Investigating Structural Changes in Commuting Mode Choice Preferences with Repeated Cross-Sectional Travel Survey Data: The Contexts of Greater Toronto and Hamilton (GTHA) Area

Khandker Nurul Habib, University of Toronto
Joffre Swait, University of Technology, Sydney
Sarah Salem, University of Toronto

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Dr. Khandker M. Nurul Habib, PEng
Assistant Professor
Department of Civil Engineering
University of Toronto
Canada
khandker.nurulhabib@utoronto.ca

Dr. Joffre Swait
Research Professor
Deputy Director, Center for the Study of Choice - CenSoC
University of Technology, Sydney
Australia
Joffre.Swait@uts.edu.au

Ms. Sarah Salem
PhD Student
Department of Civil Engineering
University of Toronto
Canada
sarah.salem@mail.utoronto.ca

Abstract
Transportation supply (transportation system capacity/performance) and urban form define the opportunities and constraints operating on mode choice preferences of urban residents.
We make use of the Transportation Tomorrow Surveys (TTS), which are household travel surveys conducted in the Greater Toronto and Hamilton Area (GTHA) in 1996, 2001 and 2006. Such a large and repeated cross-sectional travel demand survey data set provides an uncommon opportunity to investigate structural changes in mode choice preferences over time, in a manner sensitive to choice context changes. In this paper, we focus on commuting mode choices, which are prime determinants of peak period congestion and peak spreading. The outcomes of this investigation yield a better understanding of peoples' mode choice preferences in GTHA, elucidate the impact of transport supply and urban form on behavior, and therefore provide guidance to better policy development to influence transit usage.

Keywords
mode choice, context influences, preference stability, work trips

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1. Background and Motivation

Transportation supply (transportation system capacity/performance) and urban form help define the opportunities and constraints operating on mode choice preferences of urban residents. Policy changes over time affect investments in transportation system, which eventually affect transportation system performance as well as urban form. This is observable for the Greater Toronto and Hamilton Area (GTHA), which has experienced significant variation in policy focus over the last three decades, from auto-oriented to transit-oriented policies, to which are added the effects of smart growth land use policies. Despite efforts to reduce automobile and encourage transit use, peak period traffic congestion in GTHA continues to increase.

Besides the obvious effects that characteristics of the social, economic, and transport systems have on mode choice, it is possible that the policy instigated changes to the transport system will not only create impacts on users via changes in transport system performance (cost, time, accessibility, etc.), but will also affect commuting mode choice decision difficulty. That is to say, transport system changes may generate decision contexts in which it is more difficult for the decision maker to correctly identify the optimal (i.e. highest utility) modal alternative, leading ultimately to a higher incidence of sub-optimal mode choices across the population. Ultimately, sub-optimal user decisions will lead to sub-optimal transport system performance. It has been suggested in the literature that this phenomenon can be recognized in random utility models by appropriate parameterization of the scale factors to capture decision context complexity (Swait and Adamowicz 2001).

Most commuting mode choice models presented in literature are based on cross-sectional datasets of travel diary surveys (among many others, recent examples are Heinen et al. 2012, Tsamboulas et al. 2012, Habib 2012, Zaman and Habib 2011). In addition to modal characteristics, such cross-sectional methods also can investigate the effects of various contextual factors involved in such situations (for example Long et al 2010).

However, it is possible that preferences for commuting mode choice evolve/change over time, but mode choice models developed using only one crossectional travel survey data set may not have the capacity to capture such changes. Clearly, though, mode choice models designed to forecast future demand and/or investigate various congestion mitigation strategies will produce more accurate and robust forecasts if they can describe preference evolution over time. While commuting mode choice models are commonly employed by almost all transportation planning agencies and many advanced choice models are tested for commuting mode choice, to our best knowledge no one has investigated the evolution of commuter preference for commuting mode choice. For such investigations, large scale multi-period datasets are necessary to capture basic trends and produce consistent estimates. While having panel data of such scale is almost impossible because of cost, repeated cross-sectional data collected from the same study area can be used.

In this paper, we use such three repeated cross-sectional household travel surveys collected from the same study area over the period of 10 years. Our objective in this paper is to detect whether changes occurred in both systematic and random components of mode choice utility over time. Potential preference changes will be linked to individual-level decision difficulty (arising from transport system performance and urban form) via the choice models to be estimated.

The paper is arranged as follows: the next section presents a brief literature review, which is followed by a section explaining the econometric model formulation used in this study; a brief description of the datasets is then presented, which is then followed by a section presenting the empirical models and temporal transferability. The paper concludes with a discussion of key findings and an agenda for further research.

2. Literature Review

Although temporal transferability of commuting mode choice models (i.e., the ability of commuting mode choice model to predict future choice behaviour) was first recognized as an important issue in the early 1970's, there has been a significant drop in interest in recent years. This may mostly be due to a shifting focus to the development of advanced models without necessarily considering temporal transferability of modelling structures to future behaviour (Fox and Hess, 2010).

One of the earliest exercises of testing transferability of mode choice model is reported by Watson and Westin (1975). They used a binary logit model for mode choice and tested transferability against an aggregate modal share model for the Edinburg-Glasgow area. They concluded that only the disaggregate choice model accurately captured generic choice behaviour and should therefore be used for predicting to future scenarios. Parody (1977) developed a multinomial logit model for commuting trips to and from the University of Massachusetts, Amherst campus. He used two datasets collected one year apart and tested the predictive capacity of mode choice models. He found that model performance remained stable over a year even though there were substantial changes in parking and public transit services.

Ben-Akiva and Atherton (1977) investigated spatial and temporal transferability of multinomial logit mode choice model. They compared parameters of transportation level-of-service attributes of logit mode choice models developed for New Bedford, Washington, Los Angeles and San Francisco. Also, they used models developed for one city to predict aggregate modal share of another city. They found that mode choice models developed for one city can give very accurate prediction for another one if the alternative-specific constants of the logit mode choice model can be updated for the local area. They also report temporal transferability test results for commuting mode choice models. They used the multinomial logit model developed by using a dataset collected in 1970 to predict aggregate modal share of 1974, which is then compared to observed modal share data collected in 1974. They found that the earlier model was capable of predicting changes in mode choice preferences resulting from the implementation of transportation management strategies such as bus-only lanes and encouraging carpooling.

Train (1979) developed a multinomial logit model for commuting mode choice by using a dataset collected in 1972 and then predicted to compare with a dataset collected in 1975 from the San Francisco Bay area. In between these time periods the Bay Area Rapid Transit (BART) was opened. The focus of this paper was purely testing the predicting capacity of different mode choice model specifications. It found that behavioural complexities in terms of changing patterns over time could only be captured through complex model specifications based on the use of interacting socio-demographics with transportation variables (cost divided income or wage, etc.).

McCarthy (1982) used household travel survey data collected in 1973-1974 and in 1975, just before and after the opening of BART in the San Francisco Bay area. He developed multinomial logit models for commuting mode choice by using two datasets and compared the coefficients. Results showed that over the short time period model parameters remained stable. Regarding the predictive capacity of the logit mode choice models, his finding was that the model developed by using older dataset and then updated with supplemental data of the future year can give very similar result to estimating the entire model solely on the future year dataset.

Silman (1981) followed a similar approach for testing temporal transferability of commuting mode choice model. He estimated logit mode choice models for datasets collected in 1972 and 1976. Silman found that most of the model parameters were stable except for household vehicle ownership level. Interestingly, most of the mode choice model parameters remained stable between 1972 and 1976, even though there were significant changes in transportation infrastructure.

Badoe and Miller (1995) were the first to investigate very long range temporal transferability of commuting mode choice models (again, a multinomial logit model). They used two datasets collected from Greater Toronto Area (GTA) in 1964 and 1986. Their first interpretation of model transferability tests was that mode choice model parameters were not temporally stable though they provided significantly useful information for planning and analyses. They also identified that appropriate specification is very important to capture the changes in model parameters over time. From the perspective of our work, an important finding of this study was that the mode choice model scale parameter (which is normally defaulted to one in multinomial logit models) is very crucial in capturing the trends in model choice preference structure over the long-term time period. This study used almost the same study area as of our current investigation and the survey used to collect those datasets eventually evolved into the Transportation Tomorrow Survey (TTS). The TTS survey evolved into a stable survey design in terms of questionnaire and study area in 1996. Since then, two more surveys were conducted in 2001 and 2006 (and the most recent one is currently underway). These three consistent TTS datasets are used for the investigation in our paper.

Karasmaa and Pursula (1997) investigated transferability of mode choice models for Helsinki Metropolitan area between 1981 and 1988. They identified that appropriate method and sample size are two major factors affecting the temporal transferability of mode choice models. Gunn (2001) used datasets collected in 1982 and 1995 in the Netherlands to investigate transferability of mode choice models. They highlighted the importance of considering the scale parameter of the logit model in explaining changes in mode choice preferences over time. In a recent study, Sanko and Morikawa (2010) investigated the factors that may affect temporal transferability of mode choice model. They used datasets collected in 1971 and 1991 in the same study area in Japan and highlighted the importance of considering utility scale for explanation of better transferability. Their investigation was mostly focused on developing updating techniques for better transferability rather than investigating the evolution of mode choice preference structure.

Key lessons learned from our literature review are that investigating changes in mode choice preference structure over time requires a) large scale and consistent datasets collected from the same study area, b) as well as an appropriate modelling structure that can capture the changes in preference and scale over time. All of the previous temporal transferability studies focus mostly on how transferable the model forecasts are rather than looking at how stable the preference structures remain over time. Studies that found that earlier mode choice models captured the changes in mode choice preferences over time used very short time periods for temporal transferability analysis or smaller datasets and a simple modelling structure (smaller numbers of alternative modes, smaller number of observations, etc.). Investigations that found that the multinomial logit model did *not* capture the changes in mode choice preferences over time used very long time period for temporal transferability analysis (over 15 to 20 years) and also investigated the reasons and/or factors that might underlie the issue of non-transferability.

To advance knowledge in this critical area of travel demand modelling, in this study we focus on investigating the stability of commuting mode choice preference structures over time. Rather than simply testing model performance in temporal transferability (or forecasting), we probe more deeply into the reasons or factors that might cause non-transferability of mode choice models. We used three large scale household datasets collected from the same study area over 5 year time intervals.

Our data come from the Transportation Tomorrow Survey (TTS), which is a household travel survey conducted in GTHA among five percent of households in 1996, 2001 and 2006 (DMG 2012). Such a large and repeated cross-sectional travel demand survey data set provides an opportunity to use an advanced econometric modelling approach to investigate structural changes in mode choice preferences over time, in a manner sensitive to context changes. We focus on commuting mode choices, which are prime determinants of peak period congestion and peak spreading.

