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Evolution of latent modal captivity and mode choice patterns for commuting trips: A longitudinal analysis using repeated cross-sectional datasets

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ABSTRACT

This paper presents an investigation of the temporal evolution of commuting mode choice preference structures. It contributes to two specific modelling issues: latent modal captivity and working with multiple repeated crossectional datasets. In this paper latent modal captivity refers to captive reliance on a specific mode rather than all feasible modes. Three household travel survey datasets collected in the Greater Toronto and Hamilton Area (GTHA) over a ten-year time period are used for empirical modelling. Datasets collected in different years are pooled and separate year-specific scale parameters and coefficients of key variables are estimated for different years. The empirical model clearly explains that there have been significant changes in latent modal captivity and the mode choice preference structures for commuting in the GTHA. Changes have occurred in the unexplained component of latent captivities, in transportation cost perceptions, and in the scales of commuting mode choice preferences. The empirical model also demonstrates that pooling multiple repeated cross-sectional datasets is an efficient way of capturing behavioural changes over time. Application of the proposed mode choice model for practical policy analysis and forecasting will ensure accurate forecasting and an enhanced understanding of policy impacts.

1. Introduction

Commuting trips are the major and most repeated trips of urban residents. Patterns of commuting trips in any urban area define its transportation system performance cycles: peak versus off-peak period traffic congestions. As such, major transportation policies and planning decisions always target commuting trips to manage travel demand, land use and emissions (Zaman and Habib, 2011). Mode choice for commuting is a primary factor in defining any urban area's traffic congestion levels. Thus, research on commuting mode choice behaviour always has planning and policy implications. Modelling mode choice behaviour for commuting trips has fascinated many researchers from the early age of behavioural analysis of travel demand (Wilson et al., 1984). The availability of alternative modes as well as captivity to certain types of modes is recognized to be extremely critical in defining mode choice behaviour (Tardiff, 1976; Stopher, 1980).

Captivity to a specific mode refers to not considering alternatives, either because there are no other feasible options or there is no desire to consider alternatives. Modal availability refers to the feasibility of alternative modes and it defines

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explicit captivity. Alternative modes that are not feasible are not available and hence cannot be considered. However, a lack of desire to consider alternatives to the chosen available mode refers to an implicit captivity in mode choice. If modal availability is deterministically introduced (whether a specific mode should be in the choice set or not) in a mode choice model, then the leftover modal captivity is definitely latent in the choice process. Hence, the implicit captivity can also be referred to as the latent captivity. However, the issue of implicit or latent captivity in mode choice is often ignored or misrepresented in mode choice modelling (Jacques et al., 2012). Also, the concept of modal captivity is often debated as the various definitions of captivity can be possible (Polzin et al., 2000). For example, latent captivity is often referred to as captivity by choice and modal unavailability is referred as captivity by force (Jacques et al., 2012). While captivity by force is easy to identify (factors such as having no driving license or having no transit service nearby), latent captivity is difficult to predict in choice models. Such captivity may be the result of mostly positive or negative experiences or alternatively, satisfaction or dissatisfaction with specific modes (Ergun, 1999). The attributes of specific modes (e.g., higher mobility with private car, less mental engagement while travelling with transit, and physical exercise for non-motorized modes) can create different levels of attractiveness and thereby latent captivity.

Latent captivities to different commuting modes have a wide variety of policy implications. For example, latent captivity to the driving private car option may cause major hindrances to successful implementation of many sustainable transportation policies. However, latent captivity to transit modes or non-motorized modes would be quite positive from a sustainable transportation point of view. Understanding the factors that can influence the latent captivity to different modes will be beneficial to transportation planners and policy makers in devising sustainable plans and policies. Specialized surveys are often used to identify various levels of attractiveness to different available alternative modes (Paez and Whalen, 2011; Abou-Zeid and Ben-Akiva, 2011; Creemers et al., 2012). Specialized surveys can provide rich datasets for modelling latent captivity. In the absence of any such specialized survey, explicit modelling of choice set formation by using regular travel survey data can allow the capture of latent captivity in commuting mode choice (Swait and Ben-Akiva, 1986). The concept of such choice models is not new, but its application in travel demand modelling is very rare, perhaps because of model estimation difficulties. Only a very limited number of applications of such modelling exercises are available in the literature.

There are two main modeling issues treated in the paper: modal captivity and working with pooled samples. Latent modal captivity recognizes that some individuals may not have considered what an analyst defines as a choice-set, but, instead blindly uses a single mode. This first difficulty is addressed in the paper using the modeling framework proposed by Swait and Ben-Akiva (1986, 1987), which can be seen as a generalization of Gaudry and Dagenais (1979). The second modeling issue that is treated in this paper is working with a pooled database built as the combination of different years. This problem is addressed by considering different scales for each sample along with different coefficients of some key variables that have shown changing influences over the year, equivalent to what is done for the combination of RP and SP data. The main objectives of the paper are evaluating the factors that influence the evolution of latent captivity and preference structures for commuting mode choices over time in the Greater Toronto and Hamilton Area (GTHA). The lessons learned from this investigation will help to develop better commuting mode choice prediction models by using repeated cross-sectional datasets.

For empirical investigations, we used three repeated cross-sectional datasets of a large-scale household travel survey collected in the Greater Toronto and Hamilton Area (GTHA). These datasets were collected in a five-year cycle from 5% of the population of the GTHA. Using these datasets, we developed a captivity choice model for commuting mode choices. In addition to the three separate models, we pooled the datasets to estimate a pooled model. The pooled model provides an estimate of latent modal captivity to the seven sets of modes used in the study area. The pooled model also reveals the evolution of latent modal captivity, systematic utility function, mode choice model scale parameters and changing patterns of key policy indicators (e.g., value of travel time savings (VOTS)). The paper presents the behavioural interpretations of the pooled model parameter and policy implications of the findings.

The remainder of the paper is organized as follows. The next section presents a brief literature review on modelling efforts used to capture modal captivity. The literature review section is followed by other sections that explain the data sets, econometric model formulations and empirical models. The paper concludes by identifying key findings and offering recommendations for future studies.

