What about the Dynamics in Daily Travel Mode Choices? A Dynamic Discrete Choice Approach for Tour-based Mode Choice Modelling

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ABSTRACT

The paper presents a heteroskedastic dynamic discrete choice (HDDC) model for tour-based mode choices modelling with an empirical investigation of university students' daily mode choices in Toronto. The reality of connected trips and resulting constrained mode choices are captured through the HDDC framework that is suitable for fitting in an activity-based travel demand modelling system. Data from a web-based travel survey of the students of four universities in Toronto are used. The empirical model highlights the importance of capturing the dynamics in tour-based mode choices modelling. The dynamic model reveals that students' sensitivity to cost vary by trips of the day, while their sensitivity to travel time remains stable. Results of this investigation have policy implications and the proposed methodology has applications in activity-based travel demand modelling.

1. INTRODUCTION

From daily travel demand modelling perspective, two types of approaches to mode choice modelling exist: trip–based and tour-based. Trip-based mode choice models have been traditionally used in Four-Stage Models (FSM). However, the need for tour-based mode choice model is obvious for an Activity-Based Model (ABM) of travel demands. A tour refers to a chain of trips that commence from a location and return to the same location at the end (Bowman et al. 1998). A tour-based approach for an ABM is necessary to recognize the dynamics in mode choice behaviour in a tour through the consideration of inter-dependence among various aspects of mode choices (Ho and Mulley 2013).

In the ABM framework, the recognitions of the time-space constraints shaped by time budget and transportation system performances is the fundamental tenet (Habib et al. 2017). However, this basic tenet is often compromised to fit in the mode choice models. Most ABMs use some sort of a hybrid mix of rules and econometric approaches for modelling activity-travel schedules. Mode choice models are parachuted in to apply in the steps subsequent to the schedule formation (Arentze and Timmermans, 2004; Miller et. al., 2005). Thus, many ABM systems rely on either a trip-based or a simplified tour-based mode choice models that in many cases completely overlooks the dynamics of mode choice behaviour.

Efforts of developing tour-based mode choice models for the ABMs are rare in literature. In some cases, where tour-based mode choice modelling is done explicitly, the mode choice model follows the activity scheduling model. This approach considers the predicted schedule as an external input to the mode choice model, which overlooks the endogenous relationship between activity scheduling and travel mode choices (Miller et. al., 2005). In fact, there are insufficient number of modelling techniques available for using in a tour-based mode choice context that can accommodate the dynamics of mode choices in a tour. This is a serious gap in ABM practices.

To contribute in filling this gap, this paper proposes a deductive tour-based mode choice modelling structure that uses the classical Dynamic Discrete Choice Modelling (DDCM) approach. The deductive DDCM approach uses a sequential applications of discrete choice models with explicit consideration of state dependence and expectation feedback in the mode choices in a tour. The proposed model is developed as a part of the recently proposed dynamic activity-based model, named CUSTOM, which uses the same approach of modelling daily activity scheduling under continuous time and space constraints (Habib et al 2017). For empirical application, the proposed DDCM model is applied for a tour-based mode choice model of post-secondary students in Toronto.

The paper is organized as follows. The next section presents a brief literature review on mode choice modelling approaches used by various activity-based models to explain the context of current investigation. This section is followed by the section explaining the dynamic discrete choice model formulation; data for empirical investigation and results of the empirical modelling. The paper concludes with a summary of key findings and set of recommendations for future studies.

2. LITERATURE REVIEW

Activity-based models (ABMs) have traditionally been using rule-based approach to develop activity-travel scheduling where mode choice model is accommodated in various ways (Habib 2011). Some noteworthy rule-based ABMs include: AMOS (Pendyala et al. 1997), PCATS (Kitamura and Fujii 1998), ALBATROSS (Arentze and Timmermans 2004), TASHA (Miller and Roorda 2005), FAMOS (Pendyala et. al. 2005), ADAPTS (Auld and Mohammadian 2012). Mode choice modelling components of these modelling systems are often shaped by the approach used for the activity scheduling process models. In AMOS, only trip based commuting mode choices are used, overlooking the tour aspects in the mode choice modelling (Pendyala et al. 1997). PCATS uses a two-tier nested logit model for joint destination and mode choices of a trip and considers one model specification for all trips (Kitamura and Fujii 1998). In ALBATROSS, it is assumed that there are no mode changes between the trips in a tour. As such, one mode for the full tour is assumed in ALBATROSS (Arentze and Timmermans 2004). Such unimodal tour mode choices is a generalization of trip-based model.

The tour-based mode choice component of TASHA uses deterministic rules for household level car and task allocations considering the activity schedules of the household members as exogenous inputs. For the choice model formulation of this tour-based mode choice model, an un-orthodox probit approach is used, where random utilities of scheduled activity episodes are independently simulated to derive the tour-level mode choice utility functions (Miller et al. 2005). The result is a non-closed form mode choice probability that may suffer from model identification issue if the intra-household constraints are not properly specified. Moreover, the use of deterministic rules poses concerns over prediction validity when those rules may not remain valid. In FAMOS, discrete trip-based mode and destination choice are modelled jointly for each activity and does not consider a tour-based approach of mode choice modelling (Pendyala et al. 2005). ADAPTS incorporated a mode plan component in its generation-scheduling model framework. However, the mode choice model is estimated as trip-base model and then added into this system (Auld and Mohammadian 2012).

