ANALYSIS OF VEHICLE OWNERSHIP EVOLUTION IN MONTREAL, CANADA USING PSEUDO PANEL ANALYSIS

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ABSTRACT

This paper employs a pseudo-panel approach to study vehicle ownership evolution in Montreal region, Canada using cross-sectional origin-destination (O-D) survey datasets of 1998, 2003 and 2008. Econometric modeling approaches that simultaneously accommodate the influence of observed and unobserved attributes on the vehicle ownership decision framework are implemented. Specifically, we estimate generalized versions of the ordered response model – including the generalized, scaled- and mixed-generalized ordered logit models. Socio-demographic variables that impact household's decision to own multiple cars include number of full and part-time working adults, license holders, middle aged adults, retirees, male householders, and presence of children. Increased number of bus stops, longer bus and metro lengths within the household residential location buffer area decrease vehicle fleet size of households. The observed results also varied across years as manifested by the significance of the interaction terms of some of the variables with the time elapsed since 1998 variable. Moreover, variation due to unobserved factors are captured for part-time working adults, number of bus stops, and length of metro lines. In terms of the effect of location of households, we found that some neighborhoods exhibited distinct car ownership temporal dynamics over the years.

Key words: car ownership evolution, generalized ordered logit, scaled generalized ordered logit, mixed generalized ordered logit, Montreal boroughs

1. INTRODUCTION

Private vehicle ownership (fleet size and composition) plays a vital and ubiquitous role in the daily travel decisions of individuals and households influencing a range of long-term and short-term decisions. In the past few decades, there has been an enormous increase in the number of personal automobiles both in European (Whelan 2007; Caulfield 2012) and Asian countries (Wu et al. 1999; Senbil et al. 2009; Li et al. 2010). The increased auto dependency in the developed and developing world can be attributed to high auto-ownership affordability, inadequate public transportation facilities (in many cities), and excess suburban land-use developments (particularly in developed countries). In Canada, the importance of car ownership is no different. In fact, personal vehicles are an essential household commodity as evidenced by the statistics that 84.4 percent of households owned or leased at least one vehicle in 2007 (Canada NR 2009). At the provincial level for Quebec, there has been a 17 percent increase in the number of cars over the last decade (Canada NR 2009). In the Greater Montreal Area (GMA) of Quebec, the average household car ownership increased from 1.06 in 1987 to 1.18 in 2003 (Roorda et al. 2008).

Given the increasing vehicle ownership, it is no surprise that the proportion of individuals using the auto mode for travel has increased from 68 percent in 1992 to 74 percent in 2005 as observed from the time-use data from the Canadian General Social Survey (CGSS) (Turcotte 2008). The negative externalities of the resulting traffic congestion include travel time delays, financial losses (excess fuel usage and lost work time), and rising air pollution and greenhouse gas (GHG) emissions (Canada T 2006). The wide ranging implications of vehicle ownership decisions have resulted in the emergence of vast literature on this topic over the past two decades. These studies examined household vehicle ownership defined as fleet size, vehicle type and usage while controlling for different exogenous variables such as household socio-demographics, land use and urban form attributes, transit and infrastructure characteristics. Hence, they offer useful insights on the role of exogenous variables on the ownership decision processes. Typically, these studies employ cross-sectional databases that can only provide a

snapshot of fleet size decision at one point in time. However, to study the evolution of vehicle ownership over time, longitudinal databases that track vehicle ownership decisions of the same households across multiple years are likely to be more informative (Woldeamanuel et al. 2009). Unfortunately, compiling such detailed data is prohibitively expensive and provides many challenges associated with respondent fatigue and retention (Hanly and Dargay 2000).

The current study is primarily motivated from the need to address this data availability challenge. Specifically, we intend to develop vehicle ownership frameworks employing cross sectional databases compiled over multiple time points. The availability of multiple cross sectional datasets for different years provides a useful compromise between a single year cross sectional dataset and a truly longitudinal dataset collected across multiple years. Though the multiple waves are not compiled based on the same set of households, they still provide us an opportunity to examine the impact of technology, altering perceptions of road and transit infrastructure, changing social and cultural trends on vehicle ownership (see for example Sanko 2013; Dargay 2002; Dargay and Vythoulkas 1999; for studies employing pseudo-panel data for examining different travel behaviour dimensions). Further, pooled datasets allow us to identify how the impact of exogenous variables has altered with time. For example, with improved perception of public transit, impact of a metro stop near the household might affect vehicle ownership reduction more in 2010 compared to its corresponding impact in 2000. Policy makers can utilize this information to propose mechanisms that will target vehicle ownership reduction.

Data pooling of different respondents across multiple waves offers unique methodological challenges. The methodology should recognize the differences across multiple time points adequately since the choice process for the respondents in a particular year might be influenced by various observed and unobserved attributes (Train 2009; pp. 40-42). For example, if there is a significant spike in households with multiple employed individuals (from say 1995 to 2005) the vehicle ownership pattern might alter substantially across these two databases. This is an instance of how observed attributes affect vehicle ownership decision process. The outcome

based models can accommodate such transitions reasonably through appropriate model specification ("number of workers in a household" variable). However, say we are interested in measuring the impact of growing environmental consciousness between 2000 and 2010 on vehicle ownership. This is the case of an unobserved variable (as it will be very hard to define exogenous variable of this type) specific to the study time period on the decision process. The accommodation of such unobserved effects becomes crucial in the analysis process. In our study, we implement modeling approaches that simultaneously accommodate for the influence of observed and unobserved attributes on the vehicle ownership decision framework across multiple time points.

Specifically, this study aims at investigating the factors affecting vehicle ownership and its evolutions in recent years in the Greater Montreal Area (GMA) using three origin-destination (O-D) surveys from years 1998, 2003 and 2008. The study approach is built on the generalized ordered logit (GOL) framework. The GOL framework relaxes the restrictive assumption of the traditional ordered response (OR) models (monotonic effect of exogenous variables) while simultaneously recognizing the inherent ordering of the vehicle ownership variable (information that unordered model alternatives fail to consider). Further, to incorporate the effect of observed and unobserved temporal effects, we specifically consider two versions of the GOL model – the mixed GOL model and the scaled GOL model. The two variants differ in the way they incorporate the influence of unobserved attributes within the decision process. We estimate both models and employ data fit comparison metrics to determine the appropriate model structure. The model specification is undertaken so as to shed light on how the changes to Montreal region across the study years and boroughs has affected household vehicle ownership.

