Towards a better understanding of changes in subsidy per riders for bus routes before and after the COVID-19 pandemic in Montréal, Canada

Lancelot Rodrigue
McGill University
Email: lancelot.rodrigue@mail.mcgill.ca
orcid: 0000-0001-6878-3601

Kevin Manaugh
McGill University
Email: kevin.manaugh@mcgill.ca
orcid: 0000-0003-2975-030X

Ahmed El-Geneidy
McGill University
Email: ahmed.elgeneidy@mcgill.ca
orcid: 0000-0002-0942-4016

For citation, please use:

Rodrigue, L., Manaugh, K., El-Geneidy, A. (2025). *Towards a better understanding of changes in subsidy per riders for bus routes before and after the COVID-19 pandemic in Montréal, Canada.* Paper presented at the 104th Transportation Research Board Annual Meeting, Washington DC, USA.

ABSTRACT: The COVID-19 pandemic has severely impacted the finance of transit agencies by reducing farebox revenues. Combined changes in ridership and service operation levels have further transformed the financial efficiency of public-transit services. Understanding how these changes vary between routes is crucial to inform service optimization processes to reduce transit agencies' operational deficits. Using data from the bus network in Montréal, Canada, for 2019 and 2022, we assessed changes in cost per rider at the route-level before and right after the COVID-19 pandemic. We categorized daytime multi-stops bus routes (N = 184) based on the income of the areas they served and their cost per rider across both years to assess diverging temporal and spatial patterns. Our results highlighted that highly subsidized lines were mostly located in the periphery of the study area and in the downtown core and that such patterns worsened following the pandemic, particularly for the downtown core. We observed that routes which served higher income areas tended to have higher cost per rider on average than middle- or low-income ones. We further confirmed this finding by categorizing bus routes by their level of subsidy, finding that highly subsidized routes in both 2019 and 2022 tended to be serving higher income areas than other routes. The consideration of both temporal, spatial and socio-economic variation of the cost of bus services provides nuance insight to transportation planners as they aim to optimize bus services while being mindful of potential ridership loss and vertical equity issues.

Key words: Public transit, Bus, Cost, Subsidy, COVID, Equity

1. INTRODUCTION

The COVID-19 pandemic has had lasting impacts on travel behaviour. The decline in public transport ridership at the start of the pandemic due in part to fear of contamination (Simons et al., 2021; Sträuli et al., 2022) and wider telecommuting policies (Erhardt et al., 2022; He et al., 2022; Huang et al., 2023) was substantial. A large body of research has quantified the negative effects of the COVID-19 pandemic on public-transit ridership both in terms of number of trips (Erhardt et al., 2022; Qi et al., 2023) as well as changes in destinations visited (Simons et al., 2021). Changes in travel patterns due to the pandemic were not homogenous within the population, with higher income groups reducing their usage of public-transit significantly more than their lower-income counterparts (Fernández Pozo et al., 2022; Palm et al., 2024; Parker et al., 2021; Paul & Taylor, 2024; Soria et al., 2023). Given these findings, ensuring proper service to lower-income areas could make public-transit ridership more resilient to large-scale disruptions such as the pandemic. Research in Madrid, Spain, (Fernández Pozo et al., 2022) and Sweden (Jenelius & Cebecauer, 2020) also showed a shift towards more single- or multi- tickets at the expense of monthly passes during the pandemic, signifying a shift towards more infrequent public-transit use. Such a change has important implications for long-term ridership and farebox revenue.

The reduction of ridership experienced during the COVID-19 pandemic led to important reductions in fare revenues which created large deficits for public-transit agencies, particularly for those with higher farebox recovery ratios before the pandemic (Siddiq et al., 2023). Research conducted in the US showed that while governments stepped in with temporary relief funds, several transit agencies still expected large deficit once the subsidy stopped (King et al., 2023; Siddiq et al., 2023), which could translate in additional service cuts. To adjust for reduced ridership, most transit agencies across North America did some level of service cuts during the early part of the pandemic. While some cities such as San Fransisco and Denver cut service more in higher income areas than in lower-income ones the opposite was observed in Toronto and Montréal (DeWeese et al., 2020). Post-lockdown service cuts were also found to have had a disproportionate negative impact on accessibility by public-transit in lower-income neighbourhoods (Kar et al., 2022). This could have resulted in further ridership loss given the increased dependency on lower-income riders during the pandemic (Fernández Pozo et al., 2022; Palm et al., 2024; Parker et al., 2021; Paul & Taylor, 2024; Soria et al., 2023).

Despite the widespread adoption of important service cuts during the onset of the pandemic, several transit agencies rapidly went back to or close to pre-pandemic levels of service even though the ridership was not yet significantly rebounding. This was the case of four of the largest seven transit agencies in the US which returned close to pre-pandemic levels of service as early as Fall 2020 (Karner et al., 2023). While service cuts might have helped in reducing expenses temporarily, transit agencies' budget shortfalls were for the most part filled by governmental pandemic aid. Network-level subsidies of public-transit have been shown to lead to increase in service provided and ridership by avoiding operation deficits (Karlaftis & McCarthy, 1998). Still, the scholarship on public-transit subsidies has also highlighted their inflationary effect on operating costs as the added funds tend to be used more to increase the share of the payroll within overall budgets (i.e., more employees being paid more) rather than being dedicated to added service for the users, thus increasing average per-unit costs of service provision (Gupta & Mukherjee, 2013). Several studies have suggested that public-transit subsidies be better targeted towards service provision rather than going towards the overall budget (Avenali et al., 2020; Gupta & Mukherjee, 2013), with some proposing alternative methodologies to optimize subsidy amounts (Avenali et al., 2020; Luo et al., 2022; Sun et al., 2016).

As operational debts started rising and political support for COVID relief funds started falling, several transit agencies were forced to eventually start cutting service despite not doing so in the onset of the pandemic (Kar et al., 2022). Understanding the changes in operating costs over time, due to decline in ridership, and the impacts of the service cuts adopted during the pandemic are important to strategically guide any future changes in service. Still, little research has been conducted on the temporal variation of operating costs, aside from variation in marginal costs of operation based on time of day (Bruun, 2005; Taylor et al., 2000). Similarly, limited literature has explored the spatial distribution of operating costs, with Mallett (2023) doing so for two rail systems in the US. In terms of spatial distribution of public-transit subsidies, past studies found that public-transit subsidies were higher in suburban settings compared to more central ones (Börjesson et al., 2020; Hodge, 1988), with short-distance, urban travellers tending to subsidize long-distance commuters' travel (Cervero, 1981). While this spatial disparity is partially compensated through non-fare revenues (e.g., property taxes) which are higher in suburban settings than in central areas (Hodge, 1988; Iseki, 2016), residents of central urban areas still tend to pay more for public-transit relative to their income levels (Hodge, 1988).

This study bridges the literatures on the effects of the COVID-19 pandemic on public-transit and the cost of public-transit operations by evaluating the change in cost per rider between 2019 (before the pandemic) to 2022 (after the pandemic and after a first round of service cuts) for 184 bus routes of the Société de Transport de Montréal (STM) in Montréal, Canada. Doing so we provide both spatial (i.e., between routes) and temporal (i.e., between year) comparison of the financial performance of bus service. While previous studies did assess temporal variations in public-transit operating cost based on time of day (Bruun, 2005; Taylor et al., 2000), to our knowledge no study have provided comparisons over a longer period of time or following a major disruptions such as the COVID-19 pandemic. Similarly, spatial comparisons of cost per riders have been limited (Mallett, 2023) and, to our knowledge, no previous studies have provided a comparison between a large number of routes of the same mode. Our study therefore helps in filling these gaps in the literature by considering both temporal and geographical variability in the cost of bus service per riders. We highlight routes with high level of subsidy both before (2019) and after (2022) the pandemic, which can provide potential for service changes to reduce operating costs, while being sensitive to ridership and vertical equity goals. The findings from this paper will be of value to researcher and transit agencies working to elaborate service optimization processes to bring costs down with minimal impact on ridership and low-income areas.