2. Literature review

Captivity in mode choice modelling can be captured through choice models with integrated choice set formation. Manski (1977) proposed the general framework for a choice model considering the endogenous choice set formation process. Initially, this approach defines a universal choice set that consists of any and all available options to any individual within the sample. This approach then considers a given set of alternatives as a feasible set. The concept of a feasible alternative set implicitly introduces a form of captivity within the choice model formulation, namely, forced captivity. A feasible alternative set explicitly considers forced captivity by including alternatives that are feasible and excluding those that are unfeasible. For a fixed number of feasible alternatives, there can be a number of possible combinations of feasible alternatives forming choice sets for the final choice. Manski's framework allows for the explicit capture of forced captivity in the choice model formulation, but the concept of latent captivity is not fully appreciated. The concept of latent captivity may be captured indirectly through the formation of feasible choice from the available alternatives, but it requires detailed personalized information for mode estimation. However, overlooking the latent captivity, which is often very common in the case of commuting mode choices, may overlook behavioural reality.

According to Stopher (1980), ignoring the behavioural reality of latent captivity is a serious form of choice model misspecification. Swait and Ben-Akiva (1986) argue that ignoring the choice set formation can cause a significant sacrifice in forecasting robustness for urban areas with rapidly changing social and economic structures. Gaudry and Dagenais (1979) proposed a model formulation, the Dogit model, that can explicitly capture latent captivity in the choice-making process and comply with the general framework of Manski's choice model formulation. This approach further enhances Manski's formulation by explicit capturing both forced and latent captivity to choice alternatives. Although originally developed to overcome the independent and irrelevant alternative assumptions of the multinomial logit model, the Dogit model is the first proposed model that can accommodate the concept of latent captivity along with forced captivity. Bordley (1990) proved that this type of model is robust enough in capturing captivity effects even when the individual is not perfectly captive.

The Dogit model allows the modeller to estimate variations of captivity to all alternatives in the feasible set. It considers that the final choice is conditional upon two possible choice sets: one is the captivating alternative and the other is the collection of all feasible alternatives. It assumes that the individual decision maker is either captive to a specific alternative or considers all feasible alternatives in the choice set. Swait and Ben-Akiva (1986, 1987) further elaborated upon this approach by parameterizing the captivity effects. They empirically proved that the captivity odd parameters can be fully specified as function of independent variables. Swait and Ben-Akiva (1986, 1987) referred to the parameterized form of Dogit model as the parameterized logit captivity (PLC) model.

The PLC model is less complicated than other more advanced choice set formation models that require additional information regarding choice set formation or that computationally become exhaustive because of the large number of feasible alternatives (Ben-Akiva and Boccara, 1995; Swait, 2001). For example, for all other choice set formation models, such as Ben-Akiva and Boccara (1995) and Swait (2001), any individual with seven feasible alternatives will have $(2^7 - 1)$ possible choice sets. Such a large number of possible choice sets makes those models very computation intensive. They become even more computationally intensive when large datasets are used, which is the case in this paper. The PLC model is versatile in capturing latent captivity and does not require additional information regarding choice set formation, nor has the explosions of latent choice sets with increasing numbers of alternatives.

Despite the benefits, since the first development and successful empirical applications of logit captivity models (Gaudry and Dagenais (1979); Swait and Ben-Akiva 1986, 1987), only a few examples of either the Dogit or PLC models are available in the transportation literature. Perhaps the unavailability of commercial software to estimate these models has restricted their application, even though they have tremendous potential. These models have closed form likelihood functions and can easily be estimated by classical maximum likelihood techniques in any general purpose software/language, such as GAUSS, R, SAS, STATA, etc.

After Swait and Ben-Akiva (1986, 1987), McCarthy (1997) estimated a logit captivity model for intercity mode choice. He clearly proved the power of the logit captivity model in capturing latent captivity to specific modes. He also proved that overlooking latent captivity causes biased parameter estimates of choice models. Recently, Chu (2009) applied a different form of the captivity model that replaces the logit component of the logit captivity model by an ordered generalized extreme value model in the Dogit formulation. His approach is known as the Dogit-generalized extreme value (DOGEV) model and is originally proposed by Fry and Harris (2005). Chu (2009) applied this model for departure time choice modelling for commuting trips. He proved that the captivity model clearly has superior performance relative to other discrete choice models. His findings also highlight that overlooking latent captivity causes serious misspecification of the choice models. Chu (2012) also applied a logit captivity model for a disaggregate destination choice model. In this application, he proves that capturing captivity in destination choice improves network modelling capability significantly.

In this paper, we further extended the basic formulation of the PLC model (Swait and Ben-Akiva, 1986, 1987) to accommodate the parameterized scale function for the logit component of the logit captivity model. As we are interested in investigating the evolution of commuting mode choice preferences over time, a pooled model is estimated. The pooled mode considers multiple repeated cross-sectional datasets. However, the pooled model accommodates separate year-specific alternative specific constants in the systematic utility function, the captivity function, scale parameters and some key variables that may have changing effects on mode choice over time. The next section presents the basic formulations of the model.

3. Econometric model

The formulation of the PLC model is based on the original assumption of Dogit model (Gaudry and Dagenais, 1979). The assumption is that a choice maker is either captive to a specific alternative in the choice set of free to choose from all feasible alternatives in the choice set. In reality, it is very difficult to identify whether the choice maker is captive to a specific alternative or not (especially in revealed preference based travel survey datasets). So, the Dogit model assumes that the choice of any alternative is composed of a captive choice component and a non-captive choice component. As per Dogit model formulation, for any individual i, considering a total M number of feasible modes (the choice set), the probability (P_m) of choosing a specific mode m is:

$$P_m = P_{\text{captive-}m} + P_{m|\text{non-captive}} \times (1 - P_{\text{captive-}m}) \tag{1}$$

Here, $P_{\text{captive-}m}$ refers to the probability of making a captive choice of mode m; $P_{m|\text{non-captive}}$ refers to the choice of mode m when all alternatives in the choice set are compared and given that the choice is non-captive.

Gaudry and Dagenais (1979) assumed the following formulation for the Dogit model:

$$P_m = \frac{U_m}{1 + \sum_{m/=1}^{M} U_{m/}} + \frac{1}{1 + \sum_{m/=1}^{M} U_{m/}} P_{m|non-captive} \tag{2}$$

Here, U_m refers to an alternative specific constant for mode m.

Swait and ben-Akiva (1986, 1987) further parameterized the constant terms of binary captive choice component and developed the Parameterized Logit Captivity (PLC) model as following.

$$P_m = \frac{\exp(D_m)}{1 + \sum_{m/=1}^{M} \exp(D_{m/})} + \frac{1}{1 + \sum_{m/=1}^{M} \exp(D_{m/})} P_{m|non-captive} \tag{3}$$

Here,

$$D_m = \delta_m + \sum \alpha y \tag{4}$$

D_m refers to a linear-in-parameter function of modal captivity for mode m, ASC_m refers to the alternative specific constant of mode m, $\sum \alpha y$ refers to linear-in-parameter captivity function.

