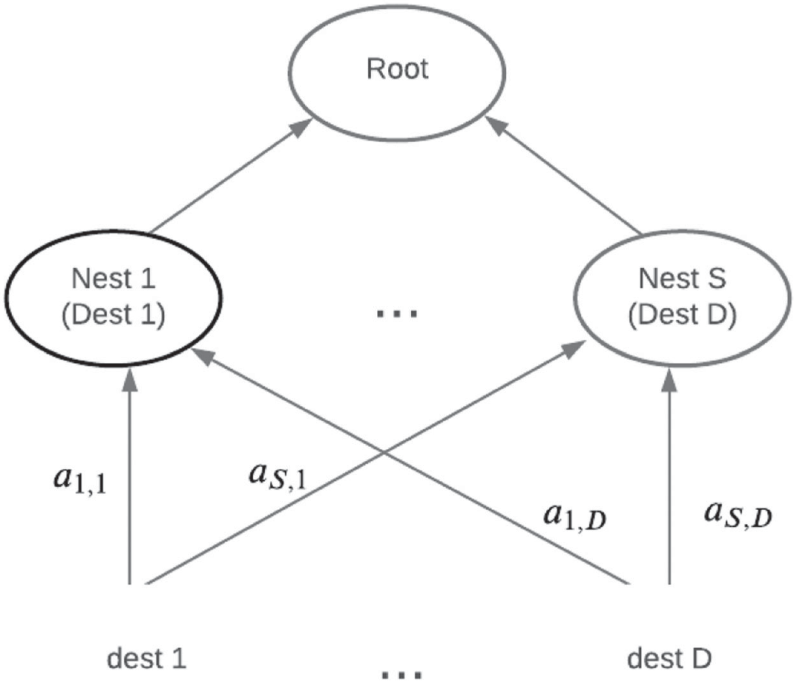


Figure 4. Proposed CNL nesting structure for destination choice model.

$$\mathbf{A} = \begin{pmatrix} 0.5574 & 0.1059 & 0.0022 & 0.0401 & 0.3373 \\ 0.0754 & 0.7823 & 0.0008 & 0.0054 & 0.0753 \\ 0.0014 & 0.0007 & 0.8730 & 0.1090 & 0.0037 \\ 0.0277 & 0.0053 & 0.1181 & 0.8054 & 0.0277 \\ 0.3381 & 0.1059 & 0.0059 & 0.0401 & 0.5561 \end{pmatrix}$$

The role of γ_{dist} is to dictate what percentage of the alternative will be allocated to the home nest and what percentage to the neighbouring ones. In the example above, we can expect that destinations located closer to the home nest will be more correlated, therefore we should expect $\gamma_{\text{dist}} < 0$. If $\gamma_{\text{dist}} = 0$, the alternatives would be equally allocated across all nests. Finally if $\gamma_{\text{dist}} > 0$, the alternatives would be allocated with a higher probability to the nests that are located at the largest distance, which is not behaviourally sensible. In order to guarantee their negative sign and avoid the latter case, the γ_{dist} parameters can be specified using a negative exponential transform, as $\gamma_{\text{dist}} = -e^{\gamma^*_{\text{dist}}}$. The aforementioned framework can be expanded with the addition of further similarity matrices with respective estimable parameters that can be negative, as the example above, or positive depending on whether the corresponding matrix is capturing dissimilarity/distance (the larger the distance the higher the dissimilarity) or similarity.

Although the above specification on its own might be sufficient enough to capture continuous spatial correlation among alternatives in the destination choice model, the joint mode and destination model would require further adjustments to simultaneously capture correlations among all choice dimensions. In that context, each alternative represents a joint choice of a destination *d* and a mode *m*. To adapt the previously described

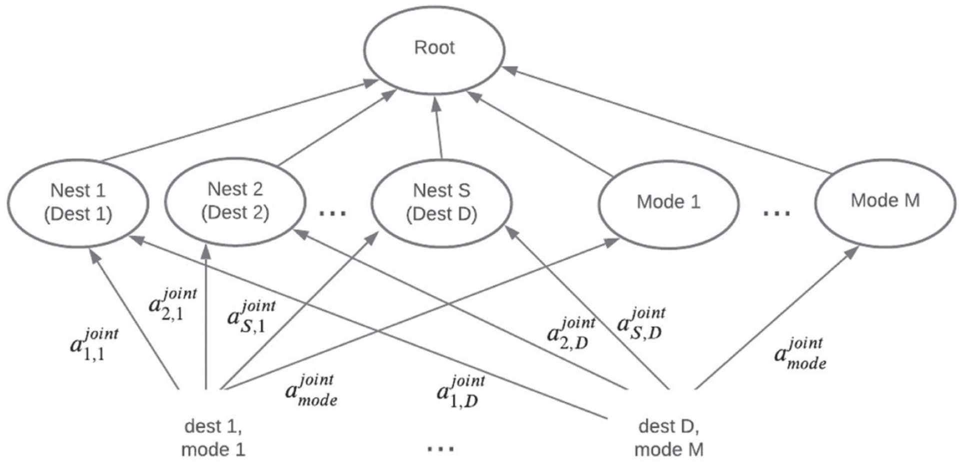


Figure 5. Proposed CNL nesting structure for the joint choice model.

formulation in that joint choice context, the nesting structure is defined as depicted in Figure 5 including nests for the destination as well as the mode choice component. Each joint mode-destination alternative is allocated into all of the destination nests, as previously described, and into one mode nest. The new combined allocation parameters still need to add up to 1.0, such that $\sum_{s=1}^{S} \alpha_{\text{sd}}^{\text{joint}} + \alpha_{\text{mode}}^{\text{joint}} = 1\ \forall d$. This is achieved by scaling down the distance-based allocation parameters to each destination nest (see Equation (5)), with

$$\alpha_{\text{sd}}^{\text{joint}} = \alpha_{\text{dest}}^{\text{joint}} \alpha_{\text{sd}} \tag{6}$$

and

$$\alpha_{\text{mode}}^{\text{joint}} = 1 - \alpha_{\text{dest}}^{\text{joint}} \tag{7}$$

We only require the additional constraint that $0 \leq \alpha_{\text{dest}}^{\text{joint}} \leq 1$, which can be achieved via a logistic transform, thus estimating $\alpha_{\text{dest}}^{\text{joint}*}$ and using the transform

$$\alpha_{\text{dest}}^{\text{joint}} = \frac{e^{\alpha_{\text{dest}}^{\text{joint}*}}}{e^{\alpha_{\text{dest}}^{\text{joint}*}} + 1} \tag{8}$$

In the case of a joint mode-destination model, the $gamma_c$ parameters can be specified as mode-specific in order to capture the impact of a similarity measure for a specific mode. That would for example capture how similar an individual perceives a destination alternative with others when travelling there with a specific mode.

We now turn to the specification of the utility functions themselves. In order to account for shopping destination attraction and to combine that with mode preferences, the specification used in Kristoffersson, Daly, and Algers (2018) based on the size variable specification in Daly (1982) was utilised. According to this, the systematic utility V_{md} for mode m and destination d, presented in Equation (9) (linear-in-the-parameters in that case), has three components: a component capturing the sensitivities related to the level of service (LOS) variables depending on the mode and destination, a component capturing the destination's quality, and a component capturing the destination's attraction.

$$V_{md} = \sum_{l \in L} b_l x_{lmd} + \sum_{q \in Q} b_q y_{qd} + \phi log(S_d) \quad (9)$$

The first component includes mode- and destination-specific variables that best describe the trip to destination *d* with mode *m*, such as travel time and cost for motorised modes and distance for active travel, as well as ASCs capturing inherent preferences for specific modes/destinations and sociodemographic interactions. With this, x_{lmd} is the *l*th LOS variable for mode *m* and destination *d*. The second component captures the impact (positive or negative) that certain characteristics could have on the utility of a specific destination, such as available parking space for car users, where y_{qd} is the *q*th quality variable for destination *d*.

The final component in Equation (9) is considered independent from the rest of the utility function and aims to capture the attraction or the *'size'* of a destination irrespective of the LOS variables to that place or the decision maker's socio-demographic characteristics. The log-size parameter ϕ is usually fixed to 1.0 assuming that utilities and subsequently the choice probabilities are not affected by the zoning discretisation that usually forms the destination alternatives. Kristoffersson, Daly, and Algers (2018), however, showed that allowing the ϕ to be freely estimated can result in estimated values different than 1.0, leading to a behavioural interpretation on the formation of destination alternatives. Specifically, if $\phi < 1$, the model captures significant correlation among the utilities of the elemental alternatives within each aggregate destination alternative. Therefore, in that sense the ϕ has a similar role as the nesting parameter λ (Kristoffersson, Daly, and Algers 2018). Finally, in addition to capturing unobserved correlations among the alternatives with the proposed CNL structure, observed correlations can also be captured with the inclusion of attraction attributes of neighbouring destinations in the size variable of destination *d*.

The size variable S_d is a composite measure of the size of destination *d* and b_l, b_q and ϕ are the respective parameters to be estimated. The composite size measure S_d is defined as:

$$S_d = a_{1d} + \sum_{z > 1} \exp(\gamma_z) a_{zd} \quad (10)$$

where a_{1d} is the attraction attribute used as a base with a γ parameter normalised to 1.0, a_{zd} are the additional attraction attributes of destination *d* relative to the base attribute, and γ_z are the parameters to be estimated capturing the effect of those attributes on the attraction of the target destination. The γ_z parameters are constrained to be positive by using an exponential transform.

3. Data

3.1. Background

The data used in the current study was collected as part of the research project 'DECISIONS' carried out by the Choice Modelling Centre at the University of Leeds, between November 2016 and March 2017. The project aimed at observing individual decisions over a range of in-home and out-of-home activities with an emphasis on travel over a 2-week period. A detailed description of the survey is presented in Calastri, Crastes dit Sourd, and Hess (2020).

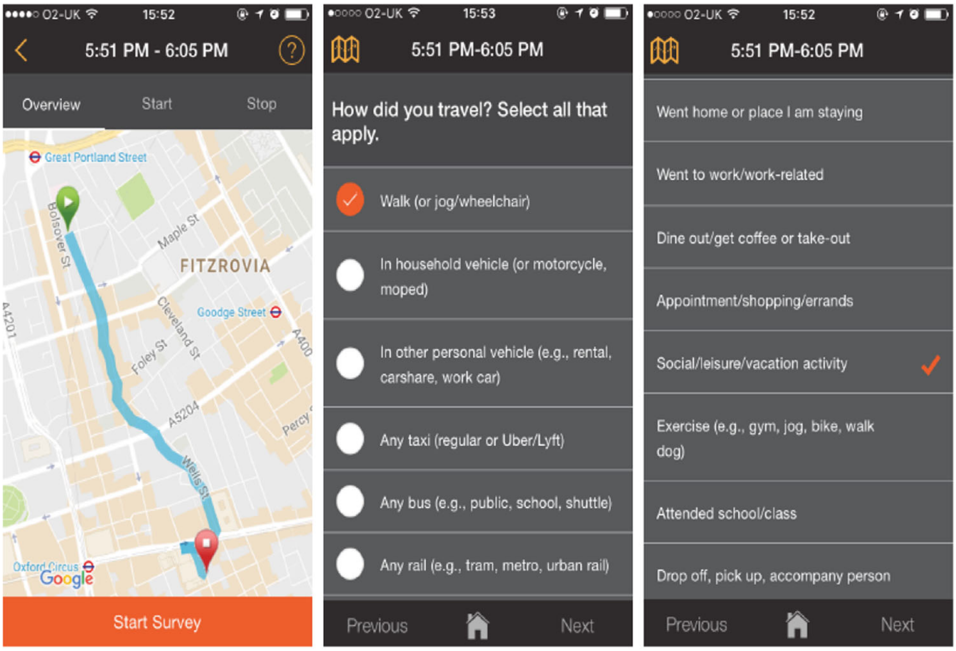


Figure 6. User interface of smartphone application used for the trip diary (Calastri et al., 2020).

The trips were captured through GPS tracking using a smartphone application at a high spatial and temporal resolution. The chosen mode and purpose of the trip were provided by the participants at the end of each trip Figure 6. Important socio-demographic information was captured from an additional household survey, giving the advantage of combining high resolution mobility data with participant characteristics, such as income, car ownership etc.

3.2. Initial data processing

The empirical analysis in the present paper focuses on shopping trips and the study area was defined as the region of Yorkshire. Only residents of the city of Leeds were selected, assuming they will have a similar knowledge of their surrounding shopping destinations (Thill 1992). The purpose of the analysis is to understand where the individuals are more likely to go for shopping with respect to the previous and the following activity locations. The locations of the previous origin *O* and the following destination *D* were considered fixed and the modelling analysis focused on the intermediate shopping destination *S*. Therefore, from the initial dataset, the shopping trips and their following trips were chosen for the subsequent analysis. The final dataset used in the analysis contained 1,541 shopping trips and an equal number of following trips performed by 270 unique individuals.

The shopping and their following trips were combined to create trip chains, which formed the basis of the analysis performed. Most trip chains, 66%, were from the origin *O* to the intermediate shopping destination *S* and then to the following destination *D*, which will be referred to as *O-S-D* trip chain. The remaining trip chains, 34%, were from the origin *O* to *S* and then back to *O*, which will be referred to as *O-S-O* trip chains. Shopping trips included three subcategories of shopping, namely grocery (82%), clothes (12.7%), and other types of shopping (5.3%), mainly for durables. The vast majority of following trips were trips going home (61.5%), while there was a small percentage of 9.3% of a consecutive shopping trip to a different shopping destination. The alternative modes of transport included car, public transport (PT) – as a combination of bus and rail – and walking.

