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Daily activity-travel scheduling behaviour of non-workers in the National Capital Region (NCR) of Canada

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ABSTRACT

This paper uses household travel survey data (of the National Capital Region of Canada) and a comprehensive random utility maximizing travel options modelling approach to investigate non-workers' activity-travel scheduling behaviour. The empirical model reveals that the presence of children shapes the daily activity-travel patterns of non-workers by reducing the flexibility of out-of-home activity-type choices. Availability of private cars increases flexibility in travelling and increases the spread of spatial locations of out-of-home activities of non-workers. Income plays a significant role in non-workers' activity-travel behaviour and it seems that non-workers from lower to middle-income households are less active (return home early) than those living in higher income households. In general, it is found that male non-workers are less active than the female non-workers and it is also evident that non-workers living in single detached houses are less active (return home early) than those living in condos/apartments. These findings have an implication to health issues as the average age of non-workers is over 50 years and the majority of detached houses are far from the central business district.

1. Introduction

Non-workers, especially unemployed individuals, retirees and homemakers share a good proportion of any urban population. Travel behaviour of non-workers can be very different from those of the workers and students (Misra, 1999). Non-workers often take care of critical household-related activities that the other household members may not have time to take care of. These include shopping, drop off, pick up, recreation, eating out, visiting and even staying at home for various household needs. Participation and scheduling of such activities of non-workers have positive impacts on local businesses and the regional economy as well as transportation system performances. Flexibility in daily activity scheduling of non-workers may encourage them to avoid peak period congestion, and contribute more to off-peak period traffic. Typically, low transit service in off-peak periods may influence increasing dependency of non-workers in activity-travel performances on private automobiles. In addition, if a significant proportion of non-workers in a region are unemployed and retired people, such auto dependency may have further implications for job-searching activities, health issues and special mobility needs (Misra and Bhat, 2000).

Conventionally, urban transportation planning and travel demand investigations are mainly focused on workers. This is perhaps due to workers' dominant contributions to the peak period traffic congestions. Recent progress in the field of

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activity-based modelling has proven the necessity of considering full-day activity-travel scheduling of all trip makers in capturing travel demand of urban residents. Most of the operational activity-based travel demand models attempt capturing household-based models daily travel demands of the target population (Rasouli and Timmermans, 2013). However, deciphering travel behaviour of non-workers from a large-scale operational demand model may be difficult. This difficulty is reflected in the limited availability of published works on non-workers' activity-travel scheduling processes in the travel demand modelling literature. Therefore, empirical investigation of non-workers' activity-travel behaviour can reveal many insights that can be useful for developing inclusive transportation and urban planning exercises. This paper contributes to the transportation planning literature by presenting such an investigation by using a comprehensive econometric model and household travel survey data.

The paper is organized as follows. Section 2 presents a brief literature review on econometric demand model-based investigations on non-workers' activity-travel demand. Section 3 presents a discussion on the data sample of non-workers' activity schedules. Section 4 presents the econometric formulation of the Comprehensive Utility maximizing System of Travel Option Modelling (CUSTOM). Section 5 provides a full discussion on the empirical models and possible findings. The paper concludes with a summary of key findings and recommendations for further research.

2. Literature review

Fifteen years ago, Bhat and Misra (2001) mentioned that non-workers' activity-travel behaviour is an under-researched area, and emphasized the need for more empirical investigations. However, there has not been a significant amount of empirical investigation attempts on assessing non-workers' activity travel behaviour until now. Rasouli and Timmermans (2013) presented a literature review on activity-based modelling and identified many modelling exercises that deal with non-workers along with all other household members combined. Specifically, research on intra-household interactions may cover non-workers' activity-travel behaviour in the context of household interactions. However, empirical investigations on the daily activity-travel behaviour of non-workers with particular focus are rare. Only a handful of evidence are available in relevant literature and are discussed below.

Bhat and Misra (2001) presented an exploratory analysis on the travel behaviour of non-workers in the San Francisco Bay Area. They used around 4000 activity-travel diaries of non-workers collected in the San Francisco Bay area in 1990. They investigated the effects of household and personal socio-economic attributes of non-workers on their activity-travel scheduling attributes, e.g., the number of activities, trip chaining and activity sequencing behaviour. The univariate regression model is used to model activity-travel scheduling attributes against socio-economic variables. They found that non-workers contribute significantly to household-related activities, e.g., serve-passengers activities. Non-workers tend to schedule household need-related activities earlier in the day. The exploratory nature of their investigation leaves many questions (mentioned as limitations) related to choice processes involved in non-workers' activity travel.

Yamamato et al. (2000) employed a joint econometric model of route and departure time choices of worker and non-workers along with a regression model of time allocation under congestion pricing scenarios. They used data from a panel survey to investigate factors affecting route, departure time and time allocation to discretionary activities. They found that workers and non-workers have fundamentally different travel behaviour as they may have very different utility perceptions of these choices under congestion-pricing contexts. It seems that non-workers' perceptions of transportation system performance are very different from those of the workers. Their modelling approach does not leverage a whole day of activity scheduling and time-space constraints in the activity-travel engagement process.

Bhat and Misra (2001) used the same dataset as they did in 2000, but applied a comprehensive econometric model to investigate the activity-travel behaviour of non-workers. They used a discrete choice model (multinomial logit) to model activity-travel pattern choice, where patterns are defined by activity type, the number of stops and activity sequencing. They argued about the necessity of depicting time as a continuous entity. Their empirical models reveal that non-workers tend to schedule serve-passenger activities earlier in the day and tend not to link those with other trips. They found that socio-economic factors may not influence activity sequencing of non-workers. One notable limitation of their model is treating prearranged sequences to define patterns and use such patterns as choice units. Effects of time-budget and time-space constraints are not modelled explicitly. Misra et al. (2003) further expanded the works of Bhat and Misra (2001) by presenting discrete choice models for mode and destination choice and a hazard model for activity episode duration. They modelled these three choices independently, overlooking endogeneity and/or nested choice possibilities.

In a recent study, Manoja and Vermab (2013) presented an empirical investigation on non-workers' activity-travel behaviour in Bangalore city in India by using an activity diary survey dataset. They used a univariate regression model for investigating the activity participation frequency of non-workers. They found that individuals' personal and household-related attributes constitute the main factors defining the activity-travel behaviour of non-workers. Manoja and Vermab (forthcoming) used structural equation modelling (SEM) in an effort to further enhance understanding of non-workers' activity-travel of the same study area. They reported that out-of-home activity durations of non-workers are not affected by travel time. They also found that mixed land use may encourage shorter travel distance, but it may further

There are also some research that also investigated activity-travel behaviour of non-work activities/trips of both worker and non-workers. For example, Saleh and Farrell (2005) investigated non-work activity commitments on work trip departure time choice. They found that non-work related activities can indirectly reduce the flexibility of commuting trip timing even though the worker may have flexible office hours. Kim et al. (2015) investigate the effects of telecommuting on work and non-work travel demands. They found that intra-household interaction plays pivotal roles in moderating the effects of telecommuting by the household heads. It is seen that in the case of telecommuting by a worker of a household, the household cars become free and available for non-work trips by non-workers of the household. Such telecommuting can allow higher number of out-of-home activity participations of non-workers. Eftekhar et al. (forthcoming), Cools and Moons (forthcoming) investigated effects of time pressure and intra-household correlations on activity-travel scheduling processes and found their distinctive effects on work versus non-work travel. Etminani-Ghasrodashti and Ardeshiri (2016) found that land use and built environment attributes may affect work and non-work activities very differently. However, none of these papers is particularly dedicated to enhanced understandings of non-workers' activity-travel scheduling behaviour.