From the modelling perspective, we address our main research question by estimating a Heteroskedastic Generalized Extreme Value (Het-GEV) model and the Het-GEV with entropy-based scale parameterization (Swait and Adamowicz 2001). Our focus is the identification of temporal evolution patterns of both systematic and random components of commuting mode choice utility in the study area. We develop individual year specific models as well as pooled data models. For pooled models, the datasets of individual years are pooled together to capture the longitudinal trends in preference structure changes by making possible the testing of the hypothesis of systematic utility stability while accounting for decision complexity arising from transport supply and urban form considerations. One of our main objectives is to identify the model specification with highest degree of temporal transferability as well as the elements of structural changes in mode choice preferences. The model formulations we examine have in common that they are expressed by closed form econometric models, thus avoiding distributional assumptions required for mixed logit models. The next section explains the econometric model formulations.

3. Econometric Model Formulation

The commuting mode choice model class we adopt here is built on the Random Utility Model

(RUM) class of choice representations. Let us define the utility function of a commuting 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 individual commuters varies from $i=1$ to $i=N$ and the number of alternative modes available to any individual may vary from $m=1$ to M (the mode allocation rule is explained later). Under the RUM assumption, an individual commuter maximizes her total utility in choosing a commuting mode. From the researcher's point of view, total utility of mode choice is therefore stochastic, though fully known to the traveler. Thus, the choice probability for a given mode is governed by the distribution of the random component of the total utility function. The Generalized Extreme Value (GEV) choice family is obtained by assuming that the random component is GEV distributed with Cumulative Distribution Function (CDF), *F(.)* taking the form:

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

Here, *G(....)* is a non-negative and homogenous of degree greater than zero function (Ben-Akiva and François, 1983 cited in Daly and Bierlaire, 2006). This defines a multivariate extreme value distribution with the probability density function of choosing any mode, *m*, as (McFadden 1978):

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

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):

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

Dubin and Zeng (1991) prove 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 equation (2) as

$$F(\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3}, \ldots.., \varepsilon_{iM}) = \exp\left(-G\left(e^{-\varepsilon_{im}\mu_{im}}\right)\right) \quad . \tag{5}$$

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

$$F(\varepsilon_{im}) = F(\infty, \ldots.., \varepsilon_{im}, \ldots\ldots, \infty) = \exp(-G(0, \ldots.., e^{-\varepsilon_{im}\mu_{im}}, \ldots\ldots, 0)) = \exp(-a_m e^{-\varepsilon_{im}\mu_{im}}) \,. \tag{6}$$

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

$$P_{im} = e^{V_{im}\mu_{im}} G_m\left(\left\langle e^{V_{im}\mu_{im}} \right\rangle\right) / G\left(\left\langle e^{V_{im}\mu_{im}} \right\rangle\right) \quad . \tag{7}$$

For a commuting mode choice situation, it is very much likely that a Tree-MNL (Daly 1985, Koppelman and Wen 1998) structure as presented in Figure 1 would be appropriate because of the presence of unobserved shared properties of certain mode clusters. In this figure, the scale parameter (μ, μ_T and μ_A) of each mode cluster is shown next to the corresponding construct node. The generating function corresponding to the tree structure depicted in Figure 1takes the form:

$$G_i = \left(\sum_{m=AD,AP} e^{\mu_A V_{im}} \right)^{\mu/\mu_A} + \left(\sum_{m=LT,RT} e^{\mu_T V_{im}} \right)^{\mu/\mu_T} + \left(e^{\mu V_{iNMT}} \right) \tag{8}$$

This G(.) function with root scale (μ) is subscribed to by the individual commuter, with the second level scales (μ_T and μ_A) varying by corresponding mode clusters.

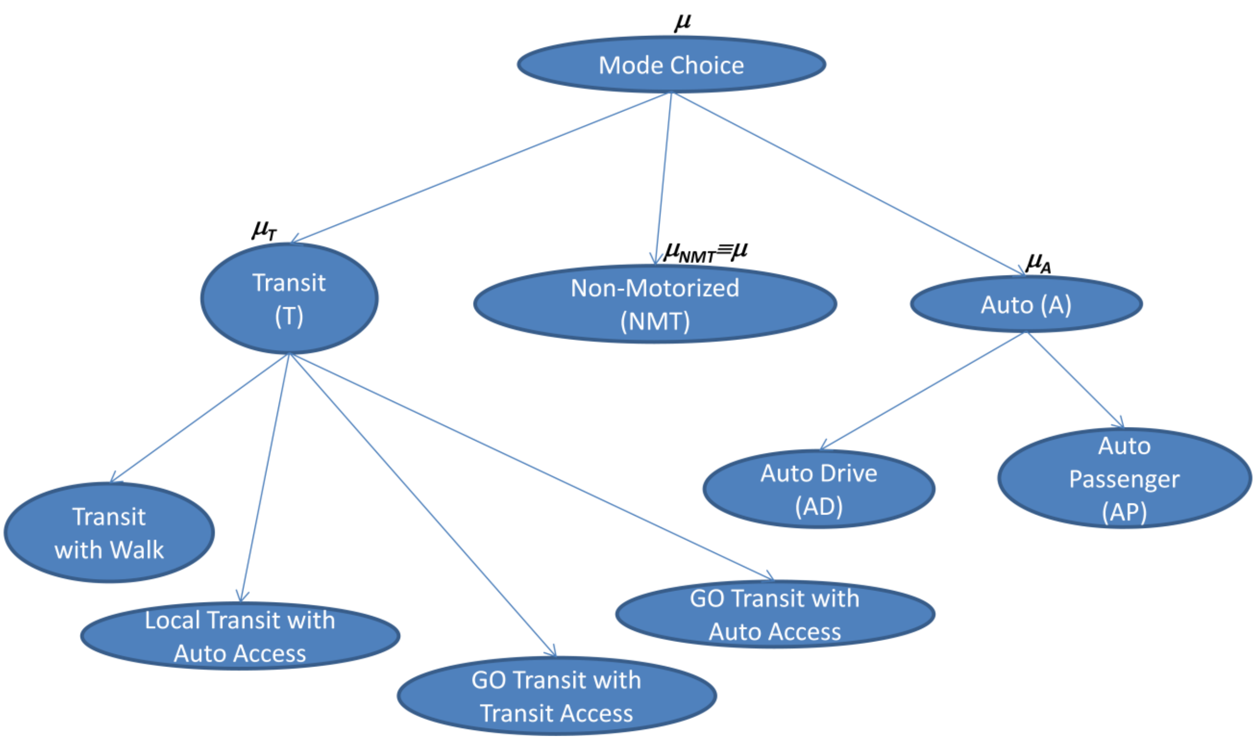


Figure 1: Mode choice tree

Since this generating function is additive (Swait 2003), 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 commuter is omitted from these expressions for clarity):

Construct Nodes:

$$Q_{NMT} = \frac{\exp(\mu I_{NMT})}{\exp(\mu I_{NMT}) + \exp(\mu I_A) + \exp(\mu I_T)} \tag{9}$$

$$Q_A = \frac{\exp(\mu I_A)}{\exp(\mu I_{NMT}) + \exp(\mu I_A) + \exp(\mu I_T)} \tag{10}$$

$$Q_T = \frac{\exp(\mu I_T)}{\exp(\mu I_{NMT}) + \exp(\mu I_A) + \exp(\mu I_T)} \tag{11}$$

Inclusive Values:

$$I_A = \frac{1}{\mu_A} \ln\left(\exp(\mu_A V_{AD}) + \exp(\mu_A V_{AP})\right) \tag{12}$$

$$I_T = \frac{1}{\mu_T} \ln\left(\exp(\mu_T V_{LT}) + \exp(\mu_T V_{RT})\right) \tag{13}$$

$$I_{NMT} = \frac{1}{\mu_{NMT}} \ln\left(\exp(\mu_{NMT} V_{NMT})\right) = V_{NMT} \tag{14}$$

Elemental Alternatives:

$$P_{AD|A} = \frac{\exp(\mu_A V_{AD})}{\exp(\mu_A V_{AD}) + \exp(\mu_A V_{AP})} \tag{15}$$

$$P_{AP|A} = \frac{\exp(\mu_A V_{AP})}{\exp(\mu_A V_{AD}) + \exp(\mu_A V_{AP})} \tag{16}$$

$$P_{LT|T} = \frac{\exp(\mu_T V_{LT})}{\exp(\mu_T V_{LT}) + \exp(\mu_T V_{RT})} \tag{17}$$

$$P_{RT|T} = \frac{\exp(\mu_T V_{RT})}{\exp(\mu_T V_{LT}) + \exp(\mu_T V_{RT})} \tag{18}$$

$$P_{NMT|NMT} = 1 \tag{19}$$

Unconditional Mode Choice Probabilities:

$$P_{AD} = P_{AD|A} \cdot Q_A \tag{20}$$

$$P_{AP} = P_{AP|A} \cdot Q_A \tag{21}$$

$$P_{LT} = P_{LT|T} \cdot Q_T \tag{22}$$

$$P_{RT} = P_{RT|T} \cdot Q_T \tag{23}$$

$$P_{NMT} = P_{NMT|NMT} \cdot Q_{NMT} = Q_{NMT} \tag{24}$$

Itcan be assumed that the systematic utilities are given by linear-in-parameters expressions such as

$$V_m = ASC_m + \beta' X_m. \tag{25}$$

Here ASC_m indicates the mode Alternative Specific Constant, X_m indicates a vector of covariates and β' indicates the corresponding parameter vector. In this investigation, we are interested in capturing the evolution over time of scale heterogeneity in commuting mode choice for the GTHA. So, later we accomplish this by parameterizing the root scale parameter as a function of time. From equations (9) to (25), it is clear that the scale of the non-motorized cluster is not identified (or essentially, must be equated to the root scaleμ) because it contains only one specific (or elemental) mode type. We parameterize the root scale parameter as a function of aggregate zonal variables (Z) capturing the spatial distribution of baseline choice behaviour:

$$\mu_{i(t)} = \exp(\gamma Z) \tag{26}$$

where γ is the coefficient to be estimated.

In contrast, two separate scale parameters (μ_A and μ_T) characterize the auto and transit modal clusters respectively. To ensure positivity of scale parameters, we use exponential function as follows:

$$\mu_{At} = \exp(\alpha_A) \tag{27}$$

$$\mu_{Tt} = \exp(\alpha_T) \tag{28}$$

where α_A and α_T are nest-specific constants corresponding to auto and transit nests.

