Is the Person or Urban Context? The Role of Urban Travel Context in Defining Mode Choices for School Trips of Post-secondary Students in Toronto

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Citation:
Hasnine, S., Lin, T, Weiss, A., Habib, K.M.N. 2017. "Is It the Person or Urban Context? The Role of Urban Travel Context in Defining Mode Choices for School Trips of Post-Secondary Students in Toronto". CD-ROM of 96th Annual Meeting of Trans. Res. Board, January 8–12, 2017.

ABSTRACT

The paper presents an investigation on the mode choice behaviour of post-secondary students commuting to school in the city of Toronto. It uses a large-scale dataset collected through a web-based travel diary survey of the students of four universities (seven campuses) in Toronto. Multinomial logit, nested logit, and cross-nested logit models are used for investigating home to school trips mode choices. Empirical models reveal that the mode choice behaviour of female students who travel to downtown campuses differ significantly from female students who travel to suburban campuses. Female students who travel towards downtown are more transit and active mode oriented than those who travel towards outside of downtown. This study also shows mobility tool ownership (i.e., transit pass, car and bike ownership) and age groups have distinctive influences on student's mode choice behaviour. In the context of policy implementation, shuttle bus services can be introduced which will connect the downtown and suburban campuses to improve the transit ridership in the suburban areas. Furthermore, bike and ride mode seems to have great potential for student commuting during peak hours.

KEY WORDS: Mode choice, school trip; post secondary students; travel behaviour of millenials

1. Introduction

Time as students in universities and colleges represents an important transitional period in most people's lives. As students move towards adulthood in this life stage, they also form preferences and habits that will likely have impacts on their later life (Kamruzzaman et al. 2011; Khattak et al. 2011; Balsas 2003). Therefore, understandings travel behaviour of post-secondary students, especially their mode choice behaviour, are valuable in the context of demand forecast and long-term planning for urban transportation. Current post-secondary students are parts of the millennials and, travel behaviour of millennials are of profound interest to the transportation and urban planners. However, it is until recently, transportation researchers started to look at travel behaviour of post-secondary students. So, most of the studies on this topic are based on descriptive statistics of travel patterns. Moreover, almost all of such studies used either household-level travel surveys or tailored surveys of a single university or a campus (Delmelle & Delmelle 2012, Whalen et al. 2013, Rodríguez & Joo 2004, Boyd et al. 2003, Shannon et al. 2006, Limanond et al. 2011).

Household level travel surveys are well known for underrepresenting the post-secondary student population, while single campus surveys will likely fail to capture the holistic behaviour of students in a regional context (Khattak et al. 2011). For instance, the household level travel survey for the Greater Toronto and Hamilton Area (GTHA), known as the Transportation Tomorrow Survey (TTS), is conducted every five years targeting a sample rate of 5% of all households in the survey area. In 2011 TTS, only 1310 university students were sampled in the city of Toronto, in comparison to the sample size of over 9000 to account for 5% of the university student population (around 185,000) of this city (Data Management Group 2011). As such, the importance of conducting a dedicated survey for post-secondary students is well percived. Besides from survey sample size issues, of the few econometric investigations on this topic, all have either relied on small range of explanatory variables or used fairly simple discrete choice model overlooking substitutions patterns and/or preference heterogeneities in mode choices of post-secondary students (Whalen et al. 2013, Wen & Koppelman 2001, Grimsrud & El-Geneidy 2013, Kuhnimhof et al. 2012, Lavery et al. 2013, Zhou 2012).

To contribute to the growing literature on post-secondary student’s mode choice behaviour, this study makes use of a comprehensive travel diary survey representing all universities (four universities and seven campuses) in Toronto, a population of 0.18 million post-secondary students. In addition, it also uses advanced discrete choice models (multinomial logit, nested logit, and cross-nested logit) to unravel the influences of various contextual factors alone or in interactions with socio-economic variables in defining trade-offs in the home to campus trip mode choices of the students.

The next section of the paper presents a brief literature on mode choice investigations of post-secondary students. The following sections present a discussion on the dataset used for empirical investigation; modelling methodology and a discussion of empirical results. The paper concludes with a summary of key findings and recommendations for future research.

2. Literature Review

Travel behaviour of university (post-secondary) students has been garnering attention in recent years even though the body of literature is still small. Post-secondary students, in general, are chronically under-represented in household travel surveys that provide the core database in most regional planning studies (Khattak et al. 2011). Among the small number of studies that are available in the literature, most relied on descriptive statistics. These studies revealed that this cohort's population niche has different travel behaviour than the general population. In terms of travel patterns and frequencies, Khattak et al. (2011) noted a higher number of trips in general and a preference to travel later in the day for the post-secondary student demographic. In terms of mode choice, post-secondary students, and young adults are found to have a higher preference for transit and active modes. Studies also revealed a general trend of decreasing affection toward private cars among this group of travellers (Grimsrud & El-Geneidy 2013).

Studies by Balsas (2003) and Shannon et al. (2006) substantiated such findings along with the fact that post-secondary student's population may have latent demand for the use of non-motorized modes. Balsas (2003) investigated survey data of eight university campuses across the United States and Shannon et al. (2006) investigated a survey dataset from the University of Western Australia. Both studies only provided the summary statistics of the corresponding dataset. However, without proper modelling tool, it is almost impossible to do proper forecasting and subsequent policy implementation. Furthermore, both studies contain some inherent bias in their data. Balsas (2003) pre-selected campuses with biking and pedestrian friendly environment for his sample of eight campuses. Shannon et al. (2006) only reported the stated preference survey.

Among all studies that focussed on transit usage, one study of a fare-free transit program for the students at the University of California at Los Angeles found that when cost is taken out of the picture, students would make use of public transit for the majority of their travels (Boyd et al. 2003). In this study, they compared the modal share before and after introducing a shuttle bus program for university students and employees. This study only shows the summary statistics of the survey data. It is found that increase in transit ridership could be amplified if the transit service frequency and the proximity of student home location to transit services increased. However, it is found in the same study (Boyd et al. 2003) that the presence of a fare-free transit program will take away the mode shares of non-motorized modes.

While fare-free transit programs are fairly common on university campuses, they present a unique scenario that reveals little in the way of general travel behaviour of post-secondary students in the wider urban environment. Grimsrud and El-Geneidy in their study of the 20-34 age cohorts in Montreal were also able to find transit preference among university students (2014). They showed summary statistics of repeated cross-sectional origin–destination survey data of Greater Montreal. Studies using descriptive statistical analysis can paint a general picture of the travel behaviour of post-secondary students, but investigation of underlying causes and the forecasting of future trends require an econometric modelling tool.

