A Comprehensive Utility based System of activity-Travel scheduling Options Modelling (CUSTOM) for Worker's Daily Activity Scheduling Processes

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Abstract

This paper presents a comprehensive utility-based system of activity-travel scheduling options modelling (CUSTOM) and applies it to simulate workers' daily activity-travel demand. CUSTOM uses a random utility maximizing econometric approach for jointly modelling activity type choices, time expenditure choices and location choices. It considers the depleting time budgets as activity-travel scheduling progresses along with shrinking potential path areas (PPA) for activity location choices. For prototype application, the model is estimated on a sample of workers and students taken from the 2011 household travel survey of the National Capital Region (NCR) of Canada. A validation exercise is performed and it is demonstrated that CUSTOM can accurately predict activity-travel behaviour. Differential travel time sensitivity is identified and it is revealed that people are more sensitive to auto travel time than transit or non-motorized travel times. Changes in choice randomness, time expenditure choices and activity type choice with time-of-day are captured in the model. Seamless integration of discrete activity type and location choices with continuous time expenditure choice in the context of shrinking time budget and resulting narrowing activity space enables CUSTOM to capture complex behavioural dynamics in activity-travel scheduling.

Key Words: Activity-based travel demand model, RUM-based activity scheduling model, destination location choice model, time expenditure choice model, CUSTOM

1. Introduction

Activity-based modelling of travel demand has become the state-of-the-art of current travel demand modelling practices. However, the inherent complexities in our daily activity scheduling processes motivated a wide variety of approaches developed by different researchers. Increasing computational capacity and increasing the necessity of detailed behavioural bolster such developments. From the early 1980s, a series of alternative modelling frameworks have been proposed. However, almost all operational activity-based models consider workers home-work-home schedules as the skeleton to build daily activity. Such approach is ad-hoc as they overlook the implicit interrelationships among start time, duration and trip chaining choices various activities in a day. It induces separate treatments (vis-a-vis modelling approach) for work and non-work activities and so the time expenditure tradeoffs in work versus non-work activities are suppressed. This paper contributes by presenting a Comprehensive Utility-based System of activity-Travel scheduling Options Modelling (CUSTOM) for workers daily activity scheduling. CUSTOM uses a simultaneous modelling approach of time budget-constrained scheduling. Moreover, it considers continuous time specifications for both work and non-work activity episode duration and start time choices. It uses the Random Utility Maximization (RUM) assumption to jointly model activity sequences, activity durations, start times and non-work activity location choices.

For an empirical application, CUSTOM is estimated for workers' daily activity scheduling choices by using a household travel survey conducted in the National Capital Region (NCR) of Canada in 2011. The rest of the paper is organised in the following manner; the next section presents a literature review on workers' activity-travel schedules. This section is followed by sections explaining the CUSTOM FRAMEWORK, econometric formulations; datasets used for empirical modelling; and a discussion about the empirical model. The paper concludes with a summary of key findings and recommendations for further research.

2. Literature Review: Workers' Activity-Travel Scheduling

Workers' activity schedules are the focus of many studies to accurately capture travel patterns of urban residences as the commuting trips are the most dominant and regular trip types. There is a long list of research focusing on individual elements of workers' travel patterns, e.g. work trip mode choice, work trip departure time choice, work duration, etc. Almost all of the modelling approaches consider workers' work trip schedules as pivots to construct full day's activity schedules. This is why the concept of skeleton activity-travel schedule for workers is very common in activity-based modelling practice (Habib and Miller 2006). The concept of skeleton schedule is convenient as it reduces modelling complexity as the time gaps available within the skeleton schedule can be used as the placeholders for non-work activity scheduling. Skeleton schedules refer to the schedules with fixed attributes, e.g. start time, duration, destination locations, etc. and it is a common element of all operational activity-based models. Operational activity-based travel demand models are of three to four broad categories: computational process approach, econometric model-based approach, hybrid approach mixing rules with various econometric models and only discrete choice model based approach. The computation process type model that use fixed and deterministic rules to develop activity schedules of different people. The econometric model-based approaches use conglomerates of univariate or multivariate econometric models to predict different aspects of activity scheduling (e.g. start time, duration, location, mode choice, etc.) and then use some sort of rule-based framework to stitch the model results together to form a daily schedule. The hybrid approach harness the power of both rule and econometric models.

The computational process models, e.g. ALBATROS and ADAPTS consider workers' skeleton activity schedule to model other activities (shopping, social, etc.) in the time gaps within the skeleton (Arentze and Timmermans 2004, Auld and Mohammadian 2012). The econometric activity-based models, e.g. CEMDEP and similar models consider work activities as temporally fixed elements to schedule around other activities (Bhat et al 2004). Hybrid activity-based models, TASHA and FAMOS randomly draw on attributes of the work schedule first and then other randomly drawn activity types (including their attributes) are scheduled around the work schedules (Miller and Roorda 2003, Pendyala et al 2005). It is often unclear how an operational activity-based travel demand model handles fixed attributes of skeleton schedules. Perhaps, a variety of rules (deterministic if-then-else type logic) are needed to fit non-work activities within a fixed skeleton schedule.

On the other hand, only discrete choice model-based approaches target modelling daily travel patterns, often considering home-based work tours (home-work-home) as the first step to building workers daily activity schedules of workers. Such models are as discussed in Bowman and Ben-Akiva (2000), Vovsha and Bradley (2006), Bradley et al (2009), Vovsha et al (2003), etc. Considering home-based work tour a separate component from sub-tours that are inserted/induced later is also synonymous to the skeleton-based approach of scheduling. Even a discrete choice model based approach can comprehensively model home-based work tour as well as sub-tour (work or non-work based), handling of time expenditure in activities (activity episodes) are overly restrictive. In almost all of such models, time is discretized and the issue of time-budget constraints is overlooked. Time discretization is also an issue for the computational process, econometric and hybrid approaches of activity-based models. In these approaches, temporal dimensions of activity episodes (e.g. start time and duration) are modelled independently and then an overarching approach is used to take the individual episodes into a schedule formation. In any case (whether the time is discretized or not), the tradeoff of time expenditure choices for any individual activity is not handled comprehensively along with all other possible activities and time budget constraints.

Besides from operational activity-based modelling systems, various researchers investigated specific temporal aspects of activity scheduling processes. In a recent study, Lo´pez-Ospina et al (2014) present a microeconomic model of time allocation to work and non-work activities considering macro-temporal constraints (5–10 years' planning horizon) on daily time allocation choices. They use a numerical exercise to highlight the importance that workers' daily activity-travel decisions are heavily influenced by longer-term choices job status, housing type, etc. However, no empirical model of application of their modelling system is presented. Although their approach is theoretically robust it is difficult to understand its full capacity in the context of available data. Vishnu and Srinivasan (2013) present models for departure time choice for daily work and non-work tours of workers. They use household travel survey data and modelled departure time choices as discrete choices. Their modelling approach does not consider activity location choices for non-work activities. This model focuses only on departure choices without considering trip chain formation, non-work activity location choices as well as interdependencies of tours (trip chains) of the same day. The presented model captures only one specific dimension of workers' activity-travel skeleton formation.

Gupta and Vovsha (2013) present a discrete choice model for activity duration to jointly model work activity schedules of workers in multiple-worker households. Their model of workers' skeleton schedule predicts tour formation and time-of-day choices. They used time discretization to apply discrete choice models for activity start time (time-of-day) and duration for tour formation choices. This model focuses only on work tour departure and arrival time without considering trip chain formation choices, non-work activity location choices and trade-offs between multiple stops in work tour and home-based tours. Ben-Akiva and Abou-Zeid (2013) highlight the necessity of considering 24-hour cycle in modelling workers' skeleton activity-travel schedule formation but applied only a discrete choice model for jointly modelling departure time choices for activities. They present this in the context of a tour-based travel demand model but do not explicitly model tour (trip chain) formation choices, and time-space constrained location choice of non-work activities. Papuri et al (2008) present discrete choice models for time-of-day choice in the context of tour/trip chain formation. Such an approach captures the only time-of-day choice dimension of workers' skeleton activity-travel scheduling. Habib and Miller (2006) present a set of hazard models that sequentially model the departure time and duration of work activities. Their model of workers' activity-travel skeleton schedule formation only considers time-of-day dimension without consideration of non-work activity location, work-based trip chaining, home-based trip chaining and interdependencies of multiple tours/chains in a day.