2. DATA AND METHODS

This study is conducted for the island of Montréal, Canada which has a total population of 2 million people (Statistics Canada, 2023a). It is served by the Société de Transport de Montréal (STM) which manages all bus and metro services on the Island. Other transit providers are not allowed to provide local bus services on the Island of Montréal, with commuter trains being the only public-transit service operated on the Island by an agency other than the STM. The STM operated 206 day-time bus lines in 2019 compared to 193 in 2022 (190 in common between the two years). In addition, the STM operated 23 night bus routes and four metro lines in both periods. The coverage of the regular buses and metro lines is displayed in Figure 1. For our analysis, we decided to focus on bus services as they account for the majority of the STM budget (~ 62% in 2019 and 2022) and represent more opportunities for service optimization due to the possibility of route redesign.

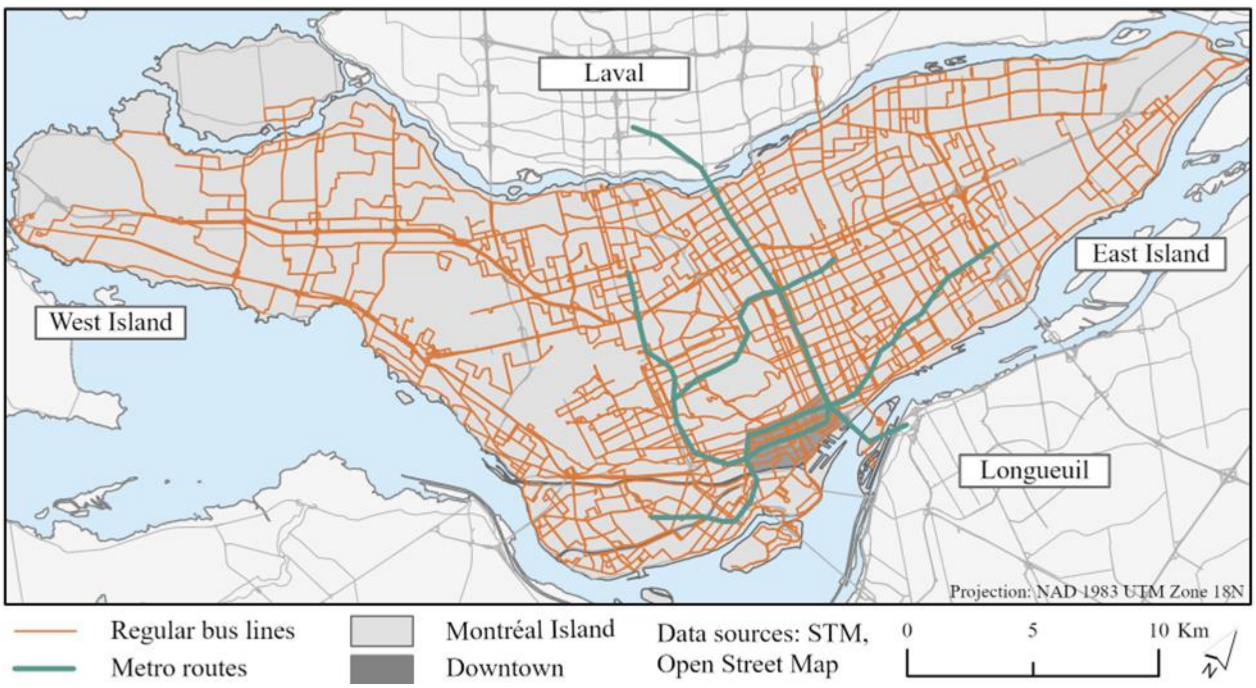

Figure 1 STM bus routes and metro lines in 2019

Lastly, the fare structure was the same across the entire STM network system (i.e., flat fare for the entire zone, integrated with all modes) with single tickets costing $3.25 for the first six months of 2019 before being raised to $3.50 after. It is important to note that fare structures are elaborated and integrated at the regional level by the Regional Metropolitan Transit Authority (ARTM) which also collects fare revenues.

2.1. Data

To derive the cost per rider for each STM bus routes before and after the pandemic (i.e., 2019 and 2022) and summarize the characteristics of the areas served, the following data was collected:

(1) STM financial information was extracted from the 2019 and 2022 STM budgets (STM, 2019, 2022). To allow for comparison, the 2022 financial amounts were adjusted for inflation to the 2019 values based on changes in average annual general consumer price index between the two years (11.12%) (Statistics Canada, 2023b).

(2) General Transit Feeds Specification (GTFS) data were obtained from Transitland. Six different GTFS feeds were downloaded to cover the five yearly service periods (January, March, June, September, and November) for 2019 and 2022. STM GTFS feeds have eight possible service types (Weekdays, Saturdays, Sundays, Special Services and four different holiday categories) which dictate the frequency of the service provided. When intersecting these eight service days with the five service periods present in a calendar year, there is a total of 40 possible combinations for service provision for each STM line. For the sake of simplicity, we refer to those as unique service days.

(3) Average weekday daily ridership data per service period (January, March, June, September, and November) and per bus routes were gathered from the STM through an access to information request for 2019 and 2022. Complimentary Automated Passenger Counting (APC) data for the month of November 2022 obtained through a previous access to information request were also used in the analysis. APC data was not used for the core of the analysis due to its implementation in all STM buses only in 2020, meaning that it could not have been used for both years.

(4) Median household income, population, and number of jobs were collected at the Census Tract (CT) level from the 2021 Canadian census (Statistics Canada, 2023a) to assess who is being served by each bus routes.

2.2 Methodology

Literature on public transit cost allocation has highlighted three primary metrics to allocate cost of service provision: (1) vehicle operating hours, which usually are used to allocate variable costs such as labor; (2) vehicle distance travelled, which are usually used to allocate variable costs such as energy and maintenance; and (3) peak vehicles, which are used to allocate semi-fixed and fixed capital costs (Bruun, 2005; Cherwony & Mundle, 1980; Mallett, 2023; Taylor et al., 2000). In this study, we decided to allocate variable and semi-fixed costs, but not fixed capital costs. This decision was made to reflect the actual spending made to support the service provision and is in accordance with past studies evaluating spatial distribution of public-transit subsidies (Börjesson et al., 2020; Hodge, 1988). As such, we opted to use a two-variable cost-allocation model, distributing labor costs (both drivers and overheard) based on operating hours and all other variable and semi-fixed costs based on vehicle kilometer (Table 1).

Table 1 STM operational cost breakdown for bus services in 2019 and 2022 in $1,000

Cost allocation method	Costs	2019	2022[1]
Operating hours	Labor	616,489	602,519
Vehicle kilometer	Energy, taxes and licenses	54,977	52,370
	Material and furniture	44,215	49,622
	Professional and technical services	17,359	19,469
	Renting	5,936	7,040
	Other operating expenses	31,688	24,587

[1]Adjusted for inflation to 2019 values (Statistics Canada, 2023b)

Using the GTFS feeds as an input in the *tidytransit* and *gtfstools* packages in R, we computed total operating hours and vehicle kilometers travelled per route per unique service days for all bus routes (n = 229 in 2019 and n = 216 in 2022). We then multiplied the frequency of each of these service days combinations in the calendar year and summed the products to arrive at the yearly operating hours and vehicle kilometers travelled per route. Lastly, we computed the annual figures for the entire network by summing across all routes. Using the operating costs in Table 1 and the network-level annual operating hours and vehicle kilometers travelled, we calculated an hourly and kilometer-based cost of service provision for 2019 and 2022.

It is important to note that our analysis focuses on average costs (i.e., costs across all service hours / vehicle kilometer travelled) and not marginal costs (i.e., costs of providing one more unit of service). While previous studies have highlighted the relevance of marginal costs and its variation with time of day (Bruun, 2005; Taylor et al., 2000), average cost approaches using vehicle hours and vehicle distance travelled remain relevant to assess network-level costs. To calculate average costs adequately, it is important to minimize variability in the service included in the cost allocation process (Bruun, 2005). To do so, we limited our analysis only to daytime, multi-stop bus service with data for both 2019 and 2022 (n =184), removing night buses (n =23) and shuttle services (n=5). While past research has highlighted that route characteristics such as topography, stop spacing and the type of vehicle used can have an incidence on overall energy consumption (Taylor et al., 2000), the later represent a small proportion of operating cost (less than 7%) and is therefore unlikely to significantly change the estimated costs.

