Evaluating the Effect of Land-Use, Parking policy and Transit Supply Strategies on Mode Choice of Downtown Commuters

Abstract:

Metropolitan regions around the world are looking for sustainable strategies to reduce motor-vehicle traffic congestion, energy consumption and emissions. These strategies include land use policies as well as improvements to public transit services. This empirical work aims at studying the potential impact of land-use (LU), public transit supply (PT) and parking pricing strategies on the mode choice of commuters living in the commuter rail line catchments in the region of Montreal, Canada. It makes use of an econometric modeling approach with both transportation mode choice and neighborhood type choice, as simultaneous decisions in order to take into account the endogeneity of these choices. The neighborhood choices are represented by neighborhood typologies derived from a cluster analysis using land use and transit supply indicators (population density, land use mix and bus transit supply). As part of the outcomes of this study, the elasticities of mode choice with respect to commuter-transit fees, travel time reductions and hourly parking costs are estimated. From the results, it is observed that a reduction of 10% in the transit fee or relative travel time would increase mode split by 10% and 3% respectively. The effect of age on both mode choice and neighborhood choice is also estimated. The individual and household structure factors associated with mode choice and/or residential neighborhood choice are also identified. Commuter age affects both outcomes. Income and gender affect mode choice while car ownership and the presence of children are linked to neighborhood choice.

INTRODUCTION

The complexity and significance of the relationships between land use (LU), public transit accessibility (PT), parking pricing and travel behavior outcomes (such as mode choice) have been identified in transportation planning and research for the decades. The intricacy of these relationships is due to the fact that:

- There are several dimensions that define land use (population density, land use mix, road network connectivity, etc), public transit accessibility (number of lines, headway, distance to stops), parking policies (parking fees, capacity, free parking at work) and travel behavior (mode choice, distance traveled, number of trips, residential location choice, emissions, etc); and
- The increasing evidence for the endogeneity of mode choice and residential location choice. In practice, and often in research, residential location and mode choice are assumed to be independent choices. Residential location choice has been modeled as a function of demographic, market housing and prices, employment location and accessibility measures, while mode choice as a function of mode-specific attributes (e.g., monetary cost in-vehicle travel time and waiting times), socio-demographics (age, income, car ownership) and land-use or built form characteristics at the residential location. There is, however, increasing evidence that households choose neighborhoods that allow them to pursue their activities using modes that are compatible with their socio-demographics (e.g., income, car ownership, life cycle) and travel preferences (e.g., preference for the use of a particular mode or short commuting travel times). This phenomenon is generally referred to as *residential self-selection* or *residential sorting* – for additional details, one can refer to the TRB (2009). Ignoring the dependence of these choices, when they are not independent, can result in the identification of false causal effects of LU attributes on mode choice and lead to misguided policy prescriptions. In order to correctly assess

the impact of LU on mode and residential location choice, the self-selection issue has to be taken into account. This can be done by modeling jointly the two outcomes, residential location and mode choice, as endogenous choices (TRB 2009).

Accordingly, the objectives of this paper are two-fold: i) to investigate the impact of commuter-transit service attributes, parking cost and residential neighborhood types on commuter-transit mode choice and ii) to model simultaneously the two choices (transportation mode and residential neighborhood location), explicitly accounting for residential self-selection.

The paper starts with a literature review looking at the link between LU, parking fees, residential location choice, mode choice and the issue of residential self-selection. The second section contains a description of the methodology adopted. This is followed by a description of the data used and developed for the analysis. The next two sections describe the statistical analysis adopted and the resulting models. A discussion and conclusion finishes the paper, with special attention given to the practical applications of the research.

LITERATURE REVIEW

The transportation literature on land use, transit accessibility, parking pricing and mode choice, including the self-section issue is abundant. This section provides a brief literature review considering the main elements of these research streams which have been studied using different approaches, cities and sources of data.

i) *Land-use, public transit accessibility and their effect on travel behavior*

A vast body of literature over the past two decades has analyzed the link between LU and travel behavior. Among these studies there are at least six comprehensive reviews of the literature (Badoe and Miller 2000; Crane 2000; Ewing and Cervero 2001; Handy 2005; Cao et al. 2008;

Gómez et al. 2009). Much of this research has concentrated on the impact of LU attributes on mode choice. Some of the studies have found a significant impact of LU characteristics on mode choice decisions (see Frank and Pivo 1994; Ewing et al. 1994; Handy 1996; Cervero and Wu 1997; Cervero and Kockelman 1997; Kockelman 1997; Badoe and Miller 2000; Crane 2000; Ewing and Cervero 2001; Rajamani et al. 2003; Rodriguez and Joo 2004; Zhang 2004; Ewing and Cervero 2010). It is, however, interesting to note that not all of the past studies have reported the significant influence of LU attributes. For example Crane and Crepeau (1998) and Hess (2001) found no relationship between LU and mode choice decisions. Kitamura et al. (1997), among others, studied the impact of LU and socio-demographic characteristics on the number and share of each mode in trips made, and reported that demographic variables have a bigger impact on travel mode choice comparing to LU attributes. Cervero (2002) examined mode choice behavior in Maryland and concluded that the effects of LU types alone tend to be more limited than those of LU mix (or land use mix indexes) on mode choice travel decisions.

ii) *Residential Self-selection*

Several of the studies mentioned above ignore the issue of residential self-selection when estimating the impact of LU variables on travel behavior. However, this is not always the case. One of the first studies to tackle the question of residential self-selection was Boarnet and Sarmiento (1998). They adopted an instrumental variables approach by using the percentage of buildings built before 1945, percentage of buildings built between 1945 and 1985, the percentage of foreign residents and residents more than 65 years old as instruments for residential density and they did not find any stable link between residential density and VMT.