None of these efforts presents a comprehensive modelling approach for workers' activity-travel scheduling that considers multiple dimensions of activity-travel choices within a consistent and comprehensive modelling framework. This paper contributes by presenting a unified modelling framework for activity scheduling. The proposed CUSTOM framework can accommodate a wide variety of possible activity-travel schedules. The next section explains the framework of CUSTOM in details.

3. CUSTOM Framework

CUSTOM considers a 24-hour modelling time frame, fixed home and work location for modelling worker's activity-travel scheduling processes. The prototype application of CUSTOM presented in this paper is an individual-based modelling system. For given home and work location, a worker's schedule starts with a choice of out-of-home activity (which may or may not be work activity) or staying-at-home the whole day. In case an out-of-home activity is chosen, the start time of the first trip is defined by the choice of time expenditure at-home before the first trip. The subsequent trips that originate from out-of-home include the option of a return home temporarily to make a trip later and a return home for rest of the day. 'Return home temporarily' implicitly models home-based tour formation. Non-home-based tours are not modelled separately as those can evolve at any stage of out-of-home activity scheduling based on location choice and activity type choice.

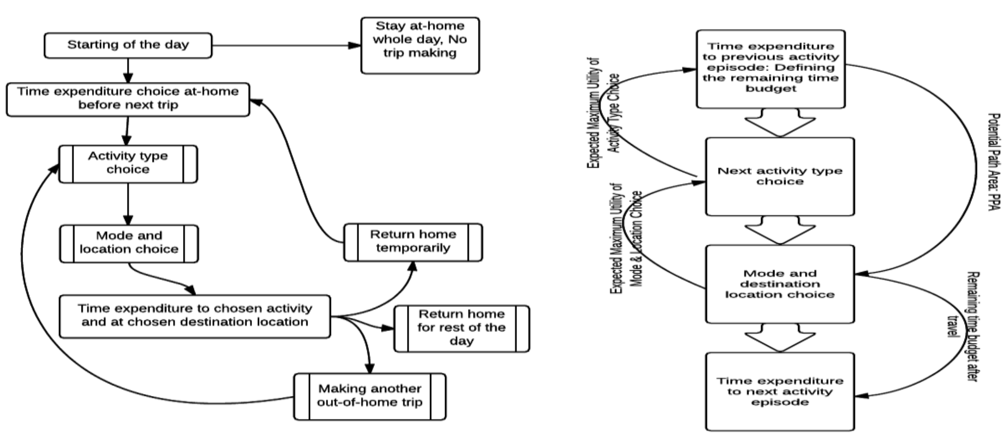

Figure 1: Flow Diagram of CUSTOM System and Feedback Mechanisms

The CUSTOM framework does not consider any hard-wired rules of activity sequences. The preference structures of activity type, time expenditure and location choice model are tested empirically. All of these three modelling components considers time-of-day specific variables to capture the dynamics of activity-travel scheduling. The resulting model can capture a wide variety of activity-travel patterns as the patterns evolve out of these three choice interactions. Figure 1 presents the flow diagram of activity-travel scheduling and interrelationships among choice dimensions (feedback mechanisms). Various values of total time budget to round-trip travel time (travel ratio) can be used to define feasible location choice alternatives. Figure 1 is an ideal flow diagram of the CUSTOM procedure. However, please note that for the empirical model presented (prototype application) in this paper, the mode choice model component is not implemented yet. The empirical application in this paper considers mode-specific level-of-service attributes in destination location choice model.

The daily activity-travel scheduling in the CUSTOM system is composed of a number of scheduling cycles. A scheduling cycle includes all choices leading to start of an activity episode. This includes the time expenditure (activity episode duration) choice to on-going activity (termination of which refers starting next activity); the joint choice of next activity type and destination location (along with mode choice is mode choice is modelled) of next activity. The time budget for any scheduling cycle is the total time available for rest of the day after the end of an on-going activity episode. This time budget defines the Potential Path Area (PPA) of feasible locations for next activity. One scheduling cycle at an out-of-home location generates one trip, either to home or to another out-of-home location. Return homes can be temporarily if the intention to go out again exists or return home for rest of the day. However, for the scheduling starting at-home location generates a trip to an out-of-home destination only. The following section explain the modelling process more elaborately.

4. Econometric Formulation

The proposed CUSTOM complies fully with Random Utility Maximization (RUM) theory. Activity type and location choices are discrete choices and time expenditure choices are based on a trade-off between time expenditure to the scheduling activity against the time savings for other (composite) activities. The composite activity is a generalized term that defines all activities that are not differentiated against the specific activity under consideration. The RUM-based direct utility function of time expenditure choices is similar to the one proposed by Habib (2011); Habib and Hui (2017) and Habib et al (2017). For time expenditure of amount (D_j) to current activity j under current time budget of (D), the total utility, U_j is:

$$U_j = \frac{1}{\alpha_j} exp\left((\beta x)_j + \varepsilon_j\right).\left(D_j^{\alpha_j} - 1\right) + \frac{1}{\alpha_c}\left(D_c^{\alpha_c} - 1\right); where\ D_j + D_c = D \qquad (1)$$

Here,

D_j and D_c are time expenditures to activity j and composite activity c.
α_j and α_c are the satiation parameter for time expenditure to activity type j and c.
$(\beta x)_j$ is a linear-in-parameter function of variable set z_j and the corresponding coefficients, which is the systematic component of baseline utility of time expenditure choice.
ε_j is the random error component of baseline utility of time expenditure choice.

Considering Type I Generalized Extreme Value (GEV) distribution for the random error component (with scale parameter μ_{t_j}) and by using the Kuhn-Tucker optimality conditions, the random utility maximizing (RUM) choice probability of spending continuous t_j to activity j is:

$$Pr(D_j) = \left(\frac{1-\alpha_j}{D_j} + \frac{1-\alpha_c}{D_c}\right)\mu_{t_j}\frac{exp\left(-\mu_{t_j}(V_c-V_j)\right)}{\left(1+exp\left(-\mu_{t_j}(V_c-V_j)\right)\right)^2} \quad (2)$$

$$V_c = (\alpha_c - 1)ln(D - D_j)\ ;\ V_j = (\beta x)_j + (\alpha_j - 1)ln(D_j) \quad (3)$$

Similarly, considering RUM based discrete choice of activity type choice for (j+1) activity, a two level GEV formulation is proposed (Habib et al 2014). For any out-of-home scheduling cycle that starts at the end of an activity j, three alternative choices are considered: choice of return home ending out-of-home scheduling of the day (H_{j+1}), return home temporarily (HT_{j+1}), choosing another out-of-home activity type (A_{j+1}). If the choice of another out-of-home activity type is made, then a choice of a specific type for (A_{j+1}) is determined. The corresponding probability functions are:

$$Pr(HT_{j+1}) = \frac{exp\left(\mu_{h_{j+1}}V_{HT_{j+1}}\right)}{exp\left(\mu_{h_{j+1}}V_{HT_{j+1}}\right)+exp\left(\mu_{h_{j+1}}V_{H_{j+1}}\right)+exp\left(\frac{\mu_{h_{j+1}}}{\mu_{A_{j+1}}}I_{A_{j+1}}\right)} \quad (4)$$

$$Pr(H_{j+1}) = \frac{exp\left(\mu_{h_{j+1}}V_{H_{j+1}}\right)}{exp\left(\mu_{h_{j+1}}V_{HT_{j+1}}\right)+exp\left(\mu_{h_{j+1}}V_{H_{j+1}}\right)+exp\left(\frac{\mu_{h_{j+1}}}{\mu_{A_{j+1}}}I_{A_{j+1}}\right)} \quad (5)$$

$$Pr(A_{j+1}) = \frac{exp\left(\frac{\mu_{h_{j+1}}}{\mu_{A_{j+1}}}I_{A_{j+1}}\right)}{exp\left(\mu_{h_{j+1}}V_{HT_{j+1}}\right)+exp\left(\mu_{h_{j+1}}V_{H_{j+1}}\right)+exp\left(\frac{\mu_{h_{j+1}}}{\mu_{A_{j+1}}}I_{A_{j+1}}\right)} \times \frac{\exp(\mu_{A_{j+1}}V_{A_{j+1}})}{\sum_{A_{j+1}}\exp(\mu_{A_{j+1}}V_{A_{j+1}})} \quad (6)$$

