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Why are people leaving public transport? A panel study of changes in transit-use patterns between 2019, 2021, and 2022 in Montréal, Canada

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ABSTRACT

The outbreak of COVID-19 caused unprecedented declines in public-transport use. As travel frequencies rebound, ridership is recovering, although it remains considerably below pre-pandemic levels. This study compares pre- to post-pandemic public-transit use among workers and non-workers, and the changing impact of local and regional accessibility. Additionally, we assess the impact of increased telecommuting on workers' transit use before, during, and after the pandemic. We estimate two weighted multilevel linear regressions using a three-wave panel survey over the years 2019–2022 in Montréal, Canada. Results indicate that the factors that determine workers' and non-workers' transit patterns have tended to diverge after the pandemic. For workers, the relevance of accessibility in promoting utilitarian transit use considerably decreased, being responsible for close to 10% of the post-pandemic transit-use reduction. The increase of telecommuting frequency due to the pandemic contributed more than 10% of the post-pandemic transit-use reduction, but the effect of transit commuting time has remained relevant. For non-workers, the effect of regional accessibility by transit has increased after the pandemic, which has partly mitigated non-workers' transit-use decline. Moreover, we find there is a joint effect of local and regional accessibility that has maintained after 2019 for non-workers. Results from this work have relevant implications for transit planners and policymakers. To help transit-use recovery, results suggest that providing good transit connection to the workplace promotes workers' transit use, while promoting transit accessibility in lower-local-accessibility areas is key for non-worker transit ridership.

1. Introduction

At the beginning of the COVID-19 pandemic public transport experienced a steep decline in ridership around the world due to various health restriction measures and the adoption of telecommuting policies (Astroza et al., 2020; Tirachini and Cats, 2020). This is worrying especially in the North American context where ridership was already on the decline prior to the pandemic (Boisjoly et al., 2018; Erhardt et al., 2022). Despite the various efforts by governments and public transport agencies in the post pandemic times, a big percentage of former transit users switched towards driving and active-mode use as travel activities started to rebound (Abduljabbar et al., 2022).

Several studies have focused on analyzing the reductions in public transit ridership among different sociodemographic groups and their partial recovery after the pandemic (Lizana et al., 2023; Long et al., 2023; Wang et al., 2022). Prior to the pandemic public-transit ridership was known to be impacted directly by accessibility, the ease of reaching destinations (Hansen, 1959). To what extent these impacts are currently present is unknown. Additionally, to the authors' knowledge, no previous studies have focused on differentiating the changing factors influencing post-pandemic transit use of workers and non-workers. This is particularly relevant in the current context of increased popularity of telecommuting, which has shown to beget large changes in travel patterns (Javadinasr et al., 2022; Victoriano-Habit and El-Geneidy, 2023).

Our study investigates the post-pandemic utilitarian (non-leisure) transit behavior of workers and non-workers, and the changing impacts of accessibility and telecommuting in this process in Montréal Canada. The main research question this work tries to answer is: what are the factors affecting the frequency of workers' and non-workers' transit use for utilitarian purposes in the post-pandemic context and how have they changed after 2019? In this context, this work focuses on the changing factors that specifically affect frequency of transit use. To answer this

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question, this work employs a three-wave panel survey applied in the city of Montréal, Canada in the years 2019 (pre-pandemic), 2021 (during the pandemic), and 2022 (post-pandemic).

2. Literature review

With the COVID-19 pandemic and its associated restrictions, reductions in travel frequency by public transport were observed around the world (Astroza et al., 2020; Tirachini and Cats, 2020). With the removal of these restrictions, travel frequency started to rebound among public transport users, yet not to the same levels it was prior to the pandemic (Abduljabbar et al., 2022; Long et al., 2023). Different sociodemographic groups have shown differing levels of reduction and return to transit use over the past 3 years (Wang et al., 2022).Women and higher-income people had stronger reductions in transit use early in the pandemic (Schaeffer et al., 2021), which have been linked to a lower recovery in their post-pandemic transit patterns (Lizana et al., 2023). Researchers have linked changing attitudes and intentions during the pandemic to have been key in shaping post-pandemic transit use (Zhao and Gao, 2022). Pre-pandemic and during-pandemic habits and behavior have shown to determine the degree to which different groups return to their pre-pandemic transit patterns (Lizana et al., 2023; Zhao and Gao, 2022). In short, post-pandemic transit use has been influenced by concerns and habits brought by the pandemic.

Studies have found that, in the post-pandemic context, reliability and convenience of service remain important for regaining ridership (Mashrur et al., 2023). It has shown that a proportion of the steep reduction in transit use after COVID-19 can be attributed to longer waiting times compared to pre-pandemic times (Nikolaidou et al., 2023), which were a result of service reductions. Moreover, as virtual activities have become more common (Palm et al., 2023; Rahman et al., 2021), new opportunities have brought changes in the relationship between transit use and the built environment (Klapka et al., 2020). For example, Victoriano-Habit and El-Geneidy (2023) found that the influence of local accessibility in promoting active travel has increased for workers that are telecommuting more frequently after COVID-19. Accordingly, it is relevant to focus on the changes in the impacts of the built environment, as they are relevant in recovering ridership and more directly intervenable by planners.