As opposed to rule-based approach, there are some ABMs that use fully econometric approach of activity-scheduling. However, the mode choice model is often accommodated in the same way it is done in the rule-based models. Such models include model by Bowman and Ben-Akiva (2001), CEMDAP (Bhat et al. 2004), etc. Bowman and Ben-Akiva (2001) uses a discrete choice modelling system to model activity scheduling, and mode choice is considered endogenous to that system. They use a tour-based approach of mode choice modelling, but only mode-specific tours are specified. This unimodal tour approach does not allow combinations of different modes within a single tour. For example, if someone dropped-off a household member at a transit station, and then the household member took transit to the end station, and then returned to the origin using a taxi, this model will not model these mode choices jointly.

The econometric ABM, CEMDAP considers a tour-based approach for mode choice modelling (Bhat et al. 2004). It allows to model the tour-level mode choices, but the tour patterns are defined in simplified ways. Such as home-work-home, and home or work based sub tours, etc. Vovsha, Bradley, and Davidson (2004, 2005 and 2010) developed an activity-based model named CT-RAMP, which uses a hybrid mix of econometric models and rules for activity scheduling. It uses a nested logit model to model tour-based mode choices, where trip-level mode choice models define the lower level and that feeds into the upper level of tour-based mode combinations. This approach explicitly considers inter-dependence of the mode choice between consecutive trips in a tour, but the tour-based mode choice modelling structure becomes fixed as it is estimated. Flexibility of the tour-based mode choice model can be an issue for general applicability of the model.

Besides these, many operational travel demand models use tour-based mode choice approach. However, in most of the cases tour-based mode choice is defined as the choice of a particular mode for a sequence of trips in a tour. That said, combination of modes in a single tour is not considered (Bowman 1998, Freedman et al. 2006, Cambridge Systematics 2002). The limitation of such approach is that single mode-specific tour-based approach is nothing different from a trip-based mode choice model. Cirillo & Axhausen (2002) proposed such a trip-based model by using the mixed logit approach to capture the implicit correlations between modes choices of a sequences of trips made in a day. However, it is still overlooks the dynamic aspects of tour-based mode choices.

In reality, the choices of travel modes for the day's activity-travel schedules are dynamic in nature. So, a dynamic discrete choice model (DDCM) is promising in this case. As proposed by Heckman (1978 and 1981), a DDCM can be formulated in a way that the choice of a mode for any specific trip of a day considers state dependence, and expectations of next trips' mode choice. To our knowledge, nobody investigated the application of a DDCM for modelling mode choices of an activity-based travel demand model. In fact, application of DDCM in transportation is very rare with few exception of modelling social interactions (Kuwano et al 2011) and car ownership choice modelling (Cirillo et al 2015).

This paper proposed a noble approach of using DDCM for the tour-based mode choice modelling. The objective is to develop a flexible modelling system that can capture the dynamic nature of tour formations and allow investigating multimodal behaviour within a single tour. The proposed model is developed for the mode choice modelling component of a recently proposed activity-based travel demand modelling system, CUSTOM, which uses a dynamic econometric approach of activity scheduling (Habib et al 2017). The next section presents the econometric formulation of the proposed DDCM for tour-based mode choice modelling.

3. ECONOMETRIC MODEL

According to Heckman's general formulation of DDCM the total utility U_{imt} of an individual (*i*) of an alternative (*m*) at time (*t*) can be written as follows:

$$U_{imt} = \beta X_{imt} + \sum_{k=1}^{t-1} \rho_{(k)} y_{im(t-k)} + \Omega \sum_{n=1}^{t-1} \sum_{k=1}^{n} y_{im(t-k)} + \varepsilon_{imt} \quad (1)$$

β= is the parameter vector

X_{imt}=attributes associated to modes

$\sum_{k=1}^{t-1} \rho_{(k)} y_{im(t-k)}$= this term captures state dependence.

$\rho_{(k)}$=time dependent parameter which captures the effect of the event occurred t seconds

$y_{im(t-k)} = 1$ if person i choose a certain mode at time t and zero otherwise

Ω is coefficient to capture the cumulative effect

ε_{imt} is random utility component with variance σ^2_{imt}

Based on Heckman's formulation, Swait et al. (2004) proposed the following dynamic generalized extreme value (DGEV) formulation by applying the concept of RUM:

$$G(e^{V_{imt}}) = \sum_{m=1}^{M}\{\sum_{r=0}^{t} \rho_{(imr)} . e^{V_{imt-r}} \ . \sum_{r=1}^{\infty} \Phi_{(imr)} . e^{V_{imt+r}} \ .\}^{\mu_t} \tag{2}$$

V_{imt} =Utility equation for individual (i), mode (m), and time (t)

G= Homogenous GEV function

$\rho_{(imr)}$= time dependent parameter which captures the effect past utilities

$\Phi_{(imr)}$= capture state dependence at time r

μ_t=scale parameter at time t

Based on equation (2) and recursive Bellman's equation we can write the following meta-utility equation in the context of tour-based mode choice modelling as follows (Bellman 2013, Cirillo & Xu 2011):

$$V_{imt} = V_{imt(0)} + \varepsilon_{imt} + \Phi_{imr} EV_{imt+r} \tag{3}$$

Here V_{imt} is the total utility and $V_{imt(0)}$ is the utility of the current state. The discount factor $(\Phi_{(imr)})$ captures the influence of future expectation (EV_{imt+r}) which value should be in between 0 to 1. EV_{imt+r} is mainly the summation of log-sum of all future modes.

