Out of Service: Identifying Route-level Determinants of Bus Ridership over Time in Montréal, Quebec, Canada

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ABSTRACT

As many cities in North America, Montréal has been seeing shrinking bus ridership trends over the past few years. Nevertheless, most of the recent literature has focused on the broader causes for ridership decline at the metropolitan or city level, none have considered ridership at the route level. As service adjustments take place at the route level and are felt by riders at this level, our study explores the determinants of STM bus route ridership between 2012 and 2017 using two longitudinal multilevel mixed-effect regression models. Our findings suggest that increasing number of daily trips and increasing the average route speed are keys to bus ridership gains. In contrast, an increase in bus stop spacing decrease bus ridership, while controlling for the impact of a few important external variables related to built environment, residents' socioeconomics, and gas prices. Our models also 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 policy-makers who are striving to increase bus ridership, by exploring the factors affecting ridership at the route level, where most of the policies are implemented and where riders actually feel them.

Key words: Ridership, Route level, Bus service, longitudinal mode

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 (i.e., in terms of rail commuter service). Yet at least one study has found no preference between modes by riders when service variables are held constant (*1*), 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 this relation between bus ridership and service frequency change, as it has lost almost fourteen percent of its bus ridership between 2012 and 2017 and many of its routes saw decline in frequency while others saw incraeses. The STM usually reference "weak economy, the growing popularity of other transportation options, lower gas prices," among other reasons, that led ridership decline (*2*). This study aims at isolating the impacts of both internal and external factors on each route in the STM system through a longitudinal analysis of bus ridership. Whilst other studies have performed analyses of bus and public transport ridership at the regional or national level (*3-5*), few have done so at the route level, 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 local-level studies within a city scale to large-scale studies comparing several cities or regions. Local 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 (*6*). Cross sectional studies were conducted at the stop level to understand the determinnants of bus ridership including the impact of infrastructure and sociodemographic variables (*7*). Route level analysis is generally rare and done to measure a specific impact of a service change. Campbell and Brakewood *(8)* examined the impact of bicycle sharing at the bus route level in Manhattan. These studies are considered locally effective, though their findings cannot be generalized beyond their own context in a region. In contrast, city-level and multi-city studies have been conducted both at the route and system-wide levels (*9*). 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. A systematic literature review to identify and assess these studies can be found at Miller et al. (*10)*.

External Factors

Common external variables impacting ridership include population density, income levels, employment levels, and sociodemographic status (*5*). These external variables are often used to explain a decline in ridership, such as declining employment rates, low gas prices, and increased competition with ride-sharing services (*2; 11*). Indeed, these variables are outside transit agencies control, and, thereby, they cannot do much to influence them.

Larger populations and greater population density, and lower income rates tend to increase ridership (*3; 12*). Income is related to other variables like the unemployment rate. Together, these two variables reflect the overall economic outlook of a region, with a high-performing economy leading to a reduction in public transport use. Specific built form characteristics can also increase public transport ridership, including proximity to public transport stops, the presence of highways, and the use of a curvilinear and mixed pattern road network (*13*). Gas prices have been found to impact public transport ridership, with higher gas prices resulting in higher public transport use in the period following the price change (*3; 14*). Changes in gas price affect certain modes of public transport more than others, with light rail being the most affected by gas prices and buses the least (*15*).

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. Bicycle share trips have the potential to replace trips made by buses, but they can also act as a first/last mile and increase overall transport ridership (*3; 16*). A study in Montréal found that 30% of bicycle sharing trips were replacing a public transport trip (*17*), while Boisjoly et al. (*3*) found an insignificant yet positive relationship between the presence of RHs and overall public transport ridership. On the other hand, Graehler, Mucci and Erhardt *(18)* and Miller et al. (*10)* found that they lead to declines in bus ridership in the case of bicycle shares.