Here,

$\mu_{h_{j+1}}$ is the root scale parameter of activity type choice.
$\mu_{A_{j+1}}$ is the scale parameter of out-of-home activity type choice.
$V_{HT_{j+1}}$ is the systematic utility of return home for rest of the day.
$V_{H_{j+1}}$ is the systematic utility of return home temporarily.
$V_{A_{j+1}}$ is the systematic utility of out-of-home activity type choice.
$I_{A_{j+1}}$ is the expected maximum utility of out-of-home activity type choice.

Where:

$$I_{A_{j+1}} = ln\left(\sum_{A_{j+1}}\exp(\mu_{A_{j+1}}V_{A_{j+1}})\right) \quad (7)$$

Here, A_{j+1} refers to the choice set for out-of-home activity type choice.

In case, the current activity location is the home location, the choices of (H_{j+1}) and (HT_{j+1}) are not options and so it collapses into a single level activity type choice, (A_{j+1}) only. Considering the fact that the out-of-home activity type choice is defined by the location choice of the activity along with other factors, the systematic utility function of activity type choice is specified as:

$$V_{A_{j+1}} = \sum(\psi z)_{A_{j+1}} + \frac{1}{\mu_{j+1}}I_{l_{j+1}} \quad (8)$$

Here,

$\sum(\psi z)_{A_{j+1}}$ is a linear-in-parameter function of the function of variables and their coefficients.
I_{lj+1} is the expected maximum utility of activity location choice.
$\mu_{l\,j+1}$ is the scale parameter of random error component of activity location choice utility.

Assuming a GEV formulation for activity location choices, the location choice model becomes:

$$Pr(l_{j+1}) = \frac{exp(\mu_{l_{j+1}} V_{l_{j+1}})}{\sum_{Loc_{j+1}} exp(\mu_{l_{j+1}} V_{l_{j+1}})} \tag{9}$$

$$V_{l_{j+1}} = \sum(\gamma y)_{l_{j+1}} + \frac{1}{\mu_{h_{j+1}}} I_{ActL_{j+2}} \tag{10}$$

Here,

$\sum(\gamma y)_{lj+1}$ is a linear-in-parameter function of the function of variables and their coefficients.
$I_{ActLj+2}$ is the expected maximum utility of activity type choice of next scheduling cycle.
$\mu_{l\,j+1}$ is the scale parameter of random error component of activity location choice utility.
Loc_{j+1} is the choice set for activity location choice.

The expected maximum utility of activity type and activity location choices of next scheduling cycle, $I_{ActLj+2}$ is:

$$I_{ActL_{j+2}} = ln\left(\exp\left(\mu_{h_{j+2}} V_{HT_{j+2}}\right) + \exp\left(\mu_{h_{j+2}} V_{H_{j+2}}\right) + \exp\left(\frac{\mu_{h_{j+2}}}{\mu_{A_{j+2}}} I_{A_{j+2}}\right)\right) \tag{11}$$

The corresponding expected maximum utility of activity location choice is:

$$I_{l_{j+2}} = ln\left(w_{j+1} \sum_{L_{j+1}} \exp\left(\mu_{l_{j+1}} V_{l_{j+1}}\right)\right) \tag{12}$$

Here, the w_{j+1} is the expansion factor

As opposed to an ad-hoc approach of sampling for location choice modelling in Habib and Hui (2017) as well as Habib et al (2017), this paper adopts the approach proposed by Guevara and Ben-Akiva (2013). In this paper, following a two-pronged approach of sampling alternative zones for activity location choice modelling within the multivariate extreme value formulation of CUSTOM is taken. In this approach, two different randomly drawn sample is used: one if for conditional location choice estimation and the other is for estimating expected maximum utility value of location choice that is added to corresponding activity type choice utility function (as shown in equation 12). The former random sample includes the chosen alternative, but the latter is a purely random sample that may or may not have the chosen alternative. The weighting factor, w_{j+1} is the ratio of the total number of feasible alternatives divided by the number of randomly drawn alternatives.

Finally, the joint likelihood (L_{j+1}) of any scheduling cycle becomes:

$$L_{j+1} = \left(\Pr(RT_{j+1})\right)^{\upsilon_1}.\left(\Pr(R_{j+1})\right)^{\upsilon_2}.\left(\left(\Pr(A_j)\right)^{\delta_a}.\left(\Pr(l_{j+1})\right)^{\delta_l}\right)^{\upsilon_3} \quad (13)$$

Here,

v_1=1 if return home for the rest of the day is chosen and 0 otherwise.
v_2=1 if temporarily return home is chosen and 0 otherwise.
v_3=1 if another out-of-home activity is chosen and 0 otherwise.
δ_a =1 for chosen out-of-home activity type A_j and 0 otherwise.
δ_l =1 for chosen out-of-home activity type l_j and 0 otherwise.

In any scheduling cycle, the baseline utility of time expenditure choice to current activity is considered to be influenced by the expectation of the next activity type and its location. The likelihood of any scheduling cycle (L_c) considering time expenditure choice to current activity along with activity type and location choice of next activity:

$$L_c = \Pr(t_j).L_{j+1} \quad (14)$$

For a maximum number of scheduling cycles C in a day, the joint likelihood of daily activity-travel scheduling process becomes:

$$L = \prod_{c=1}^{C} L_c \quad (15)$$

This joint likelihood is of closed form and can be estimated by using classical maximum likelihood estimation technique. The model is estimated by using a program written in GAUSS (Aptech System 2014) that uses a gradient search algorithm (BFGS) in maximum likelihood estimation technique.

5. Data for Empirical Modelling

Data used in this study comes from a household travel survey conducted in the National Capital Region (NCR) of Canada in 2011. The area of the study area is 4,715 square kilometres, which is divided into 673 traffic analysis zones (TAZ). It is composed of the Ottawa-Gatineau metropolitan region, which covers parts of the provinces of Ontario and Québec. The survey was based on a weekday 24-hour travel diary survey and the diaries of a total 62,897 individuals. NCR hosts the capital of Canada and has the highest concentration of government workers in the country (Armstrong and Khan 2004). The subset of this dataset (after cleaning for missing information and inconsistent activity-travel schedules) consists of 30,912 workers and post-elementary students that are separated for this study. Activity diaries of all individuals in the datasets are used to reconstruct 24-hour activity schedules. Travel times for the schedules are estimated by using a calibrated multimodal transportation network model named TransModel (TRANS Committee 2014). The estimated travel time for the corresponding chosen mode of transportation are used to reconstruct 24-hour activity-travel schedules of each individual and it includes the sequences of all activity types that are performed with start time of activity-trip, travel time, episode duration and the chosen activity locations.

The final dataset includes 24-hour activity-travel schedules of all individuals including those who did not make any trips. In addition, household and individual level socioeconomic variables are also used for empirical model development. Household attributes include household size; the number of household automobiles, the number of children in the households; household income; dwelling type; and home location (home TAZ). Personal attributes include age; gender; having a driving licence; transit passes; occupation status; occupation type; and work location (work TAZ).

