Adjusting the service? Understanding the factors affecting bus ridership over time at the route level in Montréal, Canada

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June 30th, 2020

For Citation please use: Diab, E., DeWeese, J., *Chaloux, N., & El-Geneidy, A. (accepted). Adjusting the service? Understanding the factors affecting bus ridership over time at the route level in Montréal, Canada. *Transportation.*

ABSTRACT

Like many cities across North America, Montréal has experienced shrinking bus ridership over recent years. Most literature has focused on the broader causes for ridership decline at the metropolitan or city level; few have considered ridership at the route level, particularly while accounting for various operational attributes and accessibility-to-jobs issues. Because service adjustments take place—and are felt by riders—at the route level, it is essential to explore bus-ridership phenomena at this same scale. Our study explores the determinants of bus ridership at the route level between 2012 and 2017 using two longitudinal random-coefficients models in Montréal. Our findings suggest that increasing the number of daily bus trips along a route and improving the average route speed are key factors in securing bus ridership gains. The service area's regional accessibility to jobs by public transit around the route has a positive impact on bus ridership at the route level, showing the importance of land use and network structure. Additionally, our models show that reducing service frequency along a parallel route will lead to an increase in ridership along the main route. This study can be of use to transit planners and policymakers who require a more granular understanding of the factors that affect ridership at the route level.

Key words: Ridership, Route level, Bus service, Random-coefficients model

INTRODUCTION

Buses are the oft-maligned workhorse of a public transport network, particularly in North America. Riding the bus in North Americas is often associated with lower-income populations in an auto-centric system. Montréal's local public transport authority, the Societe de Transport de Montréal (STM), has seen large declines in bus ridership over the past number of years even while its Metro system has experienced ridership growth. The shift cannot, however, be explained by a generalized preference for rail over wheels. At least one study has found no preference between modes by riders when service variables are held constant (Ben-Akiva & Morikawa, 2002), suggesting that a comparable decline in service offered may explain ridership loss in either of these systems. The Montréal system provides an excellent opportunity to explore the relationship between bus ridership and service-frequency change: The STM has lost almost 14% of its bus ridership between 2012 and 2017 and many of its routes experienced declines in daily vehicle trip frequency. Overall, in 2017, STM operated around 1200 fewer trips than they operated in 2012, which translates to an average 4% reduction in daily trips per route between 2012 and 2017. The STM generally ascribes declines in bus ridership to "[a] weak economy, the growing popularity of other transport options, [and] lower gas prices," among other reasons (Curry, 2016). This study aims to isolate the impacts of both internal and external factors on each bus route in the STM system through a longitudinal analysis of bus ridership. While other studies have performed analyses of bus and public transport ridership at the regional or national level (Boisjoly et al., 2018; Manville, Taylor, & Blumenberg, 2018; Taylor & Fink, 2003) or at the stop level (Chakour & Eluru, 2016; C. Miller & Savage, 2017), few, if any, have done so at the route level, particularly while accounting for various service operational aspects and accessibility to jobs issues. Our study tries to fill the route-based-ridership analysis gap.

LITERATURE REVIEW

Levels of Analysis

Previous research on public transport ridership has occurred at various levels, ranging from the local or city scale to the regional or even national scale. Several studies have largely focused on a particular site, such as a station or a stop. For example, a study in Brisbane examined the impacts of weather on bus ridership at the system level, destination level, and stop level (Tao, Corcoran, Rowe, & Hickman, 2018). Cross-sectional studies were also conducted at the stop level to understand the determinants of bus ridership including the impact of infrastructure and sociodemographic variables (Chakour & Eluru, 2016). Longitudinal studies of ridership at the stop level also have been conducted (Berrebi & Watkins, 2020). Longitudinal models generally provide a better solution for mitigating the endogeneity between transit supply and demand (Kerkman, Martens, & Meurs, 2015). Compared with stop-level studies, route-level ridership modelling is generally rare in the public-transport literature or it is focused on a narrow research question rather than exploring the impacts of various transit-operation aspects on ridership more generally. For example, Campbell and Brakewood (2017) examined the impact of bicycle-sharing systems at the bus-route level in New York City. Others have explored the impacts of real-time information on bus ridership in New York and Chicago (Brakewood, Macfarlane, & Watkins, 2015; Tang & Thakuriah, 2012). In contrast to the relative scarcity of route-level analysis in the academic literature, transit agencies frequently analyze service operations at the route level. To that end, they often calculate metrics, such as route travel times, speed and productivity, to assess and adapt service operations to improve efficiency and bus schedules and to measure a specific impact of a service change. Additionally, city- or multicity-scale studies are common in the academic literature and have generally been conducted at system-wide levels (Taylor, Miller, Iseki, & Fink, 2009), focusing on guiding high-level policies. Most studies at these levels explore public transport ridership through statistical analysis, generating a model to find coefficients usable by a larger number of public transport agencies (E. Miller, Shalaby, Diab, & Kasraian, 2018).

Accessibility Measures

Accessibility measures are an important tool used by planners and transport authorities worldwide to understand the performance of land use and transport systems and the impact of service improvement strategies (Boisjoly & El-Geneidy, 2017). *Accessibility* is a commonly used term in the transport literature and refers to the ease with which locations can be reached by a certain mode (Luo & Wang, 2003; Morris, Dumble, & Wigan, 1979). Accessibility measures incorporate both land use (e.g., number of jobs in different areas) and transport components (e.g., transit network design, schedules). It is expected that local and regional accessibility will be associated with higher ridership levels (Cui, Boisjoly, El-Geneidy, & Levinson, 2019). Local accessibility refers to what people can access within their neighborhoods (e.g., local stores or bars), while regional accessibility refers to what people can reach within their cities or regions by using a specific mode of transport (Handy & Niemeier, 1997). Several accessibility measures exist in the literature. The simplest measure is the cumulative-opportunity measure, which counts the number of opportunities that can be reached using a particular mode from a given location within a predetermined travel time or distance (Geurs & van Wee, 2004). This measure is simple to calculate and easy to communicate to the public, and, therefore, is the most commonly used in the planning field (Boisjoly & El-Geneidy, 2017).

Factors Affecting Ridership

A number of studies have focused on determining the factors affecting ridership at different levels ranging from the city level to the block and stop level. A comprehensive review of the most recent studies can be found in (E. Miller et al., 2018). These factors are usually broken down into internal factors that are within transit agencies' control and external factors that fall outside transit agencies' control. Internal factors that impact bus ridership include pricing, quantity, and quality of service (Taylor & Fink, 2003). Adjustments to these variables can directly impact riders' trip satisfaction and overall loyalty (van Lierop, Badami, & El-Geneidy, 2018; Zhao, Webb, & Shah, 2014). Maintaining satisfaction among existing riders is especially important for a public transport system and its bus network, as these riders are often less satisfied than automobile users and consider the bus in particular to be the least satisfying mode available (Beirão & Cabral, 2007; Eriksson, Friman, & Gärling, 2013; St-Louis, Manaugh, van Lierop, & El-Geneidy, 2014). Network coverage and service quantity are important considerations for overall ridership. Different variables have been used in the past to represent the quantity of service, including vehicle revenue kilometers (VRK) of service, frequencies, and travel time (Boisjoly et al., 2018; Taylor & Fink, 2003; van Lierop et al., 2018). Increasing the quantity of service can take many forms, including straightforward service enhancements, such as adding trips or increasing route coverage (Balcombe et al., 2004; Verbich, Diab, & El-Geneidy, 2016). Using these strategies to augment or optimize VRK and travel time can increase ridership for bus services, which are strongly affected by service levels (Boisjoly et al., 2018). Fares have a mixed impact on transit usage, where some studies suggest that the demand for urban transit services could be inelastic (Kohn, 2000; Taylor et al., 2002). These variables are traditionally grouped at an aggregate level, presenting an opportunity for new findings at the route level.