Accessibility is a central concept in transport planning and research which has been promoted as the most comprehensive land-use and transport measure (El-Geneidy and Levinson, 2022; Wachs and Kumagai, 1973). Defined as the ease of reaching destinations (Hansen, 1959), it is a tool that effectively reflects the relationship between land-use and transport systems (Geurs and van Wee, 2004). Accessibility is a mode specific tool (El-Geneidy and Levinson, 2022), and it is commonly differentiated into local and regional accessibility, as they represent accessibility at two different scales. Local accessibility is related to proximity of activities that can be easily reached by walking or cycling, while regional accessibility is related to destinations that can be reached by car or public transit (Handy, 2020). Both regional accessibility by public transit and local accessibility by walking have shown to be key in promoting higher transit mode share (Cui et al., 2022; Jacobson and Forsyth, 2008; Legrain et al., 2015). To our knowledge, no study has incurred into the changing importance of local and regional accessibility in impacting post-pandemic transit use and its recovery.

Lastly, many travel behavior studies differentiate between workers and non-workers, as they exhibit markedly different patterns and levels of complexity of travel (Chowdhury and Scott, 2020; Dharmowijoyo et al., 2018). This distinction has become more relevant with the rise of telecommuting, one of the main remote activities that has been shown to largely impact travel behavior (Javadinasr et al., 2022; Victoriano-Habit and El-Geneidy, 2023). It is in this context that this study inquires into the post-pandemic transit behavior of workers and non-workers, and the changing impact of accessibility and telecommuting in this process.

3. Data and methods

3.1. Three-wave panel data

The primary dataset of this study is composed of the panel responses from the first three waves of the Montréal Mobility Survey (Negm et al., 2023). This panel dataset is collected through an online bilingual survey administered in the Greater Montréal Area to participants aged 18 years or older. To enhance sample representativeness, various recruitment techniques were employed in all waves, as recommended by Dillman et al. (2014). 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 (Leger) was also hired in both waves to help in recruiting part of the sample, recruiting 42% of the final validated sample. The remaining 58% of the sample was collected by Transportation Research at McGill (TRAM) through the aforementioned methods. All survey respondents who provided an email address received an invitation to participate in all subsequent waves. Through this process, the sample was composed both of respondents who participated in only one wave (cross-sectional) and those who participated in two or more waves (panel).

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. Through this cleaning process, 87% of the complete responses collected by TRAM, and 75% of the complete responses collected by Leger were retained.

The first wave of the survey collected 3520 valid responses during the fall of 2019, the second wave collected 4058 valid responses during the fall of 2021, and the third wave collected 4065 valid responses during the fall of 2022. Thus, this three-wave sample collects information at three very distinct points in time. The first wave corresponds to pre-pandemic times, the second wave was collected during the pandemic while many travel restrictions were still in place, and the third wave was collected when no travel restrictions remained. Thus, the multiple waves of the Montréal Mobility Survey, which start prior to the pandemic, represent a unique opportunity to study post-COVID travel behavior changes.

This work only analyzes responses from panel participants who answered at least two waves. This work separates the panel sample into two sub-samples. The sub-sample of workers is composed only of those employed full- or part-time in all waves of the survey. Similarly, the sub-sample of non-workers are respondents with no employment in every wave they responded to. The final sample sizes by wave participation for the workers' and non-workers' sub-samples are presented in Fig. 1.

All waves of the survey included the same questions pertaining to weekly mode-use frequency. This work focuses on the frequency of weekly utilitarian transit use, which was recorded by respondents for four distinct travel purposes: work, school, grocery shopping, and healthcare. Only home-based trips were recorded, and return trips are not counted. For workers, each survey wave collected information pertaining to weekly commuting and telecommuting behavior. Respondents' sociodemographic characteristics, as well as residential-selection attitudes, which allow to control for residential self-selection, were collected in all waves. To collect information on these

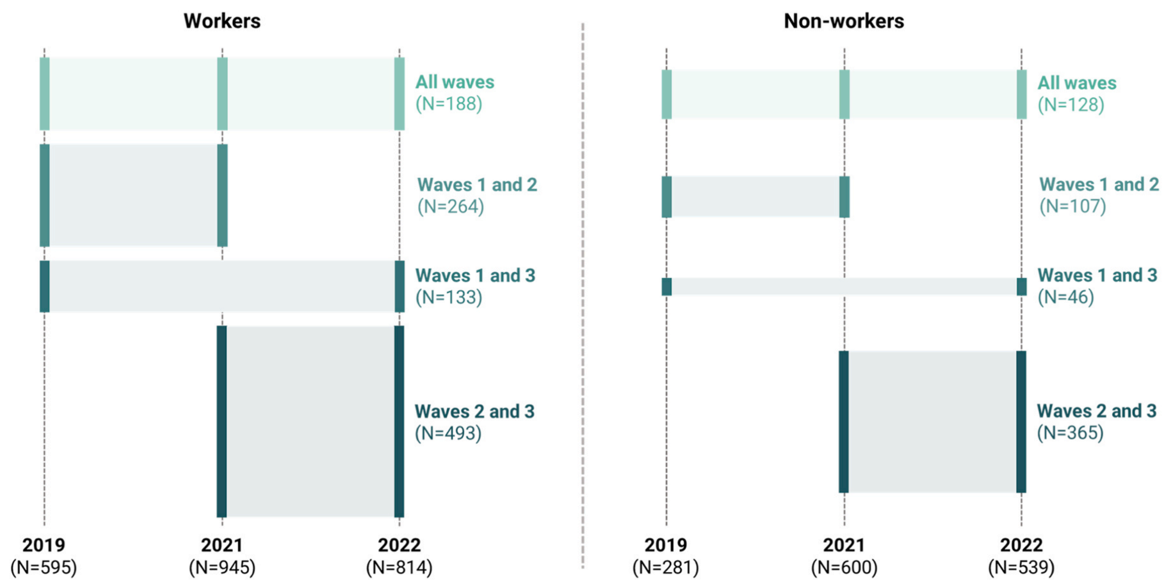

Fig. 1. Sample size by wave participation.

attitudes, respondents were asked to rate the importance of several factors on their home-location decision at the time of moving in a five-level Likert scale. This was later coded as binary for modelling ("very unimportant" to "neutral" coded as 0, "important" and "very important" coded as 1).

