

Regret Minimization based Joint Econometric Model of Mode Choice and Departure Time: A Case Study of University Students in Toronto, Canada

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ABSTRACT

With the objective of enhancing our understanding of student travel patterns, we examine their mode and departure time choice for discretionary trip purposes. There is evidence to believe that mode and departure time choices are potentially interconnected and simultaneous decisions. In our study, we hypothesize that individuals are likely to consider these joint choices or interconnected decisions in a sequence, even if the time difference between these decisions is infinitesimally small. Our proposed model allows for the incorporation of choice sequences (mode first, departure time second and departure time first, mode second) simultaneously. We employ a latent segmentation approach that probabilistically allocates individuals to the two sequences. Within this segmentation process, we allow the mode and departure time decisions to follow random utility or random regret decision framework. To the best of authors' knowledge, this is the first application of such a joint sequential system using regret based decision rule. Our results indicate that students are more likely to choose their departure time first and then mode. The estimated models are validated based on a hold-out sample. A policy exercise is also conducted to demonstrate the applicability of the proposed model system.

Key words: StudentMove TO, latent class model, random regret, mode choice, departure time choice, sequence model

1 INTRODUCTION

According to 2011 National Household Survey (NHS), 74% of Canadian commuters drive to work, compared to only 12% who take public transit and 6% who walk or bike. The 2009 Canadian Vehicle Survey (CVS) summary report states that, between 2000 and 2009, the share of Sports Utility Vehicles (SUVs) has almost doubled while the share of cars (sedans) decreased from 60.5 percent to 55.4 percent. The escalating popularity of the larger sized vehicles coupled with the increasing usage of private vehicle (for both commuting and non-commuting purposes) has often been associated with a vast array of negative externalities – traffic congestion, energy waste, smog, expeditious deterioration of roadway surfaces, injuries and deaths from traffic crashes, obesity and other health issues, and air and noise pollution – leading to overall degradation of quality of life (Bhat et al., 2009; Santos et al., 2010; Selander et al., 2009). In fact, the transportation sector in Canada is the second largest emitter of Greenhouse Gases (GHGs), after the oil and gas sector. In 2015, the total emissions from this sector was a staggering 173 million tons (CO_2 eq) (a 43 percent increase since 1990), accounting for approximately 24 percent of the total emissions of the country.

Given such wide ranging implications, government officials, stakeholders, and policy makers seek a range of “push and pull” travel demand management (TDM) strategies which would reduce vehicular dependence and at the same time, encourage people to adopt alternative sustainable transport options. A substantial amount of research in the transportation and travel behavior realm is therefore being carried out to examine and disentangle the various motivators and/or deterrents of the different trip making decisions influencing the transportation system. At the core of these efforts is the formulation of behaviorally representative discrete choice models for analyzing choice behavior. Among the several travel choices, mode and departure time window for work and non-work pursuits directly influence the number and temporal pattern of vehicle trips and thus have important implications for transportation policy (Bhat, 1998a; Bhat, 1998b; de Jong et al., 2003). Across the day, substantial variation in travel time by mode is experienced in urban regions *i.e.* the attractiveness of modes vary across different time horizons of the day. For example, transit typically has lower service frequencies during off-peak hours while the auto mode is more attractive at these hours due to lower traffic congestion. On the other hand, during the peak hours, transit typically operates at a higher frequency while auto travel times are likely to be higher due to congestion. Clearly, there is reason to believe that mode and departure time choices are potentially interconnected decisions.

Traditionally, in the transportation literature, two methodological approaches are commonly applied to study such joint decisions. The first approach involves considering the multiple choice processes as a package of decisions made simultaneously. More specifically, every alternative from each choice is coupled with alternatives from other choices to yield a set of combination alternatives. The exact number of combination alternatives is obtained by computing the product of the number of alternatives for all choice processes. Traditional ‘single’ discrete choice models can then be used to study these combinatorial decisions accommodating for the dependencies between choices through the systematic component (see, Anowar et al., 2015; Debrezion et al., 2007; Debrezion et al., 2009; Dissanayake and Morikawa, 2002; Salon, 2009; Weinberger and Goetzke, 2010). However, as the number of alternatives in the choice set increases, the number of combinatorial alternatives to be generated proliferates.

A second approach accommodates the interdependency between multiple choices by tying together the unobserved components of the various choices using appropriate distributional assumptions yielding a multivariate joint choice model framework (simultaneous equation system) (see, Anastasopoulos et al., 2012; Bhat and Guo, 2007; Eluru et al., 2009; Konduri et al., 2011;

Pinjari et al., 2011; Yamamoto, 2009). The approach, while mathematically appealing, has two limitations. First, it requires extensive simulation for model estimation and focuses predominantly on the unobserved correlations across the choice processes. Second, in this approach, the model for the first choice relates to the information from the second choice only through unobserved error correlations. To elaborate, in modeling mode choice, the departure time information is not directly considered. More recently, Chakour and Eluru (2014) developed an alternative methodological framework to study such simultaneous choices (see, Angueira et al., 2017 for application in another context). The authors hypothesize that individuals are likely to consider joint choices or interconnected decisions in a sequence, even if the time difference between these decisions is infinitesimally small. As the true sequence is latent to the analysis, they proposed a latent segmentation based approach where both possible sequences are considered. Based on the segment of interest, one of the choices is assumed to be known and the other is modeled conditional on the knowledge of the first choice. In this manner, additional information is introduced in the model structure.

In our current study, we extend the approach proposed in Chakour and Eluru (2014) by relaxing the Random Utility (RU) maximization based assumption in the choice process. RU framework is mainly a context independent and fully-compensatory behavioral framework. The implicit compensatory nature of the formulation allows for a poor performance on an attribute (such as travel time) to be compensated by a positive performance on another attribute (such as travel cost) (Chorus et al., 2008; Chorus, 2010). In some choice occasions (particularly choices characterized by alternative specific attributes), such behavior is not realistic. For instance, travelers may select mode and departure time windows to avoid negative emotions or regret (for example, being late or being stuck in traffic jam). In such cases, regret minimization approach might be helpful to increase the behavioral realism of the choice model. In fact, there is growing evidence across various fields highlighting the implications of ignoring decision processes not aligned with utility maximization (Ben-Elia et al., 2013; Chorus, 2012; Chorus et al., 2008; Chorus and Bierlaire, 2012; Chorus and de Jong, 2011; Mai et al., 2017; Prato, 2014; Wang et al., 2016). Random regret (RR) framework is a semi-compensatory behavioral paradigm under bounded rationality which allows for pairwise alternative attribute comparison. The model framework has been successfully applied in several fields including transportation (for travel mode choice (Chorus, 2010), route choice (Chorus, 2014; Charoniti et al., 2017), road pricing (Chorus et al., 2011), departure time (Chorus and de Jong, 2011), automobile fuel choice (Hensher et al., 2013), traffic calming schemes (Boeri et al., 2014), freight mode choice (Keya et al., 2018; Boeri and Masiero, 2014)), online dating (Chorus and Rose, 2013), healthcare (de Bekker-Grob and Chorus, 2013), shopping center choice (Rasouli and Timmermans, 2016; Jang et al., 2017), and recreational site choice (Boeri et al., 2012).

In our study, we consider a latent segmentation approach with segment specific models estimated based on the RR minimization model structure. The proposed model system is developed for the analysis of mode choice and departure time choices for discretionary trips of university students. We employ a unique web-based survey called “StudentMove TO” conducted among the students of four major universities within the City of Toronto in Canada for our analysis. The remainder of the paper is organized in the following manner. In Section 2, a detailed review of literature on mode and departure time choice and students’ travel behavior is presented. The proposed econometric method is explained in Section 3. Section 4 contains details of study context and contributions, empirical data, variable generation procedure, and sample descriptive statistics.

The empirical findings (estimation, validation, and policy analysis) are discussed in Section 5 followed by conclusion in Section 6.

2 LITERATURE REVIEW

To help articulate the objectives of our research and to position our paper in the context of the existing literature, we provide an overview of studies that are closely related to our research effort. Toward that end, we keep our literature review limited to (1) joint mode and departure time analysis and (2) post-secondary students' travel behavior, respectively.