2. EARLIER RESEARCH AND CURRENT STUDY IN CONTEXT

A vast body of literature is available on various forms of auto-ownership modeling. For an extensive review of the models developed see Anowar et al. (2014), de Jong et al. (2004),

Potoglou and Kanaroglou (2008a) and Bunch (2000). In our review, we limit ourselves to studies (in the last two decades) that are relevant in the context of our research, i.e. studies that examine household vehicle ownership (number of vehicles) and the associated factors that influence the ownership decision.

Most disaggregate models that consider household car ownership found in the literature are developed using cross-sectional data. The methodological approaches applied in these studies range from simple linear regression to complex econometric formulation taking into account a rich set of covariates (Brownstone and Golob 2009). These snapshot models of vehicle ownership ignore the inherent vehicle ownership evolution process that is affected by life cycle changes (such as the birth of a child, changes to marital status) and/or land use and urban infrastructure and perception (such as introduction of improved transit facilities or environmental awareness). In order to capture these behavioural changes across time, researchers have suggested the development and use of longitudinal studies (Kitamura and Bunch 1990; Kitamura 2000).

Pendyala et al. (1995) investigated the changes in the relationship between household income and vehicle ownership using longitudinal data from the Dutch National Mobility Panel Survey. They developed ordered probit (OP) models for six time points to monitor the evolution of income elasticities of car ownership over time. OP framework was also used by Hanly and Dargay (2000) for studying car ownership levels of British households. In their study, location of household in the region was found as an important determinant of vehicle fleet size. In another study, Nobile et al. (1997) proposed a random effects multinomial probit (MNP) model of household car ownership level using the same longitudinal data that was used by Pendyala et al. (1995). More recently, Woldeamanuel et al. (2009) examined the variation in car ownership across time and households using German Mobility Panel survey data of 11 years from 1996 to 2006. Along the same line, Nolan (2010) proposed a binary random effects model to analyze the car ownership decision of Irish households for the period 1995 to 2001. A highly significant state

dependence suggested that there is strong habitual effect or persistence in household car ownership levels from one year to the next. Similar persistence effect was also reported by Bjorner and Leth-Petersen (2007) for Danish households.

As is evident from the literature review, very few dynamic vehicle ownership panel model studies can be found in the literature. The studies discussed above consider the evolution of vehicle fleet that allows analysts to see how life cycle changes in a household and existing fleet influence vehicle ownership decisions. Of course, it is evident that such models require longitudinal data. To address the shortage of longitudinal data availability, a pseudo-panel approach – a process by which repeated cross sectional databases are merged to generate a panel (Deaton, 1985) - is used by the researchers to estimate car ownership models. For instance, Dargay and Vythoulkas (1999) compiled data from several cross sectional databases of United Kingdom Family Expenditure Survey. In a subsequent study, Dargay (2002) extended her work and explored the differences in car ownership and its determining factors for households living in rural, urban and 'other' areas. More recently, Matas and Raymond (2008) developed OP and multinomial logit (MNL) models to examine the vehicle ownership growth in Spain using household level data for three points in time: 1980, 1990 and 2000. Their results indicated that the car ownership levels of households residing in large urban areas are sensitive to the quality of public transport facilities.

2.1 Current Study in Context

All the studies employing OR models ignore the potential impact of unobserved time specific attributes on the decision process. The studies that explore these unobserved effects (Dargay and Vythoulkas 1999; Dargay 2002; Nobile et al. 1997) employ either linear regression frameworks or MNP models. The applicability of linear regression and unordered approaches to study vehicle ownership is arguable as the vehicle ownership variable is an ordinal discrete variable. A more appropriate framework to examine this variable would be the OR framework.

However, one important limitation of the OR models is that they constrain the impact of the exogenous variables to be monotonic for all alternatives.

To overcome this issue, researchers have resorted to the unordered response (UR) models that allow the impact of exogenous variables to vary across car ownership levels (Bhat and Pulugurta 1998; Potoglou and Kanaroglou 2008b; Potoglou and Susilo 2008). However, the increased flexibility from the UR models is obtained at the cost of neglecting the inherent ordering of the car ownership levels. The recently proposed GOL model relaxes the monotonic effect of exogenous variables of the traditional OR models while still recognizing the inherent ordered nature of the variable (Eluru et al. 2008). Recent evidence comparing the performance of GOL model with its unordered counterparts (such as MNL, nested logit (NL), ordered generalized extreme value (OGEV), and mixed multinomial logit (MMNL)) has established the GOL model as an appropriate framework to study ordered variables (see Eluru 2013; Yasmin and Eluru 2013). Hence, in our study, we employ the GOL framework to study car ownership. To elaborate, we contribute to literature by employing two variants - the scaled GOL model (SGOL) and mixed GOL (MGOL) model - of the GOL model to capture the impact of observed and unobserved attributes on car ownership levels for our analysis.

Further, we study car ownership evolution in Montreal region using a comprehensive set of exogenous variables with a particular focus on land use and urban form characteristics. We also incorporate the impact of temporal changes to borough location on the choice process. As mentioned earlier, in addition to the observed attributes, the study also considers the impact of unobserved attributes on the decision process. In summary, the current study contributes to literature in two ways. First, *methodologically*, the study employs an approach to stitch together multiple cross-sectional datasets to generate a rich pooled dataset that will allow us to study the evolution of vehicle ownership. Second, *empirically*, the study contributes to vehicle ownership literature by estimating the GOL models using a rich set of exogenous variables including household socio-demographics, transit accessibility measures, land use characteristics and

observed and unobserved effects of the year of data collection (and their interaction with other observed variables).

3. ECONOMETRIC FRAMEWORK

In this section, we briefly provide the details of the econometric framework of the models considered for examining vehicle ownership level evolution of households. For the convenience of the reader, we will first introduce the traditional ordered logit (OL) model, then discuss about the generalized ordered logit model (GOL), scaled generalized ordered logit model (SGOL), and finally present the mixed version of the generalized ordered logit (MGOL) model.

