A JOINT ECONOMETRIC ANALYSIS OF TEMPORAL AND SPATIAL FLEXIBILITY OF ACTIVITIES, VEHICLE TYPE CHOICE AND PRIMARY DRIVER SELECTION

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ABSTRACT

The current research effort examines the relationship among four individual level daily activity travel choice processes: spatial flexibility of the activity, temporal flexibility of the activity, activity vehicle choice, and primary driver (for auto users). Activity flexibility (spatial and temporal) has been suggested as a precursor to the observed activity travel pattern. The study examines the impact of activity flexibility through a unique data drawn from Quebec City, Canada from 2003 – 2006. In traditional travel behavior literature, vehicle fleet decisions are examined as a long term choice with annual usage metrics. However, the long-term vehicle usage observed (as studied in literature) is an aggregation of the household's yearly vehicle type and usage behavior. Only recently, travel behavior models have started examining vehicle usage decisions (type and mileage) as a short-term decision. By examining short term vehicle usage we explore, at a disaggregate level, the interaction of activity behavior (defined as flexibility) and vehicle type choice. A panel mixed multinomial logit (MMNL) model was applied to analyze the four choices within the decision process to account for the intrinsic unobserved taste preferences across individuals. The analysis results revealed that several individual and household socio-demographic characteristics, residential location and activity attributes as well as contextual variables influence the packaged choice of temporal flexibility, spatial flexibility, vehicle type choice and primary driver selection. We also identify the presence of common unobserved attributes among the choice alternative dimensions.

Key words: Temporal flexibility, spatial flexibility, out-of-home activity, primary driver, panel data

INTRODUCTION

Motivation

Transportation is a significant contributor to global greenhouse gas (GHG) emissions [1]. Overall, it accounts for 14 percent of the total emissions while road transportation alone accounts for about 76 percent of the total transportation emissions [2]. Increased dependency on private automobiles for daily travel is exacerbating the situation. In fact, 82% of Canadian commuters currently drive to work, compared to only 12% who take public transit and 6% who walk or bike [3]. The largest sources of transportation-related GHG emissions include passenger cars and light-duty trucks, including Sports Utility Vehicles (SUVs), pickup trucks, and minivans. These emissions not only degrade the environment, but affect various aspects of human health adversely [4]. Given the contribution of private vehicle emissions, it is not surprising that travel behavior researchers have examined household vehicle fleet choices (number, type and usage) extensively. Traditionally, vehicle fleet decisions were examined as a long term choice with annual usage metrics (see Anowar et al [5] for a review of vehicle ownership studies). Only recently, travel behavior models have started examining vehicle usage decisions (type and mileage) as a short-term decision [see 6-8] in the context of activity travel analysis.

The emphasis of the literature on short term vehicle usage is on exploring the interaction of activity participation behavior with the vehicle type chosen on a per activity basis. The long-term vehicle usage observed (as studied in literature) is an aggregation of the household's yearly vehicle type and usage behavior. Thus by examining short term vehicle usage we explore, at a disaggregate level, the interaction of activity behavior and vehicle type choice. For activity based models, the long-term models will serve as control totals for vehicular usage while the short-term models will allow for enhanced prediction of daily vehicle type choice and usage. With the growing emphasis on emission modeling based on daily travel patterns it is important to accurately predict vehicle type choice at an activity level. The current research contributes to our understanding of short term vehicle usage decisions by examining four activity travel choice processes: spatial flexibility of the activity, temporal flexibility of the activity, activity vehicle choice (characterized as vehicle type for auto users and other for non-auto users), and primary driver (for auto users).

We employ a longitudinal panel survey of households in the Quebec City region of Canada, comprised of three waves, about one year apart and carried out from 2003 through 2006. The survey attempts to investigate respondent's perceptions of temporal and spatial flexibility in the organization of their activities. The data collection procedure included a unique training process for respondents on how to classify every activity that they executed, in or out of the home, according to whether they were ‘‘routine” (or habitual), ‘‘pre-planned” (or pre-arranged) or ‘‘impulsive” (or spontaneous) in time and space. The current study explores interconnectedness of the flexibility of activities in space and time with the short term vehicle type choice and primary driver allocation.

Earlier Work

Of the four activity travel choices under consideration, vehicle type choice has received significant attention. Broadly, vehicle type choice studies can be classified into two major categories: (1) long-term[1] and (2) short-term. The relevant studies for our study are the short term studies. For example, Konduri et al [6] and Paleti et al [7] have explicitly modeled vehicle type choice in tour-based models. Both of these studies used mixed multidimensional choice model systems to better understand the complex relationship between different tour attributes (e.g. tour length, tour complexity) and the type of vehicle used to undertake the tour by individuals in a household. At the activity level, Faghih-Imani et al [8] applied mixed multiple discrete continuous extreme value (MMDCEV) framework to examine daily vehicle type and usage decisions while incorporating the influence of activity type and accompaniment type choices.

Research efforts concerning the effect of perceived flexibility of activities are comparatively fewer in number. Recently, researchers examined how the trips and activities are considered and adopted for execution, i.e. individual's perception of activity attribute and its impact on activity scheduling. For instance, Mohammadian and Doherty [9] reported that temporally and spatially flexible activities are more likely to be impulsive or near-impulsive since they need less time to plan. In a later study [10], the authors modeled the duration of time between planning and execution of pre-planned activities using the same dataset. The findings of these two studies suggested that in addition to conventional activity and individual attributes, flexibility/fixity of activities plays an important role in the choice of activity-planning sequence. Based on their findings, the authors alluded to a possible interdependency between spatio-temporal flexibility and activity-travel attributes.