While not explicitly about residential location and mode choice, Bhat and Guo (2007) use San Francisco Bay Area data to build a joint model of residential location and number of vehicles per household. Their model takes into account the self-selection effect (by allowing correlation between the error terms in their equations), but they don't find any significant effects even after controlling for a rich set of explanatory variables. They find statistically significant but quantitatively small impacts of LU measures on household car ownership.

Brownstone and Golob (2009) model the joint choice of residential density and VMT to control for the potential of self-selection effects. They include a rich data set using the California subsample of the 2001 National Household Travel Survey. Unlike previous studies they also model vehicle fuel consumption. They conclude that the impacts of increasing residential density are very small on the reduction of VMT or GHG emissions from residential vehicles.

Again, while not explicitly about residential location and mode choice, Eluru, Bhat et al. (2010) built a joint econometric model system for household residential location and vehicle composition/usage choices. In this system they controlled for self-selection issues in these choices. They concluded that there is significant dependence between these choice dimensions and that self-selection effects cannot be ignored when modeling land use-travel behavior interactions.

Ewing and Cervero (2010) conducted a meta-analysis of the built environment-travel literature existing at the end of 2009 in order to draw generalizable conclusions for practice. They focused on quantifying effect sizes, updating their earlier work, including additional outcome measures, and addressing the methodological issue of self-selection.

Miranda-Moreno, Bettex, Zahabi et al. (2011) considered the relationship between urban form, public transit accessibility, and daily mobility for residents of the metropolitan region of Quebec City. They implemented a model of two simultaneous equations, taking into account the interaction between vehicle ownership and choice of household location as an explanatory endogenous variable for total distance traveled by respondents. They concluded that a simultaneous model taking into account endogeneity of the interaction between ownership of vehicles and household choice better explains distance traveled than a simple linear regression model.

iii) *Parking Pricing*

Parking costs are an important factor on travel mode choice. Willson (1992) found that between 25 and 34 percent fewer vehicles were used to drive to work when drivers had to pay for parking compared to when they could park for free. A comprehensive study of a strategy to reduce single-occupancy commuter trips is reported in Bianco (2000). The project was a major part of a travel demand management (TDM) package in which on-street parking meters and discounted transit passes were also introduced. A before and after survey of 1000 employees found that the main shift was in commuters driving alone (7%), with the "after" drive-alone share lowering to 56% of total commute trips. Carpooling trips increased by ing 38% resulting in an "after" market share of 17% of all commute trips (Bianco, 2000). Hess (2001) studied the effect of free parking on mode choice and parking demand. A multinomial logit model was used to evaluate the probabilities of commuters with or without free parking at work choosing to: drive alone, ride in a carpool, or use transit for the trip to work in the central business district (CBD) of Portland, Oregon. He found that by increasing free parking by 1$, the modal share for solo driver and carpool decreased by 1% and 4% respectively, while the share for public transit increased by 5%. In another study, Washbrook et al. (2006) estimated greater Vancouver's commuters' mode choice in response to parking and road pricing policies. They found that by implementing the parking and road pricing (free road and parking was replaced by 1$ fee for parking and 1$ for road pricing), the probability of choosing to drive alone to work decreased by 8%. Hensher et al. (2001) used a stated preference survey of car drivers and public transport users at a number of parking locations, public transit interchanges, and shopping centers in Sydney CBD. They concluded that a 1% increase in hourly parking rates results in a 0.541% reduction in the probability of choosing to park in a sheltered parking lot, a 1.015% reduction in the probability of choosing to park elsewhere in the CBD and a 0.476% reduction in the probability of parking at the fringe.

Despite the above rich literature on residential location choice and the influence of LU on travel behavior, there remain some research gaps, in particular:

i) There is relatively little research treating household location and mode choice as a simultaneous, endogenous process accounting for residential self-selection bias;

ii) Very little research has been done that looks at commuters mode and residential location choice while also considering parking pricing strategies;

iii) Very few studies have considered neighborhood typologies generated based on LU and PT indicators to represent household location choices.

iv) Little work has been done to look at the determinants and their elasticities of travel demand of commuters living in rail catchment areas.

To provide some empirical evidence related to these issues, this study uses a simultaneous modeling method that fills these gaps.

METHODOLOGY

This paper examines the impact of LU and PT characteristics represented by neighborhood typologies, in the context of an endogenous modeling system of residential location and mode choice of commuters resided in the railway catchments of Montreal's suburban rail system. For this, a neighborhood typology classification is developed for the city of Montreal based on LU and PT variables. This approach is based on the idea that household location and mode choice are intimately linked.

In this model, neighborhood choice is a function of socio-demographic characteristics, whereas mode choice is directly influenced by neighborhood choice, parking management strategies (at work-place destination), and socio-demographics – see **Fig. 1**. It is assumed that these decisions are made jointly and since neighborhood type appears in the mode choice utility function, it is an endogenous variable.

$$\text{i) } M = f(X, T, P, K, \varepsilon_1) \qquad \text{ii) } K = g(X, \varepsilon_2) \tag{1}$$

Where:

- M: Mode chosen by commuter (auto-vehicle(0) or Transit (1))
- K: neighborhood type chosen by a given commuter
- X socio-economic characteristics of individual and household (e.g., age, gender, income, car ownership, etc.)
- T: Transportation mode attributes (fare, in-vehicle travel times, waiting time, etc.)
- P: Parking strategies (e.g. pricing and capacity)
- ε_1 and ε_2: correlated errors representing unobservable factors that influence mode and neighborhood choice