Some notable attempts are evident in the literature on using an econometric model to investigate travel behaviour of students. However, almost use the multinomial logit (MNL) model framework. Most of the studies found gender; student status; age and mobility tool ownership were significant factors in students' mode choice decisions. Zhou used MNL model to investigate post-secondary students in Los Angeles (Zhou 2012). Zhou found a high level of social interdependencies in the students' mode choice decisions, a finding previously put forward by Liamanond et al (Limanond et al. 2011, Zhou 2012). Rodríguez and Joo (2004) estimated a series of the discrete choice model to investigate the relationship between the use of non-motorized modes and the built environment (2004). They estimated used MNL, nested logit (NL) and a heteroscedastic extreme value model. However, they did not use household characteristics in their model. Grimsrud and El-Geneidy (2014) used the MNL model framework for empirical evidence to support their previous revelation that university students continue to retain higher levels of transit usage even in later life stages. While, such investigations are very intriguing, the issues of preference heterogeneity and substitution patterns in mode choice of students are grossly overlooked by over-reliance on MNL models. In many cases, key variables that influence travel mode choice are missing. For example, Zhou (2012), and Grimsrud and El-Geneidy (2014) did not include mode specific level of service (travel time, travel cost) information while.

Whalen and Paez (2013) addressed the issues of not having comprehensive variables in mode choice models of students by including variables including socio-demographic status, attitudes, built environment, and mode and trips specific factors. However, they used the MNL framework without necessary investigation on preference heterogeneity and substitution patterns. They empirical model reveals a positive utility of travel time in driving and cycle mode choices, which they highlighted as a key finding. From microeconomic perspective, a trip-based mode choice model with positive utility of modal cost attribute (travel time in this case) is counter-intuitive. Perhaps, this would require further investigation to find out whether travel time was correlated with unobserved random utility component of the model or there was a high degree of collinearity between travel time and other variables! At least, the basic 'independent and irrelevant alternatives' assumption of their MNL model should have been further tested for this.

This paper contributes to the literature in two ways. First of all, it uses a comprehensive travel survey data collected from all universities in Toronto, a post-secondary student population over 0.18 million. The dataset represents students living all over the Greater Toronto Area and having campuses both in Downtown and Suburban areas. Secondly, the paper explicitly investigates preference heterogeneity through estimation of various forms of discrete choice models. It exploits closed from advanced formulations, e.g. nested logit and cross-nested logit model to capture clustering and non-proportional substitution patterns of mode choices of post-secondary students. The study also uses wide varieties of personal, household and land use attributes to investigate the key determinants of school trip mode choices of post-secondary students in Toronto.

3. Survey Implementation and Descriptive Statistics

The data for this study come from a web-based survey, which is named as "StudentMoveTO", conducted among the university students in the City of Toronto. Four universities have been chosen based on their higher number of existing student: a) Ontario College of Art and Design (OCAD), b) Ryerson University, c) York University and d) the University of Toronto. Among these four universities, the University of Toronto and York University have multiple campuses across the region. The University of Toronto has three campuses in three locations namely, St. George, Scarborough, and Mississauga. York University has also two campuses: Glendon and Keele. As such the survey sample frame is the students from all seven campuses of these four universities. These four universities have a combined total of around 184,000 students. The time frame for the data collection of the StudentMoveTO is during Fall of 2015. Emails were sent to all students' university email addresses. Among the entire student body, 15226 students completed the survey, which corresponds to a response rate of 8.0%. The objective of this study is to develop commuting mode choice models. As such, it is required to retrieve the commuting trips of the students from the database. When breaking down the total number of trips taken by trip destination purposes, commuting trips to school represents just under a quarter of the total. Of those, around 70% are made on weekdays. A total of 3208 students' records is eventually retrieved from those reported a commuting trip to school on a weekday in their travel diary. StudentMoveTo classifies commuting modes into eight distinct classes as follows:

- Auto Drive
- Auto Passenger
- Local Transit with Walk Access
- Park and Ride
- Kiss and Ride
- Bike and Ride
- Walk
- Bike

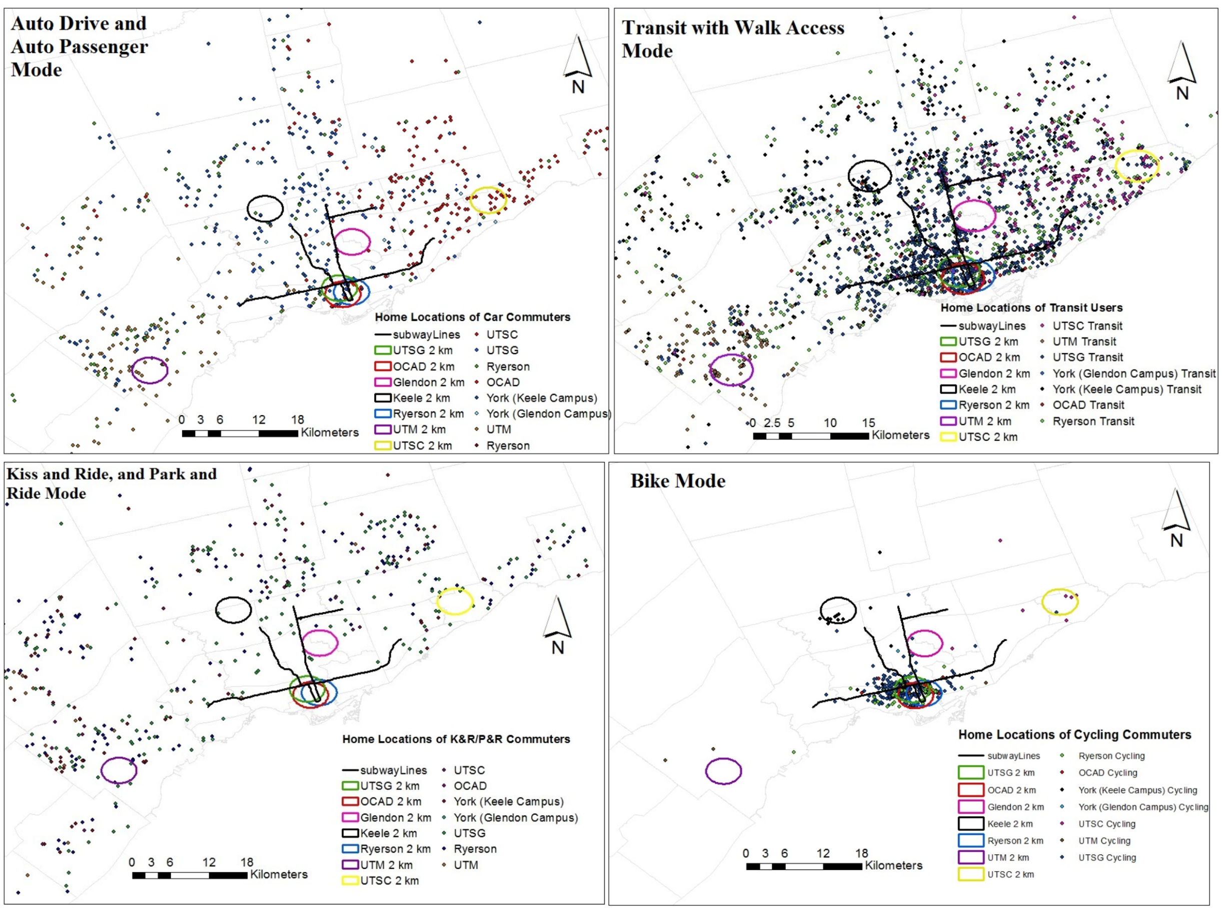
Table 1 shows the descriptive statistics of the sample dataset used in this study. A preliminary analysis of the sample statistics shows that the average household size is 3.6 and the average number of dependent children in the household is 0.25. The average age is 22.53 with a standard deviation 5.46, which is intuitive since this survey is designed exclusively for university students. The dataset includes different type of household mobility tools such as a car, bike, and transit pass ownership. It is found that only 14% of the students have their own car, while 42% have transit passes, and 32% of them have a smart fare payment card (Presto card) which allows them to pay at all regional transit stations and select local transit stations. The bike ownership percentage is also high (49%). This mobility tool ownership information has inherent relations with the mode share of the sample population. For instance, the high transit pass ownership corresponds to the high mode share of the local transit with walk access (48.57%). Walk mode also has a significant share (22.54%). Many students live near the university. As such, walking is a suitable option for them. Table 1 also shows the home to school level of service (LOS) values for the respondents. Various LOS (e.g., in-vehicle travel time, access time to transit, and waiting time for transit) values are calculated by using calibrated traffic assignment models. The traffic assignment models are calibrated by using the 2011 TTS data. Expected travel time for any given origin-destination pair at the traffic analysis zone (TAZ) level can be calculated using these models.