If we consider the car ownership levels of households (k) to be ordered,

$$y_q^* = \alpha' x_q + \varepsilon_q \,, \qquad y_q = k \qquad if \ \psi_{k-1} < y_q^* < \psi_k \tag{1}$$

where y_q^* is the latent car owning propensity of household q. y_q^* is mapped to the vehicle ownership level y_q by the ψ thresholds ($\psi_0 = -\infty$ and $\psi_k = \infty$) in the usual ordered-response fashion. x_q is a column vector of attributes (not including a constant) that influences the propensity associated with car ownership. α' is a corresponding column vector of coefficients and ε_q is an idiosyncratic random error term assumed to be identically and independently standard logistic distributed across households q. The probability that household q chooses car ownership level k is given by:

$$P_q(k) = \Lambda(\psi_k - \alpha' x_q) - \Lambda(\psi_{k-1} - \alpha' x_q) \tag{2}$$

where $\Lambda(.)$ represents the standard logistic cumulative distribution function (cdf).

GOL is a flexible form of the traditional OL model that relaxes the restriction of constant threshold across population. The GOL model represents the threshold parameters as a linear function of exogenous variables (Srinivasan 2002, Eluru et al. 2008). In order to ensure the ordering of observed discrete vehicle ownership levels$(-\infty < \psi_{q,1} < \psi_{q,2} < \cdots \ldots \ldots < \psi_{q,k-1} < +\infty)$, we employ the following parametric form as employed by Eluru et al. (2008):

$$\psi_{q,k} = \psi_{q,k-1} + exp(\gamma_{qk} + \delta'_{qk} Z_{qk}) \tag{3}$$

where, Z_{qk} is a set of explanatory variables associated with the kth threshold (excluding a constant), δ'_{qk} is a vector of parameters to be estimated and γ_{qk} is a parameter associated with car ownership levels of households (*k*). The remaining structure and probability expressions are similar to the OL model. For identification reasons, we need to restrict one of the δ'_k vectors to zero.

For both OL and GOL model, the probability expression of Equation 2, is derived by assuming that the variance in propensity over different car ownerships across years is unity. However, we can introduce a *scale parameter* (λ), which would scale the coefficients to reflect the variance of the unobserved portion of the utility for each time point. The probability expression can then be written as:

$$P_q(k) = \Lambda\left[\frac{(\psi_k - \alpha' x_q)}{\lambda}\right] - \Lambda\left[\frac{(\psi_{k-1} - \alpha' x_q)}{\lambda}\right] \tag{4}$$

where λ is the parameter of interest and is equal to $exp\,(\sigma x_i)$ and x_i are the year dummies (e.g. in our case it was year dummies for 2003 and 2008). This yields the SGOL model. If the σ parameters are not significantly different from 0, the expression in equation (4) collapses to the expression in Equation (2) yielding either the OL or GOL model depending on the threshold characterization.

The mixed GOL accommodates unobserved heterogeneity in the effect of exogenous variables on household car ownership levels in both the latent car owning propensity function and the threshold functions (Srinivasan 2002, Eluru et al. 2008). The equation system for MGOL model can be expressed as:

$$y_q^* = (\alpha' + \beta')x_q + \varepsilon_q \tag{5}$$

$$\psi_{q,k} = \psi_{q,k-1} + exp[(\delta'_{qk} + \theta'_{qk})Z_{qk}] \qquad (6)$$

We assume that β' and θ'_{qk} are independent realizations from normal distribution for this study. The proposed approach takes the form of a random coefficients GOL model thus allowing us to capture the influence of year specific error correlation through elements of x_q and Z_{qk}. This approach is analogous to splitting the error term (ε_q) into multiple error components (analogous to error components mixed logit model). The parameters to be estimated in the MGOL model are the mean and covariance matrix of the distributions of β' and θ'_{qk}. In this study, we use the Halton sequence (200 Halton draws) to evaluate the multidimensional integrals (see Eluru et al. 2008 for a similar estimation process). In our analysis, x_q vector includes the year of the data collection allowing us to estimate observed and unobserved variations with respect to time.

4. DATA

The proposed models are estimated using data derived from the cross-sectional Origin-Destination (O-D) surveys of Greater Montreal Area (GMA) for the years 1998, 2003 and 2008. These surveys are conducted every five years and are the primary source of information on individual mobility patterns in the Montreal region. The survey data, provided by *Agence Metropolitaine de Transport* (AMT) of Quebec, was at the trip level. For the current research, data from each O-D year was aggregated at the household level which yielded three datasets with 67,225, 58, 962 and 68,132 household level data, respectively. From this database, for each year, 4,000 data records were randomly sampled. These three samples were pooled together to obtain a sample of 12,000 records for model analysis.

Car ownership levels were classified as no car, one car, two cars, and three or more cars. The dependent variable was truncated at three because the number of households with more than three automobiles was relatively small in the dataset. Table 1 provides a summary of the

characteristics of selected socio-demographic and land use variables used in this study[1]. The distribution of auto ownership levels by year (1998-2008) in the estimation samples indicate that in each of the three survey years, percentage of households owning one car accounted for the largest share. We can also see that proportion of zero car owning households increased somewhat in 2008 compared to 1998. On the other hand, a slight decrease could be observed in the proportions of households owning single and two cars. Interestingly, there is a noticeable increase in the number of households owning more than two cars in 2008 (7.5%). Some other salient characteristics of the sample are: in 1998, one-half of the households belonged to low income census tracts, but in recent years, more households were residing in medium and high-income census tracts. Over the years, about two-thirds of the households had at least one full time employed adult and zero students, more than 10 percent had at least one part-time employed person and more than 50 percent had two or more license holders. As expected in a North American city, there is a gradual increase in the number of retirees in the households.

5. EMPIRICAL ANALYSIS

5.1 Variables Considered

In the current study, a comprehensive set of exogenous attributes were considered to study vehicle ownership levels. The independent variables can be broadly classified into four categories: (1) household socio-demographic characteristics, (2) transit accessibility measures (3) land use characteristics, and (4) temporal variables. *Household socio-demographic* variables that were employed in our analysis included number of employed adults (full-time and part-time), no of males, average age of the household members, presence of children of different ages, number of retirees, number of students and number of licensed drivers. The *transit accessibility measures* considered, as a proxy for ease of transit accessibility and level of service of alternative

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[1]The descriptive statistics of all the variables are available upon request from the authors.

modes, (within 600m buffer[2] of household residential location) were: bus stops, commuter rail stops, metro stops, length of bus line (km), length of commuter rail line (km) and length of metro line. In order to assess the impact of different *land use characteristics* on car ownership, the following land use variables were considered in our study: residential, commercial, government and institutional, resource and industrial, park and recreational, open and water area. Moreover, average distance of work location from the households, population density and the median income of households in the census tract (CT) based on residential location were also included. Further, we introduced location specific (borough indicators) variables to examine the degree of influence exerted by the area of residence on household car ownership levels. These variables are expected to capture attributes of household's activity travel environment as well as the utility/disutility of automobile maintenance and operation in particular areas. In terms of *temporal variables*, we introduced a variable called "time elapsed from 1998" which is the time difference between the most recent O-D survey years (2008 and 2003) from the base survey year (1998). Both linear and polynomial effects of the time elapsed were tested. Moreover, interaction of exogenous variables with the time elapsed variable (linear and polynomial) were utilized to control for time varying variable effects. As a result, it would be possible to apply the developed models for future year scenarios. The final specification was based on a systematic process of removing statistically insignificant variables and combining variables when their effects were not significantly different. The specification process was also guided by prior research, intuitiveness and parsimony considerations.

