OUT OF SERVICE:

Identifying route-level determinants of bus ridership over time in Montreal, Quebec

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1. POLICY BRIEF

The Issue

Between 2012 and 2017, the bus network of the STM lost almost 14% of its riders. The loss in ridership was experienced unequally – some routes performed well, largely in the suburban areas of the West Island, while others did not. Routes with the largest losses in ridership are found in the centre and northeast of Montreal, in areas with the highest levels of social vulnerability.

Methods & Data

This study draws on GTFS data for the STM from 2012 to 2017, Statistics Canada data from the 2011 and 2016 Census, and contextual data for the Montreal region, in order to generate a multilevel longitudinal regression model for bus ridership over time. It does so at the route level to highlight the effects of service changes and recommend localized improvements.

Findings

Our model finds several significant variables that affect annual bus route ridership. Every additional daily trip adds 0.47% to annual ridership, while every minute of increased headway reduces annual ridership by 1%. Increasing a route's average speed, number of stops, surrounding population density, and regional gas prices, as well as designating a route as 10 Minutes Max status, all lead to increased ridership. Meanwhile, increasing a route's stop spacing and travel time reduce annual ridership. For every $1,000 increase in household median incomes along a route, ridership decreases by 0.32%. Fare prices have a non-linear relationsip, with peak ridership gains from an STM monthly pass being achieved at $79.09 and every dollar added above this level resulting in reduced annual ridership. Lastly, competing with BIXI, the Montreal bicycle share system, leads to the largest drop in ridership at the route level at a level of 30.12%.

These findings demonstrate that changes in STM bus ridership at the route level are largely due to service adjustments made by the agency itself. Routes that saw reductions to their frequency experienced large ridership losses, while those that saw their frequencies increased saw ridership gains.

When comparing demographic data at the route level, it becomes clear that routes identified for service improvements between 2012 and 2017 were those serving areas with higher median incomes and less socially-vlnerable groups compared to those identified for service reductions. Routes that saw service reductions served far more riders than those given service improvements. Considering the stagnant size of its bus fleet during this time period, the service adjustments made by the STM mostly removed buses from busy routes serving socially-vulnerable, lower-income populations and placed them on routes for higher-income populations.

Recommendations

Immediate service changes to the STM bus network should undo the damage done in the past by increasing frequencies on high-volume routes for socially vulnerable areas. Future service changes should be informed by individual route characteristics, both by maximising ridership gains relative to service increases and minimising ridership losses from frequency reductions by modifying other route characteristics like speed, stop spacing, and travel time. Lastly, stopping ridership loss to BIXI will require rethinking route characteristics within the bicycle share's service area, such as stop spacing and overall travel time.

Regional policies should also be considered in order to increase bus ridership. For example, promoting higher densities along bus routes can lead to built-in ridership for the service. Maintaining and expanding high-frequency routes, like the 10 Minutes Max network, can have major returns in ridership increases.

Figure 2. Passengers boarding bus 165 Cote-des-Neiges, Summer 2016.

2. INTRODUCTION

Buses are the oft-maligned workhorse of a public transport network, particularly in North America. Riding the bus in North American cities is often associated with lower-income populations in an auto-centric system whenre it is perceived as an inferior good (Levinson, 2017). While other regions have embraced the flexibility of buses to provide high quality, high-frequency services both in the core and periphery regions of the city, many North American cities struggle to give priority to bus operations and instead focus on new and expensive rail-based services. The prioritization of rail over bus networks may appear to be logical in light of decreasing bus ridership on many systems. Montreal's local public transport authority, the Societe de Transport de Montreal (STM), has seen large declines in bus ridership over the last half of the decade even while its Metro system has experienced ridership growth. Rail-based transport is the focus of new spending programs and infrastructure, such as in the STM's two current Metro proposals and the new CAQ Tram de l'Est proposal. Yet at least one study has found no preference between modes by riders when service variables are held constant (Ben-Akiva & Morikawa, 2002), suggesting that the transferring of resources away from buses may be what is causing the loss of riders. This raises the question: are bus riders abandoning the services due to an inherent undesirability, or are they doing so in response to the lack of service improvements offered by their local transport agency? In other words, and specific to the context of the STM, what factors are leading the decline in bus ridership?

The Montreal system provides an excellent opportunity for answering this question, as it has lost almost fifteen percent of its bus ridership between 2012 and 2017. While the Agency points to contextual data beyond its control for the decline – like the "national trend… a weak economy, the growing popularity of other transportation options, lower gas prices, and a harsh winter" (Curry, 2016) - it has also made various service adjustments over the same time period and these are not mentioned. As a result, it is possible to isolate the impacts of both internal and external factors on each route in 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), none to date has done so at the bus route level. As service adjustments are applied at the route level and riders perceive these changes at the route level, this study aims to fill the route-based gap and explore the determiants for bus ridership at this scale.

This research will undertake an analysis of bus ridership at the route level through a longitudinal multilevel regression analysis approach. Previous research on factors affecting bus ridership will be discussed in the literature review, followed by a brief introduction to the Montreal context and the role of the STM in providing public transport. In the following section, the specifics of the multilevel longitudinal mixed-effect model will be discussed, as well as the sourcing and preparation of agency data from GTFS feeds, Census data from Statistics Canada, and contextual data from various other sources. Preliminary results are discussed, including the general spatial trends of ridership decline in Montreal, summary statistics between years, and the general orientation of ridership and operational change patterns, before the ridership model is presented. A comparison of the top- and bottom-performing routes is conducted in order to highlight the impact of operational changes on bus routes and the importance of considering equity in bus service delivery. Following a conclusion on the findings and their potential use, avenues for future research are discussed alongside potential limitations in the study method.

This research is important not only to the STM, its city, and its riders, but also to the broader professional sphere of transport planners and researchers seeking a better understanding of ridership determinants at the route level. In making the principal determinants of bus ridership more clear, operational decisions for bus service can be made with a better understanding of their impacts on ridership.

3. LITERATURE REVIEW

There is an extensive literature surrounding public transport ridership. Studies in different regions have tested many variables, both internal and external to public transport agencies themselves, in search of a model that can be used to inform panning and service provision. This research is grounded in these previous attempts and uses aggregated data in a causal analysis to find which internal and external factors impact bus ridership in Montreal, Quebec. This approach allows for the use of a "wider array of data than those found in descriptive studies [with] more opportunity for the conceptual development of models" (Taylor & Fink, 2003) and accepts that the findings are highly contextual to Montreal.

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 stop although occasionally the route level, usually to measure the impact of localized changes to the network. For example, Campbell and Brakewood examined the impact of bicycle sharing at the bus route level in Manhattan (2017), while 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). Other studies have focused on general determinants of public transport ridership, including the impact of infrastructure and sociodemographic variables at the stop level (Chakour & Eluru, 2016) and the effect built environment characteristics have at the subway station level in Seoul (Jun, Choi, Jeong, Kwon, & Kim, 2015). These studies are considered locally-effective, though their findings cannot be generalized beyond their own context.

City-level and multi-city studies have been conducted both at the route level and at the system-wide level and at their largest scale can be applied broadly. 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 (Miller, Shalaby, Diab, & Kasraian, 2018).

The following two sections will largely focus on the results from city-level and multi-city studies, proceeding by external variables then internal varaibles.

External Factors

Common external variables related to public transport ridership concern demographic (socio-economic) data, spatial characteristics, and the structure of public financing (Taylor & Fink, 2003). These are commonly aggregated at the metropolitan scale when considering the overall ridership of multiple public transport agencies. External variables are often the first identified by public transport agencies in explaining a decline in ridership, such as declining unemployment, a weak economy, low gas prices, fare evasion, the weather, and increased competition with ride-sharing services (Bliss, 2018; Curry, 2016). They are convenient variables for agencies to blame for ridership declines, as there is often little a public transport agency can do directly to influence them. Nonetheless, their inclusion is necessary so as to contextualize agency decisions as well as encourage action by other levels of government that may bear the responsibility and financial capacity to affect change.

External demographic variables include population and population density, income levels, employment data, and sociodemographic status. Larger populations tend to increase ridership (Boisjoly et al., 2018), although this may be a reflection of the greater ability of these areas to provide public transport service due to economies of scale. Indeed, when taking into consideration the geographic size of a region – which has been found to decrease public transport use – higher population densities support more comprehensive systems and increased overall ridership (Guerra & Cervero, 2011; Legrain, Buliung, & El-Geneidy, 2015; Taylor, Miller, Iseki, & Fink, 2009). 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 (Pasha, Rifaat, Tay, & De Barros, 2016).

