Examining the influence of stop level infrastructure and built environment on bus ridership in Montreal

Vincent Chakour
Engineer
Transports Québec
Montréal, Québec, H2Z 1W7
Canada
Ph: 514-864-1750, Fax: 514-864-1765
Email: vincent.chakour@mtq.gouv.qc.ca

Naveen Eluru*
Associate Professor
Department of Civil, Environmental and Construction Engineering
University of Central Florida
12800 Pegasus Drive, Room 301D, Orlando, Florida 32816, USA
Ph: 407-823-4815 Fax: 407-823-3315
Email: naveen.eluru@ucf.edu

*corresponding author

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Abstract

We studied transit ridership from the perspective of the transit provider, with the objective of quantifying the influence of transit system operational attributes, transportation system infrastructure attributes and built environment attributes on the disaggregate stop level boardings and alightings by time of day for the bus transit system in the Montreal region. A Composite Marginal Likelihood (CML) based ordered response probit (ORP) model, that simultaneously allows us to incorporate the influence of exogenous variables and potential correlations between boardings and alightings across multiple time periods of the day is employed. Our results indicate that headway affects ridership negatively, while the presence of public transportation around the stop has a positive and significant effect. Moreover, parks, commercial enterprises, and residential area, amongst others, have various effects across the day on boardings and alightings at bus stops. An elasticity analysis provides useful insights. Specifically, we observe that the most effective way to increase ridership is to increase public transport service and accessibility, whereas enhancements to land-use have a smaller effect on ridership. The framework from our analysis provides transit agencies a mechanism to study the influence of transit accessibility, transit connectivity, transit schedule alterations (to increase/reduce headway), and land-use pattern changes on ridership.

Keywords: Bus ridership; composite maximum likelihood; Montreal; urban form; boardings and alightings; time of day;

1. Introduction

The prevalence of sub-urban life in North American cities in the latter half of the 20^{th} century has resulted in substantially larger private vehicle usage relative to public transportation system usage (Santos et al., 2011). According to data from 2013 Canadian Vehicle Use Study (CVUS), annually an average light vehicle accrues about 16,000 kms during an estimated driving time of 385 hours (Transportation in Canada, 2013). Policy makers are challenged to find innovative solutions to counter the negative externalities of this personal vehicle dependence. The last decade has seen a strong push towards improving the sustainability of urban transportation systems in North America. This is particularly crucial given the increasing air pollution and greenhouse gas emissions resulting from increased private vehicular travel - a matter of grave concern for the health and safety of future generations (Brunekreef and Holgate, 2002; Woodcock et al., 2009). An often suggested alternative to reduce the negative externalities of the personal vehicle use is the development of an efficient public transportation system that provides equitable service and accessibility to the population as well as contributes to the reduction of air pollution and GHG emissions. Not surprisingly, many urban regions are either enhancing or considering improvements to public transportation infrastructure to address the private vehicle use challenge (for example see transportation plans of Montreal (Ville de Montreal, 2008) and Toronto (Get Toronto Moving 2014). Based on the Canadian National Household Survey, public transit commuting mode share in major Canadian urban regions ranges from a low of 2.3% to a high of 23.3% (NHS, 2011).

In this context, a number of research efforts in transportation have been focussing on promoting public transportation use. Towards this end, many studies focused on gaining an understanding of the primary determinants of public transit system usage from two perspectives: (1) User perspective – *What makes individuals opt for transit mode*, and (2) Transit system perspective – *What attributes at a system level contribute to transit usage*. In the first group of studies the focus is on examining how individual level socio-demographics, transit accessibility measures and built environment affect transit ridership choice (see for example Eluru et al., 2012a). In the latter group, the emphasis is on a systems perspective where transit ridership is studied from the perspective of the transit provider. The current study belongs to the latter category of studies with the objective of quantifying the influence of *stop level transit operational variables* and *transit accessibility* *indices* (such as headway, bus/metro/train stops around each stop), *transportation system infrastructure attributes* (such as road network characteristics, bike lanes) and *built environment attributes* (such as presence of parks, residential area) on the disaggregate stop level boardings and alightings by time of day for the bus network in the Montreal region. To be precise, the emphasis is on the quantification of the influence of various attributes on boardings and alightings by time of day (as opposed to aggregated daily counts). The results will provide transit agencies a mechanism to study the influence of transit accessibility, transit connectivity, transit schedule alterations (to increase/reduce headway), and built environment changes on ridership. The framework developed can be applied to predict ridership at potential new stop locations. Moreover, the boarding and alighting information at stop level by time of day provides the transit agency an effective mechanism to predict transit bus occupancy - an important measure for vehicle fleet allotment for various bus lines.

The reminder of the paper is structured as follows. Section 2 provides a discussion of earlier literature and positions our research study in this context. The data source and data assembly procedures are presented in Section 3 while Section 4 provides an overview of the dependent variable characterization and the econometric model structure. The results of the exploratory and empirical analysis are presented in Section 5, followed by a conclusion section.

2. Literature Review

Several studies examine transit ridership in an attempt to link ridership with socioeconomic characteristics, built environment, and transit attributes across different contexts. Earlier research has focused on understanding the different factors that affect transit ridership at a macro-level (region or country). Taylor et al. (2009), for example, have undertaken a country-wide study for 265 U.S. urbanized areas and concluded that transit ridership is influenced by the regional geography, the metropolitan economy, the population characteristics, and the auto/highway system characteristics. The authors have classified the factors that affect transit ridership as internal (fare, level of service) or external (income, parking policies, development, employment, fuel prices, car ownership, and density levels) variables. They observed that external factors generally have a greater effect on ridership than internal factors.

A stream of research examined the effect of trip costs, such as fares, fuel price, and parking price. The elasticity of transit ridership with respect to the fare is negative and inelastic for all transit, and even more so for bus ridership compared to other public transportation modes (Hickey, 2005; Wang and Skinner, 1984). There is also a general consensus that the elasticity of transit ridership with respect to gasoline price is positive and inelastic, especially in medium sized cities (Mattson, 2008; Currie and Phung, 2007). The price of parking also affects transit ridership; imposing a daily parking fee for commuters will significantly increase transit patronage (Hess, 2001). A set of studies have examined the influence of high gasoline prices between 2005 and 2008 in the United States on transit ridership (for example see Chen et al., 2011; Lane, 2010; Lane, 2012). These studies found small but statistically significant influence of gasoline prices on transit ridership – increasing fuel prices result in increased ridership.

On the other hand, a distinctive body of literature focused on the effect of transit attributes and built environment on transit patronage in the context of rail mode. Most of these studies examine the station or stop features affecting ridership or station choice for the rail mode (Brown and Thompson, 2008; Debrezion et al., 2007, 2009; Fan et al., 1993; Frank and Pivo, 1994; Sung & Oh, 2011; Wardman & Whelan, 1999; Weizhou et al., 2009). Debrezion et al. (2009) found that the availability of parking spaces and bicycle standing areas have a positive effect on the choice of the railway station. Brown and Thompson (2008) observed that rail ridership decline in Atlanta could be explained by the employment decentralisation, while Shoup (2008) observed that Transit Oriented Development (TOD) comprised of high commercial intensity positively affects transit ridership at the rail station. In fact, Sung & Oh (2011) also recognized that some TOD factors have a positive effect on transit ridership. They found that important factors affecting ridership at rail stations are land use mix, street network, urban design, and an overall pedestrian friendly area around the stations. Guerra and Cervero, (2011) found that population and employment densities are positively correlated with ridership after controlling for transit service attributes. To a lesser extent, the ridership has also been analyzed at metro stations (Chan & Miranda-Moreno, 2013; Gutiérrez, 2001; Lin & Shin, 2008). Chan & Miranda-Moreno (2013) found that commercial and governmental land use, bus connectivity, and transfer stations are all associated with attracting ridership during morning peak hours. Lin & Shin (2008) observed that transfer stations affect ridership positively. Moreover, the authors found that retail and service area and walkability around the stations (sidewalk length, 4-way intersection) have positive effects on ridership.