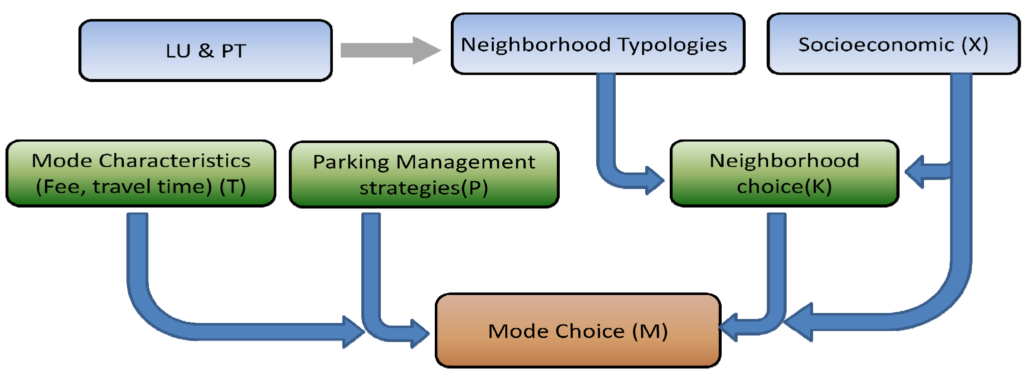

FIGURE 1: Household location and mode choice

DATA

The data used for this empirical application has different sources, including a subsample of OD survey commuting trips, socio-demographics, travel times by mode, land use and parking data. The details of each particular source of data are provided below.

a) OD Survey

Data for the mode choice model come primarily from the 2003 Montreal OD survey. In 2003, 71,400 households were surveyed, accounting for 4.7% of the households of the region. This represented 366,300 (unexpanded[1]) trips over a 24-hour period, 92,000 of which took place in the morning peak. This research concentrated on commuters with a morning peak trip originating in one of the five commuter rail catchment areas and whose destination was downtown in the morning peak. The commuter rail catchment areas (as determined by the Agence métropolitaine de transport[2] (AMT)) cover suburban communities found along the commuter rail lines. As such, the population of interest was those workers for whom commuting by public transit (primarily train) or car was a possibility. This sample consisted of 3,710 observations. A map of observations and the railway catchments is found in **Fig 2**.

b) Mode Choice Data

Public transit travel times were obtained from the AMT and were simulated using the entirely disaggregate public transit assignment software MADIGAS[3]. Public transit fees, based on origin, destination and simulated transit itinerary were also obtained from the AMT. Automobile travel times

[1] Not multiplied by the expansion factor for each trip, in order to represent the whole population.
[2] Agency responsible for: operation of commuter rail lines and the coordination of public transportation planning in the Greater Montreal Region.
[3] . http://www.transport.polymtl.ca/logiciel.htm

for each trip were obtained from the Quebec Ministry of Transportation using their modeling system known as MOTREM[4] which employs EMME for automobile traffic assignment.

For modeling purposes all transit modes (commuter rail, metro and bus) were grouped together.

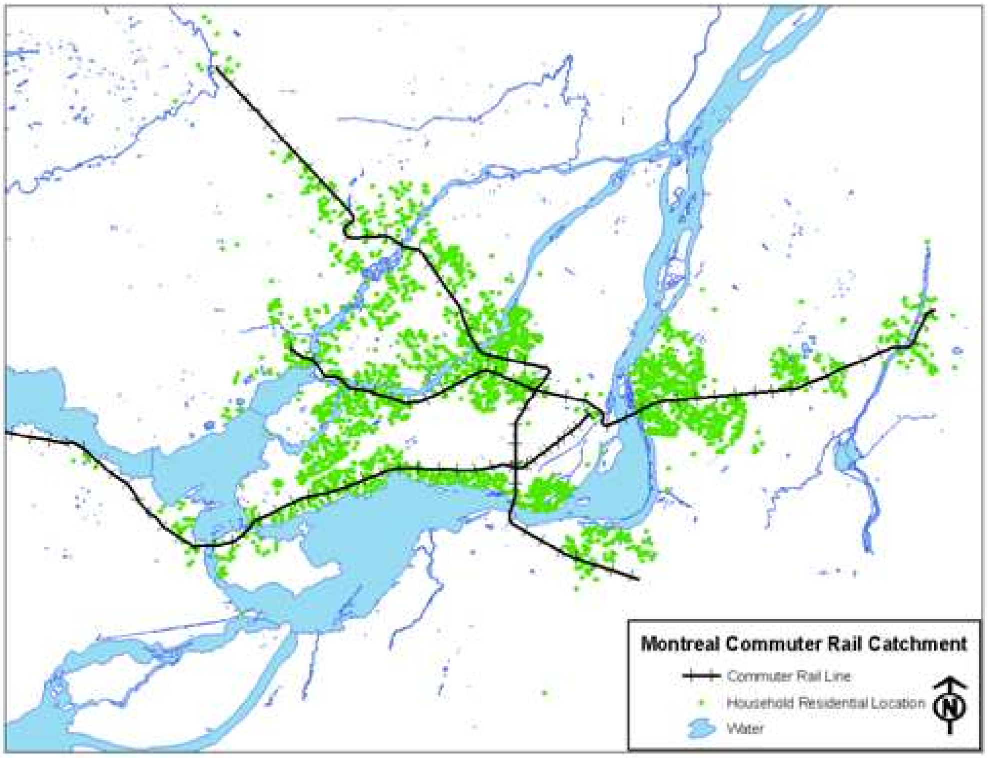

FIGURE 2: Household location and commuter rail catchment areas

c) Population Density, Land Use Mix and PT accessibility

In order to create neighborhood typologies, three built environment indicators were used: population density, land use mix, and a simple measure of PT accessibility. The data collection approach is based on a grid formed from 500- by 500-meter cells covering the entire greater Montreal region. Each household from the 2003 O/D survey is assigned the characteristics of the

[4]. Montreal region transport model for year 2003 (Modèle de transport de la région de Montréal 2003).

cell in which it is situated, as well as the eight surrounding cells – see **Fig 3**. Thus, population density around the household is calculated as the sum of the population in the nine cells divided by the area of the nine cells. Population data used are from Statistics Canada.