For modelling activity-travel scheduling processes, any pre-specified activity orders and priorities were not considered. For any scheduling cycle, all activity types are considered available for activity type choices. For activity location choice, 11 feasible locations (TAZs) are considered from corresponding potential path areas, which includes the chosen location and 10 randomly selected locations from the potential path area (using uniform random numbers). Such an approach is consistent with the RUM approach of modelling (McFadden 1978; Scot and He 2012). The survey identifies a total of 13 activity types, as follows:

1) Work at fixed out-of-home location
2) Work-related activities that are not at usual workplace
3) Work at non-fixed location
4) School
5) Shopping
6) Restaurant (i.e., for a meal)
7) Recreation
8) Visit friends or family
9) Health and personal care
10) Dropping off someone/something
11) Picking up someone/something
12) Return home (temporarily or for rest of the day)
13) Other purpose (any type that does not fall in any of the above categories)

The maximum number of activity-trips observed in the dataset is 11 and each individual in the cleaned dataset starts the day from home and return home at the end of the day. Thus, for estimation of the model, a maximum 11 scheduling cycles are considered. Also, fixed work and home locations are considered exogenous and are not modelled.

6. Empirical Model

The final datasets for empirical investigation consist of 30,912 individuals. I have randomly selected a subset of 15,000 individuals for parameters estimation and the schedules of the rest 15,912 are considered as a holdout sample for model validation. For statistical significance, a 95 percent confidence limit and two-tailed *t*-test are considered. However, some variables are retained with estimated parameters with a lower confidence limit as those variables have behavioural significance. The total number of parameters in the joint model is 228 and thus presenting all in one table is difficult. As a result, the empirical model is presented in Table 1a to Table1g in parts with the following components:

1. Scale parameters:
    a. Scale parameter of time expenditure choice to at-home before the first trip.
    b. Scale parameter for all subsequent activity time expenditure choices.
    c. Scale parameter for return and out-of-home activity type choices.
    d. Scale parameter for activity location choices.

2. Baseline utility function and satiation parameter of time expenditure choices to at-home before the first trip.
3. Activity type choice model for the first trip of the day.
4. Activity location choice model.
5. Activity type choice model for all subsequent activities after the first trip.
6. Baseline utility function and satiation parameter of time expenditure choices to the activities subsequent to the first trip.

Table 1a presents the estimation summary of the joint model.

Table 1a: Empirical Model Estimation Summary

Number of observations	15000
Log likelihood of full model	-294735
Log likelihood of null model	-405755
Rho-Squared value against null model	0.27
Chi-Square value against null model	222039
Number of estimated parameters	228

The joint model has the Rho-Squared value of 0.27 against the null model, which is a very good fit for comparing the complexities of behavioural processes that it captured. The chi-square value of the full model is also very high compared to a minimum threshold for chi-square of 226 (total number of estimated parameter) degrees of freedom. Comparison of aggregate model predictions against the observed aggregate demands also gives model's predictive capacity. However, perceiving the goodness-of-fit of such a large and multi-component joint econometric model is very difficult when comparing rho-square and chi-square value. Therefore, the study uses the holdout sample of 15,912 observed schedules, for which the estimated model is used to predict activity-travel scheduling choices of the holdout sample.

Figures 2a, 2b and 2c present the results of the validation. For simulating destination location choices, the estimated models are used in a simplified bi-level fashion: the first level is the simulation of the choice between intra-zonal destination choice and inter-zonal alternatives. If the choice of inter-zonal alternatives is simulated, the choice of a specific zone is simulated considering all feasible alternatives in the choice set. Prediction slightly deviates in activity type choices for the later part of the day and for the second activity duration choice. A possible explanation of such deviation is the bland rule of the activity type choice set (considering all activity types are feasible in any scheduling cycle) and the lack of land use (or related) variables in the dataset. In terms of predicting durations, CUSTOM captured the patterns of observed distribution, but as in any other parametric model, it gives an equivalent smooth curve for activity durations. In terms of predicting destination, the model can captures trip length distribution very well. As presented in Figure 2c, it seems that predicted trip length (travel time) are 1.08 time the value of corresponding observed trip lengths.