Of particular relevance to our research effort, there have been very few studies that have analyzed ridership as a function of the urban environment at a stop level for the bus mode. Ryan and Frank (2009) have studied the influence of pedestrian environments on bus ridership. The authors found that the built environment, specifically the walkability of an area, is a useful tool for predicting transit ridership at a bus stop level. However, they examined total ridership (no distinction between boarding and alighting) and only consider a limited amount of built environment variables. Johnson (2003) also examined ridership at a bus stop level using an ordinary least squares regression, finding that land-use and density have important effects on ridership. More specifically, it was found that multifamily residence, mixed-use, and retail-commercial land uses affect bus boardings. This study focuses its analysis solely on boardings at bus stops, neglecting any possible interactions with the alightings. Chu (2004) noted that the presence of bus or trolley stops around a particular bus stop exerts a positive effect on ridership using a standard poisson regression. Similarly, Banerjee et al. (2005) found that bus ridership was positively associated with residential density, employment density, land use mix and transit connectivity for two corridors in the Los Angeles area. Estupiñán and Rodríguez (2008) explored the effect of the built environment on boardings at Bus Rapid Transit (BRT) stations in Bogotá while accounting for the simultaneity of transit demand and supply. The authors highlight the importance of urban environmental interventions to support transit use. Pulugurtha and Agurla (2012) found that a 0.25 mile buffer around the stops is adequate for socio-demographic and land-use variables in order to study daily transit ridership. Finally, Dill et al. (2013) studied the influence of transit service attributes, socio-demographics, land use and transportation system attributes on weekday transit ridership for the regions of Portland, Eugene-Springfield and Medford-Ashland area. The authors found that transit level of service attributes had significantly larger effect on ridership relative to other attributes.

2.1. Limitations of earlier research

It is evident from the discussion above that there is emerging recognition on quantifying the influence of transit infrastructure and built environment, on transit usage. However, while offering useful insights, past research is not without limitations. A number of studies explored the association between built environment and bus ridership, but have either considered daily ridership as a sum of boardings and alightings or analyzed daily boardings only (Chu, 2004; Estupiñán and Rodríguez, 2008; Johnson, 2003; Ryan and Frank, 2009; Pulugurtha and Agurla, 2012). The analysis is adequate for an overall picture of transit ridership in the region but is inadequate to comprehensively examine the influence of various attributes highlighted earlier. To draw any conclusions on vehicle fleet decisions a daily ridership measure is inadequate.

Incorporating the stop level boardings and alightings along various time periods provides us with unique challenges of its own. For instance, the consideration of four time periods for boardings and alightings result in eight dependent variables for each stop. It is important not only to consider different time periods in the analysis, but to assess the possible unobserved interactions between them as well. The dependent variables are all reported for the same stop and hence are likely to be affected by common unobserved factors.

Earlier research efforts on transit ridership estimated a single model for all the transit stops in the urban region. It is possible that there are stops with very high levels of ridership (in the central business district region) and stops with very low levels of ridership (in suburban residential neighborhoods). Considering all stops to be homogenous across the urban region might lead to potential bias in model estimates. Hence, it is useful to identify various categories of stops for an urban region prior to developing statistical models. To be sure, categorizing stops is a city specific process depending on the urban region and transit service in place.

2.2. Current study in context

In summary, the current study contributes to literature as follows: First, we consider time period specific boardings and alightings (as opposed to just daily boardings) for our analysis resulting in eight dependent variables per stop (boardings and alightings for 4 time periods). Second, our analysis quantifies the dependencies between the eight dependent variables using an innovative Composite Marginal Likelihood (CML) method that has recently been employed in transportation literature (Ferdous et al., 2010, 2011; Seraj et al., 2012; Sidharthan et al., 2011)[1]. Third, we categorize the urban region stops into three groups (high, medium and low based on daily ridership) and estimate group specific models (more on this in Section 3). Finally, the proposed model is estimated using a host of attributes for the Montreal region with about 8000 stops.

[1] While it is likely that headway and ridership are intricately intertwined due to self-selection of smaller headway for higher ridership stops it is very challenging to account for the "true" impact of self-selection. Hence, in our analysis, we consider various other land use attributes to minimize the "error" in not accounting for self-selection explicitly. This approach referred to as statistical control is often employed in transportation (see Frank et al., 2007; Næss, 2009).

3. Data

Montreal is the second most populous metropolitan region in Canada with 3.7 million residents. According to the 2008 Montreal origin-destination (OD) survey (AMT, 2008), 67.8% of trips are undertaken by car, 21.4% by public transit, and 10.8% by active transportation (walking and bicycling). On average, residents of Montreal make 203 transit trips annually as opposed to 141 trips per year, for major American cities. Its relatively high share of transit ridership (for a North American city) can be attributed to its multimodal transit system, including bus, metro, and commuter train. There are 4 metro lines, 5 commuter train lines, and over 200 bus lines, managed by different travel agencies. The Société de transport de Montreal (STM), which serves bus and metro on the Island of Montreal, has reached a record transit ridership in 2011 with 405 million trips, exceeding the previous record of the year 1945 (STM, 2011). In the last 15 years, the transit patronage (bus, metro, train) has increased by over 25% for the Montreal Metropolitan Region. The unique characteristics of the Montreal region provide an ideal setting for our analysis.

The data employed in this study is drawn from data collected by STM. Approximately 15% of STM bus fleet is equipped with infrastructure that counts boardings and alightings with specific information, such as the location, time of day, and bus number. The sampling procedure is representative of the overall transit schedules in the city, thus enabling us to obtain an accurate average of ridership for each bus stop across the Island for a typical weekday. STM has also provided data on bus frequency for each bus stop for all time periods.

The original data has been processed in order to generate total ridership for each bus stop by time period. The dependent variable data compiled for the purpose of this analysis consists of bus boarding and alighting for different time periods for about 8000 bus stations across the Island of Montreal. The time periods considered in our analysis (as provided in the data compiled) are the am peak (6:30 – 9:30), pm peak (15:30 – 18:30), off peak day (9:30 – 15:30), and off peak night/morning (18:30 – 6:30). The average sum of boarding and alighting numbers per bus stop for the entire day amount to 110. The corresponding values for various time periods are: (1) am peak period – 28, (2) off peak day – 35, (3) pm peak period – 28 and (4) off peak night – 20.

3.1 Segmenting Stops

Across the 8000 stops in Montreal the ridership (boardings + alightings) varies significantly from 0 to 8000. If we estimate a single model for all the stops in the city we implicitly restrict the effect of exogenous variables to be same across the stops. As has been discussed in earlier research efforts, such an assumption of population homogeneity is quite restrictive and results in incorrect model estimates (see Eluru et al., 2012b for an elaborate discussion). Toward addressing this limitation, in our analysis, we consider a market segmentation approach where the 8000 stops are categorized into three groups – low, medium, and high ridership. The categorization is based on the overall daily ridership (boarding + alighting) at the stop. The stops with daily ridership of less than 50 are characterized as *low* stops; stops with daily ridership between 50 and 250 are characterized as *medium* stops and stops with daily ridership more than 250 are classified as high stops. As you would expect, the finalized groups have the largest sample of stops in the low category (3574), and the lowest sample of stops in the high category (1813).

