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A GEV model with scale heterogeneity for investigating the role of mobility tool ownership in peak period non-work travel mode choices

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ABSTRACT

The paper presents results of investigation on mode choice behaviour for peak period non-work trips (trips that are made during the peak period and are not linked to any other trips). Pure non-work trips within the peak period represent a significant portion of peak period traffic. In the case of the Greater Toronto and Hamilton Area (GTHA), the study area of this investigation, around 11 percent of peak period trips are pure non-work trips and auto driving is the dominant mode. Also more peak period non-work trips are made using the auto passenger mode than all transit modes combined. This heavy auto dependency for pure non-work trips in the peak period, when transit service is at its highest throughout the day, requires an improved understanding of such mode choice behaviour. This paper uses data from a household travel survey collected in the GTHA to investigate peak period pure non-work trip mode choice in the context of household mobility tool ownership (auto and transit pass ownership). The paper also proposes an advanced econometric modelling approach for capturing preference heterogeneity as well as scale heterogeneity (heteroskedasticity). The model involves systematic parameterization of the scale parameter of a GEV model. Empirical models highlight the superiority of the proposed model over a homoskedastic model. Empirical model also explains the influence of household mobility tool ownership on peak period pure non-work trip mode choices in terms of explaining both preference heterogeneity and scale heterogeneity.

1. Introduction

Technological innovations, urban growth and socio-demographic changes in recent decades have resulted in changed lifestyles and, in turn an increase in travel for purposes not related to work (Habib and Miller, 2009). In many North American cities, the growth of non-work trips has been faster than that of work trips (Habib, 2011). Non-work trips are now a notable reason for travel even in peak periods (Nelson and Niles, 2000). Conventionally, urban travel demand analyses rely on the assumption that commuting trips account for the majority of the demand on the transportation system. Accordingly, peak hours are assumed to involve predominantly work related travel. Evidence shows that non-work trips are consistently contributing to peak period travel in urban areas. Non-work travel in the peak period is compounded with peak spreading observed in many urban areas, resulting in longer and more severe periods of congestion (Gordon et al., 1990). Non-work trip behaviour has generally been estimated very poorly (Chatterjee, 1995). The contribution of non-work trips to peak period travel is normally considered in the context of chaining with commuting trips (Bhat, 1997a, 1997b; McGuckin et al., 2005;

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Xian-Yu et al., 2011). However, beyond the growth in trip chaining, peak period pure non-work travel (not linked with any work trip) continues to grow (McGuckin et al., 2010). Little is understood about peak period pure non-work trips. With increasing traffic congestion during peak hours as well as peak spreading, it is very important to enhance our understanding of peak period pure non-work trips.

Overall growth of non-work travel is normally caused by increasing economic growth, increasing auto ownership, improvements in the transportation system, and cultural or lifestyle changes (Lee et al., 2009). Among these reasons, increasing household level auto ownership and improved peak period urban transit services may contribute significantly to peak period non-work travel growth. Intuitively, the peak period should be the most undesirable time for making non-work trips since travel time and cost are the highest during peak hours on weekdays. Therefore, it can be speculated that peak period non-work trips are either necessary trips, which must be scheduled during peak hours or latent trips resulting from increasing mobility options (auto ownership and improved transit services). In any case, the increase in non-work trips during peak hours contributes to the further aggravation of already congested urban transportation networks. It is therefore important to understand the motivation for those who choose to make non-work trips during peak hours despite the potentially undesirable effects of high demand.

Mitigating traffic congestion and emissions during peak hours increasingly requires attention to non-work trips (Kim and Ulfarsson, 2009; Nazelle et al., 2010; Habib et al., forthcoming). Understanding the motivation behind peak period non-work trips may allow for the design of efficient transportation demand management measures targeted at trips that are supposed to be easy substitutable with respect to time of the day or mode of transportation. Moreover, understanding the behavioural processes of choosing travel modes for peak hour non-work trips would help us designing better transit services in urban areas. To improve our understanding and address deficiencies in the literature, this paper presents an investigation of peak period non-work trip mode choice behaviour. The focus of the study is the trips that are not linked to any work or school trips and are made during the peak period (referred by ‘pure non-work trips’). To further explore the nature of pure non-work trips in the peak period, we seek the relationship between household level mobility tool ownership and mode choice behaviour. Household level mobility tool ownership is defined as the combination of auto ownership (with respect to the number of licensed drivers at home) and transit pass ownership. The paper uses an advanced econometric technique to identify the level and extent of the influence of mobility tool ownership on peak period pure non-work trip mode choice behaviour. In addition, the influence of land use and demographic attributes together with an individual's socio-economic attributes and transportation system performance attributes are investigated.

The paper is organized as follows: the next section presents a brief literature review on peak period non-work trip mode choice analyses and mode choice modelling approaches. The literature review section is followed by a description of the data used for this investigation, econometric modelling techniques, discussions on empirical models and policy implications. The paper concludes with a summary of important findings and identifies directions for future research.

2. Literature review

Non-work trips have been addressed by many researchers because of their increasing growth and complexity associated with their variability. However, the context of the investigation varies widely between different studies. One of the earliest studies on this issue is reported by Heggie (1983), which investigated the valuation of travel time savings for non-work travel. The focus of this investigation was mostly on the sampling and methodological issues related to estimating the value of travel time savings. Gordon et al. (1988) investigated non-work trip characteristics using national travel survey data. They used exploratory and trend analysis to understand the nature and trends of non-work trips. They speculated that non-work trips can be priced out of peak periods through pricing policies. Their investigation did not involve any behavioural analysis or modelling techniques. Moreover, evidence shows that peak period non-work trips have continued to increase since 1983, even with the increase in peak period congestion that results in increasing travel cost/prices. Later Gordon et al. (1990) also proved that peak spreading is unlikely to reduce peak period congestion and that non-work trips have a significant presence in the peak period.

Tringides et al. (2004) use advanced econometric techniques to investigate the reasons for making peak period non-work trips. The focus of their investigation is the relationship between time-of-the day choice and mode choice of non-work trips in both peak and off-peak periods. They found that different relationships exist between departure time and mode choice for workers as compared to non-workers. For non-workers, it seems that modal availability influences time-of-the day choice. Recently Currie and Delbosc (2011) investigated the role of mode choices on non-work trips chained with work trips and found that travel mode choice influences the complexity of trip chains. Some researchers investigated non-work travel from the context of comprehensive travel activity scheduling. Bradley and Vovsha (2005) investigated daily activity scheduling behaviour and found that non-work trips are influenced by household automobile availability. The relationship between mobility options and the opportunity to make non-work trips is considered by some researchers. Petersen and Vovsha (2006) and Vovsha and Petersen (2008) investigate car allocation among household members and its influence on non-work trip characteristics. Anggraini et al. (2011) investigate factors influencing car allocation among household members for non-work activities. Lee et al. (2009) find that non-work trips during the peak period are increasing and contributing significantly to increasing traffic congestion. McGuckin et al. (2010) find that such trips are increasing rapidly. Yun et al. (2011) found that non-work trips are generally flexible in nature and are influenced by changes in accessibility and mobility.

