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Measuring the impacts of new Bus Rapid Transit (BRT) on quality of life and cost concerns: A natural experiment in Montréal, Canada

Rodrigo Victoriano-Habit [a,1], Ahmed El-Geneidy [b,*,2]

[a] Department of Civil Engineering, Universidad de Concepción, Chile
[b] School of Urban Planning, McGill University, Canada

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ABSTRACT

Investments in major infrastructure projects such as Bus Rapid Transit systems (BRT) may be accompanied by fears of gentrification and displacing residents. The fear of being priced out of a neighborhood can cause mental stress to those residing near the new infrastructure, which can have significant impacts on their well-being. The main goal of this paper is to evaluate the perceived impacts of a new BRT system on residents' perception of quality of life and increasing costs of living in Montréal, Canada. We employ a natural experiment design to analyze these impacts while controlling for potential biases due to changing trends over time. We use a panel dataset at three points in time: before the BRT opening (2019–2021), right after its opening (2022), and one year after its opening (2023). This design allowed us to measure the persistence of residents' perceptions over time with respect to a control group not living near the BRT. Our findings show that the new BRT system had a positive impact on residents living within a 0.5 km radius of newly opened stations. This positive impact became stronger after one year of operation. Additionally, we found that the BRT resulted in increased concerns about rising costs of living right after inauguration. However, this perception disappeared after one year of operation. The findings in this paper provide relevant insights supporting future BRT implementation, as they suggest long-lasting perceived benefits of a BRT and short-lived concerns and stress.

1. Introduction

Investments in large-scale public transport projects such as Light Rail (LRT) or Bus Rapid Transit (BRT) are usually accompanied with changes in the urban environment, which can lead to gentrification and displacements around the new stations (Bardaka et al., 2018; Delmelle, 2021). Recent studies have shown that areas around some newly-implemented BRT stations in North and South America have seen an influx in movements of higher income residents (Brown, 2016; Heres et al., 2014). BRT systems are usually accompanied by reductions in travel time and increases in reliability of transit service (Hoang-Tung et al., 2021; Venter et al., 2018), making the area around stations attractive to public transit users. Such attraction can be a cause of mental stress to current residents as

* Corresponding author.
E-mail addresses: rvictoriano@udec.cl (R. Victoriano-Habit), ahmed.elgeneidy@mcgill.ca (A. El-Geneidy).
[1] Orcid: 0000-0001-6328-0722.
[2] Orcid: 0000-0002-0942-4016.

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the anticipated increase in demand for housing typically leads to higher land values and rents (Stokenberga, 2014). As several BRT systems are currently under development in North American regions, it is important to understand potential impacts, both positive and negative, on residents near future projects. Understanding the impacts of such projects on neighboring residents' quality of life and potential financial concerns is essential to guide future policies to mitigate the negative impacts that might accompany BRT projects.

In November 2022, Montréal, QC, Canada inaugurated the Pie-IX BRT, a new 14-station system connecting several low-income areas to the city's metro system (STM, 2024). This new BRT implementation represents an opportunity to study its immediate effects on neighboring residents' perceptions. In this context, the main goal of this paper is to evaluate the perceived impacts of the new Pie-IX BRT system on residents' perception on two key dimensions: quality of life and concerns of rising costs of living.

To achieve this work's objective, we employ a natural-experiment design. That is, a before-and-after treatment/control design using a difference-in-differences modelling approach. This robust design controls for potential spatial and temporal biases, allowing for an effective isolation of the new BRT system's effects on neighboring residents' perceptions. Moreover, we use a panel dataset that not only collected perceptions before inauguration (2019–2021, N = 175), but also at two points in time after inauguration: right after implementation (2022, N = 322), and one year after implementation (2023, N = 401). Thus, this study design allowed us to measure if residents' perceptions immediately after inauguration persisted after one year of the system's operation. Furthermore, by implementing two treatment categories based on distance from home to closest station (<0.5 km and 0.5 to 1.0 km), we analyzed the spatial extent of the new BRT's impacts. The findings in this paper provide relevant insights supporting future BRT implementation, which can be of interest to transport professionals working towards building new BRT systems.

2. Literature review

2.1. Impacts of BRT systems

The implementation of BRT systems has consistently shown a diversity of impacts on residents and urban environments in general (Wirasinghe et al., 2013). Commonly cited positive impacts include reducing travel times, (Deng & Nelson, 2011; Hoang-Tung et al., 2021; Venter et al., 2017), increasing performance and reliability (Deng & Nelson, 2011; Hoang-Tung et al., 2021), and improving accessibility by public transport (Pereira, 2019; Singh et al., 2022). However, not all impacts of new BRT systems have been shown to be positive. For example, studies of Bogotá's TransMilenio system have shown that proximity to BRT stations can significantly increase property values and rents, reflecting the capitalization of improved accessibility into land markets (Rodriguez & Mojica, 2009; Rodriguez & Targa, 2004). In some cases, BRT projects have shown to lead to gentrification and displacement due to increase in attractiveness of the land around stations (Brown, 2016; Heres et al., 2014; Qi, 2023). These negative impacts can be a source of major mental stress to residents causing issues of wellbeing (Friedline et al., 2021; Sweet et al., 2013).

A recent study on the wider population did not find any conclusive evidence that BRT may positively or negatively affect perceived wellbeing (Lionjanga & Venter, 2018). Accordingly, studying the impacts of BRT on wellbeing and the cost of living among residents living near the station is important to understand if there is a need for policies to protect them from these life stressors.