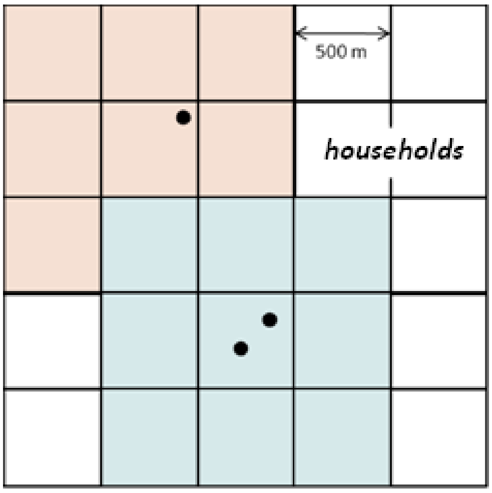

FIGURE 3: 500m grid approach

Land use mix (entropy) was calculated using data from DMTI spatial, Inc. The land use mix indicator used is modeled after an entropy index (Frank et al. 2005; Theil et al. 1971) which measures diversity or homogeneity of different land uses in each grid cell. The index is defined using the following equation:

$$E_j = -\sum_{i=1}^{n} \frac{[(\frac{A_{ij}}{D_j})Ln(\frac{A_{ij}}{D_j})]}{Ln(n)} \tag{2}$$

Where:

- A_{ij} : area of land use i in cell j
- D_j : area of cell j excluding water and open area
- n : total number of different land uses

In this study, n = 5: residential commercial, industrial, institutional, and park. The value of Ej varies between 0 and 1, 0 corresponds to a homogenous area characterized by one sole land use and 1 refers to a "perfect mix". This index has been used in many studies to measure land use mix (Cloutier et al. (2007); Frank et al. (2005)).

The PT accessibility takes into account the number of transit lines (bus, metro and rail) passing within 500 meters of the household. Finally, the neighborhood typology is generated using a cluster analysis (described below) based on the LU and PT variables mentioned above.

d) Parking charges and accessibility

In order to capture the properties of parking in the vicinity of the destination of each individual in the data set, the destination coordinates for each trip was geo-coded using ArcGIS. Using the coordinates of the off-road parking lots, these were also included (see **Figure 4**). Parking costs for a particular destination associated with the closest and cheapest parking lot (network distance) to the observed destination were considered. The number of parking spaces was also considered; however, the results with and without this factor were similar.

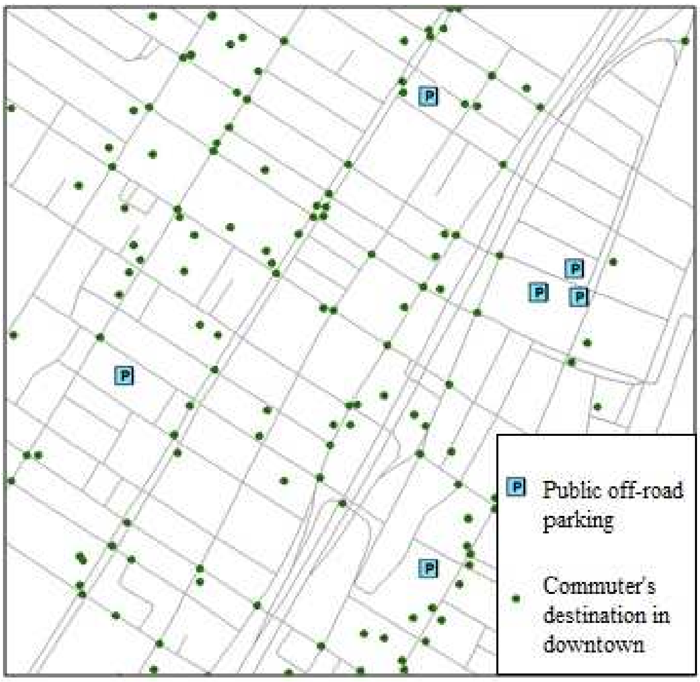

FIGURE 4: Downtown parking locations and destination of commuters

ANALYSIS

Neighborhood Cluster Analysis

The neighborhood cluster analysis carried out in this research is similar to that presented in Lin and Long (2008), Riva, et al. (2008) and more recently Miranda-Moreno (2011). K-means statistical cluster analysis is used in order to regroup households into “k” homogenous clusters according to LU and PT characteristics. This was done with the K-means function in STATA. The goal of using this technique is to maximize the inter-cluster variation while minimizing intra-cluster variation. The objective is therefore to assemble commuter households into k subgroups having similar population densities, land use mixes (entropy), and PT accessibilities.

Several attempts with different number of clusters were tried and finally it was found that four clusters were a satisfactory number (four different types of neighborhoods), where each one had an acceptable number of households and sufficient variation between clusters. The characteristics of the four clusters (neighborhoods) are described in **Table 1**. Also **Fig 5** shows the location of each neighborhood cluster.