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[2]Buffers were established around household geocoded locations with 600m radius. In earlier literature, the acceptable walking distance to transit stops and stations is often assumed to be 400m (Larsen et al. 2010). Hence, we employed a slightly larger buffer than the 400m to allow for the low-density developments in Canadian cities that might require people to walk further to reach transit stations from their households.

5.2 Estimation Results

In this research, we considered three different model specifications of the GOL model. These are: (1) GOL (2) SGOL and (3) MGOL. As explained earlier, all of these models are generalized versions of the standard OL model. After extensive specification testing, the final log-likelihood values (number of parameters) at convergence of the GOL, SGOL and MGOL models were found as: -8647.92 (49), -8646.05 (50) and -8556.61. (53), respectively. The performance of the models was tested using Log-likelihood Ratio test, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) measures. The AIC (BIC) values for the final specifications of the GOL, SGOL and MGOL models are 17393.84 (17756.08), 17392.10 (17761.73), and 17219.22 (17611.04), respectively. The improvement in the data fit clearly demonstrates the superiority of the MGOL model over its other counterparts. Hence, in the following sections, we discuss results of the MGOL model only.

The model estimation results are presented in Table 2. The reader should note that there are three columns in the table. The first column corresponds to the car ownership propensity, the second column corresponds to the first threshold that demarcates the one and two car ownership categories and the third column corresponds to the second threshold that demarcates the two and more than two car ownership categories. In the following presentation, we discuss both variable effects and unobserved heterogeneity effects on the latent car ownership propensity and the two thresholds. The effect of each category of variables on the thresholds provides a sense of how the probability of car ownership in specific ownership categories is affected.

5.2.1 Constants

The constant variables do not have any substantive interpretation. Within the set of constant parameters, the impact of the time elapsed variable was examined. The effect of the variable was found significant for both propensity and the second threshold that separates two car ownership

level from three or more cars ownership level. The effects indicate that households in recent times are more likely to have an increased fleet size. The findings confirm our observations of an increase in households with at least two cars in the data.

5.2.2 Household Demographics

Increased number of male household members increases the likelihood of multiple car ownership of households and the gender effect is found to be highly significant. For obvious reasons, presence of children in households significantly affects their fleet size decision. In particular, we found that households with children between 5 to 9 years have a higher propensity of possessing multiple vehicles presumably owing to the increased travel needs, such as, chauffeuring them to and from daycare and/or school. Presence of young children (aged between 10 to 14 years) in the household also have similar positive effect. The result is intuitively understandable since children of this age have diversified activity requirements and are mostly dependent on the adult householders for their mobility which might result in additional vehicle purchase. The presence of teenaged children (15-19 years of age) do not have a direct effect on propensity, however, a positive impact of the interaction term between the presence of 15-19 year old children and elapsed time was observed in our analysis. Moreover, the effect of the variable on the threshold indicates increased likelihood of single vehicle ownership. A plausible reason for the smaller fleet size might be that teens of this age can travel by themselves, unaccompanied by an adult or peer and are soon to move out of the house.

Our results underscore the increased latent propensity of owning multiple vehicles by middle aged households (average age of householders 30 to 60 years). The effect of this variable is also significant for the threshold demarcating two and more than two vehicles. The negative sign of the coefficient in the threshold indicates higher likelihood of owning more than two vehicles. As expected, households with more number of full time employed adults are more likely to have

higher levels of vehicle ownership; an indicator that these households have greater mobility needs complemented by enhanced buying capability (Kim and Kim 2004; Bhat and Pulugurta 1998; Potoglou and Kanaroglou 2008b). Interestingly, we also observe that with elapsed time, the impact of full time workers on vehicle ownership levels is reducing. The result is quite encouraging for policy makers highlighting that in the recent years, growing environmental consciousness and increased inclination towards using transit might actually be contributing towards lowering vehicle ownership levels. Similar to full time workers, increase in the number of part time workers also increases household's propensity to own multiple cars. The latent propensity is found to be normally distributed with a mean of 0.3719 and standard deviation of 0.6510, suggesting that in 28.43% of the households, an increase in part-time worker has a positive impact on car ownership. With increase in number of retirees, households have a higher likelihood of purchasing more cars. Retirees live primarily in single-person households (Nobis 2007) and hence, they are more likely to be dependent on cars for their mobility needs.

The negative impact of number of students on the propensity indicates that households with higher number of students are less inclined to own several cars. It is expected because households with more students would have increased budget constraints and hence, would be less inclined to own cars. Moreover, students may share their activities with friends and other household members that might further reduce the need for owning multiple cars (Vovsha et al. 2003). The results associated with the number of licensed drivers (surrogate for potential drivers in the household) reflect the anticipated higher probability of households owning multiple cars. The effect of the variable on the thresholds is quite interesting. The variable exhibits significant impact on both the thresholds. It is very hard to establish the exact impact of these threshold parameters as their impact is quite non-linear and is household specific. The GOL model with its flexibility in allowing for such variations across the households provides a better fit to the observed vehicle ownership profiles. We also found that when immobile persons are present, households become less likely to own higher number of cars.