Perhaps the most significant external variable concerns the ease of automotive use, whether measured by the plentitude of parking or the uptake in automobile ownership. Increased parking availability, low parking fees, and lax restriction lead to higher car use in a region and reduced public transport ridership (Taylor & Fink, 2003; Taylor et al., 2009; Thompson, Brown, & Bhattacharya, 2012), while reducing parking availability can reduce the overall number of trips in a region and increase those taken by a non-automobile mode (Cervero & Kockelman, 1997). Automotive use both influences and is influenced by parking policy: for example, Manville et al. (2018) suggest that an uptake in automotive use in Southern California may be the result of increased ability to purchase cars, leading to reduced public transport use. Of course, parking and automotive use is logically influenced by another set of external variables, being regional gas price. 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 (Boisjoly et al., 2018; Chen, Varley, & Chen, 2010). 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 (Currie & Phung, 2007). The reduced impact of gas prices on bus systems likely a result of their lower-income ridership, who are less likely to own a car, as well as their use by riders for non-commuting trips (Currie & Phung, 2008). It should also be noted that increasing gas prices through the increased taxation may present an important financial asset for public transport agencies, although their financial viability may decrease as fuel economy improves and modal shift towards public transport is achieved (Boisjoly et al., 2018).

Figure 3. New dedicated bus lanes, Fall 2017

A final spatial variable generally external to the public transport agency are transportation network companies (TNCs), such as Uber and BIXI. These services are a relatively new phenenon in the literature, with no clear consensus as of yet emerging 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 (Boisjoly et al., 2018; DeMaio, 2009). A study in Montreal found that a 30% of bicycle sharing trips were replacing a public transport trip (Bachand-Marleau, Larsen, & El-Geneidy, 2011), while Boisjoly et al. (2018) found an insignificant yet positive relationship between the presence of TNCs and overall public transport ridership. On the other hand, Graehler, Mucci, & Erdhardt (2019) found that they lead to declines in bus ridership in the case of bicycle shares and losses to overall ridership in the case of car shares. As these recent examples have relied on binary variables or trend variables due to a lack of data availability, more research and data is needed in this area.

Figure 4. STM Henri Bourassa terminus, date unknown

Turning to external demographic variables, increased income has been repeatedly found to decrease public transport demand and ridership, largely due to the belief that public transport – and especially bus service - acts as an inferior good (Levinson, 2017). Low-income populations are more likely to use public transport and particularly bus services (Foth & El-Geneidy, 2014; Krizek & El-Geneidy, 2007; Legrain et al., 2015; Taylor et al., 2009). While the bus might be perceived as the lowest of the public transport options, it can compete equally amongst all incomes when the service quality matches those of a rail-based mode (Ben-Akiva & Morikawa, 2002). A public transport agency does not, therefore, have to provide different kinds of service according to their population's income.

Income is related to other variables like the unemployment rate, which itself has been found to be positively impact public transport ridership (Balcombe et al., 2004; Boisjoly et al., 2018; Holmgren, 2007; Pasha et al., 2016; Thompson et al., 2012). 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. Interestingly, many public transport agencies claim that a combination of a weak economy and low unemployment rate are reducing their ridership numbers, despite the fact that low unemployment and a weak economy rarely go hand-in-hand (Bliss, 2018; Curry, 2016).

Internal Factors

Internal factors that impact public transport ridership include the pricing, quantity, and quality of service (Taylor & Fink, 2003). Adjustments to these variables can directly impact riders' trip satisfaction and overall loyalty, leading to increased ridership among existing riders and the attraction of new riders (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). As a result, changes to internal factors that affect the quality or quantity of public transport service should be understood as affecting rider satisfaction and loyalty and thereby influencing overall ridership frequency and future use.

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 (Chen et al., 2010; Curry, 2016). Fare decisions can disproportionately affect lower-income riders, who use public transport the most and buy the most fares (Verbich & El-Geneidy, 2017). Getting the fares right for all income groups is important, as it is a major determinant of overall rider satisfaction, loyalty, and overall ridership (Thompson et al., 2012; van Lierop et al., 2018). Fare elasticity has been varing 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 (Boisjoly et al., 2018; Taylor & Fink, 2003; van Lierop et al., 2018). 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, increasing route coverage, or reducing headways - through to technical interventions - like mode prioritisation, bus positioning communication, and bus bunching reduction (Balcombe et al., 2004; Boisjoly et al., 2018; Currie & Wallis, 2008; El-Geneidy, Hourdos, & Horning, 2009; St-Louis et al., 2014; Verbich, Diab, & El-Geneidy, 2016). Using these strategies to augment or optimise VRK and travel time can increase ridership for bus services, which are strongly affected by service levels (Boisjoly et al., 2018).

Having reviewed the literature on public transport ridership and its determinants, both external and internal, there is a clear opportunity for new data generated at the route level. Testing for the relationship between route ridership and existing determinants like frequency, fares, and travel time at this new scale will be one goal of this research. The time period selected identifies the lowest point of ridership decline for the STM and thus fully captures the trends for each determinant. While the selection of Montreal may limit the study conclusions, the methodology used may be adapted by researchers elsewhere for the generation of a local route-level model.

Figure 5: STM bus out of service, date unknown

4. CONTEXT

Montreal is Canada's second largest city, home to over four million people in its greater region as of the 2016 Canadian Census. The city itself consists of roughly two million people on the Island of Montreal. Recognized as one of the most cyclable cities in North America, 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 Montreal, with public transport use growing more slowly than private automotive use between 2011 and 2016 (Statistics Canada, 2016). This is despite two major car-oriented infrastructure projects (the Turcot restructuring and Champlain Bridge replacement) causing road closures for drivers headed downtown.

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 Montreal is provided by the Societe de Transport de Montreal (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. The Montreal public transport network is seen below in Figure 6.

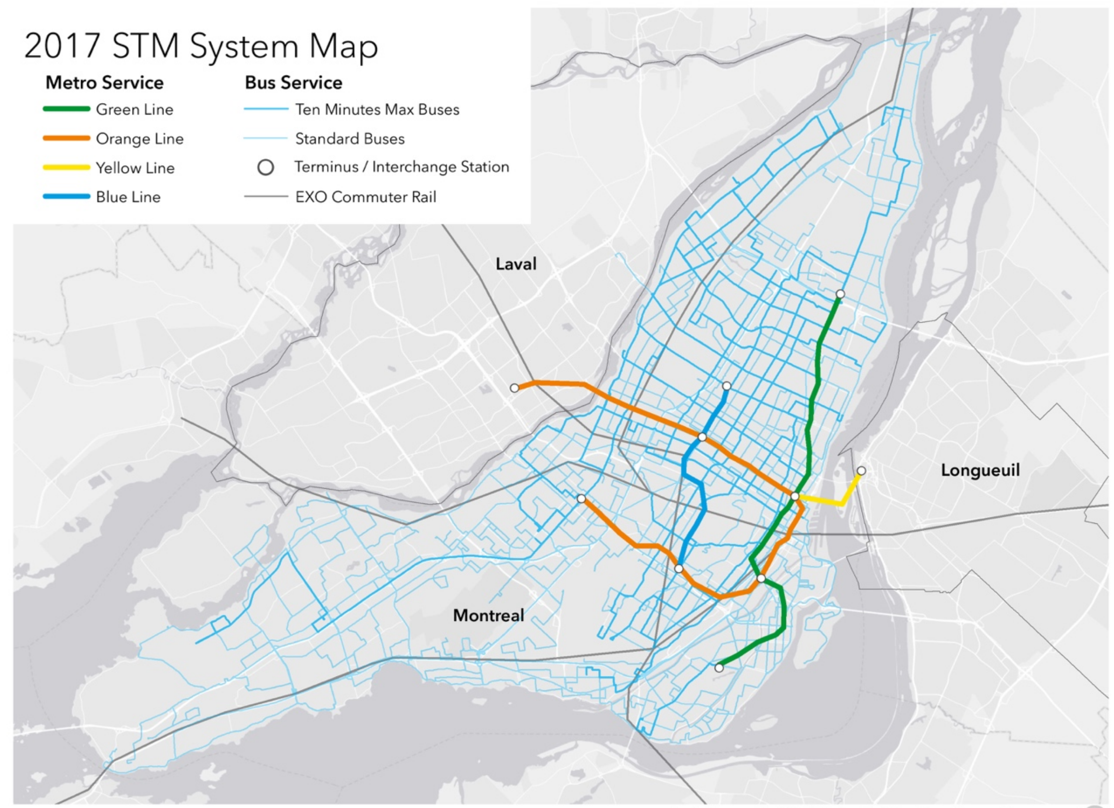


Figure 6: 2017 STM System Map

Service layer credits: Esri, HERE, Garmin, & OpenStreetMap contributors
NAD 1983 MTM 8, Transverse Mercator Projection

One major construction and congestion factor should be discussed as a factor in the operational decisions and ridership of STM bus rotues. The Turcot Interchange, visible in Figure 7, has disrupted travel from the West Island and that area's bus service. In response, the STM improved and expanded existing express routes to facilitate a faster commute for West Island residents. These routes have been assigned significant operational resources despite low overall ridership numbers. This service decision stands out in the context of limited bus service adjustments taken by the STM elsewhere. The number of daily bus trips, overall ridership figures, and available bus fleet for the STM can be seen in Table 1. Observing Table 1, it is clear that 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. The total number of bus trips per day – across all routes – declined through to 2015, before improving somewhat in 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

Figure 7, Turcot Interchange, Summer 2018 each year, the bus fleet shrank through to 2015 before being bolstered by the incoming new buses.