2.2.1 Annual ridership

To calculate the annual ridership per line, we removed lines that were only in operation in one of the two years (n = 19) in addition to non-daytime, non-multi-stop routes (n=28) as previously mentioned. One last route was removed due to a lack of ridership data in 2022 resulting in a final sample of 184 bus routes.

Since the ridership data obtained from the transit agency were the average daily ridership for weekdays per service period, we had to estimate the ridership for the non-weekdays (i.e., weekends and holidays). To do so, we first calculated the ratio between weekdays daily operating hours and non-weekday daily operating hours per service period per route. We then calculated the ratio of passenger per hour of operation for weekdays, Saturdays and Sundays for each line using complementary APC data from the month of November 2022. This allowed for a more accurate estimation of weekend ridership than if an arbitrary ratio of weekday to weekend passenger/hour was employed. We calculated ridership for Saturdays and Sundays by multiplying average daily ridership figures by the ratios of daily operating hours and the ratios of weekday to weekend passenger per hour. Lastly, we summed annual ridership by multiplying the daily ridership calculated for each of the 40 unique service days by their respective frequency in the calendar year.

2.2.2 Average cost per rider per route

To obtain the cost per rider per route, we first multiplied the hourly and kilometer-based operating cost by the annual operating hours and annual vehicle kilometer travelled respectively to obtain the annual operating cost per route. We then divided the total annual operating cost by the annual ridership for each route to obtain the average cost per rider per route for both 2019 and 2022.

2.2.3 Route level characteristics

To link CT-level data from the 2021 census to the bus lines, we generated a 400-meter buffer around the stops of a line and intersected it with the CT shapefile in ArcGIS Pro. This distance was chosen based on previous research analyzing distance walking to different modes of public transit (El-Geneidy et al., 2014) while a buffer around stops rather than the line itself was selected to reflect the actual population served by the service as was done in previous studies (Lao & Liu, 2009). We then calculated a weighted average for each of the three variables of interest (population, jobs, and median household income) at the route-level based on the proportion of a CT's area falling within the buffer zone for a line. For the median household income, the weighting process was also done based on the number of households in each CT. To provide added detail on the routes in the analysis, we calculated complementary route-level descriptive statistics. Number of trips per day, average speed, route length, and connection to the metro were calculated using the GTFS feed whereas whether a line was serving the CBD (which serves as a key area of study later in the analysis) was calculated by intersecting each line with a shapefile of the CBD in ArcGIS Pro.

2.2.4 Analysis

To provide a consistent base of analysis throughout the paper, we decided to elaborate two categorization systems for bus routes based on (1) the household income of the areas they serve and (2) their level cost per rider. For the income-based categorization, we employed the route-level average household income to separate the 184 lines into three groups (Less than \$60,000, \$60,000-\$80,000, and \$80,000). Household income of the areas around each bus routes was used as detailed income data for users per routes was not yet available for the post-pandemic period. We recognize that the income of the areas served by a bus routes are not going to be the same as the income of its users, which are more likely to be of lower income, particularly post-COVID (Soria et al., 2023). Still, we employ the household income of areas served around the routes to represent who gains access due to that service, keeping in mind that increased accessibility does not mean increased usage. We elected to create manual thresholds based on the median household income for the entire study area (\$67,500) rather than terciles, to ease the interpretability of the results and isolate extreme values. Rounded values were employed to be coherent with the income categories provided in the Canadian Census.

Subsidy brackets were derived from the cost of a single ticket on the island of Montréal (\$3.50) to allow for meaningful interpretation. The single ticket fare was chosen rather than average revenue per trip (which accounts for the discounts provided by monthly passes and other non-single ticket fares) given the aggregated nature of the fare revenue data in Montréal, which does not allow to isolate the STM average fare revenue per user. We used \$3.50 per rider as a benchmark for minimal subsidy levels rather than no subsidy as we recognize that this value is higher than actual average fare revenue per rider. We then established an additional benchmark at \$7.00 per rider which represents a route with a 50% farebox recovery ratio (assuming a fare of

$3.50 per trip). This farebox recovery ratio was chosen based on previous research that reported a farebox recovery ratio of 56% for the STM in 2016 (Verbich et al., 2017) as well as estimations derived from the 2019 ARTM financial report, which led to a regional farebox recovery ratio of 41% (ARTM, 2019). Routes with a cost per rider below $3.50 were categorized as "*minimally subsidized*" while routes with a cost per rider between $3.51 and $7.00 were classified as "*moderately subsidized*". Lastly, routes with a cost per rider above $7.00 were categorized as "*heavily subsidized*".

3. RESULTS

Our analysis highlighted notable changes between 2019 and 2022 as reported in Table 2. The average cost per rider for the 184 bus lines analyzed increased by 40.1%, from $3.11 in 2019 to $4.36 in 2022 after adjusting for inflation. A high level of variability was observed between bus lines with cost per rider varying from $1.20 to $37.76 in 2019 while they ranged from $1.60 to $52.12. Such an increase in cost per rider can be partly explained by a 2.7% increase in hourly costs (i.e., labor costs), a 4.8% increase in cost per vehicle kilometer travelled (i.e., non-labor variable and semi-fixed costs) and a 30.1% decline in ridership between 2019 and 2022, which is many folds larger than the 5% decrease in operating hours due to service cuts.

Table 2 Service characteristics, cost allocation rates and cost per rider for 2019 and 2022

Service Characteristics[1]	**2019**	**2022**	**Change (%)**
Annual operating hours (1000h)	3,600	3,420	-5.0
Annual vehicle kilometer travelled (1000)	66,263	62,789	-5.2
Annual ridership (1000 trip)	246,153	172,479	-30.1
Cost allocation rates ($)[1]			
Hourly cost	163	167	2.7
Cost per kilometer	2.3	2.4	4.8
Cost per rider ($)[2]			
Average	3.11	4.53	40.1
Minimum	1.20	1.60	-
Maximum	37.76	52.12	-

[1]Statistics are for the entire STM bus network
[2]Statistics for the sample of 184 daytime, multi-stops STM bus routes

To illustrate the changes in cost per rider and the high variability between lines, we plotted each bus lines and colored them based on their cost per rider (Figure 2). In 2019, 37.5% of bus lines fell within the minimally subsidized ($0 - $3.50) bracket while 42.9% were moderately subsidized ($3.51 - $7.00). Minimally subsidized lines were concentrated in the center-east portion of the island where there are almost no CTs falling into the highest household income quartile while moderately subsidized lines were primarily in the center portion of the island. Contrastingly, the highly subsidized routes ($7.00 and above), which represent 19.6% of all routes in the sample, were concentrated in the two extremities of the island (primarily the west end were there is a concentration of higher income CTs). In 2022, the proportion of minimally subsidized lines fell to

18.5%. While these lines were mostly in the center-east region, as was the case in 2019, there was no longer a clear geographical cluster. There were the same number of moderately subsidized routes were more numerous (42.9%) in 2022 compared to 2019, although they were not the same routes and did not show any clear geographical clustering. Lastly, the proportion of highly subsidized lines increased to 38.6%, which translated in an expansion of the geographical clusters identified in 2019 and the addition of another cluster around the downtown core.