Internal Factors

Internal factors that impact bus ridership include pricing, quantity, and quality of service (*5*). Adjustments to these variables can directly impact riders' trip satisfaction and overall loyalty (*19; 20*). 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 (*21-23*).

Public transport fare is perhaps the most straightforward variable to understand, with lower fares tend to result in higher ridership, while increases in the amount of service provided increase ridership as well (*2; 14*). Fare elasticity has been varying in studies, but the direction is agreed on; increasing fares lead to decreasing ridership. Different variables have been used in the past to represent quantity of service, including vehicle revenue kilometers (VRK) of service, frequencies, and travel time (*3; 5; 20*).

Network coverage and reliability are also important considerations for overall ridership, with reliability in this case referring to metrics like on-time performance rather than a riders' perception of reliability. Increasing the quantity of service can take many forms, from straightforward additions to service, like adding trips or increasing route coverage (*24; 25*). Using these strategies to augment or optimize VRK and travel time can increase ridership for bus services, which are strongly affected by service levels (*3*). These variables are traditionally grouped at an aggregate level, presenting an opportunity for new findings at the route level.

CONTEXT

Montréal is Canada's second largest city, home to over four million people in its greater region in 2016 (*26*). 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, with a large bicycle network that is maintained throughout the year. Automobile usage remains high, at 69.7% in 2016, particularly in the outer regions of Montréal, with public transport use growing more slowly than private automotive use between 2011 and 2016 (*26*). This is despite two major car-oriented construction projects.

Several public transport authorities operate in the greater region, with suburban transport agencies running some buses towards downtown and EXO 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 Minutes 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).