Common external variables impacting ridership include population density, income levels, employment levels, gas prices, and sociodemographic status (Taylor & Fink, 2003). Other emerging factors cited in the literature include potential competiton from ride-hailing and bike-sharing services (E. Miller et al., 2018). These external variables are often used to explain a decline in ridership (Bliss, 2018; Curry, 2016). Larger populations and greater population density, and lower income rates tend to increase ridership (Boisjoly et al., 2018; Thompson, Brown, & Bhattacharya, 2012). Income is related to other variables like the unemployment rate. Together, these two variables reflect the overall economic outlook of a region. Specific built form characteristics can also increase public transport ridership, including proximity to public transport stops (Pasha, Rifaat, Tay, & De Barros, 2016). Gas prices affect certain modes of public transport more than others, with light rail being the most affected by gas prices and buses the least (Currie & Phung, 2007). Ride-hailing companies (RHs), such as Uber, and bike-sharing systems may have an impact on transit ridership. These services are a relatively new phenomenon in the literature, with no clear consensus on their impact on overall public transport use (E. Miller et al., 2018).

STUDY CONTEXT

Montréal is Canada's second-largest city, home to over four million people in its greater region in 2016 (Statistics Canada, 2016). The city itself consists of roughly two million people on the Island of Montréal. The city has a dense urban core where active modes have been gaining in popularity and a large bicycle route network is maintained throughout the year. Automobile usage, however, remains high, particularly in the outer regions of Montréal. Auto mode commuting mode share was 62.0% in 2016. Meanwhile, public transport has grown at a slower pace compared to private automotive use between 2011 and 2016 (Statistics Canada, 2016). Several public-transport authorities operate in the greater Montréal region, with suburban transport agencies running some buses towards downtown, and EXO (the metropolitan transport system in the region) providing commuter rail and regional bus options. Public transport within the Island of Montréal is provided by the STM, which operates four Metro lines and 219 bus lines. Buses are provided in a mixture of local and express services, with a 10-Minute Max network providing a basic grid of frequent service. The Metro concentrates service in the center of the Island, with most lines connecting directly to downtown (Figure 1). In this study, we will concentrate on the STM system and the changes in its ridership between 2012 and 2017 at the route level.

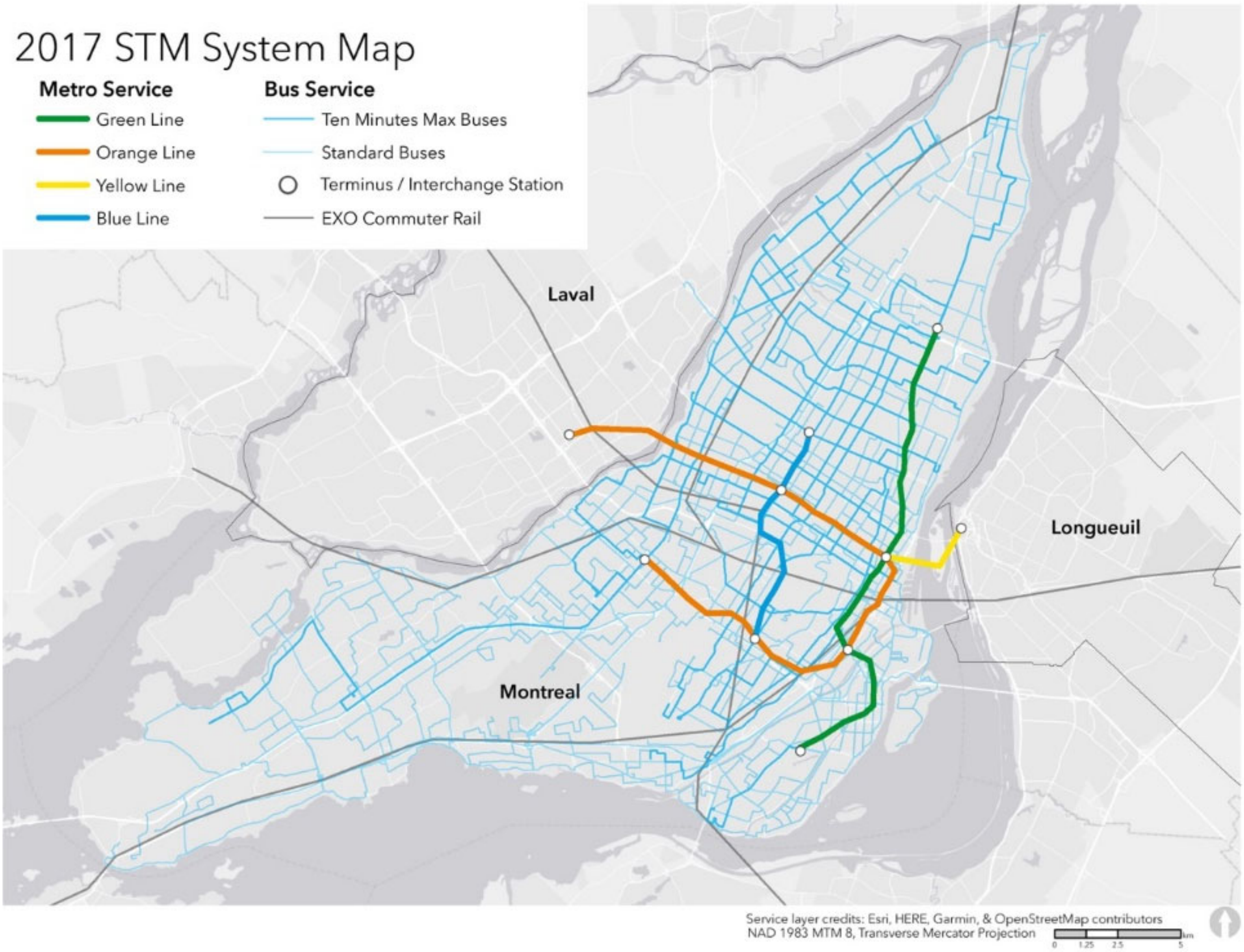

Figure 1: 2017 STM System Map

DATA

Ridership Data

STM ridership data was provided by the Montréal Gazette in the form of annual ridership for each bus route between 2012 and 2017. Annual ridership data includes total number of boardings per route made during any given day. The Gazette obtained the data following an Access to Information Act request. Certain routes were removed from the dataset before analysis. Routes not present for all six years due to their cancellations were removed (3 routes in total). This study does not consider ridership changes on the 23-night routes (300-series) operated by the STM between 2:00 am to 5:00 am. These routes are operated after the metro system is closed, with an entirely different network with different spatial coverage. A small portion of the daytime ridership declines could conceivably be explained by a shift from daytime to nighttime travel. Overall, however, we estimated the potential impact to be minimal given the small number of night routes and the absence of any exogenous indication of wholesale changes in the region's temporal work or leisure travel patterns. We, therefore, decided to exclude night routes from this analysis given that the different spatial and temporal network coverage of the night routes would require an entirely different model specification beyond the scope of this study. Additionally, shuttle routes:

250- & 260-series, Route 769, & Route 777, were removed from the analysis (12 routes). This reduced the dataset from 219 to 181 routes. A separate case was generated for each year between 2012 and 2017, resulting in a sample of 1,086 observations.

