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Modelling departure time choices by a Heteroskedastic Generalized Logit (Het-GenL) model: An investigation on home-based commuting trips in the Greater Toronto and Hamilton Area (GTHA)

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ABSTRACT

The paper presents an econometric model for departure time choice modelling. The proposed model is a discrete choice model with latent choice sets. As per the formulation of the mode, the model falls in the general category of Generalized Extreme Value (GEV) models with choice set formation, which is also known as a Generalized Logit (GenL) model. However, the proposed modelling framework uses a scale parameterization approach to capture heteroskedasticity in departure time choices. Hence, the model presented in the paper is a Heteroskedastic Generalized Logit (Het-GenL) model in general or specifically a heteroskedastic Paired Combinatorial Logit Model (Het-PCL). Empirical models are developed for the departure time choices for home-based commuting trips in the Greater Toronto and Hamilton Area (GTHA). The datasets from the Transportation Tomorrow Survey, a 5 percent household based trip diary survey conducted in 2006 is used for empirical model estimation. Separate models are estimated for private car and transit users' departure time choices. It becomes evident that transportation level-of-service attributes enter into the systematic utility function as well as the scale parameter function with significant coefficients. The proposed econometric approach captures the normalization effect of different variables in terms of simultaneously influencing systematic utility as well as the scale parameter and thereby correctly explains the elasticity of corresponding variables.

1. Introduction and motivation

Increasing peak period traffic congestion makes transportation policies such as dynamic public transit pricing and road pricing more feasible than ever before as these are intended to influence the distribution of travel demand throughout the day. However, designing such policies requires proper understanding of the nature of travel demand with respect to time-of-day choices. For any specific urban forms and land use conditions, elasticities of commuting departure time choices with respect to transportation level-of-service attributes are major factors that can define the success or failure of any demand management policies. So, this research is focused on improving our understanding of patterns and factors influencing commuting departure time choices.

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For proper and systematic investigation, it is important to use models that can capture the behavioural tradeoffs involved in commuters' departure time decisions as this decision determines the distribution of demand on road and transit networks. Proper modelling techniques that enable the testing of a wide variety of policy initiatives are required. This research aims to develop models of departure time in order to evaluate the effectiveness of various dynamic policies in managing peak period travel demand for the Greater Toronto and Hamilton Area (GTHA).

To capture tradeoffs involved in commuting trip departure time choices, we need to ensure that the time representation maintains a cumulative time-of-day sequence (for example 7:00–7:29 is just adjacent to 7:30–7:59 am and so on) and also that alternative time intervals that are not adjacent to each other are comparable (for example, the choice between travelling before or after the peak period). So, in this research, we discretize the 24-h time period into alternative departure time choice segments and apply advanced discrete choice models that can accommodate the correlations between adjacent time slots as well as allows comparing alternative slots that are not adjacent. Addressing correlation between adjacent time slots is necessary to address the issues related to boundary conditions due to time discretization. For example, a commuter departing at 7:55 am may be put in a different time slot than a commuter departing at 8:05 am. However, 7:55 am and 8:05 am are very close and may not be perceived as different time slots by the individual commuters. In our modelling approach, such artificial time boundary condition issues are avoided by accommodating the fact that adjacent time slots are, in fact, correlated in commuters' perception of alternative departure time choices. We use a Heteroskedastic Generalized Logit (Het-GenL) model that can accommodate all of these issues along with capturing the heterogeneity of departure time choices across the population. Empirical models are estimated using data from the Transportation Tomorrow Survey (TTS), a Revealed Preference (RP) household travel diary collected in the GTHA in 2006.

The paper is arranged as follows: the next section presents a review of existing relevant literature on departure time choice modelling to define the warrants for this work and to position this study in its context. Subsequently, the econometric model formulation for the departure time choices is presented. The empirical models are presented with interpretations of the model parameters and performance of the advanced models for sensitivity analyses. The study concludes by summarizing the key findings and by identifying potential future projects that may make use of this work.

2. Literature Review of Departure Time Models

Departure time models represent an individual's choice of a point or interval in time at which to begin a trip. Types of stochastic models used to represent the departure time choice include the multinomial logit model, the nested logit model, the cross-nested logit model, the mixed logit model, continuous time model, the Ordered Generalized Extreme Value (OGEV) model and its variants. Two key challenges in departure time choice modelling are accurately representing the continuous nature of time while allowing the comparison of non-adjacent alternative departure time slots and capturing the choice captivity to specific time slots. In most cases, investigations in the literature are focused on one of these issues specifically.

An early example of departure time choice modelling was reported by Small (1982) who used the multinomial logit (MNL) model for modelling commuting departure time. Hendrickson and Plank (1984) also used MNL models of departure time interval choice jointly represented with mode choice to investigate the relative influence of different variables on mode choice versus departure time choice. Chin (1990) used the MNL model to represent morning commuting departure time in Singapore. In all of these applications of MNL, the day is divided into a number of discrete alternatives and MNL is applied to capture the tradeoffs between alternative time-of-day options. In the MNL model, systematic utility functions are specified as linear-in-parameter functions of choice for commuting as a function of socio economic, level-of-service and work related variables. These applications of the MNL model show that it can capture systematic influences of various variables on departure choices, but there is no way to validate the accuracy of the estimates. There are doubts about the application of MNL for departure time choices as it does not capture the similarities/correlations between adjacent time interval choices. In the case of researcher defined time discretization, such correlation is obvious (as the commuters may not perceive time interval discretization in the same way as the researcher) and would cause a serious violation of the Independent and Irrelevant Alternative (IIA) assumption of MNL formulation (Russo et al., 2009).

Nested logit (NL) or Generalized Extreme Value (GEV) models can relax the IIA assumption by considering the nesting of alternatives in the form of hierarchical decision structures suitable for modelling departure time choice (Whelan et al., 2002). Polak and Jones (1994) used a NL/GEV model to represent departure time choice for an investigation of road pricing policies. The nesting/clustering of discretized departure time forms the context of daily tours. This is a very specialized application of a departure time choice model. In such cases, an alternative can only be part of one nest or cluster and the alternative clusters are fully independent. It cannot capture multiple adjacent correlations between alternative departure time choices. For example, 7 am and 8 am can be correlated in the same way that 8 am and 9 am are correlated. So a single alternative may be nested/clustered with different alternatives separately (such as 7 and 8 am; 8 am and 9 am).

The cross-nested logit (CNL) modelling structure can allow correlation between alternatives by placing alternatives in multiple nests and removing the assumption of fully independent subsets of alternatives as in NL or GEV (Vovsha, 1997; Papola, 2004). In a recent application, Bajwa et al. (2006) applied a CNL approach in the form of a mixed nested logit model for departure time choice. They considered only three alternative departure time options: early departure, on-time departure and late departure. This version of CNL is a mixed logit with an error component; the resulting likelihood function is in open form that requires a simulation estimation technique. As a variation on the cross-nested model structure, a continuous cross-nested logit model (CCNL) can also be used where time-of-day can be discretized into very fine resolutions and all possible correlations are to be addressed (Lemp et al., 2010). Such a model was applied for departure time choice modelling of work-tour departure time for the San Francisco Bay Area data. Such an approach is very robust, but the likelihood function no longer remains in a closed form. Estimation of such models poses considerable difficulty and cannot be estimated using classical estimation techniques. Lemp et al. (2010) used Bayesian estimation techniques and also reported that the model performs similar to a continuous logit model. Their description of the continuous logit is an application of the MNL approach for a very large number of discrete time alternatives.

The basic method that generates variations such as CNL or continuous CNL is the mixed logit model. Conceptually, the mixed logit approach is capable of capturing multilevel correlations among alternative departure time choices while maintaining the core MNL formulation (Kristoffersson, 2007). De Jong et al. (2003) used an error component logit model for departure time choice jointly with mode choice. Error component refers to inducing correlation among the random components of alternative discrete choice utility functions. Bajwa et al. (2006) used a similar concept for modelling commuting departure time choice in Tokyo. Kristoffersson (2007) combines stated preference (SP) and revealed preference (RP) data collected from drivers in Stockholm to estimate a departure time and mode choice model, connected to a dynamic traffic assignment model. Börjesson (2007) also used a combination of RP and SP data in a mixed logit model to represent departure time choice, accounting for the response variation between stated and revealed responses.

The mixed logit approach, in general, is very robust and can handle various types of correlations. However, a major challenge is the assumption of mixing distribution types for random correlations. Also, as a result of mixing distributions, the model formulations no longer remain in a closed form. Such models cannot be estimated by using classical estimation techniques. While, non-classical estimation techniques (simulation based estimation, Bayesian estimation, etc.) are now well developed, such model estimation takes considerable time and distributional assumptions are often arbitrary.