Table 1. Summary Statistics of the selected variables

Variable	Mean	St. Deviation	Maximum	Minimum
Household Size	3.60	1.50	16.00	2.00
Number of Dependent Children in the Household	0.25	0.72	5.00	0.00
Number of Cars in the Household	1.11	1.04	9.00	0.00
Age of the Respondents	22.33	5.46	62.00	0.00
Driving License Dummy (Yes=1,0=No)	0.59	0.49	1.00	0.00
Car Ownership Dummy (Yes=1,0=No)	0.14	0.35	1.00	0.00
Rideshare Membership (Yes=1,0=No)	0.05	0.21	1.00	0.00
Transit pass Ownership Dummy (Yes=1,0=No)	0.42	0.49	1.00	0.00
Presto Card Ownership Dummy (Yes=1,0=No)	0.35	0.48	1.00	0.00
Bike Ownership Dummy (Yes=1,0=No)	0.49	0.50	1.00	0.00
Bike share Membership Dummy (Yes=1,0=No)	0.01	0.11	1.00	0.00
Auto Cost ($)	2.17	2.32	17.74	0.00
Auto In-vehicle Travel Time (min)	17.59	17.85	99.29	0.00
Transit Fare ($)	2.35	2.47	13.13	0.00
Transit In-vehicle Travel Time (min)	36.31	35.57	175.80	0.00
Transit Wait Time (min)	5.02	4.73	48.27	0.00
Transit Walk Time (min)	18.00	10.79	263.53	0.00
Drive Access Time (min)	1.44	0.86	21.08	0.00
Bike Access Time (min)	4.80	2.88	70.27	0.00
Home to School Distance (Km)	15.30	15.61	94.39	0.02
The number of transit trips departing from a stop with a 400m walking distance of the postal code centroid between 07:00 and 08:59 on Mondays.	83.63	125.28	1456.00	0.00
The distance in kilometers to the nearest bus stop from the postal code centroid	0.27	0.35	10.88	0.00
The distance in kilometers to the nearest rail stop from the postal code centroid	3.54	2.08	21.06	0.05
The distance in kilometers to the nearest streetcar stop from the postal code centroid	9.64	10.55	64.59	0.00
The distance in kilometers to the nearest subway stop from the postal code centroid	6.86	9.36	64.50	0.01
The employment density (employees per sq. km) 2011 divided by 1000	9.24	18.39	271.18	0.00
Gender (%)				
Female	64.68			
Male	35.32			
University (%)				
University of Toronto	65.07			
Ryerson University	20.90			
York University	11.59			
OCAD University	2.44			
Student Status (%)				
Undergraduate	77.31			
Graduate	21.85			
Mode Share (%)				
Auto Drive	5.52			
Auto Passenger	5.33			
Local Transit with Walk Access	48.57			
Park and Ride	3.02			
Kiss and Ride	7.86			
Bike and Ride	0.22			

Walk	22.54
Bike	6.95

Figure 1 shows a spatial distribution of the students' home and school location and their commuting mode. It is clear from the figure that auto-drive and auto passenger mode users are travelling to school from comparatively further distances. In addition, transit with walk access mode users mostly lives near the subway stations and the places where they could easily access to the bus. The bike and walk mode users are only found in downtown Toronto or within close distance of the various campus. This is intuitive since bike infrastructure facility or pedestrian-friendly environments are not very common outside of the downtown Toronto. Finally, it is found that the park and ride, and kiss and ride users mostly live outside of the downtown area and are commuting long distances to school.



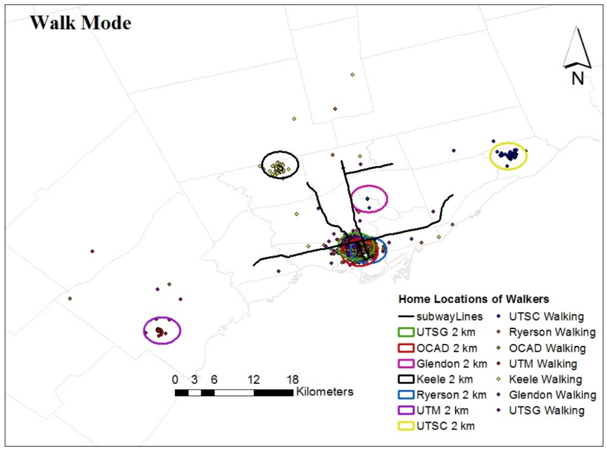


Figure 1: Home locations and mode share of the students

For estimating any mode choice model, it is required to generate the feasible alternative sets by using feasibility rules. The following rules have been set to define the availability of the eight modes under study.