Individual's perception of spatial and temporal flexibility of activity was investigated by Miranda-Moreno and Lee-Gosselin [11] and Lee-Gosselin and Miranda-Moreno [12] using data from Quebec City, Canada (same dataset explored in our current research). In the first study, they explored the activity travel patterns of baby-boomers to find out whether they lived lives that are highly routine or flexible. In the latter study, they examined the impact of information and communication technologies (ICT), on the frequency of different temporally and spatially flexible categories of the executed out-of-home activities. They reported that access to mobile phones was associated with the propensity to pre-arrange activities both in time and in space, while internet was significantly and negatively associated with the number of habitual activities, again in time and in space.

Finally, the primary driver choice has received attention more recently in travel behavior literature. Households acquire different vehicles to satisfy various transportation needs while accommodating for preferences of the household members. In multiple vehicle households, individuals routinely face vehicle type decisions for activity participation. For instance, Kitamura et al [13] reported that male primary users are more likely to use pickup trucks, and younger people are more likely to use sports cars, SUVs, and pickup trucks. People with college degrees or long-distance commuters are more likely to use four-door sedans. A decade later, Vyas et al [14] conducted another study using vehicle survey data from California. The authors found that middle aged, senior and female drivers prefer SUVs and that workers and female drivers have an inclination to drive newer cars.

Methods

With the push toward integrated modeling approaches, there is growing literature in travel behavior on accommodating the possible interdependency across the choice dimensions in the modeling

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[1] For a comprehensive review of the studies on long term vehicle fleet decisions (size, composition and use), the readers are referred to Anowar et al [5].

framework. One of the simplest approaches employed in literature is to ignore these inter-dependencies and apply a sequential approach to modeling multiple choice dimensions. The approach is intuitive and easy to employ in practice. However, in this approach not only do we neglect interdependencies between choices, but there is also the question of which sequence to be employed [15-17][2]. An alternative approach accommodates for the interdependency between multiple choices by tying together the unobserved components of the various choices using appropriate distributional assumptions yielding a multivariate joint choice model framework. The approach, while mathematically appealing, requires extensive simulation for model estimation [see 18-21].

A third approach involves considering the multiple choice processes as a package of decisions made simultaneously. In this approach, every alternative from each choice is coupled with alternatives from other choices to yield a set of combination alternatives. The exact number of combination alternatives generated is obtained by computing the product of number of alternatives for all choice processes [see 8, 22-23]. The approach, while resulting in an explosion of the number of alternatives, accommodates the dependencies between choices through the systematic component. Further, the methodology employed to study the influence of exogenous factors is usually based on traditional modeling approaches – thus making it a more appealing framework for practice and policy analysis.

Current Research Focus

Our current research attempt falls within the last category of methodology efforts. Specifically, we consider four choices – spatial flexibility, temporal flexibility, activity vehicle type choice, and primary driver (for auto users) - as a packaged choice. To model the choice dimensions, we adopt a panel mixed multinomial logit (MMNL) model that accounts for the intrinsic unobserved taste preferences across multiple records for each individual from the longitudinal survey. The data used in the paper is drawn from a panel survey conducted in Quebec City, Canada from 2003 – 2006.

DATA

The primary data used in the current analysis were collected using a longitudinal panel survey of households in the Quebec City region of Canada. The survey, titled "Quebec City Travel and Activity Panel Survey (QCTAPS)", is comprised of three waves, about one year apart for a given household and was carried out from 2003 through 2006. This section of the paper first describes the survey instrument with primary focus on the elements relevant to this analysis, and subsequently presents a descriptive analysis of the data sample used for model formulation.

Survey Instrument

The QCTAPS employed a multi-instrument package known as OPFAST (Observed and Perceived Flexibility of Activities in Space and Time) to investigate the decision processes employed by individuals and households to organize their activities in space and time. Specifically, the survey attempts to investigate respondent's perceptions of temporal and spatial flexibility in the organization of their activities. Part of the instrument was an executed activity/travel diary that

[2] The exact sequence of the choice processes has significant implications for policy analysis. More recently, a latent segmentation approach that simultaneously allows for different causal structures has been proposed [24]. However, the approach is applicable to choice contexts with a small number of dependent variables.

covered seven consecutive days in wave 1 and two days in the second and third waves. For our analysis, an individual is the unit of analysis for the panel data where repetition of observations of the same individual are accommodated. Information reported in the travel diaries was validated and augmented by a home interview following the diary week, including the geographical location of each activity. A total of 250 households took part in the survey and a high retention rate of 67% was observed from wave 1 to wave 3.

A unique feature of the survey was that respondents were trained to classify every activity that they executed, in or out of the home, according to whether they were ‘‘routine” (or habitual), ‘‘planned” (pre-arranged) or ‘‘impulsive” (or spontaneous) in time and space – using a trichotomy suggested by Garling et al [25]. The distinction between planned and impulsive is that, for the latter ‘‘one hour in advance, I did not know [that] (temporal dimension) [where] (spatial dimension), I was going to do the activity” (see Lee-Gosselin and Miranda-Moreno [12] for more detailed classification of activities by their degree of spatial and temporal spontaneity, with examples). The multi-instrument package OPFAST is described in more detail in Lee-Gosselin [26].