In case of $P_{m|\text{non-captive}}$, both Dogit and PLC model assumes a multinomial logit model formulation. Multinomial logit model assumes an IID type I extreme value distribution with scale parameter μ. Under this assumption:

$$P_{m|\text{non-captive}} = \frac{\exp(\mu V_m)}{\sum_{m'=1}^{M} \exp(\mu V_{m'})} \tag{5}$$

Here,

$$V_m = ASC_m + \sum \beta x \tag{6}$$

V_m refers to the systematic utility function of non-captive choice, ASC_m refers to the alternative mode (m) specific constant, $\sum \beta x$ refers to linear-in-parameter functions of covariates.

This results in the full formulation of PLC model as:

$$P_m = \frac{\exp(D_m)}{1 + \sum_{m/=1}^{M} \exp(D_{m/})} + \frac{1}{1 + \sum_{m/=1}^{M} \exp(\mu_c D_{m/})} \frac{\exp(\mu V_m)}{\sum_{m/=1}^{M} \exp(\mu V_{m/})} \tag{7}$$

However, both Dogit and PLC models assume the value of μ to be unity. This assumption implicitly refers to a homoskedastic choice bahaviour. We are interested in the evolution of modal captivity over time and it is argued that in the case of evolution over time, the choice model scale parameter should also be considered (Badoe and Miller, 1995). To further accommodate systematic heteroskedasticity, we parameterized the scale parameters of the multinomial choice component as following:

$$\mu = \exp\left(\sum \gamma z\right) \tag{8}$$

Here, $\sum \gamma z$ refers to a linear-in-parameter function of covariates.

An exponential function for the scale parameter (μ) is necessary to ensure the positivity of estimated scale values (Habib et al., 2012). This linear-in-parameter function can accommodate the variables that vary across the population and thus capture the systematic heteroskedasticity in choice behaviour. So, the proposed model formulation developed in this paper can be referred as a PLC model with scale heterogeneity. For empirical estimation, we pooled three datasets from 1996, 2001 and 2006 collected in the GTHA. To capture the evolution of latent modal captivity and mode choice preference structures, we used individual year-specific components in the parameterization process. This is done by estimating separate constants for each year in each parameterized function. Reformulation Eqs. (4), (6), and (8), we get:

$$D_m = \delta_{m-1996} + \delta_{m-2001} + \delta_{m-2006} + \sum \alpha y \tag{9}$$

$$\mu = \exp(\gamma_{1996} + \gamma_{2001} + \gamma_{2006} + \gamma z) \tag{10}$$

$$V_m = ASC_{m-1996} + ASC_{m-2001} + ASC_{m-2006} + \sum \beta x \tag{11}$$

Separate year-specific constants are estimated for the latent captivity component (D) and system utility component (V). However, in the case of the scale parameter function (μ), we need to consider one specific year as the reference. We therefore consider 1996, the earliest of three years, as the base reference year. This formulation still keeps the model likelihood function in closed form. The empirical models are estimated by codes written in GAUSS and using the MAXLIK component for maximum likelihood estimation (Aptech Systems, 2012). The proposed econometric formulation allows us to use multiple repeated cross-sectional datasets in combination to investigate the longitudinal evolution of the mode choice preference structure over time. However, because of the highly non-linear likelihood function, the estimation process becomes very sensitive to the starting values of the parameters. The high non-linearity refers to the multidimensional surface of loglikelihood function that may have multiple local peaks and/or apparently flat regions. In such cases, the model parameter estimation process often gets stuck within local maxima and/or in an apparently flat surface of the multidimensional loglikelihood function. Appropriate assumption of initial parameter values is necessary to arrive at optimum parameter estimation. We found that estimating a multinomial logit model of similar specification gives good starting values for the parameters of the logit model component of the latent captivity model. In the case of the parameters of the latent captivity functions, a series of binomial logit models for each mode gives very good starting values.

4. Data

The Transportation Tomorrow Survey (TTS) is a household-based trip diary survey conducted in the Greater Toronto and Hamilton Area (GTHA) every 5 years (DMG, 2012). The survey began in 1986, but the current shape used today was introduced in 1996. After 1996, two more surveys in 2001 and 2006 were based on exactly the same questionnaire and study area. This sample survey (with a sample size equivalent to 5% of the population of the GTHA) allows for the investigation of the evolution of the commuting mode choice preference structure over the 10-year time period. In general, the TTS survey classifies commuters into four major occupation groups and the commuting modes into 7 distinct types.

The occupation groups are:

1. General office
2. Manufacturing
3. Professional
4. Retail/service.

The commuting modes are:

1. Auto driving (AD)
2. Auto passenger (AP)
3. Transit with walk access (TWA), including local and regional transit
4. Local transit with auto access (park and ride) (TAA), including mostly the subway park and ride option
5. GO transit with local transit access (GTTA), including the GO bus or GO train with local transit access
6. Go transit with auto access (park and ride) (GAA), including the GO bus or GO train with auto access
7. Non-motorized travel (NMT).

Unfortunately, the TTS survey does not collect individual- or household-level income information. We considered occupation-specific variables for travel cost in the model that might capture income effect indirectly. To further supplement for the unavailability of an income variable within the TTS datasets, we imputed zonal average and median income and considered this variable in the scale parameterization of the logit choice model component. The dataset includes a series of personal and household-specific variables (e.g., age, gender, occupation, household size, household location and household auto ownership). In order to capture the effects of the home location attributes, we imputed the total zonal population from census data. The survey collects information on start time, origin zone, destination zone, distance between origin and destination, and mode of travel for each trip. So, transportation level-of-service attributes (in-vehicle travel time, waiting time for transit modes, walking access time to transit stations/stops and travel cost by different mode of transportation) are estimated by using deterministic user equilibrium (DUE) traffic assignment models. These models were calibrated and validated using EMME/2-based DUE traffic networks for 1996, 2001 and 2006 that are used by local and regional planning agencies.