If we assume the error term (ε_{imt}) as an independent and identically distributed (IID) Gumbel distribution, the conditional choice probability can be written as:

$$P_{imt|I} = \frac{e^{\mu_1(V_{imt(0)} + \Phi_{imr} EV_{imt+r})}}{\sum_{m=1}^{M} e^{\mu_1(V_{imt(0)} + \Phi_{imr} EV_{imt+r})}} \tag{4}$$

Here, μ_1 is the discount factor which is also the coefficient of the function of future dependence.

Finally, the mode choice probability of a two trips tour becomes:

$$P_{imt} = \frac{e^{\mu_1(V_{imt(0)} + \Phi_{imr} EV_{imt+r})}}{\sum_{m=1}^{M} e^{\mu_1(V_{imt(0)} + \Phi_{imr} EV_{imt+r})}} * \frac{e^{\mu_2 V_{im}}}{\sum_{j=1}^{J} e^{\mu_2 V_{ij}}} \tag{5}$$

In equation (5), μ_2 is the scale parameter. If everyone has the option of *m* alternatives and if the total number of an individual is *N*, the log likelihood function can be written as follows:

$$L(\beta) = \sum_{i=1}^{N} y_{imt} \ln(P_{imt}) \tag{6}$$

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

The model illustrated in equation (5) can capture the current utility and the future expectation (ϕ_{imr}) of the utility at the same time. This future expectation is weighted by a weighting factor, which indicates the future dependency on a set of subsequent mode choices. The following decay function is used to define the future expectation which can capture heteroskedasticity:

$$\phi_{imr} = 1/(1 + \exp(constant + \sum \alpha * Z)) \tag{7}$$

Per equation (7), we can capture the mode specific constant. The variables (Z) and parameter (α) should be specified carefully, since it affects the elasticity computation. The proposed DDCM has a closed form and can be estimated by using standard estimation technique. In this research, we programmed the likelihood function in the GAUSS programing language and used maximum likelihood estimation technique (Aptech, 2017).

4. DATA FOR EMPIRICAL INVESTIGATION

Data from a web-based travel survey conducted among the post-secondary students in Toronto are used for this study (StudentMoveTO 2016). This survey collected personal, household, socioeconomic, and travel schedule related information (Hasnine et al. 2017). The survey data were collected in Fall 2015. In the dataset, in any random day over 80% of students made 2- and 3-trips tours. The rests of them made either single trip or more than 3 trips tours. Empirical investigation of this paper uses the subset of those who made 2- and 3-trip tours in a weekday for modelling tour-based mode choice model. 2-trips tour subset of data includes 2358 students. 3-trips tour subset of data includes 1977 students.

These datasets are also fused with land use data and transportation Level of Service (LOS) data. The LOS data (e.g., in-vehicle travel time, access time, and waiting time for transit, auto cost and time) are generated using a traffic assignment models (which is used by the planning departments of the City of Toronto for their planning investigations) by using the regional travel survey data of the Greater Toronto area. The summary statistics of the datasets are shown in Table 1.

In terms of age category, it is found that 68% of the students who make two-trip-tours and 56.80% of students who make three-trip-tour are aged between 18 to 22. In terms of the gender, it is found that 61.83% of female students make a two-trip-tour and 56.80% of female students make a three-trip-tour. Preliminary analysis also shows that around 57.38% (two-trip-tour) and 61.96% (three-trip-tour) of students have a driving license. Around 50% of all students in the final datasets own a bike. Around 37.04% of the students who make two-trips-tours and around 33.22% students who perform three-trip-tours have a Presto card (smart transit fare payment system).

TABLE 1. Summary Statistics of the selected variables

	Tour with two trips (2358 records)		**Tour with three trips (1977 records)**	
Continuous Variables	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
Auto drive cost ($)	2.932	2.299	1.119	1.607
Auto drive in vehicle travel time (minutes)	19.940	14.550	7.962	9.740

Transit fare ($)		3.082	2.430	1.314	1.684
In vehicle travel time (minutes)		46.156	30.215	17.135	24.600
Transit wait time		6.948	4.492	3.153	4.319
Walk access time to transit (minutes)		18.647	12.125	16.575	13.564
Drive access time to transit (minutes)		1.492	0.970	NA	NA
Bike access time to transit (minutes)		4.972	3.233	NA	NA
Trip distance (km)		20.251	15.033	5.533	7.647
Household Size		3.826	1.444	3.397	1.388
Number of dependent children in the household		0.325	0.805	0.273	0.767
Number of cars in the household		1.393	0.985	0.928	1.062
Categorical Variables		**Percentage**		**Percentage**	
Age	Age less than 18	2.417		1.416	
	Age between 18 to 22	68.236		56.803	
	Age between 23 to 25	14.546		17.248	
	Age more than 25	14.801		24.532	
Gender	Female	61.832		67.577	
	Male	37.235		31.765	
	Not-reported	0.933		0.658	
Mobility Tool	Students who have driving license	57.380		61.963	
	Students who have bike	50.976		47.747	
	Students who own transit passes	49.279		37.481	
	Students who own Presto card	37.043		33.215	
Mode combination	**Mode share: two-trip-tour**	**Mode combination**		**Mode share: three-trip-tour**	
AD-AD	6.573	AD-AD-AD		15.276	
AP-AP	4.368	AP-AP-AP		7.334	
AP-T	2.120	AP-T-T		1.568	
AP-KR	0.297	T-AP-AP		1.062	
AP-W	0.085	T-T-T		17.198	
T-AP	1.951	T-T-AP		1.872	
T-T	61.323	T-T-W		4.350	
T-KR	1.442	T-W-T		11.634	
T-W	0.297	T-W-W		1.416	
PR-PR	4.071	W-W-W		27.618	
KR-AP	0.382	W-W-T		1.012	
KR-T	3.902	W-T-T		3.085	
KR-KR	5.513	B-B-B		6.576	
W-T	0.297	AD=auto drive, AP=auto passenger, T=local transit with walk access			
W-W	3.520				
BR-BR	0.382	PR=park and ride, KR=kiss and ride, BR= bike and ride, W=walk, B=bike			
B-B	3.478				