- Auto drive - the respondent owns a driver's license and his household owns a car
- Auto passenger - available to everybody
- Local transit walk access – depends on transit network assignment model result regarding the availability of local transit and the one-way travel time should be less than 150 min.
- Park and Ride – depends on transit network assignment model result regarding the availability of transit and the similar conditions of the auto drive.
- Kiss and Ride - depends on transit network assignment model result regarding the availability of transit and the similar conditions of auto-passenger.
- Bike and Ride – depends on transit network assignment model result regarding the availability of transit and household owns a bike.
- Walk - commuting distance is no greater than 3 km
- Bike – commuting distance is not greater than 10 km and household owns a bike

4. Econometric Modelling Framework

Three models are estimated in this study and these are multinomial logit (MNL), nested logit (NL), and cross-nested logit (CNL) models as shown in Figure 2. MNL is the most popular modelling structure in the family of discrete choice models (McFadden 1973). The MNL model assumed that the random utility components of modal alternatives are independently and identically distributed extreme values. This assumption leads to identical cross-elasticities for all other alternatives with respect to one specific alternative (Wen & Koppelman 2001; Train 2003). This represents a perfect substitution pattern where all alternatives are perceived to be exactly of the same substitute of each other. This may not be the case of student's mode choices. A Nested Logit model can overcome this assumption by allowing nests of alternatives with different substitution within the nest as opposed to alternatives that are out of the nests (Williams 1977). A further advancement of the NL model is the CNL model, where one alternative can be a member of multiple nests (Wen & Koppelman 2001; Train 2003). CNL allows us to capture different cross-elasticities between pairs of alternatives.

For an individual the random utility of mode (m) can be written as:

$$U_m = \beta X_m + \varepsilon_m \qquad (1)$$

Where, U_m is total utility of mode m

V_m are systematic utility of mode m, where $V_m = \beta X_m$

β is the parameter vector

X_m are attributes to the corresponding mode

ε_m are random utility components with zero mean and μ scale parameter.

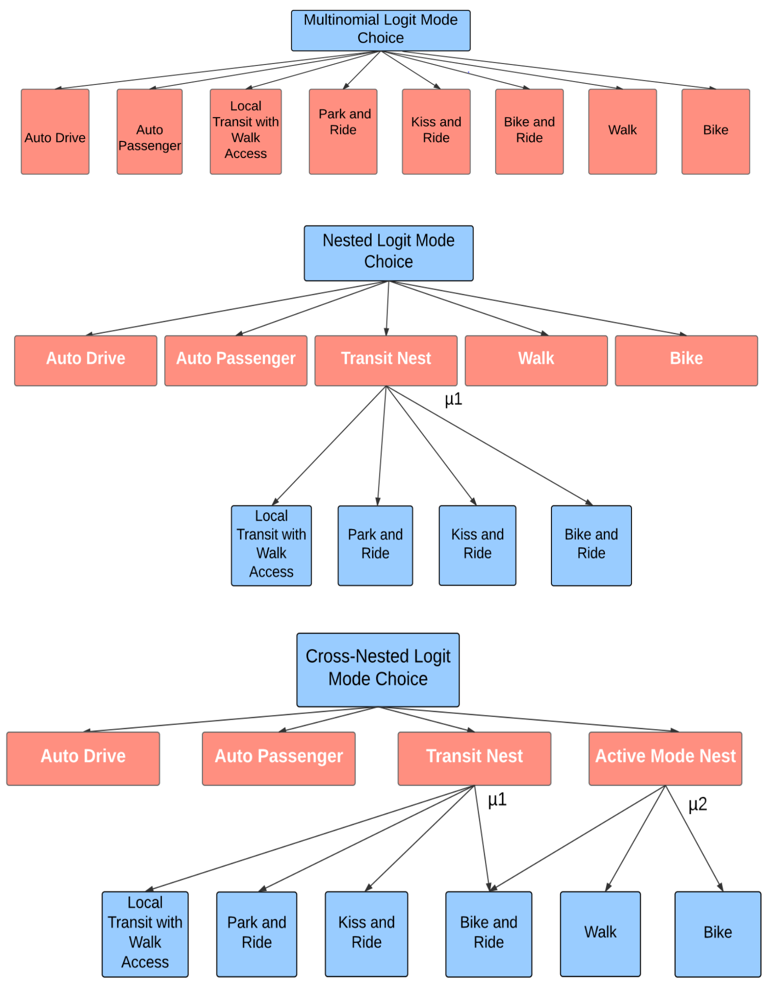


Figure 2. Various modelling structure

The general MNL formulation of the probability of choosing a particular mode can be written as:

$$P_m = \frac{e^{\mu * V_m}}{\sum_{m=1}^{8} e^{\mu * V_m}} \qquad (2)$$

In the NL model probability of choosing a mode is equal to the probability of choosing that mode (m) conditional to choosing the same nest *(T)* which the mode belongs to. In our study, the nest *T* has four alternatives *(j)*. If μ_R is the root scale parameter and μ_T is the scale parameter of the transit nest, for NL formulation probability of choosing a particular mode within transit nest can be written as follows:

$$P_{m|transit\ nest(T)} = \frac{e^{\mu_T V_m}}{\sum_{j=1}^{4} e^{\mu_T * V_{jT}}} * \frac{e^{\frac{\mu_R}{\mu_T}\ln\left(\sum_{j=1}^{4} e^{\mu_T * V_{jT}}\right)}}{e^{\frac{\mu_R}{\mu_T}\ln\left(\sum_{j=1}^{4} e^{\mu_T * V_{jT}}\right)} + \sum_{l=1}^{4} e^{\mu_R * V_l}} \tag{3}$$

In equation (3) $\frac{\mu_R}{\mu_T}$ is the coefficient of expected maximum utility which should be between 0 to 1. If a particular mode *(l)* is not within the nest then the probability of choosing the mode,

$$P_l = \frac{e^{\mu_R * V_l}}{e^{\frac{\mu_R}{\mu_T}\ln\left(\sum_{j=1}^{4} e^{\mu_T * V_{jT}}\right)} + \sum_{l=1}^{4} e^{\mu_R * V_l}} \tag{4}$$

In the CNL model, we have two nests: transit and active mode. No allocation parameter is considered in this case. In this case, the probability of choosing mode m within a nest can be written as follows:

$$P_m = \sum_k \left[\frac{(e^{V_m})^{\mu_T}}{\sum_{j=1}^{J} (e^{V_{jT}})^{\mu_T}} * \frac{\frac{1}{\mu_T} e^{\ln\left(\sum_{j=1}^{J} (e^{V_{jT}})^{\mu_T}\right)}}{\sum_k \frac{1}{\mu_{T'}} e^{\ln\left(\sum_{j=1}^{J} (e^{V_{jT}})^{\mu_{T'}}\right)}} \right] \tag{5}$$

In a mode choice model for a sample of *N* individual with each individual having the options of m alternatives the log likelihood function becomes (Ben-Akiva and Lerman 1985, Aptech Systems 2016):

$$LL(\beta) = \sum_{i=1}^{N} y_{mi} \ln(P_m) \tag{6}$$

Whereas, $y_{mi} = 1$ if person i choose mode m and zero otherwise.