Choice Set Formation and Descriptive Statistics

The following steps were followed for creating the choice set for our analysis. First, from the activity file, the out-of-home activities were separated out. Second, the several dimensions of analysis were characterized. *Perceived temporal flexibility and spatial flexibility* of activity is categorized as: (1) Routine, (2) Planned, and (3) Impulsive. The *vehicle type alternatives* are classified as: (1) Compact sedan, (2) Large sedan, (3) Van and Minivan, (4) Sports Utility Vehicle (SUV), (5) Pick-up and Trucks and (6) Other vehicles including walking, biking, and transit – these vehicle types are available to every individual for any out-of-home activity. The choice set from which households make their choices is defined by the available alternatives in the data set. Hence, the vehicle type dimensions are appropriately matched with the household vehicle ownership information (*i.e.* if a household does not own a SUV, the individual will not have alternatives corresponding to SUV available to him/her for the activity). For the purpose of our analysis, we considered as many drivers as there were adults in the household and assigned them with numbers for identification. In the dataset, a maximum of four adults are present, hence, the *driver* dimension comprised a maximum of four alternatives. Third, the MNL model component alternatives are formed as combinations of three perceived temporal flexibility alternatives with the three perceived spatial flexibility options, six travel vehicle type choice alternatives and four driver options. Overall, these categories resulted in a total of 216 discrete alternatives (3*3*6*4). Of course, the reader would recognize that across different individuals the number of alternative available will change based on vehicle fleet available and number of adults in the house.

The database contained a total of 46,730 activity records comprising of both in-home and out-of-home activities. Of these, 14,579 activities were conducted out-of-home. After removing inconsistent and missing/miscoded values, we were left with 8,098 usable out-of-home activity records of 234 households and 378 individuals. Of these households, only 8.1 percent were carless, more than 50 percent owned one private vehicle, approximately 30 percent owned two vehicles, and 6.4 percent owned three or more vehicles. Moreover, the driver count indicated that 49.6 percent of them had one driver, 46.2 percent had two drivers, 3.8 percent had 3 drivers and 0.4 percent had 4 drivers.

Table 1 provides descriptive statistics for this sample of out-of-home activities. Several interesting features can be observed from the Table. For instance, across all activities, the percentage of temporally planned activity undertaking (36.3%) is slightly lower than temporally routine activity execution (37.7%). In terms of vehicle type choice, as expected, compact sedans have the largest share (41.7%) while other vehicles alternative has a reasonable share (27.0%). Across temporal flexibility and vehicle type combination, compact sedan for routine activity is the most prevalent combination. It is interesting to note that, among activities undertaken using SUV, planned activities are common. Not so surprisingly, the largest share for other vehicle alternative is for temporally routine activities. Across all activities, spatially routine activities are the most common. Similar to the temporal flexibility the most common combination for spatial flexibility is the routine and compact sedan. In the case of activities pursued by SUV, spatially routine activities are preferred. Again, similar to temporal flexibility, the largest share for other vehicle alternatives is for spatially routine activities. Also, observed from the descriptive analysis is a clear trend of distinct proportion of vehicle type usage by temporal and spatial flexibility. The trend is particularly strong for spatial flexibility. For instance, for spatially planned activities, the vehicle type chosen ranges from 19.7 percent (for other) through 44.3 percent (pickups/trucks). We also observed (between the activity flexibility types themselves) that 18 percent of the spatially routine activities are temporally impulsive. At the same time, only 3.6 percent of activities are temporally routine but spatially impulsive highlighting the complex interaction between spatial and temporal flexibility.

The distribution of temporal flexibility, spatial flexibility and vehicle type dimensions by selected individual socio-demographic characteristics is presented in Table 2. Several observations can be noted from the Table. *First,* males perform more temporally and spatially routine activities while women engage themselves more in planned activities. For vehicle choice, compact sedan is the preferred alternative for all individuals. *Second,* temporally fixed activities are conducted more by middle aged persons; seniors prefer planned and impulsive activities both spatially and temporally. It is interesting to see the involvement of young persons in spatially routine activities. If a personal vehicle is used in the activity execution, young people mostly use compact sedans; seniors use large sedan. *Third,* as expected, university degree holders prefer routine activities and they use more compact sedans relative to non-university degree holders.

ECONOMETRIC FRAMEWORK

In this analysis, we use a panel mixed multinomial logit (MMNL) model formulation. Let i be the index for the discrete choice combination of activity flexibility (temporal and spatial), activity vehicle type choice and primary driver choice ($i = 1, 2, \ldots I$). With this notation, the random utility formulation takes the following familiar form (index for individual is suppressed):

$$U_i = \beta_i{}' x_i \ + (\mu_i + \eta_i) \tag{1}$$

In the above equation, U_i represents the utility obtained by the q^{th} individual in choosing the i^{th} alternative. x_i is a vector of attributes influencing the choice framework. β' is a corresponding vector of mean coefficients. μ_i and η_i form the complete error term. The first component μ_i is an idiosyncratic error term assumed to be identically and independently type-1 extreme value distributed (tied to the number of activity records in the dataset) while the second term η_i is a vector of normal random terms with zero mean (tied to the number of individuals in the dataset). According to the utility maximization principle, an individual q will choose the alternative that offers the highest utility. The unconditional probability expression for choosing alternative *i* across a series of activities for individual q is given by:

$$P_i = \int \prod_{t=1}^{T} \frac{\exp\ [\beta' x_i + \eta_i]}{\sum_{j\epsilon C} \exp\ [\beta' x_i + \eta_i]} d\boldsymbol{F}(\eta_i) d\eta_i \tag{2}$$

where *C* represents the choice set for individual q and *T* represents the number of records per individual. The log-likelihood function is constructed based on the above probability expression and maximum simulated likelihood (MSL) estimation is employed to estimate β' parameters. For this particular study, we use a quasi-Monte Carlo (QMC) approach with 150 draws for the MSL estimation (see Bhat [27] for more details).