3.2 Summary Statistics

The attributes considered in our analysis include stop level transit operational variables (average headway for time period, number of lines passing through the stop, night bus passes through stop), public transit accessibility indices (number of bus/metro/train stops around each stop, length of bus/metro/train lines, length of exclusive bus lanes), transportation infrastructure attributes (road length by functional classification, bike lane lengths, distance to central business district, CBD), and stop level built environment (number of parks and their areas, residential area, number of commercial enterprises and their area, government and institutional area, resource and industrial area, employment density, walkscore). The various attributes are computed for various buffer sizes (200m, 400m, 600m, 800m, 1000m) drawn around the bus stop using Geographic Information Systems (GIS). To elaborate, using GIS, the attribute within the buffer around the bus stop is aggregated to generate a quantitative measure. Since the area is fixed for an attribute within a buffer size, there is no further need to normalize the metric generated. As there is no evidence for the "efficient" buffer size for all attributes in literature we hypothesize that different attributes might have different efficient buffer sizes and allow the model results to identify appropriate buffer sizes for each attribute. At any single instance, we consider one buffer size for a variable in the model to avoid any potential correlations across the variable. The appropriate buffer size for a variable is determined based on the buffer variable that offers the best data fit in the model. The same procedure was employed for all variables. For attributes where information at a detailed spatial configuration is not available, we employ Traffic Analysis Zone (TAZ) based attribute values.

Table 1 presents summary statistics for all variables used in the models for high, medium and low ridership categories. The reader would note that only the attributes significant in the empirical analysis are shown in the summary statistics for the sake of brevity. The top block of the summary statistics on dependent variables presents the boardings and alightings for the different time periods. It is clear from the numbers presented that there is a large variance between average boarding and alighting for the different stop categories and time periods, confirming the necessity to analyze them separately. In terms of stop level variables, average headway for a time period varies from 10 minutes to 100 minutes; peak periods and high ridership stops have lower headway. More lines pass through high ridership stops than medium or low, on average. Transit infrastructure around the stop follow expected trends. The number of bus stops and metro stations in different buffer sizes consistently decrease from higher ridership to lower ridership stops. Unsurprisingly, the total length of bus routes in a 600 meter buffer around the stops decreases from the higher to the lower ridership categories, but the opposite can be observed for the same variable at a TAZ level. TAZ size varies throughout the Island of Montreal, where larger TAZs are generally located far from the city center. The bus route length will be higher in the larger TAZs not because of actual service length, but rather because of the area analyzed. The nature of TAZ variables – with impact of land area - necessitates the adoption of buffer level variables wherever possible. The same logic applies to train line length in TAZ, while metro line length in TAZ decreases since metros are only present close to the city center. Finally, on average, high ridership stops are located in areas with more reserved bus lanes.

The length of major roads and bicycle paths around the stops decreases for lower categories, whereas length of highway remains relatively constant. The number of parks and commercial enterprises and their respective areas decrease for lower categories, while government and institutional area, residential area, park and recreation area, and resources and industrial area all increase for lower ridership stops. Once again, the size of the TAZs has a large role to play in these values.

3.3 Visual Analysis

We undertake an exploratory analysis of the boarding and alighting data in the Montreal urban region. As a part of this exercise, we generate a visual representation of the bus ridership for different time periods of the day. The visual representation of the bus ridership is generated for 4 categories, namely for boardings and alightings for AM and PM peaks. To easily represent the transit ridership origin and destination in the urban region, the hourly ridership was illustrated using the kriging function in GIS, an interpolation technique in which the surrounding measured ridership values are weighted to derive a predicted value for an unmeasured location (see Chapter 2 in Wahba, 1990 for details). Figure 1 presents a visual depiction of bus boarding and alighting in Montreal for the 2 time periods. These maps clearly show similar ridership patterns for AM Boardings and PM Alightings, as well as for AM Alightings and PM boardings. These trends can be simply explained with individuals boarding buses in residential areas and alighting in the city center or near the workplace in the morning and the opposite occurring in the afternoon. On one hand, the AM Boardings/PM Alightings are characterized with high ridership in areas further from the center of the city, which are mostly considered as residential areas. On the other hand, the AM Alightings/PM Boardings present high ridership around transit infrastructure, such as along metro lines or near train stations. We also notice that for all time periods, some areas always have a high ridership. This is explained by the presence of a bus terminal or a metro station in that area - transfer points that attract higher demand particularly because of high number of bus lines and bus stops. In fact, we notice a consistently greater ridership along the metro lines. On the other hand, some areas and neighborhoods in Montreal have generally lower ridership. This is especially true for the West Island (the left-most part of the Montreal Island in Figure 1), an area in which public transportation services are generally lower than that of the rest of the city.

4. Methodology

4.1 Dependent Variable Generation

In our analysis, for the three categories of stops, separate models are estimated. Within each category of stops, the boardings and alghtings are separately examined. The use of ridership variable as a linear dependent variable usually violates the normal distribution assumption required for multivariate linear regression (see Dill et al., 2013 for a similar discussion). Researchers have usually resorted to logarithmic transformation approach. We employ an ordered grouping approach that discretizes the ridership variables (boarding and alighting counts) into multiple ordered alternatives. For example, for the high stop category the peak hour hourly boardings/alightings were separated into 4 alternatives as follows: (1) 0-10, (2) 10-25, (3) 25-50 and (4) >50). The exact thresholds employed to discretize the linear variables were based on the hourly boardings and alighting by time period and stop category. The exact thresholds employed for generating ordered alternatives for all stop categories and time periods is provided in Table 2. The reader should note that the discretization approach allows us to stitch together multiple dependent variables at the same stop without the influence of the actual magnitude of the boarding/alighting. The current thresholds were employed based on ensuring adequate representation in each discrete category. The proposed approach is flexible and the number of categories can be changed readily in our framework. The boarding and alighting counts for the 4 time periods yield an 8 dimensional dependent variable. The 8 dimensional multivariate ordered probit model is estimated using the CML approach described next.

4.2 Econometric Model

The Composite Marginal Likelihood (CML) for ordered response probit (ORP) model is employed to examine the effect of exogenous variables on ridership at bus stops. This model allows observing possible correlations between boardings and alightings for the multiple time periods. For instance, we might observe that boardings in the AM peak are positively correlated with alightings in the PM peak.