Most notably, since every question was answered by participants at three points in time, changes in all variables can be measured through time. Further information on the first three waves of the Montréal Mobility Survey, its collection, data cleaning, and description can be found in Negm et al. (2023).

3.2. Regional and local accessibility

To account for the effects of built-environment characteristics, this work includes measures of regional accessibility by transit and local accessibility. The regional transit accessibility measure used in this work is a cumulative-opportunities indicator to all jobs in the region using a 45-minute threshold. This indicator is widely used to measure accessibility mainly due to its direct interpretation (El-Geneidy and Levinson, 2022). The 45-minute threshold is selected given that it is close to the Montréal region's median transit travel time, as recommended by Kapatsila et al. (2023).

To calculate accessibility by public transit to jobs, transit travel times were computed between census tract (CT) centroids for a typical weekday between 8:00 and 9:00 AM using the r5r package (Pereira et al., 2021). CTs were chosen as the unit of analysis, as job data was obtained at this level from the 2016 census commute flows (Statistics Canada, 2018). To calculate transit travel times, the necessary inputs for r5r are the Global Transit Feed Specification (GTFS) data, and the OpenStreetMap (OSM) street network. All of these inputs were collected for each wave's year: 2019, 2021, and 2022. Thus, in the case of changes in public-transport services, either because of new introduced services (Carvalho et al., 2024) or service cuts after the pandemic (DeWeese et al., 2020), variations of accessibility by transit are fully accounted for.

For local accessibility levels, WalkScore was retrieved from *walkscore.com* for each respondent's home location at each survey year. WalkScore is a popular measure of local accessibility which has been repeatedly tested in the land-use and transport literature (Hall and Ram, 2018), and has shown reliability in predicting active travel patterns (Manaugh and El-Geneidy, 2011). The WalkScore index is produced through a gravity-based assessment of amenities within a 30-minute walk of a location (Walk Score, 2022). The index considers several types of amenities, including grocery stores, schools, parks, and restaurants. The value of WalkScore ranges from 0 to 100, where higher values indicate higher levels of local accessibility. Local-accessibility data in this work accounts for changes in residential local accessibility both in the case of respondents moving house or due to changes in time.

3.3. Weighted multilevel linear regressions

Two models were estimated with weekly use of public transport for utilitarian purposes as the dependent variable. One model was estimated for each sub-sample: workers and non-workers. Through these models, the goal is to explain the different factors affecting the frequency of using public transit for utilitarian purposes for each group, as well as its changes through time.

The independent variables selected for this analysis include personal characteristics, built-environment characteristics, and residential self-selection factors. The personal characteristics included in the final models were the respondent's age in 2019 and their yearly income level. To measure the effect of transit operations and the residential built environment, transit accessibility to jobs and local accessibility were included. An interaction term between regional and local accessibility was tested in order to analyze their joint effect on utilitarian transit trip frequency. The effects of residential self-selection were accounted for through attitudes towards neighborhood car-friendliness and public-transit proximity at the moment of selecting home location. Finally, in the case of workers, transit-commute duration and weekly frequency of telecommuting were included. Transit commuting times were gathered through the Google Maps API during the same week that the survey response was collected.

Both models include wave fixed effects for 2021 (w2) and 2022 (w3) which measure the change in weekly utilitarian transit use in time compared to 2019 while assuming all other factors remain constant. Interactions between these wave fixed effects and all independent variables were tested but were only included in the final models if they were statistically significant. In such cases, statistical significance indicates that the magnitude of an independent variable's effect on the frequency of utilitarian transit use has changed compared to pre-pandemic times. Multiple other variables were tried and removed from the models as they did not show statistical significance. These include: gender, car ownership, number of people in the household, number of years since immigrating to Canada, and living environment while growing up (urban, suburban, or rural). Further, to account for potential differences due to the differences in recruitment, an analysis including a dummy variable separating data collection methods was conducted. This dummy variable would take a value of one if the observation came from the public opinion company and zero otherwise. The analysis showed no statistically significant differences between data-collection sources.

The models were estimated through a weighted multilevel linear regression. This multilevel modelling framework recognizes that there are repeated observations of the same individual over time. The models estimated in this work incorporate two levels, where the higher level of the random effects' structure (person level) accounts for the longitudinal component of the dataset, capturing the individual-specific variance. Thus, the models' fixed-effect coefficients represent the marginal effects of the independent variables, which are systematic and consistent across individuals and waves. Another framework was tested during the construction of this work using a three-level modeling approach. In this framework, the additional third level considered a census-tract level to account for other, unobserved changes in the built environment that may influence results and not controlled for in the models. We discarded this framework as it returned a low value for the ICC associated to the census-tract level (<0.05), which indicated no need for this third-level hierarchical structure.

The weighting process is key to ensure that results are not biased by the sampling of the survey. Both 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), which follows the iterative raking process described by (DeBell and Krosnick, 2009). The weights were calculated to match each sub-sample to census-tract information of age, income, and gender from Statistics Canada, 2016 census (Statistics Canada, 2016), which was retrieved through the cancensus R package (von Bergmann et al., 2021).

3.4. Sensitivity analysis

The coefficients from the final models were then used to conduct two sensitivity analysis to help in communicating the modeling results. The first analysis focuses on illustrating the importance of different factors in explaining the decrease in transit use after 2019. The average contribution of each set of variables (wave fixed effects, personal characteristics, built environment, commuting characteristics, and residential self-selection) in explaining the decrease in transit use is measured for 2021 and 2022 compared to pre-pandemic times.