2.1 Mode and Departure Time Choice

A comprehensive review of the earlier literature on mode and departure time choice dimensions is beyond the scope of this paper. Earlier work on this topic can be divided into two distinct streams. One stream of studies investigates mode and trip timing or departure time choice independently while another group of studies analyses these choice processes jointly. To be sure, the transportation research community has examined mode choice decisions in substantial detail using advanced behavior-oriented frameworks. Factors influencing mode choice decisions can be broadly classified into four groups: (1) individual and household socio-demographic characteristics such as age, gender, income, driving license ownership, vehicle ownership, employment status (Bhat, 1997; Cervero and Gorham, 1995); (2) residential location, and urban form attributes (population density, land use mix, parking availability) (Pinjari et al., 2007; Rajamani et al., 2003; van Wee et al., 2002); (3) habit, attitude, and personality traits (Garvill et al., 2003; Johansson et al., 2006); and (4) mode specific factors such as travel time (in-vehicle, transfer, out-vehicle), and cost. Compared to mode choice, research on departure time choice is somewhat limited with the majority of the studies focusing only on commuting trips. These studies are mostly motivated from the need to evaluate the effectiveness of time-varying toll (such as congestion/peak-period pricing) schemes in reducing peak hour congestion. However, recognizing the non-trivial and growing contribution of non-work trips to urban traffic congestion, some researchers have also modelled departure times of non-work related trips. In these studies, departure time is either modeled as a continuous variable (Bhat and Steed, 2002; Ettema and Timmermans, 2003) or by dividing the continuous departure time variable into discrete intervals (de Palma et al., 1997; Small, 1982). Important factors influencing the choice of departure time include: socio-economic attributes (such as marital status, ethnicity, income), transportation system characteristics, travel time, travel cost, and flexibility of work/non-work schedules (Saleh and Farrell, 2005; Bhat and Steed, 2002; Steed and Bhat, 2000).

The other stream of research argues that there is a strong relationship between mode and departure time choice, and people often make these two choices simultaneously (Bhat, 1998a; Bhat, 1998b; Hess et al., 2007). We present a list of studies that did a joint investigation of these two choice processes in Table 1. The table provides information on the study area, data elicitation approach, methodology applied to investigate the joint decision process, level of analysis (trip/tour), purpose of travel, nature of departure time analyzed (discrete/continuous), independent variables considered in the model, and the money value of times (MVOT) obtained. We can see from the table that the majority of these studies focus on commuting trips, employ revealed preference (RP) data from formal travel survey to develop models, use random utility (RU) based multinomial logit (MNL) model and its variants using socio-demographics, level-of-service (travel time and cost), and locational attributes as explanatory variables. The value of time varied

considerably from one study to another. This is understandable, given the variability in data, methodology, and empirical context.

2.2 Students' Travel Behavior

University campuses are special communities that tend to have unique travel demand pattern with unique policy implications. With the rapid expansion in the number of universities across the globe in recent years, travel behavior of university students has garnered increasing attention from transportation researchers. A summary of these earlier studies (since 2000) is presented in Table 2. The table provides information on the study area, choice behavior analyzed, modes considered (if the choice behavior investigated is mode choice), methodology used, trip purpose, exogenous variables considered (if multivariate analysis is adopted in the study), and summary of major findings. Several observations could be made from the table. First, the majority of the studies are from North America (USA and Canada). Second, the two most commonly investigated choice dimensions in the context of university students are mode choice and trip frequency/rate, respectively. Researchers have also focused on other aspects of travel behavior such as vehicle ownership (Cullinane, 2002), cycling frequency (Titze et al., 2007), transit preference (Grimsrud and El-Geneidy, 2014), choice of bus service (Eboli and Mazzulla, 2008), distance traveled, and travel time (Limanond et al., 2011). Third, both univariate and multivariate analyses techniques are applied to examine these choice behavior(s). Among multivariate modeling techniques, multinomial logit (MNL) model and its different variants are most commonly used. Fourth, the majority of the studies have focused on commuting trips. Finally, empirical findings suggest that students tend to use a variety of transportation modes, including active travel while accessibility as well as on-campus parking permit plays a dominant role in determining their auto mode choice.

3 ECONOMETRIC MODEL

In this section, we discuss the modeling framework and its mathematical formulation in detail. Our proposed approach simultaneously considers two segments of mode choice and departure time for discretionary trips. The allocation of individuals to the two segments is achieved through a latent segmentation framework that determines the probability of assigning the decision maker to either one of these two segments as a function of multivariate attributes. Afterwards, in the first segment, mode is modeled first and then departure time is modeled using the mode choice decision, while in the second segment, the choices are reversed.

The modeling approach is comprised of three components: (1) latent segmentation component, (2) mode choice component for each segment, and (3) departure time choice component for each segment. Let, i be the index for segments ($i = 1, 2$), q be the index of the trip makers (the university students) ($q = 1, 2, \dots, Q$), m be the index for mode ($m = 1, 2, \dots, M$) characterized by k attributes ($k = 1, 2, \dots, K$), and t be the index for departure time ($t = 1, 2, \dots, T$) characterized by l attributes ($l = 1, 2, \dots, L$). The latent segmentation probability (P_{qmt}) for joint choice of mode m and departure time t can be written as:

$$P_{qmt} = P_{q1}P_{q1m}P_{q1t}|m + P_{q2}P_{q2t}P_{q2m}|t \quad (1)$$

where P_{q1} and P_{q2} represent the probability of being part of Segment 1 and Segment 2, respectively, P_{q1m} , P_{q2m} represent the probability of selecting mode m in Segment 1 and Segment 2, respectively, and P_{q1t} , P_{q2t} represent the probability of selecting departure time t in Segment 1 and Segment 2, respectively. Segmentation, mode choice, and departure time choice probabilities

are all modeled by MNL models. Following the RU decision rule, the segmentation probability (P_{qi}) can be expressed as:

$$P_{qi} = \frac{\exp(\beta'_i x_{qi})}{\sum_{i=1,2} \exp(\beta'_i x_{qi})} \quad (2)$$

where x_{qi} is a vector of attributes influencing segment choice, β' represents the vector of estimable coefficients. Note that the mode and departure time choice probabilities within the segments can be obtained by either following the RU or RR decision paradigm. With the notation mentioned above, following the RU decision rule, the choice probabilities for choice models in each segment take the following form:

$$P_{qim} = \frac{\exp(\gamma'_i x_{qim})}{\sum_{m=1}^M \exp(\gamma'_i x_{qim})} \quad (3)$$

$$P_{qit} = \frac{\exp(\delta'_i x_{qit})}{\sum_{t=1}^T \exp(\delta'_i x_{qit})} \quad (4)$$

If, on the other hand, if we consider that the mode and departure time choice follow a RR formulation, the within-segment choice probabilities take the following form:

$$P_{qim} = \frac{\exp(-r_{qim})}{\sum_{m=1}^M \exp(-r_{qim})} \quad (5)$$

$$P_{qit} = \frac{\exp(-r_{qit})}{\sum_{t=1}^T \exp(-r_{qit})} \quad (6)$$

Where $r_{qim} = \sum_{n \neq m} \sum_{k=1}^K \ln[1 + \exp\{\zeta'_{ik}(x_{qink} - x_{qimk})\}]^1$ and $r_{qit} = \sum_{t \neq s} \sum_{l=1}^L \ln[1 + \exp\{\eta'_{il}(x_{qitl} - x_{qisl})\}]$ are the regrets associated with choice of mode m and choice of departure time t , respectively. The log-likelihood function ($L = \sum_q \ln(P_{qmt})$) is constructed based on the above probability expression and all the parameters in all the models are consistently estimated by maximizing the log-likelihood function. The models are coded in GAUSS matrix programming language.

4 EMPIRICAL CONTEXT

¹ This is the modified specification proposed by Chorus, 2010 for the total systematic regret associated with a considered alternative considering all competitor alternatives. Alternatively, it can be also expressed against the best forgone alternative as proposed in the seminal paper by Chorus et al. (2008) as: $r_i = \max_{j \neq i} \left\{ \sum_m \max\{0, \beta \cdot (x_{jm} - x_{im})\} \right\}$.