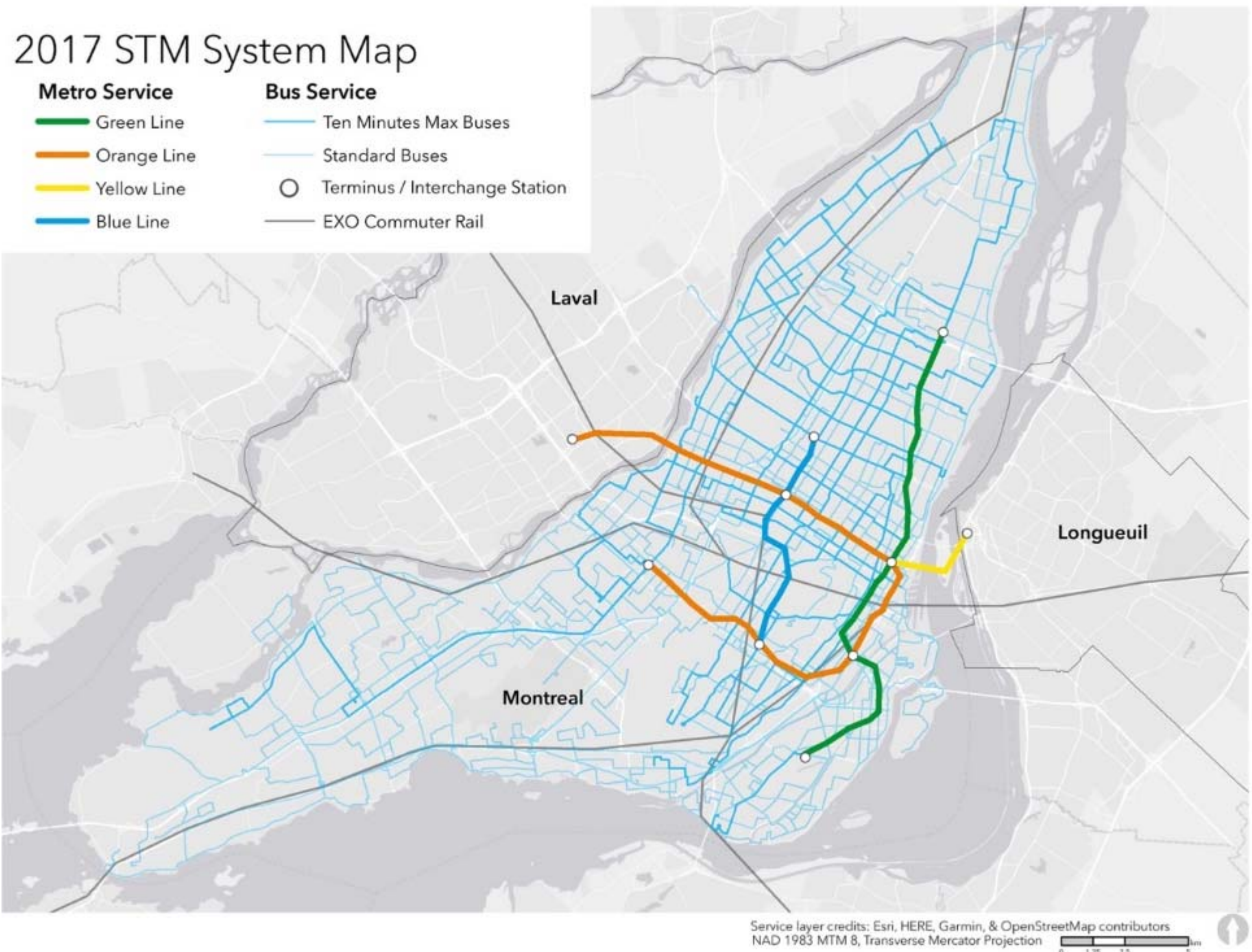

Figure 1: 2017 STM System Map

Bus ridership has traditionally made up a majority of overall ridership, although metro ridership has reached parity more recently due to its growth and declines in bus ridership (Table 1). The total number of bus trips per day declined between 2012 and 2015 before improving between 2016 and 2017. The bus fleet itself was stagnate between 2012 and 2015, before seeing new buses 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 through between 2012 and 2015 before it increased by new incoming buses in 2016.

Table 1: STM Service Statistics, 2012 to 2017

Year	Bus Ridership	Metro Ridership	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

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, while ridership gains are mostly found in the West Island. When focusing on the 10 Minutes Max network, ostensibly Montréal's highest priority bus routes on the Island, almost all routes see declines. In the meantime, fares, both cash and pass fares, have been increased several times since 2012, with the single-use cash fare being roughly comparable to other Canadian cities (at $3.25) and the monthly fare being relatively affordable (at $80).

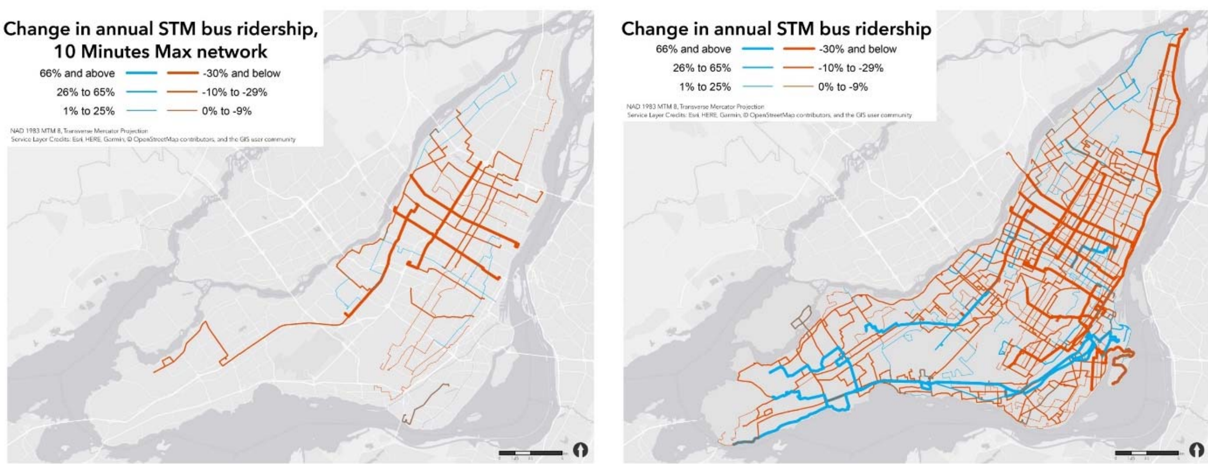

Figure 2: Change in annual STM bus ridership, 10 Minutes Max network & all routes