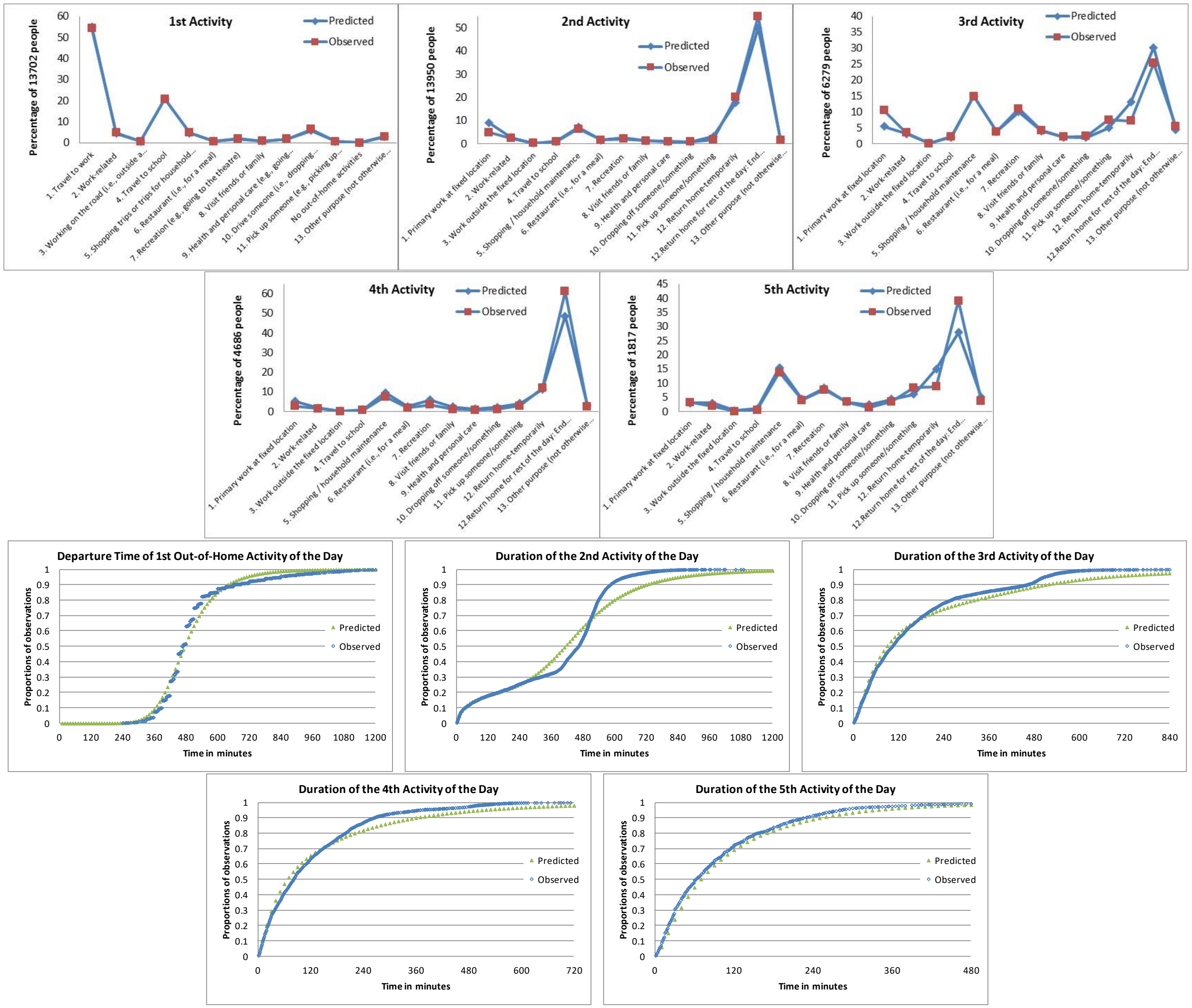

Figure 2a: Comparison of Model Predictions to Observed (Holdout Sample) Data

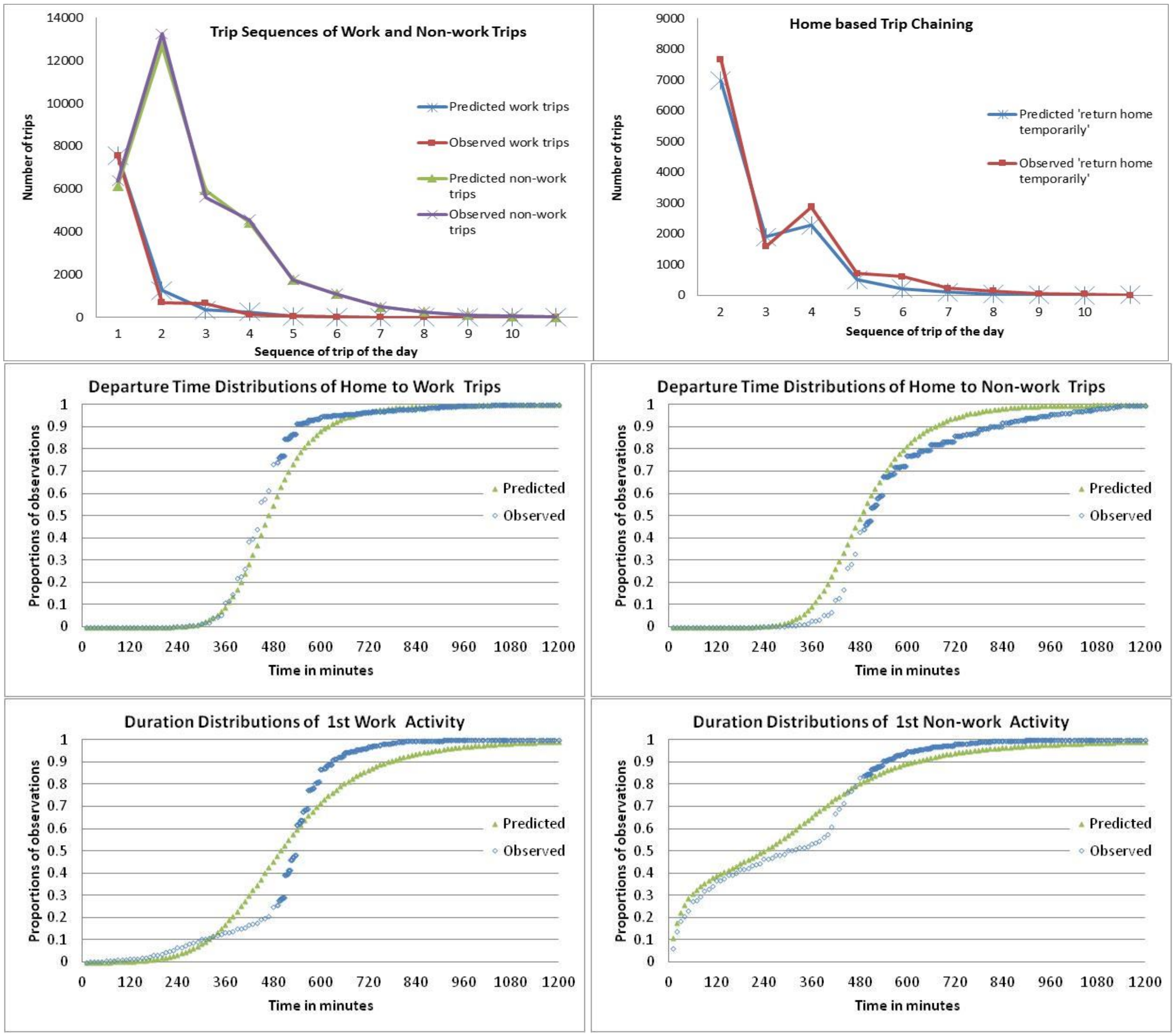

Figure 2b: Comparison of Model Predictions to Observed (Holdout Sample) Data

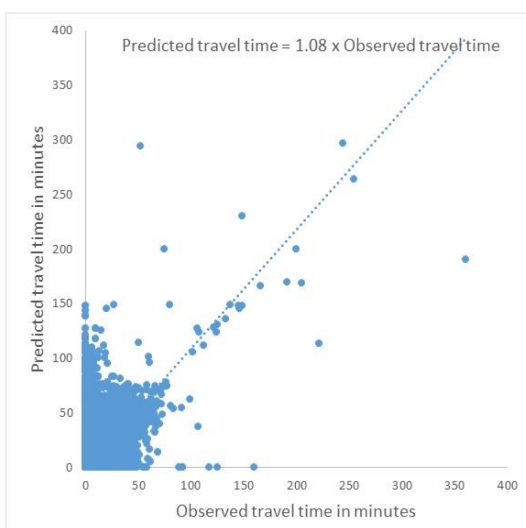

Figure 2c: Comparison of Model Predictions to Observed (Holdout Sample) Data

6.1 Scale Parameters: Capturing Choice Randomness/Variance

Table 1b presents the estimated scale parameters. The scale parameter of CUSTOM captures the correlations among alternatives relating to the scheduling process. Scale parameters of time expenditure choices represent the inverse of time expenditure variances. The scale parameter of time expenditure at-home before the first trip is a function of household income and number of cars at home. In general, for the level of car ownership, variance in time expenditure choice at-home reduces with increasing household income. For income level below $90,000 per year, variance in time expenditure choice at-home increases with increasing car ownership level, but the opposite is true for income level above $90,000 per year. For the scale, parameters of time expenditure choices of the subsequent activities are found to be a function of time-of-day, household size and income. The rate of change of scale with a time of day is influenced by household income. In general, the variance in time expenditure choices decreases with time-of-day. People from larger households have lower variance, but for the same household size, higher income group has slightly lower variance. In this empirical investigation, scale differences between activity type choice and destination location choice are not found to be significantly different from each other. Similarly, it is found that the scale parameter of the following activity type and location choices is not significantly different from that of the preceding activity type and location choices.

Table 1b: Scale Parameters

	Parameter	*t*-statistics
Scale parameter function of time expenditure choices		
At-home activities before first trip of the day:		
Logarithm of number of cars for car-owning households		
- Annual income: $150,000–$179,999	0.01	0.49
- Annual income: $120,000–$149,999	0.02	1.01
- Annual income: $90,000–$119,999	-0.05	-3.19
- Annual income: $60,000–$89,999	-0.09	-5.25
- Annual income: $30,000–$59,999	-0.26	-11.72
- Annual income: $0–$29,999	-0.30	-7.20
All other activities of the day:		
Household size x Time-of-day as a fraction of 24 hours		
- Annual income: $150,000–$179,999	0.04	6.15
- Annual income: $120,000–$149,999	0.06	11.38
- Annual income: $90,000–$119,999	0.04	8.58
- Annual income: $60,000–$89,999	0.04	7.4
- Annual income: $30,000–$59,999	0.04	6.44
- Annual income: $0–$29,999	0.02	2.02
Additional exponential component of scale parameter (to previous activity type choice) of activity-trip type and location choices		
Time-of-day as a fraction of 24 hours	-29.39	-0.97

6.2 Time Expenditure Choices to At-home before First Trip: Departure Time Choices for First Trip of the Day

Table 1c presents the estimated parameters of baseline utility and satiation function of time expenditure choice utility for at-home activities before the first out-of-home activity of the day. In addition to the expectation of first activity type choice of the day, a large constant along with age of the individual, work status and car ownership define the marginal utility of this at-home time expenditure choice. Higher marginal utility refers to a larger amount of time expenditure and thereby a late departure for the first out-of-home activity. A large positive constant indicates that there are other factors influencing the marginal utility of staying-at-home longer that is not available in the dataset. Perhaps, occupation type, wage rate, industry categories and other land use variables could explain this. In general, older people tend to leave home later than the younger people do. Full-time workers start their day earlier than the part-time workers do. Higher expected utility of first activity of the day and more than one car in household influence early start of the day's activities.