The decline in bus ridership between 2012 and 2017 is large, and it varies across the city. Not all routes lost ridership, as can be seen in Figure 8. The largest ridership losses can be found 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, visible in Figure 9 and ostensibly Montreal's highest priority bus routes on the Island, almost all routes see declines. That the STM's highest priority bus services have seen large declines in ridership over this time period is a cause for concern; in theory, these routes form the backbone of the network and should perform well in terms of ridership when compared to their counterparts.

Table 1 : STM Service Statistics, 2012 to 2017

Year	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	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

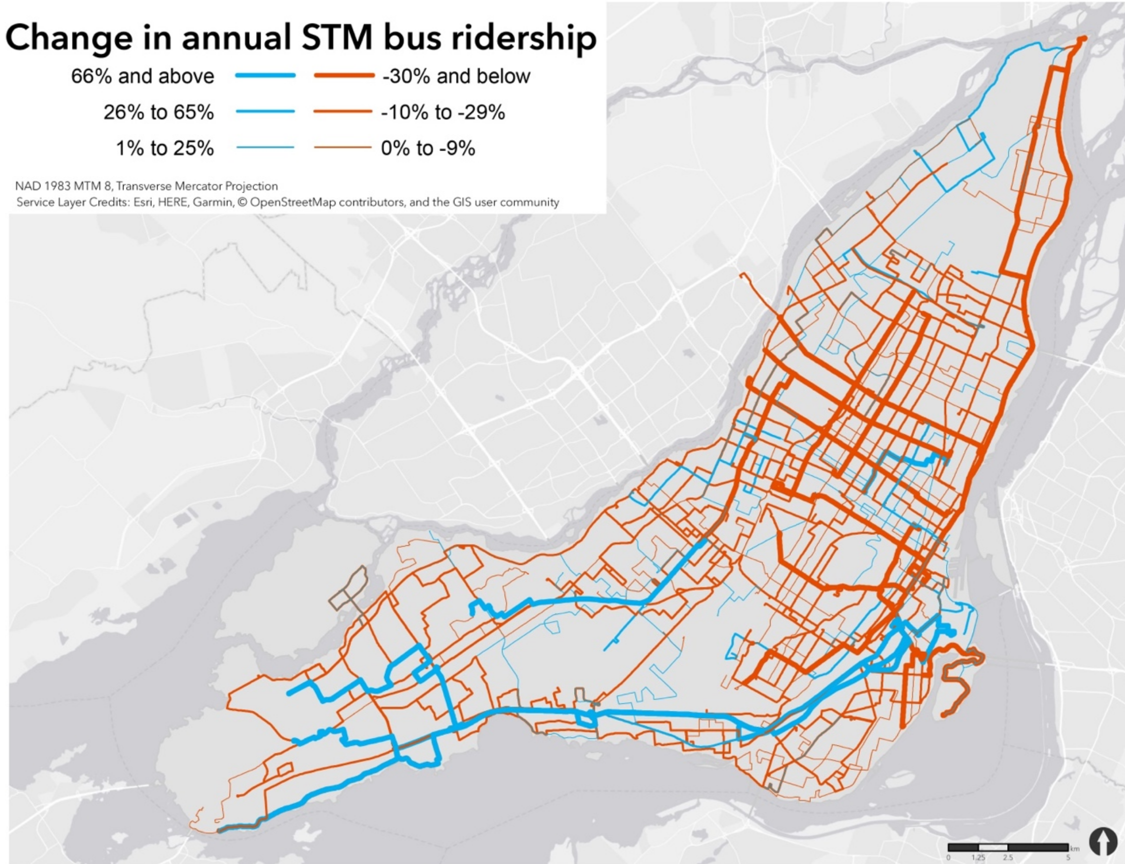


Figure 8 : Total change in STM bus ridership, all routes 2012-2017

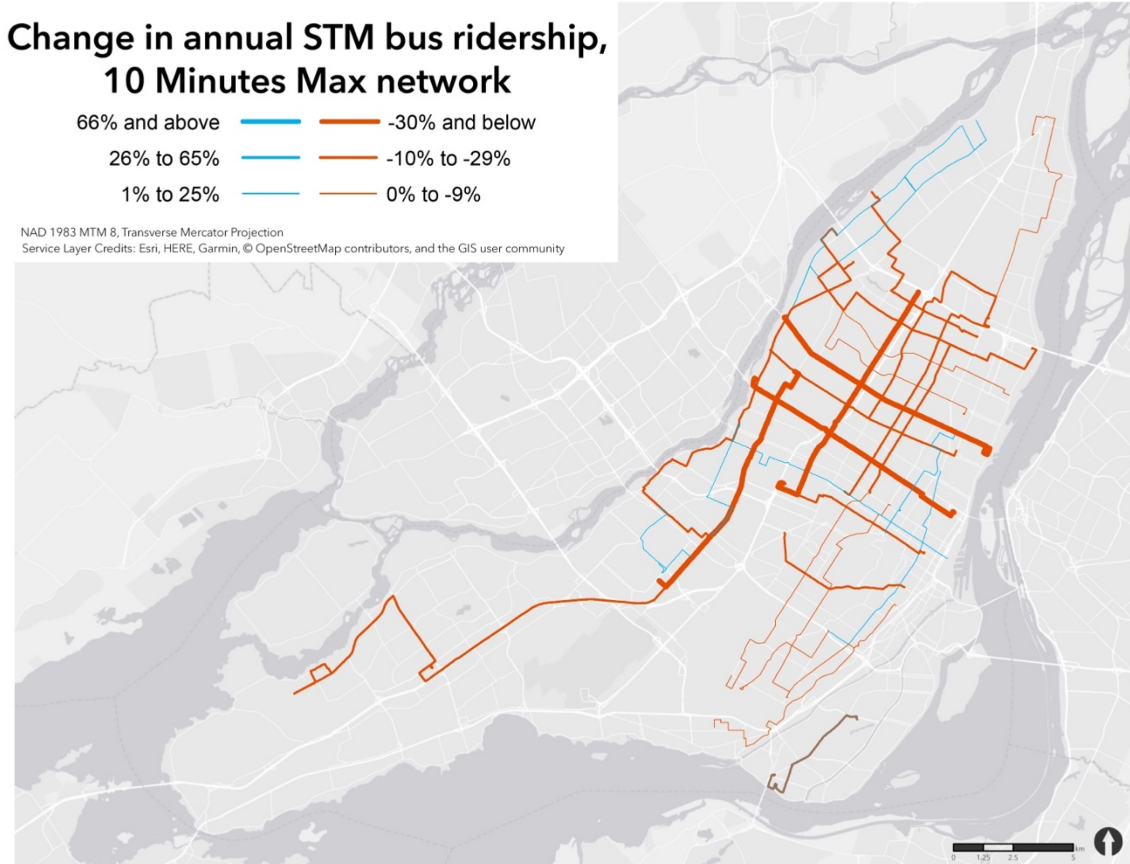


Figure 9 : Total change in STM bus ridership, 10 Minutes Max routes 2012-2017

In the meantime, the STM has focused on improvements to the quality of its service. New buses that provide air conditioning and cell phone charges for the first time have been rolled out more recently, with many more new buses on order. GPS positioning of buses was made available to the public in 2017, in order to improve customer experience, while fairly few infrastructural changes have occurred. A BRT project in the east of the city, the Pie-IX BRT, remains incomplete with only partial realization, while some dedicated lanes and advance signals for buses added at rush hour on some routes. 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).

5. DATA

This research performs a longitudinal multilevel regression analysis in order to determine the causes for bus ridership decline in Montreal. Data sources for ridership, demographic, operational, and contextual data are acquired to represent internal and external service variables. These internal and external variables are found at varying scales and must be prepared for analysis at the route level using the steps below; the statistical methods used to analyze them are then presented.

Ridership data

STM ridership data was provided by the Montreal Gazette in the form of annual ridership for each bus route between 2012 and 2017. Certain routes are removed from the dataset before analysis, including:

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

This reduces the dataset from 219 to 183 routes, with only these remaining routes extracted from GTFS feeds in the next step. A separate case is generated for each year a route operates, resulting in 1,098 total cases. All operational, demographic, and contextual variables are grouped according to these cases. Routes are separately aggregated by ridership performance using a similar approach as Grisé & El-Geneidy (2017) in order to allow a comparison between the top- and bottom-performing routes.

Internal variables: Operational data

STM operating data is retrieved from archived GTFS datasets for all years. Feeds servicing November 1st for each year are selected, with a weekday service schedule used for analysis across all years. Both ArcGIS and R are used to extract several operational variables from each feed after cleaning column names. The retrieved variables by route for each year include:

- daily weekday trips
- average weekday travel time (in minutes)
- average weekday headway (in minutes)
- average weekday peak travel time (in minutes)
- average weekday peak headway (in minutes)
- weekday headway standard deviation (in minutes)
- route length (in kilometers)
- number of stops per route
- average route speed (in km/h)

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. For example, variable names for each GTFS subfile were renamed to avoid issues with French accents. For GTFS data feeds prior to 2015, the "calendar_dates" file was renamed to "calendar" and a binary direction column was generated for the "trips" file. A value of 1 was assigned to routes heading southbound and westbound, and a value of 0 to routes heading northbound and eastbound as per GTFS feeds from 2015 on.