2.2. Measuring transport-intervention impacts

Studying the impacts of changes in urban systems calls for methodologies that adapt in complexity to the problem (Humphreys et al., 2016). Panel data, understood as that composed by repeated observations of the same subjects in time, has been at the center of the conversation in order to unravel this complexity (Kitamura, 1990; Mokhtarian & Cao, 2008; van de Coevering et al., 2015). To fully unravel the impacts of urban-transport interventions through panel data, before-and-after methodologies that control for confounding effects represent one way to solidly establish causality.

Research designs that borrow aspects from experimental designs have been gaining importance in travel-behavior research (van de Coevering et al., 2015). In particular, natural experiments, a type of research design that borrows the treatment/control design from randomized controlled trials, have gained popularity in analyzing the effects of large public-policy and built-environment changes (Bauman et al., 2014; Crane et al., 2020). This is because large transport infrastructure, such as a new BRT system, cannot be practically or ethically applied randomly with research purposes (Ogilvie et al., 2020).

In this context, many studies have measured the impacts of large transport infrastructure on multiple aspects through natural experiments. These include measuring the impact of new projects on mode choice (Heinen et al., 2017; Joseph et al., 2022; Sun et al., 2020), travel frequency (Song et al., 2023), Vehicle-Miles Travelled (VMT) (Spears et al., 2017; Widita et al., 2021), greenhouse gas emissions (Boarnet et al., 2016), land-use changes (Funderburg et al., 2010), physical-activity levels (McCormack et al., 2021), and perceived quality of life (Lanzendorf et al., 2022). Most importantly, these impacts of transport projects measured through natural experiment designs control for biases that may be introduced both by temporal trends or by differences between treatment/control groups (Humphreys et al., 2016).

With a correct study design, natural experiments can provide additional temporal and spatial insights about transport treatment effects. When an intervention is introduced, time-lagged effects may exist in perceptions and behavior (Chang et al., 2010). Employing data with three or more waves can unravel these temporal insights. For instance, Spears et al. (2017) use three waves of panel data to find interesting temporal effects of a new Light Rail Transit (LRT) in Los Angeles, California. They achieve this by estimating two models, one comparing their first two waves, and another comparing first and last. Through this, they were able to determine that a new LRT line reduced the VMT of residents living close to new stations, and that this effect was larger 18 months after the intervention compared to six months after. With similar research designs, other studies have also presented interesting time-lagged effects

(Chatterjee & Ma, 2007, 2009; Heinen et al., 2017).

In a similar manner, by defining different treatments groups based on distance to the intervention, these studies provide insight into the spatial extent of the impacts that transport projects have. This differentiation is sometimes called high- and low-dose treatments, in analogy to health studies. Examples of natural experiments using this framework for studying transport projects are those by Sun et al. (2020) and Aldred et al. (2019), both of which analyze different treatment effects based on concentric groups from an intervention.

Most studies using robust natural experiment designs to measure the impact of new BRT focus on physical-health outcomes (Li et al., 2023; McCormack et al., 2021). Few studies have used these methods to focus on other potential impacts of BRT (Joseph et al., 2022; Song et al., 2023). However, to our knowledge, no studies have used this type of study design to analyze the impacts of new BRT on the two main outcomes of this study: perceived quality of life and concerns about rising cost of living.

3. Data

3.1. Panel dataset

The primary dataset of this study is composed of a subset of responses from the first four waves of the Montréal Mobility Survey (MMS) (Negm et al., 2023). This survey collected both cross-sectional (one-time) responses and panel (repeated) responses from participants. This work exclusively uses a subset of panel responses from this survey. This panel dataset is collected through an online bilingual survey administered in the Greater Montréal Area to participants aged 18 years or older.

To ensure sample representativeness, various recruitment techniques recommended by Dillman et al. (2014) were employed in all waves of the MMS. These included the distribution of flyers at various residences and downtown transport hubs, as well as targeted online recruitment through paid and un-paid advertisements on various social media platforms. Incentives were included in the survey such as the possibility of winning a prize based on a draw. A public opinion survey company was also hired in all four waves to help in recruiting part of the sample. All survey respondents who provided an email address received an invitation to participate in subsequent waves. Through this process, the MMS sample in each wave, except wave 1, was composed of respondents who participated in two or more waves (panel) or newly recruited respondents (cross-sectional).

The same data-cleaning process was applied to all waves of the survey to ensure consistency in the exclusion criteria of unreliable responses. These exclusion criteria included removing multiple responses entered by the same e-mail or IP address, and invalid age and height changes between waves. In terms of survey-response time, the fastest 5% were excluded from the sample depending on the number of questions answered in each wave. Different groups of respondents, depending on their answers, got different sets of questions. Each of these groups were cleaned according to their own respective top 5% speed. Those who placed a pin representing their home, school and/or work location outside the Montréal metropolitan region were also excluded. The goal of the MMS survey was to collect travel behavior, attitudes towards new projects in the region, socioeconomic information, and physical activity and well-being. At the time of collecting wave 1, Montréal had several new projects being built.

The first two waves of the survey collected data prior to the inauguration of the Pie-IX BRT: 3,520 valid responses during the fall of 2019 and 4,058 valid responses during the fall of 2021. The third wave collected 4,065 valid responses during the fall of 2022, between one week and one month after the BRT's start of operations. Finally, the fourth wave collected 5,312 valid responses in the fall of 2023, one year after implementation. These sample sizes per wave include both respondents who participated once (cross-sectional) and those participating multiple times (panel).