Table 1c: Time Expenditure Choices to At-home before First Out-of-home Activity

	Parameter	*t*-statistics
Baseline utility of time expenditure choice for at-home activities before the first trip		
Constant	48.47	77.65
Logarithm of age	0.16	2.65
Full-time workers	0.21	2.97
Part-time workers	1.52	18.41
More than 1 car in household	-0.07	-1.73
Expected maximum utility of first activity type choice of the day	-0.04	-8.57
Exponential function of satiation parameter, α for at-home activities before the first trip		
Constant	-2.18	-209.54
Dwelling type: Detached house	0.00	0.287
Dwelling type: Apartment	0.003	2.80

Satiation function defines the satiation in time expenditure in an activity episode. A positive satiation effect indicates a tendency of lower time expenditure choice and vice versa. It is found difficult to have explanatory variables for satiation effect in time expenditure at-home before the first activity of the day and it largely remains constant. It seems that dwellers seem to start their day earlier than others.

6.3 First Out-of-home Activity Type Choice

Table 1d presents the choice model for first out-of-home activity type choice against 'staying-at-home whole day' option. The systematic utility of first out-of-home activity type choice is defined by the expected maximum utilities of destination location choices for non-work activities, mode-specific travel time for work activity along with personal attributes. Because of consideration of expectation of destination location choice (which is a positive quantity), the ASCs of non-work and non-school activities are all negative. This implies that the choice of first out-of-home activity as non-work and non-school activity is mostly influenced by location opportunities of such activities.

Table 1d: First Out-of-home Activity Type Choice

		Parameter	*t*-statistics
Alternative specific constant (ASC)			
	Work related	-5.40	-9.65
	Work at non-fixed location	-5.84	-7.89
	School	8.94	19.36
	Shopping	-6.18	-10.59
	Restaurants	-6.94	-6.25
	Recreation	-5.12	-7.78
	Visiting friends and family	-6.63	-7.64
	Health and personal care	-9.55	-13.08
	Dropping off someone/something	-5.49	-19.24
	Picking up someone/something	-4.80	-18.59
	Staying home whole day	8.70	45.53
	Other activities	-2.15	-10.82
Full-time workers			
	Work	1.23	7.36
	Work related	0.72	5.62
	Work at non-fixed location	1.56	4.66
	School	-2.68	-13.76
	Restaurants	0.83	1.53
	Visiting friends and family	-0.39	-1.77
	Dropping off someone/something	1.71	12.60
	Picking up someone/something	0.60	2.42
Male			
	Work	0.46	4.89
	Work related	1.36	4.99
	Work at non-fixed location	0.26	2.65
	Recreation	0.17	0.12
	Health and personal care	-2.11	-1.54
Logarithm of age in years			
	Work related	0.46	3.25
	School	-3.03	-21.75
	Shopping	1.26	8.37
	Restaurants	1.16	3.87
	Recreation	0.78	4.58
	Visiting friends and family	0.56	2.41
	Health and personal care	1.08	6.34
Travel time to work destination by private car			
	Work	12.95	9.48
Travel time to work destination by public transit			
	Work	5.69	6.29
Travel time to work destination by non-motorized modes			
	Work	8.22	3.69

A longer travel time requirement for a home to work location influences the choice of work as the first activity of the day. However, it is also clear that private car users are more likely to choose work as the first activity than transit or non-motorized mode users. This is a reflection of higher travel time variability of private car users in the region. Workers who are also involved in school-related activities are more likely to perform a school activity earlier than the work activity. In addition, there is a baseline tendency (positive and un-captured utility explained through the ASC) of the staying-at-home whole day. Full-time workers are less likely to make school and visiting family/friend type of trip at the beginning of the day. However, it is more likely that the full-time worker would choose work at non-fixed location activity or drop off or picking up activities as the first activity of the day the others. Female workers are more likely to choose non-work activities as the first activity the day than the male workers do. Older people are less likely to make a school trip at the beginning of the day than the younger people do. However, older people are more likely to make health and personal care, shopping, recreation, visiting and restaurant type activity related trip than the younger people do.

6.4 Subsequent (to the first out-of-home activity) Activity Type Choices

Table 1e presents the activity type choice model component for all activity types except the first out-of-home activity. Time-of-day, travel time and expectation of location choices are considered the explanatory variables for activity type choice that are subsequent to the first out-of-home activity. Alternative-specific constants (ASCs) are in the model to capture the effects that are not explained by these limited explanatory variables. Overall, the ASCs indicate that choice of restaurant activity is not sufficiently explained by variables used in the model and other things remaining the same, workers' preference for this activity type is the lowest.

In fact, this activity type is often confused with recreational or other activity types in household travel surveys. Investigations that consider this activity type as nested with recreational and other activity types did not result in any feasible solution. Other than this, the ASCs demonstrate that compared to work activities, all other activities have some negative utility components that are not explained by the limited set of explanatory variables in the systematic utility function of activity type choices.

Shopping activity seems to have the lowest preference compared to any other activity types for the workers in the NCR. Choices for making a shopping trip during morning and evening peak periods are the lowest. Also, preference to starting a work trip very early in the morning (before 6 am) is very low. Preferences for school activity decreases with increased time-of-day. Since work at the fixed location does not have a subsequent location choice model, therefore, the logarithm of travel time to work location by different modes is considered as a variable in the model. Travel times by car and transit have a high and positive coefficient in the work at fixed location activity type choice. This indicates a longer distance from a non-home origin to work location increases the choice of work activity by the worker. However, it should be clarified that such high coefficients of travel times to work are commensurate with the logsum of location choices that were entered as a positive quantity in all other non-work activity type choice utility functions. Clearly, workers are more sensitive to travel time by private car than that of by transit. At the same time, travel time by non-motorized modes is the least sensitive to travel times by all modes.

Table 1e: Subsequent (to the first activity of the day) Activity Type Choice

	Parameter	*t*-stat
Logarithm of origin to workplace travel time (minutes) for work		
by car	33.87	82.87
by transit	32.29	78.47
by non-motorized modes	2.13	2.60
Travel time (minutes) to return home temporarily		
Travel time by car	25.91	31.88
Travel time by transit	-1.59	-3.54
Travel time (minutes) to return home for rest of the day		
Travel time by car	-3.98	-4.60
Travel time by transit	-0.47	-0.55
Travel time by non-motorized modes	-3.61	-11.07

Similarly, since the home location is considered to be fixed, travel times by different modes from any out-of-home location to home location are considered as variables in return home temporarily and for rest of the day choices. Travel time by car has a positive effect, but travel time by transit has a negative effect on return home temporarily. Return home temporality defined multiple home-based tours. Private car users tend to have higher tendency to make home-based tours than the transit users.

6.5 Activity Location Choices

CUSTOM considers a generic location choice model for all scheduling cycles, but the choice set of location choice is constrained by the PPA defined by time budget of corresponding scheduling cycle and modal accessibility (travel time by different modes). Land use attributes of the alternative TAZs and transportation system performance (mode specific round trip travel time: origin-destination-home) are considered variables in the generic location choice model. Different variables are found to have significantly different effects on different activity location choices. Since, location choice precedes the activity type choice model, the specification of the out-of-home location choice model gives activity type-specific model specification in the CUSTOM framework.