The approaches of these previous studies on non-work trips are either exploratory in nature, or based on econometric models. Exploratory research reveals the importance of an improved understanding of peak period non-work trips. However, econometric investigations are more focused on specific aspects of non-work travel behaviour. The majority of the previous works focus on non-work trip generation or trip chain formation (Bhat, 1997a, 1997b; Boarnet and Sarmiento, 1997; Castro et al., 2010; Kim and Ulfarsson, 2009; Lee and Ahn, 2005; McGuckin et al., 2005; Nazelle et al., 2010; Rajagopalan et al., 2008; Senbil et al., 2008; Strathman et al., 1994; Wu and Xin, 2008; Xian-Yu et al., 2011). No one has investigated peak period pure non-work trip mode choice behaviour. Urban peak periods are the most congested time period in a day and pure non-work trips made during peak period do not seem to be flexible enough to schedule during the off-peak period. Some researchers investigated the role of household mobility tool ownership and its influence on creating opportunities for peak period non-work travel. However, investigations are focused either on the allocation of mobility tools among household members or the influence of mobility tool ownership on peak period linked non-work trips. None of the previous studies have had a specific focus on peak period pure non-work trips. An improved understanding of the nature of peak period pure non-work trips is necessary and has significant policy relevance.

Travel demand management and congestion mitigation policies often target peak period travel. Transit fare and service design policies are mostly based on peak period travel demand because transit is most competitive during the peak period. However, urban transportation policy measures may have very different implications for peak period non-work trips that are linked with commuting trips as compared to pure non-work trips. Linked non-work trips are different in nature from pure non-work trips in the peak period as the linked non-work trips are more opportunistic in nature than the pure non-work trips. Making detours for any non-work trips while making a commuting trip refer trip chaining compared to making a pure non-work trip in the peak period. Making a pure non-work trip during commuting peak hours refers urgency to make the non-work trip even during the commuting peak hours while the travel cost is the highest. So, it is interesting to investigate how mobility tool ownership influences such pure non-work trips mode choices. Implications of different travel demand management policies could be very different for linked and pure non-work peak period trips. If pure non-work trips are not opportunistic in nature as linked non-work trips in peak period, it is understandable that any restrictive transportation policies (e.g. pricing policies, time restriction policies, etc.) designed to reduce peak period congestion would reduce the linked trips more than the pure non-work peak period trips. However, the source of opportunistic nature can be very different for pure non-work peak period trips and linked peak period non-work trips. Unlike linked trips, the motivation of pure non-work peak period trips could be sourced from household need as well as availability of mobility tools. So, influencing such trips may require policies that simultaneously influence peak period travel time and/or cost as well as household level mobility tool ownership levels.

Previous studies provide insight into the influence of transportation policy on peak period linked non-work trips considering only the effects of transportation level of service attributes. However, findings of those studies of linked non-work trips may not be applicable for peak period pure non-work trips. Considering the increasing growth of peak period pure non-work trips, an improved understanding of such trips is a growing demand and will be necessary to develop efficient transportation policies. In a bid to contribute to this critical gap in existing research literature, this study sets its focus on peak period pure non-work trips. Considering the increasing growth and implications to urban traffic congestion, the paper considered the morning peak period, which is the most congested time of a weekday. The study deals with mode choice decisions of peak period pure non-work trips because mode choice decisions have direct urban transportation policy relevance.

With the objective of gaining a comprehensive understanding, this study considers mode choices for peak period pure non-work trips in the context of household mobility tool ownership levels. Assuming that pure non-work trips in the peak period may be influenced heavily by the mobility options, we investigate the role of household level mobility tool ownership in mode choice for peak period non-work trips. Household level mobility tool ownership is classified according to the combination of the number of automobiles with respect to the number of driving license holders and an individual's transit pass ownership. An advanced econometric modelling approach is developed to identify the systematic and random effects of mobility tool ownership on mode choice decisions. Considering the fact that higher variability is involved in non-work travel, we develop a heteroskedastic choice model through scale parameterization of the choice model. Scale parameterization as a function of household mobility tool ownership as well as aggregate zonal attributes also allows for capturing heteroskedasticity. Empirical models are developed for a dataset collected in GTHA in 2006. The next section presents a brief discussion on the dataset.

3. Data

The data source used in this study is a household travel survey, named the Transportation Tomorrow Survey (TTS), conducted in the Greater Toronto and Hamilton Area (GTHA) in 2006. The survey collects information on socio-demographic characteristics and one weekday's trip information from all household members above 11 years of age (children younger than 11 years are considered dependent). It is a 24-h weekday travel diary survey. The basic survey methods consist of an advance letter mailed to each of the selected households, followed by a telephone interview to collect demographic data and travel information. The TTS survey area covers approximately 60 percent of Ontario's total population and 5 percent of all households in the survey area are contacted. The sample is representative of the attributes of the population with respect to census data. TTS data are expanded to represent the whole population of the GTHA by using expansion factors calculated by comparing TTS data with census data.

Trip purposes are classified into several categories: work, school, shopping, facilitating passengers and others. The peak period is considered to be between 6 am and 9 am. In this study, trips that are not linked to any work or school trips and are made during the peak period are considered pure non-work trips. So, these trips include ‘shopping’ and ‘others’ trips made during peak period. After cleaning the dataset for some missing values and unreasonable attributes, it is found that in the peak period a total of 150,897 trips are recorded and 13,835 of those are pure non-work trips, which is approximately 9.1 percent of total peak period trips. In the case of the expanded sample representing the population of GTHA, an estimated total of 2.8 million trips are made in the peak period and 0.33 million of those are pure non-work trips, around 11 percent of all peak period trips. In the estimation of the econometric model, we considered the expanded sample to represent the whole population of the GTHA. The survey area is divided into approximately 2000 zones.

Travel modes in the TTS survey are classified into 7 categories:

1. Auto Driver (AD)
2. Auto passenger (AP)
3. Transit with walk access (TWA)
4. Subway park & ride (SAA)
5. GO[1] transit with transit access (GTA)
6. GO transit park 7 ride (GAA)
7. Non-motorized transport (NMT)

The drive alone mode is considered to be available to any individual holding a valid driving license and having at least one car at home. The auto passenger mode is feasible for all people. GO transit provides service at the regional level in the GTHA. TWA and GTA modes are feasible if the Origin–Destination (OD) pair is served by a valid transit line. SAA and GAA are feasible in case the OD pair does not have a feasible way to access the transit service, but the nearby subway or GO station has a park & ride facility. Finally NMT is considered feasible for any distance below 3 km. These are the modal feasibility rules used to define the choice set of mode choices. In terms of modal share of peak period pure non-work trips, AD is the most dominant mode, representing around 77 percent of total pure non-work trips. Following AD, AP is the second most dominant mode, at around 16 percent of total trips and TWA is the third most dominant mode, constituting around 5 percent of total pure non-work trips. NMT represents only around 1 percent and the rest of the modes have a very minor role. Alternative Level-of-Service (LOS) attributes are estimated using a traffic assignment model. The traffic assignment model used in this study uses the DUE traffic assignment procedure with the expanded peak period OD matrix from TTS data. It is validated using traffic cordon count survey data.