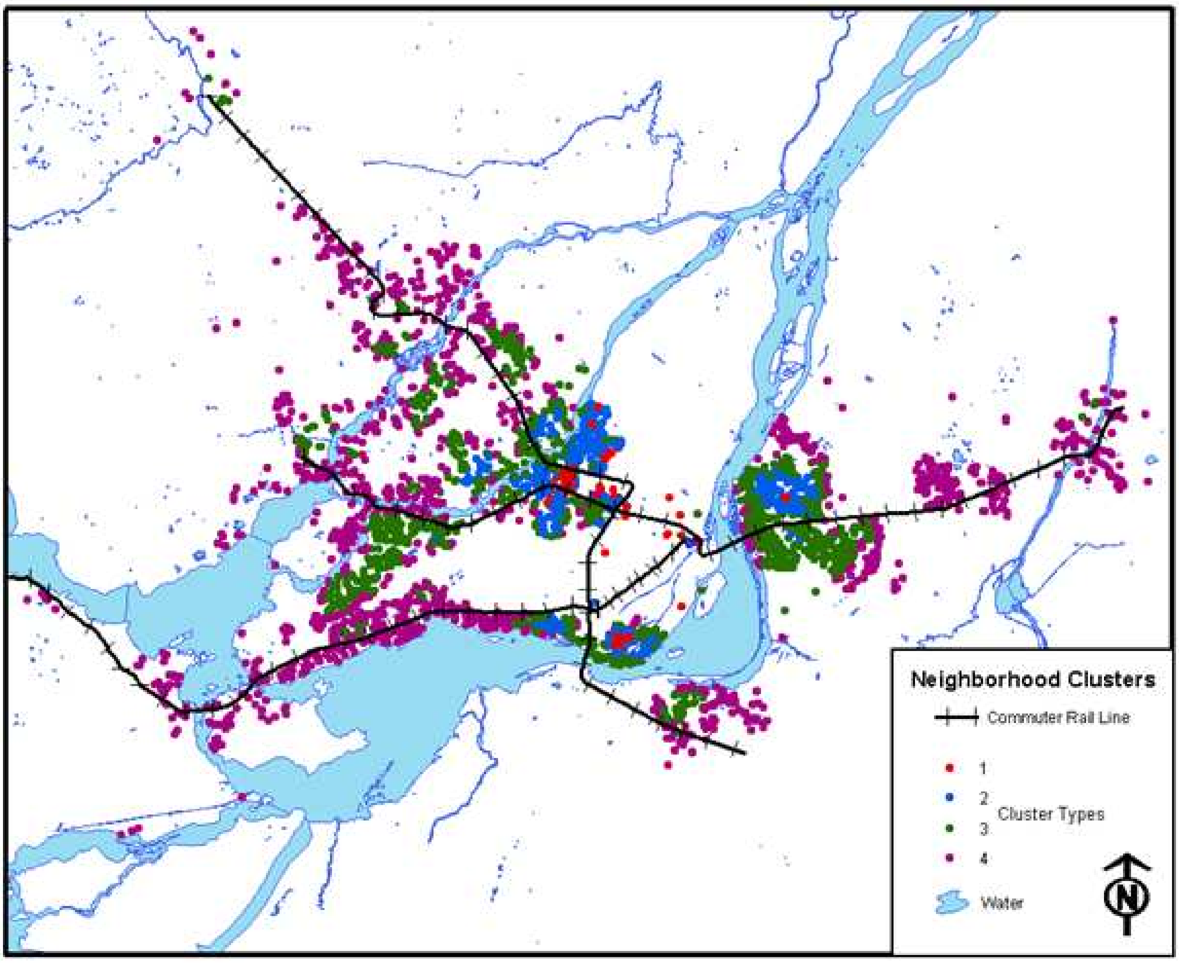

FIGURE 5: Neighborhood clusters for the data set's households

As can be seen in **Table 1,** the clusters can be characterized according to three indicators as follows:

Cluster one is characterized by the best PT accessibility, highest density and land use mixes in the region. This primarily comprises people residing in neighborhoods situated in the dense residential areas of downtown or catchment suburb areas with high proximity to the main transit axes and access to a rich variety of retail and services.[5] This cluster could be referred to as transit-oriented development cluster.

Cluster two groups households outside of downtown having relatively good PT access. It also comprises neighborhoods located along transit axes. This cluster has the second highest density and land-use mix.

Cluster three neighborhoods have moderate transit accessibility compared to clusters 1 and 2. The density and land use mix for this cluster is around the average for all clusters.

Cluster four ("periphery") includes all households with poor PT accessibility, low density, and homogenous land use. These households are mostly situated in the periphery or too far from PT lines to have satisfactory accessibility. Cluster four represents the average characteristics of the greater proportion of households in the Montreal City region.

TABLE 1: Characteristics of the Four Clusters

	Observations		Average		
	Number	%	PT accessibility (number of transit lines within 500m of dewling)	Population Density (1000 Capita/km^2)	Entropy
Cluster 1	132	3.56	6.76	8.28	0.66
Cluster 2	636	17.14	5.86	5.42	0.59
Cluster 3	1344	36.23	3.8	3.34	0.47
Cluster 4	1598	43.07	1.96	1.59	0.45
Total/average	3710	100.0	3.47	3.12	0.49

Descriptive statistics

A summary statistics of the explanatory variables used in the analyses is presented in Table 2. Some basic statistics are provided in this table.

[5] NB: some of these people while not residing in the railway catchments had a morning peak trip originating in the one of the railway catchments.