DATA

This research performs a longitudinal multilevel regression analysis in order to determine the causes for bus ridership decline in Montréal. Data sources for ridership, demographic, operational, and contextual data are acquired to represent internal and external service variables.

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 as they obtained it from an access to information act request. Certain routes were removed from the dataset before analysis:

- Routes not present for all six years (Route 428, 1 route)
- Night routes (300-series, 23 routes)
- Shuttle routes (250- & 260-series, Route 769, & Route 777, 12 routes)

This reduced the dataset from 219 to 183 routes. A separate case was generated for each year between 2012 and 2017, resulting in a sample of 1,098 observations.

Internal Variables: Operational Data

STM operating data were retrieved from archived General Transit Feed Specification (GTFS) datasets for all years that is 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 was 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, average speed was found by dividing route length by average travel time. Several dummy variables were also generated for each route. Express routes (400-series routes) were assigned as 10 Minutes Max routes. 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. 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. Local routes were identified in terms of having shorter spacing between stops and/or shorter routes. Additionally, a dummy variable for local routes that have experienced a cut in their number of trips along the study years was generated for the routes running alongside. Both variables will help in controlling for the local impacts of service overlapping and service changes. Lastly, fare pricing was retrieved from STM budgets, with both a single ride and standard monthly pass included (Société de Transport de *27; 28*-*32*). The percentage of the STM bus fleet removed from service for maintenance is sourced from the Montréal Gazette and displayed by year (*33*).

External Variables: Demographic and Socioeconomic Data

Demographic and socioeconomic data were retrieved at the census tract level from Statistics Canada for both 2011 and 2016, including 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. (*3*). Shapefiles for each census tract in 2011 and 2016 were retrieved from Statistics Canada, then intersected with a 400-meter buffer generated around each route. Proceeding by route, each intersected area were weighted to give a geographic weight for each census tract served by the line. Finally, each demographic variable is weighted accordingly before being summed by the route number. Overall, 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 (%).

External Variables: Contextual Data

Several contextual variables were generated for inclusion in the models, including the average price of gas for the Montréal region retrieved from Statistics Canada (*34*). RHs are included as dummy variables, with Uber selected as the dominant ride sharing 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 RHs (*3; 18*). 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.

With all data prepared for analysis and grouped by route and year, the average for each variable by year is presented in Table 2. The largest changes, aside from ridership, are in daily weekday trips, median household income, gas prices, and fares, with most others relatively stable. Travel time has increased by just over a minute on average, whether on peak or over the course of the entire weekday. This likely reflects increasing congestion and construction along bus routes and the efforts of network planners to accommodate them. Headways are similarly steady, with a change of roughly a minute on peak and half a minute for the weekday between 2012 and 2017. Key route design and built environment factors, like route length, stop counts, stop spacing, population density, number of employment positions, are also relatively similar across all years with minor differences.

Table 2: 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
Average weekday travel time (min)	34.35	34.55	34.74	35.23	35.46	35.92
Weekday headway (min)	26.29	26.07	26.63	26.95	26.77	26.69
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 stop spacing (m)	406.99	400.45	383.65	426.27	425.06	413.69
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 ($)	3	3	3	3.25	3.25	3.25
Monthly fare ($)	75.5	77	79.5	82	82	83
Buses removed for maintenance (%)	16.3	18	20.5	21.6	19.3	21.1
Parallel routes	16.02	16.02	16.02	16.02	16.02	15.93
Parallel routes with a cut in trips	-	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 ($)	48,849	50,631	52,412	54,194	55,716	57,757
Population	47,273	47,601	47,928	48,256	48,583	48,911
Recent immigrant population	3,963	3,890	3,817	3,745	3,672	3,600
Households paying 30% or more of income towards housing	7,582	7,487	7,393	7,299	7,205	7,111
Population density (per km2)	7,805	7,872	7,939	8,005	8,103	8,170
Unemployment rate (%)	9.72	9.59	9.45	9.31	9.13	9.04
Average gas price ($)	1.37	1.37	1.37	1.16	1.08	1.19