We are using crossectional and revealed preference mode choice data of multiple years collected in Greater Toronto and Hamilton Area (GTHA). To capture the changes in heterogeneity across the commuters and across the years, the variance/scale parameter of modal utility is made sensitive to the entropy implied by a traveller's set of available modes. Parameterizing scale as a function of entropy allows capturing similarities/dissimilarities as well as the complexity (i.e. decision difficulty) implied by a choice scenario (Fiebig et al 2010; DeShazo and Fermo 2002; Swait and Adamowicz 2001).

We argue that entropy captures the difficulty for the traveller to reach an optimal decision. Low entropy contexts contain modes that tend to dominate others, so decision difficulty is low: the best alternative is easily determined. High entropy contexts contain modes with very similar levels of attractiveness, so again decision difficulty is low because any mode is just as attractive as the others. It is in medium entropy contexts (i.e. neither low nor high) that decision makers face greatest difficulty and can make sub-optimal choices. We propose to parameterize the root scale parameter as a function of entropy ($H(C_{i(t)})$),[1] along with other aggregate zonal variables (Z), where $C_{i(t)}$ is commuter i's set of available modes in year t and

$$\mu_{i(t)} = \exp\left(\theta_1 H(C_{i(t)}) + \theta_2 H^2(C_{i(t)}) + \gamma Z\right) \tag{29}$$

where,

$$H(C_{i(t)}) = -\sum_{m \in C_{i(t)i}} \pi_{im} \ln \pi_{im} \quad . \tag{30}$$

θ_1 and θ_2 are coefficients to be estimated.

We address shortly the definition of the entropy measure $H(C_{i(t)})$. This parameterization of the root scale allows the diagonal elements of the stochastic utility covariance matrix to be a function of time and the personal, point-in-time context of commuting mode choice. The quadratic argument in (29) reflects the above logic concerning the impact of context-driven decision difficulty.

Note that equations (29) and (30) depend upon mode choice probabilities π_{im}, which are as yet undefined. Probability formulations (9)-(25) are the researcher's view of the commuter's mode choice process. In these formulations, it is implicitly assumed that the true parameters of the choice making process are intermixed with random errors generated by the context of mode selection (i.e. the economic, social and transportation systems). The relative magnitude of the influence of stochastic utility compared to the systematic component on choice probability is defined by the variances of the modal stochastic utilities. However, it is fair to assume that the commuter knows his/her own true tastes and hence, the entropy proxy can directly use the taste parameters of the utility function to define decision context complexity (Swait and Adamowicz 2001). Accordingly, this proxy is defined as a simple MNL model for the π_m's in expression (27):

$$\pi_{im} = \frac{\exp(V_{im})}{\sum_{j \in C_i} \exp(V_{ij})}, \tag{31}$$

where modal utilities (V) are given by expression (25). It is clear that we consider a homoskedastic logit model formulation to specify choice entropy, which is then used to parameterize the scale parameter of the Het-GEV model. Such specification captures the non-linear and complicated relationship among user's perceptions, choice contexts and the final choices. It is also advantageous that such formulations yield a closed-form probability function for mode choice, which allows the use of classical maximum likelihood estimation techniques. In this paper, the empirical models are estimated by codes written in GAUSS and using the

[1] In these subsequent cases, the subscript t is put within the bracket. This is to indicate the individual person i at time period t. Since we don't have panel data, person i may not be in multiple time periods within the dataset.

MAXLIK component for maximum likelihood estimation (Aptech 2012).

4. Datasets for Empirical Investigation

The data used in this investigation are sourced via the Transportation Tomorrow Surveys (TTS). These are Revealed Preference (RP) surveys that randomly sample 5% of the GTHA every 5 years, recording the detailed travel records of households within the study area for a single day (DMG, 2012). The survey collects trip origin-destination zone identification, trip departure times, trip types, modes of transportation and transit route information for individual-level trip data. In addition, it also collects home and work locations information for workers, as well as household and individual-level socioeconomic attributes (e.g., household size, household vehicle ownership, transit pass ownership, individuals' age, gender, education). The survey was first started in1986 with a smaller study area than that of the later surveys. The second survey was in 1991, which experimented with a slightly different trip type classification as well as alternative sampling strategies.

The survey was stabilized from 1996, so that the 1996, 2001 and 2006 data collection efforts were conducted using the same instrument and sampling strategy. Since our interest is the exploration of the temporal stability of mode choice preferences, it would seem that tracking travel behaviour over time for a panel of households would be best. As noted before these three waves of survey data do not constitute a panel; however, they are the next best thing since they do constitute repeated cross-sections of GTHA households, collected five years apart over a ten-year period.

The TTS survey classifies commuters into four major occupation groups: general office, manufacturing, professional, and retail/service. We consider occupation-specific dummy variables to capture effects of job type on mode choice preferences. Unfortunately, the data set does not include individual- or household-level income information. In order to obtain a surrogate measure, median zonal income is considered as a variable in the empirical models. The TTS data sets do include other socioeconomic attributes: e.g., age, gender, household size, number of cars in the household.

For commuting, the TTS identifies six modes of transportation: (1) auto driver; (2) auto passenger; (3) local transit; (4) park and ride with local transit; (5) park and ride with inter-regional transit (termed 'GO Transit'); and (6) non-motorized modes. Calibrated and validated EMME/2 networks for 1996, 2001 and 2006 are used for generating level-of-service attributes of auto and transit modes. To specify choice sets for commuting mode choice, we used modal feasibility rules commonly employed by the planning agencies in the study area and are developed based on local knowledge and experience (Miller, 2007). These include:

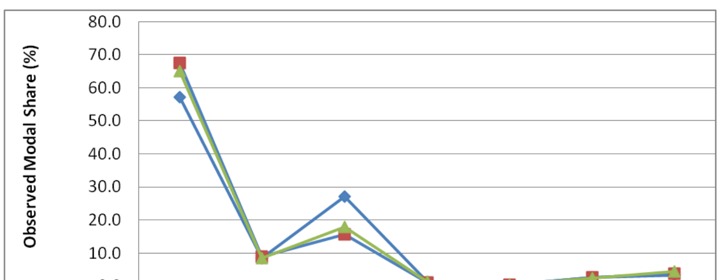
- Auto driving mode is feasible if the commuter has a driving license and own at least one private automobile.
- Auto passenger mode is available to everybody.
- Transit modes are feasible if the corresponding origin-destination pair of the commuter has transit service. In terms of reasonable transit service, we define the availability of

transit options with alternative access modes if the total travel time is less than 150 minutes in one direction.

- The non-motorized mode is considered feasible if the distance between the origin-destination pair of the commute is less than or equal to 10 kilometres (for walking the maximum threshold distance is 3 kilometres and for biking the maximum threshold distance is 10 kilometres).
- With respect to access modes (GO transit and local transit, and auto), it is assumed that the commuters access their closest (by straight-line distance) feasible station with on-site parking. This consideration is made in an effort to avoid unnecessary complexity in the mode choice model while still maintaining a practically large number of observations for econometric model estimation.

After eliminating all missing values and applying all feasibility rules a total of 67,094, 76,071 and 55,927 individual commuting trip records remained for 1996, 2001 and 2006, respectively. If sampling weights are used to expand the samples, the total number of daily commuting trips is 1,354,834 cases for 1996, 1,295,718 cases for 2001 and 1,069,252 cases for 2006. These are very large datasets and are suitable for investigating the type of behavioural trends we are researching in this paper. A total of seven alternative commuting modes are defined for these data:

1. Auto driving (AD)
2. Auto passenger (AP)
3. Transit with walk access (TWA)
4. Local transit with auto access (park & ride) (TAA)
5. GO transit with local transit access (GTTA)
6. Go transit with auto access (park & ride) (GAA)
7. Non-motorized (NMT)



	1. Auto driving (AD)	2. Auto passenger (AP)	3. Transit with walk access (TWA)	4. Local transit with auto access (park & ride) (TAA)	5. GO transit with local transit access (GTTA)	6. Go transit with auto access (park & ride) (GAA)	7. Non-motorized (NMT)
Year 1996	57.1	8.4	27.0	1.2	0.4	2.6	3.3
Year 2001	67.5	9.0	15.6	1.1	0.4	2.6	3.8
Year 2006	65.0	8.6	18.0	1.3	0.3	2.4	4.4

Figure 2: Comparison of Modal Shares for Commuting in the GTHA

Figure 2 presents a comparison of observed aggregate modal shares for the three survey years in the study area. From 1996 to 2006 auto driving dependency increased about 10 percent for the commuters in the GTHA. Auto passenger modal share was relatively more stable over the interval. Modal share of local transit with walk access mode declined from 1996 to 2001 and 2006 significantly. The local transit park and ride mode share was stable over time. Modal share of GO transit with local transit access as well as GO transit with park and ride modes slightly declined slightly with time. In general, mode choice preference changed with a significant boost towards use of the private car for commuting.

Before estimating econometric models of mode choice, we sought to understand the patterns of mode choice preference distributions in the study area. Aggregate modal share gives a high-level view of mode choice preference patterns, but it does not provide much insight into the distribution of decision difficulty across the population. To have an empirical understanding of commuting mode choice preferences, we summarized zonal average entropy of mode choice for commuting. Entropy, for a particular spatial context, can explain the aggregate status or context complexities of specific decisions or choices (Wilson 2010). In the case of commuting mode choice, observed modal shares at the zonal level can effectively represent the spatial discretization of patterns observed in commuting mode choice preference structures. In this case zones represent small spatial units in the study area used to develop TTS sampling weights, which are compatible with census track units.

We aggregated observed modal shares for each spatial zone. These shares are used to calculate observed entropy of commuting mode choice by using expression (30), but replacing individual mode choice probabilities with aggregate modal shares for the zone. It is well known that the entropy function achieves its maximum when choice probabilities or shares are equal; hence, since there are 7 possible modes, a particular zone can have a maximum entropy of 1.95≈-ln(1/7). Similarly, the minimum possible value of zonal entropy is zero, where only one mode is used and rest of all modes have no modal share. Thus, the higher the value of zonal entropy, the more no one mode dominates the others and the more varied the use of the modes across the zone's residents.