Contrary to discrete choice modelling approaches, a number of researchers used a continuous decision modelling approach for modelling departure time choices. The earliest example of a continuous time departure time choice model is the equilibrium scheduling theory (EST) proposed by Vickery (1969). Later, Hyman (1997), van Vuren et al. (1999), de Jong et al. (2003), Hess et al. (2007) used the concept of EST for modelling departure time choice. In another study involving route choice, Arnott et al. (1990) considers the effects of varying pricing regimes on morning commuters' departure time and route decisions and finds that these choices depend on travel time, and desired and achieved arrival time. They found that most of the reduction in congestion that may be realized by road tolling would be attributed to commuters' change in departure time decisions. However, Vickery's approach is narrowly defined for specific departure time options and the effects of congestion on deviation from preferred or desired time option.

A more elaborate application of the continuous time approach for modelling departure time choice is to model the departure time choice as a continuous random variable. Abu-Eisheh and Mannering (1989) used a discrete–continuous model for joint route and departure time choice model. They found that the continuous approach gives a very good fit to observed data. Bhat and Steed (2002) used a continuous hazard model to represent departure time choice for urban shopping trips throughout the day. They applied a non-parametric baseline hazard model to capture time reporting in 5 min intervals in revealed preference (RP) data sets. Habib et al. (2009) and Habib (2012) applied parametric baseline hazard models for continuous time departure time choices. Application of a hazard model for departure time choices does not necessarily capture explicit choice behaviour. In such cases, the departure time is just modelled as a non-linear regression model and it does not capture behavioural tradeoffs among alternative departure time choices.

In comparison, Ettema and Timmermans (2003), Ettema et al. (2007) and Habib (2013) presented a utility based approach for modelling continuous departure time choices. Ettema and Timmermans (2003) and Ettema et al. (2007) used the utility of activity participation within a daily activity scheduling context for modelling the departure time choices. Their approach requires specialized datasets for modelling departure time choice. Conversely, Habib (2013) explicitly modelled commuting departure time choice by using trip diary datasets. He used a random utility maximization (RUM) based time allocation model for modelling continuous time departure time choices.

The weaknesses of a purely continuous time modelling approach is its inability to capture the correlation of distant time intervals, making it unsuitable to a study of policies that may shift and spread peak period demand. Continuous time choice models are very well suited to capturing tradeoffs among adjacent alternative options. Alternatively, a continuous cross-nested model formulation (such as presented by Lemp et al. (2010)) can overcome the limitations of a purely continuous time approach, although it induces a very high computational burden.

The modelling approach that can bridge the gap between purely discrete and continuous choice modelling approaches is the ordered discrete choice model. Small (1987) provided an early definition of the theory of the ordered generalized extreme value model and studied the effect of work arrival time flexibility, occupation, and mode choice on departure time. The study found that carpoolers are likely to arrive early to work, that professional workers are likely to select later arrival times, and that workers with flexible work schedules tend to travel to work later in the morning. The Ordered Generalized Extreme Value (OGEV) captures the correlation of adjacent time interval alternatives which allows it to be used for policy analysis. Another benefit is that a closed form exists. OGEV models, unlike logit models, accept that the choice between adjacent and similar time intervals differs from the choice between distant time intervals (Kristoffersson, 2007). The OGEV model matches the sequential nature of time where the correlation between ordered points is proportional to their proximity.

A special case of the OGEV model is the dogit ordered generalized extreme value model (DOGEV). It combines an OGEV model with a dogit model, capable of capturing constraints in a choice set such as work start time captivity. Presented by

Gaudry and Dagenais (1979), the dogit model can represent the choice between both independent and related alternatives. The dogit model includes a parameter that varies the influence of all attributes on each alternative choice. Fry and Harris (2005) combined the dogit model with the ordered generalized extreme value model. The resulting DOGEV framework represents the choice between a set of ordered alternatives, where a preference for particular responses exists. Chu (2009) used the DOGEV model to represent departure time choice for morning peak work trips in the New York City metropolitan area. The study indicates that workers are more likely to be constrained (by their work start time) to depart during time intervals in the middle of the peak period as compared to time intervals at the earliest and latest parts of the peak period. Trip cost was not found to motivate departure time choice, likely due to the fact that road tolls in New York are constant during the peak period. The weakness of the OGEV and DOGEV model formulations is that they are computation intensive when representing a large number of choice alternatives. Also, the estimation of such modelling structures would require parameters to follow particular cumulative gradation and constraints. Because of such complexities, very few empirical models of this category are available in literature.

The literature indicates that the transportation industry recognizes the need for accurate departure time modelling; especially with the increasing efforts to move towards activity-based travel demand modelling approach from conventional trip-based approaches. From a practical policy application perspective, departure time needs to be represented with a discrete, but correlated, constrained, and computationally efficient modelling framework. Many existing model structures applied to study departure time choice exhibit some but not all of these characteristics.

To complement to this area, this paper presents an innovative departure time choice model. It combines a heteroskedastic GEV structure with overlapping choice sets to account for both alternative choice correlation and choice captivity. Overlapping choice sets allows for the continuous nature of departure time choices as well as a tradeoff between distant time slot alternatives. In this proposed modelling structure, the choice probabilities are expressed as the probability of a choice set being selected multiplied by the conditional probability of selecting the choice from within the choice set. The probability that a choice set is selected depends on the expected maximum utility of the choice alternatives within the set. The model formulation allows individual choice alternatives to be in multiple choice sets and hence accommodates the latent choice set approach within the choice probability calculation. The next section explains the econometric modelling framework of the proposed model. The proposed model is an enhancement of the GenL model developed by Swait (2001).

3. Econometric model for departure time choice

The departure time model used in this study applies the Heteroskedastic Generalized Extreme Value modelling framework in combination with a Generalized Logit (GenL) and Logit Captivity approaches. The model explicitly represents the correlation between adjacent choice alternatives as well as the captivity of decision makers to specific choices due to schedule constraints. Fig. 1 presents the schematic diagram of the choice model. In this demonstration diagram, there alternative and sequential departure time bands are presented (D_1, D_2 and D_3, where $D_1 < D_2 < D_3 < D_4$).

The concept is that the choice situation is composed of a series of choice sets and a particular alternative can be part of multiple choice sets. For example, in Fig. 1, there are 4 alternatives and 9 possible choice sets are considered. Choice sets C1, C2, C3 and C4 consist of only one alternative referring to the captivity of only one alternative in the choice set. The following choice sets are formed maintaining the sequence of the adjacent alternatives. In the example shown in Fig. 1, alternatives are clustered alone, with one/two adjacent alternatives.

However, the clustering of alternatives in choice sets can go further. Specifically in addition to clustering with immediately adjacent alternatives; we can even consider clustering with two adjacent alternatives, clustering with three adjacent

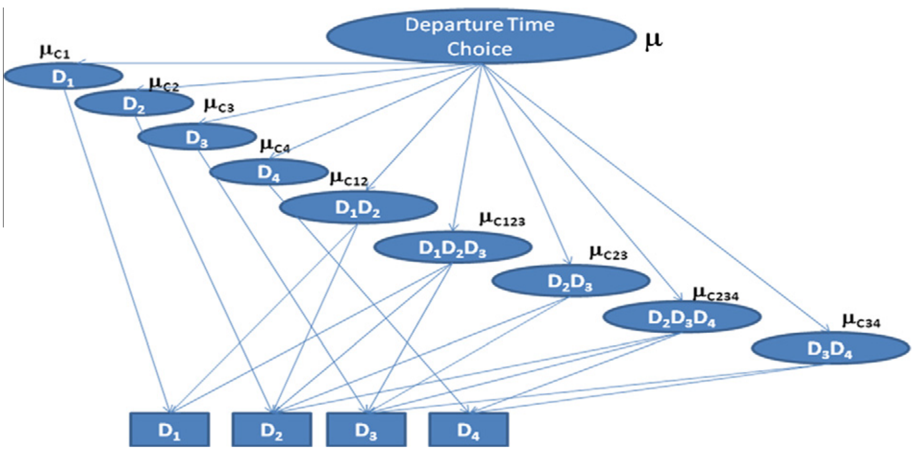

Fig. 1. Departure time choice framework.

alternatives, so on and so forth. However, if additional clusters are not identifiably different from the existing ones, there is no benefit to inducing higher numbers of clusters. The number of possible clusters of alternatives considered would be indentified through empirical investigation. In any case, the choice of any alternative is based on principles of Random Utility Maximization (RUM) where the utility of a discrete choice alternative is represented by the weighted sum of variables relevant to the choice as well a random component.

$$U_j = V_j + \varepsilon_j = (\beta x)_j + \varepsilon_j \tag{1}$$

Here U_j is the utility of an alternative choice j, V_j is its systematic utility components, and ε_j is its random utility component. V_j is expressed as a linear-in-parameter function of variables x and corresponding coefficients β. The Generalized Extreme Value (GEV) theorem (McFadden, 1978) forms the basis of the Generalized Logit (GenL) presented by Swait (2001). Considering the generalized extreme value distribution assumption for the random utility component, the corresponding generating function of the GenL model becomes:

$$G = \sum_C \left(\sum_{j \in c} y_j^{\mu_c} \right)^{\frac{\mu}{\mu_c}} \tag{2}$$