Let q (q = 1, 2, …, Q) be an index to represent bus stops, i (i = 1, 2, 3, …, I) be an index to represent boarding/alighting – time period combinations, where I=8. Then, let the ridership interval value for combination *i* be $K_i + 1$ (*i.e.*, the discrete levels belong in {0, 1, 2, …, K_i} for category *i*). The index *k* takes value of ridership intervals such as "Alighting per hour between 0 and 10" (k=1), "Alighting per hour between 10 and 20" (k=2), etc. The intervals vary for each group of models, namely for each combination of ridership (alighting, boarding) and ridership level (high, medium, low). The equation system for the standard ordered response model is:

$$y_{qi}^{*} = \beta' x_q + \varepsilon_{qi},\ y_{qi} = k \ \ if \ \ \theta_i^k < y_{qi}^{*} < \theta_i^{k+1} \tag{1}$$

where y_q^* corresponds to the latent ridership propensity for a stop *q*. x_q is an ($L \times 1$)-column vector of built environment attributes: stop level variables, public transportation accessibility indices, infrastructure attributes, and land use measures for a stop q. β' is the corresponding ($L \times 1$)-column vector of variable effects. θ_i^k is the lower bound threshold for ridership category k of combination i ($\theta_i^0 < \theta_i^1 < \theta_i^2 ... < \theta_i^{K_i+1}$; $\theta_i^0 = -\infty$, $\theta_i^{K_i+1} = +\infty$ for each category i). The model structure requires for the θ thresholds to be strictly ordered in order to adequately distribute the latent ridership propensity in the observed ridership categories. Finally, ε_q is an idiosyncratic random error term that impacts ridership propensity, which may include the presence of a bus shelter[2] at stop q. The ε_{qi} terms are assumed independent and identical across stops (for each and all i). For identification reasons, the variance of each ε_{qi} term is normalized to 1. However, we allow correlation in the ε_{qi} terms across combinations i for each stop q. Specifically, $\varepsilon_{qi} = \varepsilon_{q1}, \varepsilon_{q2}, \varepsilon_{q3}, \ldots, \varepsilon_{qI})'$. Then, ε_q is multivariate normal distributed with a mean vector of zeros and a correlation matrix as follows:

$$\varepsilon_q \sim N\left[\begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \cdots & \rho_{1I} \\ \rho_{21} & 1 & \rho_{23} & \cdots & \rho_{2I} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{I1} & \rho_{I2} & \rho_{I3} & \cdots & 1 \end{pmatrix}\right], \text{ or}$$

$$\varepsilon_q \sim N\left[\mathbf{0}, \mathbf{\Sigma}\right] \tag{2}$$

The off-diagonal terms of Σ capture the error covariance across the underlying latent continuous variables of the different combinations; that is, they capture the effect of common unobserved factors influencing the propensity of ridership at bus stops. For example, if ρ_{12} is positive, it implies that boardings in the AM peak period for a stop q will likely be positively correlated with boardings in the PM peak. Of course, if all the correlation parameters (*i.e.*, off-diagonal elements of Σ), which we will stack into a vertical vector Ω, are equal to zero, the model system in Equation (1) collapses to independent ordered response probit models for each ridership category.

Given the preliminaries above, we employ a pairwise marginal likelihood estimation approach, which corresponds to a composite marginal approach based on bivariate margins (see Ferdous et al., 2010, Varin and Czado, 2008; Apanasovich *et al.*, 2008; Varin and Vidoni, 2008; and Bhat *et*

[2] Testing the presence of shelter for bus stops could not be carried out in this research because of the unavailability of the information.

al., 2009 for the use of the pairwise likelihood approach in the past). The pairwise marginal likelihood function for station q may be written as follows:

$$L_{CML,q}(\delta) = \prod_{i=1}^{I-1} \prod_{g=i+1}^{I} \Pr(y_{qi} = m_{qi_i},\ y_{qg} = m_{qg})$$

$$= \prod_{i=1}^{I-1} \prod_{g=i+1}^{I} \left[\begin{array}{l} \Phi_2\left(\theta_i^{m_{qg}+1} - \beta_i' x_{qi}, \theta_g^{m_{qg}+1} - \beta_g' x_{qg}, \rho_{ig}\right) \quad -\Phi_2\left(\theta_i^{m_{qi}+1} - \beta_i' x_{qi}, \theta_g^{m_{qg}} - \beta_g' x_{qg}, \rho_{ig}\right) \\ -\Phi_2\left(\theta_i^{m_{qi}} \quad - \beta_i' x_{qi}, \theta_g^{m_{qg}+1} - \beta_g' x_{qg}, \rho_{ig}\right) \quad +\Phi_2\left(\theta_i^{m_{qi}} \quad - \beta_i' x_{qi}, \theta_g^{m_{qg}} - \beta_g' x_{qg}, \rho_{ig}\right) \end{array} \right], \qquad (3)$$

and $L_{CML}(\delta) = \prod_{q} L_{CML,q}(\delta)$ (4)

The above expression, just require evaluation of Bivariate normal probabilities and can be computed at a high level of precision. The estimates obtained by maximizing the logarithm of the above function are consistent and asymptotically normal distributed (see Ferdous et al., 2010 for more details on inference metrics).

5. Results

The empirical analysis in the study involves estimating the effect of the built environment and urban design on ridership at a stop level using an ordered regression model. The final specifications were obtained based on a systematic process of removing statistically insignificant variables (at the 95% level). The specification process was guided by prior research and intuitiveness/parsimony considerations. The reader would note that model specification efforts checked for correlation and multi-collinearity between independent variables considered in the models.

The model estimation results for the three stop categories are provided in Tables 3, 4, and 5. We notice that in each category, the AM Boarding and PM Alighting models have similar specifications. The same applies for PM Boarding and AM Alighting. In each case, both models present similar significant variables with comparable effects. Evidently, they capture the morning and afternoon commute impacts. This is along expected lines because an individual boarding at stop A near his residence in the morning is likely to alight at that same stop A in the afternoon. A detailed discussion of the model results are provided subsequently.

5.1 High Ridership Model

Table 3 provides the final model specification for the “high” category for boarding and alighting. The model results presented include a column for each time period. Each row represents the effect of an exogenous variable (“empty cell” indicates no significant variable effect).

5.1.1 Stop level variables and Transit Accessibility Indices

The headway (in minutes) has a negative and very significant effect for high ridership stops across all time periods. In other words, stops with higher frequency have higher ridership.

The presence of public transportation around the stop has a positive and significant effect on ridership. This holds true especially for presence of bus stops and metro stations in a 200 meter buffer, effectively showing that most high ridership stops are located in an area with substantial public transportation facilities. The number of surrounding train stations has an effect only on AM Boarding, suggesting that individuals’ board at high ridership stops after traveling by train in their morning commute. Specifically in the context of Montreal, this most likely represents individuals boarding buses at stops near the central station, where the largest train station is located. Further, we observe that metro line length at a TAZ level affects off-peak boarding while number of train stations at the TAZ level affects PM peak alighting. Overall, these high ridership stops seem to be transfer points, close to metros and located in areas with extensive public transportation facilities.

5.1.2 Transportation Infrastructure

The presence of major roads around the stop exerts a positive effect on ridership and is significant only for Off Peak Night Boarding and AM Alighting. This may be because of the location of transit on major roads. The length of highways in an 800 meter buffer exerts the opposite effect, indicating that stops in the vicinity of highways are more likely to have fewer riders. Again, this effect is only significant for Off Peak night Boarding and Off Peak day Alighting. Finally, the further the stop is to the CBD, the fewer alightings are likely to occur for the Off Peak Night period.

5.1.3 Built Environment

The variables capturing the presence of parks offer interesting results. The area of the parks around the stop has a significantly negative effect, whereas the number of parks exerts an opposite effect. This suggests that ridership is likely to be higher in an area with several parks of small dimensions, as the walkability of the area would benefit from the presence of parks without constraining road areas for transit to operate. Nevertheless, the net effect is positive overall. To demonstrate this overall positive effect, the average park area in a 600 meter buffer for the "high" category is 0.086 km^2, and the average number of parks for the same buffer size is 8.41. Therefore, in the AM Boarding, the overall park effect can be calculated as -0.632*0.086 + 0.014*8.41 = 0.0633. There is a similar equilibrium effect between the number of commercial enterprises and their area. In fact, their interaction results in an overall positive manner, effectively demonstrating that stops in these areas are more likely to have high ridership.