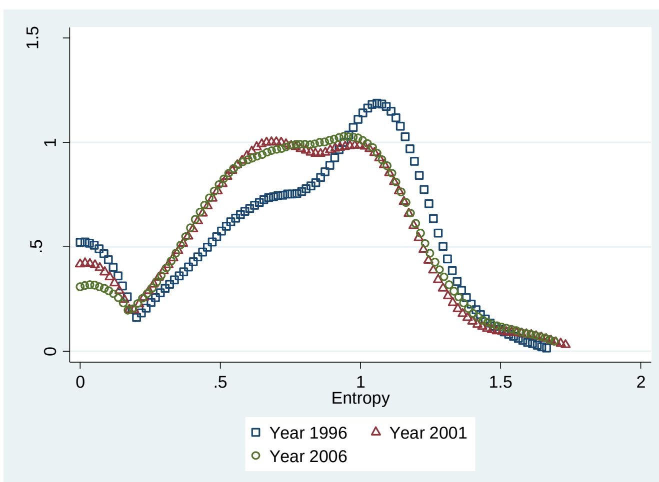


Figure 3: Distribution of observed zonal average entropy of commuting mode choices.

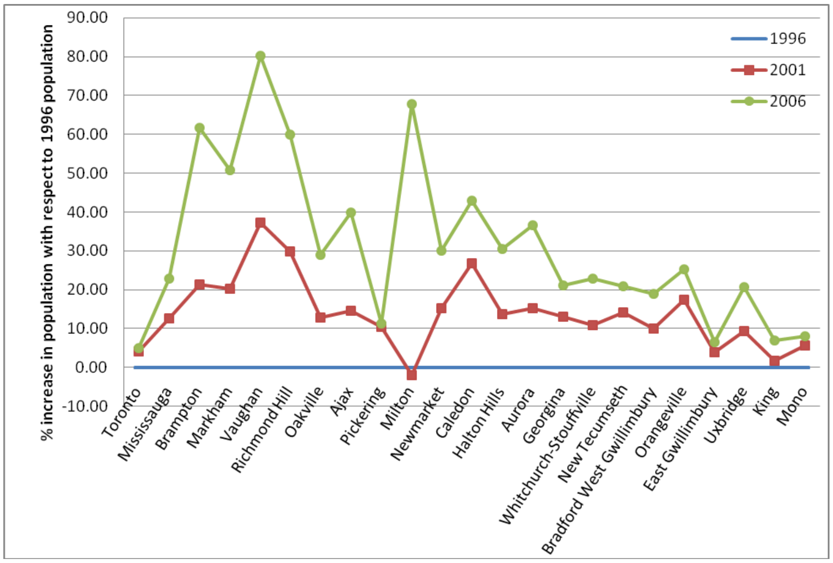


Figure 4: Changes in Population in Toronto and its Suburbs between 1996-2006 (source: Statistics Canada)

Figure 3 presents the kernel density plots of zonal average entropy values for the three TTS survey years. The distribution of commuting mode choice zonal entropy has shifted to the left (i.e. on average decreased) since 1996 in the GTHA. The modal value of zonal entropy was greatest in 1996 and dropped significantly from 1996 to 2001. After 2001, it further dropped slightly in 2006. Interestingly, Figure 3 suggests that in 2006 the distribution of zonal entropy may be moving towards a bi-modal distribution. In 1996 the entropy distribution had a very sharp peak which flattened in 2001 and onwards. Having a sharp peak and higher modal entropy at the zonal level indicates a larger proportion of commuters with commuting alternatives that were more clearly advantageous. On the other hand, the flattening out of the zonal entropy distributions after 1996 may indicate that the utilities of mode choice alternatives were more similar, making it more difficult for commuters to clearly identify the best mode for their work trips. Similarly, movement of the distribution towards bimodality may suggest multiple classes of commuters in the study area. Commuters living in zones that have greater mode choice flexibility because of access to multiple modes would be represented by an increase in a modal value towards the right of the distributions in Figure 3; those living in zones that have less mode choice flexibility would "clump" in a modal value towards the left of the distribution.

Figure 4 shows relative population changes during the analysis time period (1996 to 2006) in Toronto and its surrounding suburbs. Suburbs closer to Toronto such as Mississauga, Brampton, Milton, Richmond Hill, Vaughn, etc., have higher population growth than the suburbs farther from Toronto, such as Caledon, Aurora, Georgia etc. Relative to Toronto, every other area has experienced a large population surge. Hulchanski et al. (2007) noted that Toronto has been undergoing changes in terms of income polarization and social gentrification resulting in multiple classes of population having different lifestyles. Similar findings are also reported by Hackworth and Rekers (2005), who also recognize such changes in Toronto. There has been a significant change in socio-economic class structure in the study area between 1996 and 2006. Figure 3 suggests that the structure of commuting mode choices has also changed. Observed changes in commuting mode choice preferences should be, at least in part, the reflections of individual commuters' difficulty or complexities of making optimal or desirable decisions for commuting mode choice. The next section presents the empirical models and discussions of factors influencing commuting mode choice preferences in the GTHA.

5. Empirical Models

Table 1 presents the summary of empirical model parameters. A total of six models are presented. For each of the years 1996, 2001 and 2006, two models are presented: the HET-GEV model represents the GEV model with root scale parameterized as function of zonal median income and the Entropy-based HET-GEV model includes the additional entropy (decision difficulty) term in the root scale parameter function. Goodness-of-fit of the models is measured by estimating likelihood ratio values against the equiprobable and aggregate market share models. Goodness-of-fit values are higher against the equiprobable (or null) model than the market model. In case of goodness-of-fit against market shares, the likelihood ratio value is over 0.2 for all models, which represents a very good fit of the advanced models developed in this paper (see Ben-Akiva and Lerman 1985). It is also clear that Entropy-based HET-GEV models give slightly higher likelihood ratio values against aggregate shares.

This reveals the power of capturing choice complexities in scale parameterization through the entropy measurements. In all cases, models of 2001 provide the highest fits followed by the models of 1996 and then 2006. The reported model specifications are the best specifications among a series of alternative specifications for systematic utility function in terms better likelihood ratio values and higher numbers of statistically significant parameters. Statistical significance of the parameters is tested by comparing estimated asymptotic t-statistics with the 95 percent confidence limit of 1.96. It is to be noted that all parameters the models are highly significant except for one in the 2001 model. We retained the same parameter sets for all models to allow comparisons across the years.

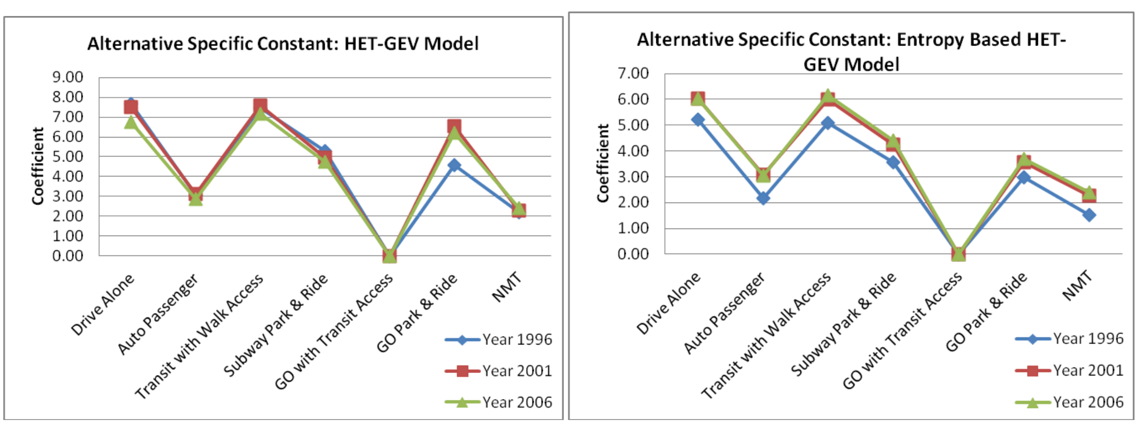


Figure 5: Comparison of alternative mode specific constants

Figure 5 allows comparison of mode-specific constants in the model. Overall, the mode-specific constants are lower for the entropy-based HET-GEV models. Note that in the case of the HET-GEV models the constants do not vary across the years except in the case of the GO park and ride mode. For the entropy-based HET-GEV model, mode-specific constants are higher across the modes for 2001 and 2006 compared to 1996 with almost equal values for 2001 and 2006. This suggests that there seem to have been some changes in overall commuting mode choice preference structures between 1996 and 2001-2006 that are not explained by the variables used in the model. This does not seem to have been detected by the HET-GEV model.

In terms of level-of-service attributes, the time and cost variables are specified as generic across the modes in the models. In the case of cost, since we did not have income available in the dataset, we estimated separate cost variables for each occupation category, but maintain the generic assumption across modes within occupation. Surprisingly, sensitivity to in-vehicle travel time remains exactly the same over the years, but sensitivities to travel cost vary substantially. Such variation of cost sensitivity is significant across the occupation groups and there is a huge jump between 1996 and 2001. Table 2 summarizes the values of in-vehicle travel time savings and Figure 5 plots the values comparatively.