METHODOLOGY

A preliminary analysis was undertaken by exploring and comparing the general trends of ridership and route design factors. Then, routes were grouped by percentile to explore the differences between the top and bottom percentiles in terms of ridership and service related factors. Having observed these relationships, a first multilevel longitudinal mixed-effects regression model was developed to explore the determinants of route ridership over time using data from 2012 to 2017. This model both includes and compares data across multiple years, allowing for the extraction of coefficients that represent changes within and across time periods. To prepare the data, each case was grouped by route, in order to capture the differences between each route, in a similar approach to that taken in recent metropolitan-level analyses of ridership (*3; 18*). The model dependent variable is the natural logarithm for annual ridership of each route, with the resulting coefficients thus describing the percentage change in ridership to be expected with each additional unit of the independent variable. Several variables were squared to account for potential nonlinear relationships. Afterwards, a second model was generated using the same dataset, while including records only 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.

Several dummy variables explaining differences between routes were tested and removed as they did not show statistical significance in the models, including that of express routes, routes that connect to EXO, parallel routes, and routes that do not connect to the Metro. Other variables were removed for correlation, including route length, headway, and variables related to peak period. Monthly fare and cash fare were found to be correlated, alongside their squared terms, with monthly fare explaining more variation than cash fare and thus maintained. External variables maintained in the model include median income, population density, households paying 30% or more, and the price of gas. Other demographic were highly correlated (with above than 0.7 Pearson's Correlation Coefficient). Employment location did not show statistical significance and was removed from the final model. The reported models achieve the lowest possible AIC and BIC scores while maintaining the maximum number of significant variables.

RESULTS

Figures 3 and 4 demonstrate the change in ridership and change in daily bus trips and fare between 2012 and 2017. As seen in the figures, as daily bus trips decrease and fares increase, ridership decreases, 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 Montreal *(35; 36)*.