To implement a natural experiment framework, this work only analyzes responses from panel participants who answered at least two waves and did not move their residence between waves. Moreover, to apply the treatment/control design in this study, only participants residing around the BRT (treatment) and from neighboring areas (control) were selected for this study. This resulted in a final panel sample size of 175 respondents pre-implementation (2019/2021), 322 respondents right after inauguration (2022), and 401 respondents one year after inauguration of the Pie-IX BRT (2023). It is important to note that sample sizes vary over time due to the fact that all participants who answered at least two waves are being considered for analysis, despite the fact that the study spans three points in time. That is, many respondents with different combinations of wave participations are being considered for the study.

All waves of the survey included the same questions pertaining to perceptions of changes in their neighborhood. The questions did not specify if the respondent thought these changes were related to the BRT or not, these were general questions. Specifically, this work focuses on analyzing agreement with the following two statements:

- *Quality of life:* "The changes in my neighborhood are improving my quality of life".
- *Cost concerns:* "I am concerned about whether I will be able to remain in my neighborhood because of rising costs".

These questions were valued by respondents on a five-level Likert scale (strongly disagree to strongly agree), which for modelling were later converted to a binary (agree and strongly agree coded as 1, other alternatives coded as zero). This simplification allows for more direct communication of results. Importantly, with this simplification, overall conclusions tend to be consistent with analyses using the full ordered responses (Bender & Grouven, 1998). This process of binarization of Likert-scale within survey-data analysis has been employed previously in the literature (La Parra-Casado et al., 2017; Wolde et al., 2025), including in the transport research field (Alousi-Jones & El-Geneidy, 2025; Marazi et al., 2022; Negm et al., 2024; Pathan & Landge, 2025), as it offers advantages in interpretability and model building (Bender & Grouven, 1998).

Respondents' sociodemographic characteristics were collected in all waves. This included participants' residential location, which was provided either as the postal code of the home location or through placing a pin on a map. Since Canadian postal code is defined at the block-level, centroids are generally precise to within 100 m of the true home location. Because this work uses a before-and-after framework of neighborhood impacts, only respondents who did not move home between waves were analyzed. Respondents were deemed to have moved between waves either if their postal code changed or if their home pin changed by a distance larger than 200 m. Most importantly, since every question was answered by participants at multiple points in time, changes in all variables can be measured through time. Further information on the Montréal Mobility Survey, its collection, data cleaning, and description can be found in the report by Negm et al. (2023).

4. The Pie-IX BRT and study area

In November 2022, the first stage of the new Pie-IX Bus Rapid Transit (BRT) was inaugurated in Montréal, Canada. With an investment of $523 M CAD, this first stage contemplated 14 stations along a 13-km corridor within the Pie-IX Boulevard, located in the East side of Montréal Island (Lacerte-Gauthier, 2022). One bus line runs along the BRT corridor, STM bus route 439, connecting residents to the existing metro system (STM, 2024).

The corridor crosses multiple areas where low-income households are predominant, and where immigrant and visible-minority populations (defined by Statistics Canada as "persons, other than Aboriginal peoples, who are non-Caucasian in race or non-white in colour") are more prevalent than in the rest of the island of Montréal (Statistics Canada, 2016). As seen in Fig. 1, the study area extends up to 3 km on each side of the Pie-IX Boulevard. Within this study area, two concentric treatment groups were defined based on distance to an operating BRT station. Treatment 1 consists of respondents living in less than 0.5 km, and Treatment 2 are respondents living between 0.5 km and 1.0 km. Respondents living more than 1.0 km and up to 3.0 km away from an operating BRT station are considered part of the control group. It is important to note that there have been no other large transport interventions in this area within the time frame of the study that may affect quality of life and concerns of rising costs. The neighborhoods encompassed by the control group, which surround the BRT corridor, share similar built-environment characteristics with the treatment areas and therefore serve as an appropriate comparison group. These similarities help meet the parallel trends assumption underlying the Difference-in-Differences framework, aiding in the isolation of the BRT's impacts from broader temporal effects.

5. Methods

This study uses a natural experiment approach to evaluate the perceived impacts of the new Pie-IX BRT system on residents' perception on two key dimensions: quality of life and concerns of rising costs of living. The study employs a before-and-after