We observe that the employment density at the TAZ level exerts a negative effect on boardings and the opposite effect on alightings. Government and institutional area near the stop is likely to increase the ridership, notably for the AM Alighting time period. The presence of residential area exhibits expected trends. Specifically, higher residential area implies lower PM boarding and lower AM alighting illustrating the presence of the commuting pattern - individuals alight buses in the morning and board them in the afternoon near their workplace. Finally, the resources and industrial area exerts a negative effect on ridership, particularly on boarding.

5.2 Medium Ridership Model

Table 4 provides the final model specification for the "medium" category. From a cursory examination of the results, the reader would notice that the exogenous variables effects for the medium category are different from the exogenous variable effects of the high category. The results provide support to our hypothesis that estimating a single model is restrictive. The results for the medium category are briefly discussed below.

<u>5.2.1 Stop level variables and Transit Accessibility Indices</u>

The headway variable has the same effect for the medium category as observed in high category model. However, the number of lines affects the ridership negatively, most notably for AM Boarding and PM Alighting. Although this may seem counterintuitive, it actually illustrates the competition between different bus lines passing through the same stop. Also, the reader would note that headway is a stop level variable; an increase in number of lines has a simultaneous effect of reducing headway. Hence the net effect on actual ridership is a function of headway and number of lines.

The effect of transit for medium ridership stops is not as straight forward as the high ridership stops. In the medium stop category, the transit infrastructure variables have varying effects (in sign and magnitude) across the day. For instance, the presence of bus stops around the stops (600m and 800m radii) impacts the ridership in a positive manner for AM Boarding and PM Alighting, while total bus line length in the TAZ exerts the opposite effect for these same time periods. The presence of buses (line length and number of stops) has an overall positive effect on ridership. Train line length at the TAZ level has a negative effect on ridership, principally on AM Boarding and PM Alighting, while the presence of train stations in the vicinity of these stops are likely to increase ridership for the PM Boarding and AM alighting. This indicates that these stops serve as transfer points for commuter trains. Overall, the medium ridership stops seem to be transfer stops for trains as well as residential stops in somewhat transit accessible areas.

5.2.2 Transportation Infrastructure

Presence of major roads around a stop is likely to increase ridership for PM Boarding and AM Alighting, whereas the distance to CBD affects ridership in a negative manner. Highway length in an 800 meter radius exerts a negative effect on patronage for the PM and Off Peak Day time periods. Finally, an increased presence of bicycle paths has a positive effect for AM Boarding and PM Alighting. Again, all these results follow intuitive expectations, given the urban region commuting patterns.

5.2.3 Built Environment

Built environment variables also clearly demonstrate commuting patterns. The ridership for AM Boarding and PM Alighting are positively affected by the number of parks and their area as well as the residential area, and negatively affected by the number of commercial enterprises near the stop. The opposite is also true for PM Boarding and AM Alighting, as stops located in residential areas are less likely to have high ridership.

5.3 Low Ridership Model

Table 5 is the final model specification for the “low” category. The results clearly show that the exogenous variables that influence ridership are different from those factors affecting ridership in the other two models.

5.3.1 Stop level variables and Transit Accessibility Indices

Once again, bus headway at stops affects ridership negatively. The public transportation infrastructure for low ridership stops has similar effect to the previous ridership models. For instance, the number of bus stop in the vicinity has a positive and significant effect on ridership, which indicates that there is higher ridership in more transit accessible areas.

5.3.2 Transportation Infrastructure

Generally, the presence of major roads impacts the ridership negatively, whereas the presence of highways has the opposite effect. Moreover, the presence of bicycle paths is likely to increase the ridership. It is however not significant for PM Boarding and negative for AM Alighting. The ridership for these two categories is also negatively affected by the distance to CBD.

5.3.3 Built Environment

The presence of parks (number and area) has the same overall positive effect as the previous models. The residential area mostly has a positive effect on ridership, except for PM Boarding and AM Alighting models, demonstrating once again that these stops are mostly situated away from areas in which housing predominates. This is also confirmed by the coefficients of commercial areas, resource and industrial, job density, as well as government and institutional areas, exerting a negative effect on ridership.

5.4 Correlation Parameters

Tables 6 through 8 provides the correlation matrix for the eight dimensions of the high, medium and low ridership stop models, where values of 0 represent an insignificant correlation effect. All the non-zero elements in the tables are statistically significant at the 95% level. For high category, we notice that boardings for all time periods are positively correlated to each other (top left corner of the tables), as are the alightings (bottom right corner of the tables). The AM Boardings have a negative correlation with alightings for the same time period, whereas the PM Boardings and AM Alightings have the opposite relationship indicating that unobserved factors that result in an increase in boardings are likely to contribute to a reduction in alightings. Finally, the results indicate that ridership in Off Peak Day and Off Peak Night time periods also exhibit significant dependencies. These results clearly highlight the presence of unobserved dependencies across the eight dependent variables for each stop. Ignoring the presence of such unobserved dependencies would result in incorrect estimates for the observed variables.

Table 7, which presents the correlation matrix for medium ridership stops, offers similar results to the high stops. In fact, boardings for all time periods have a positive relationship to each other, just like the alighings. However, all correlations between boardings and alightings are significantly negative, suggesting that medium ridership stops serve either as a boarding stops or an alighting stops. In the correlation matrix for the low ridership stops (Table 8) boardings and alightings are positively correlated to each other. However, the correlation between boardings and alightings are either positive or insignificant, with the exception of Boarding PM and Alighting OPN.

5.5 Elasticity Analysis

In order to highlight the effect of various attributes, an elasticity analysis was conducted for both boardings and alightings for the peak periods and presented in Table 9, for the high ridership category only. Specifically, we are calculating the change in ridership for changes in transit and land use attributes. To provide a sense of the resulting changes based on the proposed elasticity scenarios, the average ridership per hour for high stops is included in Table 9. Several observations can be made from the results presented in Table 9. First, we notice that the transit accessibility and service attributes (headway and number of bus and metro stops) have a stronger influence on boardings compared with land use attributes (job density, residential area, and commercial area). Second, increasing headway, which translates into a decline in service, will result in a decrease in ridership as expected. However, the effect of the change on Boarding AM and Alighting PM is more pronounced compared with the Boarding PM and Alighting AM. The results indicate that ridership is more sensitive to headway change in the direction of commute. Third, the addition of a metro station has much larger influence on ridership relative to the addition of bus stops. This is not surprising as the cost of adding a metro stop is substantially larger than the cost of adding a bus stop.

The policy implications of these findings are quite clear and provide straightforward interpretations. From our results, it is clear that the most effective way to increase ridership is to increase public transport service and accessibility. Since ridership does not seem to alter substantially due to land use changes in our model, the main priority for these transit agencies should be to expand their network. One of the priorities for the STM in the upcoming years is to extend the metro network to the east. Our study findings provide evidence that expanding the network is likely to increase bus ridership. Moreover, our approach can be applied to calculate expected ridership with new stops.