4.1 Study Context and Contributions

University students are a unique cohort with diverse demographic composition and backgrounds, who are at different stages in their life-cycle strata (Christie et al., 2008). The challenges of balancing study, work, and social life may lead to complex trip making behavior (Limanond et al., 2011). For example, newly admitted or junior undergraduate students are more likely to live on-campus or near-campus to allow themselves quick access to various educational and recreational activities as well as to socially interact with their peers. On the other hand, senior or graduate research students who are possibly married, may reside in traditional residential communities located away from campus and might not be as outgoing as the undergraduate students. On a different note, compared to their predecessors (the baby boomers and the generation “X”), students of today (predominantly generation “Y”) are labelled as frugal (Garikapati et al., 2016), and virtually-mobile-physically-“go-nowhere” generation (Buchholz and Buchholz, 2012) who are less likely to be licensed drivers, and are less likely to drive even when they have a license (McDonald, 2015). Hence, time-varying demand management policies might have a different impact on this cohort’s trip making than the general population. Furthermore, students have intermittent and flexible class schedules that enable them to engage in various discretionary activities not only in the evening but also at any time (for example, in between classes) during the day (Limanond et al., 2011).

To date, most research related to mode and departure time choice has focused on the trips made by the general population, often neglecting the student subgroup. However, in light of the above discussion, from an empirical standpoint, the investigation of the inter-relationship between mode and departure time window choices is particularly important in the context of discretionary trips of university students. For instance, students who have access to automobiles at home might make decision about their mode (automobile) first and then depending on their perception or knowledge about the congestion condition on the potential trip route, may choose their trip start time. Similarly, if the trip destination is nearby, students might decide on their departure time first and then either walk or take transit to travel to the intended destination. Hence, it is plausible that the two decision processes are essentially connected and there is a need for a modeling framework capable of exploring the inter-dependency. The current research contributes to the existing travel behavior literature by modeling these two choice processes in a unified framework that allows for possible choice sequences (similar to Chakour and Eluru, 2014). Further, the proposed framework builds on earlier research by Hess et al. (2012); Hess and Stathopoulos (2013); Boeri et al. (2014) by allowing the choice models to consider two different decision paradigms – traditional RU based choice mechanism and recently proposed RR based choice mechanism. It accounts for the latent nature of the choice sequence where the first segment follows mode first and departure time second sequence and the second segment follows departure time first and mode second sequence. From here on, we would refer to them as MD Sequence (mode first – departure time second sequence) and DM Sequence (departure time first – mode second sequence). The decision makers are probabilistically assigned to the two segments based on a host of exogenous variables, including socio-demographic variables, location attributes. The proposed approach, in addition to allowing for choice sequences is useful in providing insights on variables affecting individual preferences for a choice sequence. To the authors’ best knowledge, this is the first application of such a joint sequential system using a regret based decision rule.

4.2 Data Source and Sample Formation

The main data source employed in this study is a web-based survey called “StudentMoveTO”. The survey was conducted during Fall 2015 and distributed to students from four universities of Toronto including Ontario College of Art and Design (OCAD), Ryerson University, York University (Glendon and Keele campuses), and University of Toronto (main St. George campus and satellite campuses in Mississauga and Scarborough). The survey received completed responses from 15,336 students (8.3% response rate) with more than 36,000 trip records from a single day trip diary. It elicited information on students’ socio-demographics, residential locations, and household characteristics along with information on departure time, mode chosen, and purpose for the reported trips. This is a unique across-university survey dataset for acquiring in-depth understanding of travel behavior of students who form a major part of the traveler community in Toronto.

The sample formation exercise involved a series of transformations of the original survey data. First, the discretionary trips (trips for shopping, visiting friends and family, recreational purposes) were extracted. Then, the individual and household socio-demographics, and contextual characteristics (day of week, weather, average temperature of travel day) were appropriately added to the trip database. Finally, records with missing or inconsistent data were eliminated. The final dataset contained 10,042 discretionary trips which represents 27.33% of the overall number of trips reported in the survey. Of these, we randomly selected 7,050 trips for model estimation and kept aside the remaining data (2,992 observations) for model validation.

4.3 Dependent and Independent Variables Generation

Travel modes in the dataset were grouped into six categories: drive alone, passenger (shared ride), transit, walk, bike, and other modes (park and ride; kiss and ride). Please note that all modes are not available to all students. To account for availability, we created the following rules; drive mode was only available to students with driver licences, bike mode was available for students with a bike or bikeshare membership while walking was only available for trips less than 15 km². Further, considering the start time of the trips, four discrete departure time periods were created: AM (6:00-9:00), Midday (9:00-15:00), PM (15:00-18:00), and Evening (18:00-24:00) – similar to the intervals used in Greater Toronto Area Model (GTAModel V4.0). The overnight period (24:00 – 6:00) had very few trips and thus was not considered in our analysis. Please note that while it is intuitive to consider a continuous representation of departure time choice, the assumption imposes a strict linearity on the parameter effects on the dependent variable. Along the same lines of Bhat (1998b), we wanted to test if an unordered representation that allows for non-linear variable impacts is of value in examining departure time choice. Hence, we discretized the time choice into four categories (discussion on methodological issues in modeling time-of-travel preferences can be found in Ben-Akiva and Abou-Zeid, 2013).

The independent variables can be broadly classified into three categories: (1) individual and household demographics (age, gender, lifecycle stage, household size, household fleet size), (2) location attributes (campus location, distance to campus, household location), (3) trip and

² We are analyzing discretionary trips – these types of trips do not have the space-time constraint as that of work trips and hence, have more variability involved in terms of route choice, duration, and distance. Students might end up walking more because of their flexible time schedules. In light of that we considered walk mode availability only for extreme cases. Please note there were a small sample of trips with longer walk times and we did not want to exclude them. Given the utility/regret functional form and parameters for travel time, the inclination to select walking mode will drop with increasing travel time. So, any alternative beyond 60 minutes will have a very low probability of being chosen (effectively becoming unavailable).

activity characteristics (trip distance, trip purpose, activity duration), (4) contextual attributes (day of week, weather, temperature), and (5) level-of-service attributes (travel time, travel cost). For drive alone and transit, zonal (Traffic Analysis Zone, TAZ) level travel time and travel cost were drawn from GTAModel V4.0 for each time period being modeled. For inter-zonal (TAZ to TAZ) trips by these two modes, the distance between origin and destination and the average speed were used to calculate the travel times. Passenger mode was assumed to have the same travel time as drive mode but without any cost. The distance between origin TAZ and destination TAZ was also used to compute travel times for walk and bike (assuming average travel speeds of 4 km/h and 13 km/h for walk and bike mode, respectively). Travel cost associated with active modes was considered zero. For the other mode, transit travel time plus ten additional minutes was considered accounting for park-and-ride and kiss-and-ride trips. Travel time may vary depending on the choice sequence; to address this, we created two sets of travel time. In mode first – departure time second sequence, the time of departure is unknown. Hence, average travel times of the four departure time periods are generated for drive alone, passenger, and transit modes. In departure time first – mode second segment, instead of average travel time over the four departure time periods, the travel times for drive and transit modes for each time window are generated.

4.4 Descriptive Statistics

Table 3 presents a descriptive summary of the estimation sample. We can make several observations from the table. The majority of the trips were made on foot (40.2%), or using transit (21.1%). These trips are mostly made between 9.00 AM in the morning to midnight. Other salient characteristics of the sample are: two-fifths of the discretionary trips are taken for recreational purposes while the lowest share of trips was for visiting friends/families and others (15.6% and 12.3%, respectively). Interestingly, the table shows that students are equally likely to take part in shorter and longer duration discretionary trips – a manifestation of flexible time schedules of this cohort. Moreover, our sample is mostly comprised of female full-time undergraduate students with a mean age of 25 years, of which approximately two-thirds hold a driving license and half of them either own a bicycle or hold a bikeshare membership.

5 EMPIRICAL ANALYSIS

5.1 Model Performance Evaluation

We estimated four separate models and two latent class models. The separate models are:

1. RU based multinomial logit (RUMNL) model (mode first – departure time second).
2. RU based multinomial logit (RUMNL) model (departure time first – mode second).
3. RR based multinomial logit model (RRMNL) (mode first – departure time second).
4. RR based multinomial logit (RRMNL) model (departure time first – mode second).