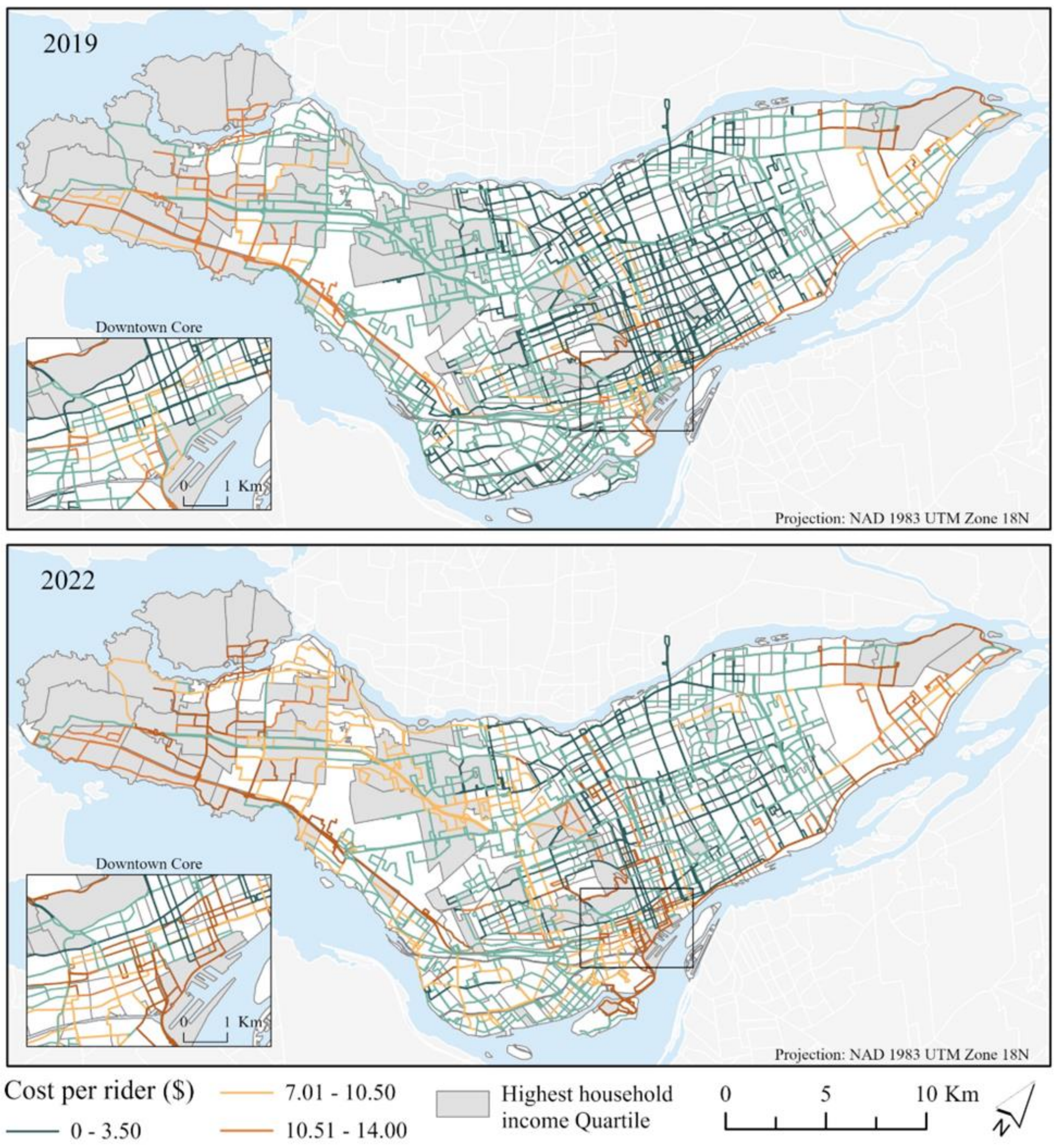

Figure 2 Cost per rider per STM bus routes for 2019 and 2022

To better understand the changes in the cost per rider per route, we mapped all bus lines and categorized them by the percentage change in cost per rider between 2019 to 2022 (Figure 3). The majority of bus lines (63.0%) saw an increase in cost per rider of less than 50%, including 16.8% that saw increases smaller than 25%. Another 19.0% of the bus lines saw an increase in cost per rider of 50 to 75% between 2019 and 2022. Still, none of these first three bracket formed discernible geographical patterns. Contrastingly, bus routes that increased by 75 to 100% (8.2%)

or by more than 100% (9.8%) were heavily clustered in the downtown area as well as in the areas directly to the north and south of it.

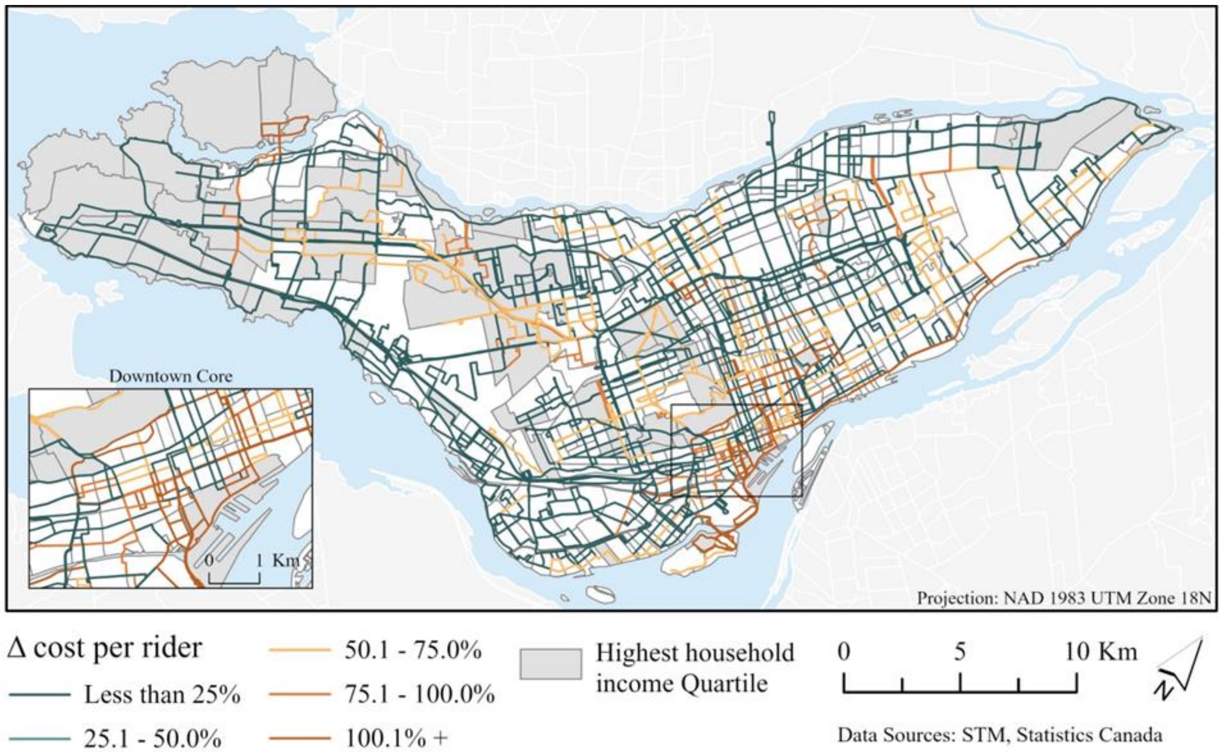

Figure 3 Change in cost per rider by bus routes between 2019 and 2022

3.1 Variation in cost per rider between income groups and subsidy levels

To analyze changes in cost per rider per route, and the variation in the level of subsidy based on the socio-economic context, we separated the studied routes in three groups according to the average household income of the CTs around their stops (Table 3). Most lines (62.5%) served, on average, middle income areas ($60,000 to $79,000) while a smaller proportion served lower income areas (17.9%) or higher income areas (19.6%). Routes serving lower income areas had the lowest cost per rider in 2019 at $2.22, followed by the middle-income routes at $3.10 and finally the higher income routes at $6.11. This gradient is also observable when looking at population and job density as routes serving lower income areas had higher population and job densities (8,816 people / km^2 and 4,943 jobs/km^2) than routes serving middle-income areas (5,919 people/km^2 and 2,382 jobs/km^2) and routes serving higher income areas (2,525 people / km^2 and 1,259 jobs/km^2). Routes serving lower income and middle-income areas had similar characteristics with 93.9% and 90.4% of these routes connecting to a Metro station respectively and with an average route length of 10.0 km for both groups. Routes serving higher income areas were notably different with only 44.4% of the routes connecting to the metro and an average route length of 16.9km.