In the mode choice model, we deterministically determined the feasible alternative sets by using feasibility rules. These feasibility rules are commonly employed by the planning agencies in the study (Miller, 2007). These include:

- Having a driving license and owning at least one private automobile makes auto driving feasible.
- The auto passenger mode is available to everybody.
- Transit modes are feasible if the corresponding origin–destination pair has a reasonable transit travel time (less than 150 min 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 km.
- With respect to access modes to transit, it is assumed that commuters access their closest (by straight-line distance) feasible station with on-site parking.

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. For proper comparisons of individual year-specific models as well as pooling the individual year-specific datasets to develop a pooled model, the travel cost variables of 1996 and 2001 datasets are converted into 2006 Canadian dollars using corresponding year-specific consumer price indices (CPI). Travel cost variables used in the models refer to the total cost for the corresponding modes. In the case of auto driver and auto passenger modes, travel cost includes running cost (gasoline cost as well as road toll, if any) and parking cost at destination. In the case of transit modes, travel cost includes transit fare and parking cost at the station (only for the subway park and ride option, as parking was free for the GO park and ride option).

5. Empirical models

A series of alternative model specifications are tested and the final models are defined based on expected signs and statistical significances (for 95% confidence limit the corresponding t-statistics is 1.96 for a two-tailed test and 1.64 for a one-tailed test) of the parameters. Model goodness-of-fit is measured by estimating the rho-squared value against the null model (equiprobable model) (Ben-Akiva and Lerman, 1985). First of all, individual year-specific cross-sectional models are estimated. A comparison of parameters of the cross-sectional models provides an understanding of the changing influences of the models' various variables. This understanding is necessary for developing the pooled model. Estimated year-specific cross-sectional model parameters are compared to have a better idea about the variability of parameters' values across the years. The same specification is maintained for each individual year-specific model for fair comparison.

While we cannot really compare the corresponding parameters of different year-specific models one to one, as they are estimated by using different year-specific datasets, a graphical comparison for the parameters' relative values can provide a good understanding of the variations of parameter values over the year. This graphical comparison gives a better idea about the parameters that have individual year-specific effects versus parameters that are stable over the years (Swait and Bernardino, 2000). In order to identify the parameters that cause large deviations over the years, we plotted individual model parameters pair by pair (1996 versus 2001, 1996 versus 2006, and 2001 versus 2006). Fig. 1 presents the individual year-specific parameter comparisons. The straight lines along the dots in the graphs represent 45° lines. Dots (the corresponding parameters) that are aligned close to the 45° line are stable or relatively unchanged between the years. Dots (the corresponding parameters) that are aligned far from the 45° line have changed significantly between the years. Conceptually, parameters that are aligned close to the 45° line can have the same values for all years in the pooled model. Similarly, the parameters that are aligned far from the 45° line should have individual year-specific values in the pooled model.

Fig. 1 makes it clear that large variations exist between 1996 and 2001, as well as between 1996 and 2006. However, the 2001 model parameters are very similar to those of the 2006 model parameters. In addition to a visual comparison of parameters of two different year-specific models, we also used an arbitrary measurement of average squared differences between parameter sets (ASDPS). ADSP is estimated as:

$$ASDP_{Year\,i-j} = \sum_{\beta=1}^{N_\beta}((\text{Parameter}_{\beta_i} - \text{Parameter}_{\beta_j}))/N_\beta \tag{12}$$

$N_\beta = \text{Total number of parameters in each model}$

It is clear that the ASDP between 1996 and 2006 is the highest, which is 3.18. This is followed by the ASDP between 1996 and 2001, which is 2.96, and the lowest ASDP is between 2001 and 2006, which is 0.15.

Investigating the parameters aligning far from the 45° line reveals that between 1996 and the other two years the alternative specific constant of the systematic utility function and the alternative specific constants of the latent captivity functions showed apparently large deviations. Similarly, between 2001 and 2006, slight deviations are caused by the corresponding alternative specific constants of the systematic utility and latent captivity functions. Interestingly, the parameters that did not show huge variations and thereby apparently aligned close to the 45° line, but that have a significant policy impact, are the coefficients of the travel cost variables. Slight variations between years is observed in travel cost coefficients that may result in an evolution of value of travel time savings (VOTS) for commuting trips.

Based on understandings from the comparisons of individual year-specific model parameters, the pooled model specifications are developed. For the pooled model, we considered separate year-specific alternative specific constants for the systematic utility and latent captivity functions. We also consider separate year-specific travel cost coefficients to capture the evolution of VOTS in the GTHA. Three types of pooled models are estimated:

1. A pooled parameterized logit captivity model.
2. A pooled multinomial logit model with parameterized scale functions.
3. A pooled simple multinomial logit model.

The pooled parameterized logit captivity model is considered as the final model. The other two multinomial logit models are estimated to evaluate the superiority of the logit captivity approach of the final model. The second multinomial logit model has the same systematic utility function and parameterized scale function as the final model, but it does not have the captivity function (the corresponding choice model is the probability function specified in Eq. (6) only). The third multinomial logit model has the same specification of systematic utility function but the scale parameter is parameterized and