The two models from the latent class regimes are:

1. RU based latent class multinomial logit (RULCM) model.
2. RR based latent class multinomial logit (RRLCM) model.

In estimating the models, independent sequential models (MD sequence and DM sequence) assuming the two alternative interrelationship structures from the two choice paradigms are used as starting point for estimating the latent segmentation based model. Please note that these models are non-nested, hence, their performance is compared based on the Bayesian Information Criterion (BIC). The empirical equation for BIC is:

$$BIC = -2\ln(L) + K \ln(Q) \quad (7)$$

where $\ln(L)$ denotes the log likelihood value at convergence, K denotes the number of parameters, and Q represents the number of observations. The advantage of using BIC over other information criterion is that it imposes a substantially higher penalty on over-fitting in terms of the number of parameters. The computed BIC values for the final specifications of all the models are presented in Table 4. The model with the lowest value is the preferred model.

The summary of model estimation results in Table 4 clearly points towards a significantly superior performance by the latent segmentation based models. Moreover, the model which imposes DM sequence offers better fit compared to the model with MD sequence. In terms of model structure, based on the BIC value, RRLCM (pure RRM structure) offers the best data fit. Although the percentage difference in BIC might appear small, any difference larger than 10 points is considered to be a significant difference in literature (Burnham and Anderson, 2004; Kuha, 2004; James and Taylor, 2008). Please note that the underlying behavioral paradigm in both the independent models as well as the latent segmentation based models is the same across respondents (either pure RUM or pure RRM). However, several decision rules may coexist in the same population for different choice situations (Hess et al., 2012; Hess and Stathopoulos, 2013; Boeri et al., 2014; Dey et al., 2018). In our model estimation, we also estimated the models for all possible combinations of random utility and regret components within the latent segmentation model system - a total of 16 models (including the two discussed). The comparison highlighted that the model system where all models followed a regret regime offered the best data fit. The results for the 16 model systems are available upon request from the authors. In addition, we conducted a component by component comparison of log-likelihoods using the best specified models from the two choice paradigms. The comparison serves as a diagnostic tool, rather than having to estimate all possible combinations of RUM and RRM decision rules for the two choice dimensions. The log-likelihoods of the four individual components (RUM vs RRM) are: (1) mode first (-12995.31 vs -12452.01), (2) departure time second (-8558.33 vs -8500.81)³, (3) mode second (-11251.78 vs -10166.88), and (4) departure time first (-8356.242 vs -8354.37). The results of the comparison exercise further indicated that a pure RRM treatment of parameters for both choice dimensions is preferred to the pure RUM treatment suggesting that RRM fits this dataset better than RUM. Of the four model components, for three model components the RRM framework offers significantly improved performance (for departure time first, the difference is marginal). Hence, in the subsequent sections, we only discuss the results from RRLCM (pure RRM structure) model.

5.2 Segment Characteristics

Prior to examining the impact of various coefficients on segmentation and mode choice-departure time decisions, it is important to discuss the overall segment characteristics. We can estimate three measures based on the model estimation results of the latent segmentation component to glean a better behavioral understanding of the two segments. These are: (1) population share across the

³ We have also tried to estimate the max operator version of the random regret model for departure time component. However, for our dataset, the logarithmic function regret version provided a better data fit.

two segments⁴, (2) overall mode and departure time level shares within each segment⁵, and (3) the distribution (mean) of independent variables within each segment⁶. These estimates are presented in Table 5. We can see from the table (top panel) that approximately two-thirds (64.65%) of the students are likely to be in Segment 2 (departure time first – mode second) while the probability of students belonging to Segment 1 (mode first – departure time second) is only 35.35%. At the aggregate level, the distribution of departure time in the two segments are quite similar. However, the percentage of AM and mid-day period trips are slightly higher in Segment 1 while Segment 2 has a higher share of PM and evening period trips. On the other hand, mode share between the two segments shows significant variations. For instance, while drive alone mode is the prevalent mode (32.7%) followed by passenger mode or rideshare (30.2%) in Segment 1, approximately 50 percent of the trips in Segment 2 are undertaken on foot. The significantly shorter travel distance (3.69 km) for Segment 2 trips is in agreement with the chosen modes. Quite interestingly, the share of transit mode are similar across the two segments. Other salient characteristics of the two segments include: students in Segment 1 are younger, live significantly far from campus, belong to a larger household with large fleet size while nearly half the students in Segment 2 are in their late twenties, live near campus, and the majority of them do not own cars (64%).

5.3 Model Results

The universal set of explanatory variables was tested in the estimation process (latent segmentation sequence choice component, mode choice component, and departure time choice component). The final specification was based on a systematic process of removing statistically insignificant variables (in our analysis we used a 95 percent significance level) and combining variables when their effects were not significantly different (the rationale for doing this is maintain a parsimonious specification without any loss of data fit). The specification process was also guided by prior research, intuitiveness, and parsimony considerations.

5.3.1 Sequence Choice Component

The latent segmentation component determines the probability that a student is assigned to one of the two choice sequence segments. In our analysis, we selected the DM sequence as the base and used individual demographics, and location attributes as the segmentation variables. The parameter estimates of the sequence component offer some interesting insights on the decision process. For instance, the results indicate that young students in their 20's (Age 20-29 years) or whose campus is located in the downtown area have an inclination towards choosing their departure time first and then decide which mode to use for the trip. On the other hand, students who are single parents or have multiple vehicles available in their household or whose residence is located away from the school campus prefer to make mode decision first. All of these suggest that these are students who are more likely to live in suburban areas. To be sure, we mapped the probability of belonging to Segment 1 against home location TAZ and presented in Figure 1. We can see that students living further away from the city core are more likely to select their mode first and then their departure time for discretionary trips while students residing in inner sections of the City of Toronto, who

⁴ To obtain the population share across the two segments, the probability of each individual belonging to either of the MD sequence or DM sequence was calculated using Equation (2). Then the probabilities are averaged across the entire sample for each latent class.

⁵ The mode and departure time shares within each segment were obtained by averaging the individual level predicted probabilities for each choice across the entire sample.

⁶ The mean of the attributes characterizing each segment is obtained by averaging the product of individual level probability of belonging to each segment with the attribute indicators over the segment share.

have higher accessibility to amenities and alternative modes of transport, are more likely to choose their departure time first. Clearly, their trip decision making is less dependent on their mode of travel and more reliant on their schedule.

5.3.2 Mode Choice First-Departure Time Second Sequence (MD Sequence)

The sequence of decisions in the first segment is assumed to be mode first and departure time period second. The results of this sequence are presented in columns two and three of Table 7 and Table 8. The positive constant for drive alone mode indicates that when students choose their mode of travel first, they have a preference towards driving. This makes intuitive sense since these are the students who have access to cars. In this segment, recreational trips are less likely to be pursued by transit and more likely by walking. The positive coefficient of drive alone and passenger mode for shopping trips highlights the utility of car when carrying parcels, shopping bags, etc. Interestingly, no such preference for modes is found significant when departure time is chosen first. Long activity trips are less likely to be undertaken by car. This might be because of parking restrictions or limited parking availability at the destinations or because students might share the cars with other household members and cannot use it for long durations. During weekends, students in this segment are more likely to drive or be a passenger, presumably because the use of a car is easier in weekends due to less congestion. However, the impact of weekend is insignificant for trips where departure time is chosen first. It might be the case that during weekends, students are more relaxed and hence, might be more likely to undertake temporally impulsive activities without planning for mode (similar results in another context can be found in Anowar et al., 2015). As expected, students are more inclined to choose modes that minimize their travel time.

In terms of the departure time choice parameters for Segment 1, the variable effects are intuitive. The negative constants for AM, PM, and evening periods indicate that in Segment 1, trips are more likely to be pursued during the mid-day period. When mode is chosen first, mid-day to evening periods are preferred for undertaking recreational, shopping, and visit trips. It might be the case that flexibility of knowing the mode enables the students to plan trips at different hours of day. Weekend trips as well as trips during warm temperature are more likely to be made during mid-day or PM hours plausibly to take advantage of the daylight hours. Considering the fact that the student sample in our study is from Canada where high temperature days are rare, the result makes intuitive sense. However, trips are less likely to be undertaken during the hours when it is raining. Further, as the mode of travel is known in this segment when making decisions regarding departure time, we included dummy variables for each chosen mode in our estimation. The results indicate that when drive alone is the chosen mode, students are less likely to travel during PM, perhaps due to heavy congestion during that period. Passenger trips are more likely to be made during mid-day and evening – students might be taking a lift from their parents for going to school for attending classes or for going home after classes. The coefficient for walk mode is positive for mid-day trips.