For two-trip-tours, it is found that transit-transit mode pair is the most dominant one (61.32%). For the three-trip-tour, it is found that the complete walk tour (walk-walk-walk) has the highest mode share (27.61%), and the second highest mode share is found when a student makes the complete tour by transit (17.20%).

In terms of trip modes, a total of eight possible modes are identified: auto drive, auto passenger, local transit with walk access, park and ride, kiss and ride, bike and ride, and walk and bike. A total of seventeen mode combinations are found for two-trip tours and for three trips a total of thirteen mode combinations are found for three trips tours. The auto drive is considered available if the student owns a driver's license and the student's household owns a car. The auto passenger is considered available if the household owns a car. Walking is considered available if the travelling distance is less than 3 km. The bike is available if the student has a bike and the commuting distance is less than 10 km. For the second and third trip, conditional choice sets are defined. Auto drive is considered only available if the auto drive mode is chosen in the first trip and the car should be returned at the end of the tour. If the first trip is made by auto passenger or local transit with walk access mode, four modes are considered available in the subsequent trips, such as auto passenger, local transit, kiss and ride, and walk. If the home to school trip is kiss and ride, three modes are considered available to the respondent in the subsequent trips, such as auto passenger, local transit, and kiss and ride. Average kiss and ride distance if longer than 3 km and that makes walking as infeasible for kiss and ride leg the tour. If the first mode is walking, then local transit with walk access and walk are available for the second trip.

5. EMPIRICAL RESULTS

Figure 1 presents the modelling approach used in this paper. The final datasets are divided into two parts: 80% randomly selected records are used for model estimation and the rest of the 20% samples are used for model validation of the estimated models. Table 2 and 3 present the results of the heteroskedastic dynamic discrete choice (HDDC) tour-based mode choice for two trips and three trips. Personal, household, level of service, and land use attributes are used in both models. The final specifications of the models are selected by considering the parameters with sign and a 95% confidence limit of their estimated parameter values (t-statistics 1.64 or higher). However, some parameters with lower t-value are retained as they have expected sign and provide behavioural explanation.

For both models, the goodness-of-fit (Rho-squared value) is measured against the null model as well as the constant only model. The two-trip-tour model's goodness-of-fit against the null model is 0.51 and the goodness-of-fit against constant only model is 0.12. The three-trip-tour model's goodness-of-fit against the null model is 0.40 and the goodness-of-fit against the constant only model is 0.104. Having considering the complexity of these two models it can be said that both models show reasonably good fit.

A total of 16 alternative specific constants (ASC) are estimated for the two-trip-tour model and 12 ASCs are estimated in the three-trip-models. Most of the ASC's in both models are highly statistically significant. For both models, all LOS parameters are showing expected signs. Depending on the paired-t test result we have decided which cases it is required to use generic parameters for the same variable in different trips and in which cases it is required to estimate trip specific parameters for the same variable in different trips.

In the two-trip-tour model (Table 2), different cost per kilometer distance travelled parameters are estimated for the home-school trip and school-home trip. It is found that students are more sensitive to their cost of the home-school trip. In terms of the travel time, there are not many differences between the home-school and school-home commute. The model reveals that students are more sensitive to home-school commuting distance than school-home commuting distance. Transit pass and presto-card ownership are tested as a dummy variable in this model. It is found that if a student has a transit pass or presto-card, the student is more inclined to choose transit modes (e.g., local transit, park and ride, kiss and ride, and bike and ride).

Household structure seems to influence tour-based mode choice of the student. Presence of dependent children seems to increase the attractiveness of motorized modes, e.g. auto drive, auto passenger, park and ride, and kiss and ride. It is found that female students who commute to downtown campuses are less inclined to take public transit with walk access in comparison do the male students. Females are more likely to choose bike, park and ride, and kiss and ride in their commuting mode choice. In contrast, females who commute to suburban campuses are less inclined to bike to school which is intuitive, since the suburban areas don't have sufficient bike infrastructure. This lack of biking infrastructure pushes the female students to take an auto drive and auto passenger modes.