Overall, it is clear that non-workers' activity-travel behaviour is an under-researched topic. Even the limited number of investigations reported in the literature use myopic objectives or a limited scope methodology. A comprehensive investigation of only non-workers' daily activity-travel behaviour is not available. This paper presents such an investigation by using household travel survey data. The next section presents the econometric modelling framework used in this investigation.

3. Data for empirical investigation

Household travel survey data collected in the National Capital Region (Ottawa-Gatineau metropolitan regions covering parts of the provinces of Ontario and Quebec) of Canada in 2011 are used for an empirical investigation of this paper. The survey area is divided into 673 traffic zones (TAZ) and the survey is a 5 percent sample of all households in the region. The dataset contains 24-h travel diaries. However, travel times are estimated using a calibrated EMME based traffic assignment model (TRANS Committee, 2014). The estimated travel time for the corresponding chosen mode of transportation is used to reconstruct 24-h activity-travel schedules. After cleaning the dataset for missing values of key personal and household attributes, activity start time, purpose, destination locations and infeasible activity durations, a total of 6760 coworker's schedules is available for empirical investigation. Table 1 presents the summary statistics of key variables of the dataset.

It is clear that the majority of non-workers are female and many are over 50 years of age, most of which are unemployed and many are retired individuals. More than one-third of non-workers in the NCR do not make any trip on a typical day. Returning home in between two trips is a common behaviour. Travel distances decrease with increasing activity of the day. It should be noted that around 2.1 percent of total activity types is of work-relate activities. It may sound odd that the paper focusses on non-workers' behaviour, but some of the non-workers have work-related activities. We could have removed individuals who have participated in these activities, but it would not be fair. In fact, all individuals in this dataset for investigation are non-workers, but some of them may still look for a job. So, some of the non-workers spend time in work related activities and by this it means they spend the time to look for a job. Even though these are work related activities, these are not purely work activities. So, we decided to retain then and consider work-related activity as a separate activity type.

4. Activity scheduling model

We used the Comprehensive Utility Maximizing System of Travel Options Modelling (CUSTOM) proposed by Habib (2011, 2015) and Habib and Hui (2015). The model can predict immobility (no out-of-home activity) and/or any feasible number of activities covering an entire 24-h day. Fig. 1 depicts the modelling framework of CUSTOM. It considers that a day is composed of panels of sequential scheduling cycles composed of three choices: time expenditure choice to an ongoing activity, the activity-type choice for the next activity and destination choice of the next activity if it is an out-of-home activity.

The three parts of the figure explain how an increasing number of activity participation reduces the available time budget; how the expected maximum utility of subsequent scheduling choices feed into current scheduling choices, and how the dynamics of activity type, destination and time expenditure choices are modelled. Details of the mathematical formulation of CUSTOM are available in Habib (2011, 2015) and Habib and Hui (2015). Nonetheless, we would like to present in this paper the three key choice model components of any scheduling cycle: Activity type choice, destination location choice and time expenditure choice.

Destination location choices are nested into out-of-home activity-type choices, which in turn are nested within the previous cycle's out-of-home destination choice. The connection between time expenditure choices on an activity and the following activity type-destination choices are based on expected maximum utility of activity type-destination choices (accessibility to activity-travel engagement). This measure of accessibility influences time pressure and resulting changes in the marginal utility of time expenditure on ongoing activity. On the other hand, the time expenditure choice in an activity

Table 1
Summary statistics of dataset for empirical investigation.

Variable	Mean	Minimum	Maximum	Proportion (%)
Household size	2.5	1	5	
Number of vehicles at home	1.5	0	7	
Age (years)	52	16	64	
Male				38
Female				62
Dwelling unit: Single-detached house				61
Non-worker types:				
Unemployed individual				57
Homemaker				14
Retired or another type				18
Unsure about type				11
Number of scheduled activities				
No out-of-home trips				38.0
2 activities				32.1
3 activities				10.6
4 activities				13.4
5 activities				1.1
6 activities				3.0
7 activities				0.5
8 activities				0.7
9 activities				0.3
10 activities				0.2
11 activities				0.1
Proportion of observed activities by purposes				
Work related				2.1
School				0.5
Shopping				22.7
Restaurant (e.g., for a meal)				2.5
Recreation				7.4
Visiting family/friends				4.5
Health/personal care				5.0
Drop off				3.4
Pick up				2.8
At-home in between two trips				43.2
Other activities				5.9
Travel distances in km				
1st trip of the day	8.9	<0.25	79.3	
2nd trip of the day	8.5	<0.25	69.8	
3rd trip of the day	7.9	<0.25	52.3	
4th trip of the day	8.1	<0.25	56.9	
5th trip of the day	7.1	<0.25	52.3	
6th trip of the day	6.9	<0.25	44.3	
7th trip of the day	6.7	<0.25	46.4	
8th trip of the day	6.6	<0.25	43.6	
9th trip of the day	6.6	<0.25	36.8	
10th trip of the day	4.3	<0.25	20.7	
11th trip of the day	1.0	<0.25	7.4	

Table 2
Summary of the empirical model estimation.

Log likelihood of full model	113903
Log likelihood of null model	153340
Number of observations	6760
Number of estimated parameters	164
Adjusted Rho-Squared value	0.26

The time-space prism defined by available time for the rest of the day along with round-trip travel time captures the feasibility of destination location choices. Various rules can be used to outline the feasible location to reduce the number of possible locations for destination choices. In this empirical investigation, we assumed the rule that the total time budget remaining should be more than 1.5 times the round-trip travel time (“previous activity location”-“all potential locations”-“home location”). This rule reduces the destination choice set drastically. However, even with this rule, for larger than 10