5.3.3 Departure Time First-Mode Choice Second Sequence (DM Sequence)

In this section, we discuss the results of the second sequence of choice – departure time first and mode choice second. The results of this sequence are presented in columns four and five of Table 7 and Table 8. From the values of the time period constants, we can see a higher preference for evening and mid-day periods for discretionary trips. Unlike Segment 1, students in this segment do not prefer mid-day periods for undertaking recreational trips. However, shopping trips are more likely to be taken during the PM periods while PM or evening periods are preferred for visit trips.

When mode is chosen first, duration of activity has no effect on departure time. However, when mode is unknown, mid-day and PM periods are likely to be chosen for trips involving longer duration activities, presumably to utilize the most of the daylight hours. Similar to Segment-1, students in this segment are also more likely to choose post-afternoon period for trip making during weekends or when the temperature is high.

The mode second parameters offer intriguing results, highlighting the heterogeneity in the two segments in terms of trip making and modal choice behavior. For instance, the positive coefficient for walk mode constant indicates that the students in this segment are more inclined to choose walk mode for discretionary trips (when departure time choice precedes mode choice) over other alternatives. In this segment, visit trips are less likely to be pursued using transit or active modes. These might be longer distance trips requiring the students to use auto mode. For long duration activities, students are more likely to use public transit and less likely to walk plausibly because they have access to different transit options (bus/subway). Preference for drive mode during rainy weather makes intuitive sense. As expected, regret decreases as the difference in time between the chosen and non-chosen travel mode increases because the non-chosen mode requires longer travel time. It is interesting to note that students who choose their departure time first are more sensitive to trip travel times than students who choose their mode first. In this segment, since students have made their decision regarding the trip departure time, we can estimate coefficients for departure time choice categories. During the mid-day period, transit, walk, and bike are more likely to be selected for discretionary travel compared to other modes.

5.4 Validation Analysis

A validation exercise was also carried out on a hold-out sample (2,992 observations not used in the model estimation process) for all model frameworks. We computed the predictive log-likelihood for the validation sample and various sub-samples. This exercise provides an indication if the results on the estimation sample carries over to the hold-out sample and sub-samples as well. Higher (less negative) values are preferred over the lower ones. In our case, the subsamples were drawn for campus location downtown, weekend, recreational trip purpose, shopping trip purpose, visit trip purpose, student is female, and student's household is carless. Please note that the same data preparation approach for estimation sample was followed for the validation sample. Table 9 presents the computed predictive log-likelihoods. The results clearly highlight that the LCM models clearly outperform all single sequence systems. Among the LCM models, the gain in log-likelihood using RR based latent class multinomial logit model was more than 40 units for the total validation sample. For the subsamples, the variation in log-likelihood gain varied from 7 (for shopping trip purpose) to 32 units (for campus location downtown). In all instances, the RRLCM model outperformed the RULCM.

5.5 Policy Analysis

In order to better understand the magnitude of the effects of exogenous variables on the mode and departure time decisions, we generated the predicted change in choice probabilities for several variables of interest in policy making. We computed the percentage change of aggregate mode and departure time shares (the individual disaggregate probabilities across all individuals are averaged to obtain the mean) due to changes to the exogenous variables using the parameter estimates of the best specified models. For the sake of comparison, the changes in elasticity were calculated for the following models: (1) RU based latent class multinomial logit (RULCM), (2) RR based latent class multinomial logit (RRLCM), (3) RR based multinomial logit model (RRMNL) (mode first –

departure time second), and (4) RR based multinomial logit (RRMNL) (departure time first – mode second). The scenarios considered were: 1) change in home to school distance variable accounting for policies that might influence students’ residential location choice such as providing affordable housing near campuses, 2) change in car travel time, and 3) change in travel time for all modes except for walk and bike. The policy analysis results are presented in Table 10, Table 11, and Table 12. The reader would note that the distance to school variable is present only in the LCM models and thus has no impact on the single segment models. Hence, Table 12 does not include this variable.

The following observations can be made from the policy analysis results. First, reduced distance to school increases the likelihood of choosing walk, bike, and transit mode for discretionary trips. Living nearer to school increases the share of departure time first – mode second segment; an indication that living nearer to school allows students to have better scheduling flexibility. Second, as expected, increase in drive travel time leads to a drop in the probability of selecting drive alone or passenger mode with higher impact on passenger mode. As a result of this modal shift, other mode (park-and-ride/kiss-and-ride) experiences the most attraction, followed by the transit mode. With increase in drive mode travel time, the choice of walk mode becomes inelastic. Third, we can observe that when both transit and drive time increases, students are less likely to choose transit and the other mode. In fact, although the drive time has also increased, students are still switching from transit and other modes to drive and passenger modes. Active modes of travel also attract students with largest attraction towards cycling. This scenario shows that students are highly sensitive to transit travel time. Fourth, change in predicted mode shares for the three scenarios were very similar in magnitude between the RUM and RRM based latent class models. The changes predicted by the RRLCM model were consistently lower than that predicted by the RULCM model. Fifth, change in predicted mode shares for the independent models are consistently higher than the predicted mode share changes obtained from the sequence model. Overall, this section demonstrates how the proposed model system can be used to investigate different policy scenarios and understand students’ responses (in terms of changes to behavior) to each scenario. Caution should be exercised while interpreting the results, given the results are obtained for mode and departure time choice for discretionary trips.

6 CONCLUSIONS

Understanding the travel behavior of university students can help universities and other stakeholders to formulate policies, develop programs, and build infrastructures that encourage students’ use of public transport or active mode for travel. Despite this, students’ travel behavior, particularly mode choice for discretionary trips, has not received much attention from transportation professionals. In the current paper, with the objective of enhancing our understanding of student travel patterns, we examine their mode choice for discretionary trip purposes along with departure time choice. Toward this end, we propose a latent segmentation based approach to jointly consider the mode and departure time choice decisions without imposing any sequence. We simultaneously consider two possible sequences while also determining the individual allocation of students as a function of socio-demographic (individual and household) and location attributes. The interdependency between the mode and departure time choice was captured via specification of the systematic component. The method is elegant but not without limitations. Unobserved taste preferences are only accounted for based on the latent segmentation component. The model does not explicitly consider for taste variations within each segment. The model formulation can also be improved by incorporating another segment where the decision

processes are jointly considered (as opposed to a particular sequence). The extension is a potential direction for future research. In addition, the proposed regret approach follows a logarithmic formulation. It would be interesting to test the max operator formulation to examine how the results of the regret approach would alter in this empirical context.

The proposed model system is estimated using data extracted from a unique survey of university students in the City of Toronto, Canada. We estimate the models following classical random utility based framework as well as newly proposed random regret based decision paradigm. Our results provide evidence to the presence of two hierarchies in the choice process and indicate that students are more likely to choose their departure time first and mode second plausibly because they have less restrictive time schedules. Our results are also in line with the existing literature that students who have access to vehicles at home are more likely choose their mode first and then their departure time. In the mode first segment, students prefer using drive mode for weekend shopping trips but are less inclined to use it for long duration trips. On the other hand, in the mode second segment, for longer duration trips students have a higher propensity of opting for transit. The members of this segment also have a tendency to make trips during any time from PM hours to evening. The disinclination to make discretionary trips during rainy weather condition is observed in both segments.

The results from our policy analysis also provide intuitive policy interpretations. Since students are highly sensitive towards transit travel time – increasing transit frequency and adjusting the transit schedules will encourage the students to adopt this travel mode for their discretionary travel. The understanding of what factors motivate or deter students from choosing transit or active mode might also help transit agencies and government stakeholders plan services (introduction of shuttle services) and facilities to meet the needs of this young cohort. It will also help universities to carry out promotional campaigns to encourage students to adopt greener and sustainable modes. In our model specification, we use the 2010 version of the RRM framework that calculates regret with regard to all available alternatives; a future extension could involve testing the performance of the different regret specifications on multiple empirical contexts.