EMPIRICAL ANALYSIS

Variable Specification

Several categories of exogenous variables were considered in the model including individual and household socio-demographics, household residential location characteristics, activity attributes and contextual variables. The *individual socio-demographics* considered are: gender, age, education, and cellular phone usage. *The household and residential attributes* considered include household income, dwelling type, family type and location of household. The residential location and type variables capture attributes of a household's activity–travel environment. Three types of *activity attributes* were considered in our analysis: activity location, activity type and accompaniment type. In terms of *contextual variables*, we included season and day of week. The choice of these independent variables was guided by prior research on activity-based modeling and also constrained by data availability. Note that in the current context, we do not have any alternative specific variables for drivers since the driver alternatives are *unlabeled* and characterized by driver attributes. Moreover, it is not possible to evaluate the effect of household and residential location characteristics on primary driver selection directly.

The final variable specification was based on a systematic process of removing statistically insignificant variables (in our analysis we considered 90 percent significance level), combining and constraining variables when their effects were not significantly different. Estimating all potential exogenous variable effects for all of the alternatives (up to 216) would result in a cumbersome and likely inefficient model specification. Hence, in this paper, variable effects are considered across the four dimensions. This allows capturing majority of the exogenous variable impacts while retaining a fairly parsimonious model specification (see Faghih-Imani et al [8] for a similar analysis).

Estimation Results

The model estimation process began with the estimation of the traditional MNL model. Next, the panel mixed MNL model was estimated. After extensive specification testing, the final log-likelihood values at convergence of the MNL and MMNL models were found as: -20363.23 and -19977.52, respectively. The improvement in the data fit clearly demonstrates the superiority of the MMNL model over its traditional counterpart. The Log-likelihood Ratio (LR) test comparison between the MMNL and MNL model yields a test statistic value that rejects that hypothesis that all the models are similar at any reasonable level of significance. Hence, in the subsequent sections, we discuss about the results of the MMNL model only.

The final specification results of the joint model are presented in Table 3 (the t-stats are presented in parentheses). A positive (negative) coefficient for a certain variable-category combination means that an increase in the explanatory variable increases (decreases) the likelihood of that alternative being chosen relative to the base alternative. A blank entry corresponding to the effect of variable indicates no statistically significant effect of the variable on the choice processes. In the following sections, we discuss the effects of variables by variable category.

Constants

The constant term clearly indicates that there is a greater probability of temporally pre-planned activities being pursued. Spatially impulsive activities are the least likely to be chosen as evidenced by the high negative constant relative to other flexibility indicators. Among the vehicle type themselves, SUVs and sedans (both compact and large) are the most likely vehicle type choice for out-of-home activity participation, if they are available. On the other hand, vans/mini-vans and pick-ups/trucks are the least likely vehicle type choice.

Within the set of constant parameters, the impact of wave indicator was examined. Specifically, these indicators are expected to capture the across wave variations. The effect of the wave dummy variable was found significant for both types of activity flexibility and vehicle type choice. We observed that individuals in wave 1 were more inclined towards performing routine and pre-planned activities. The negative coefficient for spatial flexibility indicates that individuals were less likely to take part in pre-planned or impulsive activities. Compact sedan has higher propensity of being chosen compared to large sedan, vans/minivans and SUVs.

Individual Socio-demographics

The parameter estimates for individual demographic characteristics underscore their importance on daily activity travel decisions. We find that females are unlikely to drive sedans and vans/minivans. In terms of the role of primary driver, we find that females are more likely to be assigned to the responsibility relative to men. The result might be explained in light of the fact that compared to men, women are in charge of taking care of kids and they pursue more household chores which might require them to be the primary driver of the household.

We introduced age as dummy variables since they provided the best model fit. Our analysis results regarding young aged people supports the notion that they are more likely to perform temporally impulsive activities [9]. People of this age also tend to be disinclined to use compact sedans and vans/minivans for activity engagements. The choice of vehicles of young people might be driven by their preference for environmentally friendly alternatives (such as transit and active forms of transportation) or personal view towards the vehicles - i.e. they might think sedans and vans as *"boring"* and hence, they would rather drive the stylish SUVs or rugged pick-up trucks. Also, young individuals are likely to be designated primary drivers relative to middle aged individuals. This is plausible because these individuals are likely to be living alone and do not share their car with anyone. Seniors are found to be indifferent towards any type of activity flexibility indicators which is understandable since people of this age are generally free from fixed employment and have the liberty to pursue activities at their will without any time and space constraint. With respect to vehicle type choice dimension, seniors have a lower preference for compact sedans and SUVs for out of home activities. Similar to young individuals, seniors are likely to be designated primary drivers in their household.