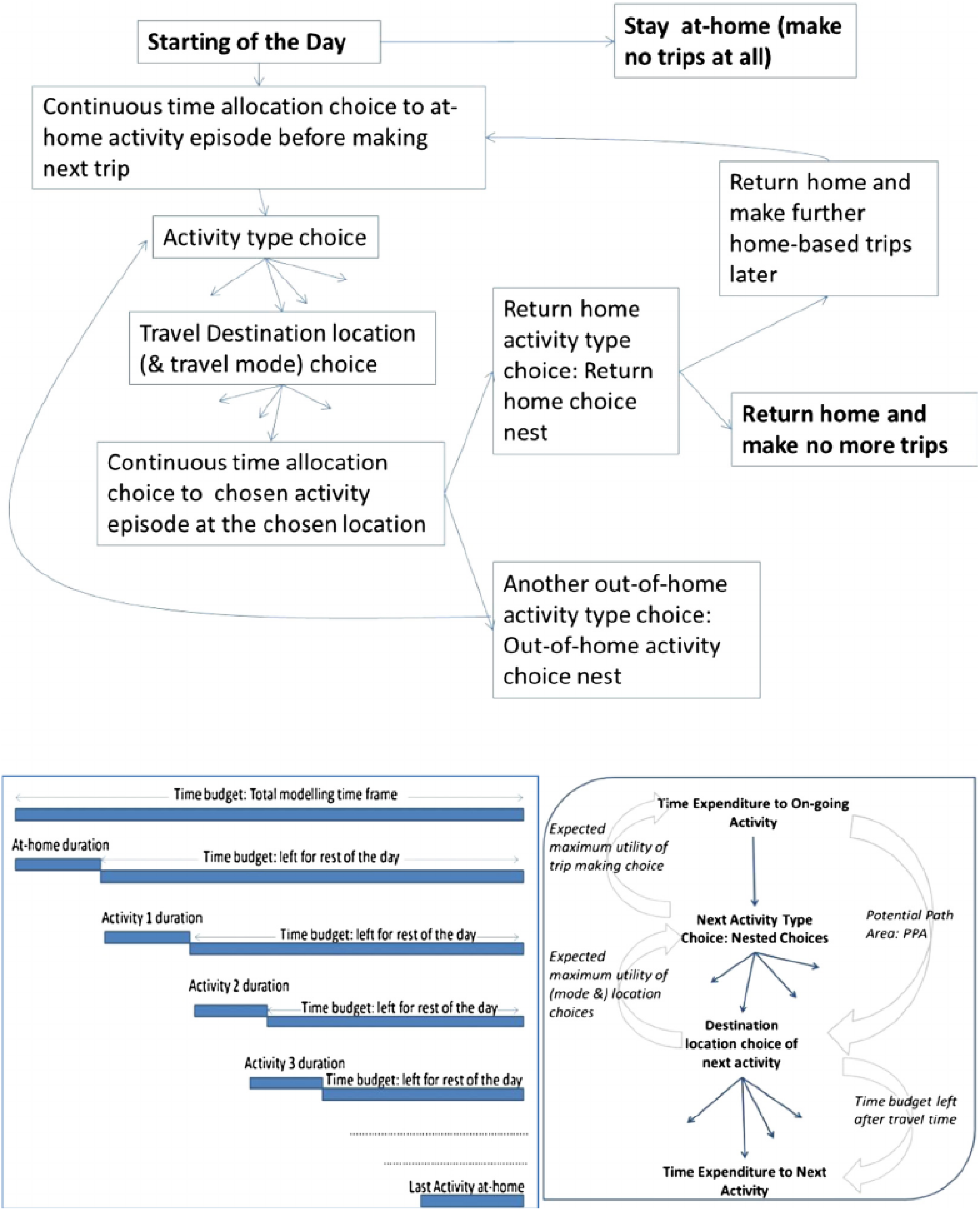

Fig. 1. Schematic diagrams of CUSTOM framework.

As the CUSTOM system models the schedule of the whole day, we start explaining from an arbitrary point of the day when an individual (suppressing the identification of the individual) is in a current activity. The probability of time expenditure choices (t_j) to the current activity (A_j) is:

$$\Pr\ t_j \quad 1 \quad {}_j \quad t_j \quad 1\ t_c \quad {}_{t_j} \exp \quad {}_{t_j} V_c \quad V_j \quad 1 \quad \exp \quad {}_{t_j} V_c \quad V_j \qquad 2$$

Here,

t_c is the time remaining as time budget for the next activity (j + 1).
$_j$ is the satiation parameter for time expenditure to activity type j, which is further specified as (1 exp(y)) to make sure that the maximum possible value is 1[1]
y refers to variable sets and is the corresponding parameter.
$_j z_j$ 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.

Upon termination of the current activity, the following activity type and destination location choice takes the Generalized Extreme Value (GEV[2]) structure. The probability of choice of return home (R_{j+1}) ending an out-of-home activity A_j is

$$\Pr R_{j\,1} \quad \exp\ {}_{h_{j\,1}} V_{R_{j\,1}} \quad \exp\ {}_{h_{j\,1}} V_{RT_{j\,1}} \quad \exp\ {}_{h_{j\,1}} V_{R_{j\,1}} \quad \exp\ {}_{h_{j\,1}} I_{A_{j\,1}} \quad {}_{A_{j\,1}} \tag{2}$$

The probability of return home temporarily (RT_{j+1}), after completing the current activity A_j with option of choosing another out-of-home activity A_{j+1} is

$$\Pr RT_{j\,1} \quad \exp\ {}_{h_{j\,1}} V_{RT_{j\,1}} \quad \exp\ {}_{h_{j\,1}} V_{RT_{j\,1}} \quad \exp\ {}_{h_{j\,1}} V_{R_{j\,1}} \quad \exp\ {}_{h_{j\,1}} I_{A_{j\,1}} \quad {}_{A_{j\,1}} \tag{3}$$

The probability of choosing another out-of-home activity (A_{j+1}) instead of returning home is

$$\Pr A_j \quad \exp\ {}_{h_{j\,1}} I_{A_{j\,1}} \quad {}_{A_{j\,1}} \quad \exp\ {}_{h_{j\,1}} V_{RT_{j\,1}} \quad \exp\ {}_{h_{j\,1}} V_{R_{j\,1}} \quad \exp\ {}_{h_{j\,1}} I_{A_{j\,1}} \quad {}_{A_{j\,1}}$$

$$\exp\ {}_{A_{j\,1}} V_{A_{j\,1}} \quad \sum_{A_{j\,1}} \exp\ {}_{A_{j\,1}} V_{A_{j\,1}} \tag{4}$$

here,
$_{hj+1}$ is the scale parameter of return home activity nest
$_{Aj+1}$ is the scale parameter of out-of-home activity type choice
V_{RTj+1} is the systematic utility of return home for rest of the day
V_{Rj+1} is the systematic utility of return home temporarily
V_{Aj+1} is the systematic utility of out-of-home activity type choice
I_{Aj+1} is the expected maximum utility of out-of-home activity type choice, which is

$$I_{A_{j\,1}} \quad \ln \sum_{A_{j\,1}} \exp\ {}_{A_{j\,1}} V_{A_{j\,1}} \tag{5}$$

The out-of-home activity type (A_{j+1}) choice and corresponding destination location choice also takes the TGEV form and so,

$$V_{A_{j\,1}} \qquad x\ {}_{A_{j\,1}} \quad I\ {}_{l_{j\,1}} \quad {}_{l_{j\,1}} \tag{6}$$

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

The corresponding probability of destination location choice of out-of-home activity (lj + 1)

$$\Pr l_{j\,1} \quad \exp\ {}_{l_{j\,1}} V_{l_{j\,1}} \quad \sum_{Loc_{j\,1}} \exp\ {}_{l_{j\,1}} V_{l_{j\,1}} \tag{7}$$

$$V_{l_{j\,1}} \qquad x\ {}_{l_{j\,1}} \quad I\ {}_{ActL_{j\,2}} \quad {}_{h_{j\,2}} \tag{8}$$

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

[1] A value of 1 indicates constant marginal utility of time expenditure choice (i.e. absence of any satiation effect) and the values closer to 0 are indicators of increasing satiation effect with increasing time expenditure choices.