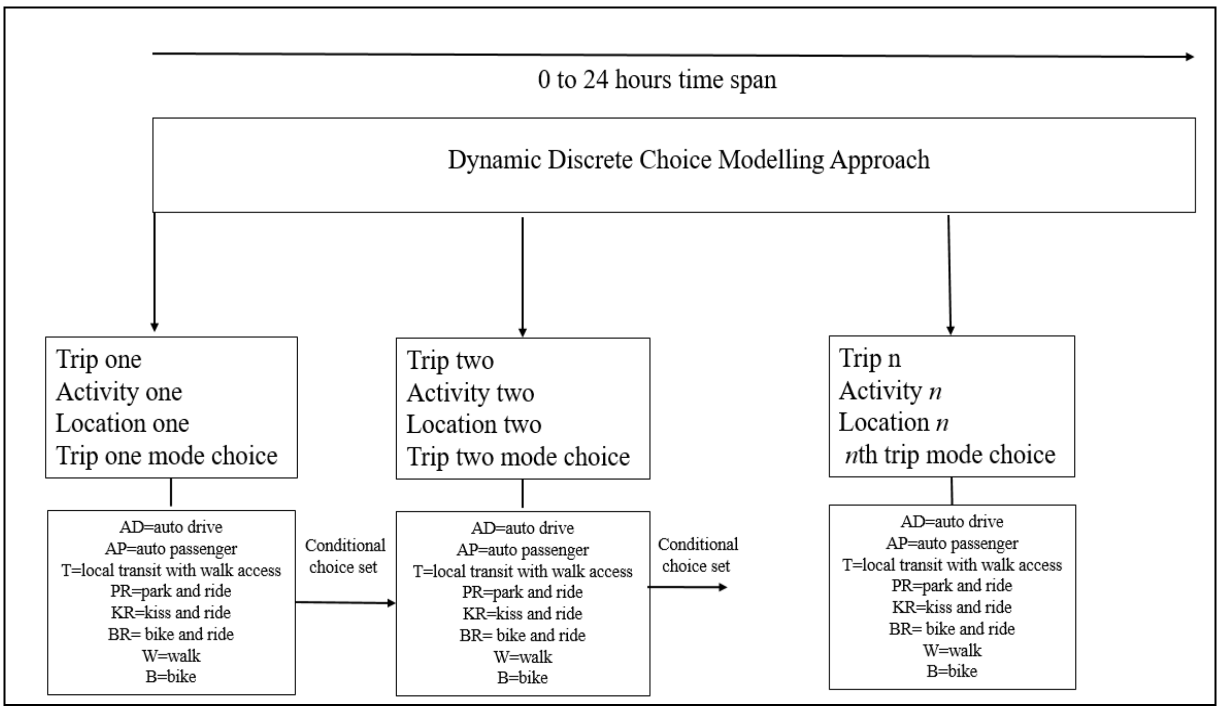


FIGURE 1: HDDC Modelling Framework

It is also found that females who commute to suburban campuses are less inclined to choose transit with walk access as a commuting mode. Poor accessibility to transit and low transit frequency may be the reason behind this negativity to transit. The model result also shows that students who commute home-school are more inclined to choose the park and ride in comparison to bike and ride. In fact, bike and ride are not allowed by the Toronto Transit Commission (TTC) during the morning peak period, which influences people to choose other modes. It is found that students are highly sensitive to the access distance to the subway. If the access distance to the subway is higher students are less likely to choose public transit as their commuting mode.

In this model, the future expectation of mode choice is parameterized as a function of the number of cars per number of household members. This parameter is highly significant and it has a high magnitude, which reveals that there is a higher correlation between the future modes of local transit with walk access and kiss and ride. For example, there are four possible modes for the second trip, while the first trip is made by local transit with walk access, such as auto passenger, local transit with walk access, kiss and ride, and walk. This result reveals the strong correlation among those four modes. The future expectations have 71.3% weight factor for local transit with walk access alternative which is very high. This means the four above mentioned future modes occupy a significant portion of the utility. On the other hand, for kiss and ride the future expectation have only 10.8% weight factor, which suggests that three future modes (auto passenger, local transit and kiss and ride) occupy a negligible portion of the future utility. Due to identification restriction, the parameters for the function of the future dependence of auto-passenger and walk are kept constant.

In the three-trip-tour model (Table 3), it is found that unlike the two-trip-tour model, students perceive cost as cost per distance has a diminishing rate of return (logarithmic). In fact, students are more sensitive to the cost of auto drive and auto passenger mode of the last trip. Monthly transit pass users in Toronto need to pay flat monthly fee. As such, they don't perceive transit fare for every trip. In this model, the transit cost variable is estimated for those who don't own a transit pass. It is found that students are highly sensitive in their second trip, which is more likely a non-home return trip. Based on a pair-t test value we estimated a generic travel time parameter for all trips for the same mode. We estimated auto drive and transit travel time parameters separately and it is found that for all trips students are more sensitive to transit travel time than auto drive travel time. It is found that female students travelling downtown are more likely to choose auto passenger mode. Female students are less likely to choose transit for any part of their tour.

The future expectation of mode choice is parameterized as a function of the number of cars per number of household members. This parameter is found significant and it has a high magnitude. This essentially suggests that the future probable mode alternatives are highly correlated. It is found that the future expectations have 22.9% weight factor for auto passenger and 31.6% for walk mode. The future expectations have 81.5% weight factor for local transit with walk access. As such, like two-trip-tour local transit with walk access occupy a large portion of the utility. The weight factor for the transit-transit and walk-walk is found as 34%. In the decay equation, the constant was found to be insignificant. As such the future expectation for these two mode combinations (transit-transit, and walk-walk) are the same.

Figure 2 shows the validation results of the two-trip-tours and three-trip-tours. The 80% randomly selected sample is used for the model estimation and the rest of the 20% is used for validation. Figure 2(a) shows the validation result for the two-trip-tour and figure 2(b) shows the validation results of the three-trip-tour. In both cases, the predicted mode shares are very close to the observed mode share, which states that the model is capable of accurately replicating the students' tour-based mode choice context. By using the conditional probability, we also calculated the probability of each mode at every trip level. Validation results of the two trips of the two-trip-tour are shown in Figures 2(c) and 2(d). For all trips the observed and predicted probabilities are very similar. Validation results of every trips of the three-trip-tour are shown in

Figures 2(e), 2(f), and 2(g). For all three trips the predicted mode shares are very close to the observed mode share, which essentially suggests that this HDDC model can accurately predict every trip within the tour as well.