The first step in the analysis involved the identification of home and work locations per individual, which were not reported initially. The nature of the GPS dataset requires a different way of analysis compared to a traditional dataset, where the destinations are usually defined at the traffic analysis zone (TAZ) level. In the current GPS dataset, the destinations of each trip are represented by a unique pair of latitude/longitude coordinates. Consequently, the identification of unique activity locations included the clustering of all destinations per individual using Hierarchical Agglomerative Clustering (HAC) with a 200 metres distance threshold. HAC was chosen as it does not require knowledge or a priori assumptions about the number of clusters. The distance threshold was chosen in order to group together in the same cluster points that have a small average straight distance difference among them (100 metres approximately). In total, 6,361 unique clusters were created. Following the clustering analysis, the enumeration of all trip purposes for the tagged trips per cluster was performed. At this point, potential home and work locations were identified as the clusters with the majority of 'home' and 'work' trips, respectively. In the rare cases where more than one cluster per individual had the same number of home/work trips, home/work locations were assigned to the clusters where the individual spends most of her time during night/early morning (22:00–06:00) and during working hours (09:00–17:00), respectively. The geographical boundary of those clusters was then identified at the Middle Super Output Area (MSOA), Lower Super Output Area (LSOA), and local authority level using the 2011 Census boundaries.[1]

3.3. Definition of general shopping areas

In order to take advantage of the high spatial resolution provided by the GPS data, we decided not to limit our analysis to the usual UK geographical boundaries, such as Middle layer Super Output Areas (MSOA) zones. For that reason, the destination alternatives were defined by clustering the observed elemental shopping destinations. HAC was implemented with a 800 metres distance threshold between the shopping trip destinations. The centroids were defined as the mean of the latitude/longitude coordinates of the points in each cluster and were then used to replace the original destination points of each shopping trip belonging to the cluster. Therefore, the main goal was to choose an appropriate distance threshold that would result in a small average distance difference between the original destination points of a cluster and its centroid. Because of that and after trying different distance thresholds between 500 m–1,000 m, a 800 m distance threshold was selected resulting in small average distance differences of around 4–5 minutes of walking (assuming a 5 km/h average walking speed). A 400 m buffer was defined around each cluster centroid, as a final step of creating the aggregate shopping destinations used in the analysis.

In the case of overlapping buffers, especially in Leeds city centre, the polygons within them were deterministically assigned to their closest cluster centroid (cf. Figure 7). This approach was used to ensure that each elemental shopping destination (in the form of

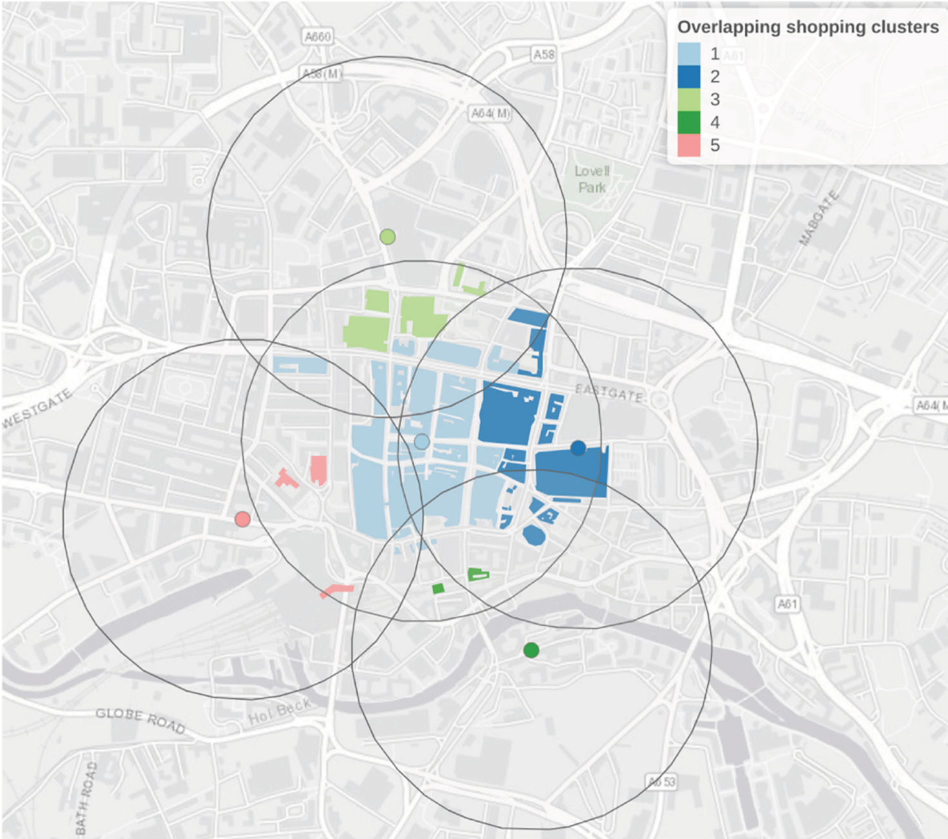


Figure 7. Allocation of retail polygons located within overlapping shopping clusters.

polygons/individual stores) would belong to a single aggregate alternative (in the form of the shopping areas defined). A deterministic allocation was performed in the current study, but future research could explore the option of performing a weighted allocation of overlapped polygons on their neighbouring clusters, weighted by the distance from them. The current deterministic allocation resulted in the creation of 176 general shopping areas around the region of Yorkshire, capturing 76% of the retail polygons, as defined in OpenSteetMaps (OSM), located within the Local Authority of Leeds. It is safe to say that shopping locations exist in other places within the study area, not captured by that process, mainly in areas further away from the city of Leeds. For the purpose of this study, however, it is assumed that those shopping locations have not been considered by the individuals in the sample or that the individuals are not aware of them, hence they have not been included in the subsequent analysis (Thill 1992).

Shopping clusters were also grouped with regard to their location relative to Leeds city centre. In total, 9 general areas were defined, namely Leeds city centre, North-East-South-West Leeds and North-East-South-West Yorkshire as shown in Figure 8. The number of trips per mode combination and general area are presented in Table 1. Most clusters are located around the city of Leeds, while Leeds city centre attracts the vast majority of trips with a preference for more sustainable modes. The remaining areas around Leeds attract a similar

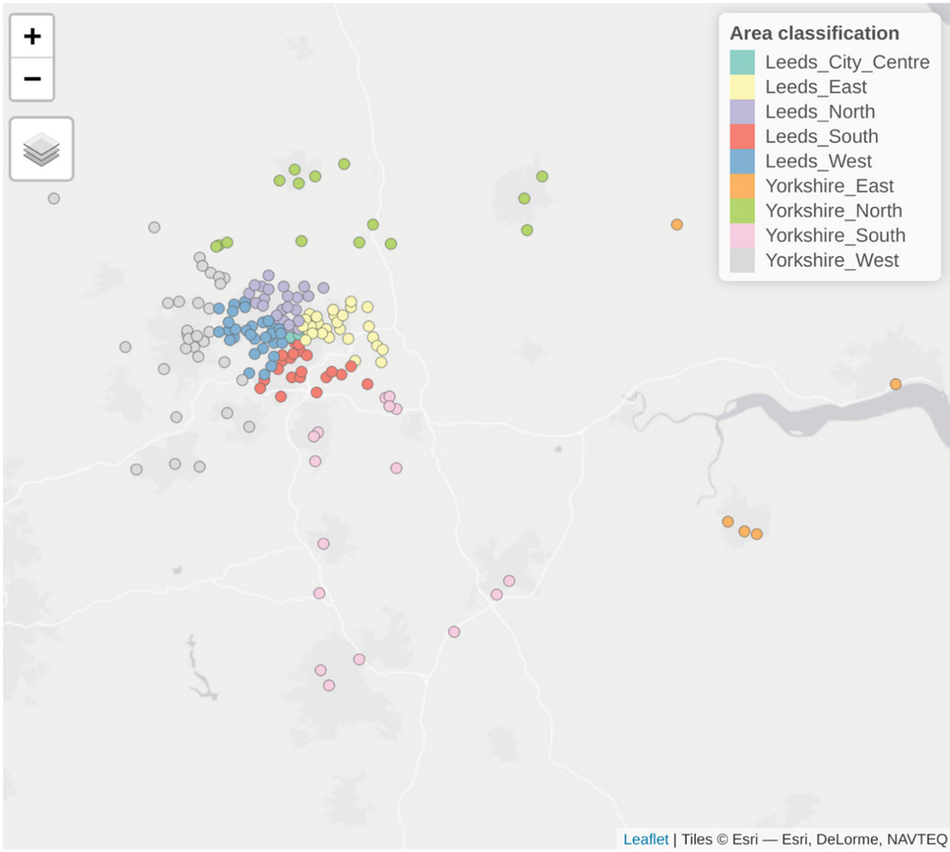


Figure 8. General area of shopping destinations in the study area.

number of trips, while from the remaining region of Yorkshire, West Yorkshire, which is the area surrounding the city of Leeds, attracts the highest number of trips. Trips in the rest of the Yorkshire region (North–East–South) are far less frequent, and mostly performed by car.

3.4. Data enrichment

Additional steps towards data enrichment were necessary to add further information that was important for the specification of a behavioural model. Initially, the dataset contained only the self-reported travel times/distances for the chosen modes, however, the values of the unchosen mode alternatives were also required. For that reason, the Bing maps route API[2] was used in order to obtain the travel times and distances for all the modes (car, bus/rail, walk) and for the trips starting from each initial origin to each shopping cluster and from each shopping cluster to each following destination. For consistency reasons, the travel times/distances of the chosen mode alternatives were recalculated as well, an approach also followed in Calastri et al. (2018). The total number of queries passed to the API was 1,627,296 (1,541 trips × 176 shopping destinations × 3 modes × 2 for the current and the subsequent trip). After that stage, deterministic mode availability was assigned based on logical checks of the results obtained from the API, such as cases of PT trips where the

Table 1. Chosen mode and general locations.

General location	C-C (%)	C-PT (%)	C-W (%)	PT-C (%)	PT-PT (%)	PT-W (%)	W-C (%)	W-PT (%)	W-W (%)	Total (%)
Leeds city centre	17 (1.1)	–	6 (0.4)	–	28 (1.8)	24 (1.6)	16 (1.0)	59 (3.8)	173 (11.2)	323 (21.0)
Leeds north	120 (7.8)	–	3 (0.3)	–	5 (0.3)	4 (0.3)	7 (0.5)	1 (0.07)	123 (8.0)	264 (17.1)
Leeds east	181 (11.7)	–	12 (0.8)	–	4 (0.3)	3 (0.2)	6 (0.4)	–	20 (1.3)	226 (14.7)
Leeds south	159 (10.3)	–	2 (0.1)	1 (0.07)	4 (0.3)	1 (0.07)	4 (0.3)	1 (0.07)	24 (1.6)	196 (12.7)
Leeds west	197 (12.8)	–	–	–	4 (0.3)	2 (0.1)	5 (0.3)	4 (0.3)	66 (4.3)	278 (18.0)
Yorkshire north	28 (1.8)	–	3 (0.2)	–	1 (0.07)	–	1 (0.07)	1 (0.07)	8 (0.5)	42 (2.7)
Yorkshire east	5 (0.3)	–	–	–	–	–	–	–	–	5 (0.3)
Yorkshire south	27 (1.8)	–	1 (0.07)	–	–	–	4 (0.3)	–	2 (0.1)	34 (2.2)
Yorkshire west	149 (9.7)	1 (0.07)	4 (0.3)	2 (0.1)	–	1 (0.07)	2 (0.1)	–	17 (1.1)	176 (11.4)
Total	880 (57.1)	1 (0.07)	32 (2.1)	3 (0.2)	46 (3.0)	35 (2.3)	45 (2.9)	66 (4.3)	433 (28.1)	1541 (100)

C: Car, PT: Public Transport, W: Walk.

API returned only walking segments, or in specific cases where car was the chosen mode and the participant had to return it back home. For that latter case, special attention was given to the stated size of the party that participated in the trip in order to understand whether the participant of the survey was the actual driver. As such, if the individual was the only person in a car trip, then she was assigned as the car driver and all the remaining modes would become unavailable only in the case where the following trip was to return back home. For other trip purposes for the following trip, it is assumed that the individual is free to consider all the available modes. On the contrary, if there were more than 1 people participating in a car trip, then we could not safely assume that the individual was the driver and all the modes would remain available for the following trip, as well.

Car travel cost was computed using the UK's official Transport Appraisal Guidance (WEB-Tag) specifications for fuel and operating costs (Department for Transport 2014). Parking cost was also calculated for trips with destinations in central areas/high streets across the region of Yorkshire based on information on hourly or fixed parking costs provided by the respective Local Authorities. For PT, an average distance-based fare was used for bus and rail and a total PT cost was calculated per trip based on the distance of the leg performed by bus or rail. A discount was also applied for trips made by season ticket holders.

3.5. Locational variables

Characteristics of the shopping clusters and their respective surrounding areas were also defined. Parking and retail store areas in a buffer zone of 400 m around the shopping cluster centroids were calculated using data extracted from OSM. The population of those areas (LSOA level) was extracted from the Office of National Statistics (ONS). Average residential price statistics for the LSOAs in Yorkshire, during the years 2016–2017, were acquired from the ONS, and their average was computed around shopping and home locations. Based on this, a variable was defined to analyse whether the immediate environment around the home location will have an influence on the behaviour of the individual, e.g. whether people living in richer areas are willing to go shopping in poorer areas or vice versa.