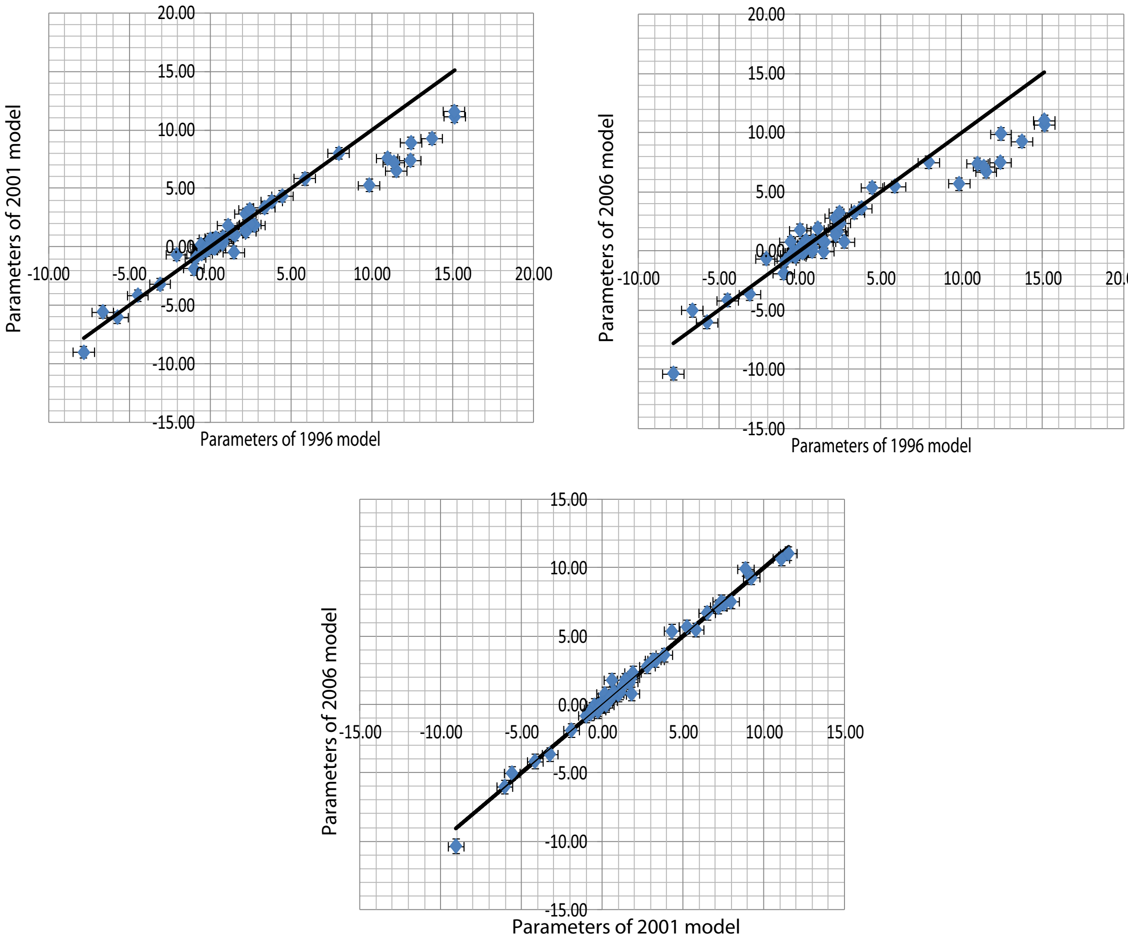

Fig. 1. Comparison of individual year-specific model parameters.

estimated. The pooled models are tested for goodness-of-fit against the year-specific constant-only model (market segmentation model) and the equiprobable model (considering all alternatives are equally likely). Goodness-of-fit is measured by the loglikelihood ratio test (Ben-Akiva and Lerman, 1985). Table 1 summarizes the results.

The pooled models clearly show a very high degree of fit against the equiprobable model and reasonable fit against the market segmentation model. This proves the potential of pooling for a multiple cross-sectional dataset to estimate the commuting mode choice model. Among the three pooled models, it is clear that goodness-of-fit improves signification for the consideration of latent captivity through the parameterized logit captivity approach. The final model outperforms the corresponding multinomial logit models by fitting against both the equiprobable model and the market share model. The final model (parameterized logit captivity model) has 23 parameters more than the corresponding multinomial logit model with parameterized scale and 20 parameters more than the corresponding simple multinomial logit model. The estimated likelihood ratio of the final model against the multinomial logit models passes the critical chi-square values with 99.99% confidence limit. This justifies accommodating the parameterized latent captivity function in the commuting mode choice model.

Table 1
Summary statistics of pooled models.

	Final model: parameterized logit captivity model	Multinomial logit model with parameterized scale function	Multinomial logit model
Number of observations	199,092	199,092	199,092
Loglikelihood of full model	−109,185	−113,385.1	−113,357
Loglikelihood of equiprobable model	−280,200.1	−280,200.1	−280,200.1
Loglikelihood of market share model	−140,641.8	−140,641.8	−140,641.8
Likelihood ratio against equiprobable model	0.610	0.595	0.595
Likelihood ratio against market share model	0.224	0.194	0.194

The datasets available for this study do not have income information, but it is important to investigate whether income has a very strong effect or not. Jara-Diaz and Videla (1989) suggest a straightforward way of testing the importance of income effect in mode choice modelling. Income effect can be detected by incorporating 'squared travel cost' as a variable in the systematic utility function of the mode choices. The resulting zero coefficient of this variable suggests insignificant income effect and vice versa. We have tested this variable in all three types of pooled models and in all cases the coefficients are found to be close to zero. This reveals that in our case income effect is not very strong and the omission of an income variable in the model will not cause model misspecification problems. Moreover, we tested including a zonal average income variable in the systematic utility function, scale parameter function and captivity function. However, it seems that this variable is only significant in the scale parameter function to allow for the capture of an endogenous segmentation of commuters based on continuous zonal average income.

The final model (the pooled parameterized logit captivity model) has a total of 81 parameters and they are all statistically significant. The final model has three major components:

1. Systematic utility function for rational choice (a total of 55 parameters).
2. Scale parameters of the rational choice model component (a total of 3 parameters).
3. Parameterized captivity function (a total of 23 parameters).

Based on the understandings drawn from individual year-specific cross-sectional models, each of these components is considered to have some parameters (of corresponding variables) that are difference for different years and some have the same values across the years. Individual year-specific parameters allow for the investigation of the systematic evolution of the influences of the corresponding variable on commuting mode choices over the year. Table 2 presents the year-specific parameters of the systematic utility function of the rational choice model component.

The pooled data model allows for a relative comparison between the parameters that showed significant variations across the years in the individual year-specific models. The alternative specific constants, both in the systematic utility function and the latent captivity function, are lower in the pooled data model than the corresponding year-specific models. Low alternative specific constants mean that the pooled model provides a good explanation of behaviour through model formulations and observed variables. So, we can infer that the pooled model captures behavioural changes over time efficiently and in a robust way. Comparing the alternative specific constants of the individual years in the final model, it is clear that the alternative specific constants of drive alone, auto passenger, transit with walk access and NMT drop from 1996 to 2001, and the alternative specific constants of drive alone, auto passenger and transit with walk access drop from 2001 to 2006. A reduction of alternative specific constants refers to the fact that systematic utilities of the rational choices model component are increasingly becoming predictable by the observed variables. However, the alternative specific constant of GO park and ride mode increased from 1996 to 2006. A possible explanation is that the GO park and ride mode has become more popular over the years even though there have been few notable changes in GO transit services from 1996 to 2006. Another possible explanation is that increasing suburbanization has made the GO park and ride mode more feasible to a higher number of commuters over the years. The pooled model of commuting model choice has allowed the capture of the evolution of structural changes in commuter mode choice preferences over time that could not be captured if a cross-sectional model were used.