The marginal effect of MNL, NL, and CNL model can be calculated by equation (7), (8) and (9) respectively,

$$\text{Marginal Effect (MNL)} = (1\text{-}P_m) * \beta \tag{7}$$

$$\text{Marginal Effect (NL)} = ((1\text{-}P_m) + (\mu_T - 1) * (1 - P_{m|nest})) * \beta \tag{8}$$

$$\text{Marginal Effect (CNL)} = \frac{\sum_k P_m P_{m|nest}((1-P_m)+(\mu_T-1)*(1-P_{m|nest}))}{P_m} * \beta \tag{9}$$

5. Empirical model

Three modelling structures are presented in this section: MNL, NL, and CNL. Table 2 shows the model estimation results. Variables in the final specifications are selected based on the expected sign, and statistical significance (95% confidence interval) of corresponding parameters. The final specification of MNL has 50 parameters, the NL has 42 parameters and the CNL has 51 parameters. Some of the variables in these three models are not statistically significant at 95% confidence interval, but they are retained in the models because it is felt these variables provide significant insight when comparing the three different modelling structures. For all three models, the goodness-of-fit against the constant only model is measured. However, it seems that in terms of goodness-of-fit the models do not differ by a large margin. Nevertheless, three models with three different substitution patterns allow us to compare effects of different variables on mode choice preferences of students. For discussion, we used marginal effects of the variables in each model. Figure 3 presents the marginal effect comparison of some selected variables. Marginal effects are estimated by using probability weighted sample enumeration (PWSE) technique.

These model results will be discussed in the context of three categories of variables: LOS, socio-economic and land use. In addition, rather than describing the three models' result separately, a comparison of the three models will be presented here. It is found that the goodness-of-fit (adjusted rho-square value against constant only model) for all three models vary between 0.175 and 0.311, which is a good fit. The NL model provides the highest goodness of fit (adjusted rho-square 0.311) among the three models.

In regards to the ASCs, most are statistically significant with the exception of a selected few. With regards to the level of service variables, all are found to be statistically significant with the sole exception of travel time in the MNL and NL model. The value of travel time for CNL model is $2.3 which is intuitive since this survey exclusively sampled students and 65% of them are not employed. The travel time variables consist of total travel time, access time towards transit station (by walk, bike or car) and transit wait time. For park and ride, and kiss and ride mode, travel cost is normalized by the commuting distance. In fact, from marginal effect results it is found that park and ride, and kiss and ride commuters travel longer distances and many of them are cross-regional commuters. Since students travel a longer distance for these two modes, it seems that they perceive the travel cost in terms of cost per unit distances.

Various household level mobility tool ownership level and socio-economic attributes are also investigated in this study. It is found that the "number of cars per household member" variable has a strong influence on the park and ride mode than the auto drive mode (Figure 3). A Higher number of the household car allows the household member to use the car without sharing it with someone, which encourages the park and ride mode. As such, this finding is intuitive. For all three models, this variable shows similar results. Transit pass ownership also influences commuters to choose transit related modes such as transit with walk access, park and ride, kiss and ride, and bike and ride.

The regional planning agency, Metrolinx, commissioned a discounted smart card system – the Presto card and promotes it as a convenient way to pay transit fare across different transit agencies in the region (tap on at boarding, and tap off when disembarking). The local transit agency - the Toronto Transit Commission (TTC), also accepts payment through Presto card at selected locations. The ownership of Presto card influences all four transit related modes. However, it has less influence when compared to the local transit pass. The possible explanation is the limited rollout of Presto card system across the local transit (TTC) network within the City of Toronto. As of July 2016, only 31 subway stations have presto card reading facilities out of a total of 69 subway stations (Toronto Transit Commission 2016). Card readers have been installed on all streetcars, but there are almost none on buses. As such, the accessibility of the Presto card is severely limited when compared to a metro pass, the traditional transit pass distributed by the

TTC. As such, for cross-regional commuters, Presto card can be used as a supplementary mobility tool to access other transit systems in the region.

With consideration to gender, the mode choice behaviour of female students is investigated in the context of downtown versus suburban campuses. The female students who commute to downtown campuses and who commute to suburban campuses exhibit very distinct natures of mode choice (Figure 3a and 3c). For instance, it is found that female students are more inclined to use auto passenger, park and ride, the local transit with walk access, and kiss and ride. Female students who travel to downtown campuses are less inclined to choose to walk, bike and bike and ride mode. These results echo the female bike mode share of the city of Toronto. In the city of Toronto, only 35% of the people who bike to work are female (City of Toronto, 2009)

Since the majority of the roads in the city of Toronto don't have bike lanes, the probable reason behind female students' lack of interest towards biking may be safety concerns. In the suburban campuses, it is found that females are more inclined to choose the auto drive or auto passenger in comparison to transit mode. The inadequacies of transit services in the outskirts of Toronto play a significant role in this behaviour. One probable solution of this problem is the shuttle bus service for students, which can connect the suburban campuses with the downtown campuses. There is an existing shuttle service for university of Toronto students which carry students between St. George and Mississauga campus. However, the frequency and capacity of this shuttle bus service are rather limited. As such, a more robust shuttle service is required which will connect all four suburban campuses and three downtown campuses.

Age is another important variable for understanding the post-secondary students' commuting behaviour. Typically, students aged between 18 and 22 are undergraduate students and most likely do not work. On the other hand, the students who are between 23 and 25 are most likely post-graduate students, and would likely work full time or part time. Thus intuitively, there should be significant differences in the mode choice behaviour of these two age groups. The empirical investigation of this study confirms the hypothesis. For both age groups, the auto drive is taken as the reference utility. The students who are aged between 18 and 22 are more inclined to take the auto passenger, local transit, kiss and ride, walk, and bike. On the other hand, the student aged between 23 and 25 are more inclined to take park and ride, walk and bike. This finding, in fact, reveals a threshold age of 22 when youth change their previous mode preference, and this preference might be influenced by their change in occupation (employment after graduation), change of economic situation, and change of school locations.

Table 2. Model Estimation Result for MNL, NL, and CNL

		MNL		**NL**		**CNL**	
Number of Observation		3208		3208		3208	
The number of Parameter Estimated		50		42		51	
Loglikelihood of the full model		-2088.08		-2231.90		-2305.68	
Loglikelihood of the constant only model		-2733.75		-3178.53		-2733.87	
Adjusted Rho-Squared value against constant-only model		0.254		0.311		0.175	
Variable Name	**Mode**	**Estimates**	**t-stat**	**Estimates**	**t-stat**	**Estimates**	**t-stat**
	Auto Drive	0.0	----	0.0	----	0.0	----
	Auto Passenger	0.908	2.378	3.042	9.310	0.816	2.447
	Local Transit	2.183	5.403	4.999	12.626	2.626	6.823