Table 4 Descriptive statistics of bus routes grouped by the average household income of areas served

	All lines	Less than $60,000	$60,000 - $79,000	$80,000 and above
Number of lines	184	33	115	36
Average Cost per rider				
2019 ($)	3.11	2.22	3.10	6.11
2022 ($)	4.36	3.14	4.32	8.41
Change 2019 to 2022 (%)	40.1	41.4	39.4	37.6
Service characteristics				
2022 operating hours vs 2019 (%)	95.0	93.8	95.1	96.2
2022 ridership vs 2019 (%)	69.9	68.1	70.3	72.1
% of lines connecting to the metro	82.1	93.9	90.4	44.4
Average route length (km)	11.3	10.0	10.0	16.9
Land use characteristics				
Population density (habitants/km^2)	5,605	8,816	5,919	2,525
Job density (jobs/km^2)	2,554	4,943	2,382	1,259

While the routes serving lower income and middle-income areas experienced higher increases in their average cost per rider between 2019 and 2022 (41.4% and 39.4% respectively) than routes serving higher income areas (37.6%), this was not enough to close the existing gap in cost per rider. Indeed, the routes serving lower income areas still had the lowest average cost per rider in 2022 ($3.14) followed by the routes serving middle-income areas ($4.32) and the routes serving higher income areas ($8.41). The small convergence in cost per rider between the different groups could be attributed to differential changes in ridership and operating hours. Indeed, the routes serving lower income areas saw their ridership and operating hours drop the most in 2022 at 68.1% and 93.8% of 2019 levels respectively. Conversely, the routes serving higher income areas saw the least reductions in ridership and operating hours with 2022 levels at 72.1% and 96.2% of 2019 levels respectively.

To integrate the categorization based on the cost per rider (i.e., minimally, moderately and highly subsidized routes) and the average household income (less than $60,000, $60,000 - $79,999 and $80,000 and above) we plotted the cost per rider in 2022 against the cost per rider in 2019, categorizing each bus line based on the median household income of the areas surrounding its stops (Figure 4). We then added dotted lines to represent the benchmarks values of $3.50 and $7.00 differentiating between the three categories of subsidy and deriving four areas in the graph to group bus routes: (A) routes that were minimally subsidized in 2019 and 2022; (B) routes that were either minimally or moderately subsidized in 2019 and moderately subsidized in 2022; (C) routes that were either minimally or moderately subsidized in 2019 but highly subsidized in 2022; and (D) routes that were highly subsidized in 2019 and 2022. Lastly, while we delimited the graph's extent to $30.00 to facilitate visual interpretation, the two data points that were not represented in the graph were kept in the analysis.

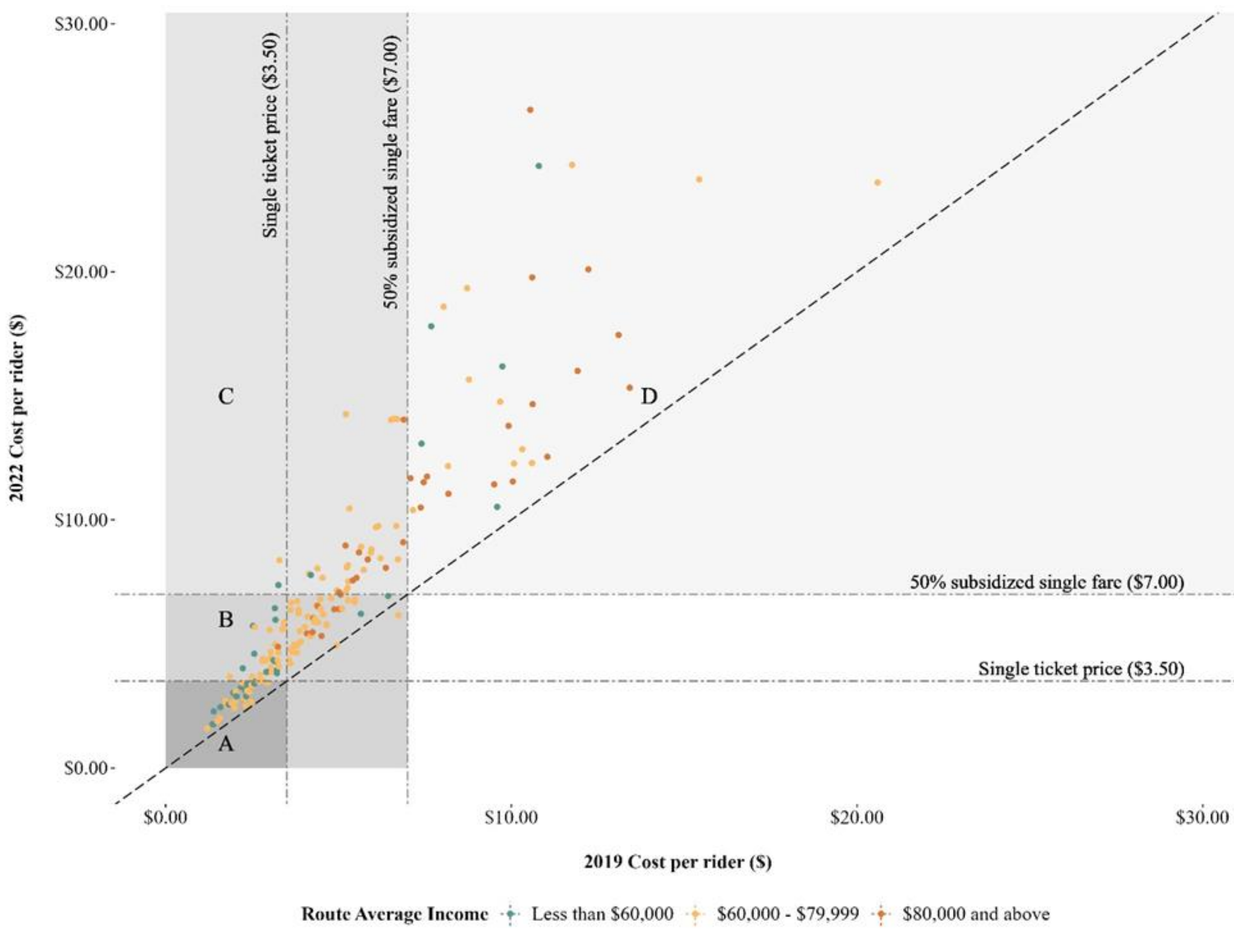

Figure 4 Cost per rider in 2019 and 2022 categorized by route household income level and separated by subsidy level

The distribution of the three different income brackets was not even between the four subsidy groups. No route serving areas with an average household income $80,000 and above was in group A while 39.4% of routes serving lower-income areas and 17.4% of routes serving middle-income areas were in that zone. Contrastingly, 50.0% of routes serving higher-income areas were in group D compared to only 15.2% of routes serving lower-income areas and 11.3% of routes serving middle-income areas. This observation is backed up by the difference in average household income between the groups, with bus routes in group A serving areas with an average household income of $61,300 compared to $64,900 for group B, $71,300 for group C and $71,400 for group D. Bus routes in group C saw the largest increase in cost per rider between 2019 and 2022 (49.8%). This can be explained primarily by the fact that these routes saw increase in operating hours between 2019 and 2022 of 0.8% (as opposed to service reductions on average for the other three groups) despite having the second lowest ridership recovery with 2022 numbers at 69.1% of 2019 levels. While bus routes in groups A and B represent respectively 32.6% and 43.6% of annual operating costs, routes in group C and D (11.8% and 12.0% of annual operating costs in 2022) represent better opportunities for service adjustment given their high level of subsidy per rider, low ridership and their higher prevalence serving wealthier areas (Table 5). That said, for the purpose of this paper we focus on bus routes in group D as these routes were consistently above the high subsidy threshold in 2019 and 2022.