Shopping store variability among the elemental shopping destinations within an aggregate destination alternative was captured using Shannon's entropy (H_d) Equation (11) (Shannon 1948; Whittaker 1949), measuring the percentage of the area covered by a specific store type $t \in T$ inside a shopping destination d from a total number of N different store types. Shannon's entropy has been widely used to quantify land-use variability mostly in studies related to walkability (Brown et al. 2009; Mavoa et al. 2018) and urban sprawl (Effat and Elshobaki 2015). In the current study, it is used to examine whether an increased variability in store types adds to the attraction of a shopping destination, since that would enable the completion of more shopping activities within the same trip. All of the aforementioned locational variables were calculated as a weighted average of the respective values of the geographical zones that are overlapped by the 400 m buffer zones from each shopping centroid.

$$H_d = -\frac{\sum_{t=1}^{T} (p_t \ln (p_t))}{\ln N} \tag{11}$$

The locations of the most popular retailers per shopping type in the UK market (Kantar world panel 2020; Retail Economics 2020; Rhodes 2018) were also identified across the study area and a binary dummy variable was created for each based on whether they are located within a 400 m buffer radius around a shopping centroid.

In order to capture agglomeration effects and the impact of neighbouring shopping destinations on the attraction of a target shopping destination, the same information on the aforementioned locational variables was extracted for additional buffers between 400–1,000 m, 1,000–2,000 m and 2,000–5,000 m from each cluster centroid, similar to the study of Kristoffersson, Daly, and Algers (2018).

Information extracted from OSM was also used to inform alternative availability in addition to the previously described API-based approach, but without having as a profound effect. More specifically, the type of the elemental shopping polygons within the aggregate destination alternatives was examined in order to identify destinations not offering a specific type of shopping activity, i.e. groceries, clothes or other. We have identified a limited number of cases mostly in rural areas with more specific types of shopping stores. Those destinations with missing shopping polygons for specific shopping types, were defined as not available for the respective shopping trips. In contrast, we did not observe such cases in more central urban areas, which typically offer a higher mix of shopping activities.

3.6. Direction of travel

The effect of the location of the intermediate shopping destination *S*, in relation to the straight distance between *O* and *D*, was also captured by calculating the angles between $OS-OD$ and $SD-OD$. The a priori assumption is that, all else held equal, shopping destinations that require a significant deviation from the straight *OD* path would be less favoured compared to others. For that purpose, a dummy variable was defined, only for *O-S-D* trip chains, capturing the impact on utility of a shopping destination located with an angular deviation greater than 90^o from either *O* or *D*.

3.7. Store type similarity

Among the different factors capturing similarity between destinations, it was also decided to capture the similarity based on the store type profiles of each. The main motivation for that was the study of Cottineau and Arcaute (2020), who applied a cosine similarity metric in order to cluster geographical boundaries based on their industrial profiles. In the current study, we employ a similar metric in order to find the similarity among destinations based on the shares of land use areas per type of store as described in OSM. Cosine similarity is mostly used in text clustering and it is defined as in Equation (12).

$$CS_{dj} = \frac{\sum_{t=1}^{T}(d_t j_t)}{\sqrt{\sum_{t=1}^{T} d_t^2}\sqrt{\sum_{t=1}^{T} j_t^2}} \tag{12}$$

where d_t and j_t are vectors containing the shares per store type t for destinations $d, j \in D$. An example is presented below among three hypothetical destinations and their respective shares for five unique store types. The calculation of cosine similarity leads to a symmetrical *DxD* matrix and for that specific example we can correctly capture that destination a has more similar store type profile with destination c than destination b (Table 2).

Table 2. Example of store type similarity among three destinations (cosine similarity).

Store types	Dest a	Dest b	Dest c
Type a	0.1	0.3	0.15
Type b	0.4	0.2	0.35
Type c	0.15	0.1	0.1
Type d	0.3	0.2	0.25
Type e	0.05	0.2	0.15
Similarity matrix	Dest a	Dest b	Dest c
Dest a	1	0.779	0.965
Dest b	0.779	1	0.892
Dest c	0.965	0.892	1

4. Results

In this section, we first present the results for the destination choice model followed by the mode-destination model, before looking at the calculation of elasticity measures from the model.

4.1. Destination model outputs

Initially, five models were estimated for destination choice, namely a base MNL, two NL models, a PCL model and finally a model based on the proposed CNL nesting structure. The models were estimated using a choice set of 176 destination alternatives. An EC specification could not be estimated due to computational reasons and the large number of alternatives in the choice set. The *NL-dest-1* specification refers to a nesting structure with 9 nests according to the area of the destination, defined as *Leeds city centre*, *north-east-south-west Leeds* and *north-east-south-west Yorkshire* (see Figure 8). The *NL-dest-2* specification presents a finer segmentation of the destination alternatives into 24 nests according to the administrative area or the city the destinations belong to Figure 9. A further segmentation with an even higher resolution, such as based on the MSOA zones, would have resulted in having a nesting structure with many degenerate nests, i.e. nests with just a single alternative, hence it was not attempted. A PCL specification, *PCL-dest*, having every pair of alternatives in a separate nest was also estimated with a nesting structure of 15,400 nests ($\frac{n!}{r!(n-r)!} = \frac{176!}{2!(176-2)!}$), in total. The allocation parameters are parameterised based on the straight distances from the destination nests, similar to the proposed nesting structure described in Section 2. Finally, *CNL-dest* follows the proposed cross-nested structure with 176 nests (as many as the number of destination alternatives in the choice set), thus presenting a more efficient specification compared to the previously described PCL model with 15,400 nests. The allocation parameters in this model were parameterised in a similar way as in the *PCL-dest* model -to provide a proper means of comparison- having a single generic γ multiplier based on the straight distances from the destination nests.

The fit statistics[3] of those specifications as well as the estimated nesting parameters are presented in Table 3. Both NL models resulted in structural parameters (λ) that were outside the theoretically acceptable range (i.e. above 1), meaning that the utilised NL nesting structures were not able to capture any meaningful correlation among the alternatives. Only the first NL model outperforms the MNL model according a likelihood ratio test, but

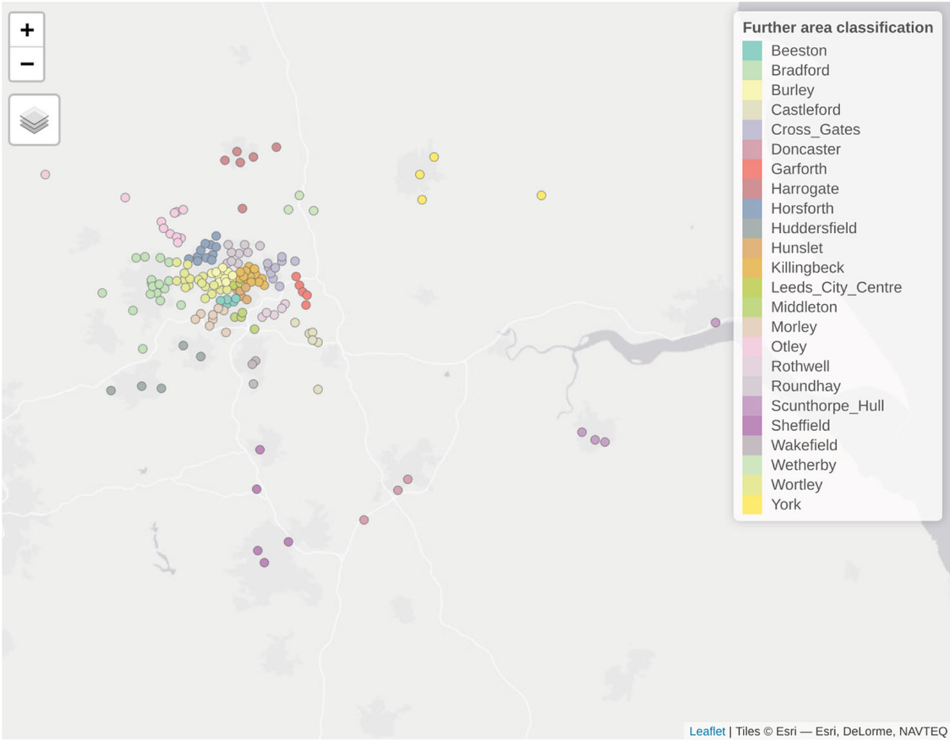


Figure 9. Segmentation of destination alternatives based on their administrative area.

the model is of course itself rejected given the findings for λ. That result provides support to our initial hypothesis that segmenting space into discrete areas/nests, even in more finer segmentations as in *NL-dest-2*, is not an efficient approach for capturing unobserved correlation among destinations. In contrast, both the *PCL-dest* and *CNL-dest-1* were able to accomplish that with estimated λ equal to 0.4502 and 0.8222 (significantly different than 1.0), respectively. Both specifications were also able to provide significant improvements in terms of model fit compared to the MNL model with −3.212 and −5.976 LL units for 2 additional parameters, respectively. A log-likelihood ratio test (LR-test) can be performed to assess the statistical superiority between a more generalised and a more constrained model. According to that definition, both *PCL-dest* and *CNL-dest-1* are more generalised specifications of the more constrained *MNL-dest-base* model, hence an LR-test can be performed for each of them with respect to eh MNL model. An LR-test is defined as $LR - test = -2 * (LL_{\text{general}} - LL_{\text{base}})$ and a p-value is derived for the resulting LR-test from a chi-square distribution. The values for the LR-tests for *PCL-dest* and *CNL-dest-1* are 6.424 and 11.952 leading to p-values of 0.0403 and 0.0025, respectively, meaning that those models provide statistically significant improvements over the base MNL model at least at the 95% confidence level for *PCL-dest* and at least at the 99% confidence level for *CNL-dest-1*. The *CNL-dest-1* model also outperformed the equivalent PCL specification of *PCL-dest* in terms of model fit. An approach different to LR-test had to be employed in that case in order to statistically compare two non-nested models. The Ben-Akiva & Swait test (Ben-Akiva and Swait 1986) is such a test, which allowed us to conclude that *CNL-dest-1* is statistically

Table 3. Fit statistics and nesting parameters of destination choice models.

Fit statistics	MNL-dest-base	NL-dest-1	NL-dest-2	PCL-dest	CNL-dest	CNL-dest-2
Log-likelihood (0)	−7,961.332					
Log-likelihood (model)	−3,166.947	−3,163.624	−3,165.307	−3,163.735	−3,160.971	−3,134.54
Adjusted ρ^2	0.5972	0.5975	0.5973	0.5973	0.5977	0.6006
AIC	6,413.89	6,409.25	6,412.61	6,411.47	6,405.94	6,359.09
BIC	6,627.5	6,628.2	6,631.56	6,635.76	6,630.23	6,599.4
Number of parameters	40	41	41	42	42	45
Number of individuals	270					
Number of observations	1,541					
Nesting parameters λ	Estimates (Rob. *t*-ratio w.r.t. 1.0)					
λ_{generic}	–	1.1267 (1.92)	1.0848 (1.53)	0.4502 (−2.55)	0.8222 (−3.99)	0.5766 (−9.12)

superior to *PCL-dest* with a p-value $= 0.0060$. At the same time *PCL-dest* required a longer estimation time by a factor of 10 compared to *CNL-dest-1*.

In addition to straight distances, an attempt was also made to capture similarities based on routed distances. The routed distances were obtained using the same API (Bing maps) for the mode of car and for the off-peak period in order to avoid having historical congestion affecting our results. The routed network distances were tested on the allocation parameter specification of the simpler destination choice model. The results obtained were similar, but slightly worse than the *CNL-dest-1* model with straight distances (LL$= -3,262.1$ compared to LL$= -3,260.9$). That on itself could also be a finding suggesting that straight distances influence more the individuals' perceived similarity. In fact, it could be said that individuals might have a more abstract perception of topological similarities as also described in Kazagli, Bierlaire, and Flötteröd (2005) and Manley (2016).

Despite capturing significant unobserved spatial correlation, the *CNL-dest-1* specification did not outperform the base MNL model in terms of BIC as shown in Table 3 (6,630.23 compared to 6,627.5). That prompted us to expand the proposed cross-nested structure of *CNL-dest-1* in order to include additional similarity measures in the formulation of the allocation parameter as described in Section 2. That led to the specification of *CNL-dest-2* where allocation to nests is now based on the difference of retail areas, the difference of parking areas and the land use profile similarity between destinations (as described in Section 3.7), in addition to the straight distances, which were already included in *CNL-dest-1*. Therefore, *CNL-dest-2* provides a more generalised specification of *CNL-dest-1*. The fit statistics of that specification are depicted in the same table alongside the rest of the models previously described Table 3. That model outperforms *CNL-dest-1* by 26.431 LL units for 3 additional parameters (LR-test$= 52.862$, p-value $= 0$), while also being able to capture a higher degree of spatial correlation among alternatives with the inclusion of the additional similarity measures in the allocation parameter specification. It also manages to outperform the base MNL model by 32.407 LL units for 5 additional parameters (LR-test$= 64.814$, p-value $= 0$) and more importantly to achieve a significantly better BIC statistic (6,599.4) contrary to the more constrained *CNL-dest-2* specification. A validation test was performed for *CNL-dest-2* estimating the same specification on 70% of the unique individuals in the dataset and their respective plans and applying the estimates of that model on a holdout sample of the remaining 30% of individuals. The evaluation of that validation test was performed on the basis of the average choice probability of correct prediction. According to that, the 70% training set led to a 0.192 average probability of correct prediction, while the 30% validation set resulted in a slight drop of 0.187 – such a drop is expected and does not suggest overfitting.