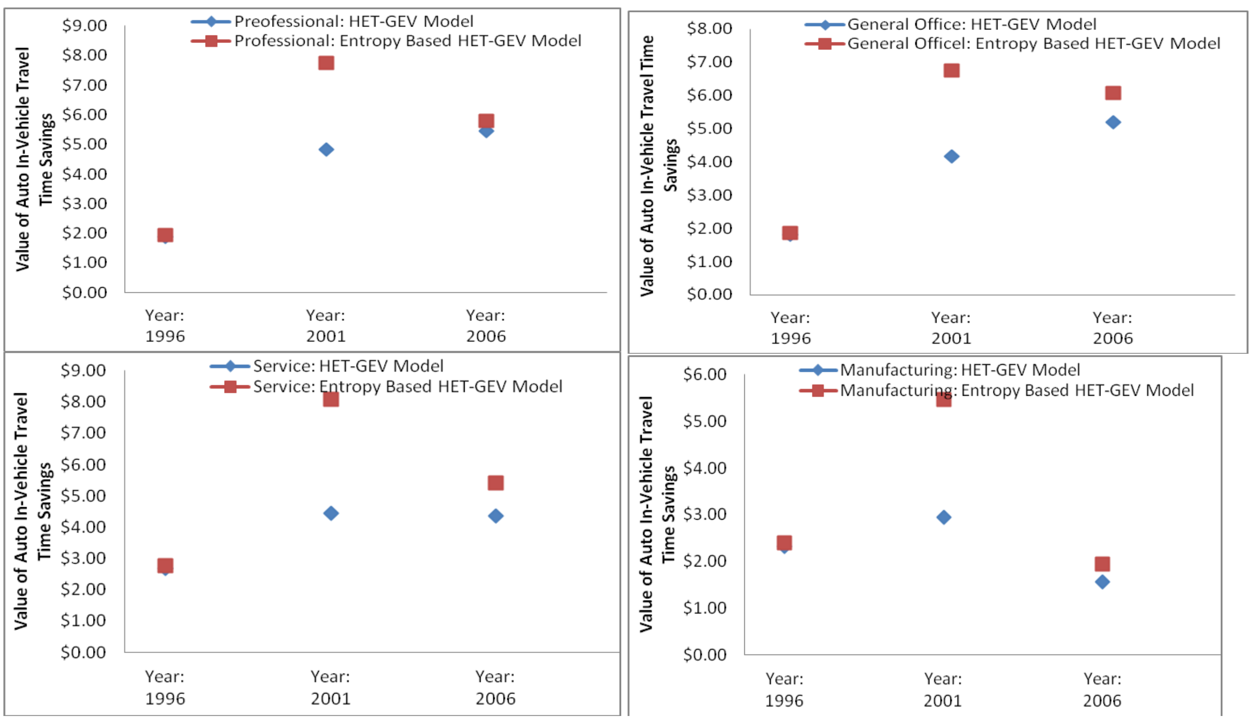


Figure 5: In-vehicle travel time savings

Both types of models suggest that willingness to pay for reduced in-vehicle travel time increased significantly in 2001 compared to 1996, and then decreased somewhat in 2006. It is to be noted that the cost variables are specified in the corresponding year's dollar values. The HET-GEV model predict that between 1996 to 2001 the willingness to pay increased 2.54 times for professional occupation group, 2.30 times for general office occupation group, 1.66 times for service occupation group and 1.27 times for manufacturing occupation group. However, the Entropy-based HET-GEV model predicts a much higher rate of increase: 3.98 times for professional occupation group, 3.63 times for general office occupation group, 2.92 times for service occupation group and 2.28 times for manufacturing occupation group. The CPI index reported by Statistics Canada for the study suggests that the cost adjustment between 1996 and 2001 would be at most 1.11 times (Statistics Canada, 2012). So, it is clear that willingness to pay increased beyond the regular price adjustment rate for inflation. Since in the model formulation we assumed that the marginal disutility of time remains constant, the marginal disutility of cost must necessarily decrease (become less negative in magnitude). This is plausible given the usual assumption of the diminishing utility of consumption associated with increased income.

As noted before, we did not have access to personal or household income data to capture income effects. However, comparing the zonal average income we realized that average income did not increase significantly from 1996 to 2001. Also, there were no significant transport infrastructure changes during that period in the GTHA. So we are left with the explanation that there may have been changes in social structure, economic activities and demography (in-migration and out-migration) resulting from the very high suburbanization in the study area, causing a significant decrease in marginal disutility of cost for commuting trips. Compared to 2001 and 2006, the HET-GEV model predicts a small increase in willingness to pay for in-vehicle travel time savings, but the Entropy-based HET-GEV model actually predicts that the values decrease slightly for all occupation groups. However, it is interesting to note that after a huge drop in marginal disutility of commuting trip cost in 2001, it stabilized by 2006.

Disutility of the access and egress distances for non-motorized modes is captured by discretizing walking distances. Empirically, it is seen that the utility of non-motorized modes decreases sharply with increasing distance. The highest utility of non-motorized mode is for the distance below 1 kilometre and it drops significantly for the distance between 1 to 2 kilometres and so on for the distance between 2 to 3 kilometres. These coefficients do not change significantly across the years despite the continuous efforts to promote active transportation (non-motorized mode of transportation) for commuting by various government and non-government organizations in the study area. However, it is clear that the HET-GEV model overestimated the distance effects on non-motorized mode choice compared to the Entropy-based HET-GEV model. Access walking time has proven to be very influential factor in transit mode choice option. The HET-GEV model predicts that the negative influence of access walking time increased 5 times from 1996 to 2001 and then decreased slightly in 2006. However, the Entropy-based HET-GEV model predicts that it in fact increased 3 times from 1996 to 2001 and then become constant.

We also calculated the willingness to pay for reducing walking time and waiting time for transit access as reported in Table 2. Both types of models predict that there was a huge jump in willingness to pay for reducing walking and waiting time for transit access between 1996 and 2001, and that it then stabilized in 2006. This parallels what was discussed earlier for in-vehicle travel time savings. In terms of absolute values of willingness to pay for saving walk access time to transit in 1996, commuters' willingness to pay was nearly similar to the willingness to pay for reducing in-vehicle travel time. However, in 2001 and 2006, willingness to pay for transit walking access time becomes more or less 4 times larger than the corresponding willingness to pay for in-vehicle travel time savings. Intuitively the willingness to pay for reduced waiting time for transit is the highest and it also suffered sharp jumps between 1996 to 2001 and 2006.

To us, these effects are all indications of the massive suburbanization that occurred between 1996 and 2001, which resulted in poor walking accessibility to transit services, leading thereby to a big rise in auto driving as well as a sharp drop in transit modal share. However, between 2001 and 2006 there had been investments in transit infrastructure: two notables examples are a) a subway link was added to Toronto's existing subway network and b) the VIVA bus rapid transit was introduced in the York region, one of the suburbs in GTHA. Such investments caused the commuting mode choice preference structures to be stabilized after 2001.

In addition to level-of-service attributes, we also considered a series of household socio-economic and personal characteristics in the systematic utility function. Having more than 2 cars in the household increases the availability of car for commuting and has a positive effect on the auto driving commuting option. However, the HET-GEV models predict that the influence of this variable remain more or less constant over the years, but the influence of this variable is larger in the HET-GEV model compared to its influence in the Entropy-based HET-GEV models. Similar effects also obtain for having one car in the household on auto passenger mode choice utility. For more than 2 cars per household, the HET-GEV model predict much higher effects on systematic utility of auto driving and auto passenger mode choice utility compared to those predicted by the Entropy-based HET-GEV model. Similarly, having a higher number of cars in the household increases the opportunity for a park and ride option and both types of models predicts this. It seems that effects of this variable remain stable over time, but the HET-GEV models over predict its impact compared to the Entropy-based HET-GEV model.

In terms of personal characteristics, it seems that the effects of gender (females preferring all other modes over auto driving options compared to males) on mode choice utilities of auto passenger, local transit with walk access and subway park and ride and non-motorized modes decreased over time from 1996 to 2006. Also, it seems that the HET-GEV models overstate gender effects for these modes compared to Entropy-based HET-GEV models. Commuters' ages seem to have significant effects in commuting mode choice preferences. Clearly, compared to younger and older generations, the age group of 30 to 55 years old prefer auto driving and park and ride type commuting modes over all other modes. However, this age group prefers non-motorized and local transit modes more than the older age group (age over 55 years). It is also clear that the HET-GEV models estimates larger age effects on commuting mode choice utilities compared to those in the Entropy-based HET-GEV models.

The root scale of the HET-GEV models are parameterized as exponential functions of zonal median incomes. In addition, modal nest specific constants are also estimated considering the non-motorized modes as the base case. In this model specification, it is only possible to identify the coefficient of the auto nest (auto driving and auto passenger modes), while those of other nests (transit nest and non-motorized nest) must be held constant. This is a clear indication of higher correlation between auto driving and auto passenger modes over time. The coefficient of zonal median income decreased over time in the Entropy-based HET-GEV model. Decreasing values of this coefficient indicates decreasing root scale parameters and thereby decreasing heterogeneity across the study area. However, this effect is balanced by the entropy function included in the root scale parameterization. Estimated coefficients clearly identify the quadratic effects of mode choice entropy on scale parameterization as expected in the formulation. The coefficients are highly statistically significant, which suggests that the model formulations capture the hypothesized difficulty of decision making for commuting mode choices.

Table 3 summarizes the estimated average values of root scale parameters for each survey year by the two types of models. It is clear that the HET-GEV model gives a lowers estimate of the root scale parameters and thereby the commuting mode choice heterogeneity across the population. The Entropy-based HET-GEV model attributes higher values to the root scale parameters and their variations across the year. The latter model estimates that the root scale suffered a drop from 1996 to 2001 and remained constant in 2006. These imply fundamental structural changes in commuting mode choice preferences in the study area over the time period of 1996 to 2006. Reduction of root scale implicitly refers to increasing complexities/difficulties in making desirable mode choice preference for commuting.

Table 3: Estimated Average Root Scale Parameter

	Average Root Scale parameter	
Year	HET-GEV	Entropy-based HET-GEV
1996	0.92	1.37
2001	0.83	1.24
2006	0.93	1.23

These results jointly raise the possibility that there may not be temporal transferability of mode choice models across the three years studied here. In the next section, we further investigate temporal transferability of the individual models for better guidance to develop a modelling framework for multiple repeated crossectional datasets that can accommodate evolution of structural preferences over time.

5.1 Temporal Transferability and Pooled Data Meta Model

Temporal transferability in general refers to the fact that the model developed in one year can replicate choice behaviour for any future year. We test below whether the 1996 models can be forward transferred to 2001 and 2006, as well as whether the 2001 model is transferable to 2006. We consider two disaggregate transferability measures, the transferability index (TI) and likelihood ratio (Transfer Rho-square) for evaluating temporal transferability of the models. TI is a relative measure of strength of the transferred model over a market share model in comparison to the originally estimated model. The transfer index is calculated:

$$TI = \frac{LL_j(\theta_i) - LL_j(Market\ Share)}{LL_j(\theta_j) - LL_j(Market\ Share)} \tag{31}$$

where $LL_j(\theta_j)$ indicates the loglikelihood value for the context year j of the model developed by using j^{th} year's data; $LL_j(\theta_i)$ indicates the loglikelihood value for the context year j of the model developed by using i^{th} year's data and LL_j(Market Share) denotes the log-likelihood of the market share model for the application context j. The upper bound for this metric is 1, but negative values are possible (indicating that the transferred model is worse than the market share model). A similar measurement of transferability is defined by calculating the goodness of fit of the transferred model against market share model of the target year.

$$Transfer\ \ Rho\text{-}Square = 1 - \frac{LL_j(\theta_i)}{LL_j(Market\ Share)} \tag{32}$$

The upper bound for this metric is 1 and a higher indicates better goodness of fit against market share. It gives the fit against market share for the forecasting year.