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

$$I_{ActL_{j\ 2}} \quad \ln \ \exp \quad {}_{h_{j\ 2}} V_{RT_{j\ 2}} \quad \exp \quad {}_{h_{j\ 2}} V_{R_{j\ 2}} \quad \exp \quad {}_{h_{j\ 2}} I_{A_{j\ 2}} \quad {}_{A_{j\ 2}} \tag{9}$$

The corresponding expected maximum utility of activity location choice is:

$$I_{l_{j\ 1}} \quad \ln \quad \frac{Number\ of\ feasible\ Locations_{J\ 1}}{Loc_{j\ 1}} \quad \underset{L_{j\ 1}}{} \exp \quad {}_{l_{j\ 1}} V_{l_{j\ 1}} \tag{10}$$

Here, the *number of feasible locations*$_{J+1}$ refers to the total number of feasible activity locations considering the remaining time budget constraints and Loc_{j+1} is the number of randomly selected locations.

In the CUSTOM, the TGEV structures of scheduling choices along with the embedded continuous time expenditure choices are ensured to remain consistent with the Random Utility Maximization (RUM) theory of consumer choice behaviour. It treats time expenditure choices as time consumption, destination locating choice as space consumption, travel time as a time to reach destination and travel time cost as the cost of activity-travel scheduling. It does so in a constrained environment of a daily maximum 24-h time budget, and potential path areas of urban space for destination location defined by reasonable travel time cost (round trip) from the remaining budget at any point of the day. Ensuring the RUM criteria in CUSTOM requires the following parameterization of the scale parameters:

$$\begin{aligned} & {}_{t_j} \quad \exp \quad A \\ & {}_{h_{j\ 1}} \quad {}_{l_j} \quad \exp \quad B \\ & {}_{A_{j\ 1}} \quad {}_{h_{j\ 1}} \quad \exp \quad C \\ & {}_{l_{j\ 1}} \quad {}_{A_{j\ 1}} \quad \exp \quad D \end{aligned} \tag{11}$$

Here, A, B, C and D are the variable sets explaining scale function, and , , and are corresponding parameter sets.

The CUSTOM formulation as explained above has a closed-form likelihood function and is estimated by using the classical maximum likelihood estimation method. Two notable aspects of this version of CUSTOM need further discussion and these are sequential scheduling process and the inclusion of mode choice model. Even though CUSTOM appears to follow a sequential scheduling process, each scheduling step considers expectation of further unscheduled activities and thereby it is not purely sequential scheduling. Current application of non-workers scheduling is unique as non-workers do not apparently have fixed location like work or school locations. Obviously, it is possible to have pre-scheduled activities in fixed location, but for a typical day modelling based on a typical day household travel survey, we really do not observe those. So, for the current application, we did not assume any fixed activities in any fixed location for the non-workers of the NCR. In addition to considering expected schedules of the later part of the day, one can also modify the activity type choice set to further accommodate activity priority. However, we could not do this for this application as we really did not have any information of such from the survey.

In case of mode choice, two possible approach could be taken: considering trip-based mode choice model for each scheduling cycle considering appropriate and feasible (available) modal alternatives and considering a tour-based mode choice model. Integration of trip-based mode choice model within the formulation is very straight-forward as an additional nest with location choice. However, considering a tour-based mode choice requires additional investigation as the question of whether scheduling should precede to define feasible tours for the tour-based mode choice model or the vice versa are still open. Many operational models (e.g. TASHA), consider that activity schedules are needed to be known for tour-based mode choice model, which needs to be further investigated. Our understanding is that mode choice requires a comprehensive approach that should consider household-level mode allocation and possibilities of intra-household joint trips, etc. So, instead of jumping into a fixed assumption of mode choice, we considered mode-specific travel times in the location choice model that leaves the option of integrating trip-based model choice model in current framework, while we are currently working on developing a more comprehensive tour-based mode choice modelling approach for CUSTOM.

5. Empirical model

The summary of the empirical model is presented in Table 1. The final model has a total of 164 parameters, and all parameters (except a few) are statistically significant with a 95 percent confidence limit. We retained some parameters with low t-statistics as they provide interesting behavioural insights. The goodness-of-fit of this specification is tested against a null model, which considers an equally likely option for all discrete choice components and an estimated constant time expenditure choice marginal utility. The adjusted Rho-squared value is estimated as:

$$\text{Adjusted Rho} \quad \text{Squared Value} \quad 1 \quad \frac{\text{loglikelihood value of full model} \quad \text{excess parameters}}{\text{Loglikelihood value of null model}} \tag{12}$$

The excess parameter refers to the differences in a number of parameters between the full and null model. The adjusted Rho-Square value is 0.26, which is considerably high for such a complex model. Since the components of the model are parameterized as functions of individual-specific variables, the model provides a customised scheduling process model for each individual level. For example, for 5 out-of-home activities in a day, the model will take the form of a ($5 \times 3 = 15$) level nested GEV structure that is fully consistent with RUM theory.

5.1. Scale parameters of the CUSTOM of non-workers

Scale parameters of CUSTOM for non-workers are parameterized to better capture preference heterogeneity (correlated choice clusters/nests) as well as heteroskedasticity (variation in sources of choice randomness). Table 3-Part 1 presents the estimated parameters of scale functions of the model. Scale parameter of time expenditure (inverse of the variance) is an exponential function of household size. It captures the systematic heteroskedasticity in time expenditure choices. Non-workers from larger household sizes tend to have lower variances in time expenditure choices. This variance further normalizes the effects of expected maximum utility of following activity type choices on time expenditure choices of an ongoing activity.

The scale parameter of first out-of-home activity type choice is the reference and is fixed to unity. Once an individual is in an out-of-home location, the activity type choice follows two nests: return home activity types (temporarily and for rest of the day) and further out-of-home activity types. The scale parameter of destination location choices for out-of-home activity types has an additional exponential (to maintain positivity) function over the corresponding out-of-home activity type choice scale. Out-of-home activity type choice scale has an additional exponential component over that of the scale parameter of return home activity type choices. Correlation coefficients of random utility of alternative choices at any nest can be estimated as (Swait, 2003):

$$\text{Correlation Coefficient} = 1 - \left(\frac{\text{upper level Scale}}{\text{Lower Level Scale}}\right)^2 \qquad (13)$$

Estimated correlation coefficients reveal that in any scheduling cycle, the out-of-home activity destination location choices are more correlated than the out-of-home activity type choices, and out-of-home activity type choices are more correlated than the return home activity type choices. This is a multilevel substitution pattern captured succinctly through a closed-form econometric formulation of CUSTOM. Heteroskedasticity of out-of-home activity participations of non-workers is captured by the number of vehicles at home if the non-worker has a driver's license. It indicates that car availability to the non-workers' plays a significant role in defining the correlations among unobserved factors of their out-of-home destination choices. It is clear that correlations among alternative choice dimensions diminish with the increasing number of activities scheduled in a day.