TABLE 2 - Summary statistics for explanatory variables

	Number of observation: 3,710					
	Variable	Mean	Std. dev.	Min.	Max.	Variable type
Mobility	Mode choice 0(auto)1(transit)	0.57	0.49	0.00	1.00	Binary
	PT access time (min)	10.31	6.81	0.00	46.74	Continuous
	PT waiting time (min)	23.57	10.20	6.50	76.25	Continuous
	PT in vehicle time (min)	34.07	14.59	4.96	107	Continuous
	Delta_t (Auto total time - PT total time)	-18.36	14.45	-96.38	19.89	Continuous
	Public transit fee	98.52	28.81	39	222.00	Continuous
	Parking hourly cost	3.19	2.57	0.00	7.60	Continuous
	Parking capacity	204.82	244.48	14.00	1252.00	Categorical
Land use	Cluster 1-4	3.18	0.84	1.00	4.00	Categorical
	PT accessibility	3.470081	4.446203	0	34	Categorical
	Density (people/km^2)	3124.091	1799.98	0	14243.03	Continuous
	Entropy index	0.49	0.192	0	0.999	Continuous
Household characteristics	Number of vehicles	1.61	0.84	0.00	12.00	Categorical
	Number of people	3.03	1.23	1.00	12.00	Categorical
	Number of children	0.63	0.91	0.00	7.00	Categorical
	Income(1 to 6)*	4.07	1.51	1.00	6.00	Categorical
	Number of workers	1.73	0.70	0.00	6.00	Categorical
Individual characteristics	Age	39.50	11.98	5.00	84.00	Continuous
	(Age)2	1703.79	965.58	25.00	7056.00	Continuous
	Age Less than 35 years	0.37	0.48	0.00	1.00	Dummy
	Age 35-50 years	0.47	0.50	0.00	1.00	Dummy
	Age 50-64 years	0.21	0.41	0.00	1.00	Dummy
	Age More than 64 years	0.02	0.13	0.00	1.00	Dummy
	Sex(0=female, 1=male)	0.49	0.50	0.00	1.00	Dummy
	Driver's license(1=yes,0=No)	0.90	0.30	0.00	1.00	Dummy
	Full-time	0.83	0.37	0.00	1.00	Dummy
	Part-time	0.03	0.17	0.00	1.00	Dummy
	Student	0.01	0.11	0.00	1.00	Dummy
	Retired	0.11	0.32	0.00	1.00	Dummy
	Other	0.01	0.11	0.00	1.00	Dummy

** Income ranges for each category: 1=(less than 20,000$); 2=(between 20,000$ & 39,999$); 3=(between 40,000 & 59,999);4=(between 60,000$ & 79,999$);5=(between 80,000$ & 99,999$);6=(more than 100,000$);*

Statistical modeling

The next step was to estimate the two-simultaneous equation models using the approach proposed by Deb and Trivedi (2006). As specified in the methodology section, the choice of residential neighborhood is modeled simultaneously with the choice of transportation mode t as a binary outcome (car and transit options). That is, the individuals select simultaneously where to live and what mode of transport they would use to get from a given origin to a particular destination. According to the four neighborhood typologies previously defined and whether the individual used auto-vehicle or transit for its trip, 4 different choices are set up for residential location and two for transportation modes. Equations 4 and 5 present the utility functions for the different choices taking into account the self-selection phenomenon between household location choice and mode choice.

$$M_{qi} = \alpha_q x_{qi} + \sum_{j=1}^{4} \mu_j k_{ij} + \sum_{j=1}^{4} \lambda_j \, l_{ij} + \varepsilon_{qi} \qquad (4)$$

$$N_{ij} = \beta_j z_i + \delta_j l_{ij} + \eta_{ij} \quad j = 1, \dots, 4 \qquad (5)$$

Where:

- M_{qi}: Utility function of mode choice of individual i (q=0,1 auto-vehicle and transit)
- N_{ij}: Utility of cluster choice j for individual i, j = 1, …, 4
- x_{qi} : socio-economic or mode characteristics of individual *i* (age, income, travel time, cost) for mode *q* and individual *i*
- z_i : socio-economic characteristics of individual *i* associated to cluster choice
- k_{ij}: dummy variables representing neighborhood cluster j for the household of individual i
- l_{ij}: Latent explanatory variable of unobserved heterogeneity by endogenous variables (Follows a normal distribution)
- ε_i: random independent error (Logistic distribution)
- n_{ij}: random independent error (Logistic distribution)
- $\alpha, \beta, \delta, \lambda, \mu$: model parameters (vectors)

Note that correlation among the outcomes is considered through the unobserved latent variable l_{ij} that appears in both utility functions. The model is estimated with STATA 10.1 using the estimation method proposed by Deb and Seck (2009) and Deb and Trivedi (2006). This estimation method models multinomial treatments and a binary outcome using maximum simulated likelihood. In this case, the mode choice variable is represented by a binary outcome while the treatment choice (neighborhood type) is assumed to follow (conditionally on the latent factors) a mixed multinomial logit (MMNL) structure defined as:

$$P_r\left[K_{ij} \middle| x_i, l_{ij}\right] = \frac{\exp\,(\beta_j z_i + \delta_j l_{ij})}{\sum_k^J \exp\,(\beta_k z_i + \delta_k l_{ik})} \quad (6)$$

With the normalization structure $\beta_4=0$ and j=1, 2, 3 and 4. The model parameters are then estimated using maximum simulated likelihood and the simulator uses Halton sequences (Deb and Trivedi 2006a and 2006b). In our model the mode choice outcome variable has a logistic distribution. The simultaneous model considers household location choice as an endogenous variable explaining mode choice by individuals and thereby takes into account potential self-selection bias. Using this estimation method in order to be able to identify the variances of the unobserved factors, normalization is required on either λ_j or δ_j. It is assumed that $\delta_j=1$, and λ_j is a free parameter estimated by the model.