Internal Variables

STM operating data were retrieved from archived General Transit Feed Specification (GTFS) datasets for all years available online. Feeds servicing November 1st for each year were selected, with a weekday service schedule used for analysis across all years. Both ArcGIS and R were used to extract several operational variables from each feed after cleaning column names.

Tidytransit, an R package, was used to read the GTFS feeds and determine the number of stops and daily weekday trips for each route. This package automatically derives headways and frequencies by route, although the STM GTFS datasets required some cleaning. Average travel time was found by subtracting the arrival time at the maximum stop sequence from the departure time of the initial stop sequence for each trip, then averaging by route and trip. The average and standard deviation of headway were found by finding the difference between departure times at the initial stop sequence of each trip, then averaging the difference by route. Route length was found by exporting the stop sequence for every trip on the given service schedule to ArcGIS. Network Analyst was used to create polyline shapefiles for each trip, using a Montréal street centerline network. The length of each polyline was measured, with the maximum value for each route maintained for analysis. Finally, the average speed was found by dividing route length by average travel time. For weekend data, a similar process was used, while averaging Sunday and Saturdays values (e.g., weekend trips = (Saturday trips + Sunday trips)/2).

Several dummy variables were also generated for each route. Express routes (400-series routes) were distinguished in the models using a dummy variable. Similarly, routes with 10-Minute Max designation were identified using a dummy variable. Additional dummy variables for connections to the Metro and EXO system were generated using buffers, with routes outside a 500-meter buffer of a Metro station being identified as not connecting to the Metro and those within a 500-meter buffer of an EXO station being identified as connecting to commuter train. The distances were chosen to accommodate multiple station entrances not reflected by point shapefiles.

A dummy variable for parallel local routes was generated for the routes running alongside other routes. Local routes were identified in terms of having shorter spacing between stops and/or shorter routes, which is related to STM operations. More specifically, local routes which are overlapping with the 400-series express bus service were identified. To give an example, STM in Montréal operates Route 467: Express Saint-Michel with average stop spacing of 400 meter that shares the exact corridor with the local route, Route 67: Saint-Michel, with average stop spacing of 200 meter. Both routes almost start and end at the same locations. In this cases, Route 67 was identified as a local route and had a value of one in the dummy variable (i.e., parallel local routes variable). Afterward, another dummy variable was created for the routes running alongside the local routes that have experienced a cut in their number of trips (Route 467, in this example). This variable was called "parallel routes with a cut in number of trips in a previous year (dummy)." Both variables will help in exploring the local impacts of service overlapping and service changes. Whilst, other small overlaps can exist between routes, yet in this study we concentrate mostly on routes with a higher than 90% of overlap indicating competition between these two routes. Lastly, fare pricing was retrieved from STM budgets, with both a single ride and standard monthly pass included (Société de Transport de Montréal, 2012; Montréal, 2013, 2014, 2015, 2016, 2017). The percentage of the STM bus fleet removed from service for maintenance is sourced from the Montréal Gazette and displayed by year (Magder, 2018).

External Variables

Demographic and socioeconomic data were retrieved at the census-tract level from Statistics Canada for both 2011 and 2016. Data included each year's Census data and commuting flows data. Linear interpolation was used to generate demographic variables for years 2012 through 2015 and linear extrapolation to predict demographic variables for year 2017, an approach similar to that used by Boisjoly et al. (2018). Shapefiles for each census tract (CT) in 2011 and 2016 were retrieved from Statistics Canada and then intersected with a 400-meter buffer generated around each route to calculate the area of each census tract falling within the buffer zone. This area was then divided by the area of the whole census tract to produce a ratio of each intersected area located within the buffer zone. The resulting ratio for each census tract was then used to weight the variables associated with each census tract before computing the value for each route's service area. Finally, each demographic variable is weighted accordingly before being summed by the route number. The prepared demographic variables were population, population density, median household income ($), number of recent immigrants (arriving in Canada in the last five years), households paying more than 30% of their income on housing, and unemployment rates (%).

A cumulative-opportunities measure of accessibility was calculated to count the number of jobs that can be reached by public transit in 45 minutes during the morning peak (the mean travel time on the island of Montereal is 42 minutes by public transit). Public-transit travel times were calculated using GTFS data for each year using Open Trip Planner, which was previously validated by Hillsman and Barbeau (2011). Travel time was calculated for various departure times in the morning peak (every 10 minutes between 8 and 8:30 am for a November weekday) and then averaged to account for fluctuation in service frequency during the peak morning period. The number of jobs in each census tract in each year between 2012 and 2017 was determined from the Canadian Census commuting flows data using linear interpolation and extrapolation discussed above. Using the spatial intersection process discussed earlier, the average accessibility for every route was computed based on the weighted average of all the CTs that fall within the route buffer.

Walkscore index assesses local accessibility to a range of different amenities while employing a distance-decay function to weight nearby locations higher than those more distant (Walkscore, 2019). Walkscore values were obtained from Walkscore.com in 2013 and 2019 at the postal code level. Walkscore values for years 2012 through 2017 were estimated using the linear interpolation process discussed earlier. Then, to estimate an average Walkscore value for each route, the postal code's centroids were intersected with a 400-meter buffer generated around each route.

Several contextual variables were generated for inclusion in the models, including the average price of gas for the Montréal region retrieved from Statistics Canada (2019). Ride-hail services are included as dummy variables, with Uber selected as the dominant ride-hailing company and BIXI for the bicycle-sharing company. The presence of Uber was created as a dummy variable by year, with 2015 being identified as the first full year they operated in Montréal, as there is little information on the number of trips taken by Uber. A dummy variable for the presence of BIXI was generated, albeit differently from a typical city-wide dummy variable as previous research has specified the need for more detailed variables for bike-sharing (Boisjoly et al., 2018; Graehler, Mucci, & Erhardt, 2019). A 500-meter buffer was generated around each BIXI station in Montréal. Routes that have more than 25% of their length within the service area were deemed as being in competition with BIXI and were coded as one, allowing for the distinguishing of routes that are actually affected by the presence of BIXI. Table 1 shows the list of variables prepared for the analysis.