Detailed estimated parameters for the *MNL-dest-base*, *PCL-dest*, *CNL-dest* and *CNL-dest-2* are depicted in Table 4. Robust t-ratios are also reported in the same table capturing the panel effect from repeated observations of the same person (Daly and Hess 2010). The two NL specifications are not presented as they resulted in not behaviourally accurate estimated nesting parameters. The destination choice model presented is conditional on the choice of mode, therefore level-of-service attributes relevant to the chosen mode are used in the utility functions. Socio-demographic variables were included in the model and interacted with the LOS variables as shifts from their base level. In general, the estimated parameters were behaviourally reasonable with the expected signs. The ASCs were defined using *destination 1* as the base alternative, which represents the most central shopping mall of Leeds,

Table 4. Modelling outputs of the estimated destination choice models.

	Estimate (Rob. t-ratio w.r.t. 0)			
Parameter	MNL-dest-base	PCL-dest	CNL-dest	CNL-dest-2
Locational constants (base: dest 1)				
ASC rest Leeds city centre	−1.3588 (−8.57)	−1.2590 (−8.07)	−1.1110 (−7.16)	−1.2327 (−7.95)
ASC rest Leeds city centre shift for PT-PT	−0.6774 (−1.70)	−0.6860 (−1.79)	−0.5367 (−1.54)	−0.6656 (−1.80)
ASC rest Leeds city centre shift for PT-walk	1.0888 (1.92)	1.0099 (1.86)	0.8957 (1.86)	0.9720 (1.83)
ASC Leeds	−0.5484 (−4.51)	−0.5707 (−4.77)	−0.4782 (−4.32)	−0.3281 (−2.86)
ASC Leeds shift for PT-PT/PT-walking/walking-PT	−2.9533 (−7.80)	−2.7605 (−7.29)	−2.6413 (−7.15)	−2.7368 (−7.95)
ASC Leeds shift for walk-walk	−2.1704 (−6.76)	−2.0020 (−6.38)	−1.8334 (−6.15)	−2.0063 (−7.26)
ASC Yorkshire shift for PT-PT/PT-walking/walking-walking	−4.1652 (−5.78)	−3.9960 (−6.04)	−3.8267 (−6.24)	−3.9521 (−6.82)
LOS variables				
Travel time for first trip (base)	−0.1059 (−5.35)	−0.0967 (−4.98)	−0.0924 (−5.24)	−0.0818 (−4.91)
Travel time shift for clothes shopping	0.0451 (4.41)	0.0391 (4.05)	0.0396 (4.42)	0.0343 (3.96)
Travel time shift for O-S-O trip chains	0.0229 (2.69)	0.0206 (2.64)	0.0201 (2.76)	0.0195 (2.89)
Travel time shift for HWH tours	−0.0291 (−2.49)	−0.0250 (−2.31)	−0.0237 (−2.41)	−0.0260 (−2.76)
Travel time shift for pm peak/night/ weekend evening	−0.0173 (−2.36)	−0.0137 (−2.06)	−0.0142 (−2.31)	−0.0136 (−2.41)
Travel time shift for morning/weekend night	−0.0905 (−3.78)	−0.0833 (−3.51)	−0.0786 (−3.74)	−0.0788 (−3.45)
Travel time shift for grouping size$>$1	0.0134 (1.76)	0.0121 (1.75)	0.0111 (1.73)	0.0093 (1.65)
Travel time multiplier for car/PT IVT/PT first access/PT last egress	1.0000 (–)	1.0000 (–)	1.0000 (–)	1.0000 (–)
Travel time multiplier for following trip	1.2118 (16.26)	1.2141 (15.84)	1.2121 (15.88)	1.2331 (14.70)
Travel time – Shopping duration elasticity	−0.3497 (−8.58)	−0.3519 (−8.27)	−0.3315 (−8.43)	−0.3274 (−7.99)
Box-cox lambda for car travel time	1.0653 (19.37)	1.0743 (19.24)	1.1069 (19.91)	1.1062 (19.29)
Box-cox lambda for PT travel time	0.7424 (10.14)	0.7525 (9.77)	0.7696 (10.67)	0.8033 (10.99)
Travel walking distance for first trip (base)	−1.3522 (−6.59)	−1.2926 (−6.52)	−1.1904 (−6.73)	−1.2059 (−6.83)
Travel walking distance shift for O-S-O trip chains	0.2790 (1.83)	0.2691 (1.83)	0.2505 (1.96)	0.2514 (1.96)
Travel walking distance shift for am peak	−0.8699 (−2.31)	−0.8274 (−2.23)	−0.7496 (−2.36)	−0.8400 (−2.43)
Travel walking distance shift for pm peak/night/morning/weekend morning/weekend evening	−0.3740 (−2.49)	−0.3661 (−2.53)	−0.3111 (−2.45)	−0.3307 (−2.51)
Travel walking distance multiplier for following trip	1.2404 (11.50)	1.2402 (11.39)	1.2467 (11.33)	1.2227 (12.02)
Box-cox lambda for travel walking distance	0.7933 (11.63)	0.7884 (11.53)	0.8246 (12.28)	0.7795 (11.66)
Travel walking distance – Shopping duration elasticity	−0.2185 (−4.72)	−0.2168 (−4.59)	−0.2110 (−4.72)	−0.2164 (−4.87)
Travel cost	−0.4015 (−3.20)	−0.3855 (−3.12)	−0.3900 (−3.33)	−0.4231 (−3.70)
Box-cox lambda for travel cost	0.6596 (7.91)	0.6394 (7.72)	0.6636 (8.32)	0.6545 (8.99)
Travel cost – Personal income elasticity	−0.6106 (−3.16)	−0.5882 (−3.10)	−0.5864 (−3.22)	−0.5308 (−3.19)
Direction of travel				
Presence of angle$>$90^o between O-S and O-D	−0.2687 (−2.14)	−0.2483 (−2.16)	−0.2279 (−2.01)	−0.2141 (−1.92)

(*continued*)

Table 4. Continued.

	Estimate (Rob. *t*-ratio w.r.t. 0)			
Parameter	MNL-dest-base	PCL-dest	CNL-dest	CNL-dest-2
Locational variables				
Living in rich areas-shopping in poor areas	−0.7531 (−2.74)	−0.6475 (−2.69)	−0.6316 (−2.61)	−0.6254 (−2.64)
Parking areas (400 m buffer))	0.1112 (4.00)	0.0986 (3.79)	0.1002 (3.96)	0.0637 (2.58)
Box-cox lambda for parking areas (400 m buffer)	0.4531 (6.50)	0.4608 (6.40)	0.4547 (6.35)	0.4750 (4.30)
Major clothes shopping retailers (400 m buffer)	1.3338 (6.13)	1.3060 (6.39)	1.1264 (5.52)	1.2170 (6.01)
Major grocery retailers (400 m buffer)	0.4952 (5.05)	0.4334 (4.89)	0.4506 (5.19)	0.4246 (4.96)
Major durables retailers (400 m buffer)	2.1515 (2.66)	2.0406 (2.73)	1.9668 (2.48)	2.2425 (3.08)
Size variables				
Natural logarithm multiplier ϕ	0.5102 (7.05)	0.4586 (6.64)	0.4817 (6.45)	0.4453 (6.58)
Population (400 m buffer) (base)	1.0000 (–)	1.0000 (–)	1.0000 (–)	1.0000 (–)
Retail areas for clothes (400 m buffer) (log.)	0.8813 (1.52)	0.6959 (1.23)	0.8487 (1.49)	0.8151 (1.38)
Retail areas for groceries (400 m buffer) (log.)	1.7314 (3.53)	1.7256 (3.53)	1.5094 (2.80)	1.8036 (3.58)
Retail areas for durables (400 m buffer) (log.)	0.9916 (1.14)	0.7713 (0.89)	0.8795 (1.04)	0.6938 (0.83)
Shopping store variability when following trip purpose is shopping (1000–2000 m buffer) (log.)	3.4918 (4.91)	3.4386 (4.77)	3.4427 (4.84)	3.4827 (4.92)
Nesting parameters λ				
$\lambda_{generic}$	–	0.4502 (−*2.55*[a])	0.8222 (−*3.99*[a])	0.5766 (−*9.12*[a])
Distance multipliers γ				
γ_{dist}	–	−0.4022 (−4.40[b])	−1.3552 (−3.90[b])	−0.3174 (−4.93[b])
$\gamma_{parking\ areas}$	–	–	–	−0.1611 (−4.93[b])
$\gamma_{retail\ areas}$	–	–	–	−0.0844 (−3.17[b])
$\gamma_{store\ type}$	–	–	–	1.5317 (2.74[b])

[a]Robust *t*-ratio w.r.t. 1.0
[b]The robust standard error was calculated using the delta method (Daly, Hess, and de Jong 2012).

and constants for the remaining alternatives were specified based on the 9 general areas of the alternatives, as described in Section 3.3. The remaining destinations in the city centre are less likely to be chosen compared to destination 1 (base alternative), while destinations in the remaining study area are even less favourable, especially for modes other than car. All of the specified level-of-service parameters of the chosen mode were statistically significant validating our approach of explaining destination choice conditional on the choice of mode. The LOS variables of travel time, travel distance and travel cost were specified using a Box-Cox transform as $\frac{x^{\lambda}-1}{\lambda}$ in order to capture possible non-linear sensitivities. As a result, statistically significant non-linearities were found for PT time, walking distance and travel cost suggesting that individual sensitivities are decreasing as those variables are increasing. On the other hand, only linear sensitivities were found for car time. Decreasing travel time and walking distance sensitivities were found as the shopping duration increases, while decreasing cost sensitivities were found as personal income increases. Finally, travel time for motorised modes and walking distance sensitivities were slightly higher for the following trip relative to the first shopping trip.

Individuals living in richer areas are less willing to go shopping in poorer areas with very low residential prices with a similar finding also presented in Pellegrini, Fotheringham, and

Lin (1997). A Box-Cox transformation was used to capture the preference for parking areas, specifically for trips using car for both legs, uncovering positive but decreasing sensitivities. The presence of major retail attractions per shopping category (clothes, grocery, other) significantly increases the likelihood of visiting the shopping destination for trips of the respective shopping category. The estimated multiplier ϕ of the logarithm of the composite size variable is significantly lower than 1.0 in all of the models presented. According to Kristoffersson, Daly, and Algers (2018), this means that there is significant unobserved correlation among the elemental alternatives within the aggregate shopping destinations used in the choice set. This also gives a behavioural meaning to the clustering approach that was utilised in order to form the aggregate alternatives, described in Section 3.3. An increased cumulative retail floor area of grocery, clothes and durable stores in a destination acts as a more significant attractor for trips of the respective shopping category than population that was used as the base size variable. Furthermore, an increased store type variability in neighbouring destinations in medium distances (1000–2000 m) will add to the attraction of the shopping destination, when the subsequent trip is also for shopping.

With regard to the direction of travel, shopping destinations located in places where the angular deviation between *OS* and *OD* is greater than (90°) are less likely to be chosen compared to others, conforming to our initial assumptions. The same dummy variable measuring the impact of an angle above (90°) between *SD* and *OD* was still negative, but not statistically significant, hence was not included in the specifications reported here. Finally, regarding the estimated distance multipliers, *CNL-dest-1* results in $\gamma_{\text{dist}} = -1.3552$ conforming with our initial assumption of increased correlation among closer destinations, which decreases with distance. The *PCL-dest* specification resulted in a much lower estimated distance multiplier of $\gamma_{\text{dist}} = -0.4022$ (rob. *t*-rat $= -4.40$) meaning there is a more even allocation to the neighbouring nests. For the *CNL-dest-2*, all four specified γ multiplier parameters are statistically significant, but a comparison between them is not as straightforward due to scale differences among the four similarity matrices used. Their signs, however, offer a behavioural interpretation. More specifically, the signs of the γ multipliers for straight distances, retail area and parking area differences are negative meaning that destinations with smaller differences will be more correlated with each other. Similarly, the sign of the γ multiplier for store type similarity is positive meaning that destinations with more similar land use profile (i.e. a cosine similarity closer to 1.0) will be more correlated, hence they will lead to higher allocation probabilities.

4.2. Joint mode and destination model outputs

For the more complex joint mode and destination model, results from the previously described destination model and from simpler mode choice models, conditional on destination, were used as a guideline during the specification search. In that model, the mode and destination choices are assumed to happen at the same time. In total, the choice set of that model includes 1,584 joint destination and mode alternatives (176 destinations × 3 modes for the shopping trip × 3 modes for the following trip). A range of different specifications is presented in the following, namely a base MNL model, two NL models utilising an MoD and DoM nesting structure (see Figure 2), respectively, a base CNL (see Figure 3) and finally two CNL specifications based on the proposed nesting structure, one capturing correlation based on straight distances and one based on four different similarity measures similar to the simpler destination choice model previously described. The PCL specification presented in Section 4.1 was not possible to be extended to the more complex mode-destination context due to the prohibitive computational cost. In Table 5, the fit statistics of the different specifications are presented, while in Table 6 the respective estimated parameters are reported.

For the *NL-joint-MoD* specification, the alternatives were allocated into 9 nests according to the modal combinations for the shopping and the following trip and a generic λ_{mode} was specified assuming the same level of correlation across all nests. Similarly, for the *NL-joint-DoM* specification, 176 nests were specified, one for each shopping destination, with a generic λ_{dest} for each. Regarding the CNL models, the first specification, *CNL-joint-base*, is based on the specification of Ding et al. (2014). Alternatives that use a single mode for both legs are allocated simultaneously into a destination nest and a single mode nest, while alternatives that use different modes across the two legs (e.g. car-walk) fall into a destination nest and two mode nests for different-mode alternatives. We attempted to estimate allocation parameters for this model, but this resulted in numerical issues. An alternative was thus allocated evenly to all the nests it belongs to, meaning a 50–50 split into a destination and a mode nest for single mode alternatives, and an even three-way split into a destination and two mode nests for alternatives using two separate modes.