To clearly illustrate the effects of regional and local accessibility on frequency of utilitarian transit use presented by the models, a second sensitivity analysis is performed for each of them. This analysis is performed by using each model to predict weekly utilitarian transit trips by fixing each independent variable to its mean and simultaneously varying transit accessibility to jobs and WalkScore across their full range of variability in 2019, 2021, and 2022.

4. Results

4.1. Descriptive statistics

The panel sample description is presented in Table 1 segregated into the two sub-samples: workers and non-workers. Descriptive results are presented by each of the three survey waves. Differences in characteristics can be observed both between the sub-samples and within each sub-sample through time.

In terms of personal characteristics, expected differences can be seen between workers and non-workers. The workers' sample mainly consists of respondents who were between 30 and 64 years old in 2019, whereas the non-workers' sample has considerably more respondents over the age of 65. This is to be expected, as a sample of non-employed participants throughout multiple years of surveying are much more likely to be of retirement age. Similarly, yearly income levels tend to be slightly higher among workers compared to non-workers. These expected sociodemographic differences between sub-samples are inherent to continuous employment (or unemployment) as a segregating factor. More importantly, there are no major sociodemographic differences within each sub-sample through time.

In terms of the built environment around respondents' homes, both sub-samples present a trend of decreasing transit accessibility over time, particularly after 2019. Fig. 2 shows respondents' households' geographical location, as well as their level of accessibility to jobs by public transit. As seen in this figure, the sample presents large variability both in spatial distribution and accessibility levels.

The number of weekly utilitarian transit trips, the dependent variable of this study, varies both between sub-samples and through time. In 2019, workers' transit use was slightly more frequent than non-workers'. However, their trends through time vary considerably. As seen in Fig. 3, the share of workers using transit at least once per week decreased from 66.4% to 29.4% between 2019 and 2021. In 2022, this

Table 1
Descriptive statistics by survey wave.

Variable	Workers			Non-workers		
	Mean (std dev.)			Mean (std dev.)		
	2019	2021	2022	2019	2021	2022
N	585	945	814	281	600	539
Personal characteristics						
Age in 2019						
(18−29)	19.3%	17.5%	15.6%	8.2%	6.2%	5.0%
(30−49)	54.4%	55.1%	55.5%	9.3%	7.5%	7.6%
(50−64)	25.3%	25.8%	26.9%	39.5%	42.0%	43.2%
(65 or more)	1.0%	1.6%	2.0%	43.1%	44.3%	44.2%
Yearly income						
($60k or less)	28.9%	20.3%	19.2%	56.9%	46.0%	45.5%
($60k to $150k)	40.2%	42.8%	41.2%	34.9%	42.0%	42.1%
($150k or more)	30.9%	36.9%	39.7%	8.2%	12.0%	12.4%
Built-environment characteristics						
Transit accessibility to jobs [100k jobs]	4.09 (3.12)	2.99 (2.61)	2.83 (2.50)	3.33 (3.04)	2.44 (2.51)	2.32 (2.42)
Walkscore [0–100]	58.6 (27.6)	57.5 (26.9)	65.1 (29.9)	53.7 (26.1)	53.2 (27.4)	59.4 (30.7)
Transit use						
Total utilitarian weekly transit trips	2.92 (2.82)	0.85 (1.88)	1.21 (2.12)	1.18 (1.57)	0.57 (1.60)	0.34 (1.10)
Work weekly transit trips	2.36 (2.48)	0.63 (1.48)	1.02 (1.84)	-	-	-
School weekly transit trips	0.30 (1.00)	0.07 (0.47)	0.05 (0.47)	0.56 (1.05)	0.16 (0.76)	0.13 (0.74)
Shopping weekly transit trips	0.18 (0.63)	0.09 (0.42)	0.09 (0.40)	0.42 (0.99)	0.26 (0.89)	0.13 (0.62)
Healthcare weekly transit trips	0.08 (0.41)	0.06 (0.35)	0.06 (0.29)	0.20 (0.56)	0.15 (0.57)	0.08 (0.32)
Commuting patterns						
Transit commute time						
(0 min - telecommuters)	8.9%	40.1%	26.9%	-	-	-
(1–15 min)	24.1%	6.3%	8.2%	-	-	-
(15–30 min)	41.0%	19.9%	21.0%	-	-	-
(30–60 min)	24.1%	21.9%	28.5%	-	-	-
(60+ min)	1.9%	11.8%	15.4%	-	-	-
Weekly telecommuting days	0.60	2.52	2.20	-	-	-
Residential-selection attitudes						
Being near public transit [binary]	83.6%	76.3%	76.2%	79.0%	73.8%	69.0%
Neighborhood car-friendliness [binary]	48.2%	49.6%	47.9%	61.9%	59.2%	63.1%