In addition to alternative specific constants, separate year-specific coefficients are introduced for travel costs that are further interacted with occupation categories (professional, general office, service and manufacturing). However, no difference between the cost coefficients of 2001 and 2006 are found. A wide variation in cost coefficient is evident across the occupation

Table 2
Year-specific coefficients of the systematic utility function for rational choice.

Variable	Mode	Year 1996		Year 2001		Year 2006	
		Parameter	*t*-Stat	Parameter	*t*-Stat	Parameter	*t*-Stat
Alternative Specific Constant:							
Drive Alone		9.827	5.31	8.673	4.46	8.503	4.29
Auto passenger		5.802	3.14	5.099	2.62	5.001	2.53
Transit with walk access		10.050	5.43	8.572	4.41	8.440	4.26
Subway park and ride		8.495	4.58	6.332	3.25	6.333	3.19
GO park and ride		6.432	3.47	8.508	4.37	8.663	4.36
NMT		4.896	2.65	4.182	2.15	4.201	2.12
In-vehicle travel time (min)							
All modes		−0.022	−21.98	−0.022	−21.98	−0.022	−21.98
Travel cost (Generic for all modes)							
Occupation group							
Professional		−0.254	−45.34	−0.139	−27.10	−0.139	−27.10
General Office		−0.280	−33.12	−0.153	−19.22	−0.153	−19.22
Service		−0.200	−25.03	−0.141	−16.63	−0.141	−16.63
Manufacturing		−0.207	−23.19	−0.233	−21.91	−0.233	−21.91

category between 1996 and 2001–2006. Interestingly, travel cost sensitivity dropped for all occupation groups except manufacturing.

Compared to 1996, the professional and service occupation groups seem to have the same travel cost sensitivity, which is also very close to that of the general office group. After 1996, travel cost sensitivity dropped by 45% for the professional and service groups and by 30% for the general office group. Conversely, travel cost sensitivity increased by 22% for the manufacturing group. As a result the value of travel time savings (VOTS) increased to almost double the value in 1996 for all occupation groups except the manufacturing group. In the case of the manufacturing group, the VOTS reduced slightly over the years. Table 3 summarizes the VOTS of different years for different occupation groups that are estimated from the final model.

It is difficult to explain the reasons for such changes in cost coefficient from this modelling exercise. Further analyses such as macroeconomic investigations are required to find a proper explanation of such changes and their relationship with changes in household income, employment and regional productivity. Motivation of considering occupation group for interaction with travel cost is to overcome the drawback of not having income information in the dataset or not being able to capture the effects of the distributions of jobs in the study area. With a shrinking manufacturing sector in the study area, it seems that commuters need to travel to the locations that incur systematically higher travel costs for manufacturing jobs than other job categories. Perhaps this results in the higher sensitivity to travel cost for the commuters of manufacturing sector. However, whether the effects of income are being captured in this exercise remains unanswered. Further investigations with more detail income data are necessary in this case. An empirical test of income effect as suggested by Jara-Diaz and Videla (1989) reveals that income effect is not significant in this case. Other than the cost coefficient, the effects of other variables in the model seem to have consistent effects on the systematic utility function of commuting mode choice over the years.

These variables are considered to have the same coefficients across the year. Table 4 presents the estimated parameter of the final model that represents these variables in the systematic utility function of the rational choice component. The attractiveness of NMT seems to decrease as commuting distance increases. NMT refers to all non-motorized modes, but in our dataset it predominantly represents walking. One reviewer identified that distance is a good representative for walking, but it may not be as well representative for cycling. In our dataset, the share of NMT is very low and further dividing this group into walking and cycling would cause estimation problems because of the difficulty in properly indentifying NMT modes into further categories. Household auto ownership level seems to have consistent systematic effects on commuting mode choice over the year. It is clear that a higher number of cars at home increases the attractiveness of auto-based modes. The drive alone mode becomes more attractive if the household has two cars than one car and even more attractive if it has more than two cars. Similarly, the auto passenger mode becomes more attractive if the household has a car than has no car and even more attractive if it has two or more cars. Park and ride modes become more attractive if the household has a higher number of cars. However, a higher number of household cars makes the GO park and ride more attractive than the subway park and ride. A possible explanation is that parking availability is easier for the GO park and ride than the subway park and ride. Also, the increasing suburbanization in the study area along with a higher private car ownership level may make the GO park and ride more feasible with time.

Commuters' gender and age are found to have consistent effects on the systematic utility of the rational mode choice component over the years. It is clear that the drive alone mode is more attractive to male commuters than female commuters. Regional transit with local transit access is found to be the most attractive to the female commuters in the study area. The next-most popular is the auto passenger option. The non-motorized mode seems to be less preferred than local transit and park and ride options by female commuters in the study area. The age of commuters seems to have an influencing factor for commuting mode choice. We investigated linear and piece-wise linear functional forms for age coefficients. It is proven that age has non-linear effects on systematic mode choice utility function. In the case of a linear-in-parameter specification of systematic utility function of mode choice, this non-linear effect can only be captured through piece-wise linear specification of age variables. Pieces-wise linear specification is induced by separate age group-specific dummy variables used in the final model. It is clear that the attractiveness of NMT, local transit and park and ride models reduce with age. The estimated age coefficients of the final model reveal that younger commuters in the study area are less likely to drive alone when commuting than older commuters.

In order to capture the evolution of the heteroskedasticity of commuting mode choice, we parameterized the scale parameter of the rational choice component of the final model. In this case heteroskedasticity indicates more than one

Table 3
Estimated value of travel time savings (VOTS) in 2006 Canadian dollars.

Occupation groups	Year		
	Year 1996	Year 2001	Year 2006
Professional	5.24	9.57	9.57
General office	4.76	8.73	8.73
Service	6.67	9.48	9.48
Manufacturing	6.43	5.71	5.71

Table 4
Non-year-specific coefficients of the systematic utility function for rational choice.