The last two CNL models based on the proposed nesting structure, *CNL-joint-proposed-1* and *CNL-joint-proposed-2*, follow the proposed nesting structure with alternatives using the same mode for both legs being allocated to a total of 177 nests (*176 destination nests+1 mode nest*), and alternatives combining different modes being allocated to 178 nests (*176 destination nests+2 mode nests*). In both cases, a generic λ_{dest} is assumed for the destination nests, in addition to three mode-specific λ for car, PT and walk. For the proposed specifications, the allocation parameters were specified as follows.

- $\alpha^{\text{joint}}_{\text{dest,same mode}}$ was used to scale down the destination α_{sd} of same mode alternatives, as $\alpha^{\text{joint}}_{\text{dest,same mode}}\alpha_{\text{sd}}$ (defined in Equation (6)). The allocation parameters of same mode alternatives were computed as $\alpha^{\text{joint}}_{\text{dest,same mode}} = \frac{e^{\alpha^{\text{joint}*}_{\text{dest,same mode}}}}{(e^{\alpha^{\text{joint}*}_{\text{dest,same mode}}}+1)}$ for the destination nest, while for the mode nest the allocation parameter was $1 - \alpha^{\text{joint}}_{\text{dest,same mode}}$.
- $\alpha^{\text{joint}}_{\text{dest,diff. mode}}$ was used to scale down the destination α_{sd} of alternatives with different mode combinations, as $\alpha^{\text{joint}}_{\text{dest,diff. mode}}\alpha_{\text{sd}}$ (defined in Equation (6)). The allocation parameters of those alternatives were computed as $\alpha^{\text{joint}}_{\text{dest,diff. mode}} = \frac{e^{\alpha^{\text{joint}*}_{\text{dest,diff. mode}}}}{(e^{\alpha^{\text{joint}*}_{\text{dest,diff. mode}}}+2)}$ for the destination nest, while an equal allocation was assumed for the two mode nests, which was computed as $(1 - \alpha^{\text{joint}}_{\text{dest,diff. mode}})/2$.

The nesting parameters in both of the NL models were not statistically different from 1.0, meaning that those nesting structures were not able to uncover any significant unobserved correlation among the alternatives, in either mode or destination choice dimensions, and those models effectively collapse to the base MNL. The *CNL-joint-base* model presents significant improvements in model fit compared to the *MNL-joint-base*, with 9.75 LL units for 4 additional parameters. It is also able to capture unobserved correlations along the

Table 5. Fit statistics and nesting parameters of joint mode and destination choice models.

Fit statistics	MNL-joint-base	NL-joint-MoD	NL-joint-DoM	CNL-joint-base	CNL-joint-proposed-1	CNL-joint-proposed-2
Log-likelihood (0)	−11,045.05					
Log-likelihood (model)	−4,093.78	−4,093.339	−4,093.699	−4,084.03	−4,067.899	−4038.06
Adjusted ρ^2	0.6238	0.6238	0.6238	0.6244	0.6254	0.6276
AIC	8,309.56	8,310.68	8,311.4	8,298.06	8,275.8	8,226.13
BIC	8,635.31	8,641.77	8,642.49	8,645.17	8,649.61	8,626.64
Number of parameters	61	62	62	65	70	75
Number of individuals	270					
Number of observations	1,541					
Nesting parameters λ	Estimates (Rob. t−ratio w.r.t. 1.0)					
$\lambda_{generic}$	–	0.9491 (−0.86)	1.0267 (0.34)	–	–	
λ_{dest}	–	–	–	0.9601 (−0.23)	0.5094 (−6.80)	0.5481 (−10.82)
λ_C	–	–	–	0.8614 (−2.90)	0.7968 (−2.36)	0.5749 (−3.03)
λ_{PT}	–	–	–	0.5143 (−1.75)	0.7708 (1.62)	0.9220 (−0.32)
λ_W	–	–	–	1.2488 (2.93)	1.2474 (2.26)	1.4246 (2.91)

Table 6. Modelling outputs of the proposed CNL joint mode and destination choice model.

	Estimate (Rob. *t*-ratio w.r.t. 0)			
Parameter	MNL-joint-base	CNL-joint-base	CNL-joint-proposed-1	CNL-joint-proposed-2
Households with car ownership (base: car-car/dest 1)				
ASC dest 1 shift Car-PT/Car-Walk	−1.8422 (−2.76)	−1.8596 (−2.61)	−1.4908 (−2.42)	−1.2722 (−2.29)
ASC dest 1 shift PT-PT	1.4351 (3.76)	1.1193 (3.14)	0.9859 (2.55)	1.0248 (3.49)
ASC dest 1 shift Walk-PT	2.2307 (6.61)	2.0996 (6.07)	1.8277 (5.85)	1.6414 (5.97)
ASC dest 1 shift Walk-Walk	2.9396 (8.43)	3.1739 (8.27)	2.8060 (8.41)	2.5098 (7.91)
ASC rest Leeds city centre	−2.4229 (−6.66)	−2.2915 (−5.89)	−1.6733 (−4.86)	−1.4655 (−5.08)
ASC rest Leeds city centre shift for PT-Car/Walking-Car	1.5158 (3.07)	1.1726 (2.24)	0.7783 (1.71)	0.5991 (1.42)
ASC rest Leeds city centre shift for PT-PT/PT-Walking	2.0782 (4.24)	1.9045 (3.78)	1.4308 (3.00)	1.2791 (3.47)
ASC rest Leeds city centre shift for Walk-PT	2.9640 (6.17)	2.7177 (5.01)	2.2688 (4.67)	1.8215 (4.73)
ASC rest Leeds city centre shift for Walk-Walk	4.2020 (8.69)	4.1345 (7.50)	3.1404 (6.76)	2.7683 (6.59)
ASC Leeds	−0.6204 (−5.51)	−0.5659 (−5.33)	−0.4705 (−4.01)	−0.3523 (−3.52)
ASC Leeds shift for Car-PT/Car-Walk	−2.9758 (−8.72)	−3.2035 (−6.89)	−2.7244 (−8.23)	−2.3347 (−8.17)
ASC Leeds shift for PT-Car/Walk-Car/PT-PT/Walking-PT	−1.1104 (−4.39)	−1.2301 (−3.70)	−1.0093 (−3.50)	−0.8741 (−3.71)
ASC Leeds shift for PT-Walk	−1.6197 (−3.44)	−1.9888 (−3.79)	−1.6952 (−3.54)	−1.4901 (−3.81)
ASC Leeds shift for Walk-Walk	0.9279 (2.98)	0.8061 (2.51)	0.4094 (1.32)	0.4076 (1.52)
ASC Yorkshire shift for Car-PT/Car-Walk/PT−PT/PT−Walking/Walking−PT	−2.2500 (−5.78)	−2.2803 (−5.26)	−1.8428 (−5.40)	−1.7213 (−5.23)
ASC Yorkshire shift for PT-Car/Walk-Car	−1.3606 (−2.74)	−1.3601 (−2.52)	−1.1141 (−2.90)	−1.0384 (−2.77)
Shifts for households with no car ownership				
Car-PT/Car-walking/Walking-PT/Walk-Walk	2.5480 (7.34)	2.5133 (6.63)	2.1796 (6.83)	1.9561 (7.13)
PT-PT	4.2311 (10.13)	4.4191 (8.81)	3.7996 (8.77)	3.3477 (9.22)
PT-Walk	3.3736 (6.53)	3.2976 (5.80)	2.8590 (5.97)	2.5592 (5.97)
Shifts for central areas outside Leeds city centre				
PT-Car/Walk-Car	1.3175 (1.81)	1.3133 (1.83)	0.9176 (1.72)	0.8656 (1.74)
Walking-PT/Walk-Walk	2.5745 (4.06)	2.5341 (3.66)	2.0684 (4.04)	1.8098 (2.90)
Shifts for individuals with season ticket ownership				
Walk-Walk	−0.6076 (−1.86)	−0.6580 (−1.87)	−0.5831 (−1.87)	−0.5055 (−1.82)
Shifts for trips with more than 1 passenger				
PT first/shopping trip	−1.8713 (−5.54)	−1.7142 (−4.68)	−1.3942 (−4.71)	−1.2114 (−4.45)
PT following trip	−0.9034 (−2.54)	−0.8292 (−2.28)	−0.8418 (−2.62)	−0.7759 (−2.67)
Walk first/shopping trip	−0.7367 (−3.19)	−0.7595 (−3.36)	−0.6472 (−3.19)	−0.5293 (−2.89)
Walk following trip	−0.4232 (−1.72)	−0.4830 (−1.90)	−0.4592 (−2.06)	−0.4537 (−2.32)
Shifts for students				
Walk-Walk	1.0321 (2.82)	1.0412 (2.63)	0.8619 (2.39)	0.7782 (2.48)
Shifts for married individuals				
Walk-Walk	−0.7109 (−2.66)	−0.7525 (−2.61)	−0.7207 (−2.76)	−0.6658 (−2.83)
Shifts for individuals living in 3-member households				
Walk-Walk	0.6768 (1.84)	0.7520 (1.92)	0.7202 (1.97)	0.6972 (2.18)
LOS variables				
Travel time for first trip (base)	−0.0844 (−5.61)	−0.0682 (−5.14)	−0.0624 (−4.44)	−0.0596 (−5.26)
Travel time shift for clothes shopping	0.0355 (3.89)	0.0312 (3.85)	0.0281 (3.54)	0.0232 (3.68)
Travel time shift for O-S-O trip chains	0.0127 (2.08)	0.0114 (2.03)	0.0103 (2.14)	0.0107 (2.46)
Travel time shift for HWH tours	−0.0417 (−4.33)	−0.0369 (−4.19)	−0.0321 (−3.70)	−0.0312 (−4.31)

(*continued*).

Table 6. Continued.

Parameter	Estimate (Rob. *t*-ratio w.r.t. 0)			
	MNL-joint-base	CNL-joint-base	CNL-joint-proposed-1	CNL-joint-proposed-2
Travel time shift for pm peak/night/weekend evening	−0.0088 (−1.56)	−0.0080 (−1.58)	−0.0076 (−1.70)	−0.0060 (−1.55)
Travel time shift for morning/weekend night	−0.0408 (−2.45)	−0.0343 (−2.25)	−0.0294 (−2.26)	−0.0298 (−2.33)
Travel time multiplier for car/PT IVT/PT first access/PT last egress	1.0000 (–)	1.0000 (–)	1.0000 (–)	1.0000 (–)
Travel time multiplier for remaining PT OVT	0.4378 (2.32)	0.4196 (1.95)	0.4655 (2.38)	0.5160 (2.56)
Travel time multiplier for following trip	1.2585 (15.13)	1.2692 (14.49)	1.2522 (14.50)	1.2525 (14.34)
Travel time – Shopping duration elasticity	−0.3238 (−9.97)	−0.3537 (−9.48)	−0.3358 (−9.15)	−0.3188 (−9.14)
Box-cox lambda for car travel time	1.0568 (19.71)	1.0949 (19.84)	1.1047 (20.66)	1.1009 (19.78)
Box-cox lambda for PT travel time	0.8272 (−12.83)	0.8586 (13.11)	0.8659 (12.94)	0.8609 (12.69)
Travel walking distance for first trip (base)	−1.5993 (−12.83)	−1.6909 (−12.21)	−1.5943 (−11.75)	−1.4220 (−11.39)
Travel walking distance shift for O-S-O trip chains	0.2138 (1.91)	0.1693 (1.49)	0.1167 (1.09)	0.1001 (1.02)
Travel walking distance multiplier for following trip	1.2634 (13.03)	1.2935 (12.52)	1.3240 (11.89)	1.3482 (11.62)
Box-cox lambda for travel walking distance	0.7956 (15.22)	0.8137 (15.11)	0.8128 (15.23)	0.8320 (13.17)
Travel walking distance – Shopping duration elasticity	−0.1425 (−4.24)	−0.1369 (−4.11)	−0.1202 (−3.74)	−0.1135 (−3.10)
Travel cost	−0.5578 (−7.55)	−0.5682 (−7.57)	−0.5138 (−6.95)	−0.4818 (−8.03)
Box-cox lambda for travel cost	0.5870 (10.18)	0.5598 (9.90)	0.5536 (9.74)	0.5353 (8.84)
Travel cost – Personal income elasticity	−0.3000 (−2.85)	−0.2988 (−2.93)	−0.2872 (−2.86)	−0.2678 (−2.92)
Direction of travel				
Presence of angle $>90^o$ between O-S and O-D	−0.2438 (−2.04)	−0.2551 (−2.15)	−0.2451 (−2.37)	−0.1914 (−1.99)
Locational variables				
Living in rich areas-shopping in poor areas	−0.7828 (−2.86)	−0.7622 (−2.89)	−0.6460 (−2.76)	−0.6346 (−2.75)
Parking areas (400 m buffer)	0.0951 (3.73)	0.0889 (3.70)	0.0697 (3.40)	0.0434 (2.42)
Box-cox lambda for parking areas (400 m buffer)	0.4540 (5.83)	0.4473 (5.78)	0.4576 (5.31)	0.2965 (2.22)
Major clothes shopping retailers (400 m buffer)	1.3317 (6.08)	1.3813 (6.43)	1.1858 (6.04)	1.1387 (6.31)
Major grocery retailers (400 m buffer)	0.4860 (4.90)	0.4385 (4.49)	0.3661 (3.57)	0.3656 (4.28)
Major durables retailers (400 m buffer)	2.0975 (2.61)	2.0353 (2.66)	1.7233 (2.37)	2.0297 (3.21)
Size variables				
Natural logarithm multiplier ϕ	0.6186 (7.63)	0.5809 (7.73	0.5451 (5.41)	0.5498 (7.04)
Population (400 m buffer) (base)	1.0000 (–)	1.0000 (–)	1.0000 (–)	1.0000 (–)
Retail areas for clothes (400 m buffer) (log.)	0.6162 (1.24)	0.5841 (1.13)	0.4293 (0.85)	0.5025 (1.03)
Retail areas for groceries (400 m buffer) (log.)	1.1082 (2.62)	1.2994 (2.95)	1.1443 (2.35)	0.9252 (2.21)

(*continued*).