Here, G is the generating function, y_j refers to a binary variable indicating the choice of alternative j; μ is the root scale parameter, μ_c is the scale parameter of a particular choice set (c) and the summation over C indicates the summation over all possible choice sets. In this case, the possible choice sets are composed of either a single alternative or set adjacent alternatives. For each alternative departure time, the set of alternative that composes the multi-alternative choice set is composed of the alternative itself as well as the left adjacent and/or right adjacent alternative. Of course, the formulation allows that any individual would have multiple choice sets and some of the choice sets have overlapping members of alternative choice. The allowance of multiple choice sets with overlapping choice alternatives is mainly to allow various patterns of correlation across the alternatives. Finally, in case of N alternative departure time choices, each individual traveller has the same number of total alternatives, but with various combinations of alternative clusters (in the form of multiple choice sets) that allows various types of substitution patterns. So, in case of a total of C possible choice sets (clusters of alternatives) the unconditional probability of choosing one alternative j, P_j is

$$P_j = \sum_{c=1}^{C} (P_j|c) Q_c \tag{3}$$

Here $P_j|c$ is the conditional probability of alternative j in the choice set c and Q_c is the choice node probability or probability of the choice set c.

$$Q_c = \frac{\exp(\mu I_c)}{\sum_{\tilde{c}=1}^{C} \exp(\mu I_{\tilde{c}})} \tag{4}$$

Here I_c is inclusive value of a particular alternative choice set c.

$$I_c = \frac{1}{\mu_c} \ln \left(\sum_{j=1}^{J} \exp(\mu_c V_j) \right) \tag{5}$$

Finally the conditional probability of any alternative j in a particular choice set c is

$$P_j|c = \frac{\exp(\mu_c V_j)}{\sum_{\tilde{j}=1}^{J} \exp\left(\mu_c V_{\tilde{j}}\right)} \tag{6}$$

Here, j is the particular alternative and J is the total number of alternatives in the choice set c and an individual can have multiple choice sets. In the case of a choice set with one alternative, the conditional probability is 1. This approach allows that a single alternative can be part of multiple choice sets. Hence the actual choice set formation is latent, where the final choice probability of any alternative is composed of probabilities of being part of multiple choice sets. Such a latent choice set approach better captures captivity to specific alternatives as well as correlation across the alternatives. This formulation is very much similar to the Paired Combinatorial Logit (PCL) model presented by Koppelman and Wen (2000). However, we further parameterize the scale parameters of the model, which accommodates systematic heteroskedasticity as well.

Scale parameters representing correlation among the alternatives (choice set/nest scales) within a choice set as well as overall scale of the utility function of choosing discrete departure times (root scale) are crucial in properly capturing the choice behaviour. In terms of scale parameters, there are two types of scale parameters in this model formulation: root scale parameter (μ) and scale parameter of a particular choice set c (μ_c). For theoretical consistency with RUM, it is necessary that μ_c should be greater that μ (Swait, 2001). Also, it should be maintained that all scale parameters must be positive. To ensure such conditions, we further parameterized the scale parameters as follows:

$$\mu = \exp\left(\sum \gamma z\right)$$
$$\mu_c = \mu + \exp\left(\sum \lambda y\right) \tag{7}$$

Here $\sum \gamma z$ represents a linear-in-parameter function of variables z and corresponding coefficients γ. Similarly, $\sum \lambda y$ represents a linear-in-parameter function of variables y and corresponding coefficients λ. Empirical estimation of the model requires identification restriction, which includes the normalization of the root scale parameter. Such scale parameterization ensures that the estimated models comply with basic assumptions of RUM and that the resulting models become a heteroskedastic model. Hence the model proposed in this paper is a Heteroskedastic Generalized Logit model (Het-GenL) or specifically a heteroskedastic paired combinatorial logit model. In general, the Het-GenL framework represents a decision process where an individual may select a time interval directly, or by comparing it to adjacent time intervals. This is representative of decision making behaviour in reality where choice of a specific time slot for departure time would be more correlated to the choice of adjacent time slots than the far-away time slots. However, the general formulation of the model allows a wide variety of possible correlation/substitution patterns across the alternative departure times. Accommodate of multiple and overlapping choice set in the choice formulation is mainly due to facilitating complex correlation/substitution patterns among the time slot alternatives for the departure time choice.

Finally, the probability equations of the proposed model are of closed form and hence can be estimated by using classical estimation techniques. Since the alternative choice sets are latent in nature, such a type of model requires full-information maximum likelihood estimation (Koppelman and Wen, 2000). The scale parameterization allows model estimation by the unconstrained maximum likelihood estimation approach. This is unlike the PCL model specified by Koppelman and Wen requiring constrained maximum likelihood estimation techniques (see Koppelman and Wen, 2000, p. 84). In this paper, the empirical models are estimated through the maximum likelihood estimation technique using codes written in GAUSS, which uses the gradient search algorithm, BFGS (Aptech, 2011). The next section presents a brief summary of data used for empirical investigation.

4. Data description

The data used in this study was collected by the 2006 Transportation Tomorrow Survey (TTS), a household based travel demand survey conducted in the Greater Toronto (and Hamilton) Area every five years. (DMG, 2012) The survey provides detailed information on trips made on a typical weekday by all individuals in the selected households. Five percent of households in the GTHA are contacted by telephone and all trips made by residents eleven years of age or older on a specific weekday are recorded.

To prepare the survey data for analysis and modelling, all trips reported in TTS were linked to the corresponding level of service attributes. Auto mode level-of-service attributes are generated by using EMME/2 traffic assignment model, which is developed and calibrated for the study area (INRO, 2011). 24-one-hour assignments are used to develop 24-h level-of-service attribute tables for the auto mode. However, the transit assignment model was only available for peak period conditions. To expand the peak hour transit level-of-service attributes for all twenty-four hours of the day, the following principles are defined:

- Wait times vary proportionally to the variation in headways over time.
- Subway travel times do not vary throughout the day due to the designated right-of-way.
- Bus/Streetcar transit zone-to-zone travel times vary similarly to auto travel times.
- Walk times and fares are known to be constant through the day.

Finally, information about home zone population density and median income was attached to each trip based on the individual's home location. Trip duration and work duration were calculated according to reported departure time and estimated travel times. Kernel density plots are used to investigate the departure time choice distribution for each mode (Auto and Transit users) and to find the degree of granularity required to represent the departure time choices. For both travel modes, Kernel Density Bandwidths are investigated for different occupation groups.

TTS classifies occupation groups into four categories: general office/clerical, manufacturing, professional, and retails sales/services. Trends indicate that the work trips of general office workers and professionals tend to be contained within the conventional morning peak period while manufacturing workers and retail workers are more likely to travel to work outside of the morning peak. Smooth kernel density plots are used to identify proper discretization of the departure time distributions. From investigation, it is found that a 30-min bandwidth is the minimum level of detail required for representing the variability in the departure time choice distribution. We also investigated the possibility of 15-min intervals, but found that it results in a lack of observations for a significant number of alternative departure time options.

The common assumption among the planning agencies in the study is that the peak period starts at 6 am and ends at 9 am (Miller, 2007). However, in our case, based on the observed distributions of departure times in the dataset, we classified the alternative departure times into the following seven categories:

1. Before 6:30 am.
2. 6:30–7:59 am.
3. 8:00–8:29 am.
4. 8:30–8:59 am.
5. 9:00–9:29 am.
6. 9:30–10:00 am.
7. After 10:00 am.

The reason for clustering all alternative departure times into one category after 10:00 am is that the dataset contains very few home-based commuting trips departing after 10:00 am. Also, the observations with such departure times are too dispersed to consider 30 min interval alternatives after 10:00 am.

The dataset also includes individual and household specific socio-economic attributes, such as age, gender, occupation type, household vehicle ownership and household size. These variables are used as explanatory variables in the empirical investigation. After cleaning for missing values, two datasets are prepared for auto and transit departure time choice models.

5. Empirical models of departure time choice

Separate departure time choice models are estimated for two travel mode categories: auto and public transit. Different models were estimated for each mode because the trip attributes affecting departure time choice behaviour are believed to vary between mode categories. The departure time choice is represented by nine discrete time intervals spanning 24 h of the day. For each travel mode, the departure time choice model involves alternative specific constants, coefficient variables defining systematic utility functions, coefficients of variables defining root scale parameters and coefficients of variables defining nest scale parameters. The empirical model for the auto mode is presented in Table 1 and the empirical model for transit users is presented in Table 2. The reported specifications are the best among all alternative specifications that were tested. We define the final specification based on the statistical significance of the parameters and overall goodness-of-fit measures (the rho-square value). All reported parameters are highly significant. The dataset for the auto departure time choice model contains 81264 trip records and the dataset for the transit departure time choice model contains 22952 trip records. Considering trip expansion factors, the auto trip dataset represent 1.56 million trips and transit trip dataset represents 0.44 million trips. The models are estimated by using the sample datasets considering the expansion factors. This results in high t-statistics and soundly capturing the statistical significances. The auto users' departure time choice model has 74 statistically significant parameters and the transit choice model has 78 significant parameters. Estimation of such a large number of statistically significant parameters indicates that the model formulation is robust in identifying influential variables for explaining specific components of choice model formulations. In terms of goodness-of-fit measure, transit model gives better fit than that of the auto model. However, in both cases, the rho-square values are the low. Possible reason would be the complicacy of model formulation.