5.2.3 Transit Accessibility Measures

The results corresponding to transit accessibility measures highlight the important role of public transit in Montreal. Increase in the number of bus stops as well as bus and metro line length within the household buffer zone negatively impact household's propensity to own cars. The result lends support to the concept that increased transit access and high quality of transit service can significantly reduce the number of automobiles owned by households (Ryan and Han 1999; Bento et al. 2005; Kim and Kim 2004; Cullinane 2002). Of particular interest are the effects of number of bus stops and metro line length. The impact of number of bus stops on fleet size is normally distributed with a mean of -0.0324 and standard deviation of 0.0473. The effect of metro line on vehicle ownership propensity is also normally distributed with a mean of -0.2939 and standard deviation of 0.6368. It suggests that the impact of number of bus stops and metro line varies substantially across the various parts of the urban region. The distribution measures indicate that for approximately 25% of households number of bus stops have a reduced propensity for vehicle ownership while the metro variable has reducing effect for 32% of households.

5.2.4 Land Use Measures

It is evident from previous literature that income is one of the most influential factors affecting household's decision regarding their vehicle fleet size. In our analysis, household income was unavailable to us. However, to address the unavailability we employed census tract median income as a proxy measure for the affluence of households. From our analysis results, we find that households living in medium income areas have a stronger preference to have more cars. The result is in close agreement with the findings of previous literature (Karlaftis and Golias 2002; Li et al. 2010). Interestingly, we also observe that with elapsed time, the impact of living in medium income census tract on vehicle ownership levels is reducing. Location of households in highly advantaged areas does not have any effect on the vehicle ownership propensity, however, its

impacts on threshold parameterization are relatively complex. It has a negative impact on the threshold between one and two cars and a positive impact on the threshold between two and more than two cars. From the results of the interaction of high income with time elapsed variable, we observe that with time, high income households are becoming more inclined towards owning two cars and less inclined to have a fleet size of more than two cars.

As expected, when distance between household and work location increases, households have a higher likelihood of owning multiple vehicles and the effect is getting stronger with passing time. This is perhaps the consequence of the fact that when home and work locations are far apart, car ownership becomes a necessity since driving appears to be the only convenient and reliable mode to reach work destination. Our results indicate that households in census tract areas with increased commercial as well as government and institutional land use are less likely to have multiple cars. When households are located in such areas with increased heterogeneous land use mix, their members have the option to easily access many activities and amenities by walking or biking in addition to riding transit, thereby minimizing their need to procure and use cars (Cervero and Kockelman 1997; Hess and Ong 2002).

In our analysis, in addition to the above land-use measures we considered a host of borough variables. Of these variables, some regions considered exhibited distinct car ownership profiles across the years. These include Ville-Marie (VM), Cote-des-Neiges (CDN), and Plateau-Mont-Royal (PMR). These boroughs represent medium to high dense neighbourhoods around the downtown region with good transit accessibility in general. We find that the impact of all three of the borough dummies on vehicle owning propensity of households is negative and significant, indicating that households in these areas tend to have lower automobile ownership. The interaction effects of the VM and CDN boroughs with the time elapsed variable showed similar in magnitude positive impacts. It is suggesting that the trend of reduced propensity is diminishing with passing time. Interestingly, VM borough also has a negative impact on the second threshold meaning an increased tendency of households to own more than two cars which tends to increase

in recent years. These two results involving VM borough suggest that the vehicle ownership is likely to be in the extremes in the region (either 0 or ≥3). The local agencies of these boroughs need to investigate the reasons for this dramatic change. The impact of CDN and PMR boroughs are normally distributed suggesting the presence of unobserved factors influencing the vehicle fleet size decision of households living in these areas. More specifically, the distribution measures indicate that for approximately 23.5% of households located in CDN borough have a reduced propensity for vehicle ownership whereas living in PMR borough has reducing effect for 33% of households. Given that PMR borough has emerged as one of the most environmentally conscious neighbourhoods in Montreal, the results are not surprising. In fact, the borough policies (such as parking cost mechanisms, altering traffic flow patterns) serve as a case study for policy makers interested in reducing vehicle ownership.

5.3 Policy Analysis

The exogenous variable coefficients do not directly provide the magnitude of impacts of variables on the probability of each car ownership levels. Moreover, the impacts of coefficients of the MGOL framework might not be readily interpretable due to the interactions between propensity and thresholds. Hence, to provide a better understanding of the impacts of exogenous factors, we compute two disaggregate level changes in vehicle ownership levels. We focus on the borough level variables (VM and PMR) to illustrate the variation in vehicle ownership probabilities across the years. Towards this purpose, we consider synthetic households (SH1 – SH4) with certain attributes and generate the probability profiles by changing the attributes for the household.

The first household (SH1) is a two person household located in low income area comprised of a young male and a young female adult who are students and do not possess a driving license. For this type of household, the probability of being carless is the highest in 1998 and 2003 (ranging from 64-71%) which is expected (see (a) in Figure 1 and 2). Interestingly, the probability drops to 46% in 2008. The probability of zero car ownership for PMR borough

highlights the increase of such households whereas for the VM borough the trend is reversed particularly for 2008.

The second household (SH2) is similar to HH1, except that the male householder is a full-time worker and holds a driving license. Also, a toddler (0-4 years of age) is present in the household. The status of the female member was unchanged. As we can see, with employment and driver license, the probability of zero car ownership drops down drastically. For such households we see that VM borough has larger probability for one car in 1998 and 2003 (see (b) in Figure 1). However, for 2008, these households have higher likelihood of owning two cars. On the other hand, for the PMR region, the most likely outcome for the household is to own one car (see (b) in Figure 2).

The third household (SH3) is formed by changing the employment status of the female member into a part-time worker with a driving license from HH2. Also, the household resides in a medium income census tract area. In VM borough, the vehicle ownership shares vary substantially for the household across the three years (see (c) in Figure 1). In the PMR borough, the probability plots indicate that for all years, the probability of owning two cars is the highest (60-65%) (see (c) in Figure 2).

The fourth and the final synthetic household (SH4) was formed by changing the employment status of the female adult of HH3 into full time worker as well as changing their age from young to middle age. Also, the child member was considered to be between 5-9 years. For VM borough, the household is more likely to own three or more cars in 1998and 2003 while two cars in 2008 (see (d) in Figure 1). In PMR borough, the household fleet is more likely to be composed of either two or more than two cars (see (d) in Figure 2).

6. SUMMARY AND CONCLUSIONS

The current study examines vehicle ownership evolution in the Greater Montreal Area (GMA), Canada using cross sectional databases compiled over multiple time points. Though the multiple

waves were not compiled based on the same set of households, they still provided us an opportunity to examine the impact of technology, altering perceptions of road and transit infrastructure, changing social and cultural trends across the population on vehicle ownership. Further, pooled datasets allowed us to identify how the impact of exogenous variables has altered with time. Therefore, in the absence of panel data, travel behaviour analysis could benefit from such application of the multiple year cross sectional databases.