The first out-of-home destination location choices are the most correlated, and the correlation drops drastically afterwards. With increasing time-of-day, the randomness of alternative out-of-home activity type choices and corresponding location choices drop. This clearly proves that the first out-of-home activity type and its destination choice of non-workers in the NCR are the most crucial choices defining the day's activity-travel pattern. Such findings are also consistent with Bhat and Misra (2001). The econometric formulation of CUSTOM also allows indirect capturing of serial correlations among subsequent participation choices. Estimated correlation coefficients clearly show that with increasing time-of-day such correlations changes from positive to negative values. This captures that fact that the tendency of making out-of-home trips reduces with time-of-day.

5.2. Activity type choice for first activity of the day

Activity type choice for the first activity of the day is modelled as a function of non-workers' personal attributes, household attributes and expected maximum utility of possible destination location choices. Table 3-Part 2 presents this model component. It is clear that the first activity type choice is influenced by the presence of children at home, homemaker status, unemployment, accesses to the private automobile, gender and household income. Alternative-specific constants are negative and capture the unexplained systematic preferences to different out-of-home activities to start the day with. It seems that the high number of children influences the choice of drop-off (perhaps to daycare or school) and recreational activities as the first activity of the day. Non-workers, who identify themselves as homemakers (as opposed to retired, jobless or unemployed) ceteris paribus, are most likely to choose drop-off, school and pick-up trips as the first trip of the day. However, they are least likely to choose work related activities, eating out in a restaurant, visiting, health/personal care recreation, and shopping trips as the first activity of the day.

A high number of vehicles (provided the person has a driving license) at home have both marginal and interaction (with having a driver's license) effects on first activity type choice of the non-workers in the NCR. A Higher number of vehicles at home increases the attractions of activities as the first trip of the day and even increases if the non-worker has a driver's license. For the unemployed non-workers looking for a job, the number of vehicles at home is a crucial factor influencing the choice of work related trips as the first activity of the day. A higher number of vehicles at home increase the choice

Table 3-Part 1
Scale parameters of the joint model.

	Parameters	t-Statistics
Time allocation choices		
Household size	0.252	50.72
Activity type choice of first activity of the day		
Constant	1.000	–
Additional Exponential Function to that of return home activity types for subsequent activity type choice:		
Out-of-home activity types		
Constant	8.432	0.97
Additional Exponential Function to that of out-of-home activity types for subsequent activity type choice:		
Activity location choice		
Constant	3.951	28.51
Number of vehicles at home & Having driving license	2.563	3.01

Table 3-Part 2
Systematic utility of activity type choice model for the first activity of the day.

	Parameters	t-Statistics
Constant		
Work-related activities	5.677	2.65
School	11.003	16.80
Shopping trips or trips for household maintenance	0.257	0.09
Restaurant (i.e., for a meal outside)	1.490	0.23
Recreation (e.g., going to the theatre)	4.745	8.73
Visit friends or family	8.490	50.75
Health and personal care (e.g., going to the doctor's office)	8.056	47.00
Dropping off	3.711	2.04
Picking up	4.956	2.89
Other purpose (not otherwise identified)	3.405	8.42
Number of children at home		
Recreation (e.g., going to the theatre)	0.112	1.00
Dropping off	0.573	5.71
Job status: Homemaker		
Work-related activities	1.161	3.99
School	0.839	2.06
Shopping trips or trips for household maintenance	0.340	4.08
Restaurant (i.e., for a meal outside)	0.990	3.32
Recreation (e.g., going to the theatre)	0.507	3.72
Visit friends or family	0.758	4.00
Health and personal care (e.g., going to the doctor's office)	0.666	4.36
Dropping off	0.897	6.08
Picking up	0.524	2.04
Other purpose (not otherwise identified)	0.574	4.04
Number of vehicles at home & Having driving license		
Work-related activities	0.292	3.56
Recreation (e.g., going to the theatre)	0.228	4.79
Visit friends or family	0.185	3.18
Picking up	0.349	2.22
Other purpose (not otherwise identified)	0.052	0.98
Number of vehicles at home, Having driving license & Unemployed		
Restaurant (i.e., for a meal outside)	0.352	1.56
Recreation (e.g., going to the theatre)	0.113	1.38
Dropping off	0.401	3.83
Gender: Male		
Health and personal care (e.g., going to the doctor's office)	0.411	3.78
Household income category: $30,000 to $59,999 per year		
Staying home whole day: No trips	0.065	0.79

the day. Male non-workers are less likely to choose health/personal care activity as the first activity of the day than the female non-workers.

income group (annual household income between $30,000 and $59,000) are most likely to be immobile than those from any other income groups.

5.3. Activity type choice for subsequent activities to the first out-of-home trip

Activity type choices subsequent to the first trip are modelled as a function of time-of-day, expected maximum utility of destination location choice, travel time and some socio-economic factors. Table 3-Part 3 presents this model component.

We accommodated the individual day-segment specific time-of-day coefficient in the model to capture the nonlinear relationship of time-of-day with subsequent activity type choices. In order to explain the parameters of the time-of-day variable, we estimated sample average (weighted by choice probability) marginal effects of time-of-day on activity type choices, and the marginal effect of accessibility (log sum of destination location choice) on activity type choices (Hensher et al., 2005). Considering the space constraints, Figs. 2a and 2b presented marginal effects of time-of-day on type choice (of the 2nd of the day for an example) activity of the day and marginal effect of accessibility of the first five activities of the day. It presents a clear picture of the time-of-day effect and accessibility to the activity-travel scheduling of non-workers in the NCR.

All out-of-home activity type choices are nested within the nest of return home choices. While the reference alternative varies for the out-of-home activity nest, the reference alternative for the return home nest is the return home for the rest of the day. The highest time-of-day effect is on school activity and it decreases with the time of day. Pick-up activities do not start before 9 am, rather after 9 am, the time-of-day has large positive effects in a choice of scheduling this activity type. The marginal effect of time-of-day on temporary return home activity is the highest between 9 am and 3 pm, but the lowest after 7 pm. It indicates that non-workers in the NCR are more likely to return home between 9 am and 3 pm to start another out-of-home activity later. This captures the home-based trip chaining patterns. Accessibility to destination locations has a positive marginal utility of all activity types. It validates the concept that higher accessibility (lower travel time to destinations and higher density of activity attractions) always influence more activity participations. However, changes in marginal effect of accessibility with increasing number of activity participating do not vary noticeably except for shopping and other activities. For these two activity types, it is clear that impact (positive) of accessibility increases with increasing number of activities in the day.