We found that only alternative specific constants, transportation level-of-service attributes and occupation type enter into the systematic utility function of alternative departure time choices for auto and transit users. Systematic utility components capture relative utilities of alternative departure choices and hence the transportation level-of-service attributes corresponding to alternative departure time segments play the major role. Commuters' occupation type, sometimes imposes restrictions/flexibilities in departure time choice and so it influences the relative attractiveness of alternative departure time segments. However, individual commuter's personal and socio-economic attributes may not have very direct influences on defining the attractiveness of alternative departure time segments. Hence, we found that all socio-economic attributes enter only into the scale parameter, which defines the absolute utility of total choice contexts (commuting departure time) and captures heterogeneity and heteroskedasticity in choice behaviour. We also found that some level of service attributes and work related attributes enter both into the systematic utility and scale parameter functions defining a highly non-linear and complicated relationship with departure time choice.

5.1. Systematic utility function

It is found that alternative specific constant values are very low in magnitude for both auto and transit users (the highest absolute value is 1.3 for the auto user's departure time choice model and 2.8 for the transit users' departure time choice model). Low alternative specific constant values are indicators of better model formulations that can accommodate variable effects accurately. However, the interpretation of alternative specific constants should be done very carefully as it captures the systematic utility components that are not explained by any explanatory variables used in the model. It seems that the positive utilities of departing between 7:30 am and 9:29 am or after 10 am by auto are not fully explained by the variables in the model. Similarly, the positive utilities of departing after 7 am by transit are not fully explained by the available variables. Interestingly, both auto and transit departure time choice models indicate that the systematic utility of the departure time during the off-peak period, specifically after 10 am, is the least explained by the available variables.

In terms of level-of-service attributes, travel time and travel cost both enter into the systematic utility functions of the auto user's departure time choice model. However, in the case of transit, since the study area has a flat fare system for transit,

Table 1
Departure time model for auto mode.

Mean loglikelihood of full model		−1.986
Mean loglikelihood of null model		−2.251
Rho-square value		0.12
Variable	Parameter	*t*-Stat
Systematic utility function of departure time choice		
Alternative specific constant		
Before 6:30 am	–	–
6:30–6:59 am	−0.4508	−214.8
7:00–7:29 am	−0.2099	−109.813
7:30–7:59 am	0.1803	97.562
8:00–8:29 am	0.3659	213.785
8:30–8:59 am	0.1143	58.82
9:00–9:29 am	0.007	3.431
9:30–9:59 am	−0.3665	−145.853
10 am or later	1.3054	469.407
Total cost		
Before 6:30 am	0.000	–
6:30–6:59 am	−0.0097	−66.962
7:00–7:29 am	−0.0194	−156.233
7:30–7:59 am	−0.0229	−172.383
8:00–8:29 am	−0.0205	−142.646
8:30–8:59 am	−0.0327	−122.655
9:00–9:29 am	−0.0045	−17.554
9:30–9:59 am	−0.0085	−23.828
In-vehicle travel time		
Before 6:30 am	0.000	–
6:30–6:59 am	−0.0107	−138.18
7:00–7:29 am	−0.0087	−202.097
7:30–7:59 am	−0.0149	−286.325
8:00–8:29 am	−0.0196	−333.466
8:30–8:59 am	−0.03	−229.276
9:00–9:29 am	−0.0332	−288.511
9:30–9:59 am	−0.0182	−447.023
Work duration		
Before 6:30 am	0.000	–
6:30–6:59 am	−0.0505	−277.131
7:00–7:29 am	−0.066	−374.513
7:30–7:59 am	−0.0955	−480.123
8:00–8:29 am	−0.12	−534.866
8:30–8:59 am	−0.1242	−529.06
9:00–9:29 am	−0.1501	−503.339
9:30–9:59 am	−0.147	−449.278
10 am or later	−0.1389	−477.49
Destination of the trips: downtown Toronto		
Before 6:30 am	0.000	–
6:30–6:59 am	−0.0435	−15.153
7:00–7:29 am	−0.0768	−33.144
7:30–7:59 am	−0.1521	−67.264
8:00–8:29 am	−0.0927	−40.813
8:30–8:59 am	−0.076	−27.67
9:00–9:29 am	0.137	40.142
9:30–9:59 am	0.2292	55.216
10 am or later	0.0266	15.939
Occupation category: general office		
Before 6:30 am	0.000	–
6:30–6:59 am	0.7184	291.721
7:00–7:29 am	1.0024	449.689
7:30–7:59 am	1.2126	532.713
8:00–8:29 am	1.3148	561.975
8:30–8:59 am	1.3008	509.856
9:00–9:29 am	0.9194	359.092
9:30–9:59 am	0.6711	217.326
10 am or later	0.000	–
Occupation category: manufacturing		
Before 6:30 am	0.000	–
6:30–6:59 am	0.5818	305.786
7:00–7:29 am	0.2376	159.657
7:30–7:59 am	−0.0249	−20.352
8:00–8:29 am	0.000	–

Table 1 (*continued*)

Mean loglikelihood of full model		−1.986
Mean loglikelihood of null model		−2.251
Rho-square value		0.12
Variable	Parameter	*t*-Stat
8:30–8:59 am	0.000	–
9:00–9:29 am	0.000	–
9:30–9:59 am	0.000	–
10 am or later	−0.0844	−91.658
Occupation category: professional		
Before 6:30 am	0.000	–
6:30–6:59 am	0.7551	335.369
7:00–7:29 am	0.9685	468.749
7:30–7:59 am	1.1875	541.814
8:00–8:29 am	1.2635	569.569
8:30–8:59 am	1.235	529.469
9:00–9:29 am	0.9806	447.848
9:30–9:59 am	0.7608	310.499
10 am or later	0.0921	84.439
Root scale: Exponential function		
Gender: male	0.0472	67.774
Age: less than 25 years old	0.0482	44.687
Age: 25–35 years old	0.0241	27.259
Age: 35–45 years old	0.0127	16.224
Job status: full time	0.1128	122.956
Total cost/total distance	−0.1454	−65.17
In-vehicle travel time/total distance	−0.0107	−14.832
Trip origin: downtown Toronto	−0.1003	−40.903
Trip destination: downtown Toronto	−0.0657	−34.855
Additional exponential function to root sale for alternative nests		
Logarithm of distance between origin and destination		
Before 6:30 am & 6:30–6:59 am	−0.9758	−35.232
6:30–6:59 am & 7:00–7:29 am	−0.2351	−15.051
7:00–7:29 am & 7:30–7:59 am	0.2185	31.862
7:30–7:59 am & 8:00–8:29 am	0.3707	46.623
8:00–8:29 am & 8:30–8:59 am	0.6102	88.533
8:30–8:59 am & 9:00–9:29 am	−0.1915	−12.018
9:00–9:29 am & 9:30–9:59 am	0.000	–
9:30–9:59 am & 10 am or later	0.000	–

transit fare could not be included in the systematic utility components of the departure time choice. For auto users, the cost variable has a negative coefficient for all departure time choice alternatives in reference to earlier than 6:30 and later than 10:00 am departure time slots. Similarly, the in-vehicle travel time has a negative coefficient for all departure time choice options in reference to earlier than 6:30 and later than 10:00 am departure time slots. Also, it is found that the choice of the time slot between 7:00 and 7:29 am seems not to be influenced by travel time. It is difficult to explain such as isolated evidence and perhaps it reflects the artifacts of the dataset. However, transit waiting time, which is a function of transit service frequency as well as transportation system performance (schedule delay) enters into the model of transit user's departure time choices with a negative sign for all alternatives. This indicates that a higher waiting time always increases disutility. Interestingly, the disutility increases until 9 am and then gradually reduces. Typically, in the study area, transit peak period service is defined as being between 7 am and 9 am. It seems that higher waiting times encourage departures either earlier than 8:30–8:59 am or later than 9:00 am.

For work duration, both auto user's and transit user's departure time choice models demonstrate the effect where longer work durations induce a disincentive to travel later in the morning. In all cases, the disutility of alternative departure time slots for increasing work duration increases continuously with the time-of-day. In terms of the magnitude of the coeffcient, auto users are less sensitive to work duration than transit users for the departure time slots after 9 am. This can be explained by the fact that transit service becomes less frequent after the peak work travel period. Thus, transit users with long work durations are more likely to depart earlier in the morning, both because they are hoping to begin and end work early and because they do not want to risk tardiness due to infrequent service. Level-of-service attributes are found to have an effect on departure time choice behaviour.

In the public transit model, the parameter estimates for the downtown destination variable are positive for all time slots with respect the departure time earlier than 6:30 am and later than 10:00 am. Positive signs refer the people tend to choose time slots between 6:30 and 10:00 am if the destination is the downtown. In fact, this complies with the peak period transit service coverage in the downtown. For the purposes of this study, downtown Toronto is defined as the area bounded by Front Street, Bloor Street, Yonge Street, and Spadina Avenue. As expected, the effect of downtown destinations on the utility of a

Table 2
Departure time model for transit mode.