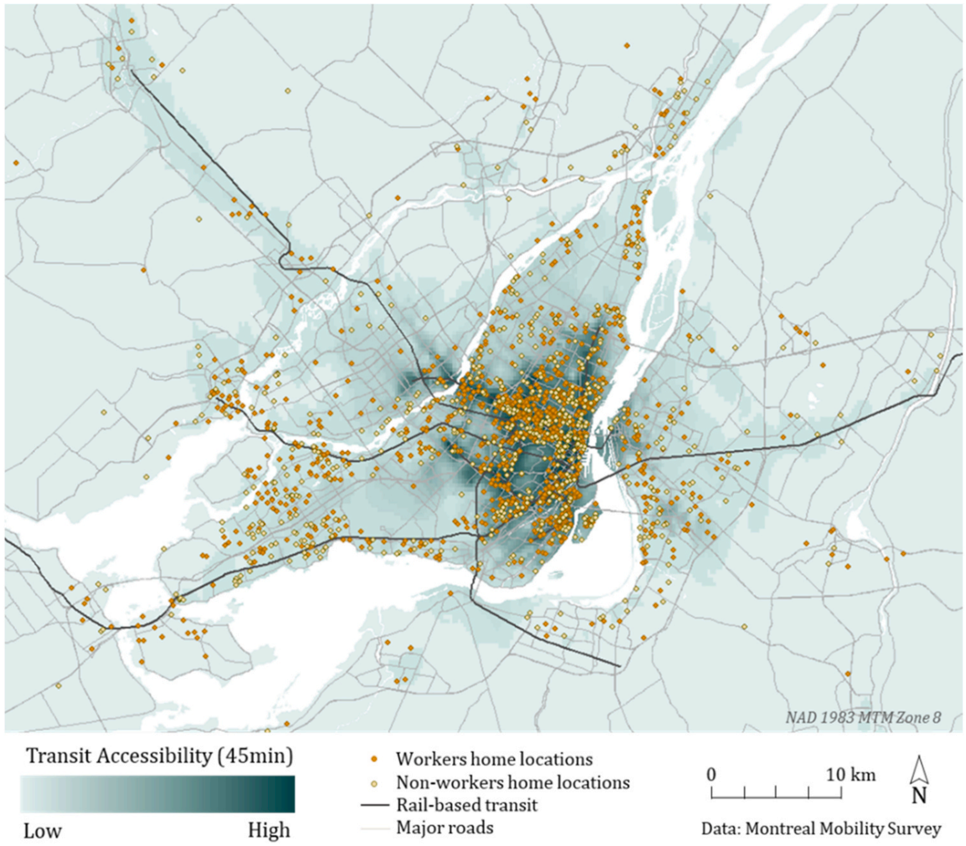

Fig. 2. Workers' and non-workers' home location at baseline.

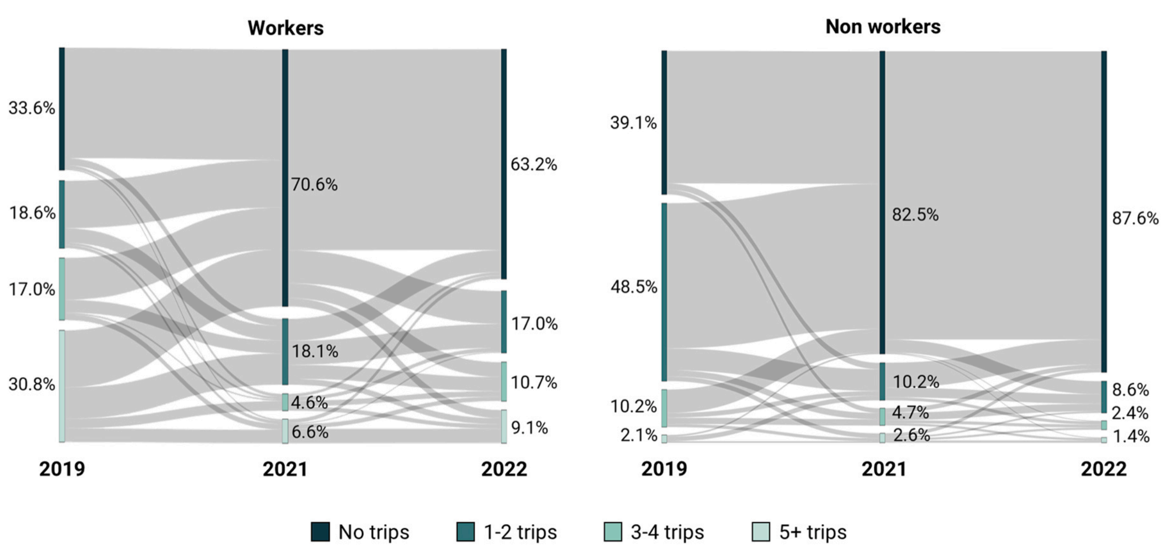

Fig. 3. Changes in weekly frequency of transit use between survey waves.

share suffered a slight recovery to 36.8%. In the case of non-workers, there was an even steeper decline in transit use between 2019 and 2021, from 67.2% to 19.3%, and in 2022 this share declined to 13.6%.

Workers' commuting and telecommuting patterns presented drastic changes after the occurrence of the pandemic. The share of people exclusively telecommuting (represented in Table 1 by people with a 0-minute commuting time) increased from 8.9% to 40.1% between 2019 and 2021. This share later decreased to 26.9% in 2022. Similarly, the average number of weekly telecommuting days considerably increased between 2019 and 2021. However, it only slightly decreased in 2022. This shows that telecommuting has not become significantly less prevalent overall, but that workers are moving towards a hybrid commuting/ telecommuting schedule.

4.2. Modeling results

Results for the two estimated models are presented in Table 2. Each of these models presents, for workers and non-workers respectively, the importance of different factors on weekly transit use for utilitarian purposes. Both models control for age and income, presenting expected

Table 2
Weekly transit use modeling results.