In terms of personal attributes, age and gender are found to be influential in out-of-home activity participation choices. It is clear that older non-workers are more likely to shop and perform recreational activities than younger people. Younger non-workers are more likely to participate in visiting friends/family and picking up activities. It is also clear that younger non-workers are more likely to make home-based tours as they are more likely to temporarily return home in between out-of-home trips in a day. Female non-workers in the NCR are more active than the male non-workers, which are reflected in gender-specific dummy variables. Male non-workers are only more likely to make work-related trips than female non-workers. Also, female non-workers are more likely to make shopping trips than male non-workers. Interestingly, it is clear than non-workers living in the single detached household are likely to return home earlier than those living in condos and apartments. These findings have an implication to health issues as the average age of non-workers is over 50 years and the majority of detached houses are far from the central business district. Similarly, workers from lower to middle-income households (between $30,000 to $90,000 per year) are likely to return home earlier than those living in higher income household.

5.4. Destination location choice model

The destination choice model presented in Table 3-Part 4 presents the model of the activity locations (destination) choice model component.

The systematic utility functions of destination choices are a function of land-use variables, round-trip travel time and expected maximum utility of next activity type choices (return home types and out-of-home activity types). Non-workers are most sensitive to travel time for other (undefined) activity type destination choice and least sensitive to restaurant destination choices. This indicates that non-workers are willing to travel longer distances to eat in a restaurant than for any other activity type. Interestingly, drop-off, pick-up and work-related activity destination choices have similar types of sensitivity to travel times that are lower than those of all other activity types except the restaurant. Drop-off and pick-up type activities are related to intra-household interactions and responsibilities of non-workers. Work-related activities are important for non-workers who are unemployed, homemakers or retired. Lower travel time sensitivity is intuitive for these types of activities.

It is clear that high population density at alternative destinations increases the potential for drop-off or pick-up activities, hence increasing the probability of being chosen for such activity destinations. Similarly, high population density reduces the attraction of alternative destinations for shopping, recreational, work-related and other activity types of non-workers. The distance from the central business district (CBD) defines the relative position of an alternative destination location in the context of the urban form. It is clear that the destination of non-workers for drop-off and pick-up activities is more likely to be closer to the CBD. We did not have information in the dataset to identify the further type of drop-off and pick-up activities, but this finding infers that perhaps such drop-off and pick-up activities are related to facilitating other household

Table 3-Part 3
Systematic utility of activity type choice models for activities subsequent to the first trip of the day.

	Parameters	t-Statistics
Constant		
Work-related activities	8.546	8.06
School	11.698	11.46
Shopping trips or trips for household maintenance	8.304	13.64
Restaurant (i.e., for a meal outside)	7.373	19.64
Recreation (e.g., going to the theatre)	8.659	6.99
Visit friends or family	9.364	8.76
Health and personal care (e.g., going to the doctor's office)	10.739	14.86
Dropping off	9.119	19.10
Picking up	4.980	3.36
Return home temporarily	0.622	0.97
Time-of-day as fraction of 24 h: Before 9 am		
Work-related activities	3.451	1.75
Shopping trips or trips for household maintenance	6.374	6.55
Restaurant (i.e., for a meal outside)	2.400	1.58
Recreation (e.g., going to the theatre)	4.945	2.10
Health and personal care (e.g., going to the doctor's office)	3.277	1.38
Dropping off	6.521	6.09
Return home temporarily	19.333	33.22
Time-of-day as fraction of 24 h: Between 9 am and 3 pm		
Work-related activities	1.764	2.01
School	5.044	2.79
Shopping trips or trips for household maintenance	4.296	7.79
Restaurant (i.e., for a meal outside)	1.528	2.53
Recreation (e.g., going to the theatre)	3.866	2.79
Visit friends or family	6.603	8.01
Health and personal care (e.g., going to the doctor's office)	6.536	5.24
Picking up	6.176	3.51
Return home temporarily	6.729	19.22
Time-of-day as fraction of 24 h: Between 3 pm and 7 pm		
Work-related activities	0.732	1.41
School	3.063	3.59
Shopping trips or trips for household maintenance	1.490	5.06
Restaurant (i.e., for a meal outside)	1.208	4.05
Recreation (e.g., going to the theatre)	2.596	3.53
Visit friends or family	3.701	8.46
Health and personal care (e.g., going to the doctor's office)	2.400	3.59
Dropping off	0.273	1.43
Picking up	3.729	3.73
Return home temporarily	2.065	10.30
Time-of-day as fraction of 24 h: after 7 pm		
Shopping trips or trips for household maintenance	0.750	1.96
Recreation (e.g., going to the theatre)	2.062	2.28
Visit friends or family	3.367	5.91
Health and personal care (e.g., going to the doctor's office)	1.444	1.52
Picking up	3.043	2.56
Logarithm of age in years		
Shopping trips or trips for household maintenance	0.552	4.23
Recreation (e.g., going to the theatre)	0.242	1.02
Visit friends or family	0.309	1.33
Picking up	1.752	6.03
Return home temporarily	0.464	3.01
Gender: Male		
Work-related activities	0.544	2.13
School	1.418	2.06
Shopping trips or trips for household maintenance	0.213	3.33
Restaurant (i.e., for a meal outside)	0.323	1.83
Recreation (e.g., going to the theatre)	0.324	2.56
Picking up	0.272	1.59
Logarithm of travel time (minutes) to home		
Return home temporarily	0.407	12.71
Logarithm of travel time (minutes) to home & Unemployed		
Return home temporarily	0.338	3.05

Table 3-Part 3 (*continued*)

	Parameters	t-Statistics
Return home for rest of the day	0.168	3.88
Household income: Income un-disclosed		
Return home for rest of the day	0.075	1.48
Household income:: between $60,000 and $89,999 per year		
Return home for rest of the day	0.278	4.86
Household income: between $30,000 and $59,999 per year		
Return home for rest of the day	0.233	3.00