An individual's age, gender, working and student status, possession of a valid driver's license and transit pass are available for capturing individual specific preference heterogeneity. In terms of household specific attributes, household size, location in the GTHA and the number of private automobiles is available. Land use and demographic attributes of home location zones are included using census data and land use inventory data. The area of the home zone, population size, population density, zonal average auto ownership, total employment and employment per unit area per zone, and proportions of employment categories are also included for investigation. Unfortunately, the dataset does not include income information at all. So, we could not investigate the effect of household or personal income on peak period non-work trip mode choice preferences. We combine the information of an individual's possessions of a transit pass and the number of private automobiles per valid driving license holder in the household to categorize household mobility tool ownership level. Table 1 defined 8 mobility tool ownership categories and the corresponding proportions in the dataset.

It is clear that majority of the individuals in the dataset belong to the category of household mobility tool ownership where less than one car is available per valid license holders in the household. However, the majority of peak period pure non-work trips are made by the drive alone mode. This reveals that there is a complex relationship between household level mobility tool ownership and mode choice for peak period pure non-work trips. The next section explains the econometric model developed in this study.

4. Econometric modelling approach

We consider a Random Utility Maximization (RUM) approach to model peak period pure non-work trip mode choices. In order to explain the model formulation, let us define the utility of a mode as

$$U_{im} = V_{im} + \varepsilon_{im}, \tag{1}$$

where U_{im} refers to the total utility of choosing mode m by individual i; V_{im} refers to the systematic component and ε_{im} to the random component of this total utility. Here, the number of individuals varies from $i=1$ to $i=N$ and the number of

[1] GO transit is commuter transit service in Greater Toronto and Hamilton Area. For detail description of GO transit service, please see: http://www.gotransit.com/public/en/aboutus/whatisgo.aspx (accessed in January 2014).

Table 1
Categories of mobility tool ownership.

Category	Description	Observed proportions (%)
1	No car and no transit pass	2.5
2	Less than one car per valid driving license holders and no transit pass	75
3	One car per valid driving license holders, but no transit passes	16
4	More than one car per valid driving license holders and no transit pass	1.8
5	No car, but transit passes	1.3
6	Less than one car per valid driving license holders and transit passes	3
7	One car per valid driving license holders and transit passes	0.3
8	More than one car per valid driving license holders and transit passes	0.02

alternative modes available to any individual may vary from $m=1$ to M (the mode allocation rule is explained in the data description section). The Generalized Extreme Value (GEV) choice family is obtained by assuming that the random vector (ε_{im}) is GEV distributed with Cumulative Distribution Function (CDF), $F(\cdot)$ taking the form

$$F(\varepsilon_{i1},\ \varepsilon_{i2},\ \varepsilon_{i3},\dots,\ \varepsilon_{iM})=\exp(-G(e^{-\varepsilon_{i1}},\ e^{-\varepsilon_{i2}},\ e^{-\varepsilon_{i3}},\dots,\ e^{-\varepsilon_{iM}})) \tag{2}$$

Here G (…) is a non-negative and homogenous function of degree one. This defines a multivariate extreme value distribution with the probability of choosing any mode, m, as (McFadden, 1978; Ben-Akiva and Lerman, 1985)

$$P_{im}=\frac{e^{v_{im}}G_m(e^{v_{i1}},\ e^{v_{i2}},\ e^{v_{i3}},\dots,\ e^{v_{im}},\ \dots e^{v_{iM}})}{G(e^{v_{i1}},\ e^{v_{i2}},\ e^{v_{i3}},\dots,\ e^{v_{im}},\ \dots e^{v_{iM}})} \tag{3}$$

Here G_m (…) indicated a partial differential of G (…) with respect to mode m. In this formulation, the fundamental assumption is that the marginal distribution of each random element has constant variance. The CDF of an extreme value distribution takes the form (Johnson et al., 1994)

$$\begin{aligned}&F(\varsigma)=\exp(-e^{-(\varsigma-\xi)/\mu})\ \text{with}\\ &\quad\text{Mean},\ \ E(\varsigma)=\xi+\mu\gamma,\quad \gamma\ \text{ is Euler's Constant}\\ &\quad\text{Variance},\ \ \mathrm{Var}(\varsigma)=\pi^2/(6\mu^2),\quad \mu>0\ \text{ a scale parameter}\end{aligned} \tag{4}$$

Dubin and Zeng (1991) found that introducing heteroskedasticity in the marginal distribution of the random error term of the mode choice utility is not possible; rather we need to use the scale parameter to induce heteroskedasticity across the alternative modes and individuals. As per Dubin (1985), for a non-zero scale parameter with linear homogeneity assumption, we can re-write Eq. (2) as

$$F(\varepsilon_{i1},\ \varepsilon_{i2},\ \varepsilon_{i3},\dots,\ \varepsilon_{iM})=\exp(-G(e^{-\varepsilon_{i1}\mu_{i1}},\ e^{-\varepsilon_{i2}\mu_{i2}},\dots e^{-\varepsilon_{im}\mu_{im}},\dots e^{-\varepsilon_{iM}\mu_{iM}})) \tag{5}$$

The corresponding marginal distribution of any random element, ε_{im} is

$$\begin{aligned}F(\varepsilon_{im})&=F(\infty,\dots,\ \varepsilon_{im},\dots,\ \infty)\\ &=\exp(-G(0,\dots,\ e^{-\varepsilon_{im}\mu_{im}},\dots,\ 0))=\exp(-a_m e^{-\varepsilon_{im}\mu_{im}}).\end{aligned} \tag{6}$$

Here $a_m=G(\delta_{1m},\ \delta_{2m},\ \delta_{3m},\dots,\ \delta_{Nm})$ and where $\delta_{im}=1$ if $i=m$, 0 otherwise. Eq. (6) is an extreme value distribution with variance $(\pi^2/6\mu^2_{im})$. This leads to the formulation of the probability of choosing mode, m, by an individual, i, as

$$P_{im}=e^{V_{im}\mu_{im}}G_m(e^{V_{i1}\mu_{i1}},\ e^{V_{i2}\mu_{i2}},\dots e^{V_{im}\mu_{im}},\dots e^{V_{iM}\mu_{iM}})/G(e^{V_{i1}\mu_{i1}},\ e^{V_{i2}\mu_{i2}},\dots e^{V_{im}\mu_{im}},\dots e^{V_{iM}\mu_{iM}}) \tag{7}$$

For the peak period non-work trip mode choice situation, it is very much likely that a Tree-logit (Daly, 1985; Wen and Koppelman, 2001) structure would be appropriate because of the presence of unobserved shared properties of certain mode clusters. According to the transportation system configuration of the study area, there are four possible types of modes, which may result in four possible modal clusters. These are: auto cluster, local transit cluster, GO transit cluster and non-motorized cluster. Let us define:

- The scale parameter for auto cluster (including Auto Driving: AD and Auto Passenger: AP) by μ_A.
- The scale parameter for local transit cluster (including Transit Walk Access: TWA and Transit Auto Access: TAA) by μ_T.
- The scale parameter for regional transit cluster (including GO transit with Transit Access: GTA and Go transit with Auto Access: GAA) by μ_{TA}.
- The scale parameter for Non-Motorized Transportation (NMT) mode, which is the root scale, by μ.