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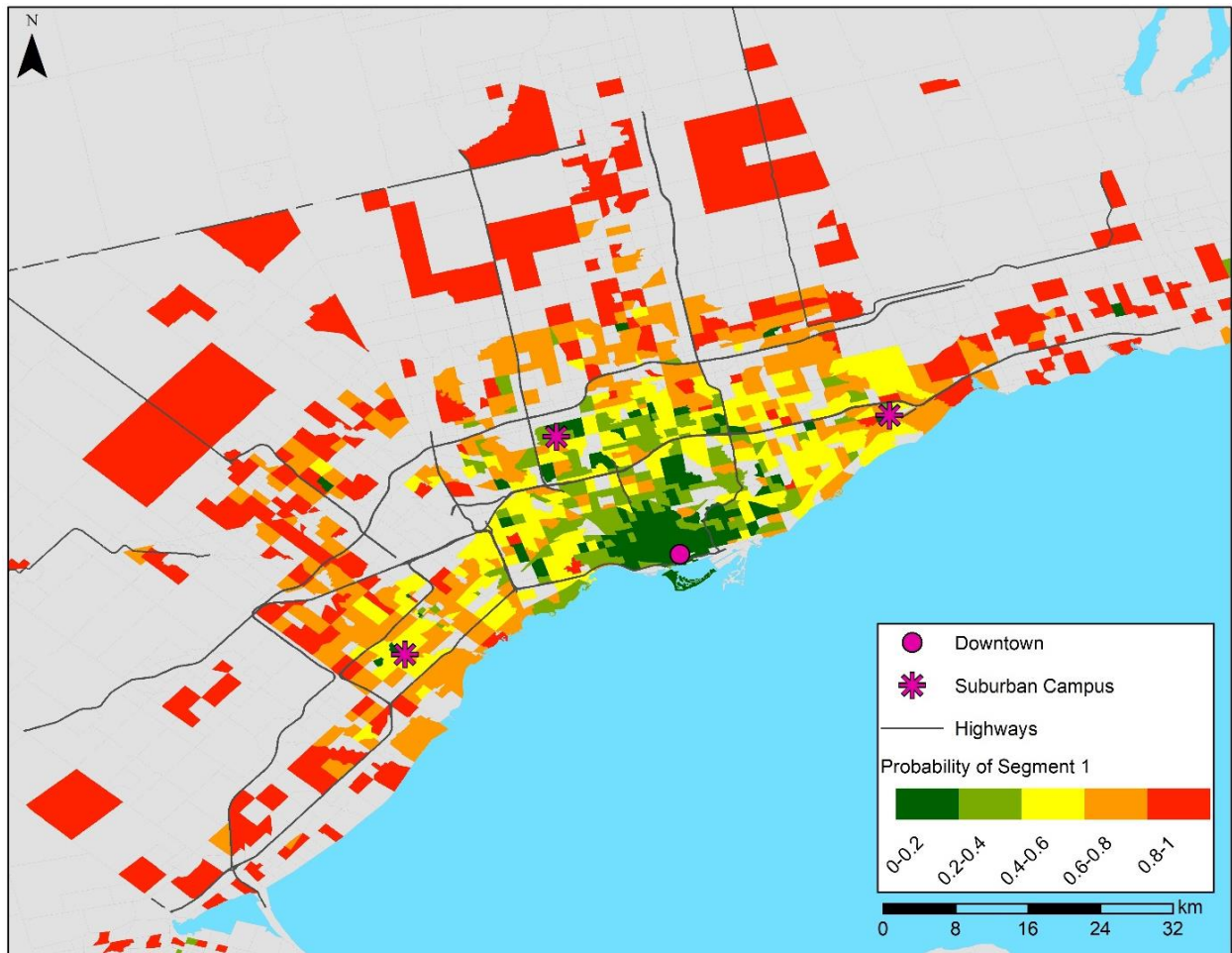


FIGURE 1 Segment Choice Probability Distribution Plot against Home Location TAZ.

Table 1 Literature on Joint Modeling of Mode and Departure Time Choice

Study	Study Area	Data Source	Methodology	Level of Analysis	Purpose	Nature of Departure Time	Independent Variables			Money Value of Time
							Demographics	Level-of Service	Spatial Attribute	
Bhat (1998a)	San Francisco, USA	RP	Mixed MNL	Trip	Social-recreational	Discrete	√	√	√	Drive alone/shared ride: 5.21-6.17 \$/hr (in-vehicle travel time) 10.80-13.66 \$/hr (out-of-vehicle travel time)
Bhat (1998b)	San Francisco, USA	RP	MNL-OGEV	Trip	Shopping	Discrete	√	√	√	Drive alone/shared ride: 1.93 \$/hr (in-vehicle travel time) 3.47 \$/hr (out-of-vehicle travel time)
de Jong et al. (2003)	Netherlands	SP	Mixed MNL	Tour	Work/ Business/ School	Continuous	√	√	-	Car and train 65-76 guilders/hr and 23-69 guilders/hr (commuting) 92 guilders/hr and 73 guilders/hr (business trip) 10 guilders/hr and 52 guilders/hr (education trip)
Tringides et al. (2004)	Florida, USA	RP	Recursive bi-variate probit	Trip	Non-work/ School	Discrete	√	√	√	-
Hess et al. (2007)	London, UK Netherlands West Midlands, UK	SP	MMNL	Tour	Work	Discrete	-	-	-	-
Bajwa et al. (2008)	Tokyo, Japan	SP	MNL, NL, CNL	Trip	Commute	Discrete	√	√	√	Car 28-38.5 yen/min
Habib et al. (2009)	Toronto, Canada	RP	MNL-Hazard based Duration	Trip	Work	Continuous	√	√	√	Auto/Transit \$43.14 \$/hr (professional work) \$12.99 \$/hr (manufacturing work) \$32.32 \$/hr (general office work) \$16.10 \$/hr (retail work)

Habib (2012)	Toronto, Canada	RP	Tri-variate discrete-continuous	Tour	Work	Continuous	√	√	√	Auto ▪ \$37 \$/hr (professional work) ▪ \$32 \$/hr (general office work) ▪ \$21 \$/hr (retail and service work) ▪ \$16 \$/hr (manufacturing work)
Habib (2013)	Toronto, Canada	RP	Discrete-continuous	Tour	Work	Continuous	√	√	√	Auto driver/Auto passenger (in-vehicle travel time) ▪ \$45.62 \$/hr (professional work) ▪ \$16.25 \$/hr (manufacturing work) ▪ \$27.63 \$/hr (general office work) ▪ \$16.26 \$/hr (retail work)
Yang et al. (2013)	Beijing, China	RP	CNL, NL	-	-	Discrete	√	√	-	-
Ding et al. (2014)	Maryland, USA	RP	CNL	Trip	Work	Discrete	√	√	-	▪ \$20.53 \$/hr
Zou et al. (2016)	Beijing, China	Joint RP and SP	Agent based choice model	Trip	All purpose	Continuous	√	√	-	-

Note: MNL = Multinomial logit; NL = Nested logit; CNL = Cross nested logit; OGEV = Ordered generalized extreme value; MMNL = Mixed multinomial logit; SP = stated preference; RP = revealed preference

Table 2 Literature on Student Travel Behavior

Study	Study Area	Choice Behavior	Modes Considered	Method Applied	Trip Purpose	Independent Variables			Major Findings
						Demographics	Level-of Service	Spatial Attribute	
Cullinane (2002)	Hong Kong	Car ownership	-	Univariate analysis	-	-	-	-	Male students have a latent inclination towards owning vehicles
Rodriguez and Joo (2004)	North Carolina, USA	Mode choice	Drive alone, carpool, bus, park and ride, bicycle, walk	MNL, NL, HEV	Commute	√	√	√	Sidewalk availability encourages non-motorized mode choice
Ubillos and Sainz (2004)	Bilbao, Spain	Mode choice	Car, bus, train, metro	NL	Commute and non-commute	√	√	-	Increased frequency of trains and metro along with reduced bus ticket can increase their mode share
Shannon et al. (2006)	Perth, Australia	Mode choice	Drive alone, public transit, bike, walk	Univariate analysis	Commute	-	-	-	- Travel time is the major deterrent reported against active modes - Health and fitness improvement is the major motivator for active modes
Titze et al. (2007)	Graz, Austria	Cycling frequency	-	Linear regression	Commute	√	-	√	Pleasure, fitness concern, relaxation, aesthetics encourages students to cycle more frequently
Eboli and Mazzulla (2008)	Cosenza, Italy	Choice of bus service	-	MNL	Commute and non-commute	-	√	-	Fare is the most important attribute for choice of bus transit
Eom et al. (2009)	North Carolina, USA	Trip rate	-	NB	Commute and non-commute	√	-	-	Undergraduate students and students living on-campus engages in more activities than graduate students and off-campus residents
Molina-Garcia et al. (2010)	Valencia, Spain	Active commuting	-	SEM	Commute	√	-	-	Access to private automobiles is a major deterrent to active commuting amongst university students
Limanond et al. (2011)	Thailand	Trips rate, mode split, distance traveled, travel time	Drive, ride, bus, walk, bike	Univariate analysis	Commute and non-commute	-	-	-	- Private vehicle owners are more inclined to use drive mode - Non-private vehicle owners either share a ride, borrow friend's vehicle or take bus