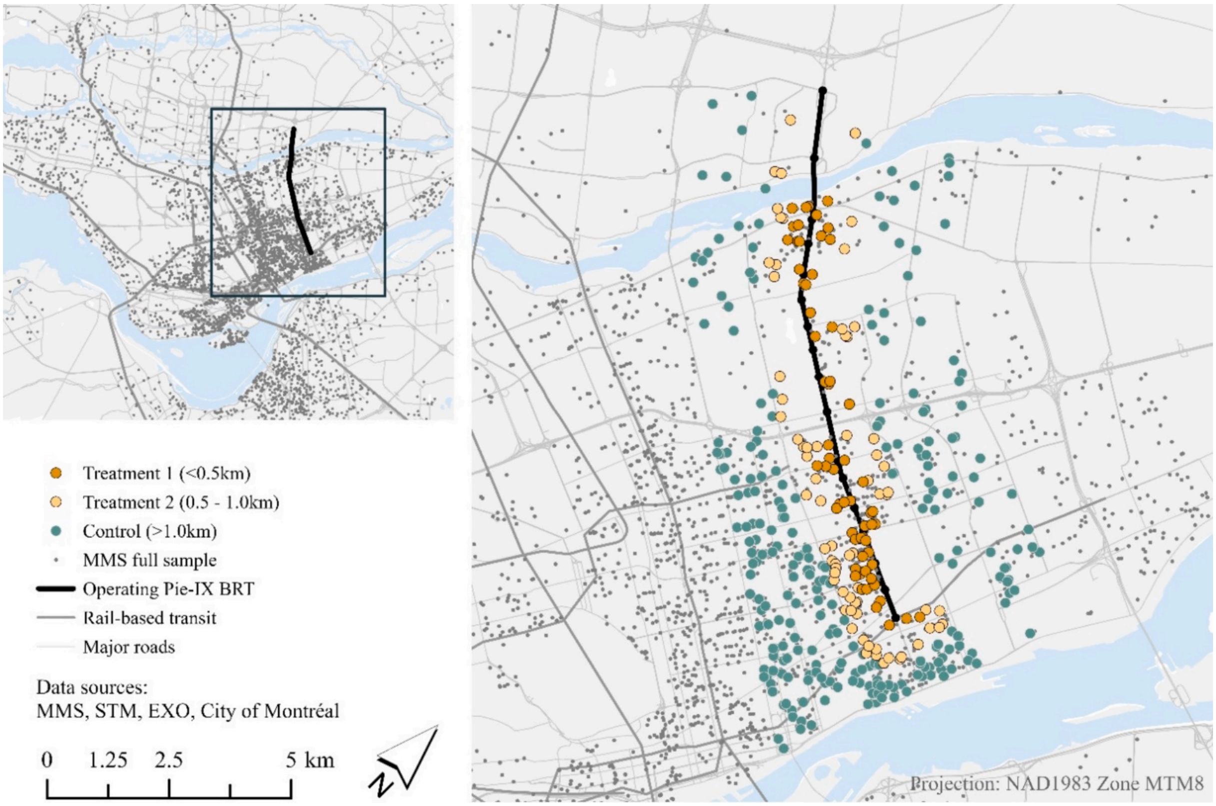

Fig. 1. Home location of respondents by treatment/control group.

treatment/control design to isolate these impacts. The main reason this type of design is recommended to measure impacts of new transport projects is that it isolates the impacts from unobserved effects associated to any broader trends unrelated to the studied intervention (Craig et al., 2017).

It is important to note that pre-existing differences between treatment and control groups might cause a bias in measuring treatment effects (Humphreys et al., 2016). This type of bias is named observed effect. Although treatment and control groups must be carefully designed to be similar at baseline, in practice they will never be identical. A statistical-modelling approach that deals with both observed and unobserved effects is difference in differences (DiD). This approach relies on the parallel trends assumption, which states that, in the absence of the intervention, the treatment and control groups would have followed similar trends in the outcome over time. In other words, any divergence in these trends after the intervention can be attributed to the treatment effect. This framework is most simply defined as follows (Craig et al., 2017):

$$Y_{it} = \beta_0 + \beta_1 exposure_i + \beta_2 time_t + \beta_3 exposure_i \times time_t + \beta_4 X_i \tag{1}$$

here, Y_{it} is the outcome for observation i at time t. The variable $exposure_i$ is most simply coded as 1 for observations in the treatment group and 0 for those in the control group. Thus, the coefficient β_1 controls for spatial differences at baseline, also called observed effects. That is because this coefficient represents the difference in the outcome between treatment and observation groups before the intervention. The binary dummy variable $time_t$, is most usually simply coded as 0 for pre-intervention times, and 1 for post-intervention. Thus, the coefficient β_2 controls for temporal trends, also named unobserved effects. This represents the average change in the outcome post-intervention regardless of exposure. Finally, the coefficient β_3 is the treatment effect, as it measures the change in the outcome for exposed observations post-intervention. In this sense, the treatment effect β_3 is the most relevant result in this type of model, as it isolates the impact of the intervention from spatial and temporal biases. It directly captures how outcomes change over time between treatment and control groups, effectively testing whether the outcome remains stable across periods in the absence of treatment. The variable X_i represents a confounding effect. For simplicity, Eq. (1) only presents one treatment measured at only one point in time, as well as only one confounding variable. However, multiple measures of exposure at different points in time, as well as multiple confounding variables may be introduced. These confounding effects are included as control variables to isolate the treatment effect, and their individual coefficients are generally not the main focus of interpretation in this type of framework.

The validity of the parallel trends assumption depends strongly on the absence of self-selection processes, such as residents systematically moving into or out of treatment areas following the BRT announcement and implementation. To assess this, we evaluated residential mobility rates within both treatment and control areas for the studied years. No significant differences were found between groups, suggesting that residential self-selection is unlikely to bias the observed treatment effects. Moreover, only 34% of respondents in the treatment areas moved in after the official announcement of the Pie-IX BRT in 2016, and of these, only 22% after the beginning of construction in 2018, further supporting that the results are not biased by self-selected residents. These rates are lower than those observed in the broader Montréal Mobility Survey sample, where 40% of respondents moved in after 2016 and 30% after 2018, suggesting no disproportionate influx of new residents into the treatment areas following the BRT announcement.

In this study, we employ two sets of DiD models; one set for each dependent variable: perceived improvements on quality of life, and rising-cost concerns. Each set of models is composed of two models. The first measures BRT impacts right after its inauguration (2022) compared to baseline (2019/21). This model employs observations of those who responded before implementation and in 2022 to measure the treatment effects at this point in time. The second model measures the impacts after one year of operation (2023) compared to baseline (2019/21). Through this framework, we measure the persistence (or non-persistence) of the BRT impacts after one year. As presented in the previous section, exposure is divided into two treatment groups by distance from home to a station (<0.5 km and 0.5 to 1.0 km), which are evaluated in each model.