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. A separate value is found for all trips and for those falling within a peak period (defined as 6:00:00am to 9:00:00am and 4:00:00pm to 7:00:00pm, based on expanded STM Metro peak hours)

The average and standard deviation of headway is found by finding the difference between departure times at the initial stop sequence of each trip, then averaging the difference by route. A separate value is found for all trips in a day and for those falling within a peak period.

Route length is found by exporting the stop sequence for every trip on the given service schedule to ArcGIS. Network Analyst is used to create polyline shapefiles for each trip, using a Montreal street centerline network. The length of each polyline is measured, with the maximum value for each route maintained for analysis. Finally, average speed is found by dividing route length by average travel time. Several dummy variables are also generated for each route, either by manual assignment or ArcGIS. Express routes (400-series routes) are manually assigned, as are 10 Minutes Max routes. Dummy variables for connections to the Metro and EXO system are 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 are chosen to accommodate multiple station entrances not reflected by point shapefiles.

Lastly, fare pricing is 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 Montreal Gazette and displayed by year (Magder, 2018).

External variables: demographic data

Demographic data is retrieved at the census tract level from Statistics Canada for both 2011 and 2016, including each year's Census data and commuting flows data. Several variables related to public transport ridership are extracted from these sources, including:

- population,
- population density
- employment positions
- median household income ($)
- population that are recent immigrants (arriving to Canada in the last five years, %)
- households paying over 30% of their income to housing costs (%)
- the unemployment rate (%)

Linear interpolation is 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) in their study of North American ridership trends.

In order to prepare these variables for analysis, they must be aggregated at the bus route level. Shapefiles for each census tract in 2011 and 2016 are retrieved from Statistics Canada, then intersected with the polyline shapefiles for each route derived in the operational data section. Proceeding by route, the length of each intersected segment is divided by the sum of each segment to give a geographic weight for each census tract served by the line, a method used previously to study bus routes in London, UK (Grisé & El-Geneidy, 2017). This method accounts for routes that both cross a census tract and that run along the boundary of a census tract and allows for each demographic variable is weighted accordingly before being summed by the route number.

Finally, a social vulnerability index is created by standardizing and aggregating four highly-correlated variables previously been associated with public transport captivity in Montreal. Similar indexes have been used in discussing public transport ridership throughout the literature (Farber & Grandez, 2017; Foth & El-Geneidy, 2014; Krizek & El-Geneidy, 2007; Verbich & El-Geneidy, 2017). Scores are calculated for each year studied, with higher scores reflecting higher levels of social vulnerability.

External variables: Contextual Data

Several contextual variables are generated for inclusion in the model. The average price of gas for the Montreal region is retrieved from Statistics Canada (2019). TNCs 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 is created as a dummy variable by year, with 2015 being identified as the first full year they operated in Montreal. This is based on the available data in Montreal, as there is little information on number of trips taken by Uber. A dummy variable for the presence of BIXI is generated, albeit differently from a typical city-wide dummy variable as previous research has specified the need for more detailed variables for TNCS (Boisjoly et al., 2018; Graehler et al., 2019). A 500-metre buffer is generated around each BIXI station in Montreal and dissolved to create a general service area for BIXI use. Routes that have more than 25% of their length within the service area are deemed as being in competition with BIXI and are coded as one, allowing for the distinguishing of routes that are actually affected by the presence of BIXI and those that are not.

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 for these changes in schedules.

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
External Variables						
Employment positions	3105.35	3097.59	3089.82	3082.06	3074.29	3066.52
Median household income ($)	38,265.02	42,419.05	46,573.08	50,727.11	54,881.14	59,035.17
Recent immigrant population (%)	4.68	4.56	4.45	4.34	4.23	4.12
Households paying 30% or more of income towards housing (%)	16.48	16.03	15.59	15.14	14.78	14.26
Unemployment rate (%)	6.27	6.15	6.03	5.91	5.79	5.67
Population	2648.83	2664.48	2680.13	2695.79	2711.44	2727.09
Gross population density (per km2)	4064.04	4090.58	4117.11	4143.64	4170.18	4196.71
Average gas price ($)	1.37	1.37	1.37	1.16	1.08	1.19

However, one minute added to schedules to accommodate for congestion and construction issues is not a large adjustment and does not seem likely to significantly decrease ridership, contrary to the STM's claims that increased travel times are partially to blame. 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 figures, like route length, stop counts, and stop spacing, are also relatively similar across all years. As the series of dummy variables are applied consistently across the study period based on the 2017 STM network, there is no change here; however, no significant change was experienced on the STM network during this time period. As the routes did not see large-scale physical changes, the demographic changes are largely reflections of the interpolated demographic data from the 2011 and 2016 Canadian census.

Gas prices varied significantly over the study period, remaining at $1.37 per litre until dropping in 2015 and 2016. Cash and monthly fares increase over the course of the study period, while the percentage of buses removed for maintenance at the agency level generally hovered around 20% for the duration of the study period

6. METHODOLOGY

A preliminary analysis is undertaken by comparing and contrasting the general trends of ridership and route design between routes based on their ridership performance. Routes are grouped by percentile, with mean values for several route design variables compared between the top and bottom percentiles. The five top- and bottom-performing routes are selected for further examination, with the general relationship between their ridership performance, daily weekday trips, and average weekday headways from 2012 to 2017 graphed and discussed.

Having observed these relationships, a multilevel longitudinal mixed-effects regression model is developed to explore the determinants of route ridership overtime. This model both includes and compares data across multiple years, allowing for the extraction of coefficients that speak to changes within and across time periods. To prepare the data, each case is 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 (Boisjoly et al., 2018; Graehler et al., 2019). The 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, all other variables held to their means. Several variables were squared to account for potential nonlinear relationships, with travel time and monthly fare found to be significant.

Several dummy variables explaining differences between routes were removed due to insignificance, including that of express routes, routes that connect to EXO, and routes that do not connect to the Metro. The 10 Minutes Max dummy variable was found to be significant and maintained. Otherwise, internal variables related to route design make up the bulk of the model, including the number of weekday trips, weekday headway, weekday travel time and its squared term, average route speed, the number of route stops, and stop spacing. Other variables are removed for correlation, including route length and all variables related to the 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, and the price of gas. Other demographic variables – namely those used to generate the social vulnerability index – were highly correlated, and only median income was significant on its own. Employment positions was not found to be a significant variable and was removed from the final model. Overall, the model achieves the lowest possible AIC and BIC scores while maintaining the maximum number of significant variables.

Having generated this model, three route types are pulled from the data in order to provide specific recommendations for intervention. These route types are determined by dummy variables and consist of EXO routes (connecting to the EXO service), BIXI routes (competing in BIXI's service area), and 10 Minute Max routes. Changes to the average characteristics of these routes between 2012 and 2017 are compared to the change in characteristics of the typical STM route, in order to discuss how STM approached service adjustments in each case.

7. RESULTS

As was discussed briefly at the conclusion of the Data section, most route variables were relatively stagnant between 2012 and 2017 at the aggregate level. Route design was largely untouched during the study period, with connections to other services like EXO and BIXI remaining stable. While some small changes occurred with stop spacing and stop counts, in general the typical STM route maintained its form even as its quantity-of-service was adjusted. As a result, demographic changes are largely a result of the linear interpolation between the 2011 and 2016 Canadian Census rather than significant route redesigns. Nevertheless, the typical route became more socially privileged over time, with higher median incomes, a smaller portion of recent immigrants and households in housing need, and a lower unemployment rate over time.