Table 6. Continued.

	Estimate (Rob. t-ratio w.r.t. 0)			
Parameter	MNL-joint-base	CNL-joint-base	CNL-joint-proposed-1	CNL-joint-proposed-2
Retail areas for durables (400 m buffer) (log.)	0.5206 (0.71)	0.5535 (0.76)	0.3303 (0.49)	−0.0862 (−0.12)
Retail areas for groceries when following trip purpose is shopping (1000−2000 m buffer) (log.)	−0.8087 (−0.94)	−0.6591 (−0.76)	−0.3967 (−0.48)	−1.2999 (−1.47)
Shopping store variability when following trip purpose is shopping (1000−2000 m buffer) (log.)	2.2519 (1.89)	2.3729 (2.00)	2.2730 (1.88)	2.3282 (2.43)
Nesting parameters λ				
λ_{dest}	–	0.9601 (*−0.23*[a])	0.5094 (*−6.80*[a])	0.5481 (*−10.82*[a])
λ_C	–	0.8614 (*−2.90*[a])	0.7968 (*−2.36*[a])	0.5749 (*−3.04*[a])
λ_{PT}	–	0.5143 (*−1.75*[a])	0.7708 (*−1.62*[a])	0.9220 (*−0.32*[a])
λ_W	–	1.2488 (*2.93*[a])	1.2474 (*2.26*[a])	1.4246 (*2.91*[a])
Distance multipliers γ				
γ^{C}_{dist}	–	–	−1.2279 (−6.48[b])	−0.4282 (−3.85[b])
γ^{PT}_{dist}	–	–	−0.8388 (−4.16[b])	−0.5181 (−3.06[b])
γ^{W}_{dist}	–	–	−2.3426 (−7.73[b])	−0.3233 (−2.15[b])
Retail area multipliers γ				
$\gamma^{W}_{retail\ area}$	–	–	–	−0.1574 (−4.39[b])
Parking area multipliers γ				
$\gamma^{C}_{parking\ area}$	–	–	–	−0.4533 (−11.37[b])
Store type multipliers γ				
$\gamma^{C}_{store\ type}$	–	–	–	1.4590 (8.15[b])
$\gamma^{PT}_{store\ type}$	–	–	–	1.6680 (2.52[b])
$\gamma^{W}_{store\ type}$	–	–	–	5.275 (10.52[b])
Allocation parameters α				
Dest. allocation for same mode combos $\alpha^{joint*}_{dest,same\ mode}$ *(log.)*	–	–	−0.3765 (−0.50)	2.1350 (2.03)
Dest. allocation for diff. mode combos $\alpha^{joint*}_{dest,diff.\ mode}$ *(log.)*	–	–	1.7945 (2.85)	3.6312 (4.98)

[a]Robust t-ratio w.r.t. 1.0
[b]The robust standard error was calculated using the delta method (Daly, Hess, and de Jong 2012).

mode dimension for car and PT (although not statistical significant at the 90% confidence level), but not for walk. Using that specification, however, it was not possible to capture any unobserved correlation along the destination dimension, since the estimated λ_{dest} is not statistically different than 1.0. Therefore, using this specification would lead to the conclusion that correlation exists only along the mode dimension for car and PT (again not statistical significant at the 95% confidence level), and not along the destination dimension. That assumption, however, is rejected if we look at the *CNL-joint-proposed-1* and *CNL-joint-proposed-2* models. Both specifications resulted in significant model fit improvements over the base MNL model with 25.881 and 55.72 LL units for 9 and 14 additional parameters, respectively. Furthermore, the *CNL-joint-proposed-2* model was the only specification outperforming the *MNL-joint-base* model in terms of BIC, with a statistic of 8,626.64 as opposed to 8,635.31. More importantly, however, the proposed specifications were able to capture significant unobserved correlation along the destination dimension, in addition to car mode dimension. The presence of correlation along the PT mode dimension was more clearly rejected especially in the *CNL-joint-proposed-2* model, while again no correlation was captured for walk. Furthermore, the estimated λ_{dest} in both cases is smaller than λ_{car}, indicating a higher correlation in the destination nests than in car nests. The additional similarity factors in the specification of the allocation parameters led the *CNL-joint-proposed-2* to outperform the *CNL-joint-proposed-1* by a significant margin (29.839 LL units) for 5 additional parameters. A validation test was also performed for *CNL-joint-proposed-2* similarly to the test performed for *CNL-dest-2* described in Section 4.1. Results from that test indicate a reasonable level of stability with the training and validation set leading to an average probability of correct prediction of 0.188 and 0.179, respectively.

The ASCs for the joint model were specified in a similar notion as for the destination choice model, but this time the alternative *dest 1/car-car* was used as the base for the remaining 1583 alternatives, which were grouped according to their general area and their mode combination. The estimated parameters have the expected signs, with mode combinations not including car being more preferred for shopping destinations in the city centre of Leeds, where more sustainable modes are increasingly promoted. The opposite is true, however, for locations in the rest of Leeds, such as suburban stores, and in the rest of the Yorkshire region, where car combinations are more favourable. Nonetheless, destinations in local high streets that are further away from Leeds city centre, are still less likely to be performed by car possibly due to car restriction measures and limited parking availability. Individuals living in households with no car ownership are less likely to use car-car combinations, while shopping trips including more than 1 passenger are more likely to be performed by car, at least for one of the two legs again probably due to its convenience. Out of all PT-related travel time components, the remaining out-of-vehicle time sensitivity was found to be significantly lower than the base travel time sensitivity (car travel time for first/shopping trips), while the remaining PT travel time components were found to be equal to the base travel time sensitivity, hence their multipliers were fixed to 1.0. Finally, the estimated income elasticity to cost is similar to the empirical evidence suggested by previous studies regarding non-work trips in the UK (Batley et al. 2019; Sanko et al. 2014). The behavioural interpretation for the remaining level-of-service parameters and for most of the estimated size variables is similar to the destination choice model previously described. This time, however, the cumulative floor area of grocery stores in neighbouring destinations at medium distances (1,000–2,000 m) also adds to the attraction of the shopping destination, when the following trip is again for shopping, albeit at a lower rate than the grocery store area in the immediate neighbourhood of the shopping destination (400 m buffer).

In *CNL-joint-proposed-1* and *CNL-joint-proposed-2*, the γ multipliers were parameterised by mode, which allows for a more detailed analysis of the impact of each similarity measure among destinations on the allocation of each alternative to the destination nests. In the *CNL-joint-proposed-1* model, the distance multipliers for a car-car alternative were specified as $\gamma_{\text{dist}}^{C-C} = -(\gamma_{\text{dist}}^{C} \times \gamma_{\text{dist}}^{C}) = -\mathrm{e}^{2\gamma_{\text{dist}}^{C*}}$. In a similar notion, the distance multipliers for a PT-walk alternative were specified as $\gamma_{\text{dist}}^{PT-W} = -(\gamma_{\text{dist}}^{PT} \times \gamma_{\text{dist}}^{W}) = -[(-\mathrm{e}^{\gamma_{\text{dist}}^{PT*}}) \times (-\mathrm{e}^{\gamma_{\text{dist}}^{W*}})]$. It is assumed that combinations such as car-PT and PT-car will have the same γ. In the *CNL-joint-proposed-2* model, the γ multipliers were parameterised for all of the three mode alternatives, but only the statistically significant ones were kept in the final specification reported here. They were specified in a similar way as in the *CNL-joint-proposed-1* with the only exception of the γ multipliers for store type similarity, which were defined as strictly positive, e.g. as $\gamma_{\text{store type}}^{C-C} = -(\gamma_{\text{store type}}^{C} \times \gamma_{\text{store type}}^{C}) = \mathrm{e}^{2\gamma_{\text{store type}}^{C*}}$.

Regarding the detailed γ estimates of *CNL-joint-proposed-1*, combinations of mechanised modes, i.e. car and PT, lead to less negative γ, with the lowest one being for PT-PT trips. That means that individuals travelling by PT for both trip legs will perceive the target destination to be more similar with its neighbouring destinations. On the other hand, mode combinations that include walking on either of the two trip legs have a more negative γ with the largest one being for walk-walk trips. That means that individuals walking for both trip legs will perceive their target shopping destinations as a more isolated alternative compared to its neighbouring destinations. Regarding the estimated allocation parameters, same-mode alternatives will belong with a larger allocation probability to their mode nest, while the opposite is true for different mode alternatives. A similar analysis for *CNL-joint-proposed-2* shows that higher allocation probabilities are estimated for destination nests relative to mode nests compared to *CNL-joint-proposed-1*. Furthermore, higher allocation probabilities are also expected for destinations with more similar store type profiles with the target alternative relative to the rest.

4.3. Demand elasticity analysis

In order to illustrate the importance of accounting for correlation among all destinations in a spatial choice model, either a simple destination or a joint mode and destination choice model, a demand elasticity analysis is performed in both of those cases and presented below.

4.3.1. Destination elasticities

The demand elasticity analysis for the destination choice model has been performed for *MNL-dest-base*, *PCL-dest* and the two proposed specifications, *CNL-dest* and the more flexible *CNL-dest-2*. The two NL models, namely *NL-dest-1* and *NL-dest-2*, have not been considered, since they collapse to the base MNL. The forecasting scenario involved the increase of car travel cost for destination 47, a suburban shopping centre at the outskirts of Leeds, by 1%. The individual level elasticities and cross-elasticities for a specific participant, who initially chose that shopping destination, are presented in Table 7 and are calculated as $\log \frac{demand_{\text{after}}}{demand_{\text{base}}}/(\log(1.01))$. The cross-elasticities for 3 specific destinations are examined, where destination 71 is the closest alternative to destination 47 in the choice set at a distance of 0.99 km, alternative 34 is located at a distance of 7.88 km and finally alternative 131 is located at a distance of 28.31 km from the target alternative. Looking at the elasticities obtained from *MNL-dest-base*, the impact of the *IIA principle* is clearly visible as it results in a proportionate demand increase across the other three destinations regardless of how far away from the target destination they are located. The *PCL-dest*, also, resulted

Table 7. Individual level demand elasticities for forecasting scenario 1.

	Destination alternatives			
Model	Dest 47	Dest 71	Dest 34	Dest 131
Distance (km)	0.00	0.99	7.88	28.31
MNL-dest-base	−0.082	0.084	0.084	0.084
PCL-dest	−0.083	0.079	0.079	0.079
CNL-dest	−0.082	0.112	0.081	0.081
CNL-dest-2	−0.077	0.229	0.209	0.125