The DiD models were estimated through weighted multilevel binary logistic regressions. With this modelling framework, the lower level corresponds to the person-wave level. That is, each row of the dataset represents a specific person at a specific point in time. The higher level of the random-effects' structure corresponds to person level, accounting for the fact that each person is present in the dataset multiple times, thus capturing the longitudinal component of the dataset. This statistical framework is required to analyze a panel dataset given that there are repeated observations of the same individuals over time. By modeling the data hierarchically, this approach controls for unobserved individual-level heterogeneity and allows for more accurate estimation of within- and between-person effects. Employing multilevel regressions in this manner has repeatedly been done in the travel behavior literature (El-Assi et al., 2017; Faghih-Imani et al., 2014; Victoriano-Habit & El-Geneidy, 2023, 2025), including within DiD frameworks for analyzing the impacts of new transport infrastructure (Crane et al., 2017; Keall et al., 2015).

All regressions were estimated using the lme4 R package (Bates et al., 2015). The weightings in the model were calculated for all valid responses in the panel using the anesrake R package (Pasek, 2018). This weighting process is key to ensure that the resulting treatment effects and other coefficients are not biased by the sampling of the survey. The weights were calculated to match our sample to census tract information of age, income, and gender from the Statistics Canada 2016 Census (Statistics Canada, 2016), retrieved through the cancensus R package (von Bergmann et al., 2021). Further information on the Montréal Mobility Survey, its collection, weighting process, and representativity can be found in the report by Negm et al. (2023).

The confounding variables included in each model are yearly household income, number of people in the household, and the respondent's gender and age. These confounding effects are incorporated as fixed effects within the random-effects multilevel model, a common approach in the transport literature using DiD frameworks (Crane et al., 2017; Dill et al., 2014; Keall et al., 2015; Spears et al., 2017; Sun & Du, 2023). This specification allows the model to control for observed socio-demographic characteristics while also accounting for unobserved heterogeneity across individuals. Even for time-invariant characteristics such as gender and age, including them as fixed effects in a random-effects model remains meaningful. This adjusts the estimation of treatment effects by accounting for baseline differences in these attributes across respondents. In this way, this combination of fixed and random effects enables a more accurate estimation of within-person changes over time while maintaining control for between-person variation.

6. Results

6.1. Descriptive statistics

The descriptive statistics of the studied sample are presented in Table 1. This description is presented by survey time and by treatment/control group, providing a descriptive overview of the subsamples to summarize the data and highlight broad temporal patterns prior to the DiD analysis. It is important to note sample sizes vary across survey waves because the analysis includes all panel participants who answered at least two waves. As a result, different combinations of wave participation contribute to each timepoint, which can lead to apparent increases or fluctuations in the number of observations over time. Of the 175 pre-implementation respondents, 94 also participated in the 2022 wave and 174 in the 2023 wave. Of the 322 respondents in 2022, 320 also participated in 2023.

The two dependent variables are presented in Table 1 both in the binary coding in which they were modeled, as well as in their original 5-point Likert scale coding. In terms of trends in time, a general pattern can be observed of decreasing perception of quality of life due to neighborhood concerns, except for Treatment group 1 (<0.5 km). In terms of the differences at baseline in this variable, although Treatment group 2 (0.5 to 1.0 km) and the control group don't present large differences, Treatment 1 has a lower initial perception of quality of life. Although this fact is not ideal for the natural experiment design, the DiD framework can control for these observed differences at baseline (Craig et al., 2017).

A general pattern can be seen of decreasing cost concerns over time for Treatment group 1 (<0.5 km) and the control group, while Treatment group 2 (0.5 to 1.0 km) shows a less clear trend. Similar to quality of life, there are slight differences between initial levels between treatment groups and the control. These differences, if significant, would be captured by the DiD design.

In terms of household size, the sample composition tends to stay relatively stable between survey waves and treatment/control groups, with each household-size group being represented by at least 20% of each sub-sample. The same is true for the three household-income groups. The percentage of women in each sub-sample varies between 35% and 60%, while mean age at baseline (2019) varies between 47 and 52 years. It is important to note that subsample sizes and time invariant characteristics such as age and gender vary over time because of the sampling scheme used for the collection of the Montréal Mobility Survey. That is, the sample used

Table 1
Descriptive statistics by survey time and treatment group.