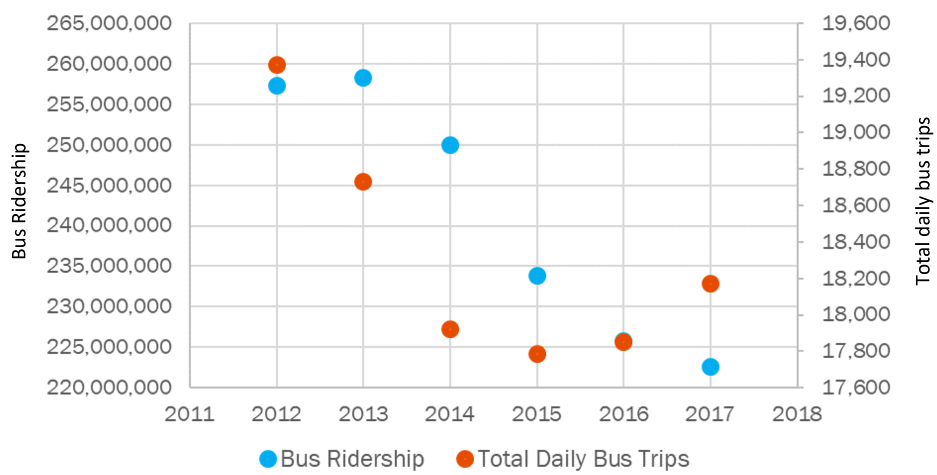

Figure 3: STM Bus Ridership & Daily Bus Trips, 2012-2017

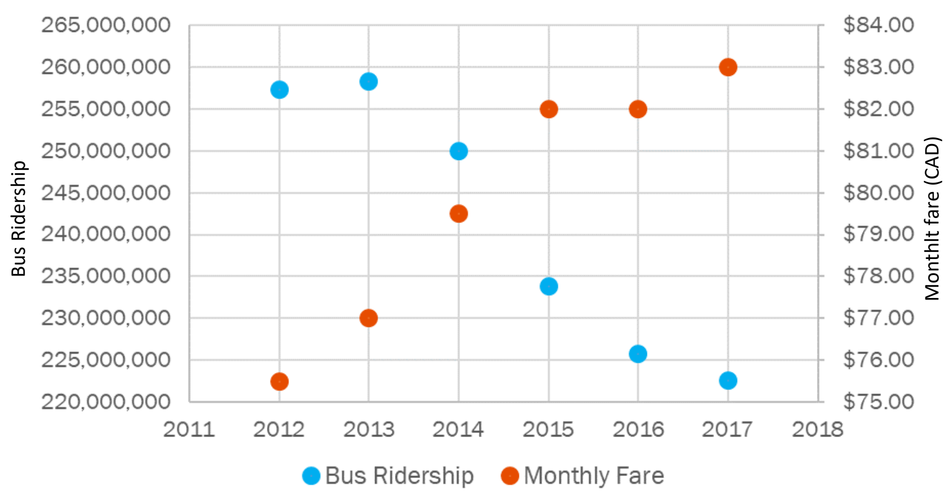

Figure 4: STM Bus Ridership & Monthly Fare Prices, 2012 to 2017

As seen in Table 3, routes that saw the largest declines in ridership and the greatest cuts to service have the lowest 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 service adjustments (Table 4), routes that saw trips added to them generally have higher median incomes than routes that saw trips taken away. In fact, the group with the lowest household median income (i.e., *Bottom 10%*), saw one of the largest declines in terms of average number of daily trips. 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%*

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 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.