Table 4: Transferability Index and Transfer Rho-Square Values

	Base Year	Forecasting Year	HET-GEV Model	Entropy-based HET-GEV model
Transferability Index				
	1996	2001	0.6127	0.6207
	1996	2006	0.6782	0.6818
	2001	2006	0.9803	0.9811
Transfer Rho-Square				
	1996	2001	0.1071	0.1150
	1996	2006	0.1180	0.1250
	2001	2006	0.2983	0.3060

Table 4 summarizes the results of forward transferring both model types. Overall, the TI values indicate that the 1996 model can give more than 0.6 compared to the maximum limit of 1.0 in disaggregate transferability test. Interestingly, the 1996 model is more transferable to 2006 than 2001. However, the 2001 model gives more than 98 percent accuracy in forecasting 2006 choices. In all cases, it is clear that entropy-based scale parameterization clearly improves temporal transferability of the models as the TI values are higher for entropy-based HET-GEV models. In case of Transfer Rho-Square measures, the 1996 model gives less than 0.2 goodness of fit for 2001 and 2006. However, the 2001 model gives more than 0.25 goodness of fit for 2006 year forecast, which is considered reasonably good fitting (Ben-Akiva and Lerman, 1985). As in the case of TI, the Transfer Rho-Square values also prove the superiority of entropy-based HET-GEV model over HET-GEV model in temporal transferability.

While the TI and Transfer Rho-Square measures give numerical evaluation of temporal transferability, it does not give any direction for improving model transferability by developing better specifications. So, in an effort to develop a comprehensive modelling framework that can capture temporal evolution of mode choice preference structures, we compared individual model parameters graphically. The main objective of this simple analysis is to identify the parameters that cause higher deviation from one model to the other (see Swait and Bernardino 2000).

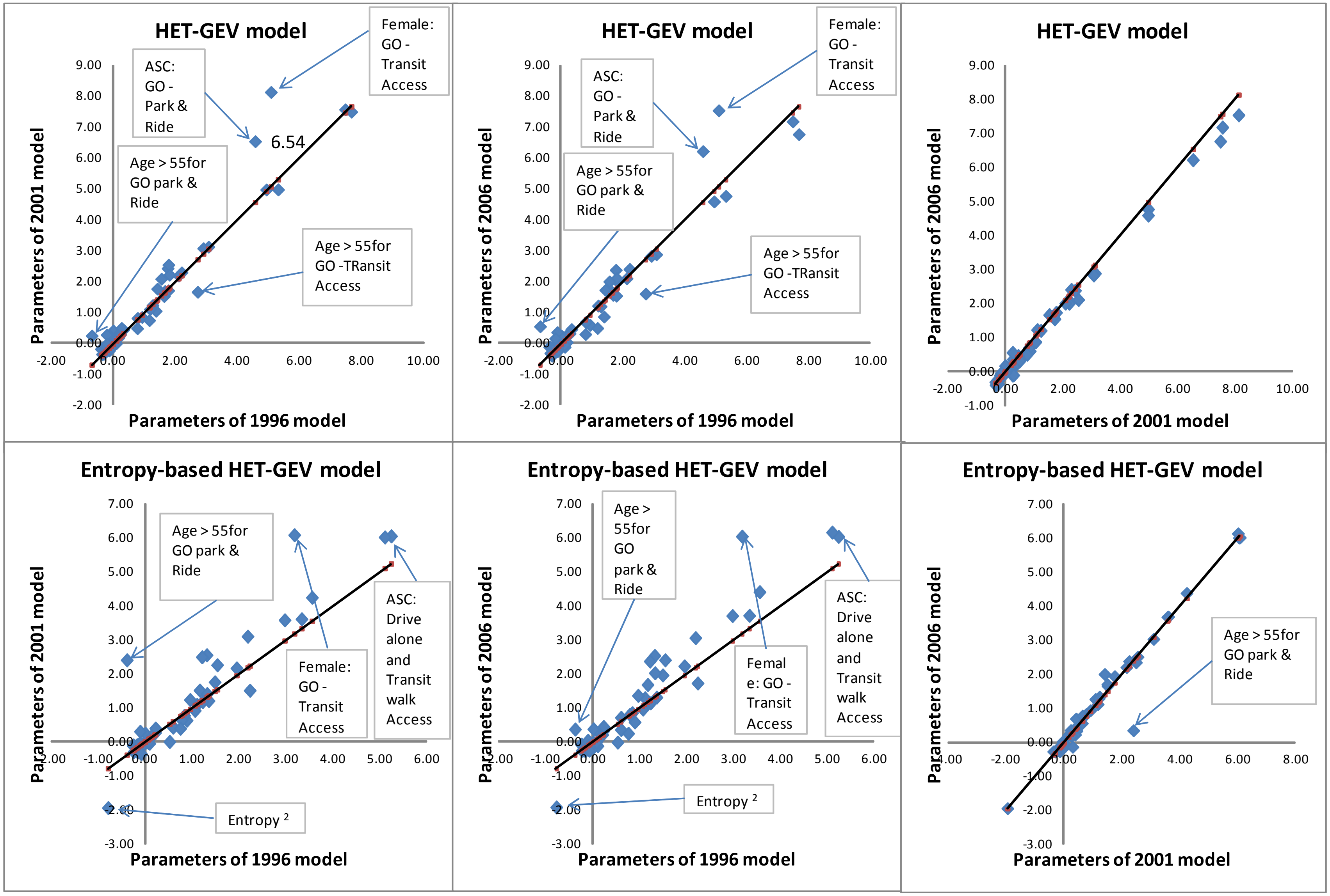


Figure 6: Comparison of Estimated Model Parameters

Figure 6 presents the comparisons of model parameters. Both HET-GEV and entropy-based HET-GEV model parameters are pair wise plotted (1996 versus 2001, 1996 versus 2006 and 2001 versus 2006). In each plot the straight line represents the line on which all dots should align if both comparing models have exactly same parameter values. Parameters that differ most between the models are represented by the dots far away from this line. In all cases, 2001 model parameters are closer to 2006 parameters and 1996 model parameters are closer to those of 2001 model than 2006 models. In case of HET-GEV model, alternative specific constants (ASC), scale parameter, age and gender are they three major variables that cause big deviations. In case of entropy-based HET-GEV models, the coefficient corresponding to the square of entropy measurement (components of root scale parameter) causes deviation while comparing 1996 model with 2001 and 2006 models. Interestingly, parameters of the entropy-based HET-GEV model for 2001 shows perfect alignment with the parameter of corresponding 2006 model, except one age-specific variable.

TI and Transfer Rho-Square value measurements show that crossectional models are not always transferable and the major probable reason is the evolution of preference structures of mode choices. While HET-GEV model captures deviations in ASCs and socio-economic variable parameters, entropy-based HET-GEV model also clearly shows that in addition to these, the scale parameter is also showing deviations. So, the challenge is to develop a modelling approach that can take advantage of multiple repeated crossectional datasets available for the same study area and at the same time comprehensively capture the evolution of preference structures.

One of the possible ways is to pool the repeated crossectional datasets to support a generalized modelling framework. Pooling datasets collected in different years obviously requires updating cost variables considering the inflation rates. Also, various possible ways of specifying generalized modelling structures can be hypothesized. Based on the analyses of individual year-specific models and transferability measurements, it is clear that the pooled data model should, at least, consider changes in ASCs and scale parameters over time. Our analysis above suggests that the entropy-based HET-GEV model is the best option for model formulation in terms of temporal stability. For such a model formulation, one possible way of specifying the pooled data model is to consider alternative year specific ASC and scale parameters. However, in that case, the problem would be the difficulty in forecasting for future years for which the ASC and scale parameters would be unknown. To overcome this issue, we consider the year 1996 as the base year and included an additional component to each ASC and the scale parameter identifying the year of concern. So, for the pooled data over 1996, 2001 and 2006, we consider an entropy-based HET-GEV specification with equations 25, 27, 28 and 29 modified as follows:

$$V_m = ASC_m + \delta_{ASCt} \ln(t - 1996) + \beta' X_m \tag{33}$$

$$\mu_{At} = \exp\left(\alpha_A + \delta_{At} \ln(t - 1996)\right) \tag{34}$$

$$\mu_{Tt} = \exp\left(\alpha_T + \delta_{Tt} \ln(t - 1996)\right) \tag{35}$$

$$\mu_{i(t)} = \exp\left(\theta_1 H(C_{i(t)}) + \theta_2 H^2(C_{i(t)}) + \gamma Z + \delta_t \ln(t - 1996)\right) \tag{36}$$

where t is year and δ's are parameters and in equation 33-36 there is an implicit normalization condition met by setting the reference year effect for 1996 to zero. This means, the temporal effects will only be added for the year 2001 and 2006. We consider logarithmic scale for temporal progression so that the linear-in-parameter temporal functions follow diminishing rate of changes with increasing time. It will ensure that for forecasting, the temporal progression effects do not dominate at least for short- or medium term forecasting. However, long-term forecasting may be problematic as these temporal components may become enormous and dominate the model predictions.

Estimated model parameters of the pooled data model are presented in Table 5. The pooled data model accommodates temporal evolution of ASCs and scale parameters. Comparing the individual year-specific models, we found that the larger coefficients for the socio-economic variables cause problems in model transferability. In general, all socio-economic variables have smaller parameter values in the pooled data model than the individual year-specific models. Also several age specific variables are found statistically insignificant in the pooled model, but those were significant in the individual year-specific models. It seems that accommodation of the evolution of ASCs and scale parameters can reduce effects of socio-economic variables that may be the artifacts in the individual year-specific models. In terms of temporal effects, it is clear that ASCs of all modes decrease over time except for the GO Park & Ride and GO with Transit Access mode options. Interestingly, the root scale parameter decreases with time (the temporal effect is negative), but the auto nest scale parameter increases over time (the temporal effect is positive). While comparing parameters of the pooled model with individual year-specific models is difficult, we consider measuring model transferability of the pooled data model for the individual year specific models.

We used the pooled model to test transferability to 1996, 2001 and 2006. Both TI and Transfer Rho-Square values are estimated to investigate how transferable the pooled model is to 1996, 2001 and 2006. The results are:

- *Transferability Index (TI)*:
    1. Pooled model applied to 1996: 0.9464
    2. Pooled model applied to 2001: 0.9821
    3. Pooled model applied to 2006: 0.9787
- *Transfer Rho-Square Value*:
    1. Pooled model applied to 1996: 0.2532
    2. Pooled model applied to 2001: 0.3030
    3. Pooled model applied to 2006: 0.3213

The proposed pooled data modelling structure which is an entropy-based HET-GEV model with temporal adjustment factor clearly outperforms any individual year specific model. Interestingly, the TI values are very similar for 1996, 2001 and 2006, indicating that its performance is very nearly as good as each year-specific model. It seems that the pooled data model can give more than 0.94 compared to the maximum limit of 1.0 for transferability test. According to the Transfer Rho-square values, the pooled data model gives more than 0.25 goodness-of-fit for any year. Interestingly, it is clear that the temporal evolution of mode choice preference structure is mostly reflected in changing patterns of ASCs and the scale parameters. Also, it is clear that a proper capturing of such evolution can eliminate artificial influences of socio-economic variables that cause major problems in temporal transferability of the models.