Table 1: Annual means of route characteristics

Variable name	2012	2013	2014	2015	2016	2017
Internal Variables						
Annual ridership	1,421,540	1,426,700	1,380,971	1,292,189	1,247,150	1,223,133
Daily weekday trips	107.02	103.48	99.02	98.28	98.63	99.84
Weekend trips*	34.97	33.75	31.85	30.23	30.20	30.04
Average weekday travel time (min)	34.35	34.55	34.74	35.23	35.46	35.92
Average weekend travel time (min)*	21.15	21.25	21.39	21.50	21.60	21.70
Weekday headway (min)	26.29	26.07	26.63	26.95	26.77	26.69
Weekend headway (min)*	24.62	24.98	25.73	26.19	25.19	25.24
Weekday peak travel time (min)	35.23	35.49	35.81	36.56	36.71	36.51
Weekday peak headway (min)	24.98	25.41	25.77	26.15	26.17	23.21
Weekday headway standard deviation (min)	17.37	17.8	17.15	17.55	16.85	18.03
Route length (km)	11.68	11.79	11.74	12.55	12.32	12.49
Route average speed (km/h)	20.45	20.12	19.95	20.92	20.75	20.55
Route stops	36.22	36.22	36.22	36.27	36.29	36.33
Route is express (%)	18.68	18.68	18.68	18.68	18.68	18.68
Route connects to EXO (%)	11.54	11.54	11.54	11.54	11.54	11.54
Route does not connect to Metro (%)	13.19	13.19	13.19	13.19	13.19	13.19
Route is 10 Minutes or Less (%)	17.03	17.03	17.03	17.03	17.03	17.03
Route is in BIXI service area (%)	26.37	26.37	26.37	26.37	26.37	26.37
Cash fare ($)	3.0	3.0	3.0	3.25	3.25	3.25
Monthly fare ($)	75.5	77	79.5	82	82	83
Buses removed for maintenance (%)	16.3	18	20.5	21.6	19.3	21.1
Parallel local routes	16.02	16.02	16.02	16.02	16.02	15.93
Parallel routes with a cut in number of trips in a previous year (dummy)	-	7.73	9.94	11.60	6.08	3.30
External Variables						
Employment positions	36,145	36,263	36,382	36,501	36,619	36,762
Median household income ($)	48,849	50,631	52,412	54,194	55,716	57,757
Population	47,273	47,601	47,928	48,256	48,583	48,911
Recent immigrant population	3,963	3,890	3,817	3,745	3,672	3,600
Households paying 30% towards housing	7,582	7,487	7,393	7,299	7,205	7,111
Population density (per km2)	7,805	7,872	7,939	8,005	8,103	8,170
Unemployment rate (%)	9.72	9.59	9.45	9.31	9.13	9.04
Average gas price ($)	1.37	1.37	1.37	1.16	1.08	1.19
Walkscore	71.57	72.18	72.79	73.39	74.00	74.61
Access to jobs 45 min (ln)	34,7015	34,6839	34,0973	35,1249	35,0919	34,1069

** Several routes did not have a weekend service, which will impact the overall presented average*

METHODOLOGY

We start our analysis with an exploration and comparison of the general trends of ridership and route-design factors. Then, routes are grouped to explore the differences between the top and bottom percentiles in terms of ridership and service-related factors. This exploration helped in understanding major trends and relationships in the data before modelling. For the modelling, all non-dummy variables were transformed into the natural logarithmic form. The log-log formulation is common in the transport literature and allows for the interpretation of model results in terms of elasticities. A log transformation is known to help in meeting the normality assumptions in regression models and helps non-linear relations to be more linear.

The data are organized as a longitudinal panel, with six repeated observations for each route with dependent and independent variables values for different years. In this case, several hierarchical models (i.e., multilevel) can be used including fixed-effect models, random-effect models (i.e., random intercept models), and random coefficients models. In the literature, some researchers have used random-effects models to model transit ridership, (Tang & Thakuriah, 2012), which provide more generalized results (Borenstein, Hedges, Higgins, & Rothstein, 2011). Others have used fixed-effect models (Brakewood et al., 2015; Campbell & Brakewood, 2017), while referencing the results of the Hausman Test as a major factor in determining the modeling approach. The Hausman test provides an answer to the question if fixed- or random-effects should be used. Fixed-effects models control for unobserved time invariant individual characteristics, though they have several limitations related to external validity and the omission of important key variables that do not vary over time (Hill, Davis, Roos, & French, 2020). More importantly, both modeling approaches (fixed-effect and random-effect) fail in accounting for varying slopes of the regressors across the sample. Therefore, it is essential to use a poolabilty test, known as Chow Test, to measure if the slopes of regressors are the same across individual entities or not (Baltagi, 2008). If the null hypothesis of poolability test is rejected, individual entities (routes in our case) will have their own slopes of regressors and, therefore, neither fixed- nor random-effects models are suggested and the use of random-coefficients models are instead recommended.

An initial random-effect model was run to explore the determinants of ridership while using an upward stepwise method for the inclusion of dependent variables by removing insignificant variables one at a time. After determining the initial set of influencing factors, the testing of several models was conducted in Stata 15.1. Both fixed and random effects were statistically significant in comparison with the pooled ordinary least squares (OLS) models based on the likelihood ratio (LR) test ($p=0.000$). This was followed by conducting the Chow test for 20 routes that were randomly selected from the sample to understand the poolability of the data. The F statistic was significant ($f(3,114)=1119.8$, $p=0.000$), therefore, we rejected the null hypothesis of poolability and concluded that the panel data are not poolable with respect to routes. Accordingly, both fixed- and random-effect models were discarded as it was essential to use a random coefficients model (Park, 2011). Afterward, various random-coefficients models were estimated in Stata while using different covariance structures and random slopes. These models were compared to random intercept models using AIC and BIC scores and LR tests. The LR test yields ($LR= 20.39$, $P=0.001$) that by employing access to Jobs variable for the random slope and unstructured covariance structure a better model fit in comparison with random intercept models can be found. Afterward, more testing for the incorporation of more independent variables was done. The final selected model achieved the lowest AIC and BIC scores while maintaining the maximum number of significant variables following previous findings and theory. For all models, ridership was nested within the routes. The final model specification is:

$$Ridership_{it} = \lambda + \beta(Internal\ factors)_{it} + \beta(external\ factors)_{it} + \alpha_{1i} + \alpha_{2i}(access\ to\ jobs)_{it} + \mu_{it} \quad \text{.......} 1$$

Where i and t respectively denote route and time point. $\lambda + \beta(Internal\ factors)_{it} + \beta(external\ factors)_{it}$ are the fixed components of the model, while $\alpha_{1i} + \alpha_{2i}(access\ to\ jobs)_{it}$ are the random components. α_{1i} is the deviation from the mean intercept. α_{2i} is the deviation from the mean slope. λ is the model constant, while μ_{it} is the residuals estimates. *Internal factors* and *external factors* are the built environment and socioeconomic, and transit service variables, respectively. The model dependent variable in our case is $Ridership$, which is the natural logarithm for annual ridership of each route, with the resulting coefficients (β) that describes the percentage change in ridership expected with each additional percentage of change in the independent variable. The first model was developed to explore the determinants of route ridership over time using data from 2012 to 2017. A random sample of 15% of the total observations was withheld from the data used to generate the models so they could be used in model validation. Afterward, a second model was generated using the same dataset, while only including records from 2013 and 2017. The second model is used to assess the stability of the first model and to include a variable that controls for the impact of changes in the number of trips in an overlapping route in the previous year. In this case, then, 2012 data are excluded.

Several dummy variables explaining differences between routes were tested and removed as they did not show statistical significance in the models. The included routes that connect to EXO (the regional commuter train), parallel local routes, presence of ride-hailing companies (i.e., Uber) and routes that do not connect to the Metro. Other variables were removed for correlation indicated by the Pearson coefficient (above than 0.7 Pearson's Correlation Coefficient) and the models' mean collinearity showed by the variance inflation factor (VIF) indicator. For example, headway, route length, and variables related to peak period were correlated with daily number of trips and route travel times. Similarly, weekend variables were correlated with the number of trips during the weekend. Monthly fare and cash fare were found to be correlated with year dummy variables. Similarly, route overlap with the BIXI (bicycle sharing service in Montréal) service area (%) and average gas prices were found not significant while incorporating the year dummy variables. Most of the external variables at the route level were also correlated. For example, Accessibility, measured as the number of jobs reachable in each year by public transit in 45 minutes of travel time, was found to be strongly correlated with population density, number of local jobs within the routes' service area, number of households paying 30% of their income to housing costs, and average Walkscore for the route service area. Other variables did not show statistical significance, such as unemployment rates around the routes service area.