The study approach is built on the GOL framework that relaxes the restrictive assumption of the traditional OL model. Further, to incorporate the effect of observed and unobserved temporal effects, we consider two variants of the GOL model – the mixed GOL model and the scaled GOL model. After extensive specification testing, we found that the MGOL performed better than its counterparts. The empirical model specification was based on a rich set of exogenous variables including household socio-demographics, transit accessibility measures, land use characteristics, and temporal factors. Further, observed and unobserved effects of the elapsed time from the base year (1998) of data collection (and their interaction with other observed variables) are explicitly considered in our analysis enabling us to examine trends in variable impacts across the years.

In accordance with the existing literature, socio-demographic variables were found to be an important predictor of automobile ownership of households. Our results also confirmed that the impact of some socio-demographic variables varied with time. For instance, we observed that in recent years, the impact of full time workers on vehicle ownership levels has been reducing. The result is quite encouraging for policy makers highlighting that in the recent years, growing environmental consciousness and increased inclination towards using transit might actually be contributing to lower vehicle ownership levels. Policy makers can ponder upon softer policies such as encouraging workers to telework and/or teleconference or car share or make multi-modal commute trips by increasing transit accessibility at the work location. In fact, the results corresponding to transit accessibility measures highlighted the important role of public transit in

Montreal. The number of bus stops, and increase in bus and metro line length within the household buffer zone negatively impacted household's propensity to own cars. Since households tended to own more cars when they lived farther away from the work location, focusing on establishing good network connections between place of residence and place of work might reduce reliance of cars for day-to-day commute.

In our analysis, the boroughs which exhibited significant impact on car ownership include Ville-Marie, Cote-des-Neiges, and Plateau-Mont-Royal. Specifically, Ville–Marie borough transitioned from a negative propensity for car ownership towards a positive car ownership propensity from 1998 to 2008. The local agencies of this borough need to investigate the reasons for this dramatic change in such dense neighbourhood. In fact, they might need to review the borough policies such as parking cost mechanisms and/or altering traffic flow patterns with congestion pricing or implementation of more one way streets. In fact, combining different policies with information and advertising campaigns that promote more sustainable transport choices can help to bring about behavioural change and discourage unnecessary car use and in the long run, the ownership of multiple cars.

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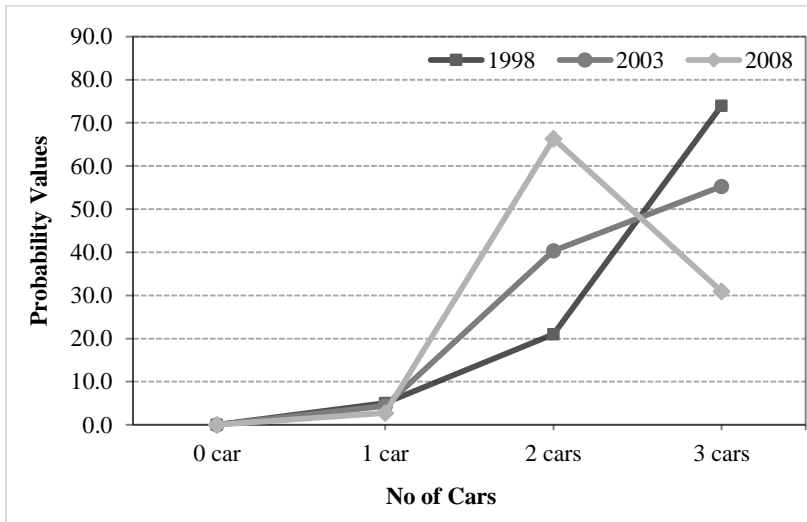
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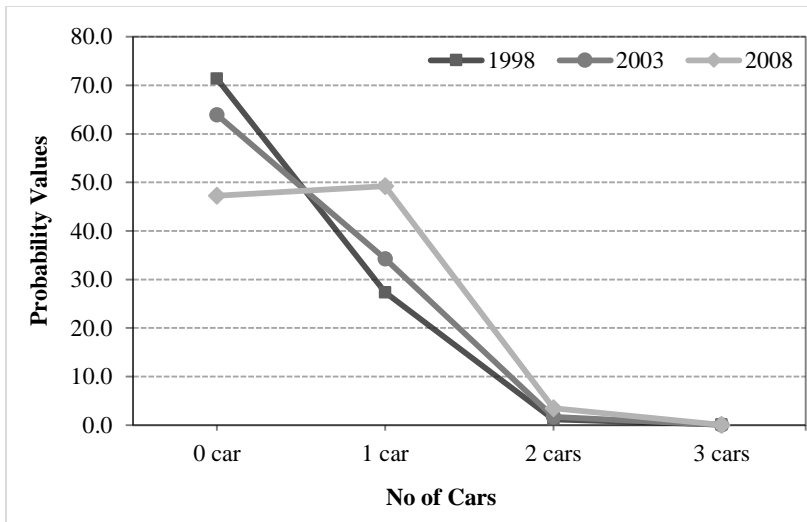
(a) SH1
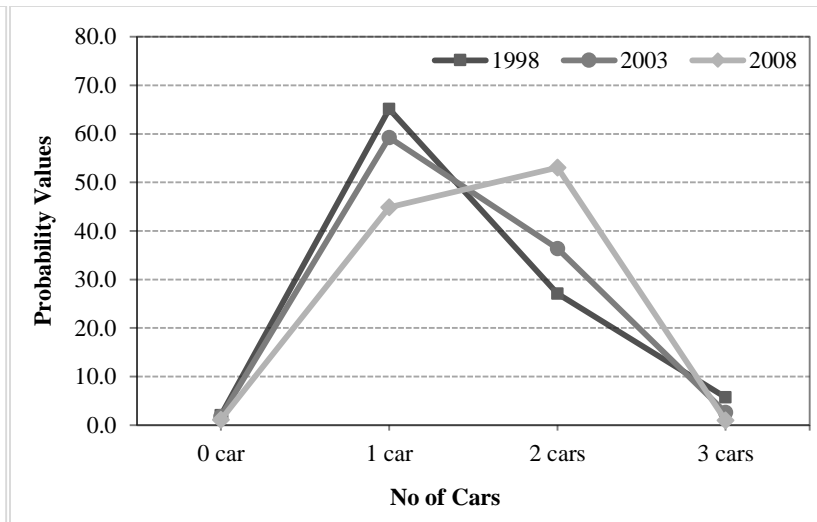
(b) SH2