6. Conclusions and Recommendations for Future Research

The paper presents an investigation on stability of commuting mode choice preference structure over a 10 year time period. The study area is the Greater Toronto and Hamilton Area (GTHA), which is one of the major economic hubs in Canada and North America. The study makes use of a large scale household travel survey conducted in the GTHA every 5 years, named Transportation Tomorrow Survey (TTS). TTS survey data from 1996, 2001 and 2006 are used for our study. The datasets represent three repeated cross-sectional surveys in the same area at 5 year intervals. We used these datasets to develop commuting mode choice models. As pointed out in the literature review, it seems that the choice model scale parameter can play a significant role in defining temporal transferability of the mode choice models. We are therefore led to employ an advanced econometric model formulation to address our research question.

For commuting mode choice trips, we developed two related types of models: heteroskedastic GEV model (HET-GEV) and HET-GEV model with scale parameter parameterized as a function of entropy; this latter measure is argued to represent context complexity (Swait and Adamowicz 2001). It is established that parameterizing scale parameter as a function of choice entropy in the entropy-based HET-GEV model is consistent with the assumption of a quadratic functional form, as suggested by Swait and Adamowicz (2001). Also the Entropy-based HET-GEV allows better highlighting the changes in preference structure than HET-GEV model.

In terms of model specifications, two types of models are estimated: three individual year-specific crossectional models and a pooled data model that captures the evolution of ASCs and scale parameter of an entropy-based HET-GEV model over time. In term of temporal transferability, the pooled data model outperforms all other crossectional models in every count.

A dey finding of this investigation is that there have been significant changes in commuting mode choice preference structure between 1996 and 2006 in the GTHA. Important social, economic and transportation system changes, all of which occurred in the GTHA during this period, create a forecasting challenge for any model based on a single cross-section. Interestingly, our analysis further suggests that temporal evolutions of preference structures may not be gradual over time. Major changes in preference structure happened between 1996 and 2001 and stabilized between 2001 and 2006. Fundamentally, it is clear that the ensuing changes to the transport systems, urban forms and population patterns have not only created impacts on commuters via changes in transport system performance (cost, time, accessibility, etc.), but also in terms of commuting mode choice decision difficulty. It seems that decision contexts for commuting mode choice in GTHA has been changing to a direction in which it is increasingly becoming difficult for commuters to correctly identify the optimal (i.e. highest utility) modal alternative, leading ultimately to a higher incidence of sub-optimal choices in the population.

Commuters' sensitivity to in-vehicle travel time for commuting remains exactly the same over the years, but sensitivities to travel cost changed substantially between 1996 and 2001. However, the latter remained stable between 2001 and 2006. Such variation of cost sensitivity is significant across the occupation groups. As a result, the willingness to pay for reduced in-vehicle travel time increased beyond the regular price adjustment rate for inflation over time. In the case of transit users, the willingness to pay for reduced waiting time for transit is the highest and it also suffered sharp jumps between 1996 to 2001 and 2006.

While a gradual change in preference structure over time is explainable, a drastic and sharp change and then stabilization is more difficult to explain. Apparently, there were no significant transportation infrastructure change in the study area between 1996 and 2001, when the sharp changes in preference structure happened. Also, the average and median income of the population did not change significantly during this time period. However, between 2001 and 2006 new infrastructure was in operation when the stabilization of preference structure is observed. What drove the sharp changes in preference structure between 1996 and 2001 remain an issue for further study, but it is clear that massive suburbanization happened in the study area during this time, as supported by the observation that transit modal share for commuting dropped and auto driving modal share for commuting jumped during the period. Perhaps only suburbanization (and probably the resulting gentrification and other side effects of suburbanization) can cause such significant changes in commuting mode choice preference structures. While the suburbanization continued after 2001, new transportation infrastructures, planning policies, etc., might have caused the stabilization in mode choice preferences. This finding clearly suggests that mode choice models developed by using a single crossectional dataset should be used carefully for forecasting, and that change to the urban form and transport supply need to be accounted for in the process. Our work has suggested a systematic process for taking these factors into account.

It is clear that preference structures for commuting mode choices are non-static and evolve over time. Mode choice models developed by using only one crossectional travel survey data set are highly unlikely to have the capacity to capture such changes. While commuting mode choice models are considered to be a critical work horse for almost all transportation planning agencies, it is important to find out appropriate model formulations that can give reliable forecasts for the future years. In general, it is almost impossible to state that a particular mode choice model will be temporally transferable in general. For example, our mode choice model developed by using 1996 data does not transfer well to 2001 or 2006. However, the 2001 model performs quite well on the 2006 data (i.e., parameters remain very close for models developed for these two years). The correct economic modelling structure that can provide acceptable level of transferability in the face of any drastic changes in preference structure is something that needs further rigorous research, but it is clear that simple modelling structures (such as multinomial logit or even GEV) may not be sufficient.

Based on such understanding, this paper proposes a pooled data model specification that can take the advantage of multiple repeated crossectional datasets. The proposed model considers the earliest year as the base reference year and accommodates a logarithmic function of increasing time to capture evolution of preference structures over time. In this paper, the proposed model is estimated by pooling 1996, 2001 and 2006 datasets for the GTHA. Our empirical model reveals that the root scale parameter decreases with increasing time, but that the auto nest scale parameter increases over time. This is an indication of increasing auto dependency and modal captivity that are evident in aggregate data. The pooled data model outperforms in all measures of model transferability.

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Table 1: Individual Year Specific Models

	HET-GEV Model						Entropy-Based Scale HET-GEV Model					
	Year: 1996		Year: 2001		Year: 2006		Year: 1996		Year: 2001		Year: 2006	
Number of Cases	1354834		1295718		1069252		1354834		1295718		1282420	
Loglikelihood of Full Model	-771548		-718616		-606598		-769905		-710604		-719524	
Loglikelihood of Equiprobable Model	-1743062		-1607455		-1342467		-1743062		-1607455		-1610104	
Loglikelihood of Aggregate Market Share Model	-1051008		-1027574		-774293		-1051008		-1027574		-928658	
Likelihood Ratio against Equiprobable Model	0.56		0.55		0.55		0.56		0.56		0.55	
Likelihood Ratio against Aggregate Market Share Mode	0.27		0.30		0.22		0.27		0.31		0.23	
Systematic Utility Function												
Variable	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**
Alternative Specific Constant												
Drive Alone	7.66	168.5	7.49	157.3	6.76	133.4	5.23	69.9	6.04	179.2	6.03	146.5
Auto Passenger	3.06	95.1	3.13	90.9	2.88	77.0	2.18	62.4	3.09	118.4	3.05	95.4
Transit with Walk Access	7.47	161.4	7.57	153.9	7.18	133.1	5.10	69.6	6.01	178.3	6.15	147.6
Subway Park & Ride	5.31	111.1	4.98	102.0	4.77	94.0	3.55	62.9	4.24	118.4	4.40	105.1
GO with Transit Access	---		---		---		---		---		---	
GO Park & Ride	4.57	106.2	6.54	105.5	6.22	94.8	2.97	56.7	3.57	74.3	3.70	67.4
NMT	2.20	69.9	2.29	67.6	2.40	64.6	1.53	54.5	2.25	90.2	2.40	78.0
In-Vehicle Travel Time in Minutes												
Generic for all modes	-0.01	-41.7	-0.01	-36.5	-0.01	-27.8	-0.01	-37.6	-0.01	-55.7	-0.01	-31.9
Travel Cost (Generic for all modes)												
Occupation group:												
Professional	-0.38	-161.1	-0.16	-80.6	-0.11	-55.7	-0.25	-67.0	-0.10	-85.7	-0.09	-64.7
General Office	-0.39	-134.5	-0.18	-56.3	-0.11	-43.2	-0.26	-64.3	-0.12	-56.1	-0.08	-43.7
Service	-0.27	-98.4	-0.17	-46.0	-0.13	-50.3	-0.18	-60.0	-0.10	-40.2	-0.09	-48.7
Manufacturing	-0.31	-99.6	-0.25	-66.9	-0.37	-74.3	-0.20	-58.6	-0.15	-61.6	-0.26	-75.0

Table 1 (Continued): Individual Year Specific Models

Systematic Utility Function												
Variable	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**
Distance Less than or equal to 1 km												
NMT	4.93	158.3	4.98	156.2	4.59	139.7	3.33	67.3	3.60	165.0	3.71	143.6
Distance Greater than 1 km, but lesst than or equal to 2 km												
NMT	2.90	111.1	3.08	113.2	2.83	104.9	1.94	62.8	2.16	121.1	2.22	109.5
Distance Greater than 2 km, but lesst than or equal to 3 km												
NMT	1.63	56.9	1.53	51.9	1.66	59.5	1.10	46.6	1.09	58.3	1.28	63.2
Access Walking Time (Minutes)												
All Transit Modes	-0.01	-11.4	-0.05	-75.2	-0.04	-64.3	-0.01	-12.1	-0.03	-77.3	-0.03	-63.6
Access Waiting Time (Minutes)												
All Transit Modes	-0.08	-121.6	-0.13	-97.0	-0.12	-88.9	-0.05	-64.0	-0.08	-95.8	-0.09	-88.9
2 Cars in Household												
Drive Alone	1.66	150.1	1.69	141.1	1.57	130.1	1.06	67.8	0.91	140.8	0.95	133.6
1 Car in Household												
Auto Passenger	1.42	90.7	1.77	97.4	1.73	89.4	0.95	56.3	1.23	96.9	1.35	88.6
More than 2 Cars in Household												
Drive Alone	2.10	134.2	2.19	135.8	2.10	124.7	1.35	65.4	1.20	135.7	1.30	128.6
More than or Equal to 2 Cars in Household												
Auto Passenger	1.75	94.7	2.43	108.9	2.38	100.0	1.16	57.0	1.51	99.4	1.67	91.8
Total Number of Cars in Household												
Subway Park & Ride	1.77	93.9	1.71	105.3	1.54	96.2	1.22	58.6	1.17	109.4	1.13	98.4
GO Park & Ride	1.81	96.7	2.22	85.1	2.00	76.2	1.31	65.7	2.55	113.1	2.53	97.5
Dummy Variable (1) for Female												
Auto Passenger	1.37	114.5	1.05	100.7	0.87	86.3	0.88	65.8	0.62	110.1	0.57	92.4
local Transit (Bus/LRT) with Walk Access	0.92	110.6	0.85	92.0	0.60	70.8	0.59	64.4	0.44	79.2	0.35	60.1
Subway Park & Ride	0.77	30.5	0.49	19.8	0.30	13.2	0.52	26.9	0.00	-0.1	-0.02	-1.2
GO with Transit Access	5.08	103.5	8.13	126.9	7.54	108.0	3.17	60.7	6.08	121.9	6.03	91.1
GO Park & Ride	0.78	34.1	0.82	25.2	0.69	20.6	0.59	33.8	0.42	17.6	0.71	26.7
NMT	0.17	11.7	0.19	12.9	0.04	2.9	0.09	9.2	-0.05	-5.2	-0.13	-11.6