RESULTS

Mode choice model

In **table 3**, we have reported the AIC[6] values for 3 models as a way to compare our simultaneous model with 2 separate binary logit and multinomial logit (MNL) models. The likelihood ratio (LR) test[7] for exogeneity of the models is also provided. Comparing the models, we see that the AIC value of the simultaneous model is smaller than the independent model (12,977 vs. 13,036). This indicates a better fit of the simultaneous model compared to the two separate logit models. Also the likelihood ratio (LR) test is 63.0 and statistically significant different from zero, indicating that the null hypothesis of exogeneity is overwhelmingly rejected at any level of significance.

[6] Akaike's information criterion (AIC) is a measure of the goodness of fit of an estimated statistical model
AIC = -2*ln(likelihood) + 2*k, where k=estimated variables + constants.

[7] LR test for exogeneity of treatment, is a test for a joint hypothesis that λ's are equal to zero. It follows a Chi-square distribution with q=3 (number of treatments).

Table 4 shows the results of the simultaneous model of mode and household location choice versus a simple Binary logit model that is not estimated jointly with neighborhood choice. In these models as explained in the statistical modeling section, the outcome of the mode-choice part takes 1 for PT and 0 for auto-vehicle respectively.

As suggested from the literature review, socio-demographic variables have statistically significant impacts on mode choice. In this empirical study, age, income and gender appear to be significant. From these variables, the highest elasticity is attributed to sex for female suggesting that being male decreases the probability of choosing PT by 62% on average. For age, its coefficient implies that as it increases by one year, a 1% decline in the chance of using PT is observed. Income also has a negative effect on choosing PT. By increasing the annual income in $10,000, the chance of PT being selected is reduced by 10 % on average.

Regarding the mode choice attributes, the transit fee, the difference in travel time and hourly parking cost resulted statistically significant and right-sided coefficient estimates. As expected, an increase in the transit fair reduces the probability of commuters selecting transit modes. Based on its elasticity, a 10% increase in PT fee would on average result in 10 % reduction in probability of choosing PT. Difference in travel time (Delta_t = travel time by car – travel time by PT) has an inverse effect on the likelihood of selecting PT. In other words, if the absolute value of Delta_t increases by 10%, the chance of selecting PT decline by 3%. Finally the only factor in our model that positively affects the probability of PT being selected is parking hourly cost. A dollar increase on the parking hourly cost for auto-vehicles implies the probability of using PT instead of car increases by 5%. This is consistent with some estimates in the literature (e.g. Hess 2001)

TABLE 3: AIC comparison *(Simultaneous model Vs a binary Logit and MNL model)*

	AIC	LR test	
		Coeff.	P-value
Binary logit *(for the mode choice)*	4716	-	-
MNL *(for the cluster choice)*	8320	-	-
Binary logit +MNL *(sum of rows 1 and 2)*	**13036**	-	-
Simultaneous multinomial treatment model *(study's model)*	**12977**	63	0.000

TABLE 4: Mode choice- Household Location choice

	Binary Logit model			Simultaneous model		
Variables	**Coef.**	**P-value**	**Elasticities**	**Coef.**	**P-value**	**Elasticities**[8]
Cluster1	-0.526	0.008	-18%	2.770	0.081	13%
Cluster2	-0.205	0.073	-7%	6.001	0.028	14%
Cluster3	-0.298	0.000	-10%	-1.184	0.218	-22%
Cluster4	Reference			Reference		
Age	-0.014	0.000	0%	-0.084	0.035	-1%
Income	-0.140	0.000	-5%	-0.652	0.031	-10%
Sex (0=female, 1=male)	-0.544	0.000	-19%	-2.627	0.02	-62%
Public transit fee[9]	-0.012	0.000	-4%	-0.065	0.021	-10%
Delta_t (Auto total time – PT total time)[10]	0.023	0.000	-1%	0.115	0.032	-3%
parking hourly cost	0.034	0.013	1%	0.495	0.042	5%
Constant	3.448	0.000	-	14.789	0.023	
λ Clus. 1	-			0.293	0.126	
λ Clus. 2	-			-8.928	0.016	
λ Clus. 3	-			-0.322	0.393	
λ Clus. 4	-			Reference		

For the neighborhood endogenous variables, individuals living in clusters 1 and 2 who are located in central neighborhoods are more likely to choose PT for the trips than those living in the periphery. For these individuals, the probability of using PT increases by 13% and 14 %

[8] *Elasticities represent the percentage change in the probability of choosing PT. ((new Prob of choosing PT- base[8] prob of PT)/ base prob of PT)*

[9] *This fee is not constant and varies by distance for the commuter rail users.*

[10] *Note that the values of Deta_t are negative. This means that as this negative difference increase, the likelihood of selecting PT is reduced*

respectively. For those households located in cluster 3 the impact of household location on mode choice is negative in comparison to the reference case but this is not statistically significant.

Household location choice model

Table 5 presents the household location choice model. In this case, households are divided into 4 categories based on the cluster (neighborhood) in which they are located. Thus, it is possible to consider the effect of household location on their mode choice. Cluster 4 which also represents the households in the periphery is designated as the reference group.