Table 1f: Out-of-home Activity Location Choice

	Parameter	*t*-Statistics
Logarithm of travel time by car from the CBD (Central Business District)		
Work related	-0.164	-3.91
Work at non-fixed location	0.251	1.37
Shopping	-0.064	-2.43
Restaurants	-0.656	-14.10
Recreation	-0.136	-3.73
Visiting friends and family	-0.084	-1.41
Health and personal care	0.230	3.09

Dropping off someone/something	0.429	7.72
Other activities	-0.223	-5.56
Logarithm of population density in the zone		
Work related	-0.079	-10.08
Work at non-fixed location	0.108	2.59
School	-0.031	-4.92
Shopping	-0.081	-15.85
Restaurants	0.018	1.64
Recreation	-0.022	-2.78
Visiting friends and family	0.086	6.22
Health and personal care	-0.041	-2.87
Dropping off someone/something	0.077	6.57
Picking up someone/something	0.091	8.16
Other activities	0.010	1.09
Logarithm of round trip (origin-destination-home) travel time (minutes) by car		
All non-work activity types	-0.477	-90.41
Logarithm of round trip (origin-destination-home) travel time (minutes) by transit		
All non-work activity types	-0.618	-61.17
Logarithm of round trip (origin-destination-home) travel time (minutes) by non-motorized modes		
All non-work activity types	-0.463	-9.99
Logarithm employment density in the zone		
Work related	0.217	13.53
Work at non-fixed location	-0.016	-0.28
Health and personal care	0.301	11.63
Dropping off someone/something	0.184	9.89
Logarithm school or school related institution density in the zone		
School	1.433	45.49
Dropping off someone/something	0.313	3.54
Logarithm arts and entertainment centre density in the zone		
Recreation	0.286	3.27
Visiting friends and family	0.173	1.36
Logarithm of restaurants density in the zone		
Visiting friends and family	0.299	4.44
Health and personal care	0.381	5.37
Logarithm shop/service centres density in the zone		
Shopping	0.530	26.00
Recreation	0.193	4.85
Dropping off someone/something	0.147	3.08
Picking up someone/something	0.241	5.72
Other activities	0.320	8.12
Logsum of next activity type choice	*Inverse of scale parameter of following activity type choice*	
All non-work activity types		

Distance from CBD to any alternative TAZ is found to have significant and different effects for different activity location choice models. It seems that in the NCR, work related shopping, restaurants; recreation, others and visiting friends/family activity locations of workers in weekdays are more likely to be closest to the CBD than the farther away from the CBD. However, it is also clear that non-fixed work locations, health/personal care and dropping off locations of the workers in the NCR tend to be farther away from the CBD. Zonal population density seems to capture relative attractions of different zones for different activity types. Clearly, work-related, school, shopping, recreational and health/personal care activity locations are more likely to be in areas/zones with lower population density. However, non-fixed work location tends to be most likely to be in higher population density locations. Visiting friends/family, dropping, picking and restaurants activity locations are more likely to be in higher population density locations. Intuitively, round-trip travel time has significantly negative effects on the attractiveness of activity location choice utility. However, people are more sensitive to transit travel time and travel time by car or non-motorized modes. Transit travel time includes waiting and transferring time and these, perhaps, make transit travel time to have higher negative effects on activity location choice than those of private car and non-motorized modes.

Higher employment density increases the attractiveness of different locations (zones) for work-related, health/personal care and dropping off activities. Similarly, higher school density increases the attractiveness of different locations (zones) for school and dropping activities. The Higher density of arts and entertainment centres increases the attractiveness of a location (zone) for recreation and visiting friends/family activities. The Higher density of restaurants increases the attractiveness of a location (zone) for visiting friends/family and health/personal care activities. The Higher density of shopping centres increases the attractiveness of a location (zone) for visiting shopping, recreation, dropping off, picking up and other activities.

6.6 Time Expenditure Choices to the Activities Subsequent to the First Trip: Activity Episode Durations

Time expenditures to scheduled activities are explained through baseline utility function and the satiation parameter function. Baseline utility function captures the constant marginal utility of spending the time to scheduled activity types. Table 1g presents the baseline utility and satiation parameter function of scheduled activity time expenditure choices. CUSTOM captures which workers have the highest constant marginal utility to work at a fixed location and school activities, which captures the high level of minimum duration these two activity types usually have. The slightly higher marginal utility is seen in work activity that is scheduled as the first and second out-of-home activity of the day. Among others work related, shopping, recreational and health/personal care activities have the higher marginal utility of time expenditure choices to all non-work/school activities. However, these constant marginal utilities are balanced by positive expected maximum utility of subsequent activity type and location choices. This ensures minimum positive durations to all scheduled activities that are implicitly ensured in the CUSTOM framework. Time-of-day has a significant influence on defining the total marginal utility of time expenditure choices. The marginal utilities of time expenditure in work and school activities decrease drastically with time-of-day. However, the marginal utility of time expenditure choices for restaurants, picking up and at-home between two home-based tours activities increases with time-of-day. This indicates that these workers tend to spend the longer duration of time on these types of activities if these are scheduled at later parts of the day.

Table 1g: Time Expenditure Choice to Activities

	Parameter	*t*-Statistics
Baseline utility component		
Constant for activity types		
Work		
as the first activity of the day	30.836	53.66
as a second activity if the day	30.426	53.02
as the third or later activity of the day	29.050	49.78
Work related	-5.909	-6.25
School	17.279	16.71
Shopping	-8.427	-15.03
Restaurants	-13.045	-14.57
Recreation	-8.652	-9.13
Visiting friends and family	-11.055	-23.80
Health and personal care	-8.802	-19.93
Dropping off someone/something	-9.933	-22.01
Picking up someone/something	-13.819	-17.24
At-home in between two home-based tours/trip chains	-12.074	-20.84
Other activities	-11.728	-18.89
Time-of-day (as a fraction of 24 hours) of activity starting time		
Work	-39.949	-43.53
Work related	-7.655	-4.34
Work at non-fixed location		
School	-17.454	-7.42
Shopping	-5.594	-7.57
Restaurants	1.769	1.35
Recreation	-1.618	-1.21
Visiting friends and family	-1.443	-2.10
Health and personal care		
Dropping off someone/something	-7.925	-11.58
Picking up someone/something	0.958	0.89
At-home in between two home-based tours/trip chains	1.751	2.35
Other activities	-3.418	-3.84
Logsum of activity type choice		
All activity types	*Inverse of next activity type choice scale*	
Exponential function of satiation parameter, α for all activity durations subsequent to the first trip		
Constant		
Work	-1.900	-132.63
Work related	-0.280	-2.55
Work at non-fixed location	-0.675	-16.42
School	-1.500	-39.55
Shopping	-0.423	-6.12
Restaurants	-0.386	-2.93
Recreation	-0.399	-3.64
Visiting friends and family		

Health and personal care	-0.360	-6.94
Dropping off someone/something	-0.996	-15.21
Picking up someone/something	0.183	1.40
At-home in between two home-based tours/trip chains	0.306	4.35
Other activities	0.268	2.34
Time-of-day (as a fraction of 24 hours) interaction with		
Work	0.619	18.96
Work related	-0.342	-1.59
Work at non-fixed location	-1.120	-13.57
School	-0.094	-1.01
Shopping	-0.324	-3.01
Restaurants	-0.283	-1.43
Recreation	-0.425	-2.67
Visiting friends and family	-0.568	-9.37
Health and personal care	-0.802	-15.52
Dropping off someone/something	1.146	7.01
Picking up someone/something	-1.356	-7.19
At-home in between two home-based tours/trip chains	-1.445	-13.43
Other activities	-0.674	-3.65

The satiation parameter function captures the rate of change of marginal utility of time expenditure choice. Workers in the NCR tend to enjoy spending more time in at-home in between two out-of-home trips, others and picking up activities. Constant positive satiation parameters for these activity types indicate tendencies of increasing time expenditure to these activity types.

However, with increasing time-of-day, at-home and other activity durations increase. CUSTOM captures that people work longer if they start earlier in the day and if they work shorter hours if they start later in the day. However, people shop longer if they start later in the day. Work activity has the lowest constant satiation parameter that refers to the fact that considerable portion of work activity durations is determined by external factors (e.g. long-term commitments, office regulations, salary structure, job types, etc.) and individuals have little freedom in unilaterally increasing or decreasing the duration. A similar effect is also found to be true for school activity time expenditure choices. Interestingly, it seems that people enjoy spending time more on picking up activities than dropping off activities. Similarly, people enjoy more spending time on visiting friend/family than shopping, restaurants and recreation activities. Stating time of the activity as time-of-day has a significant impact on the rate of change in marginal utility of time expenditure choices. In fact, starting time changes the patterns of satiation effects that are through constant satiation function parameter.