Turning to education effects, household members with university degree and greater level of education are averse to performing spatially pre-planned activities. These individuals prefer vans/minivans as their vehicle choice. Individuals' education levels are certainly correlated to their occupations and income [28]. As such, they are more inclined towards routinized life and driving large vehicles such as vans/minivans. For the same reasons, they are also more likely to be the primary driver of the household. Contrastingly, individuals with diploma degrees tend to engage more in temporally impulsive activities and less in spatially pre-planned activities. Large sedans, vans/minivans, and pick-ups/trucks are their preferred choice of vehicle for activity participation. Non-usage of cell phones is significantly and negatively associated with temporally and spatially pre-planned and impulsive activities and these individuals are disinclined to use large sedan for performing their out-of-home activities.

Household Socio-demographics

Among household demographics, several behaviourally intuitive yet interesting findings were observed. For instance, individuals residing in single-detached dwellings are more likely to undertake temporally pre-planned as well as impulsive and spatially pre-planned activities. For travel, they tend to prefer sedans. The single detached dwelling housing stock is predominantly owner-occupied and located in low density areas. Preference for luxury cars of this type of households is noted in the literature [13]. Moreover, residents of apartment are more likely to use compact sedans for their activity participation. Both medium and high income is negatively associated with temporal flexibility meaning that individuals belonging to these households are less likely to take part in planned or impulsive activities, presumably reflecting their time constraints resulting from job commitment issues. Members from medium income households are more disinclined towards spatially pre-planned activities. Similar vehicle type choice preference is observed between the members of these two types of households. Individuals from medium income group are more likely to opt for large sedans and vans/minivans for their activity participation while members of affluent households prefer both vans/minivans and SUVs [13, 29].

An individual from a household with children is disinclined to engage in temporally pre-planned or impulsive activities presumably owing to the responsibility of tending to the child/children; individuals from these households might have decreased ability or desire to take part in activities which are planned in a short period of time. They are more likely to choose van/minivan for their activity execution. The results are intuitively understandable - for chauffeuring kids they use vans/minivans since these vehicles are more spacious, safe and comfortable for travel with children [29]. Very interestingly, individuals belonging to a childless household are also unlikely to pursue non-routine activities and avoid large sedans for travel.

Household Residential Location Attributes

With regards to residential location attributes, we considered the following categories: peripheral areas, old suburbs, new suburbs and Central Business Districts (CBD). The categories were created applying a k-means cluster analysis using population density, land use mix and transit accessibility indices. The peripheral areas have the lowest values for all three indices. Old suburbs have medium land use mix and population density, and are served by the main transit lines. New suburbs are characterized by low to medium density, land use mix and transit accessibility. CBD represents mostly downtown core and central neighborhoods, with the highest values for all three indices. The modeling results show that individuals living in peripheral areas have a higher propensity of getting involved in temporally and spatially impulsive activities. Peripheral areas have the lowest land use mix, transit accessibility and population densities, and are very auto oriented neighborhoods thus allowing for impulsive activity participation (temporal and spatial). As is expected, these individuals also tend to prefer large sedans, vans/minivans, and SUVs for their traveling purposes. Persons living in CBDs are also more likely to conduct temporally and spatially impulsive activities. On the other hand, these individuals are unlikely to employ sedans and SUVs highlighting an overall preference for non-auto oriented travel. People living in older suburbs are more inclined towards temporally pre-planned and spatially impulsive activities and disinclined towards using any types of sedans.

Contextual Variables

Walk/bike/transit appears to be the preferred vehicle type choice in summer season. This is intuitive, since the weather is more conducive to undertaking activities by walking or biking or taking public transit than winter. During winter individuals tend to be less inclined towards temporally impulsive activities. Preference for routine activities during winter might be explained in light of the unfavorable weather for activities outside home during this season. People prefer not to choose vans/minivans during winter. During winter maintaining larger cars such as vans is expensive (increased heating leading to increased gas cost) and difficult (more snow cleaning, parking difficulty) in Canada and this might be deterring individuals from using these vehicles for their out of home travel purposes. During weekends, people are free and relaxed and hence, they tend to undertake more pre-planned and impulsive activities - a result which is intuitively understandable. Sedans and vans/minivans are the preferred vehicle choices for weekend activities. It appears that people also allocate Fridays for spatially impulsive activities and prefer to use compact sedans for these activities, presumably due to possible congestion on Fridays.

Activity Attributes

Activities undertaken in peripheral and CBD areas tend to be of temporally impulsive in nature. In case of CBDs, the activities are also spatially flexible. As expected, contrasting choice of vehicles is observed between these two activity locations. In peripheral areas people prefer larger vehicles such as vans/minivans and SUVs whereas in CBDs people tend to undertake activities by walk/bike/transit. The results are in line with expectations. Unlike peripheral areas, these neighborhoods have diverse land use mix and increased number of activity centers. Moreover, these areas are also known for their "pedestrian oriented" urban form and parking restrictions which might be deterring individuals from using vehicles and opting for walk/bike/transit mode instead. Individuals tend not to use compact sedans and/or pick-ups/trucks for undertaking activities in old suburbs.

Activities that involve basic need (e.g. meals) are either routine or impulsive in time and less likely to be pre-planned (see Mohammadian and Doherty [9] for similar results). On the other hand, the location is more likely to be pre-planned or selected impulsively. It might be indicating that dining out or doing grocery might be a temporally routine/impulsive activity for individuals but the location (restaurant or superstore) for these activities might be either pre-planned or impulsive. For activities involving basic needs, people tend to prefer walk/bike/transit (except pick-up trucks). Among all activity types, work/school is considered to be fixed or mandatory in time and space and our results conform to this expectation. In terms of vehicle choice, pick-ups/trucks are likely to be chosen (please note that if pickup trucks are available in the household they are potentially work related vehicle purchases). As expected, our results suggest that both shopping and social/recreational activities are more likely to be impulsively undertaken by individuals. For shopping activity types, individuals tend not to use sedans presumably due to the fact that these activities are usually conducted in groups and thus people might prefer larger vehicle. Activities conducted alone tends to be of routine nature and pursued using walk/bike/transit indicating that usage of vehicle is deemed required with increased number of accompanying people (except for pickup trucks which could be related to small share of pickup trucks).