6. Conclusion

In this paper, we examine the influence of the urban form and land use factors affecting bus ridership at the stop level by time of day in Montreal. The data employed in our study was drawn from data collected by the STM consisting of counts of boardings and alightings at each bus stop in the public transit network of Montreal. The time periods considered in our analysis were the am peak (6:30 – 9:30), pm peak (15:30 – 18:30), off peak day (9:30 – 15:30), and off peak night/morning (18:30 – 6:30). The various stops were categorized into three groups – low, medium, and high ridership – to accommodate for the large variability in ridership for different stops. The exploratory analysis through visual representation allowed us to observe the following ridership characteristics. Similar ridership patterns exist between AM Boardings and PM Alightings, as well as between AM Alightings and PM boardings. These trends can be simply explained with individuals boarding buses in residential areas and alighting in the city center or near the workplace in the morning and the opposite occurring in the afternoon. On one hand, the AM Boardings/PM Alightings are characterized with high ridership in areas further from the center of the city, which are mostly considered as residential areas. On the other hand, the AM Alightings/PM Boardings present high ridership around transit infrastructure, such as along metro lines or near train stations.

The empirical analysis in the study involves quantifying the effect of the built environment and urban design on ridership at a stop level using a CML ordered probit model. The analysis considers a host of exogenous factors including public transit infrastructure and accessibility indices, infrastructure attributes, and land use factors. We analyzed boardings and alightings for three categories of stops - high, medium, and low ridership stops - for four time periods -am peak, pm peak, off peak day, off peak night, estimating a total of 3*2*4 = 24 models.

Transit facilities (such as presence of metro stations, bus stops, and reserved bus lanes) and the presence of parks have a positive effect on ridership, while presence of highway has a negative effect. The effect of certain land use indices (commercial area, government and institutional areas, and residential areas) is temporally dependent. The results from the correlation estimates highlight the intricate nature of unobserved factors affecting boarding and alighting across various time periods. The elasticity analysis undertaken provides useful insight. Specifically, we observe that the most effective way to increase ridership is to increase public transport service and accessibility, whereas changes in land-use result in small increases to ridership.

To be sure, the research is not without limitations. We recognize that capturing the effects of the urban design is a delicate process. For instance, in our analysis, the endogeneity of transit infrastructure attributes is not explicitly considered i.e. transit stops with higher service are inherently likely to have higher ridership. While we capture indirect impact through our model specification (statistical control method), explicitly considering transit infrastructure endogeneity is quite challenging and is an avenue for future research. Although our approach considers temporal correlations at the stop level, we have not considered spatial correlation in our analysis framework. In our study, we explored several Euclidean based buffer sizes for each model. We decided on a buffer size for a variable based on the best data fit offered by the variable. It might be beneficial to also explore the influence of variables in network distance based buffers to evaluate the influence of various exogenous variables on ridership. It would also be beneficial to employ land use variables at a fine resolution. In our analysis, variables such as residential and commercial area were considered at a TAZ level due to data limitations. Finally, in terms of stop level attributes, the research findings can be further enhanced by considering other stop related variables such as presence of stop shelters, presence of crosswalks, and traffic signage. This is a future avenue for research.

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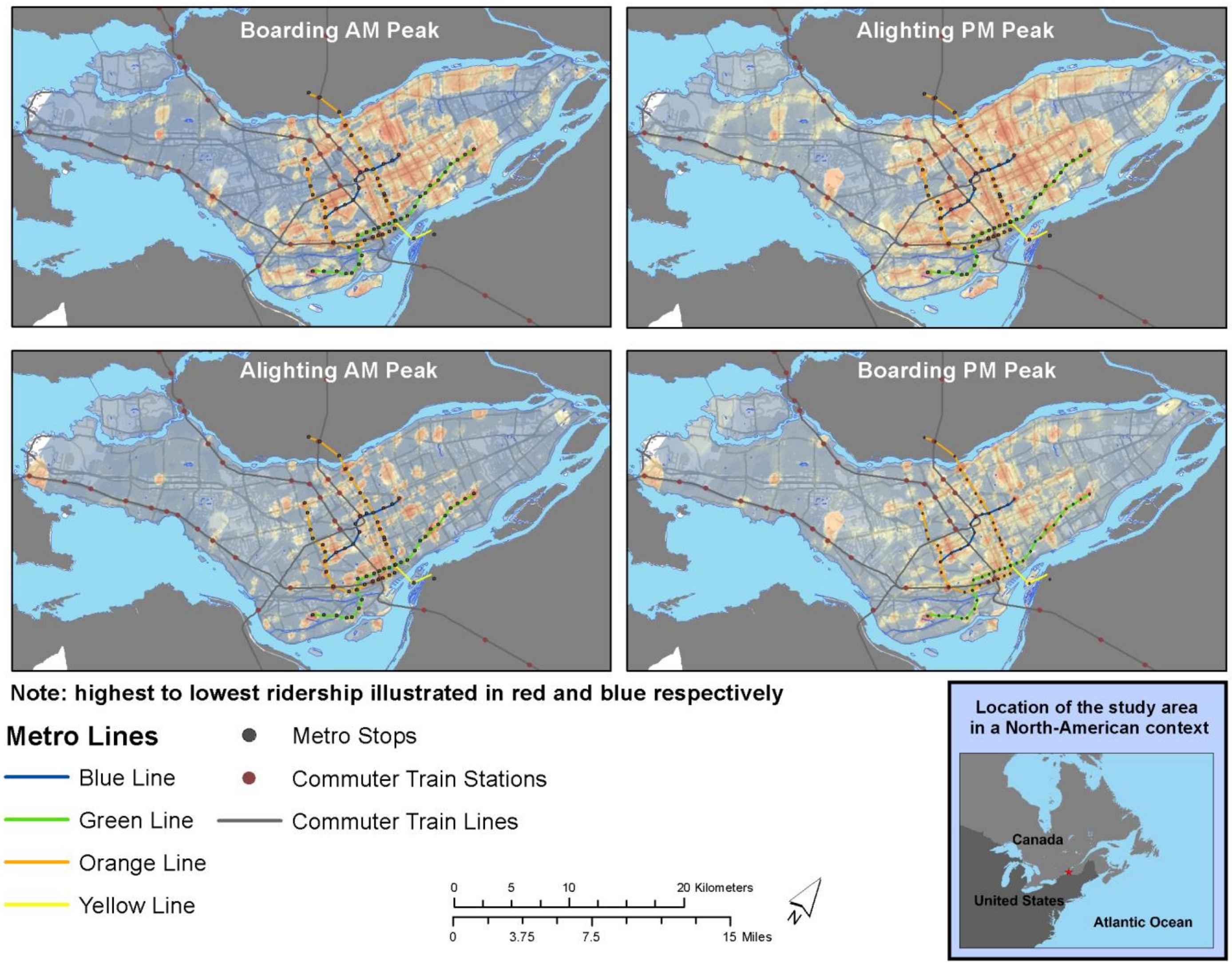

Figure 1: Ridership for Different Time Periods

Table 1: Summary Statistics

	Mean		
	High	**Medium**	**Low**
N	**1813**	**3350**	**3574**
Dependent Variables			
Boardings per hour			
AM Peak	31.62	6.15	0.94
PM Peak	36.59	4.36	0.79
Off Peak Day	21.48	3.06	0.44
Off Peak Night	9.18	1.18	0.18
Alightings per hour			
AM Peak	34.74	4.54	0.89
PM Peak	32.95	6.15	0.99
Off Peak Day	21.40	3.12	0.50
Off Peak Night	8.49	1.47	0.26
Independent Variables			
- Stop level variables			
Headway AM	10.00	17.41	34.73
Headway PM	10.52	18.81	35..35
Headway OPD	13.38	22.87	74.91
Headway OPN	19.39	32.94	100.97
Number of lines passing through stop	2.19	1.75	1.37
Night bus passes through stop	0.46	0.26	0.16
- Transit around the stop*			
Number of bus stops in a *200m buffer*	6.67	5.33	4.49
Number of metro stops in a *200m buffer*	0.17	0.05	0.03
Number of train stations in a *200m buffer*	0.03	0.01	0.01
Bus line length in a *600m buffer*	15.92	13.52	12.39
Metro line length in the TAZ	0.11	0.08	0.08
Train line length in the TAZ	0.80	1.69	2.79
Reserved bus lane length in a *200m buffer*	0.14	0.05	0.03
- Infrastructure around the stop			
Major roads length in a *400m buffer*	2.25	1.84	1.80
Highway length in a *800m buffer*	2.48	2.35	2.74