Alternative Specific Constants	Park and Ride	-3.502	-7.631	-1.083	-1.860	-2.517	-5.252
	Kiss and Ride	-0.625	-1.342	3.273	6.732	-0.345	-0.778
	Bike and Ride	-1.166	-1.055	2.047	3.184	-0.791	-1.204
	Walk	6.642	9.142	10.985	19.965	9.274	16.705
	Bike	2.659	2.463	7.844	17.633	5.580	5.948
Travel Cost	All modes	-0.251	-8.168	-0.228	-9.655	-0.258	-7.004
Travel Cost/Distance in Kilometers	Park and Ride, Kiss and Ride	-3.947	-3.379	-3.892	-3.937	-3.799	-3.327
Travel Time (In vehicle travel time+out of vehicle travel time+waiting time)	All modes	-0.0003	-0.125	-0.0003	-0.115	-0.010	-3.818
Distance	Walk	-1.718	-9.968	-2.1075	-12.248	-1.831	-7.756
	Bike	-0.462	-8.644	-0.6220	-11.891	-0.642	-13.462
Number of household members	Auto Drive, Park, and Ride	4.497	10.324	6.927	14.956	4.128	8.990
Transit pass ownership dummy (1=yes, 0=no)	Local Transit, Park and Ride, Kiss and Ride, Bike and Ride	1.817	12.769	2.213	9.432	2.071	14.850
Presto Card ownership dummy (1=yes, 0=no)	Local Transit, Park and Ride, Kiss and Ride, Bike and Ride	0.911	6.504	0.912	5.465	1.034	7.586
Bike ownership dummy (1=yes, 0=no)	Bike	1.554	1.606	-----	-----	1.248	1.526
Female Students Dummy Who Commute to Downtown Campus	Auto Passenger	0.254	0.969	-0.508	-1.653	0.212	0.675
	Local Transit	0.155	0.691	1.112	3.447	0.160	0.642
	Park and Ride	0.720	2.241	1.987	5.781	0.407	1.284
	Kiss and Ride	0.557	2.179	1.627	5.105	0.664	2.455
	Bike and Ride	-0.725	-0.608	0.027	0.027	-0.952	-0.827
	Walk	-0.291	-0.863	0.757	2.205	-0.199	-0.613
	Bike	-0.265	-0.840	0.823	2.601	-0.226	-0.745
Female Students Dummy Who Commute to Suburban Campus	Local Transit	-----	-----	-0.590	-4.091		
	Walk	-----	-----	-2.433	-6.409		
	Bike	-----	-----	-2.666	-6.170		
Age between 18 to 22	Auto Passenger	0.435	1.629	0.211	0.844	0.386	1.432
	Local Transit	0.352	1.518	0.244	0.975	0.353	1.534
	Park and Ride	-0.067	-0.194	-0.070	-0.224	-0.069	-0.203
	Kiss and Ride	0.259	0.977	0.170	0.629	0.342	1.329
	Bike and Ride	-1.654	-1.317	-1.498	-1.558	-2.068	-1.740
	Walk	0.184	0.528	0.316	0.968	0.127	0.402
	Bike	0.121	0.362	0.301	0.964	0.072	0.244
Age between 22 to 25	Auto Passenger	-0.474	-1.180	-0.615	-1.803	-0.548	-1.374
	Local Transit	-0.180	-0.557	-0.305	-1.255	-0.381	-1.215
	Park and Ride	0.061	0.144	-----	-----	-0.117	-0.293
	Kiss and Ride	-0.483	-1.308	-0.480	-1.728	-0.772	-2.159
	Bike and Ride	-0.658	-0.505	-0.743	-0.788	-1.292	-1.126
	Walk	0.357	0.751	0.293	0.738	0.175	0.413
	Bike	0.595	1.361	0.494	1.396	0.497	1.255
Number of dependent children per number of household members	Auto Drive	0.649	1.180	2.039	4.007	0.603	1.110
	Bike	-1.346	-1.817	-1.683	-2.141	-1.419	-2.446
The area (in kilometers squared) of the 1000m walk buffer around the postal code centroid	Walk	0.135	0.412	----	----		

The number of transit trips departing from a stop with a 400m walking distance of the postal code centroid between 07:00 and 08:59 on Mondays.	Local Transit	0.002	2.399	0.004	4.754	0.004	6.999
The distance in kilometers to the nearest bus stop from the postal code centroid	Local Transit	-0.467	-2.454	----	----	-0.412	-2.289
The distance in kilometers to the nearest rail stop from the postal code centroid	Local Transit	-0.054	-1.892	----	----	-0.041	-1.535
The distance in kilometers to the nearest subway station from the postal code centroid	Local Transit	-0.025	-3.183	----	----	-0.030	-3.698
The employment density (employees per square kilometer) 2011 divided by 1000	Auto Drive	-0.024	-7.512	----	----	0.019	6.205
	Auto Passenger	-0.033	-11.861	----	----	0.011	4.211
	Local Transit	-0.008	-3.324	----	----	0.024	12.630
	Park and Ride	-0.004	-1.070	----	----	0.030	9.507
	Kiss and Ride	-0.005	-1.917	----	----	0.028	11.508
	Bike and Ride	-0.023	-1.505	----	----	-0.233	-19.463
Coefficient of Expected Maximum Utility of Transit Nest		----		0.810	2.703	0.927	-1.702
Coefficient of Expected Maximum Utility of Active Transport Nest		----		----	----	0.893	-1.007

This study has also found influence from the number of dependent children on mode choice. The influence of the number of children is captured through the normalized variable called “number of dependent children per number of household members”. Households with a higher number of children are less likely to choose biking as a mode and are more likely to choose the auto drive. This result is intuitive since household with a higher number of children will need to drop off their children at school or the day care. Furthermore, seating for children are not easier accommodated on a bike, and even when it can be the number of children that can be accommodated is very limited. That is to say nothing of the safety concerns most parents will have when bringing their children on their bicycles. As such, it is more likely for a household with a large number of children to choose to use the car.

This study also investigated the reason behind the high mode share of local transit with walk access. Various transit system performances related attributes were used in the utility function of local transit with walk access utility. All those system performances related variables are generated at the postal code level. The model results show that higher transit frequency during the AM peak, in fact, encourages commuters to choose transit. The systematic utility of the transit mode decreases as the distance to the nearest bus stop and subway station increase. We have also incorporated several land use variables in the models.

It is found that a number of available sidewalk areas, around the postal code centroid, increase the likelihood of choosing walk mode. The effect of the employment density (employees per square kilometre) is also investigated in this study with walk and bike modes as reference utility. It is found that when post-secondary school zones employment density is high, students are more inclined to take transit. In the context of employment density, high parking costs of these areas may be the reason behind choosing transit.