Mean loglikelihood of full model		−1.915
Mean loglikelihood of null model		−2.229
Rho-square value		0.14
Variable	Parameter	*t*-Stat
Systematic utility function of departure time choice		
Alternative specific constant		
Before 6:30 am	0.000	–
6:30–6:59 am	−0.4668	−115.54
7:00–7:29 am	0.454	127.13
7:30–7:59 am	0.8342	205.65
8:00–8:29 am	1.6124	351.32
8:30–8:59 am	1.2307	239.92
9:00–9:29 am	1.004	179.09
9:30–9:59 am	0.1203	11.07
10 am or later	2.8198	298.24
Transit in-vehcile travel time		
Before 6:30 am	0.000	–
6:30–6:59 am	0.000	–
7:00–7:29 am	0.000	–
7:30–7:59 am	−0.0054	−80.19
8:00–8:29 am	−0.0116	−160.68
8:30–8:59 am	−0.0223	−213.94
9:00–9:29 am	−0.025	−216.25
9:30–9:59 am	−0.0304	−173.19
10 am or later	−0.0216	−216.04
Transit waiting time		
Before 6:30 am	0.000	–
6:30–6:59 am	−0.0325	−144.98
7:00–7:29 am	−0.0762	−308.72
7:30–7:59 am	−0.0954	−319.60
8:00–8:29 am	−0.1526	−385.68
8:30–8:59 am	−0.1772	−302.87
9:00–9:29 am	−0.0632	−134.25
9:30–9:59 am	−0.0435	−73.28
Work duration		
Before 6:30 am	0.000	–
6:30–6:59 am	−0.0312	−87.67
7:00–7:29 am	−0.0516	−160.51
7:30–7:59 am	−0.0889	−252.82
8:00–8:29 am	−0.1175	−316.13
8:30–8:59 am	−0.1276	−285.84
9:00–9:29 am	−0.1806	−337.20
9:30–9:59 am	−0.2084	−254.07
10 am or later	−0.2628	−301.16
Destination of the trips: downtown Toronto		
Before 6:30 am	0.000	–
6:30–6:59 am	0.3347	101.70
7:00–7:29 am	0.2693	93.36
7:30–7:59 am	0.2815	93.19
8:00–8:29 am	0.1946	65.87
8:30–8:59 am	0.3452	96.36
9:00–9:29 am	0.4759	121.02
9:30–9:59 am	0.6405	107.58
10 am or later	−0.0893	−27.87
Occupation category: general office		
Before 6:30 am	0.000	–
6:30–6:59 am	0.5325	124.74
7:00–7:29 am	0.6071	156.80
7:30–7:59 am	0.6348	160.14
8:00–8:29 am	0.504	128.80
8:30–8:59 am	0.4387	94.07
9:00–9:29 am	−0.1582	−30.14
9:30–9:59 am	−0.1779	−23.49
Occupation category: manufacturing		
Before 6:30 am	0.000	–
6:30–6:59 am	−0.3966	−78.71
7:00–7:29 am	−0.7169	−149.62
7:30–7:59 am	−1.4173	−228.88
8:00–8:29 am	−1.5098	−254.48

Table 2 (*continued*)

Mean loglikelihood of full model		−1.915
Mean loglikelihood of null model		−2.229
Rho-square value		0.14
Variable	Parameter	*t*-Stat
8:30–8:59 am	−1.7196	−212.65
9:00–9:29 am	−1.9819	−218.24
9:30–9:59 am	−1.7796	−139.70
10 am or later	−1.2983	−218.26
Occupation category: professional		
Before 6:30 am	0.000	–
6:30–6:59 am	0.4876	129.96
7:00–7:29 am	0.535	157.70
7:30–7:59 am	0.6767	192.37
8:00–8:29 am	0.5907	171.50
8:30–8:59 am	0.5499	136.26
9:00–9:29 am	0.1166	27.46
9:30–9:59 am	0.1315	22.44
10 am or later	−0.4464	−117.94
Root scale: Exponential function		
Age: less than 25 years old	−0.1206	−80.12
Age: 25–35 years old	−0.0239	−17.28
Age: 35–45 years old	−0.0382	−27.35
Fare/total distance	0.004	3.62
Total travel time/total distance	0.001	20.41
Trip origin: downtown Toronto	0.04	22.81
Trip destination: downtown Tore	0.1749	117.63
Job status :full time	−0.033	−25.70
Additional exponential function to root sale for alternative nests		
Transit access time: Waiting time + walking time		
Before 6:30 am & 6:30–6:59 am	−1.2217	−2.34
6:30–6:59 am & 7:00–7:29 am	−1.2905	−2.51
7:00–7:29 am & 7:30–7:59 am	−1.0515	−2.51
7:30–7:59 am & 8:00–8:29 am	−0.1072	−17.58
8:00–8:29 am & 8:30–8:59 am	−0.0684	−15.66
8:30–8:59 am & 9:00–9:29 am	−0.0562	−11.69
9:00–9:29 am & 9:30–9:59 am	−0.0404	−25.92
9:30–9:59 am & 10 am or later	−0.0617	−33.02

departure time choice alternative is much higher for transit trips than auto trips, due to the radial nature of the transit system. Transit trips that end downtown experience a positive utility for peak period travel.

Occupation type variables are shown to influence departure time choices: office and professional workers depart in the morning peak to meet conventional work start times while manufacturing workers travel outside of the peak due to work schedules. The effect of job type on the utility of departure time choices differs between travel modes. Office and professional job types have the largest effect on departure time choice among auto users. Among transit users, there is a large disutility attached to the manufacturing job type, at any time of day. By contrast, auto users, those who are most likely to have a manufacturing job, experience only a small disutility for most of the morning. Manufacturing work is often located in suburban areas and demonstrates a lower utility in transit departure time choices.

5.2. Scale parameter (exponential function)

The root scale parameter defines the common scale parameter of individual alternatives as well as the alternative nests. It defines the overall scale of random utility of choosing discrete departure time alternatives. The higher the value of the root scale parameter, the more stable the choices are. It also captures the heteroskedasticity and heterogeneity in departure time choices. We specified the root scale parameter as an exponential function to ensure positive values. In the exponential function, any positive coefficient increases the root scale parameter value and any negative coefficient decreases the scale parameter value. In general, increasing the root scale indicates that the choice model prediction should be more certain and vice versa (Swait and Erdem, 2007 – Fig. 1). Swait (2001 – Fig. 3) presents a schematic diagram to explain the nonlinear effects of root scale and nest scale parameter in individual choice probabilities. In general, the higher values of nest scale parameter indicate higher correlation between the shared alternatives within the nest. We specified nest scale parameter as additive exponential functions of root scale and an additional exponential function. This ensures that nest scale is higher than the root scale. So, for the additional exponential component, a positive coefficient indicates increasing correlation between the alternatives with the nest and vice versa.

Fig. 2 presents the kernel density plots of the estimated root and nest scale parameter for the auto user's departure time choice model and Fig. 3 presents the kernel density plots for the transit users' departure time choice model. The auto root