- Land use around the stop			
Park area in a			
200m buffer	0.01	0.01	0.01
600m buffer	0.09	0.08	0.06
Number of parks in a			
200m buffer	1.31	1.19	0.97
600m buffer	8.41	7.65	5.68
Number of commercial enterprises in a			
200m buffer	49.93	33.04	20.17
600m buffer	306.80	222.09	170.59
800m buffer	507.17	377.38	293.70
Commercial area in the TAZ	0.03	0.02	0.02
Governmental and institutional area in the TAZ	0.04	0.05	0.07
Residential area in the TAZ	0.30	0.40	0.51
Park and recreational area in the TAZ	0.06	0.07	0.09
Resources and industrial area in the TAZ	0.08	0.15	0.33

* All lengths and areas are in kilometers and kilometers squared respectively.

Table 2: Ridership intervals for different stop categories

		AM Peak	PM Peak	Off Peak Day	Off Peak Night
High	k=1	0-10		0-10	0-2.5
	k=2	10-25		10-20	2.5-5
	k=3	25-50		20-30	5-10
	k=4	50 +		30 +	10 +
Medium	k=1	0-2		0-1.5	0-0.5
	k=2	2-6		1.5-3	0.5-1
	k=3	6-10		3-4.5	1-1.5
	k=4	10 +		4.5 +	1.5 +
Low	k=1	0-0.5		0-0.25	0-0.25
	k=2	0.5-1		0.25-0.5	0.25 +
	k=3	1 +		0.5 +	-

Table 3: Ordered probit models for the High ridership category

	Boarding				Alighting			
	Am peak B (t-stat)	Pm peak B (t-stat)	Off peak day B (t-stat)	Off peak night B (t-stat)	Am peak B (t-stat)	Pm peak B (t-stat)	Off peak day B (t-stat)	Off peak night B (t-stat)
- Stop level variables								
Headway	-0.075 (-13.03)	-0.041 (-9.82)	-0.057 (-11.11)	-0.01 (-3.13)	-0.043 (-7.97)	-0.08 (-16.03)	-0.064 (-10.49)	-0.04 (-8.24)
- Transit accessibility indices								
Bus stops in a								
200m buffer	0.059 (6.85)	0.069 (7.48)	0.064 (7.05)	0.066 (7.32)	0.026 (2.83)	0.037 (4.11)	0.045 (4.88)	0.043 (4.81)
Metro stations in a								
200m buffer	0.583 (6.36)	0.569 (5.57)	0.424 (4)	0.777 (7.25)	0.546 (6.29)	0.381 (3.88)	0.7 (7.18)	0.495 (5.68)
Train stations in a								
200m buffer	0.507 (3.18)							
Metro line length TAZ			0.334 (3.14)					
Train stations TAZ						0.171 (4.16)		
- Transportation Infrastructure								
Major Roads 400m buffer				0.055 (3.42)	0.09 (5.62)			
Highway length 800m buffer				-0.026 (-3.06)			-0.02 (-2.7)	
Straight line distance to CBD								-0.01 (-2.53)
- Built Environment								
Park area in a								
600m buffer	0.014 (3.86)					0.013 (3.71)	0.006 (2.47)	
Number of Parks in a								
200m buffer					0.031 (2.08)			
600m buffer	-0.632 (-2.25)					-0.66 (-2.51)		
Number of Commerces in a								
200m buffer		0.002 (3.75)						
600m buffer	-0.001 (-4.61)					-0.001 (-4.34)		
800m buffer								-0.001 (-5.05)
Commercial area in a TAZ		0.916 (2.92)	0.679 (2.1)	1.205 (3.66)		0.54 (1.88)	1.894 (6.45)	
Job Density in a TAZ	-0.003 (-2.07)	-0.003 (-2.5)	-0.009 (-5.25)	-0.006 (-3.11)		0.003 (2.63)		0.003 (2.35)
Government &Institutional area TAZ					2.373 (5.97)		0.7 (2.58)	
Residential area TAZ		-0.395 (-5.45)			-0.431 (-5.2)			
Resources & Industrial area TAZ	-0.47 (-3.15)		-0.699 (-4.53)			-0.475 (-3.86)		
Threshold 1	-0.77 (-9.06)	-0.456 (-5.83)	-0.426 (-6.04)	-0.113 (-1.53)	-0.189 (-2.2)	-1.091 (-13.76)	-0.363 (-4.5)	-0.925 (-9.56)
Threshold 2	0.029 (0.35)	0.529 (6.7)	0.422 (6.04)	0.611 (8.2)	0.542 (6.29)	-0.18 (-2.4)	0.473 (5.91)	-0.339 (-3.6)
Threshold 3	0.837 (10.34)	1.19 (14.22)	0.894 (12.53)	1.436 (18.46)	1.142 (12.85)	0.674 (9)	0.98 (11.7)	0.398 (4.3)

Table 4: Ordered probit models for the Medium ridership category

	Boarding				Alighting			
	Am peak B (t-stat)	Pm peak B (t-stat)	Off peak day B (t-stat)	Off peak night B (t-stat)	Am peak B (t-stat)	Pm peak B (t-stat)	Off peak day B (t-stat)	Off peak night B (t-stat)
- Stop level variables								
Headway	-0.047 (-20.06)	-0.015 (-6.73)	-0.011 (-3.1)	-0.005 (-7.34)	-0.015 (-5.3)	-0.047 (-20.58)	-0.026 (-5.67)	-0.006 (-6.95)
Lines through stop	-0.041 (-2.13)					-0.067 (-3.41)	-0.049 (-2.11)	
Night bus through stop				0.238 (6.61)				
- Transit accessibility indices								
Bus stops in a								
600m buffer	0.012 (6.37)		0.009 (5.61)	0.009 (5.75)		0.009 (5.02)		
800m buffer								0.004 (2.83)
Metro stations in a								
400m buffer	-0.246 (-5.6)							
600m buffer								-0.058 (-2.2)
Train stations 400m buffer								
400m buffer		0.334 (3.36)			0.308 (2.74)			
Bus line length TAZ	-0.025 (-7.28)	0.014 (3.9)			0.013 (3.35)	-0.022 (-6.52)	0.017 (5.17)	
Train line length TAZ	-0.008 (-3.41)					-0.009 (-3.19)	-0.006 (-3.17)	
- Transportation Infrastructure								
Major roads length in a								
400m buffer	-0.062 (-5.29)							
600m buffer		0.052 (5.69)			0.051 (6.94)			
Highway length 800m buffer		-0.045 (-4.7)	-0.026 (-4.11)			-0.029 (-4.16)	-0.049 (-6.8)	
Bicycle path length in a								
400m buffer	0.105 (4.58)							
600m buffer					-0.057 (-3.99)	0.046 (3.76)		
Straight line distance to CBD		-0.01 (-3.11)			-0.011 (-2.66)			
- Built environment								
Park area in								
400m buffer	0.016 (4.2)							
1000m buffer								0.003 (2.72)
Number of Parks in a								
400m buffer						0.013 (3.51)		-1.021 (-2.65)
600m buffer			0.585 (3.82)					
Number of Commerces in a								
400m buffer	-0.001 (-3.67)	0.001 (4.2)				-0.001 (-3.36)		
Commercial area in a TAZ		1.034 (3.16)						
Job density TAZ			-0.003 (-2.6)	-0.003 (-2.98)				
Walkscore in the Postal Code					0.004 (3.59)			
Government &Institutional area TAZ					0.466 (3.4)			
Residential area TAZ	0.311 (5.6)	-0.267 (-4.38)			-0.336 (-4.99)	0.221 (3.99)		-0.141 (-3.02)
Threshold 1	-1.015 (-11.15)	-0.515 (-7.5)	-0.427 (-5.61)	-0.344 (-5.1)	-0.228 (-2.04)	-1.309 (-14.29)	-1.001 (-8.35)	-0.576 (-8.03)
Threshold 2	-0.14 (-1.57)	0.585 (8.71)	0.288 (3.92)	0.252 (3.75)	0.674 (6.07)	-0.292 (-3.29)	-0.246 (-2.09)	-0.067 (-0.94)
Threshold 3	0.366 (4.07)	1.163 (17.05)	0.789 (10.68)	0.66 (9.77)	1.138 (10.23)	0.299 (3.43)	0.311 (2.7)	0.305 (4.26)