Finally, a validation step was conducted to understand the quality of the used models' in predictions. The original dataset was split into a training sample (85%) and a validation sample

(15%). Then, the two models were estimated using the training sample, while setting aside the model validation sample. Using the developed models' coefficients, ridership was then estimated for the validation sample and compared with the actual ridership using Pearson correlation test.

RESULTS

Summary Statistics

Table 1 shows a general summary of all data prepared for analysis. The data are grouped by route and year in the table to illustrate the average for each variable by year. The largest changes, aside from ridership, are in daily weekday vehicle trips provided, weekend trips, median household income, and fares, with most others relatively stable. Average route travel time has increased by just over a minute on average, whether on peak or over the course of the entire weekday. Headways are similarly steady, with an increase of roughly a minute on peak and half a minute for the weekday between 2012 and 2017. Key route design and built environment factors, such as route length, stop counts, stop spacing, population density, number of employment positions in the area, are also relatively similar across all years with minor differences.

Table 2 shows bus and metro systems ridership and the number of available buses per year. As seen in the table, bus ridership has traditionally made up a majority of overall ridership, although metro ridership has reached parity more recently. The total number of bus trips per day declined each year between 2012 and 2015 before reversing that trend between 2016 and 2017 (Table 2). The bus fleet itself was stagnant between 2012 and 2015, though new buses were added in 2016 and 2017. However, when considering the number of buses actually available for service on an average day each year, the bus fleet shrank between 2012 and 2015 before it increased with new purchases of buses in 2016. This increase in metro ridership can be attributed to the growth of employment centers outside the island of Montréal, or due to the metro system capacity improvement. The decline in bus ridership between 2012 and 2017 varies across the city. Not all routes lost ridership (Figure 2). The largest ridership losses are in the center, North, and East of the Island of Montréal , while ridership gains are mostly found in the West Island. When focusing on the 10-Minute Max network, ostensibly Montréal's highest-priority bus routes on the Island, almost all routes experienced declines in ridership.

Table 2: STM Service Statistics, 2012 to 2017

Year	Total Bus Ridership	Metro Ridership	Total Daily Bus Trips	Total Bus Fleet	Maintenance Rate (%)	Available Bus Fleet
2012	257,298,797	155,301,203	19,370	1,712	16.3	1,433
2013	258,232,718	158,267,282	18,730	1,746	18.0	1,432
2014	249,955,832	167,244,168	17,923	1,721	20.5	1,368
2015	233,886,129	179,413,871	17,788	1,721	21.6	1,349
2016	225,734,114	190,465,886	17,852	1,771	19.3	1,411
2017	222,610,236	206,889,764	18,170	1,837	21.1	1,449

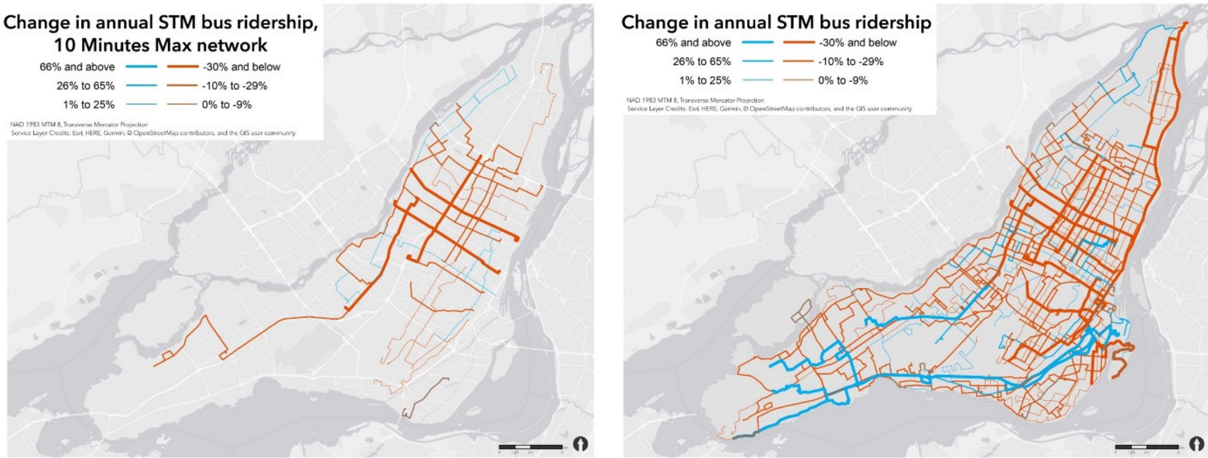

Figure 2: Change in annual STM bus ridership, 10 Minutes Max network & all routes

Figures 3 demonstrates the change in ridership and change in daily bus trips between 2012 and 2017. As daily bus trips decrease ridership decreased, which is expected. Grouping routes by their ridership performance and service adjustments, the upper- and lower- percentiles of routes can be compared relative to their household median incomes (Table 3 and 4). Lower median income levels are usually correlated to social vulnerability and have been associated with public transport captivity in Montréal (Farber & Grandez, 2017; Verbich & El-Geneidy, 2017).

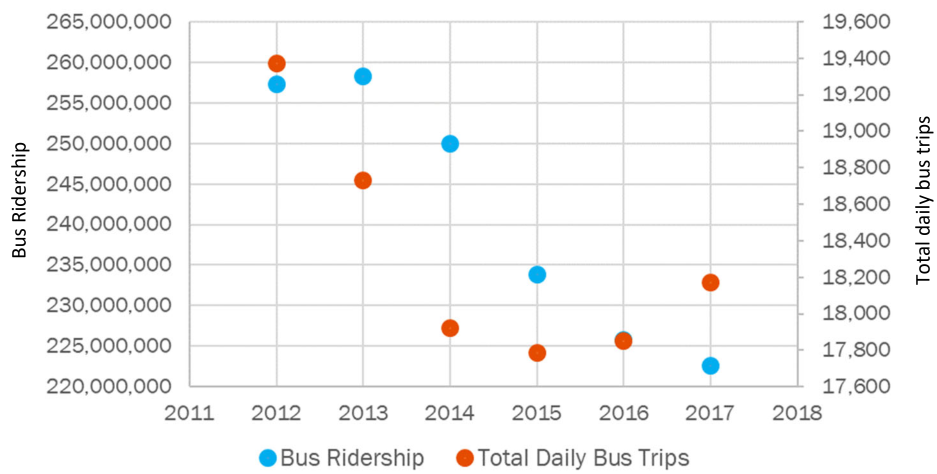

Figure 3: STM Bus Ridership & Daily Bus Trips, 2012-2017

As seen in Table 3, routes that saw the largest declines in ridership and the greatest cuts to service have the lowest average median incomes. These routes (i.e., *Bottom 10% and Bottom 25%*) have considerably higher total levels of ridership compared to other routes (i.e., *Top 10% and Top 25%*). In the case of changes in the number of trips (Table 4), routes that saw trips added to them generally have higher average median incomes than routes that saw trips taken away from them. In fact, the group of routes with the lowest average household median income (i.e., *Bottom 10%*), saw one of the largest declines in terms of average number of daily trips. Figure 4 further underscores the relationship between route-level service reductions and the median income of the areas the routes serve. The figure plots percentage change in the number of daily weekday trips for each route (y-axis) against the scaled average median income for the route-service area (z-score). The trend line dips to the left, indicating that cuts tended to be more severe for routes serving lower-income areas. These results suggest that the STM has added service to lower ridership routes at higher income areas, which may reflect their efforts in attracting choice riders, rather than focusing on keeping captive and captive by choice riders (people who can afford a car, but they do not own one) in the system.