Variable	Before opening N = 175			Newly opened N = 322			1 year after opening N = 401		
	[2019 / 2021]			[2022]			[2023]		
	<0.5 km	0.5–1.0 km	Control	<0.5 km	0.5–1.0 km	Control	<0.5 km	0.5–1.0 km	Control
Dependent Variables									
Improved Quality of Life **[Binary]**	**21.7%**	**66.7%**	**61.7%**	**51.8%**	**43.3%**	**51.9%**	**33.8%**	**33.8%**	**36.6%**
Strongly Agree	*4.3%*	*33.3%*	*14.1%*	*3.6%*	*10.0%*	*8.7%*	*0.0%*	*1.4%*	*1.5%*
Agree	*17.4%*	*33.3%*	*47.7%*	*48.2%*	*33.3%*	*43.2%*	*33.8%*	*32.4%*	*35.1%*
Neutral	*34.8%*	*25.0%*	*17.2%*	*17.9%*	*36.7%*	*28.2%*	*22.1%*	*25.4%*	*18.3%*
Disagree	*30.4%*	*4.2%*	*12.5%*	*16.1%*	*16.7%*	*14.1%*	*17.6%*	*18.3%*	*16.8%*
Strongly Disagree	*13.0%*	*4.2%*	*8.6%*	*14.3%*	*3.3%*	*5.8%*	*26.5%*	*22.5%*	*28.2%*
Cost Concerns **[Binary]**	**47.8%**	**58.3%**	**46.1%**	**41.1%**	**53.3%**	**39.3%**	**36.8%**	**57.7%**	**37.4%**
Strongly Agree	*4.3%*	*29.2%*	*22.7%*	*19.6%*	*20.0%*	*16.0%*	*13.2%*	*18.3%*	*14.5%*
Agree	*43.5%*	*29.2%*	*23.4%*	*21.4%*	*33.3%*	*23.3%*	*23.5%*	*39.4%*	*22.9%*
Neutral	*30.4%*	*25.0%*	*19.5%*	*23.2%*	*20.0%*	*29.1%*	*23.5%*	*19.7%*	*26.3%*
Disagree	*13.0%*	*8.3%*	*24.2%*	*21.4%*	*23.3%*	*18.0%*	*25.0%*	*14.1%*	*21.0%*
Strongly Disagree	*8.7%*	*8.3%*	*9.4%*	*14.3%*	*3.3%*	*13.6%*	*14.7%*	*8.5%*	*15.3%*
Confounding Variables									
Household Size									
[One person]	26.1%	62.5%	48.4%	39.3%	40.0%	39.8%	33.8%	36.6%	39.3%
[Two people]	47.8%	20.8%	34.4%	33.9%	35.0%	33.0%	33.8%	33.8%	32.8%
[Three or more]	52.2%	33.3%	38.3%	26.8%	25.0%	27.2%	32.4%	29.6%	27.9%
Yearly Income									
[$150 k or more]	43.5%	20.8%	28.1%	25.0%	21.7%	20.9%	30.9%	28.2%	24.4%
[$60 k to $150 k]	60.9%	33.3%	48.4%	33.9%	41.7%	35.0%	33.8%	36.6%	34.7%
[$60 k or less]	21.7%	62.5%	44.5%	41.1%	36.7%	44.2%	35.3%	35.2%	40.8%
Gender [1 = woman]	34.8%	41.7%	46.1%	60.7%	50.0%	48.1%	52.9%	50.7%	48.5%
Age at baseline (mean)	49.9	47.7	46.6	52.0	47.7	50.2	52.2	48.0	49.3
N	23	24	128	56	60	206	68	71	262

in this work is not composed only by people who completed all waves of the survey, but by respondents who participated in any combination of at least two waves of the survey.

6.2. Quality of life modeling results

Models 1 and 2, presented in the first two columns of Table 2, relate to the natural experiment results of perceived quality of life. Since results are presented as odds ratios, values over 1 represent an increase in the odds of perceiving an improvement in quality of life due to neighborhood changes, and vice versa.

The temporal effects in both models show a tendency, although not significant, of decreasing perception of quality of life over time compared to the baseline. This effect is measured for the entire study area (treatment and control groups) and is independent of the Pie-IX BRT. The spatial effects are significant in both models for Treatment group 1 (<0.5 km), indicating that the DiD framework is correcting for observed biases at baseline. These spatial differences reflect pre-existing conditions in the corridor, such as potential differences in traffic volumes or land use patterns, rather than effects of the BRT itself. Identifying these baseline differences is an expected and important component of the DiD approach, as it helps ensure that the BRT treatment effects are separated from these initial differences. These coefficients show that, keeping all else constant, the first treatment group has 75% lower odds of perceiving higher quality of life in 2022 and 83% lower odds in 2023 compared to the control. It's important to note that the small variation in spatial effects between the two models does not represent a change over time but rather reflects differences in estimation when each post-intervention year is compared separately to the common baseline. Slight differences in sample composition across waves can naturally produce minor fluctuations of this magnitude. No observed biases can be seen for Treatment group 2 (0.5 to 1.0 km).

The treatment effects, the main results from the DiD framework, represent the direct effect of the new BRT on each treatment group. Both models indicate statistically significant treatment effects for the first group (<0.5 km) but no significant effects for Treatment group 2 (0.5 to 1.0 km). Model 1 shows that, right after opening, the BRT increased the odds of perceiving higher quality of life in Treatment group 1. The magnitude of this increase in odds is 3.99 times what it would have been with no intervention. Model 2 shows that, after 1 year of operation of the BRT, this effect became even stronger. The odds of perceiving increased quality of life are 4.52 times larger after one year than what they would have been without the BRT in Treatment group 1. Although the difference between these coefficients is not statistically significant, the pattern may suggest a tendency toward increasing positive effect over time. On the other hand, the BRT had no significant effect on perceived quality of life in Treatment group 2.

In both quality of life models, all confounding variables present expected tendencies, although most of them are not statistically

Table 2
BRT impacts compared to 2019/21 baseline − DiD modeling results (odds ratios).