Error Components

The final model specification included two error components, confirming the presence of common unobserved attributes among joint choice alternatives. Specifically, the dimensions that exhibited strong correlations include: spatial flexibility (pre-planned) and temporal flexibility (pre-planned). The error component parameters provide important insights regarding the sensitivity of joint choice alternatives sharing the same temporal and spatial flexibility.

CONCLUSIONS

Given the overwhelming contribution of private vehicles towards GHG emissions, it is not surprising that travel behavior researchers have examined vehicle fleet choices (number, type and usage) extensively. Traditionally, vehicle fleet decisions are examined as a long term choice with annual usage metrics. Only recently, travel behavior models have started examining vehicle usage decisions (type and mileage) as a short-term decision in the context of activity travel analysis. Our study contributes to the growing literature on short term vehicle usage decisions by examining four activity travel choice processes: spatial flexibility of the activity, temporal flexibility of the activity, activity vehicle type, and primary driver (for auto users). The four choice dimensions considered in this paper are of significance for policy making and urban transportation planning purposes.

The data used in the study is drawn from a longitudinal panel survey of households in the Quebec City region of Canada. The survey comprised of three waves, about one year apart for a household and carried out from 2003 through 2006. The survey attempts to investigate respondent's perceptions of temporal and spatial flexibility in the organization of their activities. In terms of methodology, a panel mixed multinomial logit model (MMNL) is applied to account for the intrinsic unobserved taste preferences across individuals from the longitudinal survey.

The analysis results revealed that several individual and household socio-demographic characteristics, residential location and activity attributes as well as contextual variables influence the packaged choice of temporal flexibility, spatial flexibility, vehicle type choice and primary driver selection. For example, we observed non-inclination of university degree holders towards spatially pre-planned activities while young individuals' temporally impulsive activity proneness was confirmed. Individuals belonging to both medium and high income households are less likely to take part in temporally pre-planned or impulsive activities. We also observed that compared to the central business districts, individuals living in the peripheral areas are more likely to conduct impulsive activities and use larger automobiles. Making the land use more heterogeneous and spatially densified might help in this regard as suggested by literature. It will increase accessibility to amenities which in turn is expected to encourage changes in the spatial organization of activities (even travel reduction in the longer term) and their chosen mode [30]. Reduction in parking spaces or increase in the parking cost at or in the vicinity of the workplace or shopping centres might be one possible solution to deter individuals from using larger vehicles for these activity purposes. Moreover, we also identify the presence of common unobserved attributes among the joint choice alternatives. Since, the dataset used in the analysis is a quite unique and rare-to-obtain longitudinal dataset (more so in the Canadian context), this study offers valuable insight into the daily activity travel patterns in a large urban context in Canada. The findings reported in the study lends credence to the notion of packaged nature of activity-travel choices, warranting simultaneous modeling of various choice dimensions in a unifying framework. The model developed can be incorporated in an activity based forecasting system of travel and emissions. The analysis conducted and the model developed in the paper is the front-end of actual GHG emission analysis. That is, once the vehicle type choice in the short term is determined in an activity based model, it can be embedded within an emission modeling module to obtain actual emissions estimates.

The study is not without limitations. The dataset used in the study has a relatively small sample size. Additional research on larger data samples would be useful in confirming our findings. The current study may be enhanced by incorporating trip length or duration and activity type into the model system. Of course that would require the formulation of a discrete-continuous modeling framework. Further, it might be beneficial to compare our categorization with models that employ activity type categorization while using spatial and temporal flexibility as independent variables.

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List of Table Titles

Table 1 Distribution of Perceived Temporal and Spatial Flexibility by Vehicle Type

Dimensions	Vehicle Type						Within Vehicle Type Choice (%)
	Compact Sedan	*Large Sedan*	*Van/Minivan*	*SUV*	*Pick-ups/Trucks*	*Walk/Bike/Transit*	
Perceived Temporal Flexibility							
Routine	1179 (34.9%)	475 (33.6%)	178 (31.8%)	124 (30.7%)	48 (30.4%)	938 (42.9%)	2942 (36.3%)
Planned	1345 (39.8%)	606 (42.9%)	235 (42.0%)	185 (45.8%)	67 (42.4%)	617 (28.2%)	3055 (37.7%)
Impulsive	852 (25.2%)	332 (23.5%)	146 (26.1%)	95 (23.5%)	43 (27.2%)	633 (28.9%)	2101 (25.9%)
Perceived Spatial Flexibility							
Routine	1971 (58.4%)	796 (56.3%)	319 (57.1%)	205 (50.7%)	68 (43.0%)	1343 (61.4%)	4702 (58.1%)
Planned	928 (27.5%)	428 (30.3%)	150 (26.8%)	141 (34.9%)	70 (44.3%)	430 (19.7%)	2147 (26.5%)
Impulsive	477 (14.1%)	189 (13.4%)	90 (16.1%)	58 (14.4%)	20 (12.7%)	415 (19.0%)	1249 (15.4%)
Within Temporal and Spatial Flexibility (%)	3376 (41.7%)	1413 (17.4%)	559 (6.9%)	404 (5.0%)	158 (2.0%)	2188 (27.0%)	8098 (100.0%)