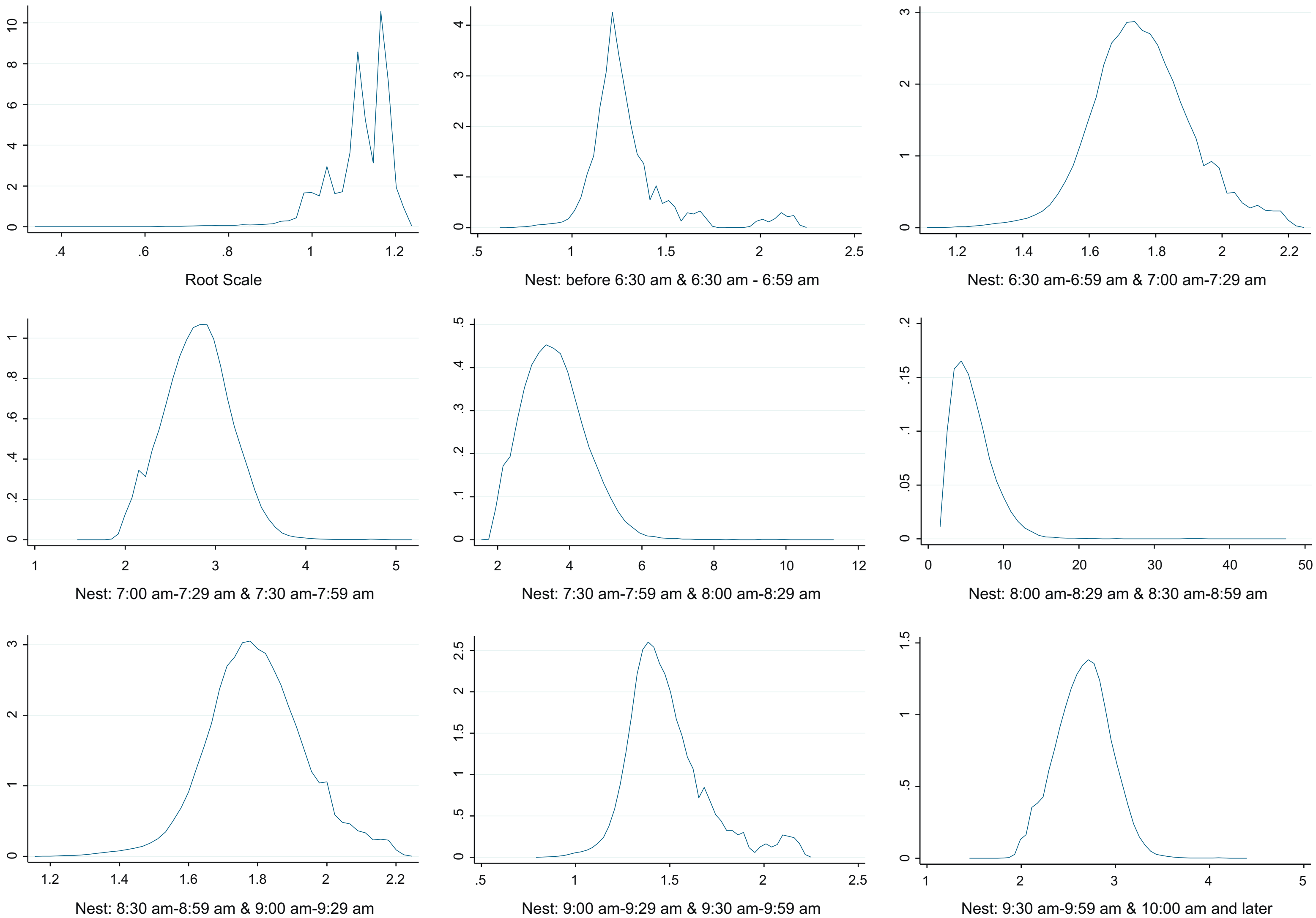

Fig. 2. Kernel density plots of root and nest scale parameters for auto user's departure time choice.

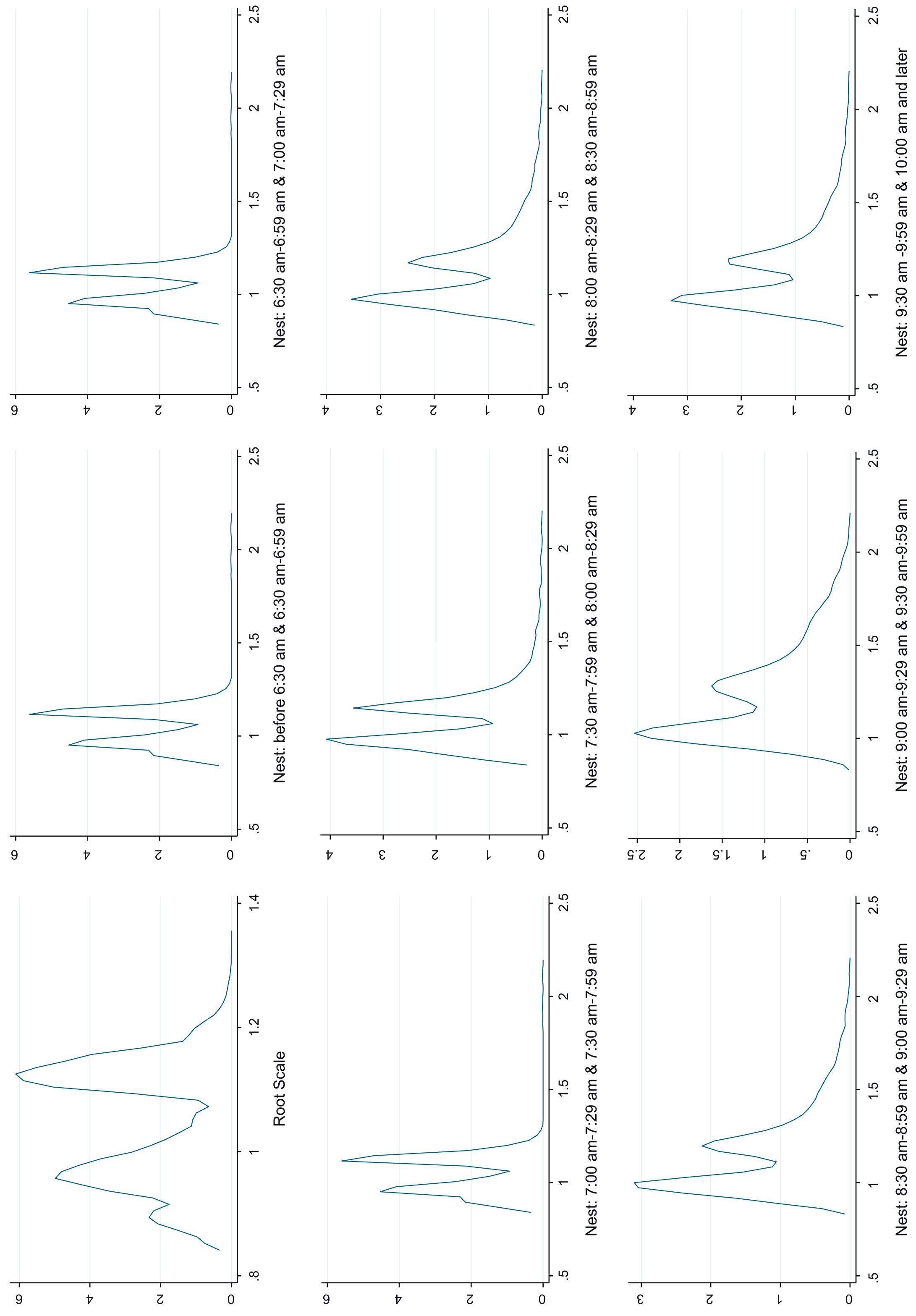

Fig. 3. Kernel density plots of root and nest scale parameters for transit user's departure time choice.

scale parameter has multiple peaks and the transit root scale parameter has two distinct peaks. Having multiple peaks in the kernel density plot indicates the existence of multiple distinct classes of commuters. As opposed to the fixed root scale parameter, the parameterization of root scale clearly proves the ability of the proposed Het-GenL model to capture a wide range of heterogeneity and heteroskedasticity present in the commuters of the study area. Also, having a higher number of peaks in the root scale parameters of auto users as compared to that of transit users indicates the existence of higher numbers of distinct auto user classes than the number of transit users' classes. Comparing the modal values of the root scale peak, it is clear that auto users' classes are very close in terms of modal root scale values. However, in case of transit users, two distinct classes have distinctively different modal root scale parameter values. The class with the lower root scale modal value refers to the choice users compared to the class with higher modal value of root scale parameter who are more captive users. The choice users have a lower root scale and hence their choice behaviour is less predictive than the captive users. It is clear that the Het-GenL model is capable of capturing such behavioural paradigms in the choice model within a closed form model formulation.

Interestingly, contrary to its root scale parameter distribution, the nest scale parameters of the auto users' departure time choice model shows a unique single-peak distributional pattern. However, the nest scale parameters of the transit users' departure time choice model show a similar double-peak distributional pattern to its root scale parameter. The correlation between adjacent time slots increases from early morning 9 am and then decreases gradually. This exactly follows the departure time distribution of commuting trips. The frequency of departure increases from early morning until the peak of the peak period (around 9 am) and then gradually decreases. So, it empirically validates the capability of Het-GenL model to accommodate artificial boundary aggregation errors induced by such discretization. In the case of the transit users' departure time choice model, bimodal distributions of the nest scale parameter are stable across the time-of-day. It indicates the fact that transit users' departure time choices are constrained by transit schedules. So, the choice users are more discrete about alternative 30-min time slots than the captive users and hence have lower modal values of the nest scale parameter. However, both choice and captive users show a generally uniform perception of the correlation between adjacent departure time slots throughout the day. A possible explanation is that such a perception is basically defined by the transit service quality (the posted transit service schedules), which do not change day by day.

In terms of covariates, commuter's personal attributes as well as transportation service attributes are found to be highly significant in influencing the root scale parameter. The root scale parameter basically explains the baseline heterogeneity across the population. A high value of the scale parameter indicates more stable choice (more predictive). An interesting finding is that variables used to parameterize root scale have completely opposite effects in the auto and transit departure time choice models. Root scale parameterization captures the basic and distinctive characteristics of auto and transit users in the study area. Age plays a significant role in defining the root scale parameter of both auto and transit departure time choices with completely opposite effects. In the case of auto departure time choices, commuters younger than 45 years old have more predictive choice patterns than the commuters aged more than 45 years.