Variable	Improved quality of life				Cost concerns			
	Model 1		Model 2		Model 3		Model 4	
	Newly opened		1 year after		Newly opened		1 year after	
	(2022)		(2023)		(2022)		(2023)	
Intercept	6.04	***	6.36	***	0.84	***	1.81	***
Temporal Effects [ref: 2019/2021]								
Newly opened [2022]	0.75				0.52	*		
1 year after [2023]			0.90				0.83	
Spatial Effects [ref: >1.0 km]								
[<0.5 km]	0.25	**	0.17	***	0.26	**	0.33	
[0.5 km-1.0 km]	1.37		1.31		0.36		0.42	
Treatment Effects								
[2022] * [<0.5 km]	**3.99**	**			**4.62**	**		
[2022] * [0.5 km-1.0 km]	0.53				2.81			
[2023] * [<0.5 km]			**4.52**	**			3.26	
[2023] * [0.5 km-1.0 km]			0.58				1.23	
Confounding variables								
Household Size [ref: One person]								
[Two people]	0.92		0.77		1.55		1.09	
[Three or more]	0.89		1.17		1.36		1.24	
Yearly Income [ref: $150 k or more]								
[$60 k to $150 k]	0.73		0.77		1.88	*	1.46	
[$60 k or less]	0.82		0.62		2.94	***	3.00	**
Gender [1 = woman]	0.94		1.00		1.15		1.10	
Age at baseline [continuous]	0.98	***	0.97	**	0.99		0.98	**
N_{person}	402		398		402		398	
σ^2	3.29		3.29		3.29		3.29	
$\tau_{00\ person}$	1.40		3.51		1.46		2.77	
ICC	0.30		0.52		0.31		0.46	

*p < 0.1 **p < 0.05 ***p < 0.01.

significant. Results show that, at baseline, different income groups present comparable perceptions of improvements on quality of life related to neighborhood changes. This is consistent with the notion that the benefits of improved neighborhood characteristics are not exclusive to any particular income group. In terms of age, older respondents were less likely to perceive improved quality of life due to neighborhood changes, possibly reflecting greater attachment to pre-existing neighborhood conditions and lower receptiveness to change in general.

6.3. Cost concerns modeling results

The third and fourth columns of Table 2 present models 3 and 4, measuring changes in odds of having financial concerns about the rising cost of living in the neighborhood. The temporal effects in these two models show a slight tendency of decreasing financial concerns over time in the study area, although it is only significant for the 2022 model. In this year, the odds of having cost-related concerns was 48% lower than at baseline. This temporal pattern is independent of the BRT implementation and may instead reflect broader contextual factors, such as temporary relief or adaptation following the COVID-19 pandemic, or short-term variations in inflation and perceived financial stability. The spatial effects are only significant in the 2022 model, indicating that there are no significant observed biases being introduced by the treatment/control design in the 2023 sample. Model 3, however, is controlling for observed effects for both treatment groups. The Treatment 1 group (<0.5 km) has 74% lower odds of perceiving cost concerns.

Similar to the quality of life models, results show that there are no significant effects of the BRT for the second treatment group (0.5 to 1.0 km). Model 3 shows that, when it was newly inaugurated, the new BRT had a statistically significant impact in the odds of perceiving rising-costs concerns of Treatment 1 (<0.5 km). The magnitude of this increase in odds is 4.62 times what it would have been with no intervention. However, Model 4 shows that, after one year of operation, no significant cost concerns remain.

Confounding variables, as in the quality of life models, present expected tendencies. In the case of the cost concerns models, as expected, income takes a more relevant role. Middle-income households ($60 k to $150 k per year) are 1.46 to 1.88 times more likely to have financial concerns compared to high-income households ($150 k per year or more). For low-income households the effect is even larger, with 2.94 to 3.00 more odds to perceive cost concerns than high-income households. These results align with the intuitive expectation that households with more limited financial resources experience greater sensitivity to perceived increases in living costs. Age, on the other hand, decreases concerns about costs of living, with a 1% to 2% decrease in the odds of being concerned per additional year of age of the respondent. This may reflect greater housing tenure security associated with neighborhood change.

7. Discussion

Our results provide multiple insights into the changing perceptions of residents in the study area over time, both due to the implementation of the BRT or unrelated. First, we observed a general tendency of decreasing perception of quality of life over time seen in the descriptive analysis and in the DiD models' temporal effects, although not significant. This decline in quality of life observed among the entire group aligns to what has been observed in Canada due to the COVID-19 pandemic (Wen et al., 2022). Within this context, the positive treatment effects suggest that the implementation of the BRT may be contributing to sustaining levels of perceived quality of life in areas near the corridor. Perhaps more importantly, this significant impact of the BRT became stronger after one year in operation. This fact becomes even more relevant when considering that these results apply to residents overall, regardless of their individual frequency of public transport use (only 27% of the studied sample reported more than half of their trips are done by transit). Thus, our findings show that the implementation of the new BRT system not only has the potential of positively affecting its users as shown in previous studies (Navarrete-Hernandez & Zegras, 2023), but also its overall surrounding neighborhoods.

This work provides evidence that a new BRT may result in increased financial concerns in its immediate surroundings around the time of its implementation. These concerns may be particularly relevant for lower-income populations, as the same increase in living costs will naturally generate greater financial strain on them than for higher-income households. However, our results also show that these negative impacts of the BRT are not sustained in time, as we found no significant impact after one year of implementation. This pattern suggests that the introduction of a BRT may not lead to persistent financial stress or perceived increases in living costs within the first year. Longer-term monitoring would be required to assess whether these concerns evolve into more sustained affordability pressures or potential displacement effects over time.