In fact, the greatest changes for the typical STM route are in daily weekday trips, median household income, gas prices, and fares. Only daily weekday trips and fares are directly under the STM's responsibility. Figures 10 and 11 demonstrate the change in ridership and the change in daily bus trips and fare

FIgure 10 : STM Bus Ridership & Daily Bus Trips, 2012-2017

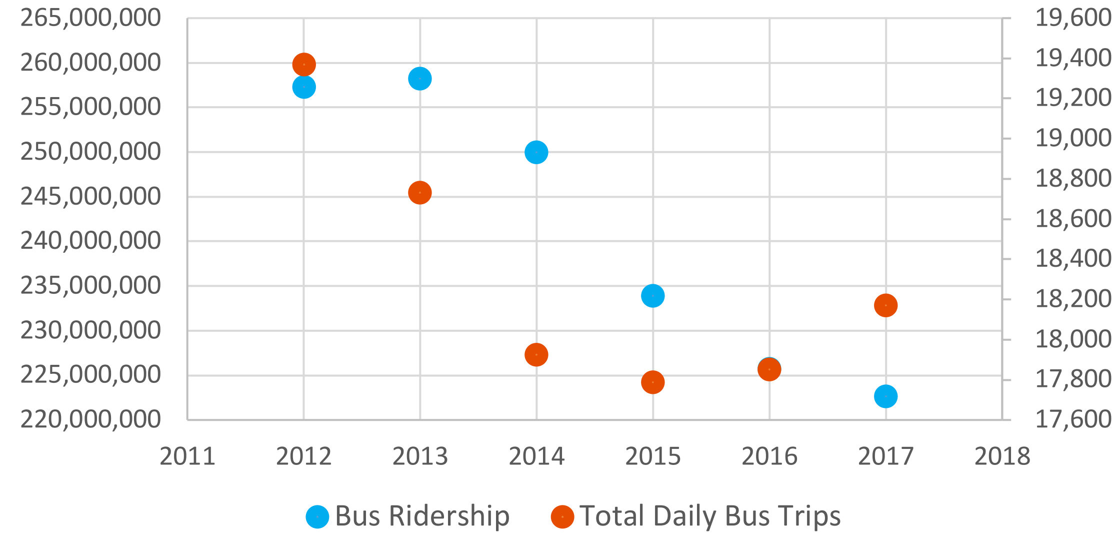
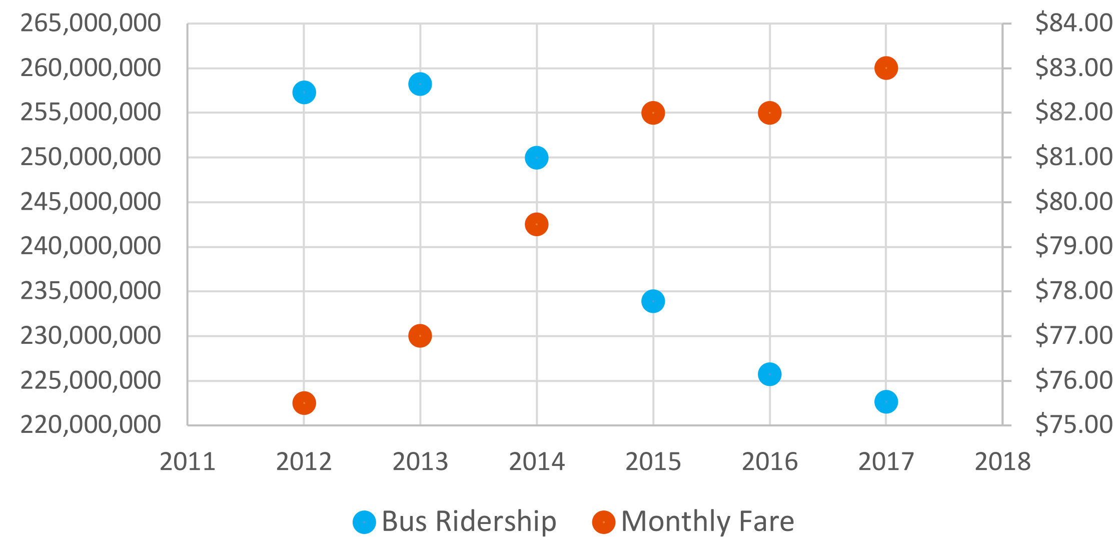


Figure 11 : STM Bus Ridership & Monthly Fare Prices, 2012 to 2017



between 2012 and 2017, revealing two trends in line with previous findings for ridership (Boisjoly et al., 2018; Graehler et al., 2019; Taylor & Fink, 2003; Taylor & Norton, 2010). As daily bus trips decrease, ridership decreases, as has been found with other level-of-service variables like VRKs. Secondly, as the monthly fare increases, ridership decreases, again in line with previous findings. While fare adjustments do not affect all riders equally, they do apply equally to each route and appear to be related to the decline in ridership. Again, as these variables saw the greatest change during the study period, they will likely have the greatest impact in the model as a result.

As ridership did not decline universally across the routes, neither did service adjustments to daily bus trips. Figure 12 displays the overall change in daily bus trips by route between 2012 and 2017 alongside the city's most socially-vulnerable census tracts. While most routes saw some level of service reduction, routes with the largest declines can be found servicing socially-vulnerable census tracts in Montreal Nord, Cote-des-Neiges, and Lasalle. Some socially-vulnerable census tracts in the West Island see a more mixed experience with daily bus trips, as some routes see large service reductions and others small increases. This is also seen in sections of downtown, where improvements to the 24 Sherbrooke route and to those serving Pointe-Saint-Charles and Ile-des-Soeurs stand out against smaller service cuts. However, the further east in the Island one goes the more consistent and large-scale cuts to service appear. As it appears that there may be some correlation between service adjustments and census tracts of high social vulnerability, the distribution of service adjustments, ridership performance, and social vulnerability will be explored in the following section.

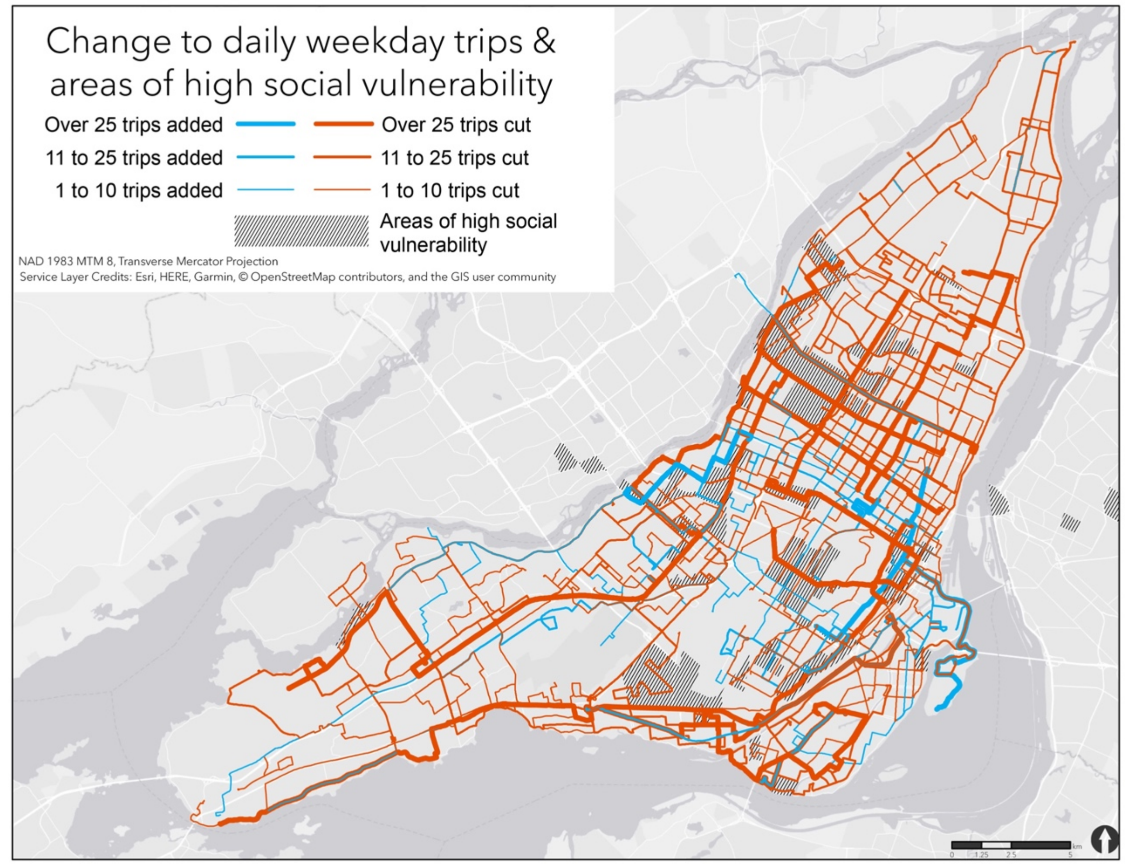


Figure 12: Change to daily weekday trips & areas of high social vulnerability

Grouping routes by their ridership performance and service adjustments, the upper- and lower- percentiles of routes can be compared relative to their social vulnerability and household median incomes in particular. While median incomes make up a component of the social vulnerability index, it is included as a separate variable to make clear the differences between the route percentiles. Tables 3 and 4 are shown below.

Whether grouping by ridership performance or service adjustments, it is clear that most changes are concentrated in the top and bottom percentiles of routes. In both cases, routes at the top- and bottom-percentiles of change had greater median incomes than the average, while in the case of ridership change social vulnerability is highest along routes with the greatest ridership losses. In the case of service adjustments, social vulnerability is highest along routes that saw the greatest amount of change; however, routes that saw trips added to them generally have higher median incomes than routes that saw trips taken away. This is particularly noticeable for the five most affected routes, with those receiving an average of 36 new daily trips during the study period having median household incomes almost $7,000 greater than those that saw a cut of 71 daily trips.