Table 2 Distribution of Individual Characteristics across Temporal Flexibility, Spatial Flexibility and Vehicle Type Dimensions

Dimensions	Gender		Age			Education		Total (%)
	Male	*Female*	*Young (<= 30)*	*Middle Aged (31 - 60)*	*Senior (> 60)*	*University*	*Others*	
Perceived Temporal Flexibility								
Routine	1589 (38.9%)	1353 (33.8%)	557 (37.4%)	2085 (38.8%)	300 (24.3%)	1126 (39.0%)	1816 (34.8%)	2942 (36.3%)
Planned	1486 (36.3%)	1569 (39.1%)	514 (34.5%)	1980 (36.8%)	561 (45.5%)	1093 (37.9%)	1962 (37.6%)	3055 (37.7%)
Impulsive	1015 (24.8%)	1086 (27.1%)	419 (28.1%)	1309 (24.4%)	373 (30.2%)	665 (23.1%)	1436 (27.5%)	2101 (25.9%)
Perceived Spatial Flexibility								
Routine	2409 (58.9%)	2293 (57.2%)	891 (59.8%)	3182 (59.2%)	629 (51.0%)	1690 (58.6%)	3012 (57.8%)	4702 (58.1%)
Planned	1061 (25.9%)	1086 (27.1%)	357 (24.0%)	1408 (26.2%)	382 (31.0%)	777 (26.9%)	1370 (26.3%)	2147 (26.5%)
Impulsive	620 (15.2%)	629 (15.7%)	242 (16.2%)	784 (14.6%)	223 (18.1%)	417 (14.5%)	832 (16.0%)	1249 (15.4%)
Vehicle Type								
Compact Sedan	1555 (38.0%)	1821 (45.4%)	709 (47.6%)	2152 (40.0%)	515 (41.7%)	2403 (46.1%)	973 (33.7%)	3376 (41.7%)
Large Sedan	804 (19.7%)	609 (15.2%)	47 (3.2%)	950 (17.7%)	416 (33.7%)	898 (17.2%)	515 (17.9%)	1413 (17.4%)
Van/Minivan	291 (7.1%)	268 (6.7%)	32 (2.1%)	504 (9.4%)	23 (1.9%)	337 (6.5%)	222 (7.7%)	559 (6.9%)
SUV	248 (6.1%)	156 (3.9%)	37 (2.5%)	304 (5.7%)	63 (5.1%)	170 (3.3%)	234 (8.1%)	404 (5.0%)
Pick-ups/Trucks	151 (3.7%)	7 (0.2%)	1 (0.1%)	133 (2.5%)	24 (1.9%)	149 (2.9%)	9 (0.3%)	158 (2.0%)
Walk/Bike/Transit	1041 (25.5%)	1147 (28.6%)	664 (44.6%)	1331 (24.8%)	193 (15.6%)	1257 (24.1%)	931 (32.3%)	2188 (27.0%)
Total (%)	4090 (50.5%)	4008 (49.5%)	1490 (18.4%)	5374 (66.4%)	1234 (15.2%)	5214 (64.4%)	2884 (35.6%)	8098 (100.0%)

Table 3 Estimation Results (N=378 individuals and 8098 records)

Variables	Temporal Flexibility *(Base: Routine)*		Spatial Flexibility *(Base: Routine)*		Vehicle Type *(Base: Walk, bike and transit)*					Primary Driver
	Planned	**Impulsive**	**Planned**	**Impulsive**	**Compact Sedan**	**Large Sedan**	**Van/ Minivan**	**Sport Utility Vehicle (SUV)**	**Pick-up/ Trucks**	
Constants	1.272	0.114	0.110	-1.219	2.518	0.691	-2.575	1.656	-2.8889	---
	(8.837)	(0.731)	(0.450)	(-8.383)	(11.983)	(2.103)	(-4.402)	(4.179)	(8.380)	---
Wave1	---	-0.316	-0.193	-0.527	0.956	0.363	0.461	0.461	-0.461	---
	---	(-4.497)	(-2.627)	(-6.505)	(11.526)	(3.116)	(3.462)	(3.462)	(-1.692)	---
Individual Characteristics										
Female	---	---	---	---	-1.071	-0.666	-0.325	---	---	1.433
	---	---	---	---	(-10.942)	(-5.571)	(-2.020)	---	---	(18.096)
Age (Base: Middle aged (31-60))										
Young (Age ≤30)	---	0.429	---	---	-0.889	---	-0.889	---	---	0.862
	---	(4.505)	---	---	(-6.688)	---	(-6.688)	---	---	(7.490)
Senior (Age >60)	---	---	---	---	-1.481	---	---	-1.666	---	2.159
	---	---	---	---	(-9.138)	---	---	(-5.511)	---	(14.965)
Education Level (Base: Other degree)										
University Degree	---	---	-0.339	---	-2.857	---	1.006	-1.529	---	2.101
	---	---	(-1.742)	---	(-12.124)	---	(2.283)	(-6.438)	---	(12.180)
Diploma Degree	---	0.264	-0.383	---	-0.852	1.414	2.641	2.091	---	---
	---	(3.844)	(-2.065)	---	(-5.042)	(7.462)	(6.489)	(6.401)	---	---
Don't Use Cell Phone	-0.236	-0.457	-0.310	-0.464	---	-0.630	---	---	---	---
	(-2.677)	(-6.385)	(-3.486)	(-6.436)	---	(-6.051)	---	---	---	---
Household Socio-demographics										
Housing Type (Base: Others)										
Detached House	0.320	0.379	0.317	---	0.385	0.531	---	-1.306	---	---
	(2.978)	(4.584)	(2.930)	---	(3.830)	(3.985)	---	(-4.308)	---	---
Apartment	---	---	---	---	0.331	---	---	---	---	---
	---	---	---	---	(2.682)	---	---	---	---	---
Income (Base: Low Income (< 20K))										
Medium Income (20K-60K)	-0.539	-0.539	-0.292	---	---	0.448	2.616	---	---	---
	(-5.099)	(-5.099)	(-2.919)	---	---	(3.623)	(6.373)	---	---	---
High Income (> 60K)	-0.525	-0.525	---	---	---	---	1.030	1.371	---	---
	(-4.160)	(-4.160)	---	---	---	---	(2.445)	(5.368)	---	---
Family structure (Base: Single Adult)										
Couples with Children	-0.535	-0.535	-0.347	-0.373	---	-0.381	0.529	-0.596	1.051	---
	(-5.294)	(-5.294)	(-2.545)	(-4.067)	---	(-1.931)	(2.625)	(-2.383)	(4.078)	---
Couples without Children	-0.323	-0.458	-0.335	-0.243	---	-0.807	---	---	---	---
	(-2.661)	(-4.846)	(-2.488)	(-2.660)	---	(-3.994)	---	---	---	---
Household Residential Attributes (Base: New Suburbs)										
Peripheral Areas	---	0.217	---	0.196	---	0.384	0.384	1.671	---	---