Variable	Workers			Non-workers		
	Coefficient		C.I. (95%)	Coefficient		C.I. (95%)
Intercept	1.97	***	1.46 – 2.48	2.28	***	1.77 – 2.78
Wave fixed effects						
w2 (2021)	-1.32	***	-1.65 – −0.99	-0.76	***	-1.01 – −0.51
w3 (2022)	-1.06	***	-1.40 – −0.72	-0.99	***	-1.25 – −0.73
Personal characteristics						
Age in 2019 (ref.: 18–29)						
(30−49)	-0.16		-0.44 – 0.12	-0.86	***	-1.30 – −0.41
(50−64)	-0.05		-0.37 – 0.26	-1.45	***	-1.81 – −1.09
(65 or more)	-0.82	*	-1.65 – 0.01	-1.30	***	-1.67 – −0.94
Yearly income (ref.: $150k or more)						
Yearly income ($60k to $150k)	0.18	*	-0.03 – 0.39	0.08		-0.17 – 0.33
Yearly income ($60k or less)	0.62	***	0.36 – 0.87	0.29	**	0.03 – 0.54
Built-environment characteristics						
Transit accessibility to jobs [100k jobs]	0.07	**	0.01 – 0.13	0.25	***	0.10 – 0.40
w2 * Transit accessibility to jobs	-0.07	*	-0.13 – 0.00	0.08	**	0.01 – 0.14
w3 * Transit accessibility to jobs	-0.06	*	-0.14 – 0.01	0.10	***	0.04 – 0.17
Walkscore [0,1]		-	-	0.27		-0.23 – 0.76
Walkscore * Transit accessibility		-	-	-0.36	***	-0.55 – −0.18
Commuting characteristics						
Transit commute time (ref.: telecommuters)						
(1–15 min)	-0.48	***	-0.83 – −0.13		-	-
(15–30 min)	0.49	***	0.21 – 0.77		-	-
(30–60 min)	0.61	***	0.34 – 0.88		-	-
(60+ min)	0.27		-0.07 – 0.62		-	-
Weekly telecommuting days	-0.19	***	-0.24 – −0.13		-	-
Residential selection attitudes						
Being near public transit	0.76	***	0.53 – 1.00	0.01		-0.17 – 0.19
Neighborhood car-friendliness	-0.49	***	-0.69 – −0.30	-0.20	**	-0.36 – −0.04
σ^2	3.05			1.28		
$\tau_{00\ person}$	1.29			0.56		
ICC	0.30			0.30		
N_{person}	1078			646		
Observations	2344			1420		
Marginal R^2 / Conditional R^2	0.233 / 0.461			0.145 / 0.403		

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

results. They also control for self-selection through residential-choice attitudes finding expected results, although stronger in workers than non-workers.

Through wave fixed effects, each model measures the change in weekly utilitarian transit trips compared to 2019 while keeping other factors fixed. For workers, the number of utilitarian transit trips decreased, on average, 1.32 weekly trips from 2019 to 2021, keeping all else constant. Between 2019 and 2022, the average decrease was 1.06, representing a slight recovery from 2021. For non-workers, the decrease between 2019 and 2021 is similar, with a magnitude of 0.76, ceteris paribus. However, the decrease of 0.99 between 2019 and 2022 for non-workers indicates a continued trend of decreasing transit use after the pandemic while keeping other variables constant.

The effects of accessibility to jobs by public transit and local accessibility are drastically different between workers and non-workers. In the case of workers, the effect of accessibility to jobs by public transit had a significant change between years. This is indicated by the statistical significance of the interaction terms between accessibility by transit and 2021 and 2022 wave fixed effects (w2 and w3, respectively). The non-interacted transit-accessibility coefficient of 0.07 indicates a positive effect on the frequency of transit use for workers' utilitarian purposes in the year 2019. To obtain the effect of transit accessibility in the years 2021 (w2) and 2022 (w3), the non-interacted coefficient must be added to the interacted term of each respective wave. Thus, the interaction term between w2 and transit accessibility of −0.07 indicates that, for workers, the effect of transit accessibility in 2021 is close to zero. Similarly, the interaction term associated to w3 of −0.06 indicates that the effect for workers remains close to zero in 2022. However, for workers, no statistically significant effect was found linked to WalkScore or to an interaction between it and transit accessibility.

In the case of non-workers, the effect of transit accessibility to jobs increased after the pandemic, as reflected by the positive interacted coefficients of 0.08 and 0.10 for wave 2 and wave 3 respectively. Moreover, in the case of local accessibility (measured by WalkScore) results also show a different effect than that of workers. Although WalkScore does not, on its own, have a significant effect on non-workers' utilitarian transit trips, there is a joint effect between local and regional accessibility. This interrelated effect is more clearly understood through the sensitivity analysis presented later in Section 4.3.

The effects of transit commuting time in the workers' model are measured in reference to respondents with a 0-minute commute time. That is, respondents whose work location is exclusively their home. These results provide an insight both into the effect of transit travel time to work and the effect of exclusively telecommuting. First, it can be seen that workers with the shortest commutes (1–15 minutes by transit) have the lowest frequency of weekly utilitarian transit trips, ceteris paribus. As commuting time increases, frequency of transit use increases. However, when commuting time by transit reaches 60 minutes, again frequency of transit use decreases and there is no statistical difference with workers exclusively telecommuting.

The effects of telecommuting frequency on weekly utilitarian transit use are measured for each additional telecommuting day. This is valid both for people exclusively telecommuting or for workers with a hybrid virtual/physical schedule. The coefficient of −0.19 is interpreted as the average reduction in transit trips due to an additional day of telecommuting. This means, for people telecommuting 5 days per week, there is an average reduction of about 1 transit trip per week. Although this number seems small, it must be interpreted as the average effect for the entire sample, which includes people that do not commute by transit. A clearer interpretation can be that for each 1000 people telecommuting, there is a total decrease of about 190 weekly transit trips. To complement this interpretation, the sensitivity analysis in the following section presents aggregate estimations of the effect of telecommuting as well as other variables in the model.