It should also be noted that routes that saw the largest declines in ridership and greatest cuts to service are among the highest ridership routes of the STM, and ridership losses are heavily concentrated in these heavily-frequented routes. There is almost three times more riders on the bottom five routes than the top five routes when sorted by service adjustments, revealing that service adjustments favoured cuts to the STM's busiest routes.

Table 3 : Routes by Ridership Change, 2012-2017

Percentile	Change in Ridership	2017 Ridership	Change in Trips	2016 Social Vulnerability	2016 Median Income ($)
Top 5 Routes	291,305	952,298	23	-0.44	69,220.51
Top 10%	179,183	1,184,725	16.29	-0.153	64,306.83
Top 25%	85,993	875,542	9.04	-0.395	56,984.34
All Routes	**-191,729**	**1,247,150**	**-6.7**	**.12**	**54,950.61**
Bottom 25%	-668,805	2,700,996	-23.6	0.872	55,881.62
Bottom 10%	-1,296,241	4,273,154	-39.48	1.815	60,719.33
Bottom 5 Routes	-2,521,821	5,234,532	-53.2	2.997	60,821.34

Table 4 : Routes by Service Adjustments, 2012-2017

Percentile	Change in Trips	2017 Ridership	Change in Ridership	2016 Social Vulnerability	2016 Median Income ($)
Top 5 Routes	36	1,706,763	197,661	2.43	71,459.22
Top 10%	19.7	1,801,393	131,986	0.37	58,552.72
Top 25%	9.6	1,065,964	43,587	0.33	56,990.67
All Routes	**-191,729**	**1,247,150**	**-6.7**	**.12**	**54,950.61**
Bottom 25%	-29.6	2,332,902	-676,494	0.19	49,968.33
Bottom 10%	-48.5	3,186,142	-1,247,880	2.04	59,864.87
Bottom 5 Routes	-71	4,600,033	-1,702,218	2.51	65,229.02

These tables suggest a trend in the STM's approach to service adjustments during the study period: cuts were targeted on its busiest routes while benefits were allocated to smaller routes elsewhere. In the context of shrinking numbers of available buses, the decision to reallocate buses away from high-frequency routes and towards niche routes for wealthier areas may appear confusing. When considering service adjustments per capita for the ten most affected routes, this shift of resources appears increasingly regressive; each trip taken away affected 1.37 more riders than a trip given. The routes affected also have higher median incomes and ridership numbers than the average route, suggesting a tendency to ignore service adjustments for smaller routes frequented by lower-income riders.

While social vulnerability may not cleanly relate to the STM's service adjustments, it does relate to the resulting ridership changes; as route ridership losses increases, so does social vulnerability. This is interesting as it suggests the routes serving populations most likely to be captive riders are the ones losing the largest most, while those with less vulnerable populations are choosing to ride the bus more often. This may suggest that the STM is successfully attracting choice riders with its service adjustments at the cost of losing riders previously thought to be captive.

These findings raise important questions of causality; were trips give and taken based on previous ridership changes, or did ridership change based on the adjustments taken by the STM? To answer this question the change in daily weekday trips is compared to the ridership change from the year. The findings are found in Figure 13, with only routes experiencing changes to daily weekday trips included and all scales held constant.

The trend line for each graph reveals 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 has failed to add weekday trips to routes that experienced high ridership gain, year over year, and did not concentrate its cuts on routes that were already experiencing ridership declines. This finding puts greater weight on the impacts of income and social vulnerability on route adjustments discussed above and underscore the question of why high ridership routes saw the largest cuts to daily trips. If service adjustments were not in response to the previous year's performance, it would seem that the STM cut on routes where such cuts would be perceived as disposable, and these cuts impacted riders of lower-income and higher social vulnerability than those where service improvements were allocated.

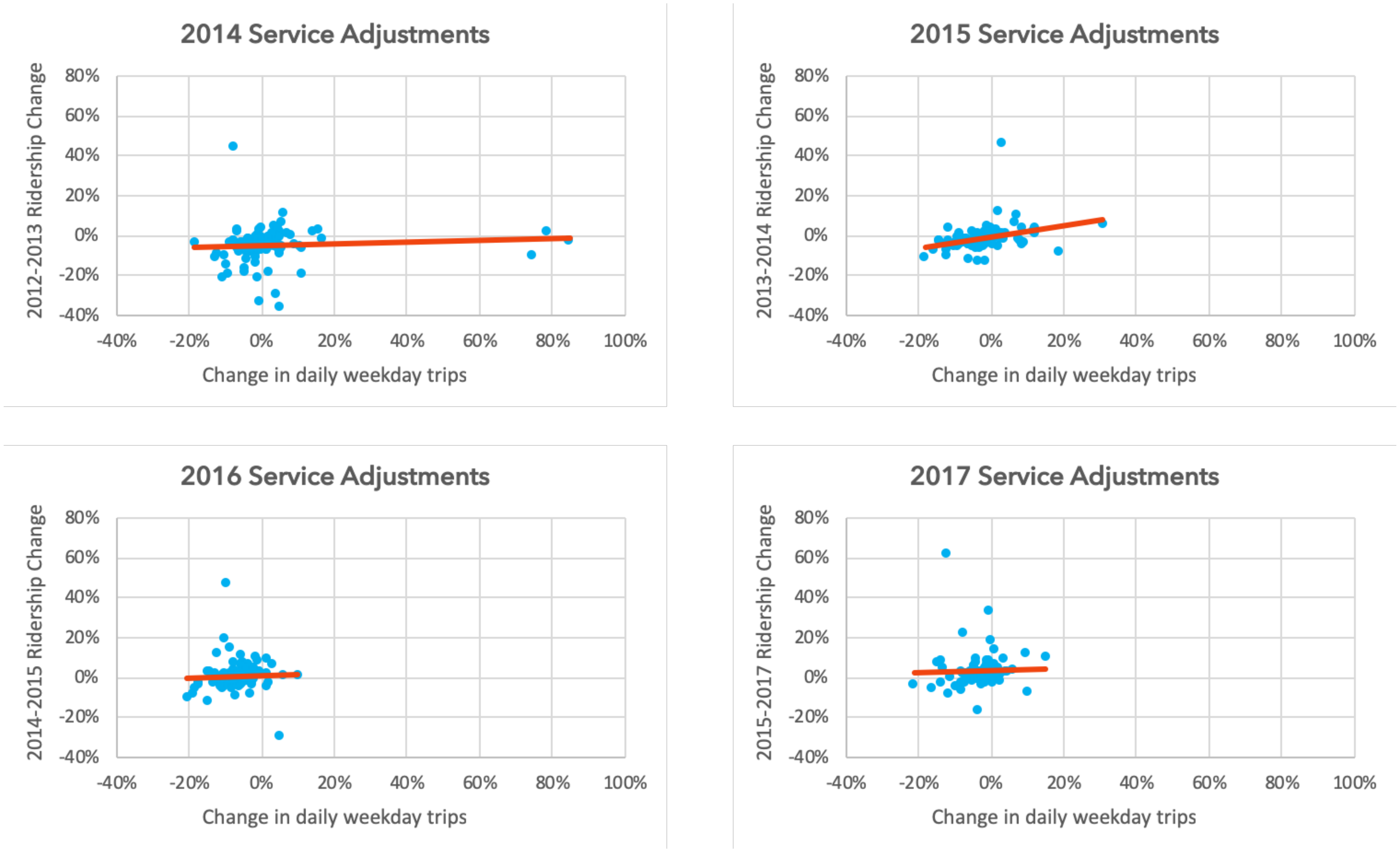


Figure 13: Adjustments to daily weekday trips compared to prior ridership change, 2014-2017

In order to make a final conclusion on the relationship between daily trips and annual ridership, as well as the other variables studied, the longitudinal multilevel mixed-effects regression model must be examined. All variables generated are included to begin, including those used to test for non-linear relationships. A step-wise approach was taken to remove insignificant variables while maintaining the overall stability of remaining variables. The model is displayed in Table 5, with the dependent variable set as the natural logarithm of annual bus ridership. As a result, each coefficient represents the percent increase in annual bus ridership that can be expected for every unit of change experienced by the variable, all others held to their means. All variables are found to be statistically significant at the 95% confidence level, while the high ICC estimate suggests excellent reliability.

The first set of variables are internal variables related to route design, beginning with the number of daily weekday trips. Increasing the number of weekday trips by 10 will increase annual ridership by 4.7%, all other variables held to their means. In contrast, every additional minute of average weekday headway will result in a 1% loss to annual ridership. Travel time is found to have diminishing returns with an inflection point of 53 minutes; every minute added above the mean gains 3.18% in annual ridership, but every additional minute decreasing this by .03%. This reflects both necessary amount of travel time riders must take to reach their destinations, as well as the inflection point where travel times get too high. Lastly, every 10km/h of additional route speed results in a 1.01% increase in annual ridership.

When considering stop spacing and stop counts, more stops and smaller spacings equal more riders. In theory, every additional stop adds 0.94% to annual ridership, although this would be affected by the location of the stop in practicality. 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.