Khattak et al. (2011)	Virginia, USA	Trip rate, mode split, travel purpose	Drive alone, shared ride, bus, walk, bus	Univariate analysis	Commute and non-commute	-	-	-	University students' weekend trip rate is higher than general population
Bopp et al. (2011)	Kansas, USA	Mode choice	Drive, walk, bike	Hierarchical regression	Commute	√	-	√	Walking is more prevalent than biking for commuting
Chen (2012)	Virginia, USA	Trip frequency	-	ANOVA, Negative binomial	Commute and non-commute	√	-	√	Undergraduate students are likely to make more trips than graduate students
Wang et al. (2012)	Virginia, USA	Trip frequency	-	Poisson and Negative Binomial	Commute and non-commute	√	-	-	Students living on campus or near campus are more likely to walk and bicycle and less likely to drive cars
Zhou (2012)	California, USA	Housing and mode choice	Drive alone, carpool, transit, bicycle/walk, telecommute	MNL	Commute and non-commute	√	√	√	- Possession of on-campus parking permit increases the probability of choosing driving mode - Possession of discounted transit pass increases the probability of choosing alternative modes
Delmelle and Delmelle (2012)	Idaho, USA	Mode choice	Car, carpool, bike, walk, bus, drive and walk	Univariate analysis	Commute	-	-	-	Possession of on-campus parking permit encourages driving, more so than commuting distance
Akar et al. (2012)	Ohio, USA	Mode choice	Drive alone, carpool, bus, walk, bike	MNL	Commute	√	√	-	Concern for safety, travel time, flexibility of departure time, and the ability to make stops on the way encourages drive alone mode adoption
Eluru et al. (2012)	Montreal, Canada	Mode choice	Car, transit	MNL	Commute	√	√	√	Reduction in number of transfers may increase transit patronage
Molina-Garcia et al. (2013)	Valencia, Spain	Bike share usage	-	Logistic regression	-	√	-	√	Having one or more bike share stations within 250 m from home increases usage
Whalen et al. (2013)	Hamilton, Canada	Mode choice	Car, bus (street rail), walk, bike	MNL	Commute	√	√	√	Travel time is positively correlated with car and bike mode choice

Danaf et al. (2014)	Beirut, Lebanon	Mode choice	Car, bus, jitney	MNL, NL	School commute	√	√	√	Male students are more likely to use bus transit
Zhou (2014)	California, USA	Housing and mode choice	Drive alone, carpool, transit, bicycle/walk, telecommute	2SLS NRM	Commute and non-commute	√	√	√	- Students are more likely to jointly decide mode and housing option - Transit pass subsidies encourage alternative mode usage
Grimsrud and El-Geneidy (2014)	Montreal, Canada	Transit mode share	-	Univariate analysis	Commute	-	-	-	A general lifecycle pattern of decreasing transit share with age was observed
Zhan et al. (2016)	Beijing, Shanghai, Nanjing, China	Travel frequency and mode choice	Walk, bike, transit	HTBR	Commute and non-commute	-	√	√	Travel distance, bicycle ownership, school location, transit station coverage and student gender significantly impacts mode choice
Shabaan and Kim (2016)	Doha, Qatar	Mode choice	Bus, non-bus	SEM	Commute	√	√	-	Service quality of bus stop, bus and drivers are important factors for increasing bus usage among students
Hasnine et al. (2017)	Toronto, Canada	Mode choice	Drive alone, passenger, transit, park and ride, kiss and ride, bike and ride, walk, bike	MNL, NL, CNL	Commute	√	√	√	- Female students are more likely to choose local transit when commuting to the downtown campuses - Students 22-25 years of age are more likely to walk or bike
Lin et al. (2017)	Toronto, Canada	Multimodality	-	SEM, bivariate probit	-	√	-	√	Latent attitudes play a significant role in shaping the level of multimodality among university students
Habib et al. (2017)	Toronto, Canada	Mobility tool ownership	-	CNGEV	-	√	-	√	Students' personal and household related attributes influence the choice of owning combinations of mobility tools and influence multimodality

Note: MNL = Multinomial logit; NL = Nested logit; HEV = Heteroscedastic extreme value; CNL = Cross nested logit; 2SLS NRM = Two stage least squares non-recurrent model; HTBR = Hierarchical tree based regression; NB = negative binomial, SEM = Structural equation model, ANOVA = Analysis of variance, CNGEV = Cross nested generalized extreme value model

Table 3 Descriptive Statistics of Sample (N=7,050)

Dependent Variables	Percentage
Mode	
Drive alone	14.7
Passenger	15.2
Transit	21.1
Walk	40.2
Bike	5.4
Other	3.4
Departure Time	
AM (6:00-9:00)	4.3
Midday (9:00-15:00)	38.2
PM (15:00-18:00)	26.6
Evening (18:00-24:00)	31.0
Independent Variables	
Trip Attributes	
Trip Purpose	
Purpose Recreational	40.1
Purpose Shopping	32.0
Purpose Visit	15.6
Purpose Other	12.3
Activity Duration	
Activity Duration < 30min	37.4
Activity Duration 30-90min	35.2
Activity Duration > 90min	34.6
Individual Socio-demographics	
Female	69.5
Graduate Student	29.2
Fulltime Student	90.5
Driver License	64.0
Bicycle Owned or Bikeshare Member	50.6
Zero Vehicle Household	42.9
Mean Age	24.18 years
Mean Household Size	3.15
Home to Main Campus Distance (km)	10.38

TABLE 4 Model Estimation Summary and Comparison

Model	Log-likelihood	Number of Parameters	Number of Observations	BIC
RUMNL (mode first-departure time second)	-17403.98	25	7050	35029.48
RUMNL (departure time first-mode second)	-16747.10	21	7050	33680.34
RRMNL (mode first-departure time second)	-17198.30	24	7050	34609.19
RRMNL (departure time first-mode second)	-16538.50	22	7050	33271.85
RULCM	-15636.60	67	7050	31866.91
RRLCM	-15530.45	66	7050	31645.70

TABLE 5 Segmentation Variable Characteristics

Variables	Segment	
	MD Sequence	DM Sequence
Segment Share	35.35%	64.65%
Departure Time		
AM (6:00-9:00)	0.053	0.031
Midday (9:00-15:00)	0.451	0.368
PM (15:00-18:00)	0.245	0.274
Evening (18:00-24:00)	0.251	0.327
Mode Choice		
Drive alone	0.327	0.039
Passenger	0.302	0.098
Transit	0.174	0.247
Walk	0.126	0.494
Bike	0.028	0.101
Other	0.044	0.021
Mean Values of Segmentation Variables		
Individual Attributes		
Age	23.986	24.290
Age = 20-24	0.462	0.454
Age = 25-29	0.115	0.212
Campus in Downtown	0.494	0.810
Home to Campus Distance (km)	18.013	6.205
Household size	3.830	2.779
Household fleet size	1.783	0.506
0 vehicle	0.042	0.640
1 vehicle	0.364	0.249
≥ 2 vehicle	0.594	0.110
Distance travelled (km)	6.738	3.693

TABLE 6 Latent Segmentation Model Results (Sequence Choice)