Table 5 Descriptive statistics of bus routes by subsidy group

	All lines	A	B	C	D
Number of lines	184	33	83	32	36
Average Cost per rider					
2019 ($)	3.11	2.02	3.61	5.67	9.89
2022 ($)	4.36	2.7	5.06	8.5	13.69
Change 2019 to 2022 (%)	40.1	33.9	40.1	49.8	38.8
Service characteristics					
2022 operating costs ($1000)	715,434	232,882	312,214	84,422	85,916
Average number of runs per day	88	150	89	60	52
Average route length (km)	11.3	8.9	10.6	11.9	14.7
Average speed (km/h)	18.3	14	17.7	19.9	22.2
% of lines connecting to the metro	82.1	97.0	95.2	75	44.4
% of lines connecting to downtown	22.4	15.1	19.3	25	33.3
2022 operating hours vs 2019 (%)	95	89.1	98	100.8	97.4
2022 ridership vs 2019 (%)	69.9	68.4	71.9	69.1	72.9
Land use characteristics					
Population density (habitants/km^2)	5,605	7,983	5,917	4,446	3,881
Job density (jobs/km^2)	2,554	2,768	2,484	2,353	2,702
Route average household income ($)*	65,800	61,300	64,900	71,300	71,400

*Rounded to the nearest $100

Key characteristics of the bus routes in group A are that they were, on average, the most frequent (150 runs per day), the shortest in distance (8.9km), the most connected to the metro system (97.0%) and the routes serving the highest density areas (7,983 people/km^2). On the contrary, bus routes in group D were, on average, the least frequent (52 runs per day), the longest in distance (14.7km), the least connected to the metro system (44.4%) and the routes serving the lowest density areas (3,881 people / km^2). Bus routes in group B and C followed the same upward trend for route length and downward trend for connectivity with the metro system and population density. An interesting outlying variable to this trend is job density, which is the second highest for routes in group D (2,702 jobs/km^2) after group A (2,768 jobs/km^2). This coincides with group D having the highest share of routes crossing the downtown area (33.3%) where most jobs are located.

3.1.1 Highly subsidized routes in 2019 and 2022 (Group D)

To understand more in-depth elements that contribute to the high cost per rider of routes in group D, we mapped them using the same income-based categories used previously (Figure 5). Bus routes highlighted as being highly subsidized in 2019 and 2022 display the same geographical patterns as highly subsidized routes in Figure 1; they are for the most part clustered in the two extremities of the island as well as in the downtown core. As previously mentioned, 12 out of 36 routes (33.3%) in this group cross the CBD which includes four routes providing local service within downtown, one route providing a local service primarily on the outskirt of downtown and seven express routes to downtown coming from inner and outer suburbs.

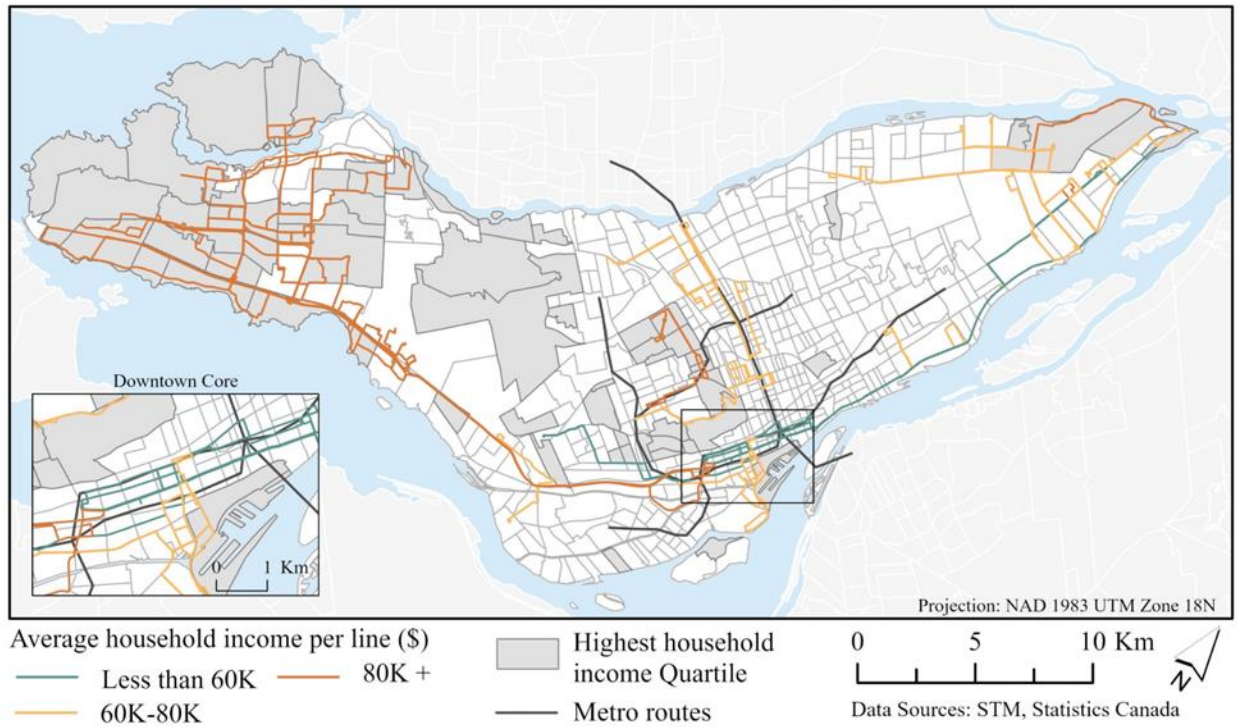

Figure 5 Highly subsidized routes in both 2019 and 2022 categorized by the average household income of the areas they serve

All routes serving low-income areas (n=5) passed through downtown, with two being local routes and three being express routes. The two local routes and two out of three express routes served corridors parallel with the Metro system. Contrastingly, all but two of the 18 routes serving higher income areas in this group served the west end of the Montréal Island. Out of these 12 routes, four served as express routes while eight provided local service.

Bus routes serving middle income areas in this group were the most dispersed. Three served local service within the east end of the island and were not connected to the Metro system. Three served low-density destinations (e.g., parks, industrial sectors). Another two provided local service in the downtown core. Of the last four routes, two provided service parallelly to a metro line while the other two provided meandering service connected at one end to the metro.

Overall, routes that were highly subsidized in both 2019 and 2022 tend to either provide (1) local service within suburban areas, (2) local service within the downtown core, (3) express service from suburban areas to downtown, (4) local service to low density destinations (e.g., large park, sport center, industrial areas), and/or (5) service parallel to the metro. A lack of connections to the metro, or connections solely downtown rather than to more peripheral stations were also common.

4. DISCUSSION

The effect of the COVID-19 pandemic on travel behaviour and public-transit service provision has been well documented (Huang et al., 2023). Yet, little is known about its impact on the distribution of subsidies within public-transit networks. In parallel, minimal research has assessed the spatial distribution of public-transit cost and subsidies between service lines (Mallett, 2023). These combined temporal and spatial effects are crucial to understand within the context of growing operational deficits faced by several public-transit agencies following the end of pandemic relief funds. Identifying bus routes that benefit from higher levels of subsidy and what are their key characteristics will allow for an equitable optimization of current services to reduce deficits without leading to massive ridership loss. This is particularly true when considering the flexibility that bus services offer in terms of route design and its high operating cost per rider compared to most established metro systems (Zhang, 2009) as is the case in Montreal. Our analysis adds to previous studies assessing cost per rider and transit subsidies at the individual level (Börjesson et al., 2020; Hodge, 1988) as well as the currently limited scholarship on the spatial distribution of operating costs (Mallett, 2023) by adapting considering temporal (before the pandemic and after the pandemic and after a first round of service cuts) and spatial variations in cost per rider at the route level for a large sample of bus routes.

Our analysis first underscores an increase in the average cost of bus service provision (both by operating hour and by vehicle kilometers travelled) between 2019 and 2022 even when accounting for inflation. This increase could be linked to the increased share of subsidies received during the pandemic as public-transit subsidies have been shown to have inflationary effects on average costs of service provision (e.g., Gupta & Mukherjee, 2013). In the context of the pandemic, the reluctance observed in some transit agencies to let go of employees or drastically cut working hours during the pandemic (King et al., 2023) combined with service cuts could have led to an increase in the ratio of payroll spending per hours of service offered. This could therefore explain the observed increase in average cost, although additional research specifically on the effects of pandemic subsidies to public-transit agencies on operating costs would be needed to demonstrate causation.