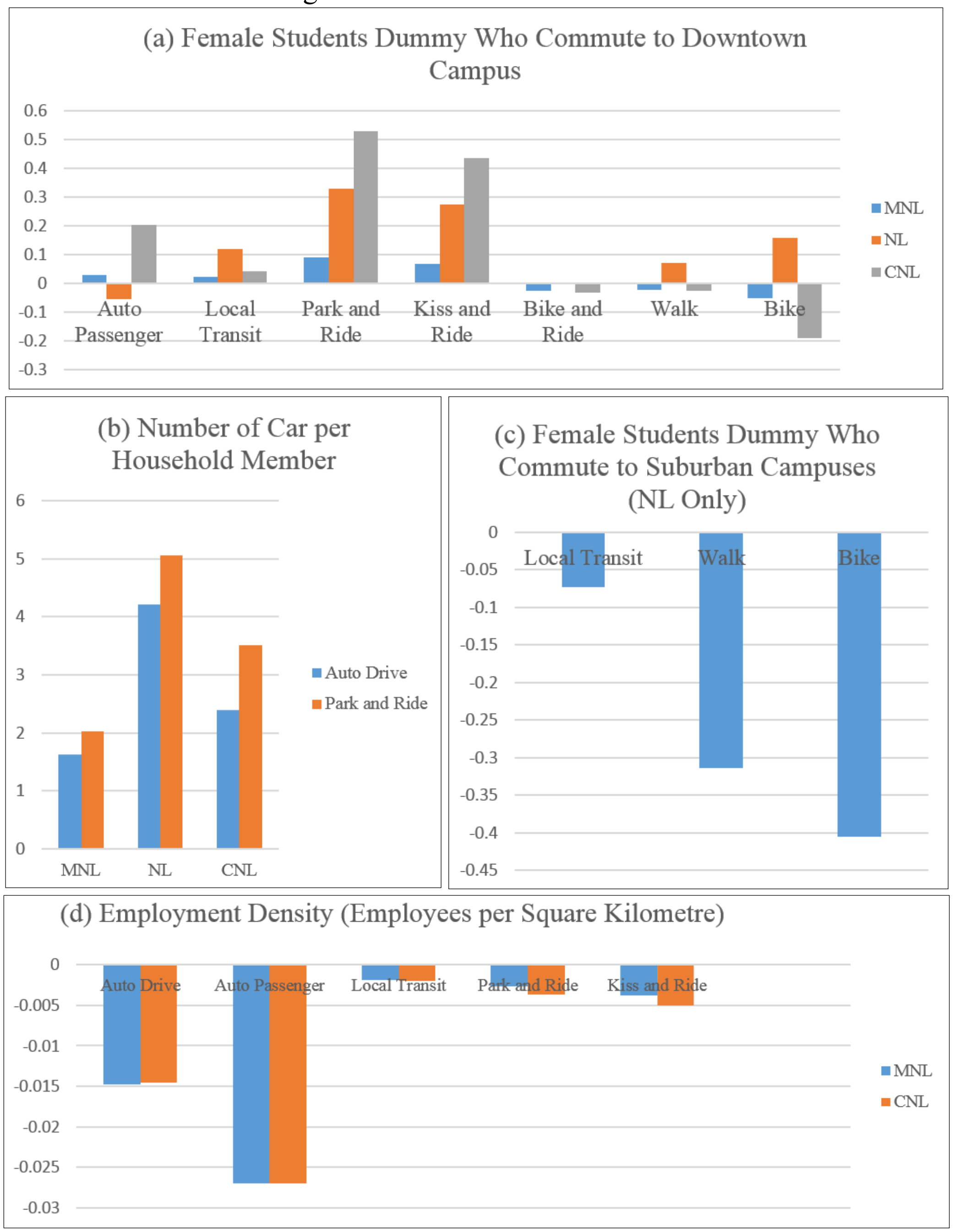
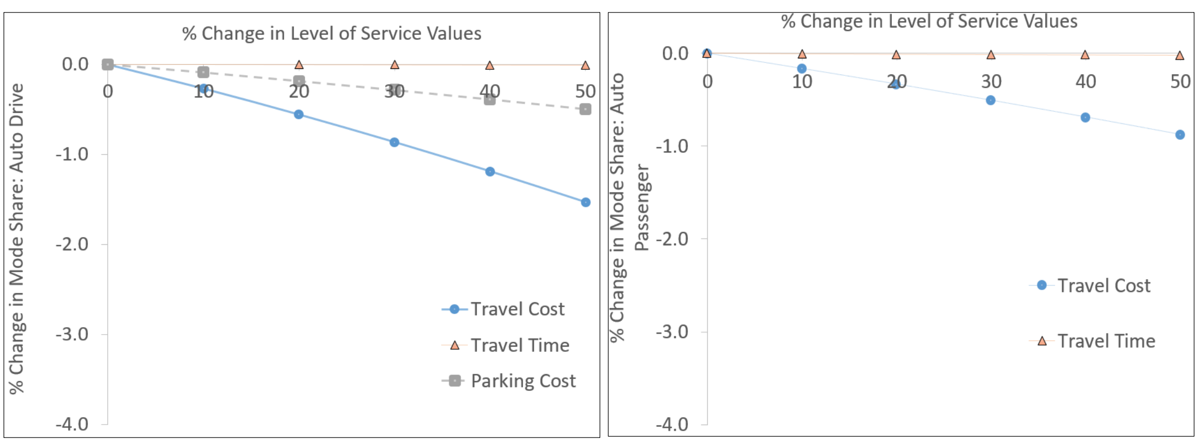


Figure 3. Marginal Effect Comparison of Selected Variables.

In the CNL model, it is found that the bike and ride mode is cutting across the nest. This suggests that there is a strong inherent correlation between the active mode and transit nests. This intuitively tells us that young people are interested in transit and they want to bike as well. Also, the marginal effect of cost (-0.0009) for bike and ride reveals that the students who choose a bike and ride as a mode wouldn't change their bike and ride mode even though the travel cost increase. This tells us that the bike and ride users are more on a captive user. It is worth mentioning that, during peak hour Toronto transit commission do not allow taking bikes on board a transit vehicle, a practice that is likely turning away student users as suggested by the nest correlation. This finding tells us if bike and ride are encouraged during peak hour commuting, there is likely a huge users group of this mode is out there ready to take advantage.

6. Policy Analysis

Figure 4 reveals the change in mode shares due to change of level of service variables for all eight modes. For example, Figure 4(a) shows how the base mode share, in this case - auto drive, changes for each percent change of the level of service values (travel time, cost). For the auto drive, it is clear that students are sensitive to both travel cost and parking cost. This has significant policy implications. If parking cost is reduced to 50%, it will encourage students to drive more (around 0.5% increase in auto drive mode share), and vice versa. Travel time has a negligible effect on students for both auto drive and auto passenger modes. For transit modes (transit with walk access, park and ride, and kiss and ride), it is found that students are more sensitive to in-vehicle travel time than wait time. In fact, the student is shown to be mostly inelastic to wait time and access time. For transit with walk access specifically, it is found that a 40% reduction in the transit fare increases the transit with walk access mode share to 3.7%. Therefore, providing some incentives to transit passes can encourage students to take local transit. For bike and walk, it is found that students are highly sensitive to commuting distance, especially for walk mode. A 30% reduction in commuting distance would increase the probability of choosing walk mode by 2.6%.