TABLE 2. HDDC tour-based mode choice model (two trips)

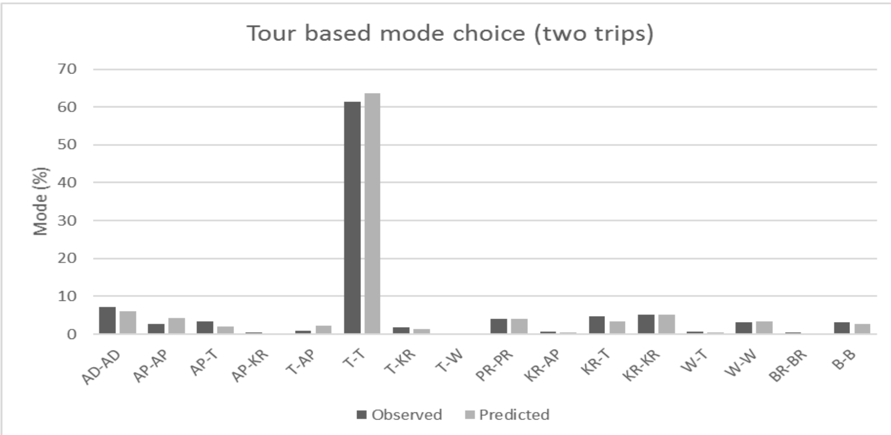
Number of observation			1922	
Rho squared against null model			0.51	
Rho squared against constant only model			0.12	
	Parameters	Mode	Estimates	t-stat
Alternative Specific Constant (ASC): Home to School	Auto drive	Auto drive	0.880	2.927
	Auto passenger	Auto passenger	-1.250	-4.444
	Local transit walk Access	Local transit walk access	0.000	----
	Park and ride	Park and ride	-1.286	-3.590
	Kiss and ride	Kiss and ride	-0.500	-1.986
	Bike and ride	Bike and ride	-3.158	-6.254
	Walk	Walk	3.265	4.991
	Bike	Bike	3.664	5.351
ASC: School to home when morning mode is auto passenger	Local transit walk access	Local transit walk access	-0.101	-0.206
	Kiss and ride	Kiss and ride	-3.272	-5.789
	Walk	Walk	-1.264	-1.466
ASC: School to home when morning mode is local transit walk access	Local transit walk access	Local transit walk access	3.643	6.754
	Kiss and ride	Kiss and ride	-0.362	-0.750
	Walk	Walk	2.083	2.936
ASC: School to home when morning mode is kiss and ride	Local transit walk access	Local transit walk access	2.673	3.795
	Kiss and Ride	Kiss and Ride	2.403	4.107
ASC: School to home when morning mode is kiss and ride	Local transit walk access	Local transit walk access	-3.165	-3.410
Home to school	Cost per km distance travelled	All motorized modes	-1.553	-3.184
School to home	Cost per km distance travelled	All motorized modes	-0.726	-1.129
Home to school	Travel Time	Auto drive and auto passenger	-0.017	-2.960
		Local transit, park and ride, kiss and ride, bike and ride	-0.002	-0.642
School to home	Travel Time	Auto drive	-0.017	-2.96
		Auto passenger, local transit, park and ride, kiss and ride, bike and ride	-0.004	-0.654
Home to school	Logarithm of distance	Walk and bike	-1.712	-2.592
School to home	Logarithm of distance	Walk and bike	-0.227	-0.355
Home to school	Transit pass ownership	Local transit, park and ride, kiss and ride, bike and ride	1.380	10.958
School to home	Transit pass ownership	Local transit, park and ride, kiss and ride, bike and ride	1.005	4.118
Home to school	Presto card ownership dummy	Local transit, park and ride, kiss and ride, bike and ride	0.789	4.853
School to home	Presto card ownership dummy	Park and ride, kiss and ride, bike and ride	0.749	3.777
Home to school	Number of dependent children	Auto drive and auto passenger, park and ride, kiss and ride	0.499	1.547