However, in the case of transit departure time choices, commuters younger than 45 years old have less predictive choice patterns than those older than 45. This is a very interesting finding and it refers to the fact that younger people who drive to work with longer work hours and defined schedules have more stable choice patters. Contrary to this, commuters older than 45 years who drive to work may not work longer hours and may have more flexible work schedules that allow for less stable departure time choices. The opposite is true for transit users. It is evident that males have more stable departure time choice patterns than females for auto departure time choices. However, a full time job status increases the root scale parameter of auto departure time choices, but decreases the same for transit departure time choices.

Travel cost enters into both the systematic utility and root scale parameter of the auto departure time choice model, but it enters only into the root scale parameter of the transit departure time choice model. It seems that higher travel cost per unit distance decreases the root scale parameter of auto departure time choices, but it increases the root scale parameter of transit departure time choice. Compared to transit users, auto users can have more flexibility in choosing departure times. So, an increasing unit cost may influence the auto users to choose a different departure time choice to reduce the total travel cost. However, departure time choices of the transit users are more defined by transit services available in the study area. While investigating the scale parameter distribution patterns, we also found that a significant portion of transit users are captive. A possible explanation would be that an increase in fare will drive the choice transit users away and thereby increase the share of captive users. Departure time choice patterns of the captive users will definitely be more stable and hence an increasing fare indicates an increase in root scale for the transit departure time choice model.

In-vehicle travel time enters into both the systematic utility and root scale parameter of the auto departure time choice model. In the case of the transit departure time choice model, in-vehicle travel time enters into systematic utility function, but the total travel time (in-vehicle + waiting + walking) enters into the root scale parameters. Travel time has opposite effects in auto and transit departure time choice models. It is clear that longer travel time reduces the root scale parameter of auto departure time choice model, but it increases the root scale of transit departure time choice. In the case of auto departure time choices, increasing travel time influences choosing alternative departure time options and hence the choice pattern becomes less stable. On the other hand, a significant portion of transit users are captive and increasing travel time may increase this portion even higher. Captive users will have little option to improve the situation by changing departure times in the face of increasing travel time.

The location of a trip origin and destination within downtown Toronto increase the root scale parameter of the transit departure time choice model, but they reduce it for the auto departure time choice model. Downtown Toronto is congested for auto drivers but well served by transit. This is true for both in-bound and out-bound traffic in Toronto. So, the explanation can be that auto users in this case would try to avoid congestion and hence would have a less stable departure time choice pattern. On the other hand, transit users in this case have highly available transit services and show very stable departure time choice patters. The logarithm of distance significantly explains the additional nest scale parameter component of auto departure time choices and the total access time (waiting time + walking time) defines the nest scale parameters of auto departure time choices. A higher value of a nest scale parameter refers to a higher perception of similarity between the corresponding adjacent departure time slots. Longer commuting distance makes the time segments within 7:00–9:00 am appear more similar than other time slots to auto users. Increasing transit access time increases the perception of similarities between adjacent time slots after 7:30 am.

A comparison of these results with previous departure time choice studies indicates similarities. For example, in one of the earliest studies on departure time choice modelling, Small (1982) shows that in San Francisco workers with flexible work schedules are likely to travel to work later in the morning. Comparing this to the departure time choices of the GTHA commuters shows that those with shorter work duration – potentially a characteristic comparable to flexible work hours – also tend to leave later in the morning. In another study of San Francisco morning commuter departure time choice, Abkowitz (1981) reveals that transit users are not likely to travel early in the morning due to infrequent off-peak transit service. The results of this work support the fact that transit is undesirable before the peak service begins; the alternative specific constant parameter for transit departure time choice has a negative value before 7 am in the morning. With regards to job type, the results of this study also show that professional workers prefer to travel to work in the middle of the morning peak period as compared to very early in the morning.

In a recent study on commuting departure time choice modelling in New York, Chu (2009) finds that work schedules strongly influence work departure time choices. Specifically, Chu's finding that those with shorter work duration depart later for work has been supported by the results of this work. Similar to Chu, these results find that drivers are more strongly motivated by travel time than by cost because neither New York nor Toronto currently use variable road pricing strategies. De Jong et al. (2003) also found that departure time choice is affected by travel time and cost, which are consistent with the findings of this investigation. Bajwa et al. (2006) found that models that recognize that alternate choices are correlated perform better than those that do not; this has been supported by a large number of statistically significant parameters defining

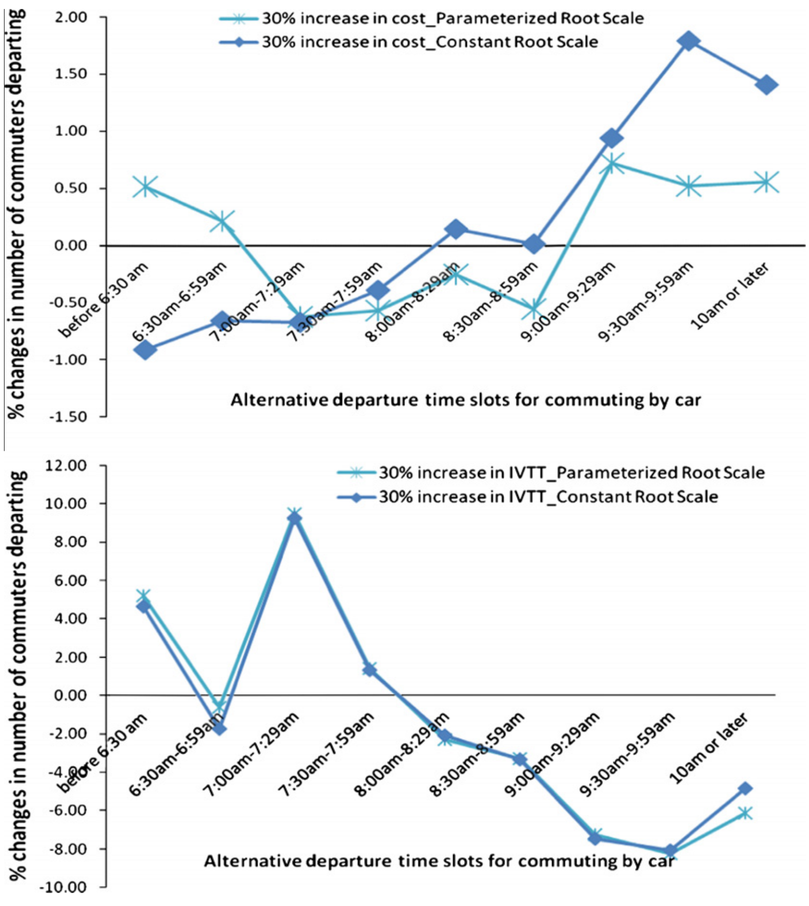

Fig. 4. Effects of root scale parameterization on auto user's departure time choice model sensitivity.

the root and nest scale parameters of the Het-GenL model presented in this paper. It is also clear that the same variable may have influence on multiple components of choice model formulation.

For example, it is clear from this investigation that, travel cost and travel time influences the both systematic utility and root scale parameter of the auto user's departure time choice model. In the case of transit users, travel cost seems to influence only the root scale parameter; in-vehicle travel seems to influence both systematic utility and root scale parameter and transit access time seems to influence both the root scale and nest scale parameter of the departure time choice model. The proposed econometric model formulation is capable of capturing such complicated relationships of different variables with departure time choices. Implications of such complicated relationships may have differential effects of transportation policies influencing different attributes of transportation system performance. For example, Fig. 4 presents the sensitivity of travel cost and in-vehicle travel time (IVTT) changes with respect to departure time choices of auto users. It is clear that travel cost (fuel cost and parking) and in-vehicle travel time may have completely different effects if these are changed independently. In both cases, the sensitivity of the Het-GenL model is compared against a Gen-L model with constant scale parameters. It is clear that overlooking scale heterogeneity would over-estimate cost effects for early (before 7:30 am) departure time choice, but under-estimate cost effects on late (after 7:30) departure time choice. However, scale heterogeneity seems to have little effects on in-vehicle travel time sensitivity.

6. Conclusion

Departure time choice models for commuting are an important analysis tool for investigating urban transportation policies. Appropriate modelling structures for departure time choices can be a very useful tool for investigating travel demand management policies such as congestion pricing and variable transit fare. Different types of departure time choice models are presented in the literature and the application of discrete choice models is one of the dominant practices. Applications of discrete choice models for departure time choice include the multinomial logit model, ordered probability model and mixed logit modelling approach. Applications of multinomial logit models have a serious issue in terms of violating the IIA assumption, but applications of the mixed logit type approach overcome this. However, applications of mixed logit type models leave the likelihood function in a non-closed form so that they cannot be estimated using classical estimation techniques. Researchers have also investigated the application of ordered or generalized extreme value models. While such models can accommodate a wide variety of substitution patterns, heterogeneity and heteroskedasticity, the estimation is always a challenge because of restrictions necessary on different parameter values.