The generating function corresponding to such tree structure takes the form

$$G_i=\left(\sum\nolimits_{m=AD,AP}e^{\mu_A V_{im}}\right)^{\mu/\mu_A}+\left(\sum\nolimits_{m=TWA,TAA}e^{\mu_T V_{im}}\right)^{\mu/\mu_T}+\left(\sum\nolimits_{m=GTA,GAA}e^{\mu_{TA} V_{im}}\right)^{\mu/\mu_T A}+(e^{\mu V_{iNMT}}) \tag{8}$$

This $G(\cdot)$ function with root scale μ is subscribed to by the individual commuter, with the second level scales μ_{TA}, μ_T and μ_A varying by the corresponding mode clusters. Under the additive generating function assumption of the GEV structure, the mode choice probabilities of this decision tree can be expressed as the product of conditional probabilities, as specified in the following expressions (the subscript for the individual is omitted from these expressions for clarity):

Construct Nodes for any nest:

$$Q_{Nest} = \frac{\exp(\mu I_{Nest})}{\sum_{nest = A,T,TA,NMT} \exp(\mu I_{nest})}; \; Nest\ refers\ to\ A\ or\ T\ or\ TA\ or\ NMT \tag{9}$$

Inclusive values:

$$I_{Nest} = \frac{1}{\mu_{Nest}} \ln\left(\sum_m \exp(\mu_{Nest} V_m)\right) \tag{10}$$

Here

- For the auto nest (A), $\mu_{Nest}=\mu_A$ and $m=$AD and AP.
- For the local transit nest (T), $\mu_{Nest}=\mu_T$ and $m=$TWA and TAA.
- For the regional transit nest (TA), $\mu_{Nest}=\mu_{TA}$ and $m=$GTA and GAA.
- For the non-motorized nest (NMT), $\mu_{Nest}=\mu$ and $m=$NMT and the inclusive value collapses to V_{NMT}.

The conditional probability of alternatives within the nests becomes:

$$\begin{aligned} &P_{m|Nest} = \frac{\exp(\mu_{Nest} V_m)}{\sum_{m'} \exp(\mu_{Nest} V_{m'})}; \\ &Nest\ refers\ to\ A\ or\ T\ or\ TA\ or\ NMT \\ &m \text{ refers to a specific alternative within a nest} \\ &\text{and } m' \text{ refers all possible alternative within a nest.} \end{aligned} \tag{11}$$

In our case,

- For the auto nest (A), m' refers to AD and AP.
- For the local transit nest (T), m' refers to TWA and TAA.
- For the regional transit (TA), m' refers to GTA and GAA.
- For the non-motorized nest (NMT), there is only one alternative and hence the conditional probability equals to 1.

Finally the unconditional Mode Choice Probabilities become

$$P_m = P_{m|Nest} Q_{Nest} \tag{12}$$

In the expressions above, it can be assumed that the systematic utilities are given by linear-in-parameters expressions such as

$$V_m = \beta' X_m. \tag{13}$$

The systematic utility function captured systematic effects of different covariates. However, capturing the variations of choice making behaviour across the population is often difficult to do using only the systematic utility function. An alternative approach of accommodating heterogeneity is to consider mixed logit or probit models, where parameter and/or scale of choice models are considered to have distributions rather than being fixed across the population; otherwise it is assumed that the random utility components follow multivariate normal distributions (Train, 2003). In the case of the mixed logit approach, we require explicit assumptions of the distribution types for the parameters and scales. In the case of both mixed logit and probit, the probability functions no longer remain in closed form. This may not be a problem for parameter estimation or even practical application; however, distributional assumptions are to be made by the researchers.

An alternative approach of capturing heterogeneous choice making behaviour without considering any distribution assumption would be parameterizing the scales of the GEV model. Parameterizing the scale allows capturing of similarities/dissimilarities as well as the complexities of choice making. It is possible to capture both heterogeneity as well heteroskedasticity through careful parameterization of GEV scale parameters. Scale parameterization for the logit model was recently investigated by several researchers and often termed as the logit model with scale heterogeneity (heteroskedasticity). Such interest stems from the idea that heterogeneity in attribute coefficients may be accounted for by scale effects since choice behaviour may be more random for some choice makers than others (Louviere et al., 1999). Hess et al. (2010) recently extended the covariance heterogeneity model of Bhat (1997a, 1997b) from fixed coefficients to random coefficients. Their approach is focussing on only the nesting parameter for parameterization. On the other hand, recently, Fiebig et al. (2010) propose a generalized modelling structure that can generate both mixed logit and/or logit model with scale heterogeneity. Greene and Hensher (2010) and Hess and Rose (2012) investigated the relationship between preference heterogeneity and scale heterogeneity for modelling choice behaviour and concluded that careful consideration is necessary in deciding one over the other while modelling through the mixed logit approach. However, this previous researches consider either parameterizing the nesting parameter of GEV model or use the mixed logit approach to capture scale heterogeneity. To complement this recently evolving body of literature, we accommodate scale heterogeneity within a closed form GEV structure. In this paper we follow a more generalized approach of parameterizing scale parameters; rather than only the nesting parameter. To evaluate the performance of the heteroskedastic GEV model, we compare model parameters against MNL and Nested Logit (NL) models. We do not intend to compare the proposed heteroskedastic GEV model with the mixed logit model because it would be difficult to identify a standard mixed logit formulation because of a multitude of distributional possibilities.

Scale parameterization for the heteroskedastic GEV model requires careful investigation for identification. Normalization is necessary to ensure proper identification of the model parameters. If we set all scale parameters to the unit value, the full tree-structure collapses to a Multinomial Logit (MNL) form. However, depending on the presence of correlations within and across the modal clusters, a variety of nesting patterns are feasible. For example, if we can estimate μ_{TA}, μ_T and μ_A by setting the root scale $\mu=1$, we can get one auto and two transit nests. Similarly, setting $\mu_T=\mu_{TA}$ and $\mu=1$, we can get one auto nest and one transit nest. In another case, setting $\mu_T=\mu_{TA}=\mu=1$, we can get one auto nest only. However, setting the reference scale parameter to 1 does not allow for capturing heteroskedasticity. Heteroskedasticity across the population can be captured by parameterizing the scale parameter as a function of different variables. Two types of parameterization are possible:

Option 1: Parameterizing the nesting scale parameters by setting the reference scale parameter to 1.

Option 2: Parameterizing both nesting and reference scale parameter as function of variables, but ensuring that for each variable, either one scale or a group of people are set as references.