Table 3: Routes by Ridership Change, 2012-2017

Percentile	Change in Ridership	2017 Total Ridership	Change in number of Trips	2016 Median Income ($)
Top 5 Routes	291,305	5,100,574	23.0	59,410.8
Top 10%	193,882	22,330,706	7.4	55,682.1
Top 25%	93,416	41,691,795	5.4	57,675.3
*Rest of routes**	-58,952	65,518,311	-3.5	59,696.9
Bottom 25%	-748,765	115,385,707	-25.5	51,956.3
Bottom 10%	-1,427,753	70,737,817	-44.7	49,304.4
Bottom 5 Routes	-2,521,821	23,460,607	-53.2	47,407.7

** Routes from 25% to 75%*

Table 4: Routes by Service Adjustments, 2012-2017

Percentile	Change in number of Trips	2017 Total Ridership	Change in Ridership	2016 Median Income ($)
Top 5 Routes	36.0	9,067,092	988,306	55,275.5
Top 10%	19.7	35,744,098	1,879,612	55,122.7
Top 25%	9.4	49,739,231	2,012,931	60,955.2
*Rest of routes**	-3.5	73,690,236	-6,273,697	57,610.0
Bottom 25%	-29.6	99,166,346	-30,442,218	52,777.4
Bottom 10%	-48.5	52,659,281	-22,461,838	50,265.9
Bottom 5 Routes	-71.0	20,507,405	-8,511,091	54,316.2

** Routes from 25% to 75%*

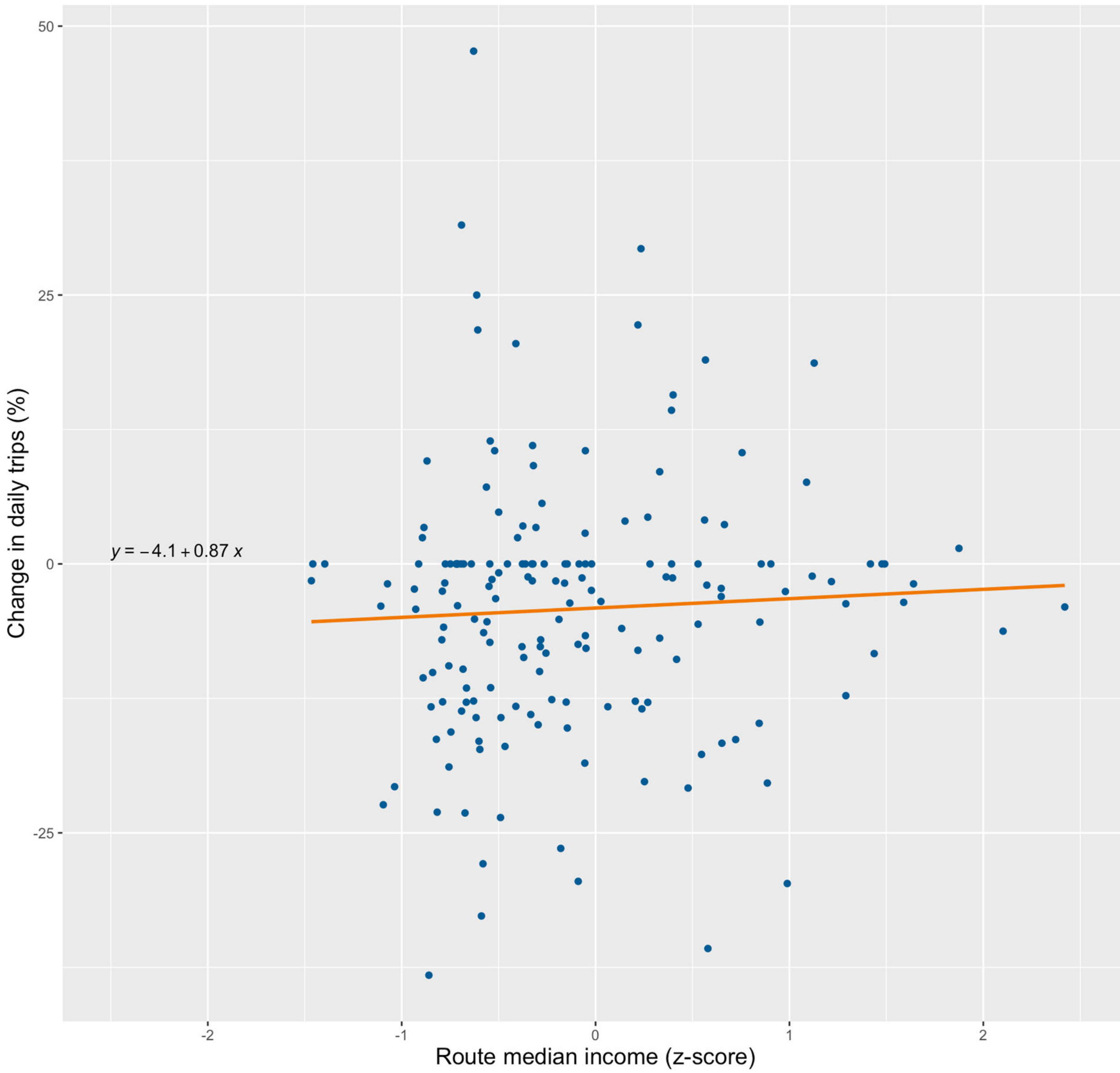

Figure 4: Route-level service changes and median income

To better understand the drivers behind the service adjustments conducted by STM, Figure 5 shows the change in daily weekday trips compared to the ridership change from the previous year. The trend line for each graph suggests that there is little and inconsistent relationship between ridership performance the year prior and service adjustments that year. The exception is in 2015, although this relationship is poor. In other words, the STM did not add weekday trips to routes that experienced high ridership gain, year over year or concentrate its cuts on routes that were already experiencing ridership declines.