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 a 108.55% 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. The dummy variable reflecting the presence of Uber was not found to be significant and resulted in a less than 3% decline in annual ridership. For routes competing in the BIXI service area, however, a ridership loss of 30.12%

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

Variable name	Coefficient	Std. Err.	z	P>z	[95% Conf]	
Internal Variables						
Daily weekday trips	0.0047	0.0004	12.29	0.000	0.004	0.005
Weekday headway (min)	-0.01	0.0013	-7.23	0.000	-0.012	-0.007
Average weekday travel time (min)	0.0318	0.0053	6.01	0.000	0.021	0.042
Average weekday travel time (^{2})	-0.0003	0.0001	-5.27	0.000	-0.0004	-0.0002
Route average speed (10km/h)	0.0101	0.0019	5.42	0.000	0.006	0.014
Route stops	0.0094	0.0025	3.72	0.000	0.004	0.014
Stop spacing (10m)	-0.0013	0.0003	-4.10	0.000	-0.002	-0.001
Route is 10 Minutes Max (dummy)	1.0855	0.1440	7.54	0.000	0.803	1.368
Route overlaps with BIXI (dummy)	-0.3012	0.1507	-2.00	0.046	-0.597	-0.006
Monthly fare	0.5853	0.1054	5.55	0.000	0.379	0.792
Monthly fare (^{2})	-0.0037	0.0007	-5.46	0.000	-0.005	-0.002
External Variables						
Median household income ($1,000)	-0.0032	0.0007	-4.52	0.000	-0.005	-0.002
Population density (1000/km^2)	0.1095	0.0219	5.01	0.000	0.067	0.152
Average gas price ($0.10)	0.0185	0.0051	3.65	0.000	0.009	0.028
Constant	-12.0140	4.1331	-2.91	0.004	-20.1147	-3.9133

Log-likelihood	503.1162	AIC	-972.2323
Observations	1,074	BIC	-887.5869
Number of groups	180	ICC	0.980514

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 30.12% is concentrated in the summer months during which BIXI operates.

The final internal variable found to be statistically significant is the monthly fare. Every dollar to the monthly fare beyond the mean increases ridership by 58.5%, but every additional dollar decreases this by 0.37%. Setting the fare beyond $79.09 results in decreases to the ridership gain as a result.

Turning to external variables, three variables are found to significantly affect annual ridership. The first, household median incomes along a route, decreases annual ridership by 3.2% for every additional $10,000 gained. Population density strongly increases ridership, generating a 10.95% increase in annual ridership for every additional 1,000 residents per square kilometer, all else held even. Lastly, increases to gas prices can lead to growing annual ridership, with a 1.85% increase in annual ridership for every additional 10 cents added to the price per litre.

The model confirms the relationship between daily trips and annual ridership explored previously, and highlights the importance of internal variables, particularly those concerning route design and fares, in attracting riders. The STM's decision to adjust daily trips on routes and its decision to raise fares beyond the inflection point of $79.09 have had impacts on the overall ridership of the system, particularly as most other route design variables have remained relatively stagnant through the study period. For the typical STM route, changes to external variables (including large increases to median incomes, small increase to population densities, and reductions in gas prices) explain an 8.41% decline in ridership. It is estimated that fare adjustments resulted in a 5.64% decrease in ridership, while the change in daily trips led to a 3.39% decrease in ridership.

8. DISCUSSION

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, gas prices, and density increases and further complicated by internal service adjustments involving fare prices and trip levels. However, service adjustments in the form of daily trips did not affect all routes equally and were found to be allocated regressively when considering social vulnerability. The bottom five routes that saw the most trips cut had on average 71 trips cut (which would result in a 33.5% loss in ridership) while the top five routes that gained the most trips received 36 (enough to expect a 17% gain in ridership). The model can identify alternative strategies to trip adjustments for increasing ridership and to temper cuts when necessary. For example, rebalancing stop spacing, and route speed may have improved the service offering on the bottom five routes, even in the middle of trip cuts, and thereby helped offset the expected ridership loss. Similar improvements to the top five routes could have avoided the need in reallocating trips here. Large-scale approaches like increasing gas taxes in the midst of falling prices may have tempered overall ridership losses, while a stronger increase to density in areas outside Montreal's core may have led to more built-in ridership. Other route design strategies were similarly left at the table by the STM; headways remained stagnant throughout the study period, even when adjustments during the peak period or off-peak could have improved the service offering for riders.

While the STM focuses on external variables as the cause of ridership declines, the results of the analysis and model demonstrate that its decision to cut trips on routes, increase fares, and ignore other route design variables available to it had a large impact on overall ridership numbers. It should also be noted that the presence of challenging external variables does not excuse a lack of response on the part of the STM; in the context of increased median incomes and lower gas prices as well as new competion from Uber (though not found to be a significant cause of ridership loss) and BIXI, route design and service levels should be adjusted.

This study has raised several conclusions that apply not only to the STM. The literature on bus ridership has identified numerous factors that can affect one's decision to take the bus, and this paper has again confirmed some of these factors. Variables for service quantity and quality, including the number of daily trips, average weekday headways, and average route speed are all found to have significant impacts 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.

Other variables found to be significant reinforce the existing literature, such as those for income, gas prices, fare prices, and population density. Affordability matters for public transport and buses, particularly as riders tend to be of a lower-income background. This study finds that a gain in median household income results in a reduction of bus ridership. Low gas prices can entice riders into their own cars, while hiking fares above an acceptable point will drive riders away. Lastly, the population density around a route positively impacts ridership, yet density alone cannot yield ridership results. Montreal has grown denser during the study period, but the STM increased fares and cut service as median incomes for Montreal rose and gas prices fell. Based on the findings of the model, it is no surprise that ridership fell.

The Montreal data demonstrates that routes servicing the most socially-vulnerable populations are susceptible to 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 maintain a level of agency and that in the face of significant service reductions and a different affordable mobility option – a bicycle share rather than a car share – some may well leave.

This study's findings 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. In this study, BIXI was found to have a large and negative impact for routes operating in their neighbourhood. In the case of Montreal, the BIXI bicycle share system succeeds in competing with and gaining riders from the public bus network likely by offering a speed, reliability, and flexibility not offered by the routes.

In order to facilitate service adjustments in the future, this section is dedicated to applying findings from the longitudinal multilevel regression model for ridership to three -route types found in the STM network. The service adjustments made by the STM over the study period will be examined in comparison to those experience on average by the "typical" STM route; the results in terms of ridership are discussed and future interventions suggested.

Table 6. Targeting interventions by route typology: 2017 Average route characteristics				
Variable	All Routes	EXO Routes	BIXI Routes	10 Minutes Max Routes
Internal variables				
Daily weekday trips	99.84	107.86	109.73	224.61
Weekday headway (min)	26.69	22.65	24.77	10.83
Weekday travel time (min)	35.92	42.52	32.95	42.54
Route average speed (km/h)	20.55	27.06	14.82	16.55
Route stops	36.33	37.29	31.33	42.58
Route spacing (m)	413.69	705.55	266.11	285.78
External variables				
Population density (1/km2)	4196.71	3200.95	7721.45	5217.63
Median income ($)	59,035.17	77,154.45	72,592.82	57,994.60
Social Vulnerability	.10	.66	2.39	1.12
Ridership	1,223,133	1,062,745	1,584,776	4,120,399
Number of Routes	182	21	48	31

In doing so, some answers about why certain routes were prioritised may be found as well. The three route types selected are EXO Routes (connecting to an EXO station), BIXI Routes (overlapping with the BIXI service area), and 10 Minutes Max Routes (the core network). The average values for route design variables are shown below in Table 6, alongside some demographic variables. The change in variables for each route type are calculated by subtracting the average value for the route type in 2012 from that of 2017 and are presented in Tables 7 through 9. These are compared to the changes for that of a typical STM route, so as to contrast how service adjustments were made across the system and how future adjustments can be allocated.

EXO Routes

EXO routes are defined by running high-speed, long-distance services through suburban areas of Montreal. They have more daily trips than average and shorter headways. EXO routes saw less ridership loss than the average STM route, in line with the smaller reductions in daily trips they experienced, limited changes to headways, and minimal travel time changes. These routes saw much higher speed increases than average, perhaps due to the larger increases to stop spacing. The service areas of EXO routes did not densify as quickly as other areas, however. With these mild service adjustments, the limited 5.15% loss in ridership is perhaps expected. The main target for EXO routes to increase service is population density, as these routes are already outperforming other STM routes in other service variables. As density is increased around these routes, the number of route stops could be revisited while maintaining routes speeds. Changes to these routes do benefit populations that are higher-income and less vulnerable than others, for routes that see lower ridership performance overall. As a result one can conclude that the past dedication of resources to these routes have successfully avoided larger ridership losses, but have been inequitable in nature by prioritising the least vulnerable and highest-income populations.