4.3. Sensitivity analysis

The first sensitivity analysis illustrates the importance of different factors in explaining the decrease in frequency of transit use after 2019. Fig. 4 presents this analysis for workers. In this case, wave fixed effects have the largest impact on the decrease of ridership in time. This is followed by the increase in telecommuting frequency, which accounts for slightly more than 10% of the decrease in workers' utilitarian transit use after 2019. The effect of transit accessibility to jobs is slightly below 10%. Note that this effect is not merely due to the slight decrease in accessibility levels shown in Table 1, but largely due to the decrease in the relevance of transit accessibility as shown in Table 2. Changes in

Fig. 4. Factors affecting decline in transit use for workers with respect to 2019.

residential-selection attitudes and in personal characteristics (yearly income) each explain close to 2% of the decrease. Finally, changes in commuting time account for a small increase in transit ridership in 2022 of under 2%.

In the case of non-workers (Fig. 5), the wave fixed effects have the largest contribution on the decrease in utilitarian transit frequency of use after 2019. As opposed to the workers' results, not all factors are explaining a decrease in transit ridership for non-workers. In fact, the increase in the post-pandemic relevance of regional accessibility mitigated the transit decline in approximately 15%. This means that, if the relationship between non-workers transit use and accessibility had remained, the post-pandemic decline would have been larger. Finally, changes in yearly income account for close to 5% of the decrease while changes in self-selection attitudes have a negligible effect.

The second sensitivity analysis illustrates the effects of local and regional accessibility on utilitarian transit use, which is represented in color as well as their changes through time in Fig. 6 for workers and non-workers. In this figure, the gray areas represent combinations not present in the Greater Montréal Area (*e.g.,* there are no areas with high transit accessibility yet low local accessibility).

In the case of workers, results show the steep decline in transit use between 2019 and 2021, as well as its slight recovery in 2022. Since no significant effect was found for WalkScore, only transit accessibility positively impacts weekly utilitarian transit trips. As previously discussed, this effect is most notable in 2019, and is close to zero in subsequent years. It is important to note that, given the spatial correlation of local and regional accessibility, the highest rates of transit use reached by those with highest transit accessibility are also from the highest WalkScore areas.

In the case of non-workers, results show the transit-use decline from 2019 and 2021, and its continued decrease in 2022. In terms of the effects of local and regional accessibility, results are drastically different. The interrelated effect of local and regional accessibility indicates that frequency of utilitarian transit use is the highest for non-workers living in higher transit accessibility areas but with lower local accessibility. On the other hand, the non-workers with the lowest frequency of utilitarian transit use are those living in either very low or in very high local and regional accessibility areas. Due to the increasing effect of regional accessibility by transit after the pandemic, the changes in transit use were not equal across different built environments. Whereas before the pandemic, the non-workers with the highest frequencies of transit use tended to be in the 300–500k-jobs range of accessibility by transit, after the pandemic this peak moved to the 500–700k-jobs range. In other words, the decline in transit ridership was steeper for non-workers living in relatively low accessibility by transit areas compared to those in higher accessibility areas.

5. Discussion and conclusions

This study employs a panel statistical framework which presents valuable insights into the determinants of workers' and non-workers' frequency of utilitarian transit trips, and their changes in 2021 and 2022 compared to 2019. The findings highlight substantial distinctions in the factors influencing transit patterns for these two groups after the pandemic. In fact, results show that the different patterns between workers and non-workers have diverged after the pandemic. Unraveling

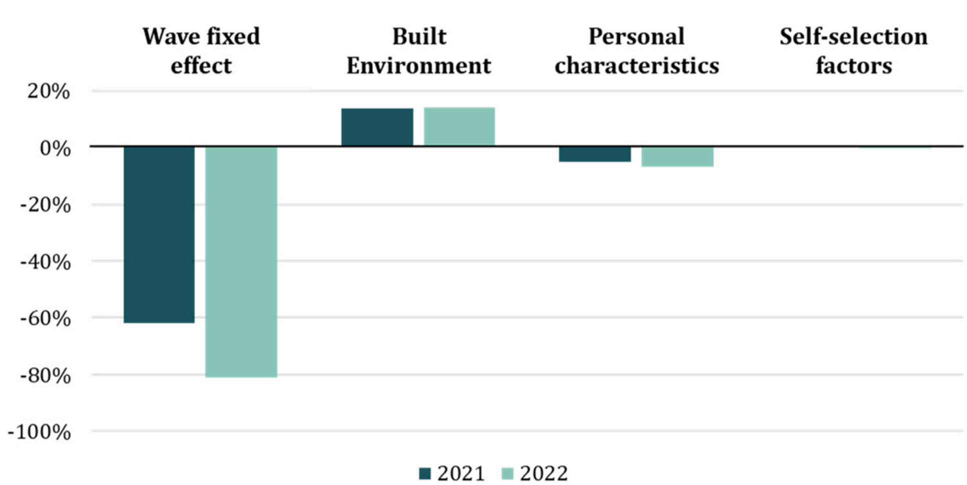

Fig. 5. Factors affecting decline in transit use for non-workers with respect to 2019.