The start time of an activity defines the satiation level (rate of changes in the marginal utility of time expenditure choice) of any activity. In other words, the scheduling context (in terms of the time-of-day) is critical in defining the total time expenditure choice for any activity type. For example, satiation effects of time expenditure to work and school activities increase with time of day. This indicates that workers in the NCR enjoy spending time on work and school activities if they can start later in the day than earlier in the day. Similarly, satiation effect increases with increasing time-of-day for shopping, restaurants and dropping off activities. However, the satiation effect decreases with increasing time-of-day for work at non-fixed locations, visiting friends/family, health/personal care, picking up, at-home in between two home-based tours/trips and other activities.

7. Conclusions and Recommendations for Further Research

The proposed CUSTOM framework is consistent with the time-geographic theory of time-space constraints in activity-travel and microeconomic theory of random utility maximizing (RUM) choice behaviour. It is a rule-free and fully probabilistic choice modelling system that also combines discrete and continuous choices seamlessly. It ensures feasible roaming space by using a dynamic time budget constraint-based PPA. The paper presents the core econometric structure of CUSTOM and a prototype application of workers'/students' daily activity-travel scheduling. The prototype model is implemented for empirical investigation by using a household travel survey dataset collected in 2011 in the NCR of Canada. The empirical application of CUSTOM is focused on daily activity scheduling of workers in the NCR. The empirical model (of 216 parameters) proves to fit the observed data with high degree of goodness-of-fit along with all parameters of expected sign and reasonable magnitudes. A validation test (by using holdout sample) of the empirical model is conducted to evaluate the power of CUSTOM framework in predicting activity-travel scheduling behaviour. Results explain that CUSTOM can predict scheduling behaviour with high accuracy. In addition, the empirical model components also reveal many behavioural details of workers'/students' activity-travel behaviour. Especially, variations of time expenditure choice, the connection between activity type choice and time expenditure choice, activity type choice and location choices as well as tradeoffs in time expenditure choices to different chosen activities at different parts of the day are captured and explained with rigour.

An empirical application of CUSTOM to workers' daily activity-travel scheduling choice modelling reveal that household income, household size and a number of cars explain variations in time expenditure choices in the context of different parts of the day. Income effects in explaining variances of time expenditure choices and eventual trip start times are explained. In general, variations/randomness in time expenditure choices reduces with time-of-day, but such variations are also defined by household size, car ownership and income interactions. An empirical application of CUSTOM for workers explains that the departure time choice for the first activity of the day is influenced mostly by personal and household characteristics along with the expectation of subsequent activity type and location choices. Activity location choice components of CUSTOM explains that land use propensity of certain types (e.g. density of population, employment, shopping centres, restaurants, entertainment centres, etc.) attracts people for similar types of activities (visiting, shopping, recreation, meeting, etc.).

The empirical model also captures the fact that workers' daily activity-travel scheduling is mostly contextual, that is it is contextual in the sense of time-space constraint defined by time budget available (eventual time-of-day) and the spatial access (to various activity locations) by various modes of transportation. Effects of urban form, in terms of distribution of different types of land, uses with respect to the distance from the CBD are captured in the activity location choice model. Differential sensitivities to auto, transit and non-motorized models are also captured. Clearly, people are more sensitive to travel time by car than transit and non-motorized modes. CUSTOM captures that fact that work at a fixed location and school activities have the highest constant marginal utility of time expenditure choice for workers and students. The empirical model explains that CUSTOM can model choices and patterns of home-based tour formation as well as effects of travel time by various modes. It also explains how time-of-day context and travel time by various modes play roles in defining such patterns.

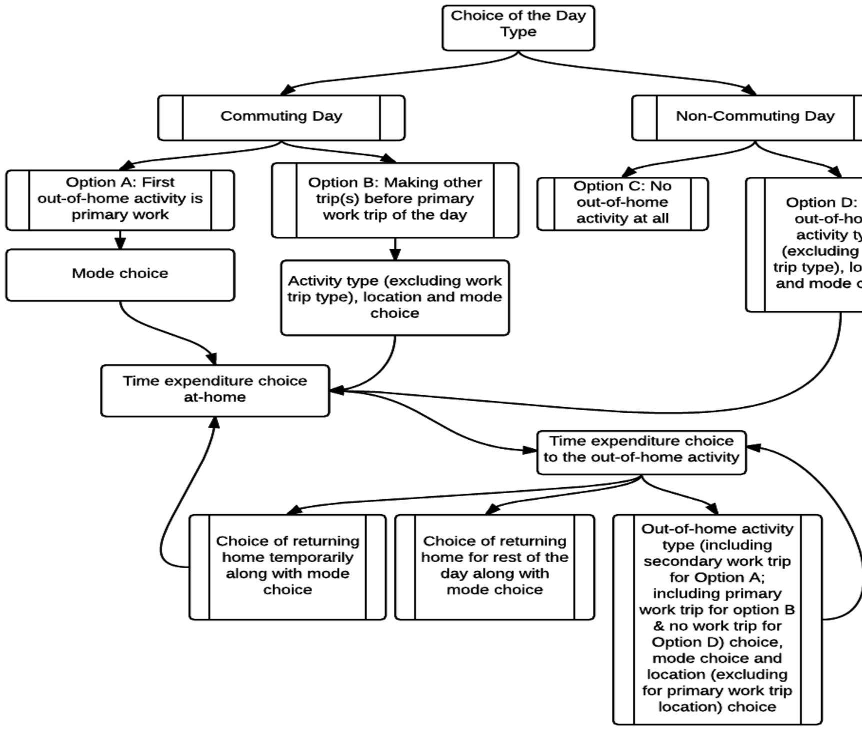

Figure 3: Capturing Specific Commuting Patterns within CUSTOM

The paper presents the first stage of CUSTOM's development, which models activity type choices, location choice and time expenditure choices. Two hard assumptions, that is the exogenous mode choice assumption and the sequential scheduling choice assumption, are apparent limitations of CUSTOM and therefore require further research. In this study, the mode choice is considered exogenous and so, mode-specific travel time is used as an explanatory variable. Alternatively, one can easily accommodate trip-based mode choice component within the scheduling cycles. Figure 3 presents a modified approach of the CUSTOM framework that captures specific patterns of commuting behaviour along with mode choice component. It assumes four possible patterns: making no trips prior to work trip; making one of more trips before work trip; making no trip at all, and making no commuting trips. Each of these four possible patterns then follows systematic steps of scheduling following the basic formulations of CUSTOM. Accommodation of modes in such an approach is easier, but specific rules need to be used to make sure that the correlation mode choices are properly addressed. For example, commuters who take their car from home will need to return it back at home. Based on this consideration, it is understood that further research is necessary to specify mode choice model that can be integrated parsimoniously considering: intra-household mode allocation choices; feasibilities of alternative combinations of mode uses during the day; and the possibility of ride sharing among the household members, etc. Thus, this is recommended as the next step for this current research. A related issue is that the presented application is individual-based and does not consider explicit intra-household interactions. Many such interactions can easily be handled through a choice set formation of activity type and location choices. However, further research on this issue is necessary for a parsimonious modelling system.

A related issue is a choice set for the destination location. In this investigation, random draws from feasible location choice set (based on dynamic PPA) are used. However, in real life destination locations may not remain random. More intelligent rules are necessary to define alternative destination locations. Although, the dynamic PPA narrows down the number of feasible choice sets significantly, in reality other issues (e.g. fixed day care locations for dependent children, fixed doctors' locations, opening hours of shopping centres, availability of parking facilities in shopping locations, etc.) can play crucial role in defining the number of alternative destination locations. While observing all such systematic information on location choice set feasibility may not always be possible, it is necessary to investigate the options of defining more constrained PPA along with probabilistic choice set formation (considering intra-household interactions into considerations) for destination location choice model.

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