All our results, both in terms of quality of life and financial concerns, show that the impacts of the BRT implementation are limited to areas within a 0.5-km radius. That is, we found that areas between 0.5 and 1.0 km of the intervention had no significant changes in these perceptions compared to areas farther away. Despite actual perceived catchment areas varying by local context and surrounding built environment (Jiang et al., 2012), it is relevant to note that for this type of transit service, service areas of 0.8 to 1.0 km are commonly considered in the literature (El-Geneidy et al., 2013; Guerra et al., 2012). This implies that, although residents living between 0.5 km to 1.0 km from a station may commonly represent potential users of the service, they do not systematically perceive it as an intervention within their neighborhood.

The positive impacts of a new BRT project seen in this study can have relevant implications for future implementation. First, given that these types of project still face recurrent political difficulties despite their increasing popularity, understanding their positive impacts is crucial. Knowing that perceived increased quality of life results in the direct surrounding of a BRT project (<0.5 km) and is sustained in time, existing positive experiences and support should be leveraged for future political support. This support would be particularly significant in areas where perceptions of quality of life are declining.

Although our findings show that the impact of BRT on financial concerns are not sustained in time, they may still have relevant implications for future implementation. It is important to consider these potentially short lived effects, especially in low-income populations, as they may produce significant stress during the first stages of implementation (Friedline et al., 2021; Sweet et al., 2013). Future BRT projects in low-income neighborhoods may benefit from providing campaigns that aim to enhance the positive perceptions of the BRT through public information or community engagement. These efforts could address residents' concerns about potential increases in costs of living while highlighting expected benefits of the service. It is important to note that, based on our knowledge, no major urban change took place in the study area except for the BRT. Our findings might not be applicable in areas where BRT projects are accompanied by urban change like transit-oriented development (TOD).

The natural experiment design employed in this work presents some limitations. First, the underlying parallel trends assumption could not be formally tested, as only one pre-intervention timepoint was available. This is a common limitation in natural experiments in the literature on the introduction of new transport infrastructure (Crane et al., 2017; Dill et al., 2014; Hong et al., 2016; Keall et al., 2015; Spears et al., 2017; Sun & Du, 2023). As in these previous studies, this work attempts to maintain the plausibility of the parallel trends assumption through careful design of treatment and control groups in terms of their comparability at baseline regarding socio-demographic characteristics and spatial location. Second, individual fixed effects or two-wave fixed effects (TWFE) could not be applied due to the small sample size and limited number of repeated measures per respondent. Although this approach could better account for unobserved time-invariant heterogeneity, the random-effects multilevel model adopted here remains appropriate and is commonly used in DiD studies on transport infrastructure (Crane et al., 2017; Dill et al., 2014; Keall et al., 2015; Spears et al., 2017; Sun & Du, 2023). This specification can still capture both within-person change and between-person variation over time.

Nevertheless, the natural experiment design used in this study is scarcely applied in the literature, despite being highly recommended to study large interventions to the built environment (Craig et al., 2017; Humphreys et al., 2016). This is because employing a before-and-after panel data approach, which additionally allows for an effective treatment/control design, is generally complex and requires thorough planning. This study shows that applying this framework is crucial to control for unrelated trends over time and other biases that may affect assessing the impacts of a transport project. Thus, this study presents an addition to the few previous studies using these study designs on the implementation of new Bus Rapid Transit (Joseph et al., 2022; Li et al., 2023; McCormack et al., 2021; Song et al., 2023).

8. Conclusions

This study takes the implementation of a new BRT system in Montréal, Canada as an opportunity to provide valuable insights into the impacts of new transportation projects on neighboring residents. Through a rigorous natural-experiment design, we assessed the system's effects on two key dimensions: quality of life and concerns about rising costs of living. Our findings reveal enduring positive perceptions of the BRT's benefits, with improved quality of life impacts even one year after implementation. While initial concerns about rising costs were observed, they proved to be short-lived.

This study contributes to the growing body of knowledge on BRT systems, emphasizing their potential for long-lasting positive effects on urban communities. The robust natural experiment research design, incorporating a panel dataset and treatment categories based on distance, enhances the reliability of our conclusions. Understanding these evolving impacts of BRT on residents is crucial for overcoming political challenges associated with BRT adoption. More specifically, this work provides relevant insights for future BRT implementation, such as leveraging the positive impacts on residents' perceptions of new BRT for future implementation. Moreover, our results show that it is relevant to minimize the negative impacts of new BRT implementation, such as financial stress, especially in lower-income areas.

By highlighting the enduring benefits and addressing initial concerns, this study contributes to the evidence base supporting the continued development and implementation of Bus Rapid Transit as a viable and impactful urban transportation solution. However, this study is not without limitations.

While we employed a robust study design, studies with a larger sample size may inquire into larger detail, for instance, about the relevance of project awareness and frequency of use. It is also relevant for future studies to analyze the impacts measured in this work in BRT systems implemented in different contexts. Both the perceptions of improved quality of life and potential financial concerns may not be the same when implementing a BRT in areas with different sociodemographic compositions. Future studies could complement subjective perceptions with objective measures, such as local rent, housing prices, and neighborhood amenities, to provide a more comprehensive understanding of how BRT systems affect both quality of life and costs of living. A methodological alternative that would allow for a more detailed exploration of the spatial extent and variation in BRT impacts is using geographically weighted regressions (GWR). Finally, it would be essential to verify through future research how the effects measured in this study one year of implementation may change in the long-term.

CRediT authorship contribution statement

Rodrigo Victoriano-Habit: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ahmed El-Geneidy:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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