Option 2 is the most comprehensive form of scale parameterization, where all scale parameters can be estimated for the sample data set. In addition to proper identification it should also be ensured that any nest specific scale parameter should be higher in magnitude than the root/reference scale parameter. Also, forcing the scale parameter to be more than or equal to 1 is necessary for the stability of parameter estimation process and the RUM condition to be satisfied. These are to ensure that the choice model structure is theoretically legitimate and consistent for welfare analysis. As per the basic definition, the scale parameters should be positive and to ensure this we can express the scale parameters as an exponential function.

$$\mu_{Nest} = 1+\exp(\alpha_{Nest}+\textstyle\sum\lambda Z);\ Nest = A,\ T \text{ and } TA \tag{14}$$

$$\mu = 1+\exp(\textstyle\sum\lambda Z) \tag{15}$$

Here α_A, α_T, and α_{TA} indicate nest specific constant terms. Variables Z and corresponding parameters λ should be carefully specified as the scale parameterization affects elasticity calculation. In the case of direct elasticity (E_D) of any variable x_m for mode m, the equation becomes

$$E_D = \frac{\partial P_m}{\partial x_m}\frac{x_m}{P_m} = \frac{x_m}{P_{m|Nest}P_{Nest}}\frac{\partial(P_{m|Nest}P_{Nest})}{\partial x_m} = \frac{x_m}{P_{Nest}}\frac{\partial(P_{Nest})}{\partial x_m} + \frac{x_m}{P_{m|Nest}}\frac{\partial(P_{m|Nest})}{\partial x_m} \tag{16}$$

Here

$$\frac{x_m}{P_{Nest}}\frac{\partial(P_{Nest})}{\partial x_m} = \beta_{x_m}x_m\mu(1-P_{Nest})P_{m|Nest}$$

and

$$\frac{x_m}{P_{m|Nest}}\frac{\partial(P_{m|Nest})}{\partial x_m} = \beta_{x_m}x_m\mu_{Nest}(1-P_{m|Nest})$$

So, the general formula of direct elasticity becomes

$$E_D = \beta_{x_m}x_m\mu_{Nest}\left(1-\left(1-\frac{\mu}{\mu_{Nest}}\right)P_{m|Nest}-\frac{\mu}{\mu_{Nest}}P_m\right) \tag{17}$$

For the alternative corresponding to the root scale, the nest and the root scale parameters are the same ($\mu_{Nest}=\mu$) and hence the direct elasticity collapses to the form

$$E_D = \beta_{x_m}x_m\mu(1-P_m) \tag{18}$$

For cross elasticity (E_C), two types of situations may occur: cross elasticity with respect to an alternative within the same nest or in different nest. In the case of cross elasticity of any variable ($x_{m\text{-}}$) with respect to an alternative (m-), which is in a difference nest or root nest (*Nest*-), it becomes

$$E_C = -\beta_{x_{m-}}x_{m-}\mu_{Nest-}P_{Nest-} \tag{19}$$

However, if the alternative is in the same nest (*Nest*), then it becomes

$$E_C = -\beta_{x_{m-}}x_{m-}\mu_{Nest}P_{m-|Nest}\left(1-\frac{\mu}{\mu_{Nest}}(1-P_{Nest})\right) \tag{20}$$

The heteroskedastic model presented in this paper allows for estimating the root scale parameter of a group (considering a specific group as the reference group). Since, we parameterized the scale parameter as functions of variables, the identification issue discussed here refer to the individual variables used for parameterization (Forsey et al., forthcoming; Sasic and Habib, forthcoming).

5. Empirical models

Empirical models are estimated using the full dataset of peak period pure non-work trips and expansion factors are considered in the estimation process so that the empirical model represents the population behaviour of the GTHA. Variables are included in the models based on previous theoretical and empirical works on mode choice modelling and intuitive arguments regarding the effects of exogenous variables. The final specifications presented in this paper are based on a systematic process of eliminating variables found to be statistically insignificant and on considerations of parsimony in representation. Coefficients are considered statistically significant if the corresponding two-tailed t-statistics satisfy the 95% confidence interval, ($t = 1.96$). Some variables with marginally significant coefficients (t-statistics lower than 1.96) are retained in the final specification because they provide useful insights in to the behavioural processes. Finally, two separate models are reported in this paper, one is a heteroskedastic GEV model and the other is a homoskedastic MNL model. Systematic utility functions of these two models are kept the same as it allows us to compare the respective parameters. Empirical models are presented in Table 2. Goodness-of-fit values reported in the table refer to rho-square values

$$\text{Rho} - \text{sqaured value} = 1 - \frac{\text{Loglikelihood of full model}}{\text{Loglikelihood of null or constant} - \text{only model}} \tag{21}$$

The null model considers that all alternatives are equally likely for every individual in the dataset and the constant-only model represents market segmentation.

Table 2 presents the heteroskedastic and a multinomial logit (MNL) model which is a Homoskedastic model. Estimation of a homoskedastic nested logit model (nested logit with constant scale parameter) did not result any statistically significant constant nest scale parameter. So, for the heteroskedastic model we parameterized the scale parameters of the clusters/nests. For the heteroskedastic model four clusters/nests are considered and these are auto, local transit, regional transit and non-motorized modes. From comparison, it is clear that both models provide an excellent fit to the datasets over the null model and a reasonable fit over the market segmentation model. In either case, the goodness-of-fit value increases for capturing scale heterogeneity over the homoskedastic model. The likelihood ratio value for these two models is 3839, which satisfies a 100 percent confidence limit for the chi-square ratio test. So, accommodating scale heterogeneity is statistic justified in our case.

5.1. Scale parameterization

We found that the level of mobility tool ownership and trip purpose enter into both systematic utility function and scale parameterization. These variables explain both preference heterogeneity and scale heterogeneity, but population density explains only scale heterogeneity. Travel distance explains preference heterogeneity of non-motorized modes and scale heterogeneity of the motorized modes. So, it is proven that careful parameterization of GEV scale can accommodate both preference heterogeneity and heteroskedasticity. Greene and Hensher (2010) find that accommodating preference heterogeneity together with scale heteroskedasticity improved the choice model significantly. However, they used the mixed logit model and also cautioned that we should be careful in defining the trade-off between preference and scale heterogeneity as identification is a painstakingly challenging task in the case of the mixed logit model.

Considering separate reference nests for different parameterizing variables induce a cross nested modelling structure within the closed form likelihood function. For example, all transit nest scale parameters are found to be the same as the root scale for all variables except trip distance. In case of trip distance, auto, local transit and regional transit nest are found to be significantly different from each other and from the root scale. Parameterizing nest scale provides interesting ways of explaining complementary/supplementary relationship among the choice alternative in terms of different common variables. Expressions of direct and cross elasticity functions provide the way of explaining the effects of different variables used in scale parameterization on competition between the modes within the nests and outside the nests. As specified in direct and cross elasticity functions (Eqs. (17)–(20)), it is clear that nesting becomes stronger or in other words the alternatives in the same nest compete stronger if they have common unobserved attributes. When we parameterize the nesting scale we can explain that the corresponding variables make this common attribute more (or less) important. Similarly, relative increase in root scale parameter compared to a nest scale parameter reduces the competition among the alternatives within the nest and thereby reduces the distinctions of the nests. The following paragraphs discuss the roles of different variables in defining the influences of the nests on mode choice preferences.