Variable	Mode	Parameter	*t*-Stat
Distance less than or equal to 1 km			
	NMT	4.423	46.21
Distance greater than 1 km, but less than or equal to 2 km			
	NMT	2.908	36.34
Distance greater than 2 km, but less than or equal to 3 km			
	NMT	1.753	22.71
Access walking time (min)			
	All transit modes	−0.033	−19.75
Access waiting time (min)			
	All Transit Modes	−0.082	−33.99
2 household vehicle			
	Drive Alone	1.494	47.78
1 household vehicle			
	Auto Passenger	1.300	31.78
More than 2 household vehicle			
	Drive Alone	1.793	39.24
More than or equal to 2 household vehicle			
	Auto passenger	1.753	37.72
Total number of household vehicle			
	Subway park and ride	1.275	28.23
	GO park and ride	2.188	28.58
Dummy variable for female			
	Auto Passenger	1.030	35.75
	local Transit (Bus/LRT) with Walk Access	0.697	31.42
	Subway Park & Ride	0.747	11.35
	GO with Transit Access	7.421	4.00
	GO Park & Ride	0.554	6.88
	NMT	0.152	4.90
Age less than of equal to 25 years			
	Auto Passenger	1.138	33.64
	local Transit (Bus/LRT) with Walk Access	1.001	29.71
	GO Park & Ride	0.302	1.91
	NMT	0.747	14.55
Age greater than 25 years and less than of equal to 30 years			
	Auto Passenger	0.224	7.91
	local Transit (Bus/LRT) with Walk Access	0.269	9.91
	GO Park & Ride	−0.291	−2.60
	NMT	0.345	7.37
Age greater than 55 years			
	local transit (bus/LRT) with walk access	−0.155	−4.83
	Subway park and ride	−0.223	−2.05
	NMT	−0.204	−4.13

source of randomness of commuting mode choice across the population. In order to maintain the fact that the scale parameter of the rational choice component can never be negative, we proposed the exponential of a linear-in-parameter function for scale parameterization. For the linear-in-parameter function, the variables that can explain variations in mode choice randomness across the population are the prime candidates. We tested a number of personal, household and home location-specific attributes for scale parameterization. In addition to an individual year-specific dummy variable, only zonal average income is found to be a statistically significant factor. Also, the effects of average zonal income did not show any significant variations across the years. Therefore, in the final model scale parameter function, we considered the same coefficients across the years for the average zonal income, but we are able to estimate separate year-specific constants for 2001 and 2006 when using 1996 as the base. We considered zonal average income variable in the systematic utility functions, but it did not show up as significant variable at all. One possible reason is that people living in the same zones have the same zonal income value and hence it did not show significant variations in the dataset to capture income effect in the systematic utility function.

However, we considered it in the scale parameter function and found it to be significant. A possible explanation is that zonal average income values explain aggregate land use characteristics that explain mode choice heteroskedasticity than systematic utility. Table 5 presents the estimated parameters of the linear-in-parameter scale function of rational choice model component.

Table 5
Scale parameter function of the rational choice model component.

	Year 1996		Year 2001		Year 2006	
	Parameter	*t*-Stat	Parameter	*t*-Stat	Parameter	*t*-Stat
Logarithm of average zonal income divided by 10,000	0.090	7.93	0.090	7.93	0.090	7.93
Year specific costant	0 (fixed)		0.087	4.66	0.074	3.52

It is evident that there has been a slight increase in the scale parameter over time, as the scale parameter increased from 1996 to 2001 then slightly reduced from 2001 to 2006. Among the many variables tested, only zonal average income is found to explain the scale variation of the choice model component and it has a consistent positive effect across the years. This means that with increasing zonal average income, the choice model scale parameter also increases. Increasing choice model scale parameters suggests a stable or predictable choice by decision makers. Therefore, the understanding is that people living in higher income neighbourhoods are more likely to have stable (less random) commuting mode choice patterns than people living in lower income neighbourhoods. It should be mentioned that the scale parameter of the rational choice component can be higher than those of simple multinomial logit or GEV models. This is because a significant portion of choice uncertainty is already captured by the latent captivity function. The empirical model of this investigation reveals that considering the evolution of the latent captivity function offers better predictive capacity of the logit choice model component (an increasing scale refers to a better prediction). The policy implication of this finding is that the policies that would increase positive latent captivity (captivity to non-driving options) would eventually result in a more stable choice context for the commuters.

Table 5 presents the latent captivity function components of the empirical model (the parameters of Eq. (7)). In the final model, we did not find any level-of-service attributes as influential factors of latent captivity. It seems that latent captivity to commuting modes is mostly driven by contextual and personal attributes along with constant latent captivity (the portion that could not be explained by available variables in the dataset). Constant latent captivity to the drive alone mode increased from 1996 to 2001 and then decreased in 2006. Constant latent captivity to the auto passenger mode consistently decreased over time, but constant latent captivity to the transit with walk access mode increased over time. No constant latent captivity was found to be statistically significant for the subway park and ride after 1996 and the GO park and ride before 2006. A possible explanation could be that with expanding suburbs in the GTHA, the GO park and ride is becoming increasingly more popular than the subway park and ride mode. The suburban population surrounding Toronto has grown significantly from 1996 to 2006 (Habib et al., 2012). This surge in population may result in a higher dependence on the GO park and ride option. However, constant latent captivity to GO with transit access remains almost same over time. This is another indication that expanding suburbs are being served by GO transit mostly through the park and ride option than the GO with local transit access option. Most promisingly, constant latent captivity to the non-motorized mode increased consistently over time.

Among contextual and personal attributes, household auto ownership, transit pass ownership and age are found to be significant factors defining latent captivity to the commuting mode choice. Intuitively, auto ownership level is found to be an influential factor that defines the latent captivity to drive alone, subway park and ride, and GO park and ride modes. It is interesting to note that a household must have more than two cars in order for car ownership to increase the latent captivity to drive alone. Therefore, increasing the number of cars per household over time does not necessarily increase the latent captivity to drive alone unless the number of cars per household is three or more. Residential parking policies in the GTHA that restrict garages with more than two-car parking seem to result in reducing the latent captivity to driving. Having at least one car per household increases the latent captivity to the park and ride type modes. However, having more than one car per household results in a marginal increase in park and ride latent captivity. Ownership of local transit passes increases latent captivity to local transit-related mode options and ownership of regional transit passes increase latent captivity to regional transit pass-related mode options (Table 6).

However, it is clear that local transit passes have a higher influence on latent captivity than regional transit passes do. Local transit services are more frequent and more widely serve areas when compared with regional transit services. Therefore, transit passes for local transit services provide more utility than passes for regional transit services. Therefore, policies that encourage local transit pass ownership will have more positive effects than policies encouraging regional transit pass ownership. Perhaps a policy that integrates transit passes into a single pass would increase latent captivity to all transit modes. This type of integrated pass system was not widely introduced in the GTHA as of 2006 and hence we cannot investigate it further here. In this investigation, considered auto and transit pass ownership levels as exogenous variable. However, in reality, these variables would have an endogenous relationship with commuting mode choice (e.g., people who like driving alone or auto-oriented modes are more likely to own more cars and transit-oriented commuters are more likely to own transit passes).