Table 5: Ordered probit models for the Low ridership category

	Boarding				Alighting			
	Am peak B (t-stat)	Pm peak B (t-stat)	Off peak day B (t-stat)	Off peak night B (t-stat)	Am peak B (t-stat)	Pm peak B (t-stat)	Off peak day B (t-stat)	Off peak night B (t-stat)
- Stop level variables								
Headway	-0.001 (-5.14)	-0.001 (-9.72)	-0.001 (-16.19)	-0.001 (-8.64)	-0.001 (-10.83)	-0.001 (-8.86)	-0.001 (-16.2)	-0.001 (-12.29)
Number of lines through stop								0.087 (2.81)
- Transit accessibility indices								
Bus stops in a								
400m buffer				0.024 (5.66)				
600m buffer	0.017 (7.95)					0.017 (7.82)		0.011 (4.57)
1000m buffer			0.007 (7.36)				0.009 (8.9)	
- Transportation Infrastructure								
Major roads length in a								
400m buffer	-0.983 (-7.32)							
600m buffer						-0.636 (-5.68)		
800m buffer					0.139 (2.79)			
800m buffer								
Hway length 800m buffer						0.282 (2.76)		
Bicycle length in a								
600m buffer					-0.846 (-5.7)			
1000m buffer	0.416 (5.25)		0.313 (4.48)	0.544 (6.91)		0.385 (4.81)	0.286 (3.81)	0.275 (3.56)
Straight line distance to CBD		-0.167 (-5.99)			-0.167 (-4.79)			
- Built environment								
Parks in a								
400m buffer								
600m buffer	0.018 (5.05)		0.019 (5.79)	0.009 (2.55)		0.015 (3.73)	0.019 (5.48)	
Commerces in a								
600m buffer				-0.001 (-3.62)				-0.001 (-3.95)
800m buffer			-0.001 (-4.74)				-0.001 (-4.65)	
1000m buffer	-0.001 (-5.16)					-0.001 (-2.8)		
Comm. area TAZ					1.057 (2.63)			
Job density TAZ						-0.006 (-2.24)		
Walkscore PostalCode					0.003 (2.19)			
Gov&Inst areaTAZ	-0.478 (-4.67)					-0.555 (-5.21)		
Residential area TAZ	0.165 (4.27)	-0.19 (-4.74)			-0.22 (-4.71)	0.196 (4.88)	0.165 (4.6)	
P&R TAZ	-0.408 (-4.17)	-0.229 (-2.5)	-0.231 (-2.53)	-0.403 (-2.7)		-0.228 (-2.88)	-0.264 (-3.01)	-0.352 (-3.21)
Reso&Ind TAZ	-0.555 (-6.52)					-0.544 (-6.2)		
Threshold 1	-0.009 (-0.08)	-0.51 (-9.38)	0.211 (3.99)	0.957 (14.24)	-0.43 (-3.79)	-0.064 (-0.7)	0.345 (5.43)	0.528 (6.81)
Threshold 2	0.428 (3.64)	0.007 (0.13)	0.743 (13.83)		0.028 (0.25)	0.433 (4.74)	0.816 (12.69)	

Table 6: Correlation matrix for high ridership stops

		Boarding				Alighting			
		AM	PM	OPD	OPN	AM	PM	OPD	OPN
Boarding	AM	1	0.5974	0.7104	0.7359	-0.1602	0	-0.0949	-0.1494
	PM		1	0.8369	0.7862	0.1439	0	0	-0.0797
	OPD			1	0.7974	0.1368	-0.0838	0.0643	-0.1264
	OPN				1	-0.0915	-0.0711	0	-0.0663
Alighting	AM					1	0.5052	0.7046	0.5104
	PM						1	0.8549	0.8789
	OPD							1	0.8191
	OPN								1

Table 7: Correlation matrix for medium ridership stops

		Boarding				Alighting			
		AM	PM	OPD	OPN	AM	PM	OPD	OPN
Boarding	AM	1	0.4275	0.6783	0.6964	-0.3698	-0.2111	-0.3018	-0.3604
	PM		1	0.756	0.674	-0.0696	-0.28	-0.216	-0.322
	OPD			1	0.7976	-0.17	-0.302	-0.1717	-0.3605
	OPN				1	-0.2728	-0.3112	-0.243	-0.3416
Alighting	AM					1	0.2788	0.5005	0.4007
	PM						1	0.741	0.7596
	OPD							1	0.714
	OPN								1

Table 8: Correlation matrix for low ridership stops

		Boarding				Alighting			
		AM	PM	OPD	OPN	AM	PM	OPD	OPN
Boarding	AM	1	0.4795	0.6751	0.6325	0	0.1461	0.0683	0
	PM		1	0.691	0.5632	0	0	0	-0.0892
	OPD			1	0.6759	0	0.0777	0.1489	0
	OPN				1	0	0.0951	0.0813	0.094
Alighting	AM					1	0.3859	0.5476	0.4931
	PM						1	0.7197	0.656
	OPD							1	0.7184
	OPN								1

Table 9: Elasticities for High Ridership Stops

	Boarding AM	Boarding PM	Alighting AM	Alighting PM
Average Ridership	31.5	36.6	34.7	33.0
Headway				
+ 1 min	-9.2	-5.1	-5.8	-9.8
+ 2 min	-18.1	-10.2	-11.5	-19.2
+ 5 min	-42.2	-24.5	-27.5	-44.3
Bus stops in 200m buffer				
+ 1	7.5	8.8	3.5	4.7
+ 2	15.3	18.0	7.1	9.6
Metro stops in 200m buffer				
+ 1	83.4	81.7	85.2	53.2
Job Density in TAZ				
+ 15%	-0.3	-0.4	-	0.3
Residential Area in TAZ				
+ 15%	-	-2.0	-2.4	-
Commercial Area in TAZ				
+ 15%	-	0.5	-	0.3