In the case of mobility tool ownership, we found that Category 1 (having no car and no transit pass) and Category 2 (having more than one car per valid driving license holder at home and having a transit pass) are the two extreme categories with a small number of observations. So, these two categories are not found explaining any scale heterogeneity of mode choices. In case of all other mobility tool ownership levels, it is clear that the scale parameters of all transit nests are similar to the root scale compared that are different from the auto nest scale parameter. In case of households with no transit passes and less number of cars than the number of driving license holders, transit and non-motorized modes compete with each other more than the auto modes. In case of households with one or more cars per driving license holders and no transit

Table 2
Mode choice models for peak period pure non-work trips.

			Homoskedastic model	Heteroskedastic model
Number of observation	264,023			
Loglikelihood of full model			−78,825.65	−80607.28
Loglikelihood of equiprobable model	−351,380			
Loglikelihood of constant-only model	−112,414		0.78	0.77
Rho-square against null model				
Rho-square against market share model			0.30	0.28
	Parameter	***t*-Stat**	**Parameter**	***t*-Stat**
Systematic utility function				
Alternative specific constant (ASC)				
Drive alone	8.29	35.61	12.09	127.63
Auto passenger	6.09	26.32	6.59	69.32
Local transit (Bus/LRT) with walk access	5.98	25.80	7.51	79.58
Subway park & ride	4.39	15.43	4.98	40.32
GO park & ride	6.56	30.81	8.77	94.67
Non-motorized modes	4.58	19.83	3.67	37.24
Trip purpose: shopping				
Drive alone	−2.95	−7.64	−4.34	−27.48
Auto passenger	−2.09	−5.42	−1.90	−12.02
Local transit (Bus/LRT) with walk access	−1.86	−4.80	−1.54	−9.79
Non-motorized modes	−2.01	−5.23	−1.42	−8.88
Trip purpose: others				
Drive alone	−1.31	−160.96	−3.38	−230.19
Auto passenger	−0.29	−46.93	−0.49	−33.73
Subway park & ride	2.51	6.56	2.65	15.89
GO transit with local transit access	7.11	31.56	9.34	108.81
Non-motorized modes	−0.20	−20.92	−0.24	−10.56
In-vehicle travel time (min)				
Drive alone & Auto passenger	−0.02	−82.29	−0.04	−103.76
All transit modes	−0.01	−70.52	−0.02	−78.85
Travel cost (2006 Canadian Dollars)				
All motorized modes	−0.06	−105.86	−0.16	−134.34
Walking time (min)				
All transit modes	−0.03	−125.92	−0.08	−165.77
Travel distance less than 1 km				
Non-motorized modes	1.06	128.15	2.56	174.84
Travel distance of 2 km				
Non-motorized modes	0.47	50.62	1.30	69.02
Dummy variable (1) for female				
Auto passenger	0.39	159.35	1.00	248.70
Local transit (Bus/LRT) with walk access	0.29	93.79	0.70	110.68
GO transit with local transit access	1.17	47.89	2.62	57.88
Non-motorized modes	−0.03	−6.70	0.00	0.07
Age less than or equal to 30 years				
Auto passenger	0.51	159.78	1.34	241.18
Local transit (Bus/LRT) with walk access	0.07	19.24	0.24	27.49
GO transit with local transit access	−1.31	−24.28	−1.13	−16.10
GO transit park & ride	1.32	39.53	2.62	44.62
Non-motorized modes	0.27	52.05	0.64	54.12
Age greater than 30 years and less than or equal to 45 years				
Auto passenger	−0.15	−73.03	−0.42	−82.83
Local transit (Bus/LRT) with walk access	−0.05	−12.92	−0.10	−12.31
Subway park & ride	−0.34	−18.89	0.65	21.25
GO transit with local transit access	−0.56	−20.96	−0.90	−18.02
GO transit park & ride	−0.16	−5.35	−0.41	−7.65
Non-motorized modes	0.26	39.64	0.69	46.93
Employment status: part time				
Auto passenger	−0.09	−36.24	−0.29	−45.67
Local transit (Bus/LRT) with walk access	0.12	25.43	0.31	29.04
Mobility tool ownership: no car & no transit pass				
Local transit (Bus/LRT) with walk access	1.10	99.95	1.32	88.02

Table 2 (*continued*)

			Homoskedastic model	Heteroskedastic model
Mobility tool ownership: less car than the number of driving license holders & No transit pass				
Auto passenger	0.52	51.12	0.82	80.99
Local transit (Bus/LRT) with walk access	0.54	48.89	−0.06	−4.58
Non-motorized modes	0.22	17.78	−1.01	−68.87
Mobility tool ownership: one car per driving license holders & no transit pass				
Drive alone	0.47	47.87	0.92	68.53
Auto passenger	0.31	24.64	0.81	55.99
Mobility tool ownership: number of car than & having transit pass				
Local transit (Bus/LRT) with walk access	2.34	163.25	3.21	154.67
Mobility tool ownership: less car than the number of driving license holders & Having transit pass				
Auto passenger	0.74	64.45	1.82	140.02
Local transit (Bus/LRT) with walk access	1.48	126.87	2.50	149.39
Non-motorized modes	0.74	49.66	0.87	35.74
Exponential function for scale parameters				
Less car than the number of driving license holders & no transit pass				
Auto nest	0.86	114.82		
Local transit nest, GO transit nest and root scale	0.90	116.19		
One car per driving license holders & no transit pass				
Auto nest	0.16	10.55		
Local transit nest, GO transit nest and root scale	0.00	–		
More car than the number of driving license holders & no transit pass				
Auto nest	0.65	31.46		
Local transit nest, GO transit nest and root scale	0.00	–		
No car but having transit pass				
Auto nest	0.00	–		
Local transit nest, GO transit nest and root scale	0.00	0.00		
Less car than the number of driving license holders & having transit pass				
Auto nest	0.00	–		
Local transit nest, GO transit nest and root scale	0.89	70.35		
One car per driving license holders & having transit pass				
Auto nest	−1.56	−13.39		
Local transit nest, GO transit nest and root scale	−0.96	−13.78		
Home zone population density in 1000 s/km^2				
Auto nest	0.00	–		
Local transit nest, GO transit nest and root scale	−6.97	−101.68		
Trip purpose: shopping				
Auto nest	0.00	–		
Local transit nest, GO transit nest and root scale	−0.07	−5.62		
Logarithm of trip distance				
Auto nest	−0.13	−68.12		
Local transit nest	−2.06	−13.50		
GO transit nest	−1.78	−1.09		
Value of auto in-vehicle travel time savings (2006 Canadian Dollars)		17.41		16.35
Value of transit in-vehicle travel time savings (2006 Canadian Dollars)		9.25		7.77
Value of transit access walking time savings (2006 Canadian Dollars)		29.70		29.62

passes, auto modes compete with each other stronger than any other modes. In case of household with no car and no transit pass, no nests are identified and all individual modes show clear independence from each other. However, having transit passes induce significant correlation among the transit and non-motorized modes as one nest against the auto nest. Transit and non-motorized modes compete stronger with each other than the auto mode if the household own transit passes. A possible explanation is that having transit passes allows household members to enjoy/realize many (that are apparently unobserved or un-captured by available variables) advantages of transit and non-motorized modes compared to the auto modes that are not revealed without having any transit passes. Similarly, not having any transit pass may make the household members realizing benefit of auto modes (that are apparently unobserved or un-captured by available variables) more than other modes.