To complement to this trend of discrete choice modelling, this paper presents a closed form generalized extreme value model with overlapping choice set formations. The structure of the model falls into the General Category of Generalized Logit (GenL) models or Paired Combinatorial Logit (PCL) models. However, the proposed model also has parameterized scales, which captures preference heterogeneity and heteroskedasticity within a closed form model formulation. Two types of scale parameters are induced: the root scale parameter capturing heterogeneity and heteroskedasticity in choice behaviour and the nest scale parameter capturing substitution patterns of alternative departure time choices that are adjacent to each other. Such an approach can overcome the boundary errors induced by time discretization for departure time choice modelling. The proposed modelling structure is referred to as a Heteroskedastic Generalized Logit (Het-GenL) model.

The paper presents empirical applications of the Het-GenL model using TTS data collected in the GTHA in 2006. Separate models are estimated for auto and transit users. Empirical models prove the capability of the proposed econometric model in capturing differential effects of different explanatory variables of commuting departure time choice. It is clear that socio-economic and personal attributes of the commuters better explain root scale parameter than the systematic utility of alternative departure time choices. Only transportation level of service attributes, work duration and occupation specific attributes explain the systematic utility functions of both auto and transit departure time choice.

However, in the case of the scale parameter, it is clear that socio-economic as well as transportation level-of-service attributes play major roles. Empirical distributions of root and nest scale parameters clearly identify the presence of multiple classes of commuters who use private automobiles for commuting. However, in the case of transit, two distinct categories are obvious: choice users and captive users. The proposed model can implicitly capture the presence of multiple classes of commuters within users of the same mode though root scale parameterization. The presence of such a latent class structure within the commuter groups defines the sensitivities of different variables used to specify the utility functions.

The same variables are found to have opposite effects in auto and transit user's departure time choices. It is evident that transit departure time choices are defined by the patterns of transit services available in the study area. For example, the downtown Toronto has the best transit service in the region and most congested auto network. Hence, commuting trips originating in or destined to downtown Toronto by transit are more stable in departure time choice patterns than the auto trip counterparts. Similarly, increasing peak period traffic congestion resulting in increased travel time and cost may influence auto users to change their departure time choices. However, increasing transit travel time and fare may force the choice transit users to change modes and increase the proportion of captive transit users. In such a case, increasing travel time and cost would cause even more stable departure time choice patters of the existing transit users.

A commuter's age is found to be very significant in defining the root scale parameter of auto and transit departure time choices, but with opposite effects. Empirical models reveal that commuters younger than 45 years have more stable auto departure time choice patterns, but less stable transit departure time choice patterns. Gender is not found as a significant variable in influencing transit departure time choice patters, but it is found that male commuters have more stable auto departure time choice patterns. The proposed model is also validated against a simpler model with fixed scale parameters. It is found that the proposed scale parameterization provides a much better explanation of choice behaviour. It is clear that a constant scale assumption gives under-estimation of the elasticity of key variables such as travel cost.

Although the departure time choice model can explain many behavioural details, the explanation of some key findings remains arbitrary. For example, distribution patterns of the transit root scale parameter need to be further investigated. It is understood that a joint model of mode and departure time choice would be the next stage of this investigation. While joint mode and departure time choice models are presented in literature in the form of a joint discrete–continuous model, we feel the need to develop a joint discrete choice modelling framework for mode and departure time choices. The complexity of such a joint discrete choice model, in terms of model parameter estimation challenges is perceivable, but it is believed to be worth considering as the next stage of this research. Also, considering access station choice for transit jointly with mode and departure time choice would be considered for future investigation.

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References

Abkowitz, M.D., 1981. An analysis of the commuter departure time decision. Transportation 10, 283–297.
Abu-Eisheh, S.A., Mannering, F.L., 1989. Discrete/continuous analysis of commuters' route and departure time choices. Transportation Research Record 1138, 27–34.
APTECH, 2011. GAUSS Products. <http://www.aptech.com/AS_prodMF.html>.
Arnott, R., De Palma, A., Lindsey, C.R., 1990. Departure time and route choice for the morning commute. Transportation Research Part B 24 (3), 209–228.
Bajwa, S., Bekhor, S., Kuwahara, M., Chung, E., 2006. Discrete choice modelling of combined mode and departure time. The Paper Presented at the 11th International Conference on Travel Behaviour Research, Kyoto.
Bhat, C.R., Steed, J.L., 2002. A continuous-time model of departure time choice for urban shopping trips. Transportation Research Part B 36 (3), 207–224.
Börjesson, M., 2007. Departure time modelling applicability and travel time uncertainty. In: European Transport Conference.
Chin, A.T.H., 1990. Influences on commuter trip departure time decisions in Singapore. Transportation Research Part A 24, 321–333.
Chu, Y., 2009. Work departure time analysis using dogit ordered generalized extreme value model. Transportation Research Record 2132, 42–49.
De Jong, G., Daly, A.J., Pieters, M., Vellay, C., Hofman, F., 2003. A model for time of day and mode choice using error component logit. Transportation Research Part E 39 (3), 245–268.
Data Management Group (DMG), 2012. Transportation Tomorrow Survey. <http://www.dmg.utoronto.ca/transportationtomorrowsurvey/index.html>.
Ettema, D., Timmermans, H., 2003. Modeling departure time choice in the context of activity scheduling behavior. Transportation Research Record 1831, 39–46.
Ettema, D., Bastin, F., Polak, J., Ashiru, O., 2007. Modelling the joint choice of activity timing and duration. Transportation Research Part A 41, 827–841.
Fry, T.R.L., Harris, M.N., 2005. The dogit ordered generalized extreme value model. Australia New Zealand Journal of Statistics 47 (4), 531–542.
Gaudry, M.J.I., Dagenais, M.G., 1979. The dogit model. Transportation Research Part B 2, 105–111.
Habib, K.M.N., 2012. Modelling commuting mode choice jointly with work start time and duration. Transportation Research Part A 46 (2012), 33–47.
Habib, K.M.N., 2013. A discrete–continuous model considering budget constraint for the continuous part: application in joint mode and departure time choice modelling. Transportmetrica 9 (2), 149–177.
Habib, K.M.N., Day, N., Miller, E.J., 2009. An investigation of commuting trip timing and mode choice in Greater Toronto Area: application of a joint discrete–continuous model. Transportation Research Part A 43, 639–653.
Hendrickson, C., Plank, E., 1984. The flexibility of departure times for work trips. Transportation Research Part A 18 (1), 25–36.
Hess, S., Daly, A., Rohr, C., Hyman, G., 2007. On the development of time period and mode choice models for use in large scale modelling forecasting system. Transportation Research Part A 41, 802–826.
Hyman, G., 1997. The Development of Operational Models for Time Period Choice. Department of Environment, Transport and Regions, HETA Division, London, UK.
INRO, 2011. EMME, <http://www.inro.ca/en/products/emme/index.php>.
Koppelman, F., Wen, C.-H., 2000. The paired combinatorial logit model: properties, estimation and application. Transportation Research Part B 34, 75–89.
Kristoffersson, I., 2007. Implementation of Model for departure time Choice. Presented at the TRISTAN VI conference, Phuket Island, Thailand 2007.
Lemp, J.D., Kockelman, K.M., Paul, D., 2010. The continuous cross-nested logit model: Formulation and application for departure time choice. Transportation Research Part B 44 (5), 646–661.
McFadden, D., 1978. Modelling the choice of residential location. In: Karlquist, A. et al. (Eds.), Spatial Interaction Theory and Residential Location. North-Holland, Amsterdam, pp. 75–96.
Miller, E.J., 2007. A Travel Demand Modelling System for the Greater Toronto Area, Version 3.0. Joint Program in Transportation. University of Toronto.
Papola, A., 2004. Some developments on the cross-nested Logit model. Transportation Research Part B 38 (9), 833–854.
Polak, J.W., Jones, P.M., 1994. A tour-based model of journey scheduling under road pricing. In: 73rd Annual Meeting of the Transportation Research Board, Washington, DC.
Russo, F., Vitetta, A., Comi, A., 2009. Estimation of target time distribution for agri food products by road transportation. In: Schedule-Based Modeling of Transportation Network. Springer, US, pp. 267–283 (Chapter 14).
Small, K.A., 1982. Scheduling of consumer activities: work trips. The American Economic Review 72 (3), 467–479.
Small, K.A., 1987. A discrete model for ordered alternatives. Econometrica 55 (2), 409–424.
Swait, J., 2001. Choice set generation within the generalized extreme value family of discrete choice models. Transportation Research Part B 35 (7), 643–666.
Swait, J., Erdem, T., 2007. Brand effects on choice and choice set formation under uncertainty. Marketing Science 26 (5), 679–697.
van Vuren, T., Carmichael, S., Polak, J., Hyman, G., Cross, S., 1999. Modelling peak spreading in continuous time. In: Proceedings of European Transport Conference – PTRC, Cambridge, UK.
Vickery, W.S., 1969. Congestion theory and transport investment. American Economic Review 59, 251–261.

Vovsha, P., 1997. Cross-nested logit model: an application to mode choice in the Tel-Aviv metropolitan area. In: 76th Annual Meeting. Transportation Research Board, Washington DC. Paper #970387.
Whelan, G., Batley, R., Fowkes, T., Daly, A., 2002. Flexible models for analyzing mode and departure time choices. In: Proceedings of Association for European Transport Conference 2002.