Looking at the geographical distribution of route-level cost per rider in 2019 and 2022, we observed clusters of highly subsidized bus routes in suburban and peripheral areas, as was the case in previous studies (Börjesson et al., 2020; Hodge, 1988). On the other hand, the cluster of highly subsidized bus routes observed in the downtown core presents a novel finding. The high level of subsidy for bus routes serving primarily the downtown core is compounded by several factors. First, most of the bus routes in the downtown core are offering service parallel to two already parallel metro lines. Secondly, there are no permanent reserved lanes in the downtown core and limited peak-hours reserved lanes meaning that buses are stuck in traffic and service is slower. As such, it is simply faster for many users to use the metro system or walk rather than take local bus services in the downtown core. The disproportionate increase in cost per rider observed between 2019 and 2022 in the downtown core could also be attributed to a slow return to office of downtown workers due to the uptake of telecommuting and hybrid work as has been observed throughout North America (Leong et al., 2023). This disproportionate increase in subsidy levels further emphasize the need to reassess the pertinence of redundant bus routes in downtown cores, especially in cities that are already well served by rail transit. Understanding whether such service increase vertical equity is crucial to propose adequate adjustments be it either on the basis of increased efficiency or furthering existing equity goals.

Our analysis allowed us to compare cost per rider between bus routes serving areas of different socio-economic status, highlighting that routes serving higher-income areas tended to have higher cost per rider on average than those serving medium- and lower-income areas. This entails that residents of higher-income areas benefit from higher levels of subsidies to increase their accessibility to opportunities by public-transit. Similarly, businesses in higher income areas benefit from the higher level of subsidy for bus services as they allow them to have increased accessibility to transit-dependent labor from other parts of the region. Still, these findings are compounded by lower residential and job densities in higher income areas, and vice-versa for low-income areas, thus limiting the ability to attribute the subsidy differential solely to differences in socioeconomic conditions. Additionally, as pointed out by Hodge (1988) and Iseki (2016), people living in higher income, lower density suburban neighborhoods tend to pay more in property taxes, thus outweighing partly their higher level of subsidy. However, public-transit in many North American cities, including Montreal, is not primarily funded by municipal taxes with several regions being funded through sales tax and provincial / state-level revenues to a greater extent. Overall, the financially inefficient service in high income areas point to a need to redesign these routes, carefully integrating desired destinations of local residents and of current users of the routes to ensure services correspond to local needs.

4.1 Limitations

As with every study, there are some limitations to our approach. First, while more complicated cost allocation models exist (Bruun, 2005; Mallett, 2023; Taylor et al., 2000), we opted to use a simpler one focused on the two principle variables used in cost allocation models for variables and semi-fixed costs (Cherwony & Mundle, 1980; Taylor et al., 2000): vehicle operating hours and vehicle distance travelled. This decision was made based on the level of detail available in the financial data used in the analysis but also based on the exclusion of fixed costs which are often allocated based on peak vehicles. While some level of precision will have been lost from the usage of only these two variables as opposed to more elaborate cost allocation models, the larger-scale spatial (i.e., route-level) and temporal (i.e., year-level) of the analysis allows to minimize the effects of this uncertainty on the study’s main findings.

Secondly, we used the price of a single ticket to set our subsidy categories meaning that we were limited to discussing minimally subsidized routes rather than profitable routes to avoid over-stating the ability of bus routes to be profitable. Furthermore, our analysis does not include individualized fare revenues per route due to the difficulty in acquiring complete data on the distribution of fare types amongst users of a route. This means that the variability in subsidies between each line is likely reduced in our analysis, placing our estimates of subsidy on the conservative side. To continue, aggregation of the analysis at the year level might have masked seasonal patterns that could be of relevance for service optimization. Additional research would be necessary to assess change in cost per rider for a bus route within a calendar year.

Lastly, bus routes are likely to serve areas with varying household income levels which is not captured in an average, route-level, value. To study more closely the relationship between household income and subsidy levels, future research could (1) categorize lines based on the socio-economic homogeneity / heterogeneity of the areas served or (2) separate bus route in segments comprised in between stops to allow for a more granular analysis. The latter approach could also allow for a more granular evaluation of the spatial distribution of cost per rider, building upon the work of Mallett (2023) on rail service. In terms of application in practice, the methods and results highlighted in this paper should not substitute disaggregated socio-demographic analyses, particularly of users, when studying service changes. Beyond cost efficiency, equity should also be a key objective of public-transit service provision.

5. CONCLUSION

Despite these limitations, our analysis provides key insights that can be levied when aiming to optimize public-transit service in the context of rising budget shortfalls. First, employing a route-level analysis allows for a better evaluation of the cost efficiency of the service provided at the system-level. Highlighting expensive routes and who they serve is crucial in efficient and equitable service adjustments. Secondly, looking at multiple years allows us to evaluate changes over time. This temporal approach could be useful to evaluate the effects of route redesign on average cost per rider and subsidy levels, particularly if combined with a link-level spatial breakdown of each route. Our findings further highlight how some routes are inherently inefficient due to their design and that such realities only worsened with the COVID-19 pandemic. To address these issues, we suggest that these routes be either modified in terms of alignment, and frequency to better respond to needs without wasting scarce financial resources. In some cases, if it is chosen to maintain high-subsidy routes in high-income areas, it might be necessary to levy property tax increases, although the implications of such policy would need to be further assessed before implementation to prevent unintended secondary effects. In all cases, any service cuts or taxation increase implemented to balance public-transit agencies' budget need to be driven not only by the principle of cost efficiency but also social equity. Understanding when to assess a public-transit route based on one or the other is heavily dependent on the intent behind the service, be it to serve the larger number of users or to provide service to underserved communities.

ACKNOWLEDGEMENTS

We would like to thank the STM for providing access to their ridership data. This paper draws on research supported by the Social Sciences and Humanities Research Council of Canada (SSHRC) Canada Graduate Scholarship Doctoral Program (CGS-D).

AUTHORS CONTRIBUTION

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

REFERENCES

ARTM. (2019). *Rapport annuel 2019*. https://www.artm.quebec/wp-content/uploads/2020/06/RP_Rapport-annuel-2019_ARTM_2020-06-01-2.pdf

Avenali, A., Catalano, G., D'Alfonso, T., & Matteucci, G. (2020). The allocation of national public resources in the Italian local public bus transport sector [Article]. *Research in Transportation Economics*, *81*, Article 100822. https://doi.org/10.1016/j.retrec.2020.100822

Börjesson, M., Eliasson, J., & Rubensson, I. (2020). Distributional effects of public transport subsidies. *Journal of Transport Geography*, *84*, 102674.

Bruun, E. (2005). Bus rapid transit and light rail: Comparing operating costs with a parametric cost model. *Transportation Research Record*, *1927*(1), 11-21. https://doi.org/10.1177/0361198105192700102

Cervero, R. (1981). Flat versus differentiated transit pricing: What's a fair fare? *Transportation*, *10*(3), 211-232. https://doi.org/10.1007/BF00148459

Cherwony, W., & Mundle, S. (1980). Transit cost allocation model development. *Transportation Engineering Journal of ASCE*, *106*(1), 31-42.

DeWeese, J., Hawa, L., Demyk, H., Davey, Z., Belikow, A., & El-Geneidy, A. (2020). A tale of 40 cities: A preliminary analysis of equity impacts of COVID-19 service adjustments across North America. *Findings*.

El-Geneidy, A., Grimsrud, M., Wasfi, R., Tétreault, P., & Surprenant-Legault, J. (2014). New evidence on walking distances to transit stops: Identifying redundancies and gaps using variable service areas. *Transportation*, *41*(1), 193-210.