Table 1 (Continued): Individual Year Specific Models

Systematic Utility Function												
Variable	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**	**Param**	**t-Stat**
Age Less than of Equal to 25 Years												
Auto Passenger	1.27	85.3	1.23	92.3	1.20	83.2	0.83	58.4	0.77	98.4	0.84	89.2
local Transit (Bus/LRT) with Walk Access	1.19	93.2	1.11	77.9	1.22	79.5	0.78	59.2	0.64	71.8	0.80	74.1
Subway Park & Ride	0.00	-0.1	0.41	10.2	0.25	6.1	0.00	-0.1	-0.04	-1.4	-0.17	-5.1
GO with Transit Access	1.78	21.3	2.54	30.8	2.11	23.0	1.48	23.5	1.75	29.9	1.95	25.2
GO Park & Ride	0.11	2.2	0.24	4.2	-0.11	-1.8	0.00	0.1	0.24	5.1	0.37	8.0
NMT	1.16	49.5	0.75	31.8	0.50	19.6	0.75	42.0	0.39	25.3	0.24	12.5
Age Greater than 25 years and Less than of Equal to 30 Years												
Auto Passenger	0.23	19.2	0.29	25.8	0.33	27.5	0.14	17.6	0.16	22.0	0.23	26.6
local Transit (Bus/LRT) with Walk Access	0.32	34.7	0.44	38.1	0.46	36.9	0.21	31.2	0.26	34.3	0.31	33.5
Subway Park & Ride	-0.14	-4.0	0.27	7.9	0.36	10.7	-0.12	-5.0	-0.04	-1.7	0.04	1.3
GO with Transit Access	1.55	26.1	2.09	27.3	2.00	22.9	1.31	28.0	1.41	25.3	2.02	22.4
GO Park & Ride	-0.21	-6.8	0.28	5.6	-0.11	-2.0	-0.11	-5.0	0.30	8.9	-0.12	-2.4
NMT	0.26	13.3	0.50	23.0	0.32	14.1	0.19	14.2	0.26	17.6	0.20	11.5
Age Greater than 55 years												
Auto Passenger	0.09	5.2	0.00	0.1	-0.04	-3.8	0.06	5.3	-0.02	-2.8	-0.03	-3.3
local Transit (Bus/LRT) with Walk Access	-0.14	-9.6	-0.23	-15.1	-0.26	-21.5	-0.09	-9.2	-0.15	-16.1	-0.15	-18.2
Subway Park & Ride	-0.31	-6.3	-0.34	-7.1	-0.40	-10.7	-0.16	-4.5	-0.31	-9.6	-0.26	-9.4
GO with Transit Access	2.72	33.0	1.67	14.2	1.61	17.2	2.23	37.2	1.50	17.3	1.72	19.6
GO Park & Ride	-0.69	-12.3	0.25	3.3	0.55	9.2	-0.39	-9.5	2.40	38.2	0.36	7.6
NMT	-0.36	-11.8	-0.35	-12.9	-0.31	-15.2	-0.24	-11.8	-0.30	-16.9	-0.26	-17.0
Exponential Function for Scale Parameters												
Scale Parameter for Auto Driver and Auto Passenger Nest												
Constant	-0.20	-32.9	-0.01	-0.8	0.16	20.0	0.22	14.9	0.39	64.4	0.44	60.7
Root Scale Parameter:												
ln(Zonal Median Income in 10,000)	-0.08	-16.4	-0.15	-35.3	-0.05	-12.1	-0.09	-19.0	-0.36	-81.9	-0.26	-60.1
Quadratic Function of Entropy												
Entropy							1.21	52.0	2.49	125.2	2.36	106.4
Entropy ^{2}							-0.79	-78.6	-1.95	-120.5	-1.93	-107.2

Table 2: Estimated Values of Time Savings from Individual Year-Specific Models

	HET-GEV Model			Entropy-Based Scale HET-GEV Model		
	Year: 1996	Year: 2001	Year: 2006	Year: 1996	Year: 2001	Year: 2006
Value of In-Vehicle Travel Time Savings						
Occupation group:						
Professional	$1.90	$4.83	$5.46	$1.95	$7.74	$5.79
General Office	$1.81	$4.17	$5.19	$1.86	$6.74	$6.07
Service	$2.68	$4.44	$4.38	$2.77	$8.09	$5.42
Manufacturing	$2.32	$2.95	$1.56	$2.40	$5.48	$1.94
Value of Transit Access Walking Time Savings						
Occupation group:						
Professional	$1.56	$17.45	$20.42	$1.68	$17.58	$18.42
General Office	$1.49	$15.08	$19.42	$1.60	$15.30	$19.32
Service	$2.20	$16.05	$16.37	$2.39	$18.36	$17.24
Manufacturing	$1.91	$10.67	$5.83	$2.08	$12.44	$6.19
Value of Transit Access Waiting Time Savings						
Occupation group:						
Professional	$12.92	$51.74	$70.46	$13.00	$48.71	$60.28
General Office	$12.35	$44.69	$67.03	$12.40	$42.42	$63.22
Service	$18.22	$47.57	$56.49	$18.50	$50.88	$56.41
Manufacturing	$15.77	$31.63	$20.11	$16.06	$34.47	$20.24

Table 5: Pooled Model

Number of Cases		3719804.00	
Loglikelihood of Full Model		-2101242.88	
Loglikelihood of Market Share Model		-2752948.82	
Likelihood Ratio Against Market Share Model		0.24	
	Systematic Utility Function		
Variable	**Mode**	**Parameter**	**t-Statistics**
Alternative Specific Constant			
	Drive Alone	5.84	200.48
	Auto Passenger	2.82	130.59
	Transit with Walk Access	6.07	202.21
	Subway Park & Ride	4.50	153.73
	GO with Transit Access	----	
	GO Park & Ride	3.09	93.74
	NMT	2.13	102.03
Temporal Factor (logarithm of the number of years after 1996)			
	Drive Alone	-0.19	-19.19
	Auto Passenger	-0.14	-15.09
	Transit with Walk Access	-0.31	-31.10
	Subway Park & Ride	-0.38	-33.65
	GO with Transit Access	----	
	GO Park & Ride	0.63	46.88
	NMT	-0.16	-16.29
In-Vehicle Travel Time (Minutes)			
	All modes	-0.01	-72.81
Travel Cost (Generic for all modes)			
	Occupation group:		
	Professional	-0.14	-187.83
	General Office	-0.15	-147.43
	Service	-0.11	-114.35
	Manufacturing	-0.16	-128.83

Table 5 (Continued): Pooled Model

Systematic Utility Function			
Variable	**Mode**	**Parameter**	**t-Statistics**
Distance Less than or equal to 1 km			
	NMT	3.51	224.29
Distance Greater than 1 km, but lesst than or equal to 2 km			
	NMT	2.10	178.28
Distance Greater than 2 km, but lesst than or equal to 3 km			
	NMT	1.17	102.38
Access Walking Time (Minutes)			
	All Transit Modes	-0.03	-114.30
Access Waiting Time (Minutes)			
	All Transit Modes	-0.06	-161.22
2 Cars in Household			
	Drive Alone	0.99	210.58
1 Car in Household			
	Auto Passenger	1.16	145.46
More than 2 Cars in Household			
	Drive Alone	1.30	201.72
More than or Equal to 2 Cars in Household			
	Auto Passenger	1.45	148.72
Total Number of Cars in Household			
	Subway Park & Ride	1.19	156.67
	GO Park & Ride	1.77	148.66
Dummy Variable (1) for Female			
	Auto Passenger	0.69	175.58
	local Transit (Bus/LRT) with Walk Access	0.48	148.20
	Subway Park & Ride	0.21	20.49
	GO with Transit Access	4.50	155.90
	GO Park & Ride	0.57	42.16
	NMT	-0.02	-3.71

Table 5 (Continued): Pooled Model

Variable	Mode	Parameter	t-Statistics
	Systematic Utility Function		
Age Less than of Equal to 25 Years			
	Auto Passenger	0.81	152.11
	local Transit (Bus/LRT) with Walk Access	0.72	132.95
	Subway Park & Ride	-0.08	-4.52
	GO with Transit Access	1.98	52.99
	GO Park & Ride	-0.11	-3.51
	NMT	0.51	54.01
Age Greater than 25 years and Less than of Equal to 30 Years			
	Auto Passenger	0.17	39.07
	local Transit (Bus/LRT) with Walk Access	0.25	59.92
	Subway Park & Ride	---	
	GO with Transit Access	1.32	40.32
	GO Park & Ride	-0.08	-4.64
	NMT	0.23	27.80
Age Greater than 55 years			
	Auto Passenger	---	
	local Transit (Bus/LRT) with Walk Access	-0.13	-25.75
	Subway Park & Ride	-0.26	-13.57
	GO with Transit Access	1.88	47.31
	GO Park & Ride	-0.24	-24.23
	NMT	----	
	Exponential Function for Scale Parameters		
Scale Parameter for Auto Driver and Auto Passenger Nest			
	Constant	0.32	64.36
	Temporal Factor (logarithm of the number of years after 1996)	0.04	14.82
Root Scale Parameter			
	ln(Zonal Median Income in 10,000)	-0.16	-65.24
	Entropy	1.77	180.37
	Entropy ^{2}	-1.28	-181.63
	Temporal Factor (logarithm of the number of years after 1996)	-0.07	-34.59