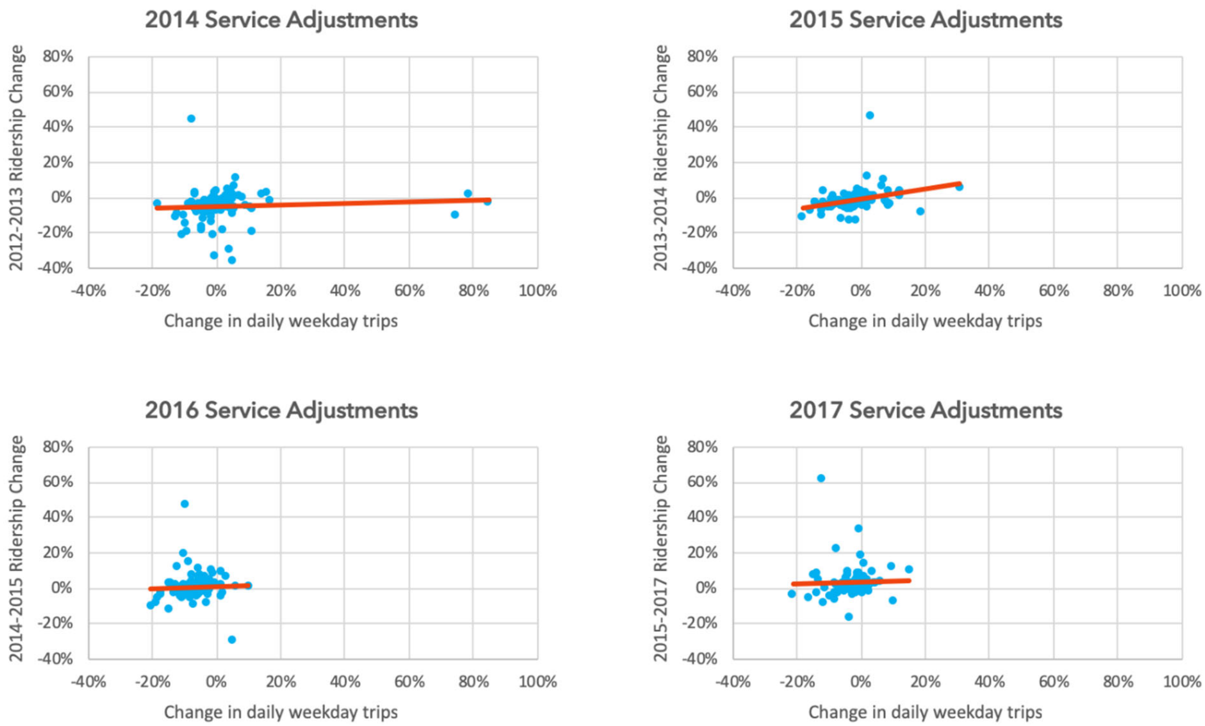

Figure 5: Change in annual STM bus ridership, 10 Minutes Max network & all routes

Ridership Models

Table 5 shows the results of two random coefficients models that were developed using the natural logarithm of annual route ridership as the dependent variable. For both models, a random slope for the effect of accessibility to jobs by public transit on evaluations of ridership was employed. Both models were estimated using the training sample. The first model (Table 5.A) includes data from 2012 to 2017, with a total of 910 records, while the second model (Table 5.B) includes data from 2013 to 2017, with a total of 760 records as the second model incorporated an additional variable accounting for service changes in overlapping routes compared to the previous year, so data from 2012 were excluded. The high ICC estimate for both models suggests considerable reliability.

In the first model, the number of daily weekday trips have a statistically significant positive impact on ridership. More specifically, increasing the number of weekday trips by 10% will increase annual ridership by 9.70%, all other variables held to their means. In comparison with other variables in the models, this variable is the largest contributor to transit ridership. Similarly, transit ridership is positively associated with the number of bus trips per route during the weekend. A 10% increase in the average number of trips during the weekend (i.e., (Saturday trips + Sunday trips)/2) is linked with a 1.45% increase in ridership. This means that at the route level, offering more trips during Saturdays and Sundays will be translated into a higher annual ridership per route, yet not as much as the increase in the frequency of service during weekdays.

Service speed has also a statistically significant positive impact on ridership. Every 10% of additional route speed is associated with a 1.24% increase in annual ridership. In other words, faster service is expected to attract more riders at the route level. While controlling for speed, route travel time is also positively associated with annual ridership. For every additional 10% increase in weekday travel time, annual ridership will increase by 2.34%. From transit planning perspective, this generally reflects that longer routes, with longer travel times, are normally able to capture higher ridership levels to a certain extent while controlling for other influencing factors such as speed as they do serve more population. When considering the number of stops per route, more stops equal to more riders. Every 10% increase in the number of stops is associated with a 3.23% increase in annual ridership. This is expected since more stops mean shorter walking distances and increase in serviced population. However, numerous closely-spaced stops will not increase transit ridership, as they will have a negative impact on speed. This decrease in speed may further result in a decline in the number of trips operated by the transit agency per route. Therefore, a delicate balance between speed, number of stops, and the number of trips per day should be considered to improve ridership at the route level.

Two dummy variables were found to be statistically significant, including whether a bus is designated as a 10-Minute Max network and if it is an express bus service. The 10 Minutes Max designation, and accompanying service levels, experience an 82% (based on the exponential value of 0.60) higher annual ridership compared to other routes. This may capture riders' preference for routes that are branded as frequent and reliable. It should be noted that STM uses a unique green color in the maps and its webpage to highlight and advertise for such a network. Overall, these results suggests a strong association between the 10-Minute Max network's routes and ridership compared to other routes, while controlling for the impacts of other operational factors such as speed and number of trips per day. Express service routes were also positively associated with ridership. As seen in the model, express service routes observe a 48% higher ridership compared to other routes. This may highlight the fact that express service offers more direct service from people's origins to destinations, which requires them to transfer less, attracting higher ridership levels compared to other routes. It is important to note that the interpretation of the dummy variables in a log model are expressed as the exponential function of the coefficient in percentage.

Table 5: Estimated ridership models

	A. All data			B. 2013 -2017 data		
Variable name	**Coef.**	**z**	**P>z**	**Coef.**	**z**	**P>z**
Route factors						
Daily weekday trips (ln)	0.970	20.51	0.000	0.995	21.10	0.000
Weekend trips (ln)	0.145	6.04	0.000	0.142	5.98	0.000
Route average speed (ln)	0.124	3.42	0.001	0.081	2.55	0.011
Average weekday travel time (ln)	0.234	3.80	0.000	0.313	5.36	0.000
Route number of stops (ln)	0.323	6.43	0.000	0.184	4.00	0.000
Route in 10-Minute network (dummy)	0.601	6.79	0.000	0.595	6.70	0.000
Express service (dummy)	0.393	4.13	0.000	0.330	3.46	0.001
Parallel routes with a cut in number of trips in a previous year (dummy)				0.059	3.05	0.002
External factors						
Adjusted median household income (ln)	-0.378	-3.68	0.000	-0.281	-2.54	0.011
Access to jobs 45 min (ln)	0.103	2.34	0.019	0.089	2.03	0.042
Year 2012	-	-	-			
Year 2013	0.064	5.52	0.000	-	-	-
Year 2014	0.092	7.33	0.000	0.025	2.88	0.004
Year 2015	0.045	3.21	0.001	-0.022	-2.22	0.027
Year 2016	0.014	1.00	0.316	-0.053	-5.07	0.000
Year 2017	0.018	1.18	0.237	-0.052	-4.37	0.000
Constant	9.084	6.69	0.000	8.515	5.87	0.000
Log-likelihood	433.113			467.957		
AIC	-828.227			-897.915		
BIC	-736.771			-809.882		
ICC	0.999			0.999		
Observations	910			760		
Number of groups	180			180		
Random-effects Parameters						
	Estimate	*95% Conf. Interval*		*Estimate*	*95% Conf. Interval*	
Stdev. of access to jobs 45 min (ln)	*0.316*	*0.237*	*0.421*	*0.309*	*0.221*	*0.431*
Stdev. of constant	*3.835*	*2.863*	*5.135*	*3.779*	*2.701*	*5.286*
St. dev. of residual	*0.095*	*0.090*	*0.101*	*0.073*	*0.068*	*0.077*

Turning to external variables, two variables were found to have statistical significance. Household average median income along a route has a statistically significant negative impact on ridership. It decreases annual ridership by 3.78% for every additional 10% increase in income. As expected, accessibility to jobs has a positive association with route usage. A 10% increase in the number of jobs that can be reached by public transit in 45 minutes is associated with a 1.03% increase in ridership. Accessibility measures are an important tool used by planners to understand the performance of land use and transport systems and the impact of service improvement. These measures include both land use and transport (i.e, transit network structure) components. As the study was done at the aggregate level of the bus route, several important external variables were strongly correlated with accessibility to jobs such as population density, number of local jobs within the route's service area, and average Walkscore for the route service area. Years also have an impact on ridership. These variables were incorporated in the models to control for any unforeseen factors that took place during the study period. Compared to 2012, 2013, and 2014 observed increases in ridership by 6.6% and 9.6%, respectively, when keeping other variables constant at their means. However, this trend of increase in ridership in comparison with 2012 declined in 2015 to only 4.6% and diminished in 2016 and 2017. Such an impact on ridership in the first couple of years in the study, indicates that ridership decline can be attributed mostly to service delivery and other external factors included in the model. It should be noted that in 2016, the metro system saw a considerable improvement by the incremental introduction of new trains with full-width open-gangways between the cars, which can be occupied by passengers, offering more capacity to users. The first train entered into service in 2016 and replaced the entire old fleet on some lines in 2018. This system changes may have resulted in the gradual impact we are seeing in the last two years of the study compared to 2012.