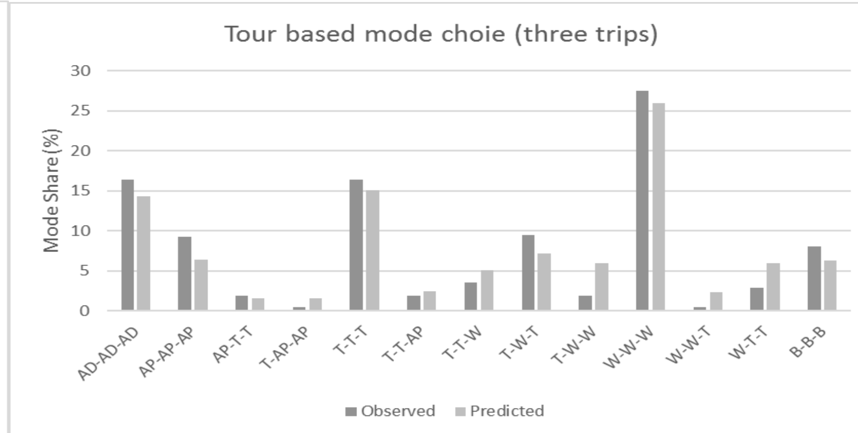
Home to school	Female students: Commute to downtown campus	Local transit walk access	0.871	4.09
		Park and ride	1.292	3.688
		Kiss and ride	1.282	4.706
		Bike	0.9354	2.476
School to home	Female students: Commute to downtown campus	Auto passenger (morning mode local transit walk access)	-0.562	-0.971
		Local transit walk access (morning mode kiss and ride)	-0.677	-2.132
Home to school	Female students: Commute to suburban campus	Local transit walk access	-0.534	-3.016
		Park and ride	-0.413	-1.116
		Kiss and ride	-0.708	-2.606
		Walk	-2.865	-5.3
		Bike	-1.979	-3.998
School to home	Female students: Commute to suburban campus	Local transit walk access (morning mode auto passenger)	-1.206	-2.748
		Auto passenger (morning mode local transit walk access)	1.113	2.86
		Local transit walk access (morning mode walk)	2.741	2.212
Home to school	Age between 18 to 22	Park and ride	2.741	-1.873
		Bike and ride	-0.487	-1.46
Home to school	Age between 22 to 25	Walk	-1.229	1.824
		Bike	1.198	1.755
School to home	The distance in kilometers to the nearest rail stop from home	Afternoon mode local transit walk access (morning modes auto passenger, local transit with walk access, kiss and ride, and walk)	-0.094	-1.354
School to home	The distance in kilometers to the nearest subway station from home	Afternoon mode local transit walk access (morning modes auto passenger, local transit with walk access, kiss and ride ,and walk)	-0.049	-2.347
Coefficient of function of future dependence	Cars per household members	Local transit with walk access, kiss and ride	6.649	6.204
	Constants	Local transit walk access	-3.129	-4.607

TABLE 3. HDDC tour-based mode choice model (three trips)

Number of observation			1555	
Rho squared against null model			0.400	
Rho squared against constant only model			0.104	
	Parameters	Mode	Estimates	t-stat
ASC home to school	Auto drive	Auto drive	-0.519	-2.865
	Auto Passenger	Auto passenger	-2.518	-9.797
	Local transit walk access	Local transit walk access	-1.804	-8.921
	Walk	Walk	0.000	----
	Bike	Bike	0.659	3.798
ASC school to home when morning mode is auto passenger	Auto passenger	Auto passenger	1.420	3.921
ASC school to home when morning mode is local transit	Auto passenger	Auto passenger	-2.673	-7.656
	Walk	Walk	1.448	0.297
ASC school to home when morning mode is walk	Walk	Walk	3.984	11.072
ASC school to home when first two morning mode is	Auto passenger	Auto passenger	-0.947	-1.985
	Walk	Walk	3.771	6.270

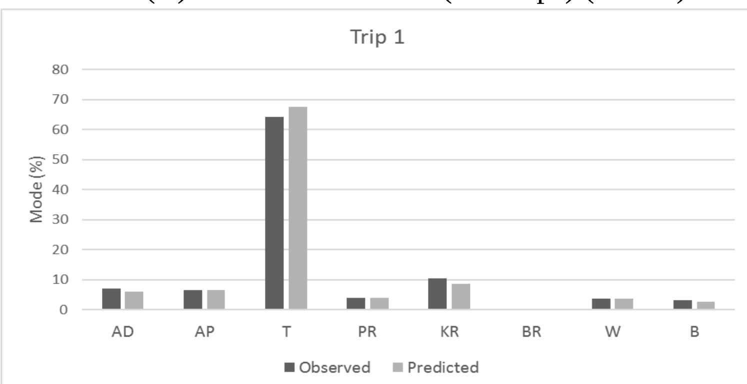
local transit walk access				
ASC school to home when morning mode is Local transit and Walk	Walk	Walk	4.930	6.693
ASC school to home when morning mode is walk and Walk	Local Transit Walk Access	Local Transit Walk Access	-6.510	-10.591
First two trips	Cost per km logarithmic distance travelled	Auto drive and auto passenger	-0.007	-0.443
Third trip	Cost per km logarithmic distance travelled	Auto drive and auto passenger	-0.150	-0.756
First trip	Cost per km logarithmic distance travelled	Local transit walk access	-0.149	-2.660
Second trip	Cost per km logarithmic distance travelled	Local transit walk access	-0.624	-0.473
Third Trip	Cost per km logarithmic distance travelled	Local transit walk access	-0.022	-0.090
All trips	Travel time	Auto drive	-0.313	-1.394
All trips	Travel time	Auto passenger and local transit walk access	-1.008	-3.264
First trip	Logarithm of distance	Walk and bike	-0.267	-8.176
Second trip	Logarithm of distance	Walk and bike	-0.612	-8.918
Third trip	Logarithm of distance	Walk and bike	-2.617	1.577
Second trip	Transit pass ownership dummy (1=yes, 0=no)	Local transit walk access	0.328	1.249
Third trip		Local transit walk access	0.757	1.577
First trip	Female students: Commute to downtown campus	Auto passenger	1.130	4.76
		Local transit walk access	0.203	1.219
First trip	Female students: Commute to suburban campus	Auto drive	-0.286	-1.227
		Local transit walk access	-0.279	-1.284
First trip auto passenger second local transit walk access	Female students: Commute to suburban campus	Local transit walk access	-1.284	-1.089
Coefficient of function of future dependence trip one	Number of car per number of household members	Auto passenger, Local transit walk access, walk	4.847	3.283
	Constants	Auto passenger	0.521	0.539
	Constants	Local transit walk access	-3.133	-3.232
Coefficient of function of future dependence trip two	Number of car per number of household members	Local transit walk access - local transit walk access, walk-walk	3.676	1.537