(c) SH3

(d) SH4

Figure 1: Evolution of Car Ownership Levels across Years for Artificial Households in Ville-Marie Borough
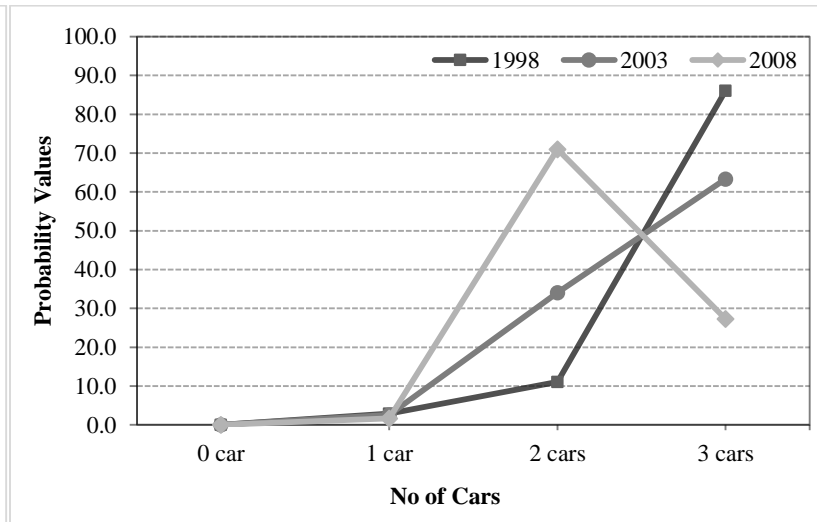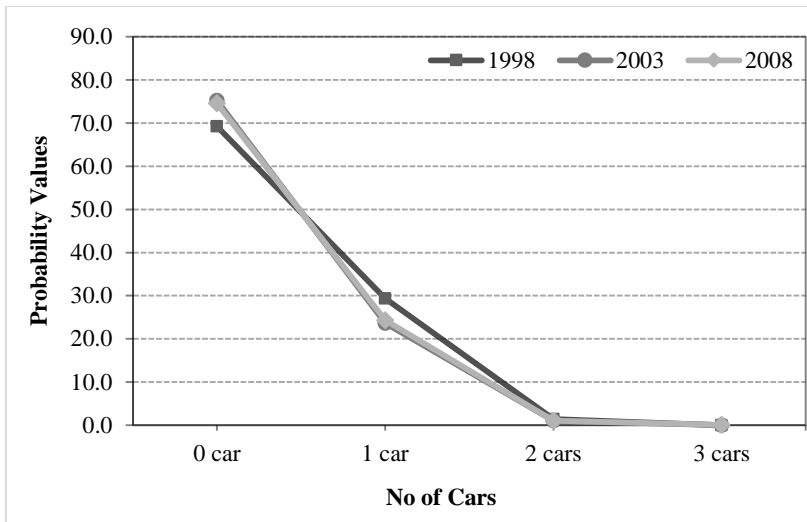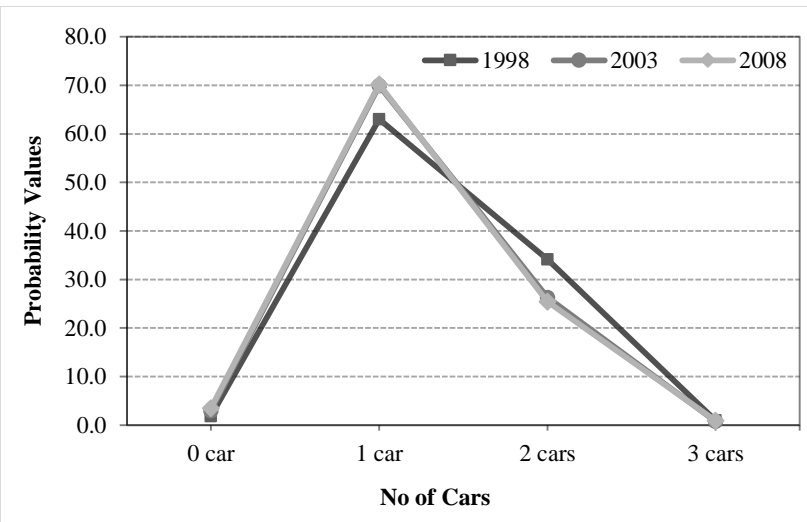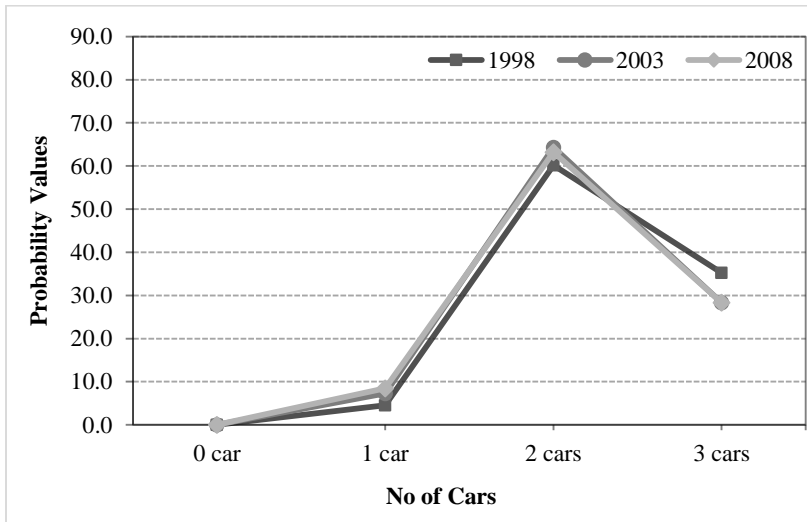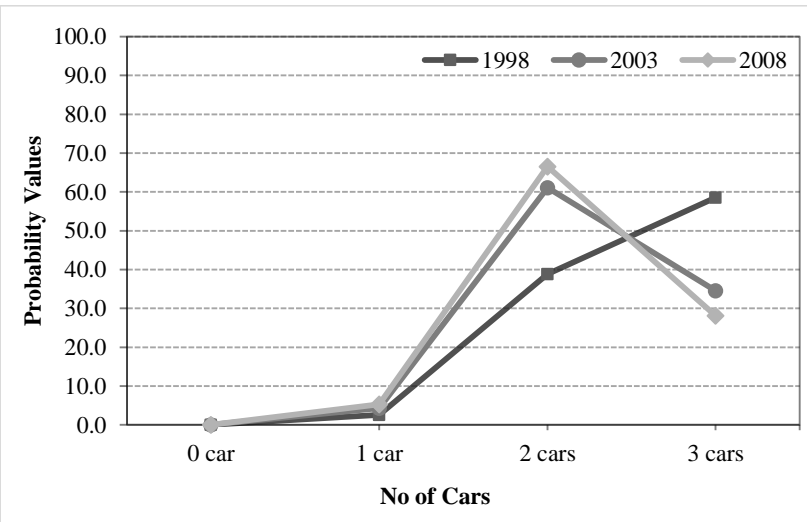
(a) SH1