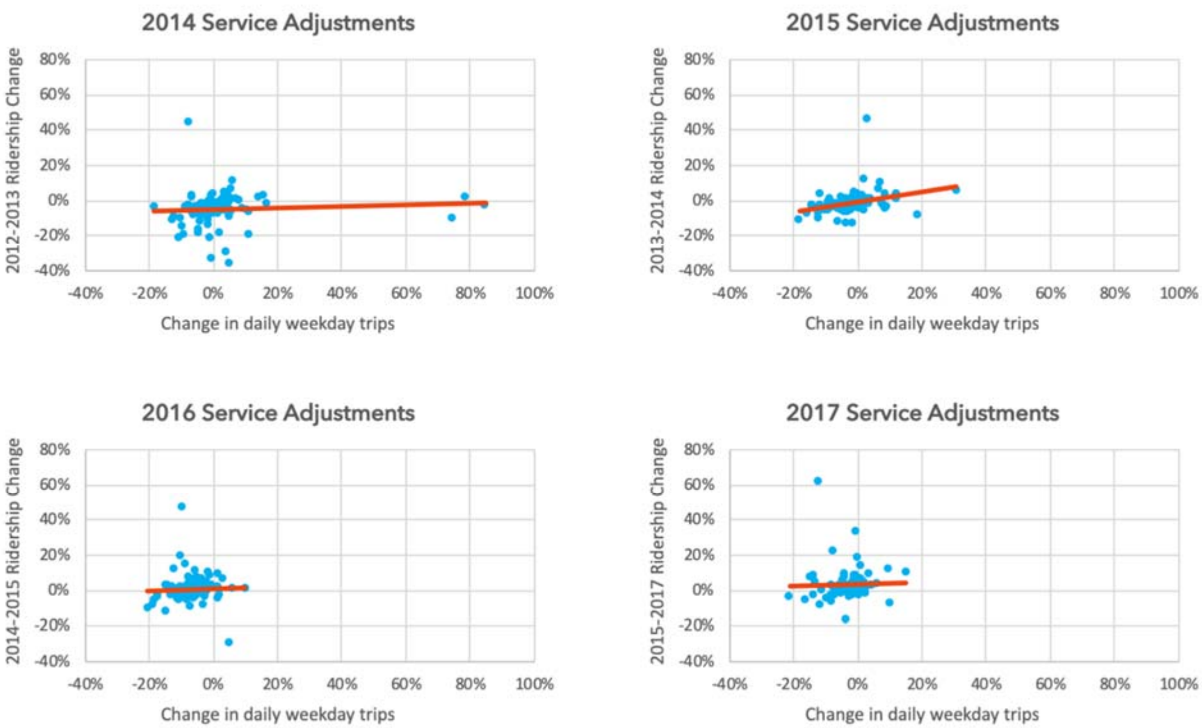

Figure 5: Change in annual STM bus ridership, 10 Minutes Max network & all routes

Table 5 shows the results of two longitudinal multilevel mixed-effects regression models were developed using the natural logarithm of annual route ridership as the dependent variable. The first model (Table 5.A) includes all data from 2012 to 2017, with a total of 1,074 records, while the second model (Table 5.B) includes data from 2013 to 2017, with a total of 898 recrods. 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 one will increase annual ridership by 1.4%, all other variables held to their means. Nevertheless, the number of daily weekday trips square term (which is used to account for non-linear relationship) has a statistically significant negative effect on ridership, indicating that after a certain frequency, no increase in ridership can be expected. In other words, every additional trip will result in a 0.1% loss to annual ridership. Similarly, travel time is found to have diminishing returns with an inflection point. For every one minute added to a route travel time a 2.8% gain in annual ridership is expected. However, every additional minute travel time will result in a 0.1% loss to annual ridership. This generally reflects that longer routes, with longer travel times, are normally able to capture higher ridership levels to a certain extent.

Service speed has also statistically significant positive impact on ridership. Every 1 km/h of additional route speed results in a 1.00% increase in annual ridership. Faster service is expected to attract more riders at the route level. When considering stop spacing and stop counts, more stops and shorter spacings equal more riders. In theory, every additional stop adds 0.9% to annual ridership, although this would be affected by stop location. Similarly, for every additional 100 meters in stop spacing added, annual ridership will decline by 1.3%. Numerous closely-spaced stops can increase ridership, although this impacts speed and travel time in practice.

Table 5: Longitudinal multilevel regression model: Annual bus ridership (ln)

	A. All Data model			B. 2013 -2017 data model		
Variable name	**Coef.**	**z**	**P>z**	**Coef.**	**z**	**P>z**
Route factors						
Daily weekday trips	0.014	17.220	0.000	0.014	17.750	0.000
Daily weekday trips^2	-0.001	-11.190	0.000	-0.001	-11.500	0.000
Average weekday travel time (min)	0.028	5.230	0.000	0.018	3.490	0.000
Average weekday travel time^2	-0.001	-4.840	0.000	-0.001	-2.370	0.018
Route average speed (km/h)	0.010	5.230	0.000	0.007	3.600	0.000
Route stops	0.009	3.760	0.000	0.006	2.890	0.004
Route spacing (100m)	-0.013	-4.280	0.000	-0.008	-2.910	0.004
Route is 10 Minutes or Less (dummy)	0.818	6.300	0.000	0.798	6.040	0.000
Route overlaps with BIXI (dummy)	-0.213	-1.800	0.072	-0.250	-2.080	0.038
Monthly fare	0.616	5.830	0.000	0.489	3.730	0.000
Monthly fare^2	-0.004	-5.700	0.000	-0.003	-3.710	0.000
Parallel routes with a cut in trips (dummy)				0.044	2.610	0.009
External factors						
Median household income ($1,000)	-0.006	-2.930	0.003	-0.004	-1.880	0.059
Population density (1000/km^2)	0.029	2.350	0.019	0.028	2.210	0.027
Households paying 30% or more (1000)	0.049	4.410	0.000	0.055	4.860	0.000
Average gas price ($0.10)	0.018	3.500	0.000	0.016	3.940	0.000
Constant	-13.996	-3.380	0.001	-8.622	-1.650	0.099
Log-likelihood	536.84			553.06		
AIC	-1037.69			-1070.12		
BIC	-948.07			-983.71		
ICC	0.97			0.98		
Observations	1,074			898		
Number of groups	180			180		