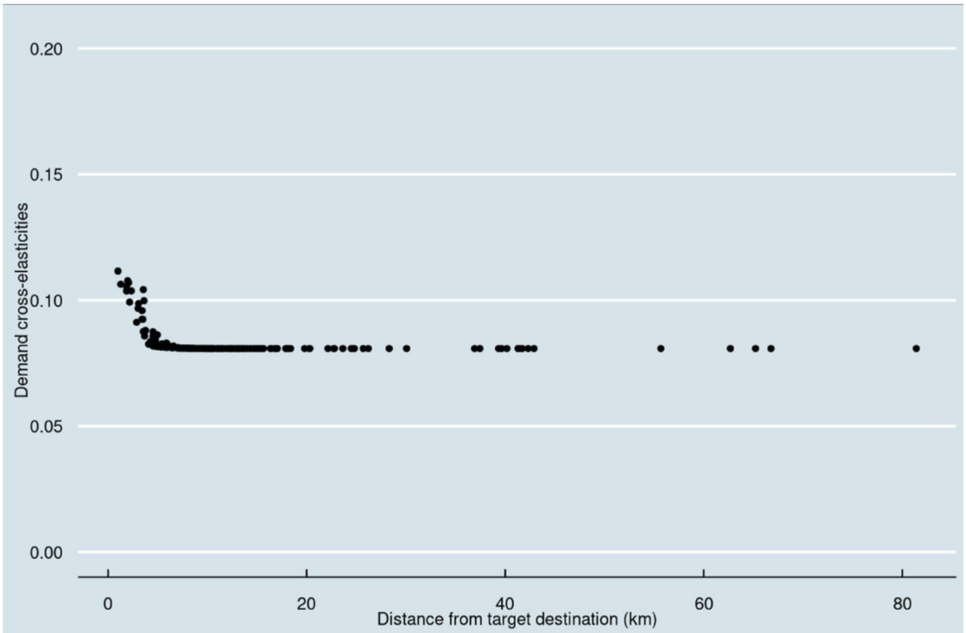
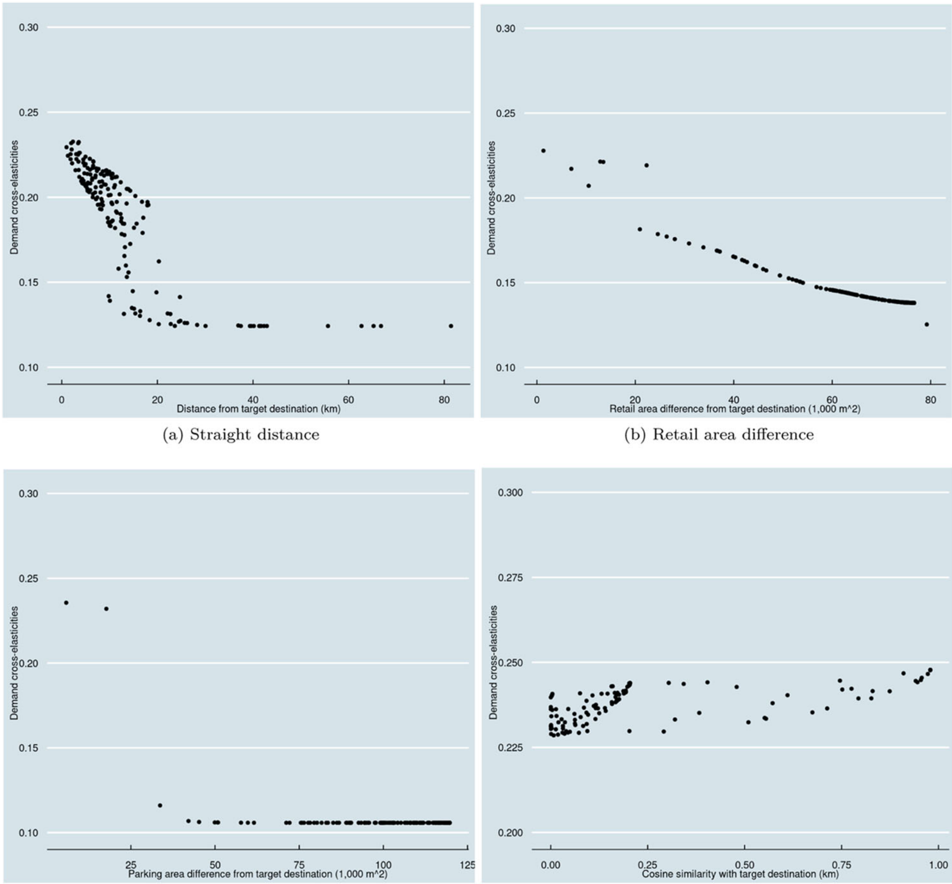


Figure 10. Demand cross-elasticities of CNL-dest model for each destination alternative based on their distance from the target alternative for forecasting scenario 1.

in an almost proportionate demand increase for the remaining three destinations due to the small estimated distance multiplier. The proposed specifications, *CNL-dest* and *CNL-dest-2*, however, present more realistic results with the distance between the alternatives now having a more profound impact on the cross-elasticities, as the closer destination, alternative 71, is showing a higher demand increase as a result of the demand decrease of its neighbouring alternative. It is also evident from the same Table that both the *MNL-dest-base* and *PCL-dest* models will significantly underestimate the change in demand of a destination located closer in favour of alternatives that are located at a greater distance. It is worth noting that the *CNL-dest* model predicts a 42% higher demand elasticity for the closer destination relative to the *PCL-dest* model (0.112 and 0.079, respectively). Adding further factors in the allocation parameter (land use similarities) in *CNL-dest-2* increases the estimated demand elasticity to the closer destination even further (0.229). A depiction of the decrease of the estimated cross-elasticities from *CNL-dest* with the increase of distance from the target alternative for the current forecasting scenario is presented in Figure 10, where there is a steep decline until a distance of about 7 km from destination 47, after which they stabilise at around 0.08. On the contrary, for *CNL-dest-2* the elasticities are decreasing at a smaller rate as depicted in Figure 11(a), which seem to stabilise after 20 km at around 0.125.

4.3.2. Joint mode and destination elasticities

For the joint mode and destination choice model, a second forecasting example is presented, where car travel cost is increased by one unit for destination 47 again. The demand elasticities and cross-elasticities for the different mode combinations and for different destinations are examined at the individual level –for the same person as before– for



(a) Straight distance

(b) Retail area difference

(c) Parking area difference

(d) Land use profile similarity

Figure 11. Demand cross-elasticities of CNL-dest-2 model for each destination alternative based on different similarity factors with the target alternative for forecasting scenario 1. (a) Straight distance. (b) Retail area difference. (c) Parking area difference and (d) Land use profile similarity.

MNL-joint-base, *CNL-joint-base CNL-joint-proposed-1* and *CNL-joint-proposed-2* and outlined in Table 8. Similarly to the elasticity analysis for the destination choice model, the two NL models, namely *NL-joint-MoD* and *NL-joint-DoM*, are not presented, since they both collapse to *MNL-joint-base*. That person chooses car-car initially to travel to destination 47 and to her following activity and PT is not available to her for the first trip. PT is also not available for both trips (shopping/following trips) for destination 71. As in the elasticity analysis for the destination choice model, the impact of the *IIA principle* is clearly evident in the demand elasticities of the *MNL-joint-base* model. The *CNL-joint-base* model results in a higher demand increase for alternative mode combinations in the same destination and those cross-elasticities are stable across the alternatives regardless of their distance from the target destination. Nonetheless, different conclusions can be drawn by examining the *CNL-joint-proposed*, where higher cross-elasticities for the same mode combination of car-car for different destinations are estimated. Therefore, *CNL-joint-base* overestimates the shift to alternative mode combinations for the same destination, while *CNL-joint-proposed-1*

Table 8. Individual level demand elasticities for forecasting scenario 2.

Destination (density band)	C-C	C-PT	C-W	PT-C	PT-PT	PT-W	W-C	W-PT	W-W
MNL-joint-base model									
Dest 47	−0.122	−0.122	−0.122	–	–	–	0.148	0.148	0.148
Dest 71	0.148	–	0.148	–	–	–	0.148	–	0.148
Dest 34	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148
Dest 131	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148
CNL-joint-base model									
Dest 47	−0.131	−0.148	−0.085	–	–	–	0.165	0.161	0.161
Dest 71	0.168	–	0.159	–	–	–	0.161	–	0.159
Dest 34	0.167	0.163	0.159	0.164	0.160	0.159	0.159	0.159	0.159
Dest 131	0.166	0.162	0.159	0.163	0.160	0.159	0.159	0.159	0.159
CNL-joint-proposed-1 model									
Dest 47	−0.133	−0.174	−0.066	–	–	–	0.175	0.148	0.145
Dest 71	0.199	–	0.145	–	–	–	0.149	–	0.145
Dest 34	0.160	0.158	0.145	0.155	0.146	0.145	0.145	0.145	0.145
Dest 131	0.153	0.153	0.145	0.151	0.146	0.145	0.145	0.145	0.145
CNL-joint-proposed-2 model									
Dest 47	−0.147	−0.123	−0.028	–	–	–	0.178	0.157	0.153
Dest 71	0.293	–	0.152	–	–	–	0.153	–	0.152
Dest 34	0.288	0.156	0.152	0.158	0.154	0.152	0.152	0.152	0.152
Dest 131	0.198	0.161	0.152	0.166	0.154	0.152	0.152	0.152	0.152

C: Car, PT: Public Transport, W: Walk.

and *CNL-joint-proposed-2* suggest that individuals would be more likely to change their destination rather than their mode and more specifically shifted to their closest destination compared to others (grey-highlighted cell). This is a key finding, and suggests that not accounting for it could affect policy decisions. It could serve as an indication of the mode captivity of individuals in the UK, especially for car users in this scenario.

The impact of the different similarity measures on the demand cross-elasticities across mode combinations is presented in the following figures. First in Figure 12, a steep decrease of car-car cross-elasticities is illustrated up to a distance of 7 km from the target destination in the model *CNL-joint-proposed-1* at a rate of -0.0129 ($elasticity = 0.2425 - 0.0129 * distance$). After that point the rate of decrease slows down as cross-elasticities stabilise at around 0.15 with a rate of -0.0002 ($elasticity = 0.1610 - 0.0002 * distance$). On the other hand, for *CNL-joint-proposed-2*, cross-elasticities for car-car combinations are more evenly spread around the target destination up to threshold of around 10 km ($elasticity = 0.2939 - 0.0008 * distance$) after which they start to decline rapidly until a distance of 40 km ($elasticity = 0.3371 - 0.0044 * distance$) as depicted in Figure 13 until they stabilise again at around 0.15, similarly to *CNL-joint-proposed-1*.

Retail area difference does not have much influence on the cross-elasticities for car-car mode combinations as expected Figure 14, as it only affects walk-walk combinations (see Table 6). The impact of parking area difference on the demand cross-elasticities of *car-car* mode combinations is depicted in Figure 15, where it seems to be quite important on the first two most similar destinations with regard to parking areas with 0.3 and 0.32 cross-elasticities, respectively. Those numbers drop in half to 0.15 before stabilising at around 0.18. Finally, the impact of store type similarity on demand cross-elasticities is depicted in Figure 16. A simple linear regression suggests that for *car-car* mode combinations cross-elasticities are increasing by 0.014 for every additional unit of store type similarity (cosine similarity) ($elasticity = 0.2776 + 0.014 * store\_similarity$).

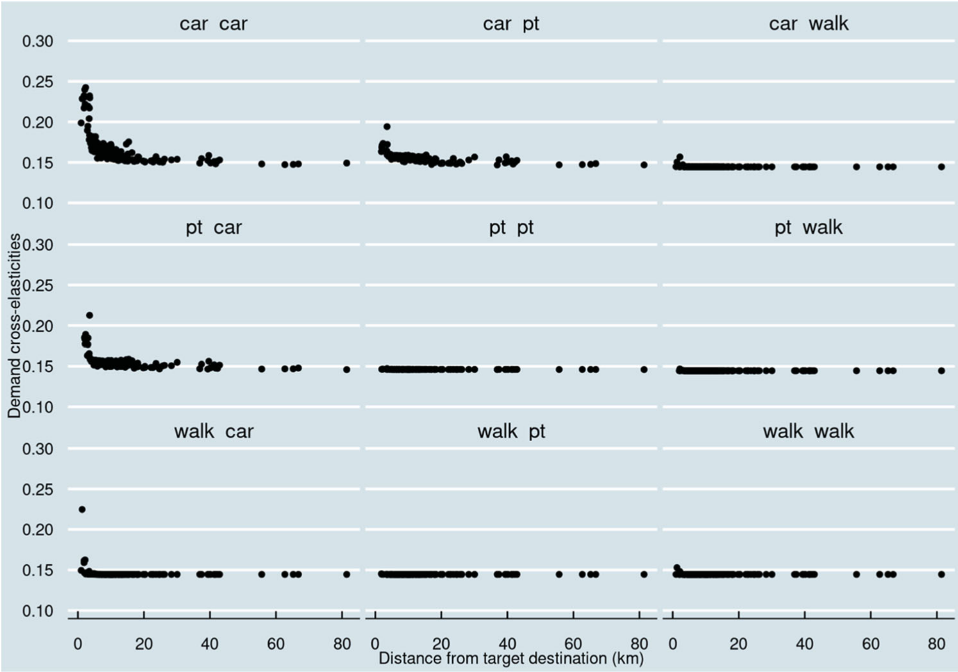


Figure 12. Demand cross-elasticities of CNL-joint-proposed-1 model for each destination alternative and per mode combination based on their distance from the target alternative for forecasting scenario 1.

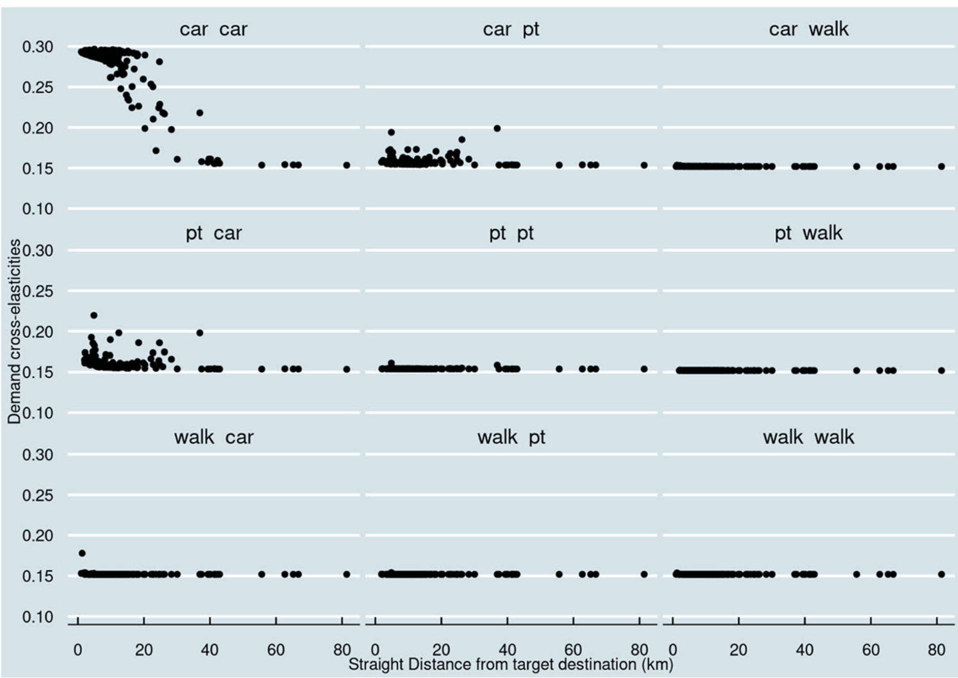


Figure 13. Demand cross-elasticities of CNL-joint-proposed-2 model for each destination alternative and per mode combination based on their distance from the target alternative for forecasting scenario 2.