Table 7. Change in service, 2012-2017 : EXO Routes

Variable	All Routes	EXO Routes
Internal variables		
Daily weekday trips	-7.18	-3.25
Weekday headway (min)	.40	.36
Weekday travel time (min)	1.37	.04
Route average speed (km/h)	.11	1.79
Route stops	.11	.25
Route spacing (m)	6.70	49.01
External variables		
Population density (1/km2)	119.72	76.58
Ridership Change, Absolute	-198,407.15	-56,504.05
Ridership Change, %	-13.96%	-5.15%

BIXI Routes

BIXI routes operate primarily in the downtown and Plateau areas of Montreal, servicing extremely dense areas with tightly-spaced stops. While these routes have high levels of social vulnerability, they also have high median incomes; this reflects the ongoing gentrification of the Plateau area by recent immigrants in particular. Their average speed is much lower than the average STM route, although their daily trips and headways slightly higher. BIXI routes did not see as many trip cuts as the average STM route and saw slightly smaller increases to headway, although the routes slowed down when the average route sped up. These routes saw the largest proportional loss of ridership as a result, largely due to the presence of BIXI. As BIXI has been present throughout the study period, the lack of service adjustments to counter its impact by the STM is noticeable. In order to counter the 30% loss in ridership caused by BIXI, these routes could be upgraded to the 10 Minutes Max standard. A reduction of ten minutes in average weekday headways and an accompanying increase in daily trips would be enough to offset the BIXI loss. Doing so while maintaining or improving route speeds would also counter ridership declines. As BIXI routes have fewer stops and are currently more local than the typical route, increasing their length to provide access to more destinations could also counter the local role BIXI plays.

Table 8. Change in service, 2012-2017: BIXI Routes

Variable	All Routes	BIXI Routes
Internal variables		
Daily weekday trips	-7.18	-5.83
Weekday headway (min)	.40	.28
Weekday travel time (min)	1.37	.1.60
Route average speed (10km/h)	.11	-.36
Route stops	.11	.15
Route spacing (10m)	6.70	10.27
External variables		
Population density (1000/km2)	119.72	302.15
Ridership Change, Absolute	-198,407.15	-289,731.40
Ridership Change, %	-13.96%	-15.46%

10 Minutes Max Routes

10 Minutes Max routes have the highest frequencies of STM routes, outperforming the average headways, travel times, and daily trips of an average STM route by far. These routes operate in well-developed parts of the city and saw the least change in population density as a result. Service changes for the study period resulted in serious reductions in service that have slowly eroded this advantage, leaving these routes to perform more accurately as the 11 Minutes Max network. These routes saw two and a half times more trips cut than the average STM route and large increases in travel times. As a result, ridership plummeted by over 700,000 per route on average, slightly above the percentage of loss experienced by the average STM route but resulting in far greater losses due to the popularity of these services. These cuts affected populations with the lowest median incomes of all groups, and higher levels of social vulnerability than average. In order to reverse these losses, reinvestments in service to reach the promised 10-minute headways should be made. As they serve mature areas of the city, focusing on these service qualities will be more effective than planning for a more-populated service area. Considering interventions to improve travel times and route speeds for these routes would be worthwhile, as interventions here will impact the largest number of vulnerable riders.

Table 9. Change in service, 2012-2017: 10 Min Max Network

Variable	All Routes	10 Min Max Routes
Internal variables		
Daily weekday trips	-7.18	-18.68
Weekday headway (min)	.40	.67
Weekday travel time (min)	1.37	2.27
Route average speed (10km/h)	.11	.20
Route stops	.11	.84
Route spacing (10m)	6.70	14.15
External variables		
Population density (1000/km2)	119.72	104.02
Ridership Change, Absolute	-198,407.15	-709,746.48
Ridership Change, %	-13.96%	-14.69%

9. CONCLUSION

Buses are a simple and effective form of public transport that can form the backbone of a network and carry many riders. By understanding the determinants of bus ridership, public transport can create an efficient and attractive service and be well-informed when making service adjustments. In this research, ridership data from the Societe de Transport de Montreal (STM) from 2012 to 2017 is used to generate key determinants of ridership and measure the extent to which service changes taken by the Agency impacted the riders of its bus network while controlling for changes in external factors.

Montreal experienced a large decline in bus ridership over the last decade, reaching almost 14%. GTFS feeds for the STM between 2012 and 2017, Canadian Census data, and contextual data were gathered by route and year in order to explain this decline. Using this data, a longitudinal multilevel mixed-effects model is generated for the natural logarithm of bus route ridership. A step-wise approachs results in fourteen statistically significant variables, divided between internal and external variables. Increasing the number of daily trips, reducing average weekday headways, and increasing average route speed while maintaining frequent stops are all effective strategies for increasing ridership. These strategies are captured in the 10 Minutes Max designation, which boosts ridership on affected routes. A route's population density and a region's gas price can also influence annual ridership, with increases to both increasing ridership levels.

Increases to stop spacing and population's median household incomes will both result in ridership losses. Both travel times and monthly fare prices have a nonlinear relationship to annual bus ridership, experiencing decreasing rates of return for every unit of increase, with the inflection point for the STM occurring at 54 minutes of travel time and a monthly pass cost of $79.09. The STM does have room for to manipulate average travel times on some routes, though in terms of fare increases to the monthly pass it can now expect ridership losses for every dollar increase.

Bus ridership is reduced when a route competes with a bicycle share system, and strongly so in the summer. The STM must now consider the competition posed by this system and reconsider the route design for routes affected, as it did not react to its presence during the study period. Increasing service and reorienting routes towards longer-distance express routes can counter the localized travel option presented by bicycle shares and is an approach the STM should consider.

The generated model demonstrates that service changes taken during this period are responsible for the overall decline in ridership –as a result of reducing trip frequency, ignoring the impact of BIXI, and increasing fares. As demonstrated by the relationship between changes to daily weekday trips and ridership change the year prior, the STM has not taken into account ridership performance when setting service levels and has not considered the impact of its own internal decisions. It is also apparent that the STM has targeted what service improvements it did make on relatively niche, lower-ridership routes, while the workhorses of the system were left with fewer and fewer buses to run effectively. By allocating its resources as it did, the STM chose to invest in routes serving higher-income and less socially-vulnerable neighbourhoods while ignoring routes serving lower-income and socially-vulnerable areas. Cuts to daily trips on routes affected 1.33 times more riders than service enhancements to routes benefited, raising the question: were the riders on these higher-income, less-vulnerable routes more valuable to the STM than those on the high-ridership routes experiencing cuts?

Value-based decisions such as these should enter early into the planning of bus networks, in order to inform the use of ridership models and their application in estimating the impacts of service adjustments. By generating ridership determinants at the route level, the impacts of route design changes can be balanced with their impact on socially-vulnerable and lower-income populations, thereby avoiding scenarios where service cuts are socially regressive in nature. The determinants generated here are also useful for communicating with riders and the public at large, so as to explain the effects

Figure 17. STM bus stuck in snow, Winter 2017

of politicised decisions around public transport provision and in particular, bus ridership.

This research has built on several previous studies to generate a replicable method for analyzing ridership changes on a bus network. By aggregating demographic data at the route level, it is possible to conduct a local-level analysis well suited for network and service planning. 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 Montreal context, the overall research methodology is reproducable in other areas and with other agencies. the research makes clear to all those involved and affected by bus routes – whether riders, planners, drivers, politicians, or otherwise – that cutting service cuts riders, and that “efficiencies” in route design have consequences.

10. LIMITATIONS & FUTURE RESEARCH

While this study has replicated methods used elsewhere and incorporated many different types of data sources, there is always room for improvement in the methods used. Perhaps the largest limitation revolves around demographic data, as it is only collected every five years and linear interpolation does not fully capture the reality of demographic changes year-to-year in the model. This could be overcome by extending the time period of the study, though this would require more data from the STM than may be available. may be similarly limited.

Data on travel times and route speed are similarly limited by being GTFS schedulings, rather than actual route performance. Incorporating Automatic Vehicle Location (AVL) and Automatic Passenger Count (APC) data presents an interesting avenue for future research that could provide fine-grained reliability data for use in a model. These could account for delays and reliability issues that push riders away from the service. The use of other service quality variables (such as cleanliness) could also add to the model.

Assignment of variables to routes using geographic weighting is a method used elsewhere but one that could be refined through the use of actual route boardings. For example, if on average a stop received 50% of the overall trip boardings for a given route, the demographic variables of the census tract that stop falls within should count for 50%. In addition, this method can create issues for express routes and routes that cross large geographic distances that are sparsely populated: simply crossing a census tract does not actually mean access to, and thereby potential use of, a line. Using land-use data or buffers in this calculation could create a more exact model.

It was noted that the correlations for variables used in the social vulnerability index are falling between the 2011 and 2016 Canadian Census. While still above 0.6, the falling correlation between variables suggest the assumption that these variables correspond to public transport use and dependency should be futher explored elsewhere.

Lastly, GTFS data used for analysis was taken from a specific service date for a specific month. Associating ridership data more closely related to this service date (for example, comparing monthly ridership data between six different years) may yield more exact and appropriate results.

Figure 18. STM buses at garage, date unknown

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