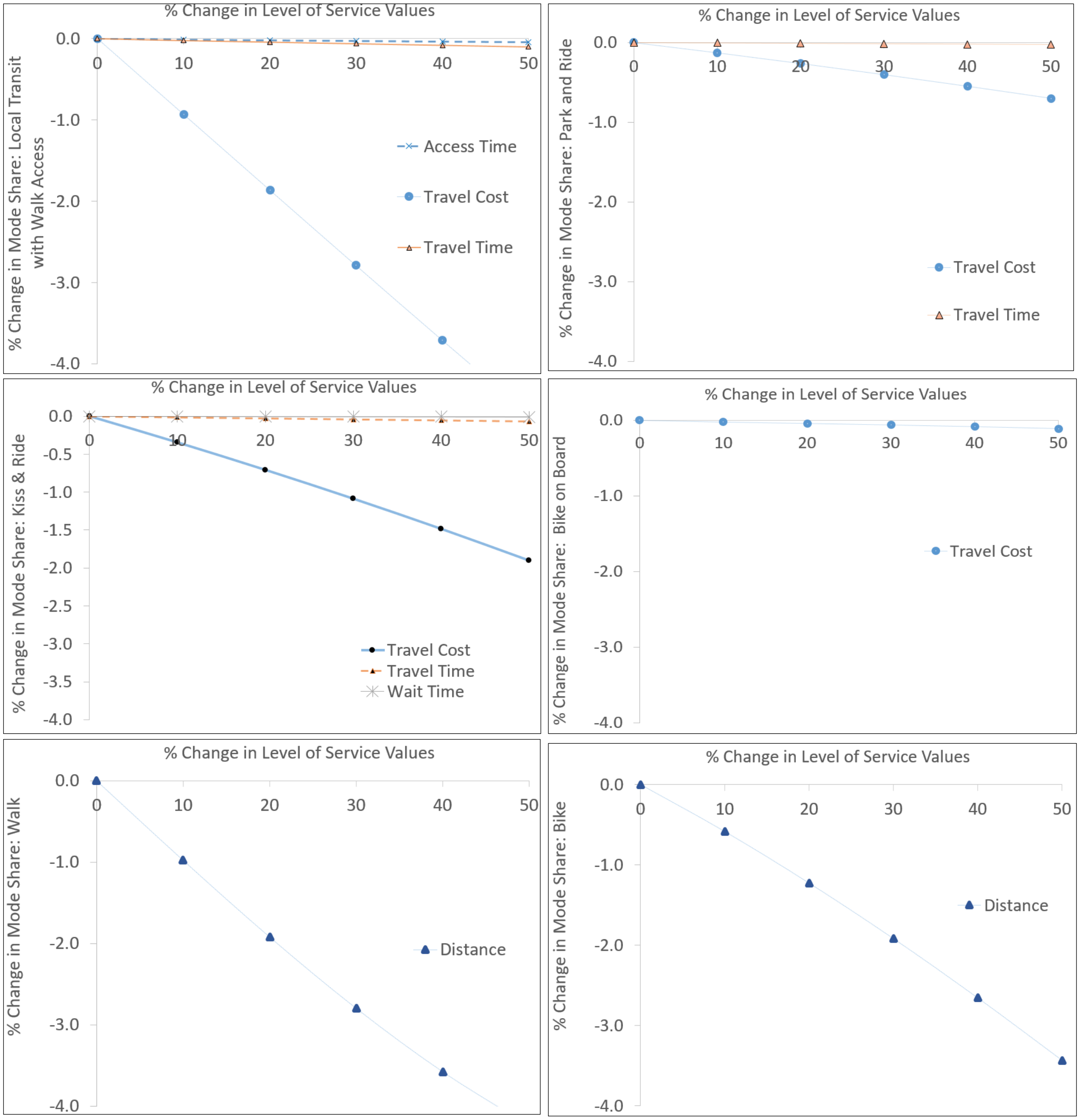


Figure 4. Change in Mode Shares due to change of Level of Service Variables

7. Conclusions and Recommendations for future studies

This paper investigated the commuting mode choice behaviour of students on seven campuses of four universities in the city of Toronto. A series of random utility maximization based empirical models (MNL, NL, and CNL) was estimated to capture different behavioural aspects of the post-secondary student commuters. It is found that NL model has the highest goodness-of-fit against the constant-only model. The outcomes from this study are expected to contribute a better understanding of the different factors (i.e., level if service, socio-economic and land use variables) that affect the students' commuting mode choice.

Various household level mobility tool ownership attributes were investigated in this study. It was found that an integrated transit payment system for both regional and local transit will provide the commuters enough flexibility to choose multimodal modes. In particular, for cross-regional commuters, smart fare payment cards (Presto card) can be a very versatile mobility tool to access other transit systems in the region if card readers are provided at all stations and on all vehicles. Gender was also investigated as a factor. It was found that female students have distinct mode choice behaviour in the context of downtown and suburban campuses.

Female commuters who commute to downtown campuses were more likely to choose auto passenger, park and ride, the local transit with walk access, and kiss and ride. Since the majority of roads lack a dedicated bike lane, safety concerns for biking are likely keeping these students off bikes. For female students who commute to suburban campuses, inadequate transit services force these students to choose the auto drive or auto passenger as oppose to transit mode. To increase transit ridership in the suburban campuses, a frequent shuttle bus services can be introduced to connect the outskirts campuses with the downtown Toronto. Across age group, it was found that student aged between 18 and 22, 23 and 25 show distinct mode choice patterns. Students who aged between 18 and 22 were mostly undergraduate students and unemployed. Empirical investigation showed that this age group preferred to be auto passengers, use local transit, kiss and ride, walk, or bike. On the other hand, students aged between 23 and 25 were more inclined to take park and ride, walk, and bike. Change in employment status, income, and work location may influence the older students to shift to auto drive oriented modes.

The inclusion of the cross-nested logit model allows for investigation of a mode's possible correlations with multiple nests. The results revealed that bike on board mode is correlated with both the active mode and transit mode nest. This suggests that if the adequate bike and ride infrastructure is provided, there is likely a large number of students who will take advantage. In particular, during morning peak period, bike and ride mode is still not encouraged by the transit agencies in the city of Toronto. As such, if sufficient facilities and conducive policies are provided to encourage this mode (i.e., allowing bikes on board during peak hour), it may encourage a large number of student commuters to shift to bike and ride mode from the auto drive and auto passenger modes.

The proposed modelling frameworks offer a flexible tool to better understand the travel behaviour of a very influential segment of the population. However, the framework in this paper can be extended by including multiple trips (tour based mode choice). In additions, this study can also be extended by investigating the implication of dynamic discrete choice on tour based mode choice modelling framework, which will reveal more behavioural insight.

Acknowledgement

The study was partially funded by an NSERC Discovery grant. Authors acknowledge the contributions of StudentMoveTO survey team for making the dataset available for this research. The contribution of Zhejiang Wang is also acknowledged for support in the data cleaning stage. However, views and opinions presented in the paper belong only to the authors.

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