Zonal population density captures size effects of the home zone and it seems that higher density induces higher competition among auto modes (drive alone and auto modes) compared to the transit and non-motorized modes. Higher competition refers to higher cross elasticity and vice versa. Trip purpose seems to influence correlation among the alternative modes. It is clear that auto modes are more correlation than all other modes in case of shopping trips. Similarly, trip distance is found significantly affecting nest scale parameters of the modes. It is clear that logarithm of trip distance can clearly identify three nest parameters: auto nest, local transit nest and GO transit nest. Interestingly, alternative modes within these nests compete with varying degree. Overall, competition among alternative modes within the nests decreases with increasing trip distance. Changes in competition with increasing trip distance are the lowest for auto nest and the highest for local transit nests.

In this paper, we find that it is possible to capture both preference heterogeneity and scale heterogeneity (heteroskedasticity) by simply parameterizing the GEV scale parameters as functions of different variables and identification in this case is not more difficult than in simple GEV models. In addition, systematic parameterization of GEV scale also proved to be very efficient in capturing distributions of heterogeneity across the population. Fig. 1 presents the distribution of scale parameters. It compares kernel density plots against corresponding normal distributions. These plots are generated by using statistical software, STATA. It is clear that both root scale and auto nest scale kernel densities show irregular and to some extent double-picked patterns. Comparative normal density plots clearly show that distributional assumption of scale parameter would under-estimate heterogeneity across the population. Normal and log-normal assumptions for scale parameterization in a mixed logit framework would miss-represent the situations. Alternatively, non-parametric estimation of mixed logit scale parameter would be comparable, but our formulation presents a more robust and closed form formulation to capture choice heterogeneity as well as heteroskedasticity.

5.2. Systematic utility

An individual's socio-economic attributes, transportation level-of-service attributes and mobility tool ownership level are used in systematic utility functions. It seems that aggregate land use and demographic attributes are difficult to accommodate in systematic utility functions. This suggests that in the case of peak period pure non-work trip mode

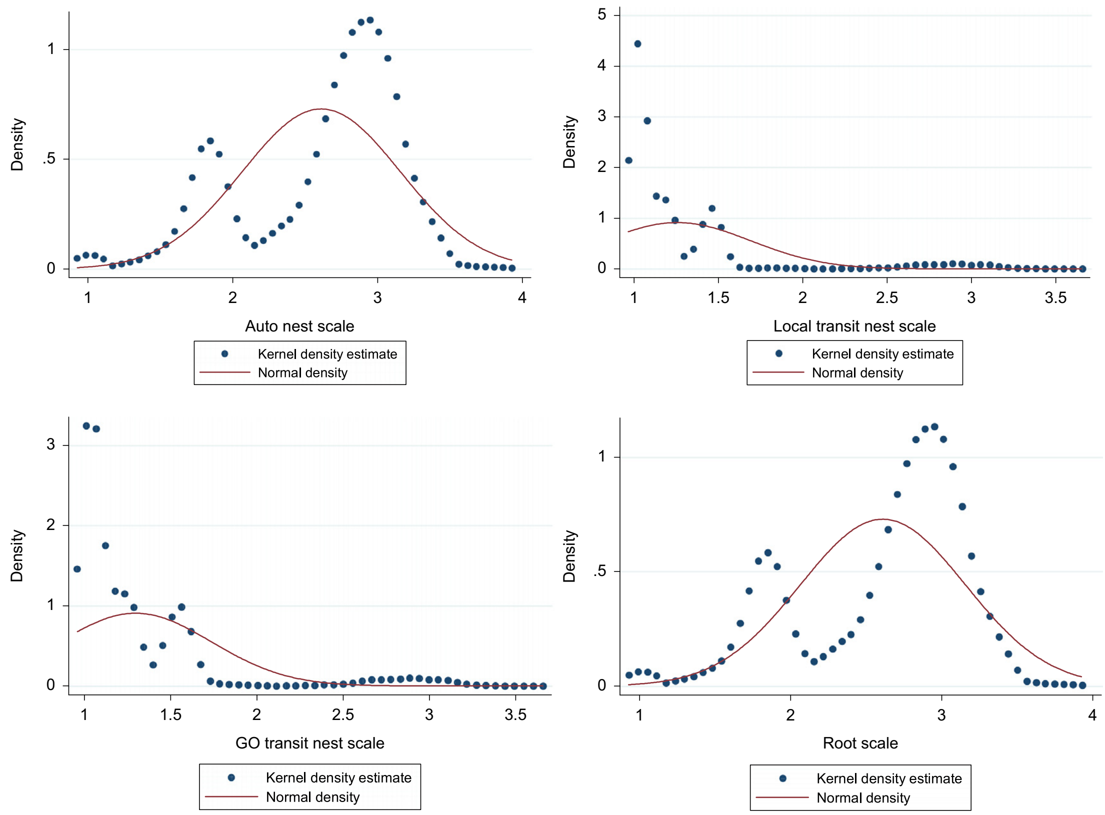

Fig. 1. Distributions of scale parameters.

choice, aggregate land use and demographic attributes do not significantly influence systematic preferences. In terms of level-of-service attributes of auto modes, travel time and travel cost are significant variables with the proper sign. However, in the case of the transit mode, we found that transit wait time does not enter into the systematic utility functions as a significant variable. A possible explanation would be that transit service is the best in peak periods, which are mostly designed to serve commuting trips. Pure non-work trips during peak period may have a lower expectation regarding transit waiting time compared to the commuting trips. However, in addition to in-vehicle travel time and travel cost, walking time proves to be very significant for transit mode choice utility functions.

Subjective Value of Travel Time Saving (VOTS) is calculated for both auto users and transit passengers. It is clear that walking time is the most sensitive for transit mode choice, even more than in-vehicle travel time. Intuitively, VOTS for in-vehicle travel time is higher than the VOTS of transit in-vehicle travel time. An interesting finding is revealed by comparing VOTS values between heteroskedastic models and homoskedastic models. It is clear that the homoskedastic models underestimate VOTS for both auto and transit. The highest underestimation is for transit in-vehicle travel time, which is around 16 percent. Overlooking heteroskedasticity and heterogeneity across the population affects the evaluation of transportation system improvement.