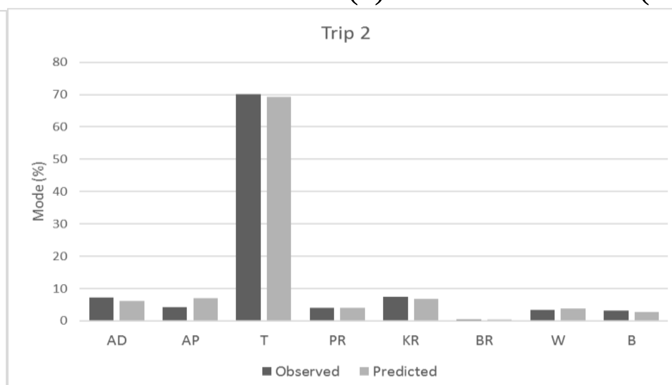




(a) Validation of tours (two trips) (n=446)

(b) Validation of tours (three trips) (n=422)

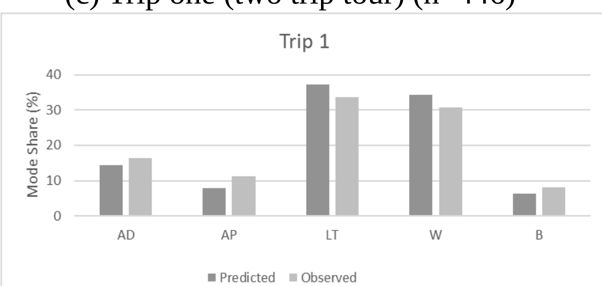


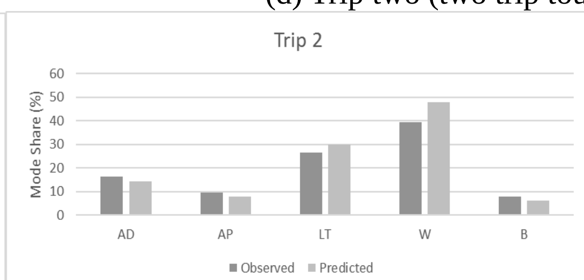


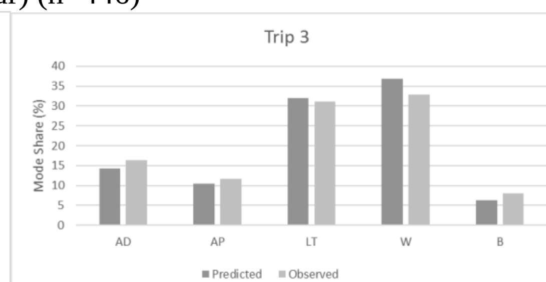
AD: auto drive
AP: auto passenger
T: local transit with walk access
PR: park and ride
KR: kiss and ride
BR: bike and ride
W: walk
B: bike

(c) Trip one (two trip tour) (n=446)

(d) Trip two (two trip tour) (n=446)







(e) Trip one (three trip tour) (n=422)

(f) Trip two (three trip tour) (n=422)

(f) Trip three (three trip tour) (n=422)

FIGURE 2. Validation Results of Trips and Tours

6. CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE STUDIES

This paper presents a closed-form tour-based mode choice modelling framework, which is based on a heteroskedastic dynamic discrete choice (HDDC) model approach. This close form HDDC model can capture behavioural dynamics by considering future expectation of modes and corresponding discount factor. The empirical model presented in this paper incorporates a wide range of personal, household, transportation level-of-service, socioeconomic and land-use attributes. The validation result shows that the model is capable of accurately capturing the tour-based mode choice phenomena. The research presented in this paper has a contribution in enhancing our understanding of the tour-based mode choice model, which can be plugged into any econometric ABM framework, such as CUSTOM (Habib et al 2017). From the perspective of methodological contribution, this paper proposes a simple closed form HDDC modelling framework, which can be potentially applied for policy testing and welfare analysis.

The empirical model is estimated for two-trip and three-trip tours. It is found that post-secondary students are highly sensitive to their cost of the first trip. In terms of the travel time, there are no significance differences between the home-school and school-home commute. It is found that having dependent children in the household forces them to choose auto-drive, auto-passenger, park and ride, and kiss and ride. Interestingly, female students commuting pattern is very different than the male students. It is found that they are less likely to choose public transit and bike for commuting to school if their campus is in a suburban area. This essentially suggests the importance of bicycling infrastructure in the suburban corridor. In addition, the bike and ride mode is not allowed in the peak hour. However, it may be an excellent policy to allow students only to take their bike on transit services during the peak hour. This close form HDDC model can capture the weight of the expectation of future modes in current utility which reveals significant behavioural dynamics. The parameterization of the future expectation allows us to capture the heteroskedasticity. The remaining 20% of the sample is used for validation in this study. The validation results show that the estimated econometric model in this study can predict both tours and trips accurately.

There are few limitations of this study. This study did not estimate mode choices for trips with four trips or more. As such, the home or work based sub-tours are not modelled in this paper. However, it is straightforward to use the proposed modelling structure for estimating tours with four trips or more. Even estimating sub-tours would be much simpler.

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