Two dummy variables were found to be statistically significant, including whether a bus is designated a 10 Minutes Max route and if it is in competition with the BIXI service area. The 10 Minutes Max designation, and accompanying service levels, results in an 82.0% increase in annual ridership. This may also capture riders' preference for routes that are branded as frequent and reliable. Competition with BIXI, on the other hand, significantly reduces annual ridership. For routes competing in the BIXI service area, however, a ridership loss of 21.3% can be expected, all other variables held constant. This loss is larger than it may appear, as BIXI only operates 8 months of the year; in other words, it is likely that the annual ridership loss of 21.3% is concentrated in the summer months. Every dollar added to the monthly fare beyond the mean increases ridership by 61.5%, but every additional dollar decreases this by 0.40%. Thereby, setting the fare beyond $79.09 results in a decreas to the ridership.

Turning to external variables, four variables were found to have statistical significance. Household median incomes along a route decreases annual ridership by 0.6% for every additional $1,000 gained. As expected, population density strongly increases ridership, generating a 2.9% increase in annual ridership for every additional 1,000 residents per square kilometer, all else held even. The number of households paying 30% of their income to housing costs variable increases ridership by 4.9% for every additional 1,000 households. Lastly, increases to gas prices can lead to growing annual ridership, with a 1.8% increase in annual ridership for every additional 10 cents added to the price per litre.

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 trips" that explores the immediate spatial impacts of service changes. The model indicates that cutting service frequency for local routes has a statistically significant positive impact on ridership for routes running alongside, increasing their ridership by 4.4% on average. 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 show a very similar impact for all investigated service-related variables as well as external variables.

DISCUSSION & CONCLUSION

Over the course of the study period, the STM saw an overall decline of 13.96% in its annual bus ridership. This decline was led by external variables like median incomes, and gas prices and further complicated by internal service adjustments involving fare prices and levels of service. However, service adjustments in the form of daily trips did not affect all routes equally. The STM directed its resources to improve service quality in terms of the number of daily trips along routes serving higher-income neighbourhoods, while decreasing the service quality at lower-income and more socially-vulnerable areas. Indeed, the Montréal data demonstrates 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, a bicycle share rather than a car share, some may leave the transit system.

Our findings suggest that the presence of BIXI has a strong effect on reducing ridership is a notable contribution to the literature concerning the integration of bicycle share programs with public transport. Previous results have been mixed, varying between a slight positive or negative relationship (*10*). In our study, we found that bicycle share system is competing with and gaining riders from the public bus network.

Our study has raised several conclusions that apply not only to the STM. Variables for service quantity and quality, including the number of daily trips and average route speed, are all found to have statistically significant impact on ridership at the route level. More trips lead to more ridership, particularly if these trips have an acceptable travel time. Reducing these variables at the route level will lead to riders gradually abandoning the service due to increases in waiting time. Affordability also matters for public transport and buses, particularly as riders tend to be of a lower-income background. 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.

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 mixed-effects multilevel model allows the inclusion and comparison of multiple years of data while extracting usable coefficients for practitioners. While the model corresponds strongly to the STM and Montréal context, the overall research methodology is reproducible in other areas and with other agencies. 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.

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AUTHOR CONTRIBUTION

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

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