TABLE 5: Household Location Choice (Cluster 4 or periphery set as base case)

	Variables	Choice model		
		Coef.	P -value	Elasticities*
cluster1	number of cars	-1.11139	0	-59%
	number of children	-0.10856	0.356	-4%
	number of workers/household	0.091718	0.539	0.5%
	age<35	0.582899	0.011	58%
	50<age<64	0.46013	0.098	34%
	age>64	0.337822	0.625	37%
	cons	-1.70909	0	-
cluster2	number of cars	-1.14189	0	-60%
	number of children	-0.28596	0	-20%
	number of workers/household	0.343653	0	29%
	age<35	0.388765	0.002	30%
	50<age<64	0.396629	0.008	26%
	age>64	0.392124	0.322	44%
	cons	-0.07894	0.655	-
cluster3	number of cars	-0.37394	0	-14%
	number of children	-0.09006	0.075	-3%
	number of workers/household	0.113035	0.098	3%
	age<35	0.178431	0.081	5%
	50<age<64	0.279148	0.025	12%
	age>64	-0.10312	0.779	-12%
	cons	0.091473	0.541	-

** elasticities represent the percentage change in the probability of choosing cluster(i). ((new Prob of choosing cluster(i)- base case prob of choosing cluster(i))/ base prob of choosing cluster(i))*

With respect to household location choice, cluster 1 and 2, which represent neighborhoods with the highest PT accessibility, population density, and greatest land use mix (entropy) and which are basically situated on central neighborhoods, are chosen primarily by individuals of 35 years and under and over 64 years of age (although this is not statistically significant for the over 64 years old variable). In fact being less than 35 years old increases the chance of residing in cluster 1 by 58% and 30% for cluster 2, respectively. This could be due to the fact that universities and jobs are mostly located in central neighborhoods and downtown, and that younger people prefer to be close to these points. The choice to live in cluster 3 is more likely for people between 50-64 years of age. Actually the chance for an individual between 50-64 years old choosing neighborhood type 3 over 4 is about 12% higher.

The increase in number of cars per household has a negative effect in choosing any cluster relative to the omitted category (cluster 4 or periphery). For example by increasing the household's number of cars by one, the probability of that household residing in cluster 1 is decreased by 59%. The number of children per household has a negative impact on choosing any other neighborhoods than peripheral neighborhoods (but this is not statistically significant for cluster 1). For instance by adding one child to the family, the chances of that household choosing to live in cluster 2 compared to cluster 4 (omitted category) declines by 20%. Number of workers per household positively affects the choice of households to live in clusters other than the reference case (this is not significant for cluster 1). This could be explained by that the households first chose their work and according to that, the location of their house. For example by raising the number of workers in households by 1, the probability of that household dwelling in cluster 2 increases by 29% comparing to cluster 4.

CONCLUSIONS AND LIMITATIONS

This paper presents some evidence on the effect of parking pricing, transit service attributes and neighborhood typologies on mode choice for downtown commuters, controlling for socio-demographics and taking into account residential self-selection. For this study, a large sample of downtown commuters with morning peak-period trips originating in commuter rail catchment areas and with destinations in downtown Montreal was used. This empirical study makes use of a two-equation simultaneous model: one equation for mode choice and the other for residential location choice (represented by neighborhood type).

The main findings of this study are that:

- Both transit mode attributes *and* parking costs appear to have an important impact on transportation mode choice of downtown commuters. The increase in PT travel time and fares negatively affect the use of PT, while increasing parking cost increases the probability of choosing PT. More specifically, a dollar increase on the parking hourly cost in downtown would imply an increase of 5% in the transit modal share for commuters. Moreover, a 10% increase in PT fee would represent a 10 % reduction in average in the probability of using PT for commuting to downtown.
- As expected, the neighbourhood type where commuters live plays an important role in the transportation mode choice even after controlling for socio-demographics and transit attributes. For instance, a downtown commuter living in cluster 1 and 2 have 13~14% higher chances of using transit than a commuter living in cluster 4, with same income, gender, age and commuter train service characteristics.
- Socio-economic attributes are also important factors in mode choice of individuals. In this regard, the increase in income, age and being male decrease the chance of using PT.

For instance being male decreases the chance of selecting PT by 62%. Also a year increase in the age of the individual results in 1% reduction in the chance of selecting PT by that individual.

- Socio-economic characteristics are also very important when it comes to selecting household residential location. The main factors affecting residential location choice are age, employment status, household structure, and number of cars at home. For instance, the empirical results show that young commuters to downtown, without kids or car access prefer to reside near their work place which is downtown (clusters 1 and 2). Household car ownership has a negative effect on choosing any cluster other than the base case (cluster 4 or periphery).

The implications of these empirical results can be viewed in different ways. Densification, land use mix and transit accessibility strategies in train catchment areas would positively influence downtown transit commuting. The results also suggest that increasing parking costs or reducing transit fares would encourage downtown commuting by public transit. More competitive travel times of transit services to downtown would also reduce car use for commuting purposes. These findings are consistent with previous work, indicating the sensitivity of downtown commuters to transit fees and parking pricing. Therefore, the combination of incentives and pricing strategies can help increasing the share of PT. The results also bring some additional light on joint decision processes. Downtown commuters simultaneously decide the type of residential neighborhood and commuting transportation mode. The results also highlight the effect of regional trends in the population aging, economy and household structure, which will certainly play a role in these two choices in the next future.

It is also important to highlight that this work presents some limitations. For instance, this work is based on a subsample of commuter trips (cross-section data) from one city. Panel or longitudinal data and data from other cities would help validating these results. Secondly what is focused on in this paper is the mode and location choice of individuals as indicators of mobility. However, other travel behavior outcomes such as number of trips, departure times, travel distances or greenhouse gas emissions could merit exploration to obtain more insights in commuter behavior.

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