(b) SH2

(c) SH3

(d) SH4

Figure 2: Evolution of Car Ownership Levels across Years for Artificial Households in Plateau-Mont-Royal Borough

TABLE 1: Summary Statistics of Socio-demographic and Land Use Variables

Variables	OD Years[*]		
	1998	2003	2008
Car Ownership Levels of Households			
0 Car	19.5	19.0	21.1
1 Car	45.2	44.5	42.8
2 Cars	29.7	30.1	28.6
≥ 3 Cars	5.7	6.5	7.5
Household Socio-Demographics			
No of Males			
0	29.5	34.4	36.1
1	33.6	33.3	33.1
≥ 2	36.9	32.3	30.8
No of Middle Aged Adults			
0	59.5	56.9	51.4
1	22.2	23.1	26.5
≥ 2	18.3	20.0	22.1
Number of Full-time Employed Adults			
0	31.6	32.6	36.2
1	38.5	37.9	33.6
≥ 2	29.9	29.5	30.2
Number of Part-time Employed Adults			
0	88.4	89.4	89.8
1	10.8	10.0	9.5
≥ 2	0.8	0.6	0.7
Number of License Holders			
0	11.7	11.6	13.4
1	33.4	33.5	32.6
≥ 2	54.9	54.9	54.0
Number of Students			
0	62.9	64.7	68.0
1	18.4	18.2	16.0
≥ 2	18.7	17.1	16.0
Number of Retirees			
0	75.2	72.7	64.3
1	15.4	18.1	23.2
≥ 2	9.4	9.2	12.5
Land Use Measures			
Income *(CT level)*			
Low (Less than 40K)	51.2	40.6	33.9
Medium (40K – 80K)	47.5	54.1	57.5
High (Above 80K)	1.3	5.3	8.6
Sample size	4000	4000	4000
[*]*The numbers in the table represent the percentage distribution of households in the sample for the OD years*			

TABLE 2: MGOL Estimation Results

Variables	Latent Propensity, y_q^*		Threshold between One and Two Cars, ψ_2		Threshold between Two and Three or More Cars, ψ_3	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant	2.5475	16.708	1.2326	44.900	1.4529	17.385
Time Elapsed	0.0526	3.385	---	---	-0.0241	-3.955
Household Socio-Demographics						
No of Males	0.2263	6.220	---	---	---	---
Presence of Children						
5-9 years	0.3549	3.688	---	---	---	---
10-14 years	0.8062	4.266	0.0625	2.258	---	---
15-19 years	---	---	0.0430	2.747	---	---
15-19 years * Time elapsed	0.0310	2.025	---	---	---	---
Middle Aged Household	0.1052	1.864	---	---	-0.1063	-3.481
Full-time Working Adults	0.4974	8.099	---	---	---	---
Full-time Working Adults* Time elapsed	-0.0385	-3.093	-0.0053	-2.978	0.0144	4.745
Part-time Working Adults						
Mean	0.3719	4.909	---	---	---	---
Standard Deviation	0.6510	4.101	---	---	---	---
No of Retirees	0.4411	5.856	0.0389	2.885	---	---
No of Seniors	---	---	0.0497	4.927	---	---
No of Students	-0.2903	-5.349	---	---	---	---
No of License Holders	4.0030	30.213	0.2921	20.756	-0.0965	-2.701
Presence of Immobile Persons	-0.2844	-5.395	---	---	---	---
Transit Accessibility Measures						
No of Bus Stops						
Mean	-0.0324	-8.015	---	---	---	---
Standard Deviation	0.0473	6.782	---	---	---	---
Length of Bus Lines (km)	-0.0063	-3.219	---	---	---	---
Length of Metro Lines (km)						

Mean	-0.2940	-5.640	---	---	---	---
Standard Deviation	0.6368	6.905	---	---	---	---
Land Use Measures						
Income (Base: Low Income)						
Medium Income (40K-80K)	0.5425	6.813	---	---	---	---
Medium Income * Time elapsed	-0.0326	-2.355	---	---	---	---
High Income (Above 80K)	---	---	-0.2849	-4.895	0.3460	2.721
High Income * Time elapsed	---	---	0.0255	3.670	-0.0426	-2.599
Ln (Distance to work)	0.0812	2.953	---	---	0.0475	3.844
Distance to work*Time Elapsed	0.0010	2.231	---	---	---	---
Type of Land Use						
Commercial (KM^2)	-1.9289	-3.950	---	---	---	---
Government and Institutional (KM^2)	-1.5299	-4.261	---	---	---	---
Population Density* Time elapsed	-0.1047	-6.149	---	---	---	---
Boroughs						
Ville-Marie	-1.0289	-2.984	---	---	-0.6569	-2.054
Ville-Marie * Time Elapsed	0.1293	2.569			0.0935	2.380
Cote-des-Neiges	---	---	---	---	---	---
Mean	-1.1942	-3.982	---	---	---	---
Standard Deviation	1.6522	5.145	---	---	---	---
Cote-des-Neiges * Time Elapsed	0.1233	3.219	---	---	---	---
Plateau-Mont-Royal						
Mean	-0.9257	-3.700	---	---	---	---
Standard Deviation	2.1003	5.686	---	---	---	---
Log-likelihood at sample shares, LL (c)	-14641.984					
Log-likelihood at convergence, LL (β)	-8556.612					
Number of observations	12000					
Note: "---"denotes the variable is insignificant at the 10% level.						