The models clearly capture the influence of distance for NMTs. It is clear that attractiveness of NMTs for peak period pure non-work trips drops exponentially with increasing travel distance. In this case, the homoskedastic model clearly overestimated the influences of trip distance. In terms of traveller's personal attributes, gender has significant impact on mode choice utility. Men prefer drive alone and use NMT more than female travellers. Auto passenger and transit modes are more preferable to females than males. In all cases, the homoskedastic model overestimates the gender effects on peak period pure non-work trip mode choices. An individual's age has an influence on peak period pure non-work trip mode choice. It is clear that the relative preference to auto driving increases with increasing age. People less than 30 years old choose the GO park and ride option more than any other age group. GO transit with local transit access is the most inconvenient option as it takes time for transfers and cause extra fares. Perhaps, for this reasons, people of age less than or equal to 30 years are least likely to choose it. The auto passenger, transit with walk access and NMT modes are least attractive to people over 30 years of age. Intuitively, full time workers are less likely to make peak period pure non-work trips and hence did not enter in to the model. However, if the trip maker is a part time employee, transit with walk access is the most attractive mode. The drive alone mode is more preferable than any other mode except transit with walk access and GO with transit access is the least attractive mode to part time workers.

Mobility tool ownership levels also affect the systematic utility function of mode choices. It is clear that people with no car and no transit pass prefer transit with walk access and NMT modes. Intuitively, people without a transit pass, with at least one car in the household, but less than one car per driving license prefer the auto passenger mode over other modes. However, transit with walk access and NMT are also attractive modes to them. Drive alone and auto passenger are most attractive modes when each valid driving license holder has a car and does not own a transit pass. Having only transit pass and no car makes the transit walk access mode most attractive. Similarly, having a transit pass with less than one car per valid driving license holder in the household makes the transit with walk access mode the most attractive followed by the auto passenger mode. Influences of mobility tool ownership on the systematic utility function of mode choices are not consistently captured in the homoskedastic model. For example, the homoskedastic model suggests that people with less than one car per valid driving license holder at home and without any transit pass would least prefer NMT, which is counter intuitive and not consistent with findings in the heteroskedastic model. So, it is clear that overlooking heteroskedasticity also affects systematic utility functions.

6. Policy implications

The model developed in this paper can be used for a wide variety of policy evaluations. Congestion mitigation and travel demand management policies are mostly targeted at reducing auto mode share during the peak period. Pure non-work trips represent more than 10 percent of peak period travel and more than 70 percent of linked non-work trips are made by the drive alone mode. Therefore, attracting peak period pure non-work travellers to transit would have a significant contribution to reducing congestion and the resulting emissions. Empirical models developed in this study reveal that auto ownership and transit pass ownership levels has opposite impacts on mode choice variability across the population. Higher auto ownership levels reduce choice variability, but higher transit pass ownership levels increase choice variability. A possible policy implication is that transit pass ownership increases choices, especially in combination with higher auto ownership levels.

Choice variation can be better explained by choice entropy, where the lowest entropy refers to the highest variation of choices and the highest variation refers to the lowest variation of choices (Swait and Adamowicz, 2001). Choices would be the most random and result in the highest choice entropy if all feasible modes are equally attractive and competitive. Similarly, choices would be the least random and result the lowest choice entropy if only one mode dominates. Increasing choice entropy refers to an increasing social surplus (Habib and Swait, 2011).[2] So, it is clear that increasing transit pass

[2] Social surplus = expected maximum utility = $\ln\sum_m \exp(V_m)$

$$= \sum_m -\Pr(m)\ln(\Pr(m)) + \sum_m \Pr(m)(V_m) = \text{choice entropy} + \text{average utility}.$$

ownership would increase social surplus. However, increasing auto ownership alone would reduce social surplus, but influencing people to own transit passes in addition to car ownership would give the consumer more choice and contribute significantly to an increase in social surplus. Transit fare policies with a variety of transit pass ownership categories would help in reducing the mode share of auto mode choices for peak period pure non-work trips.

7. Conclusions and direction for future research

This paper investigated peak period pure non-work trip mode choice. By using data from a large scale household travel survey collected in the Greater Toronto and Hamilton Area, it focuses on the relationship between peak period pure non-work trip mode choice and mobility tool ownership. The paper proposes a heteroskedastic GEV model structure. The proposed structure uses systematic parameterization of GEV scale parameters to capture scale heterogeneity or heteroskedasticity. The empirical model presented in the paper successfully implements the proposed modelling structure for peak period pure non-work trip mode choice. The research presented in this paper has contributions to enhancing our understanding of peak period pure non-work trip mode choice behaviour in the context of mobility tool ownership levels as well as to advancing econometric choice modelling techniques.

Around 11 percent of peak period trips made in the GTHA are pure non-work trips and more than 70 per of such trips are made by the driving alone mode. The total of all transit modal shares is lower than the auto passenger mode share alone. It is clear that in the peak period, the private automobile is the dominant mode for pure non-work trips. Empirical models reveal that higher levels of household automobile ownership greatly influence peak period pure non-work trip mode choice toward the auto modes. However, transit pass ownership can also significantly influence people to use transit and non-motorized modes. Empirical models also reveal that trip distance is an important factor influencing the choice of non-motorized travel modes. A policy implication of this finding would be to encourage more mixed land use so that the average trip distance for non-work trips is reduced, inducing a higher mode share for non-motorized travel.

From the perspective of methodological contributions, the paper proposes a robust and simple closed form heteroskedastic GEV model that improves model performance over the homoskedastic models. There is an improvement in estimating the value of travel time savings as well as the model's goodness-of-fit measures. It is proven that the approach is capable of capturing a wide variation and an irregular distribution shape of GEV scale parameters. In addition, it can potentially capture a wide variety of nesting choice structures for different groups of people without necessarily estimating separate models.

In this paper, we limited the analysis to closed form probability functions for choice model formulations and did not compare our proposed model with the mixed logit model. While a wide variety of possible mixed logit formulations may make the comparison cumbersome, it is a recommended task for future investigation. Also, the presented modelling structure focuses mainly on parameterization of nesting coefficients. In reality, nesting structure itself could be as important as the nest scale parameters as different people may have different views on similarities between modes (not only the degree of similarities). This cannot be achieved only with a nest structure, but can be achieved with a cross-nested structure by parameterizing the nest allocation coefficients. Moreover, for application of the proposed model, we investigated mode choice behaviour for peak period pure non-work trips considering that the mobility tool ownership levels of the corresponding households are know. In reality, mobility tool ownership level and peak period non-work trip making behaviour (trip generation as well as mode choice) may have endogenous relationship. Joint modelling of mobility tool ownership and mode choice would eliminate such endogeneity issues. However, in this paper, we considered that mobility tool ownership is a longer term decision than daily mode choice decisions. So, for the daily peak period non commuting mode choice, we considered that the mobility tool ownership information would be known. Moreover, accurate modelling of mobility tool ownership level decisions requires detailed information of cost, income and reasons of alternative mobility tool options. The household travel survey datasets available for this study does not contain such information, so, we could not investigate income effect. We did not have such information for this investigation. So we are considering it as the next step of this investigation.

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