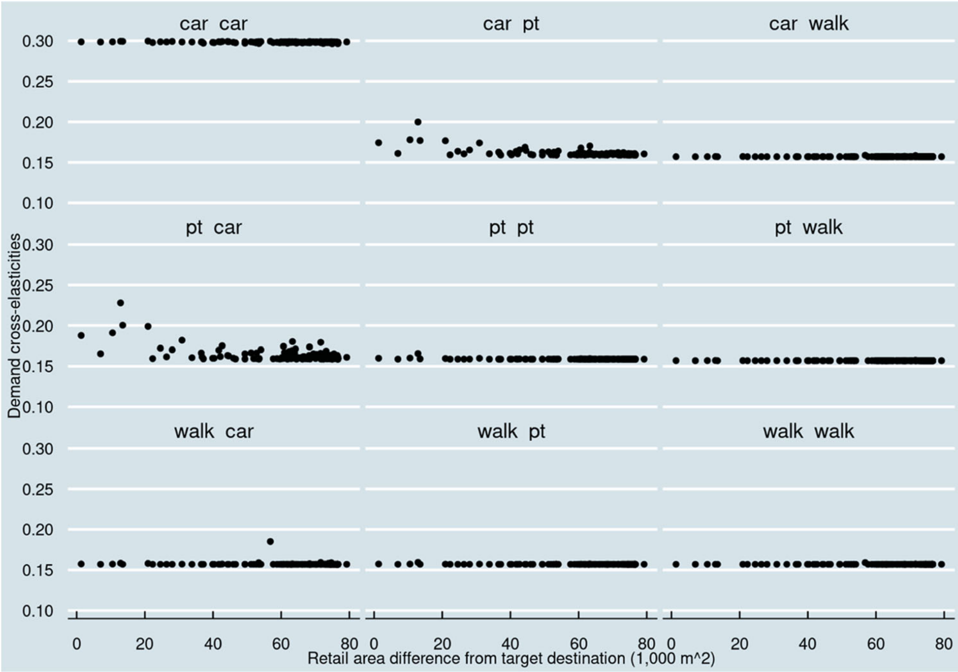


Figure 14. Demand cross-elasticities of CNL-joint-proposed-2 model for each destination alternative and per mode combination based on their retail area difference from the target alternative for forecasting scenario 2.

5. Conclusions

Destination choice is a topic of key interest to the travel behaviour community, and a key issue in this context is how to capture the fact that more similar destinations (either due to distance and/or differences with regard to land use) may be better substitutes for each other. The current paper presented a novel correlation structure for a CNL model for destination choice, or for joint mode-destination choices. A range of different similarity factors was utilised to capture spatial similarity and their impact on demand cross-elasticities, starting from spatial distance and then moving to land use similarity measure among alternative destinations. A key contribution of the current paper is that the proposed nesting structure allows us to capture continuous spatial correlations as a function of a range of factors, while breaking free from restrictive nesting structures (Nested logit). Furthermore, it achieves that without going into much higher computationally demanding structures, which would require us to have a nest for each pair of alternatives (PCL model) and without resorting into a sampling of alternatives approach to simplify the problem.

For the joint mode-destination model, the proposed nesting structure, based on Tobler's first law of Geography, was the only specification, out of the MNL, NL and base CNL frameworks examined, that was able to capture significant unobserved spatial correlations among the destination alternatives and provided RUM-consistent λ estimates. For the simpler destination choice model, the PCL specification was also able to capture spatial correlations among destinations, however the proposed CNL model was able to uncover a

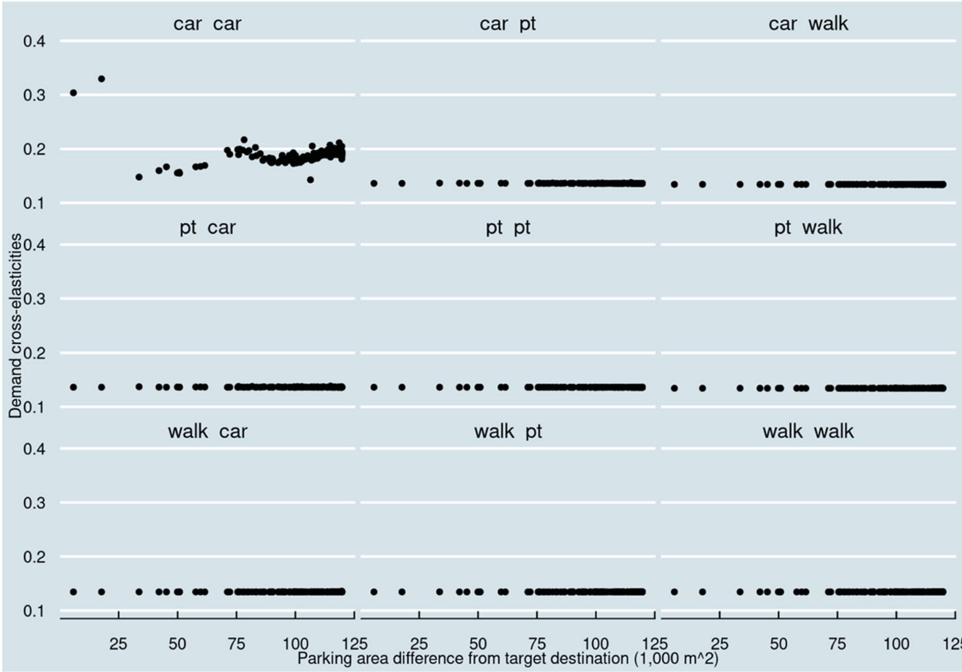


Figure 15. Demand cross-elasticities of CNL-joint-proposed-2 model for each destination alternative and per mode combination based on their parking area difference from the target alternative for forecasting scenario 2.

much higher impact of distance in addition of being more statistically efficient and resulting in much lower estimation times. That allowed the proposed CNL model to be easily extended to accommodate additional spatial similarity factors in the specification of allocation probabilities. Furthermore, the study illustrated how the proposed nesting structure can be easily modified to be suitable for the context of a joint mode and destination, where correlation is being captured across all choice dimensions simultaneously. Contrary to that, it was not computationally feasible to extend the PCL model from the destination choice application to the joint mode-destination one in the same way.

The results prove that, in general, there is a higher correlation between the error terms of alternatives that are more similar to each other relative to all the rest. For the joint mode and destination model, the results showed that mode also has an impact on the allocation parameters. Walking leads to higher allocation parameters for the nest of the target destination, while mechanised modes, i.e. car and PT, result in more balanced allocation parameters between the target and the neighbouring clusters, probably due to the flexibility those modes can provide to the decision-maker compared to walking. The proposed CNL model is also computationally more efficient than its PCL counterpart of Sener, Pendyala, and Bhat (2011) and does not require simulation like the EC model of Weiss and Habib (2017) allowing the analyst to estimate a model using the full choice set.

A deterministic approach for defining alternative availability/consideration has been proposed in the current study. Since we are working in a spatial context, it is highly likely that decisions are subject to latent spatial perception constraints (Bierlaire and Hurtubia

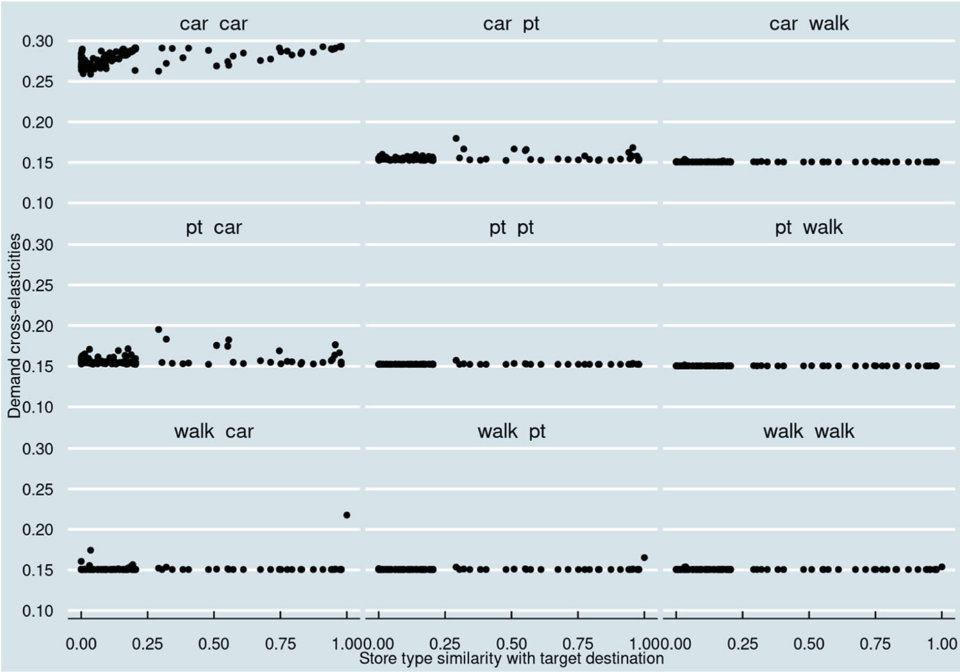


Figure 16. Demand cross-elasticities of CNL-joint-proposed-2 model for each destination alternative and per mode combination based on their store type similarity from the target alternative for forecasting scenario 2.

2010; Cascetta and Papola 2001; Haque and Hess 2019; Yao and Bekhor 2022). We have experimented with defining mode-specific distance thresholds for constraining the consideration choice sets, which showed only negligible differences with the models currently reported. A probabilistic choice set generation approach would be a better way to capture the impact of latent spatial constraints (Tsoleridis, Choudhury, and Hess 2023) and the current proposed CNL specifications can be easily extended to allow for that. Nonetheless, that could be computationally prohibitive, especially in the context of the joint mode-destination choice.

The results obtained are likely to depend to some extend on the Hierarchical Agglomerative Clustering (HAC) approach utilised to define the shopping areas that formed the destination alternatives in our analysis. The distance threshold chosen (800 m) was chosen to minimise the discrepancies from the initial elemental observed destinations, however a sensitivity test was not conducted to analyse the impact of that decision, which can be the subject of future research. Furthermore, the deterministic approach used to allocate elemental shopping polygons in overlapping clusters (described in Section 3.3) can also have an influence on the results, albeit more profound in specific cluttered areas in city centres. Future research can also explore whether a probabilistic weighted allocation (e.g. weighted by the distance to each neighbouring centroid) can affect the modelling outputs.

The joint mode-destination model showcased how the proposed CNL structure can be extended to accommodate multiple choice dimensions. In a similar way, more choice dimensions can be added that can be expected to be correlated with mode-destination, such as departure time. Having said that, however, it could have a negative computational impact due to the increased choice set size that would probably lead us to take a sampling of alternatives approach (refer to Guevara and Ben-Akiva 2013) or move to coarser spatial resolutions for defining destination alternatives.

The reported specifications in the current study captured similarities among destinations not only based on their spatial proximity, but also based on land use profiles, as well as retail and parking areas thus providing a generalised empirical proof of Tobler's first law of Geography. It does not provide, however, an exhaustive search on all the possible factors influencing spatial similarity, such as for example network topology, the distance of the shopping destinations from the respective origins or even the detour from the straight line between origins and following destinations that is required to reach each destination. Real network distances have been examined as a more detailed similarity measure contrary to straight distances, but without resulting in any significant improvements. Other continuous measures can also be used, such as network travel times among the destinations during different time periods, e.g. am peak, off-peak, pm peak etc. That would allow an additional temporal dimension to be included in the analysis for the purpose of uncovering spatio-temporal similarities among destinations. Future studies can explore the potential impact of those factors, while also linking that to demographic characteristics and capture whether different individuals have a different perception of spatial correlation among destination alternatives or whether the individuals perceive the destinations closer together or further apart based on the time of day due to network traffic in each time period. Similar to the store type similarity defined in the current study, Machine Learning algorithms can also help to identify additional complex spatio-temporal similarities among destinations. Similarities could also differ based on the context of the choice problem itself with different attributes influencing perceived similarity in a shopping location than in a residential location choice model.

In addition to the insights of individual behaviour, the present study offers a specification that can be used to enhance current national travel demand models (Department for Transport 2020). Furthermore, agent-based models or individual components of land use-transport interaction models could be enhanced with such a specification to better capture the effect of spatial similarity in the decision-making process. That would most likely lead to a different distribution of activities through space and hence to different dynamic interactions among agents or between land use developments and the transport system.

Notes

1. Details can be found at https://census.ukdataservice.ac.uk/use-data/guides/boundary-data.aspx
2. Details can be found here: https://docs.microsoft.com/en-us/bingmaps/rest-services/routes/
3. The choice set formation in the current models is defined deterministically as per Sections 3.4 and 3.5. A sensitivity analysis was performed to assess the impact of choice set formation assumptions on the stability of the estimated parameters. More specifically, destination alternatives beyond the observed chosen distances per mode were defined as non-available. The reduced choice set model resulted in similar model fit statistics and estimated parameters indicating that the exclusion of alternatives further away have a negligible impact on the model's performance.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The current research was funded by the Advanced Quantitative Methods (AQM) scholarship of the Economic and Social Research Council (ESRC) [ES/P000746/1]. Stephane Hess acknowledges the financial support by the European Research Council through the consolidator Grant 615596-DECISIONS and the advanced grant 101020940-SYNERGY. Charisma Choudhury acknowledges the financial support of her UKRI Future Leader Fellowship MR/T020423/1-NEXUS.

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