Erhardt, G., Hoque, J., Goyal, V., Berrebi, S., Brakewood, C., & Watkins, K. (2022). Why has public transit ridership declined in the United States? *Transportation Research Part A: Policy and Practice*, *161*, 68-87. https://doi.org/https://doi.org/10.1016/j.tra.2022.04.006

Fernández Pozo, R., Wilby, M., Vinagre Díaz, J., & Rodríguez González, A. (2022). Data-driven analysis of the impact of COVID-19 on Madrid's public transport during each phase of the pandemic. *Cities*, *127*, 103723. https://doi.org/https://doi.org/10.1016/j.cities.2022.103723

Gupta, S., & Mukherjee, A. (2013). Utilization of passenger transport subsidy in Kolkata: A case study of Calcutta State Transport Corporation. *Research in Transportation Economics*, *38*(1), 3-10. https://doi.org/https://doi.org/10.1016/j.retrec.2012.05.011

He, Q., Rowangould, D., Karner, A., Palm, M., & LaRue, S. (2022). Covid-19 pandemic impacts on essential transit riders: Findings from a U.S. Survey. *Transportation Research Part D: Transport and Environment*, *105*, 103217. https://doi.org/https://doi.org/10.1016/j.trd.2022.103217

Hodge, D. C. (1988). Fiscal Equity in Urban Mass Transit Systems: A Geographic Analysis. *Annals of the Association of American Geographers*, *78*(2), 288-306. https://doi.org/10.1111/j.1467-8306.1988.tb00208.x

Huang, Z., Loo, B., & Axhausen, K. (2023). Travel behaviour changes under Work-from-home (WFH) arrangements during COVID-19. *Travel Behaviour and Society*, *30*, 202-211. https://doi.org/https://doi.org/10.1016/j.tbs.2022.09.006

Interline Technologies. *Transitland*. Retrieved 2023 from https://www.transit.land/

Iseki, H. (2016). Equity in regional public transit finance: Tradeoffs between social and geographic equity [Article]. *Journal of Urban Planning and Development*, *142*(4), Article 04016010. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000328

Jenelius, E., & Cebecauer, M. (2020). Impacts of COVID-19 on public transport ridership in Sweden: Analysis of ticket validations, sales and passenger counts. *Transportation research interdisciplinary perspectives*, *8*, 100242. https://doi.org/https://doi.org/10.1016/j.trip.2020.100242

Kar, A., Carrel, A., Miller, H., & Le, H. (2022). Public transit cuts during COVID-19 compound social vulnerability in 22 US cities. *Transportation Research Part D: Transport and Environment*, *110*, 103435. https://doi.org/https://doi.org/10.1016/j.trd.2022.103435

Karlaftis, M. G., & McCarthy, P. (1998). Operating subsidies and performance in public transit: An empirical study [Article]. *Transportation Research Part A: Policy and Practice*, *32*(5), 359-375. https://doi.org/10.1016/S0965-8564(98)00002-0

Karner, A., LaRue, S., Klumpenhouwer, W., & Rowangould, D. (2023). Evaluating public transit agency responses to the Covid-19 pandemic in seven U.S. regions. *Case Studies on Transport Policy*, *12*, 100989. https://doi.org/https://doi.org/10.1016/j.cstp.2023.100989

King, H., Wasserman, J., & Taylor, B. (2023). Terra Incognita: California Transit Agency Perspectives on Demand, Service, and Finance in the Age of COVID-19 [Article]. *Transportation Research Record*. https://doi.org/10.1177/03611981231182963

Lao, Y., & Liu, L. (2009). Performance evaluation of bus lines with data envelopment analysis and geographic information systems. *Computers, Environment and Urban Systems*, *33*(4), 247-255. https://doi.org/10.1016/j.compenvurbsys.2009.01.005

Leong, M., Huang, D., Moore, H., Chapple, K., Schmahmann, L., Wang, J., & Allavarpu, N. (2023). Can we save the downtown? Examining pandemic recovery trajectories across 62 North American cities. *Cities*, *143*, 104588. https://doi.org/https://doi.org/10.1016/j.cities.2023.104588

Luo, Q., Bing, X., Jia, H., & Song, J. (2022). An incentive subsidy mechanism for bus lines based on service level [Article]. *Transport Policy*, *126*, 1-13. https://doi.org/10.1016/j.tranpol.2022.07.006

Mallett, Z. (2023). Spatial and Temporal Variability of Rail Transit Costs and Cost Effectiveness. *Transportation Research Record*, *2677*(1), 1444-1460. https://doi.org/10.1177/03611981221104807

Palm, M., Allen, J., Zhang, Y., Tiznado-Aitken, I., Batomen, B., Farber, S., & Widener, M. (2024). Facing the future of transit ridership: shifting attitudes towards public transit and auto ownership among transit riders during COVID-19. *Transportation*, *51*(2), 645-671. https://doi.org/10.1007/s11116-022-10344-2

Parker, M., Li, M., Bouzaghrane, M., Obeid, H., Hayes, D., Frick, K., Rodríguez, D., Sengupta, R., Walker, J., & Chatman, D. (2021). Public transit use in the United States in the era of COVID-19: Transit riders' travel behavior in the COVID-19 impact and recovery period. *Transport Policy*, *111*, 53-62. https://doi.org/https://doi.org/10.1016/j.tranpol.2021.07.005

Paul, J., & Taylor, B. (2024). Pandemic transit: examining transit use changes and equity implications in Boston, Houston, and Los Angeles. *Transportation*, *51*(2), 615-643. https://doi.org/10.1007/s11116-022-10345-1

Qi, Y., Liu, J., Tao, T., & Zhao, Q. (2023). Impacts of COVID-19 on public transit ridership. *International Journal of Transportation Science and Technology*, *12*(1), 34-45. https://doi.org/https://doi.org/10.1016/j.ijtst.2021.11.003

Siddiq, F., Wasserman, J., Taylor, B., & Speroni, S. (2023). Transit's Financial Prognosis: Findings from a Survey of U.S. Transit Systems during the COVID-19 Pandemic [Article]. *Public Works Management and Policy*, *28*(4), 393-415. https://doi.org/10.1177/1087724X231160097

Simons, R., Henning, M., Poeske, A., Trier, M., & Conrad, K. (2021). Covid-19 and its effect on trip mode and destination decisions of transit riders: Experience from Ohio. *Transportation research interdisciplinary perspectives*, *11*, 100417. https://doi.org/https://doi.org/10.1016/j.trip.2021.100417

Société de Transport de Montréal. (2018). *Budget 2018*.

Soria, J., Edward, D., & Stathopoulos, A. (2023). Requiem for transit ridership? An examination of who abandoned, who will return, and who will ride more with mobility as a service. *Transport Policy*, *134*, 139-154. https://doi.org/https://doi.org/10.1016/j.tranpol.2023.02.016

Statistics Canada. (2023a). *2021 Census of Population. Statistics Canada Catalogue number 98-316-X2021001.*

Statistics Canada. (2023b). *Consumer Price Index, monthly, not seasonally adjusted. Statistics Canada Catalogue number 18-10-0004-01.*

STM. (2019). *Budget 2019*.

STM. (2022). *Budget 2022*.

Sträuli, L., Tuvikene, T., Weicker, T., Kębłowski, W., Sgibnev, W., Timko, P., & Finbom, M. (2022). Beyond fear and abandonment: Public transport resilience during the COVID-19 pandemic. *Transportation research interdisciplinary perspectives*, *16*, 100711. https://doi.org/https://doi.org/10.1016/j.trip.2022.100711

Sun, Y., Guo, Q., Schonfeld, P., & Li, Z. (2016). Implications of the cost of public funds in public transit subsidization and regulation [Article]. *Transportation Research Part A: Policy and Practice*, *91*, 236-250. https://doi.org/10.1016/j.tra.2016.06.029

Taylor, B. D., Garrett, M., & Iseki, H. (2000). Measuring cost variability in provision of transit service. In *Transportation Research Record* (pp. 101-112).

Verbich, D., Badami, M. G., & El-Geneidy, A. (2017). Bang for the buck: Toward a rapid assessment of urban public transit from multiple perspectives in North America. *Transport Policy*, *55*, 51-61. https://doi.org/https://doi.org/10.1016/j.tranpol.2016.12.002

Zhang, M. (2009). Bus versus rail: Meta-analysis of cost characteristics, carrying capacities, and land use impacts. *Transportation Research Record*, *2110*(1), 87-95. https://doi.org/10.3141/2110-11