Variables	Sequence Choice			
	MD Sequence		DM Sequence	
	Coefficient	t-stat	Coefficient	t-stat
Constant	-2.524	-10.413	-	-
<u>Individual Demographics</u>				
Age (Base: Age < 20 years)			-	-
Age 20-24 years	-0.473	-3.657	-	-
Age 25-29 years	-0.745	-4.314	-	-
Single parent	0.780	4.323	-	-
Household vehicle ownership (Base: Zero vehicle household)				
Single vehicle household	2.760	12.260	-	-
Two or more vehicle household	3.794	16.198	-	-
<u>Location Attributes</u>				
Campus in downtown	-1.391	-10.864	-	-
Home to school distance	0.056	8.104	-	-

TABLE 7 Mode Choice Model Results

	<u>First (MD Sequence)</u>		<u>Second (DM Sequence)</u>	
	Coefficient	t-stat	Coefficient	t-stat
Drive alone constant	0.124	2.290	-1.014	-15.151
Passenger constant	-0.278	-5.960	-1.014	-15.151
Walk constant	-0.465	-10.841	0.521	11.598
Bike constant	-0.465	-10.841	-0.428	-8.458
Other	-0.465	-10.841		
<u>Trip Purpose</u>				
Recreation				
Transit	-0.133	-2.365	-	-
Walk	0.640	9.409	-	-
Shop				
Drive alone	0.190	3.750	-	-
Passenger	0.190	3.750	-	-
Visit				
Transit	-	-	-0.106	-1.893
Walk	-	-	-0.199	-3.277
Bike	-	-	-0.242	-3.474
<u>Activity Duration</u>				
Longer than 90 minutes				
Drive alone	-0.129	-3.483	-	-
Transit	-	-	0.144	3.536
Walk	-	-	-0.137	-3.540
<u>Contextual Attributes</u>				
Weekend				
Drive alone	0.585	8.634	-	-
Passenger	0.751	10.489	-	-
Rainy weather				
Passenger	-	-	-0.456	-3.477
Transit	-	-	-0.199	-2.544
Walk	-	-	-0.208	-2.611
Bike	-	-	-0.446	-4.594
Temperature				
Drive alone	-	-	-0.082	-10.575
Passenger	-	-	-0.063	-13.514
Transit	-	-	-0.049	-11.501
Walk	-	-	-0.044	-9.719
Bike	-	-	-0.040	-7.510
<u>Travel Time</u>	-0.004	-5.019	-0.028	-25.211
<u>Departure Time</u>				
Mid-day				
Transit	-	-	0.286	4.906
Walk	-	-	0.286	4.906
Bike	-	-	0.286	4.906

TABLE 8 Departure Time Choice Model Results

	<u>Second (MD Sequence)</u>		<u>First (DM Sequence)</u>	
	Coefficient	t-stat	Coefficient	t-stat
AM constant	-0.234	-3.072	-0.863	-15.006
PM constant	-0.234	-3.072	-0.376	-9.934
Evening constant	-0.234	-3.072	0.158	2.913
<u>Trip Purpose</u>				
Recreational				
Mid-day	0.282	2.332	-0.232	-6.199
PM	0.546	4.487	-	-
Evening	0.994	7.946	-	-
Shop				
Mid-day	0.582	4.306	-	-
PM	0.736	7.158	0.453	9.784
Evening	0.736	7.158	-	-
Visit				
Mid-day	0.517	2.802	-	-
PM	0.855	4.311	0.479	8.542
Evening	1.306	6.181	0.479	8.542
<u>Duration of Activity</u>				
30-90 minutes				
Mid-day	-	-	0.164	4.575
PM	-	-	0.164	4.575
<u>Contextual Attributes</u>				
Weekend				
Mid-day	0.495	7.619	0.338	7.613
PM	0.327	4.767	0.126	2.775
Temperature				
Mid-day	0.020	4.857	0.026	6.802
PM	0.020	4.857	0.026	6.802
Rainy weather				
Mid-day	-0.205	-2.590	-0.326	-5.703
PM	-0.205	-2.590	-0.151	-2.582
<u>Mode</u>				
Drive alone				
PM	-0.127	-2.181	-	-
Passenger				
Mid-day	0.188	2.601	-	-
Evening	0.302	4.003	-	-
Walk				
Mid-day	0.423	3.325	-	-

TABLE 9 Validation Analysis Results (N=2,992)

	Predictive LL (RRLCM)	Predictive LL (RULCM)	Predictive LL (RUMNL MD)	Predictive LL (RUMNL DM)	Predictive LL (RRMNL MD)	Predictive LL (RRMNL DM)
Total sample	-6640.86	-6681.40	-7375.92	-7105.00	-7304.04	-7018.82
Campus in downtown	-4523.99	-4556.49	-5035.67	-4808.03	-4975.00	-4747.14
Weekend	-2736.31	-2752.84	-3040.16	-2928.12	-3018.14	-2895.26
Trip purpose: recreational	-2710.43	-2727.78	-2877.79	-2857.77	-2836.32	-2826.19
Trip purpose: Shopping	-2043.13	-2050.44	-2435.27	-2236.42	-2415.15	-2207.46
Trip purpose: Visit	-1018.25	-1032.79	-1129.36	-1081.22	-1122.58	-1064.09
Female	-4609.49	-4638.24	-5108.97	-4927.72	-5066.43	-4869.55
Household fleet size: 0 vehicle	-2731.45	-2755.14	-3136.73	-2930.48	-3099.14	-2899.83

TABLE 10 Policy Analysis Results (RRLCM)

Change in Variable		Drive	Passenger	Transit	Walk	Bike	Other	AM	Midday	PM	Evening	Segment 1 Share
Home to School Distance	10% reduction	-1.75	-0.90	0.39	0.63	1.20	-0.55	-0.13	0.08	0.18	-0.56	-2.46
	20% reduction	-3.58	-1.83	0.80	1.29	2.46	-1.13	-0.27	0.15	0.36	-1.15	-5.03
	50% reduction	-9.53	-4.73	2.08	3.39	6.55	-2.97	-0.70	0.41	0.94	-3.06	-13.28
Drive Travel Time	10% increase	-0.65	-1.60	1.12	0.09	0.54	1.14	-	-	-	-	-
	20% increase	-1.29	-3.18	2.23	0.18	1.07	2.28	-	-	-	-	-
Drive, Transit and Other Travel Time	10% increase	1.42	3.66	-9.83	2.95	7.87	-12.53	-	-	-	-	-
	20% increase	2.65	6.87	-18.92	5.69	15.22	-23.06	-	-	-	-	-

TABLE 11 Policy Analysis Results (RULCM)

Change in Variable		Drive	Passenger	Transit	Walk	Bike	Other	AM	Midday	PM	Evening	Segment 1 Share
Home to School Distance	10% reduction	-1.75	-1.03	0.37	0.69	1.25	-0.66	-0.14	0.10	0.18	-0.60	-2.42
	20% reduction	-3.57	-2.09	0.76	1.42	2.57	-1.35	-0.29	0.20	0.36	-1.24	-4.94
	50% reduction	-9.48	-5.37	1.96	3.71	6.82	-3.56	-0.75	0.52	0.95	-3.29	-13.00
Drive Travel Time	10% increase	-0.58	-1.55	1.09	0.06	0.69	0.86	-	-	-	-	-
	20% increase	-1.16	-3.07	2.17	0.11	1.37	1.70	-	-	-	-	-
Drive, Transit and Other Travel Time	10% increase	1.12	3.07	-8.98	2.66	7.94	-9.56	-	-	-	-	-
	20% increase	2.08	5.72	-17.23	5.10	15.47	-17.70	-	-	-	-	-

TABLE 12 Policy Analysis Results (Independent Models)

Change in Variable		Drive	Passenger	Transit	Walk	Bike	Other
RRMNL MD							
Drive Travel Time	10% increase	-1.56	-2.10	1.29	0.21	0.87	1.44
	20% increase	-3.16	-4.21	2.60	0.41	1.74	2.91
Drive, Transit and Other Travel Time	10% increase	3.01	4.44	-8.37	3.44	5.63	-14.27
	20% increase	5.44	8.21	-16.16	6.75	11.00	-26.68
RRMNL DM							
Drive Travel Time	10% increase	-1.50	-1.95	1.54	0.24	1.14	1.61
	20% increase	-3.04	-3.91	3.10	0.48	2.28	3.26
Drive, Transit and Other Travel Time	10% increase	2.59	3.95	--9.54	2.83	5.89	-15.20
	20% increase	4.65	7.26	-18.28	5.54	11.67	-28.23