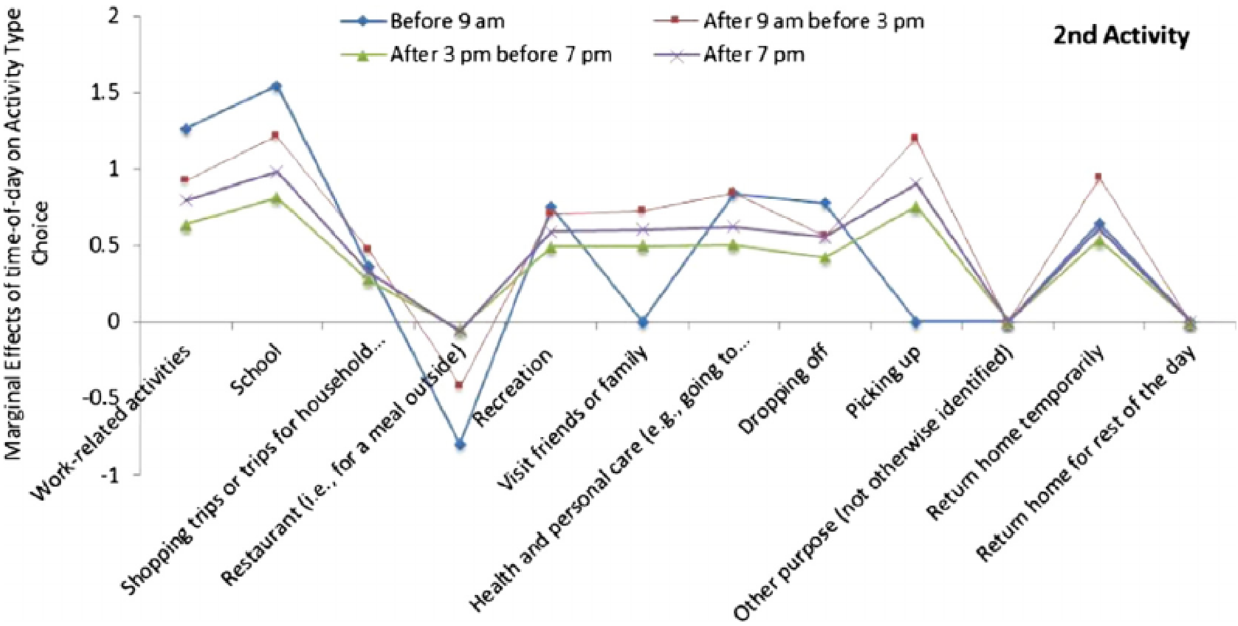

Fig. 2a. Marginal effects of time-of-day variable on activity type choices.

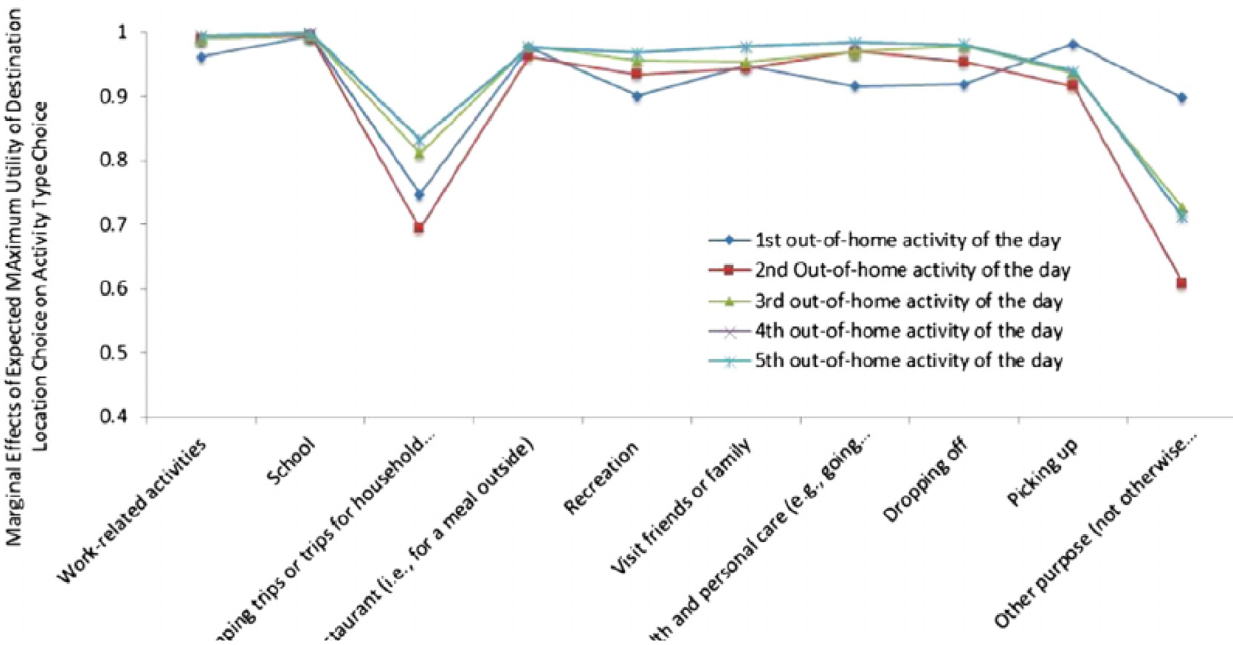

Table 3-Part 4
Systematic utility of activity (destination) location choice model.

	Parameters	t-Statistics
Logarithm of round-trip (home-destination-home) travel time (minutes)		
Work-related activities	0.385	5.54
School	0.483	3.45
Shopping trips or trips for household maintenance	0.655	33.57
Restaurant (i.e., for a meal outside)	0.629	11.07
Recreation (e.g., going to the theatre)	0.613	19.84
Visit friends or family	0.553	14.31
Health and personal care (e.g., going to the doctor's office)	0.411	9.61
Dropping off	0.650	14.66
Picking up	0.643	12.62
Other purpose (not otherwise identified)	1.294	51.22
Logarithm of population density per capita at destination zone		
Work-related activities	0.671	3.56
Shopping trips or trips for household maintenance	0.461	12.14
Recreation (e.g., going to the theatre)	0.396	5.43
Dropping off	0.318	2.65
Picking up	0.285	3.08
Other purpose (not otherwise identified)	1.161	20.27
Logarithm of distance of destination zone from the CBD in km		
Work-related activities	0.641	2.38
School	0.340	1.08
Shopping trips or trips for household maintenance	0.481	10.98
Restaurant (i.e., for a meal outside)	0.565	5.12
Recreation (e.g., going to the theatre)	0.583	8.15
Visit friends or family	0.223	2.46
Health and personal care (e.g., going to the doctor's office)	0.250	2.09
Dropping off	0.051	0.35
Picking up	0.200	1.68
Other purpose (not otherwise identified)	2.821	76.71
Logarithm of employment density per capita at destination zone		
Work-related activities	0.153	1.05
Logarithm of shops and services density per capita at destination zone		
Shopping trips or trips for household maintenance	0.393	0.98
Logarithm of restaurant density per capita at destination zone		
Restaurant (i.e., for a meal outside)	1.012	1.08
Logarithm of employment density per capita at destination zone		
Dropping off	0.273	3.63
Picking up	0.273	3.63
Logarithm of schools/colleges/university density per capita at destination zone		
Dropping off	1.332	5.50
Picking up	1.332	5.50

drop-off and pick-up types, non-workers tend to choose locations far from the CBD. This indicates that non-workers may not contribute to traffic congestion towards the city centre, unlike workers in the NCR. Shopping and restaurant density variables show a counter-intuitive sign and are also statistically insignificant. So, these variables should be removed as there is no apparent effect.

5.5. Time expenditure choices

Time expenditure choices are modelled in a holistic manner. Departure time for the first trip of the day is modelled as continuous-time expenditure choice at home before the first trip choice. It is presented in Table 3-Part 5.

Similarly, time expenditure choices for all other activities subsequent to the first out-of-home trip are modelled as a continuous choice and are presented in Part 6 of Table 2. We found it difficult to explain the baseline utility of time expenditure at home before first out-of-home activity. However, it is clear that the expectation of making out-of-home trips, number of children at home and unemployment status define the satiation of time expenditure at home before the first out-of-home activity of the day. Expected maximum utility of activity type choices has a negative effect on satiation indicating that higher expectation of making out-of-home trips reduced time expenditure at home before the first trip. However, the presence of children at home changes the scenario as the high number of children increases the tendency to spend more time at home before the first trip of the day.