In terms of personal attributes, only age is found to be significant in defining latent captivity, and only for NMT. It is clear that commuters between the ages of 35 and 45 have the most latent captivity to NMT for commuting. Latent captivity to NMT reduces for commuters who are younger than 35 or older than 45. This has implications for the aging population of the GTHA. With an increase in average age, non-motorized mode for commuting may become more unpopular and policy

Table 6
Latent captivity function components of the final model.

Variable	Mode	Year 1996		Year 2001		Year 2006	
		Parameter	*t*-Stat	Parameter	*t*-Stat	Parameter	*t*-Stat
Constant							
	Drive alone	−4.830	−18.67	−4.694	−13.47	−4.917	−12.77
	Auto passenger	−4.059	−38.39	−4.435	−31.86	−4.712	−23.31
	Transit with walk access	−4.138	−65.70	−3.664	−87.47	−3.215	−80.97
	Subway park and ride	−5.680	−10.17	–		–	
	GO with transit access	−2.592	−29.36	−2.112	−26.64	−2.187	−21.75
	GO park and ride	–		–		−3.225	−1.15
	NMT	−6.370	−21.45	−5.130	−38.80	−5.080	−33.62

Common (across all years) Coefficients of Latent Captivity Function

Variable	Mode	Parameter	*t*-Stat
1 cars in household			
	Subway Park & Ride	−4.505	−47.25
	GO Park & Ride	−4.505	−47.25
More than 2 car in household			
	Drive alone	2.527	8.02
More than or equal to 2 car in household			
	Subway park and ride	−2.613	−37.85
	GO park and ride	−2.613	−37.85
Having local transit pass			
	Transit with walk access	4.116	98.58
	Subway park and ride	4.116	98.58
Having regional transit pass			
	GO with transit access	0.102	1.19
	GO park and ride	0.102	1.19
Age greater than 35 years and less than of equal to 45 years			
	NMT	0.538	3.92

efforts are necessary to encourage it. Land use policies that can increase walkability and active lifestyles are necessary to counteract the decrease in latent captivity to NMT.

6. Conclusions and recommendations for further research

This paper uses three repeated cross-sectional non-panel household travel survey datasets collected between 1996 and 2006 (at five-year intervals) to investigate the evolution of latent modal captivity and mode choice preference structure for commuting trips in the Greater Toronto and Hamilton Area. The paper used the parameterized logit captivity model formulation incorporating a scale parameter function to capture the evolution of systematic heteroskedasticity of commuting mode choice over time. Empirical models are estimated for the individual year-specific datasets and the three datasets are pooled to estimate a pooled model. Individual year-specific models are used to identify the variables/factors that have a changing influence over time for proper specification of the pooled model. So, in the pooled model, the parameterized logit captivity model is adapted to accommodate individual year-specific effects along with generic effects that remained constant over time. The resulting pooled model of commuting mode choice allows us to investigate the evolution of the latent captivity and preference structures for commuting mode choices in the Greater Toronto and Hamilton Area.

The empirical models reveal that the pooled model not only allows for longitudinal evolutions of mode choice preference structures, but also allows for efficient exploitation of travel survey data, and for the accurate capture of balance between the systematic component and the latent captivity function of the choice models. Moreover, the proposed parameterized logit captivity model is proven to be superior to corresponding simple multinomial logit or heteroskedastic multinomial logit models. The takeaway lessons of this investigation are that the consideration of a choice model with a latent captivity function is preferable to any choice model without a latent captivity function. In addition, if available, pooling multiple repeated cross-sectional datasets for commuting mode choice modelling is proven to be more efficient.

The final empirical model (pooled PLC model with scale heterogeneity) reveals that mode choice preference structures are not stable over time and the effects of some key variables (e.g., travel cost) evolve over time. In the case of the Greater Toronto and Hamilton Area, the basic changes occurred in latent captivity to different modes, scale parameters of rational choice model and travel cost coefficients. These are three basic changes that have implications to the success or failure of previous/existing transportation/land use policies as well as the potential to play a role in future effective policy development initiatives. It is clear that the constant latent captivities to the drive alone mode remain relatively unchanged over time. However, the constant latent captivity to the auto passenger mode decreased and the constant latent captivity to transit increased over time. Perhaps increasing traffic congestion and unreliable travel time by private cars helps increase the dependence on transit in the Greater Toronto and Hamilton Area. Transportation policy development efforts should take the opportunity to further solidify the attractiveness of transit. To further aid in this effort, the empirical model reveals that increasing transit pass ownership (local as well as regional) increases latent captivity to transit options. So, it can be expected that policies to encourage transit pass ownership and/or transit pass integration (combining local and transit pass or integrated transit fare policies) will be able to cease the opportunity to increase the attractiveness of transit for commuting in the Greater Toronto and Hamilton Area. Household auto ownership levels seem to have a significant influence on increasing the latent captivity to the drive alone option, though only if households have more than two cars.

It is also evident that in the Greater Toronto and Hamilton Area the travel cost coefficient of commuting mode choice models reduced for all occupation groups except for the manufacturing group. This phenomenon is captured in the fact that although fuel cost increased significantly and transit fares were hiked from 1996 to 2006, the mode choice proportions did not change drastically. Possible explanations for changes in cost coefficient are a reduction of money value and an increase in inflation. It seems that the value of travel time savings almost doubled from 1996 to 2006. The policy implication of this finding is that transportation policies that target monetary measure to discourage commuters from driving require careful consideration.

Like all other research studies, this investigation suffers from some limitations. The majority of these limitations stem from data-related issues. One of the major limitations of the datasets used in this investigation is the unavailability of personal or household income information. Although empirical test reveal that income effect is very minor, we used zonal average income and occupation category for capturing income effect indirectly. Zonal average income is imputed from aggregate census data and we did not have any other related variables to develop multiple imputation technique as explained by Bush (2003). Availability of Supplementary datasets for multiple imputation of income variable as opposed to single imputation of zonal average income would enhance the findings of the paper. Also, in this paper we investigated whether and how much evolution or changes there were in latent captivity and mode choice preference structures in the Greater Toronto and Hamilton Area. Precise explanations for the causes of these changes are beyond the scope of this paper and are considered for the next stage of this investigation.

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