The second model includes only data from 2013 to 2017 (Table 5.B) and confirms the first model's results in terms of coefficients' direction and magnitude. The second model includes a dummy variable "Parallel routes with a cut in the number trips in the previous year" that explores the immediate spatial and temporal impacts of service changes. The model indicates that cutting service frequency for local routes overlapping with other routes for more than 90% of the service has a statistically significant positive impact on ridership for routes running alongside, increasing their ridership by 6.1% on average compared to other routes without overlapping services or those with overlapping but did not experience service cuts. In other words, some routes in the STM network saw an increase in ridership, not due to attracting new riders, but rather because of cutting the service frequency at some parallel routes. However, after controlling for that, the model (in Table 5.B) still shows a very similar impact for all investigated service-related variables as well as external variables.

Table 6 shows the results of the validation step using the randomly 15% observations not included in the modeling. As seen in the table, for the first model (Table 6.A), the average log of the actual ridership per route was 13.36, while the average log of the estimated ridership by the model was 13.42. This indicates a close relationship between the two values. Similarly, the standard deviation of the log of the actual number of linked trips was 1.29, while it was 1.06 for the estimated number of linked trips. This indicates a slightly higher variation in the actual ridership. However, using a Pearson correlation test, a statistically significant positive correlation of 0.93 between the actual and estimated ridership was identified, illustrating a very strong relationship between actual and predicted values. Similar results were found for the second model.

Table 6: Predicted and actual ridership estiamtes

	A. All data		**B. 2013 -2017 data**	
	Actual	Predicted	Actual	Predicted
Average	13.362	13.417	13.298	13.374
Standard deviation	1.296	1.068	1.325	1.061
Pearson Correlation	**0.929***		**0.932***	
Number of observations	**165**		**138**	

** Significant at 99.9%*

DISCUSSION & CONCLUSION

This study explored the factors affecting ridership at the bus route level of analysis. As transit planners and practitioners adjust service operations at this level, a better understanding of the relative impact of service operational factors and other external factors is needed. To achieve this goal, this study used a comprehensive longitudinal dataset collected at the route level for 180 routes on the island of Montréal between 2012 and 2017. Summary statistics and two multilevel random coefficient models were developed for the purpose of the study, which was then followed by a validation procedure to show the accuracy of the prediction of these models.

The summary statistics showed that over the course of the study period, the STM saw an overall decline of 13.96% in its annual bus ridership. This decline was mainly at routes that usually enjoyed higher ridership. This was also related to service adjustment in the form of removing daily trips, in average number of trips per day declined by 4%. The STM directed its resources to improve service quality by offering more trips along routes serving higher-income neighbourhoods, while decreasing the service quality at lower-income areas. This can be related to the efforts of attracting more car users into the system. However, with limited number of buses, it came at the expense of more frequent riders. Indeed, the Montréal data demonstrated that routes servicing the most lower-income populations have seen large ridership losses, contrary to the expectation that these routes would have disproportionate levels of captive ridership. While this study has not specifically explored which types of riders the STM has lost through its policy decisions, it is nonetheless a reminder that all riders in the face of service reductions and a different affordable mobility option, some may leave the transit system.

By modelling transit ridership at the route level, the relative impacts of service adjustments were explored. Variables for service quantity and quality, including the number of daily trips and weekend trips, and average route speed, are all found to have a statistically significant impact on ridership at the route level. More trips lead to more ridership, particularly if these trips have an acceptable travel time and speed. Reducing these variables at the route level will lead to riders gradually abandoning the service due to increases in waiting time. In fact, in comparison with other variables in the models, service frequency was the largest contributor to transit ridership. The relative spatial impact of service changes along parallel routes, which has rarely been explored in the literature, indicates that cutting service frequency for local routes has a statistically significant positive impact on ridership for routes running alongside. This means that some benefits in terms of ridership gains are not directly related to the previously discussed variables but rather related to reducing the service frequency of parallel routes.

In this study, over time accessibility measures to jobs were developed and incorporated in ridership models, which is not common in the literature. These accessibility measures were based on actual transit schedules and developed to examine the changes in the overall transit network design and land use system changes (in terms of jobs). Accessibility measures account for public transit network structure, so it allowed us to control for regional service structure changes, whilst accounting for changes in job locations overt ime. Our findings suggest that accessibility measure to jobs has a strong effect on improving ridership. In other words, either by improving the number of jobs that can be reached by public transit or by enhancing door-to-door travel time by public transit, cities will be able to attract more riders.

This research has built on several previous studies to generate a replicable method for analyzing ridership changes on a bus network. The use of a multilevel level random coefficient model allows the inclusion and comparison of multiple years of data while extracting usable coefficients for practitioners. Indeed, our study raises several conclusions that are not only related to the Montréal context. Other transit agencies and researchers can expect similar impacts of various operational and external factors. Nevertheless, by using the developed approach and methodology at the route level, they can analyze these impacts in different locations and contexts, improving their understanding of the local factors. By generating ridership determinants at the route level, the impacts of route design changes can be balanced with their impact on lower-income populations, thereby avoiding scenarios where service cuts are socially regressive in nature. The research also makes clear to all those involved and affected by bus routes – whether riders, planners, drivers, politicians, or otherwise – that cutting service decrease ridership, and that "efficiencies" in route design have consequences while offering the tools necessary to plan for ridership growth.

This study focused on understanding the changes within Montréal 's bus system. However, it also shows a substantial increase in metro-system ridership. In the future, it may, therefore, be useful to investigate the key drivers behind the metro system's ridership changes over time using data not available for this study, including metro ridership data at the stop and/or route level. Another limitation of this study is that it did not explore the relative impacts of transit service reliability, users' perceptions, and satisfaction issues on route level ridership as longitudinal data about these aspects were not available. Therefore, expanding this study to investigate these impacts over time in the future is recommended.

ACKNOWLEDGEMENTS

The author would like to thank the anonymous reviewres for their feedback on the earlier version of the manuscript. The authors would like to thank Social Sciences and Humanities Research Council (SSHRC) and the *Centre interuniversitaire de recherche sur les réseaux d'entreprise, la logistique et le transport* (CIRRELT) for their funding support. A big thank you to Jason Magder (Montréal Gazette) for securing the original ridership data by route from the *Societe de Transport de Montréal* (STM) through an Access to Information Act Request. The authors would like also to thank Rania Wasfi for helping in conceptualizing the required modelling approach.

AUTHOR CONTRIBUTION

The authors confirm contribution to the paper as follows: study conception and design: Chaloux, El-Geneidy, Diab; data collection: Chaloux, DeWeese; analysis and interpretation of results: Chaloux, DeWeese, El-Geneidy & Diab; draft manuscript preparation: Chaloux, DeWeese, El-Geneidy & Diab. All authors reviewed the results and approved the final version of the manuscript.

CONFLICT OF INTEREST STATEMENT

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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