Table 3-Part 5
Time expenditure choice model.

Baseline utility function	Parameters	t-Statistics
Constant:		
Work-related activities	2.177	8.01
School	3.700	8.38
Shopping trips or trips for household maintenance	3.296	51.36
Restaurant (i.e., for a meal outside)	3.086	17.77
Recreation (e.g., going to the theatre)	2.732	21.23
Visit friends or family	2.806	16.23
Health and personal care (e.g., going to the doctor's office)	2.651	19.13
Dropping off	5.147	73.18
Picking up	4.517	52.47
Other purpose (not otherwise identified)	2.921	25.84
At-home activities	3.971	40.03
Satiation parameter for All Activities Subsequent for First Trip of the Day		
Expected Maximum Utility of Next Activity Type Choices		
Work-related activities	0.090	5.58
School	0.111	3.56
Shopping trips or trips for household maintenance	0.047	9.34
Restaurant (i.e., for a meal outside)	0.071	4.94
Recreation (e.g., going to the theatre)	0.076	11.13
Visit friends or family	0.107	10.73
Health and personal care (e.g., going to the doctor's office)	0.048	6.28
Dropping off	0.080	7.19
Picking up	0.054	3.16
Other purpose (not otherwise identified)	0.081	10.18
At-home activities	0.092	9.39
Gender: Male		
All activity types	0.034	4.68
Start time-of-day as fraction of 24 h		
Work-related activities	0.769	7.50
School	1.417	4.33
Shopping trips or trips for household maintenance	0.568	16.37
Restaurant (i.e., for a meal outside)	0.757	8.01
Recreation (e.g., going to the theatre)	0.749	12.81
Visit friends or family	0.949	11.36
Health and personal care (e.g., going to the doctor's office)	0.477	8.19
Dropping off	1.979	16.50
Picking up	0.810	9.51
Other purpose (not otherwise identified)	0.873	16.28
At-home activities	1.366	17.83

utility is explained as a function of activity type-specific constant. Baseline systematic utility refers to marginal preference at the point of zero-time expenditure. A positive baseline utility indicates a willingness to participate in current activity against saving time for the rest of the day and vice versa. It seems that the sample average baseline utility of time expenditure to at-home before the first activity is positive, but are negative for all other subsequent activities. This indicates that non-workers prefer spending more time at home before starting any out-of-home activity and prefer to return home to spend time for the rest of the day at home. This is somewhat opposite to the findings for the workers in the NCR by Habib (2015).

Satiation effect explains how changes in marginal utility happen with increasing time expenditure. Expected maximum utility of next activity type choices, gender and start time of the activity define the satiation of time expenditure choices to the scheduled activities. Activity start time plays a balancing role against the effect of expected maximum utility of next activity type choices. Expected maximum utility of subsequent activity type choices (which also encapsulated accessibility to destination locations) reduces satiation parameters of time expenditure choice to an ongoing activity. This indicates that the non-workers' preference to time expenditure reduce if he/she has higher expectations to conduct further activities. Interestingly, non-workers tend to shorten time expenditure to ongoing dropping off and picking up activities the most if she/he has a higher expectation of making further out-of-home activities. On-going work related and health/personal care activity durations are least affected by the expectations of further out-of-home activities. On the other hand, the start time of the activity has positive effects that vary across the activity types. In general, school, dropping off and at home in between trips have the highest effects of time-of-day referring to the fact that if these activities are scheduled at the later part of the day, time expenditures to these activities become higher.

6. Conclusions, policy relevance and recommendations for Future research

The main objective of this paper is an empirical investigation of the activity-travel behaviour of non-workers, e.g., homemakers, retirees and unemployed individuals who share a significant portion of the urban population. The research uses 2011 household travel survey datasets of the NCR of Canada for the empirical investigation. The empirical model clearly reveals that non-workers in larger-size households have lower variances in time expenditure choices (hence more predictable patterns of out-of-home activity-travel patterns) than their counterparts in smaller-size households. The nesting structure of the empirical model reveals that the first out-of-home activity type and its destination location choice of non-workers define the pattern of the whole day's activity-travel schedules of non-workers. The presence of a high number of children at home reduces the flexibility of choosing out-of-home activity types for non-workers. The availability of a private car increases flexibility and thereby increases randomness in destination choices of out-of-home activities of non-workers.

Non-workers are found to be the least sensitive to travel time in the case of location choices of restaurants for meals. Also, travel time sensitivity of non-workers is low for destination choices of household responsibility type activities, e.g., drop-off and pick-up. In terms of destination choice patterns, non-workers tend to choose destination locations of all trips (except drop-off and pick-up) far from the CBD. This indicates that non-workers do not contribute to inbound traffic congestion to the CBD as much as the workers do. It is also clear that the drop-off and pick-up type activities of non-workers in the NCR are mainly to facilitate other household members in work or school or daycare drop in type trips. Overall, male non-workers are less active than the female non-workers.

In terms of age, older non-workers make less home-based trip chains than their younger counterparts. This has health implications as higher home-based trip chains may induce a higher number of short trips making the non-workers more active, and the average age of the non-workers in the NCR is over 50 years. Non-workers who are interested in out-of-home activities (and draw high expectation of utilities in activity participation) are most likely to start the day late, likely to avoid peak-period congestion. Investigating the marginal effect clarifies that the accessibility to destination locations is more influential to the time-of-day effect for most of the activity types. In the destination choice model, it is clear that in addition to travel time, the attraction of places for different activities, defined by the density of corresponding activity centres and distance from CBD, plays a major role in defining the accessibility of non-workers. The policy relevance of this finding is that increased high-density mixed use development in the NCR will increase the attractiveness of out-of-home activity participation of non-workers.

In terms of activity episode durations, the empirical models reveal that non-workers in the NCR prefer spending time visiting, health/personal care, shopping and recreational activities. This finding has regional economic implications as such activities tend to facilitate economic activities in the region. As we found in activity type and location choice components that non-workers tend to participate more in school, drop-off and pick-up activities, the time expenditure choice model component reveals that they tend to spend a shorter duration of these activity types than all other activity types.

From the overall travel demand point of view, the non-worker population contributes a significant share of the total urban traffic, and their activity-travel patterns are more flexible than those of the workers. From a more socio-economic point of view, non-workers often take on more activities related to household and social needs that involve more money expenditure than the workers who need to spend a large part of their day doing work activity to earn money. So, in addition to the travel demand perspective, non-work activity-travel behaviour is also important to home-economic perspectives.

The empirical investigation presented in this paper can be improved in several ways. Intra-household interactions are not modelled explicitly in this investigation but are accommodated in an implicit manner through the incorporation of the household-level variables. Explicit modelling of intra-household task and resource allocation would make it easier to be specific in identifying contributions of non-workers' roles in urban travel demands. The related efforts should be the integration of a mode choice model within the CUSTOM system. These will be the next steps of this investigation.

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