	---	(2.501)	---	(2.083)	---	(3.296)	(3.296)	(6.710)	---	---
Central Business District	---	0.267	---	0.233	-0.740	-0.623	---	-0.948	---	---
	---	(2.664)	---	(2.202)	(-6.497)	(-2.903)	---	(-3.720)	---	---
Old Suburbs	---	---	0.221	0.171	-0.651	-1.042	---	---	---	---
	---	---	(1.943)	(1.875)	(-7.430)	(-7.605)	---	---	---	---
Contextual Variables										
Season (Base: Spring and Fall)										
Summer	---	---	---	---	-0.210	-0.545	-0.989	-0.805	---	---
	---	---	---	---	(-2.894)	(-4.966)	(-5.997)	(-4.202)	---	---
Winter	---	-0.303	---	---	---	---	-1.400	---	---	---
	---	(-2.937)	---	---	---	---	(-4.796)	---	---	---
Day of Week										
Weekend	0.922	0.922	0.577	0.315	0.826	0.773	0.489	---	---	---
	(11.282)	(11.282)	(8.071)	(3.774)	(8.571)	(5.932)	(2.601)	---	---	---
Friday	---	---	---	0.171	0.364	---	---	---	---	---
	---	---	---	(1.827)	(3.989)	---	---	---	---	---
Activity Attributes										
Activity Location (Base: New Suburbs)										
Peripheral Areas	---	0.215	---	---	---	---	0.529	0.961	---	---
	---	(2.138)	---	---	---	---	(2.424)	(4.130)	---	---
Central Business District	0.245	0.386	0.325	0.461	-1.091	-0.870	-0.493	-0.493	---	---
	(3.211)	(4.572)	(4.395)	(5.539)	(-12.881)	(-7.699)	(-3.352)	(-3.352)	---	---
Old Suburbs	---	---	---	---	-0.256	---	---	---	-0.445	---
	---	---	---	---	(-2.961)	---	---	---	(-1.663)	---
Activity Type (Base: Other Activities)										
Basic Needs	-0.920	---	0.252	1.582	-1.469	-1.246	-1.580	-1.312	---	---
	(-10.209)	---	(2.573)	(12.797)	(-11.123)	(-7.790)	(-6.259)	(-5.025)	---	---
Work/School	-1.612	-2.300	-0.779	-1.487	-0.845	-0.351	-1.139	---	1.470	---
	(-19.862)	(-18.781)	(-9.352)	(-8.446)	(-7.348)	(-2.749)	(5.999)	---	(6.135)	---
Shopping	0.955	2.216	0.428	1.705	-0.293	---	---	---	---	---
	(9.238)	(20.952)	(5.521)	(15.136)	(-2.525)	---	---	---	---	---
Social/Recreational	---	0.789	---	0.864	-1.810	-1.660	-1.968	-1.729	---	---
	---	(10.113)	---	(7.559)	(-15.421)	(-12.148)	(-9.354)	(-7.917)	---	---
Accompaniment Type										
Alone	-0.451	-0.141	-0.584	-0.584	-0.514	-0.998	-0.420	-0.912	---	---
	(-6.358)	(-1.889)	(-10.316)	(-10.316)	(-6.316)	(-8.583)	(-2.557)	(-5.419)	---	---
Error Components	0.787	---	0.837	---	---	---	---	---	---	---
	(18.525)	---	(16.644)	---	---	---	---	---	---	---
Log-likelihood at convergence	-19977.52									
Note: --- denotes insignificant variables. Also, the coefficient estimates across different alternatives are constrained to be same when the effects are not significantly different.										