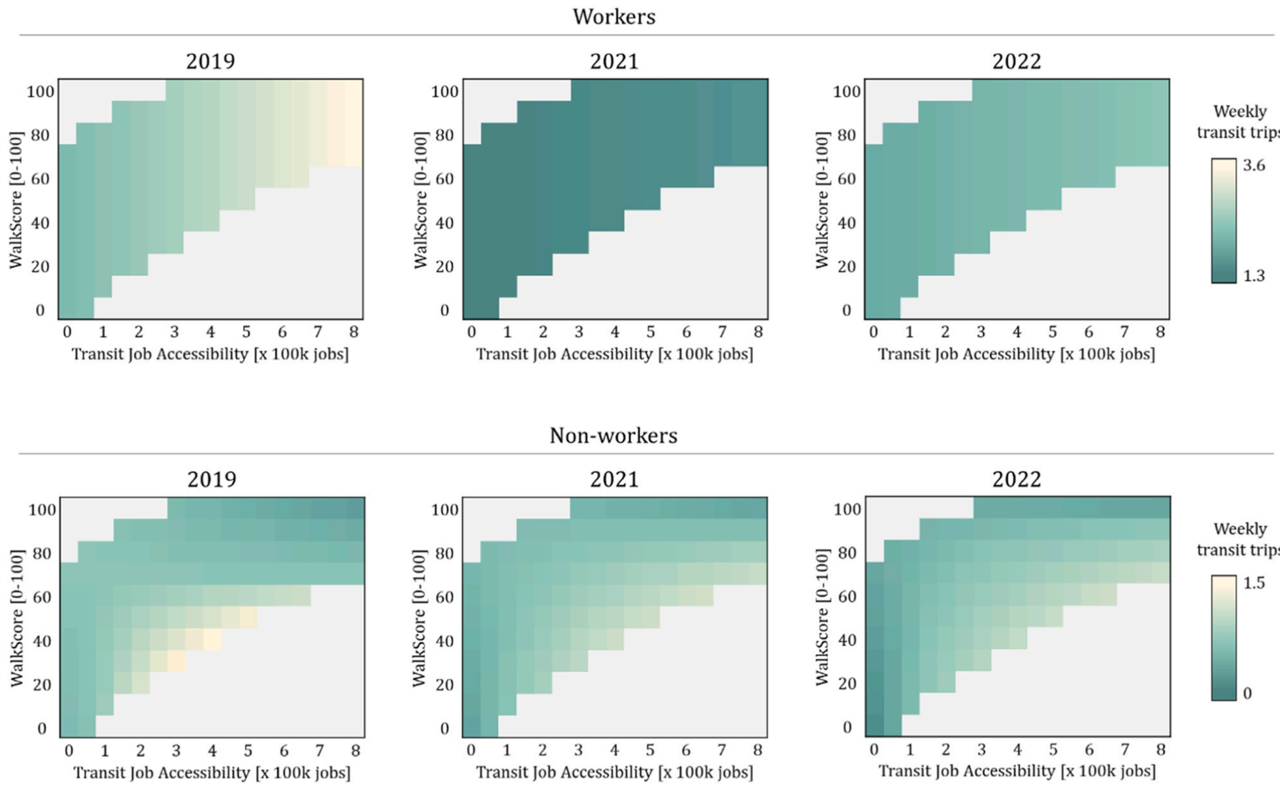

Fig. 6. Local/regional accessibility sensitivity analysis.

these patterns has relevant policy implications, particularly in advancing measures that aid in the post-pandemic transit recovery and effectively respond to post-pandemic shifts in behavior.

The results from this work corroborate a slight overall recovery from the steep declines of transit ridership as pandemic restrictions were removed (Abduljabbar et al., 2022). Results show that this recovery is mainly driven by workers. This study finds that non-workers' transit ridership did not recover but continued to decline in 2022 compared to 2021. These results complement past studies inquiring into the post-pandemic transit behavior of different sociodemographic groups (Lizana et al., 2023; Long et al., 2023; Wang et al., 2022).

In inquiring about the contribution of residential accessibility levels to transit-use decline, this study finds that, for workers, about 10% of the post-pandemic decrease can be attributed to transit accessibility. Results show that part of this contribution is due to a slight decrease in post-pandemic transit-accessibility levels. This is expected due to lowered operating frequencies after the pandemic (Nikolaidou et al., 2023). However, results show that most of the contribution of transit accessibility is not related to a decrease in accessibility itself, but to a reduction in its relevance on promoting workers' transit use. These results are in line with previous studies suggesting that a context where virtual activities are more prevalent would decouple travel behavior from the urban form (Elldér, 2017). However, these results must not necessarily be interpreted as accessibility being completely irrelevant for workers' transit ridership in the post-pandemic context. Since results from this study suggest that residential self-selection effects exist, there is still importance in the built environment changing travel-behavior in the long run, which can be seen as an indirect effect of the built environment (van Wee et al., 2019).

For non-workers, results show that regional accessibility by transit has a larger importance after the pandemic. This has resulted in a mitigating effect to non-workers' transit-use decline. Moreover, results show an interrelated pattern between residential local and regional accessibility. This pattern shows that non-workers with both high local accessibility and high transit accessibility have a lower frequency of utilitarian transit use. This effect can be expected since high local-accessibility areas provide greater opportunities for active transport (Cui et al., 2020). On the other hand, non-workers with higher transit accessibility but comparatively low local accessibility tend to have higher transit use, as active modes become less convenient for them. This presents a relevant implication for policymaking, since it indicates that increasing transit accessibility can be most relevant for non-workers living in areas with lower local-accessibility. These effects are likely not found for workers since commuting trips tend to have stronger spatial and temporal restrictions (Schwanen et al., 2008), which may result in workers having a stronger link to transit.

While accessibility has been shown to reduce its relevance in promoting workers' transit use after 2019, commuting time by transit has maintained its importance through time. This indicates that, in the post-pandemic context, what drives workers to use transit is not necessarily access to a diversity of jobs and activities but rather good transit mobility to the workplace. Because of this, to promote workers' transit ridership, public-transport services should focus on providing fast and reliable connections for workers to their respective workplaces through promoting direct transit to major employment hubs in the region.

Although transit commute time maintains its relevance after 2019, results show that increasing telecommuting frequency is producing a decrease in transit use by workers. This accounts for about 10% of the decrease in 2021 and 2022 compared to 2019. Thus, while this work corroborates previous studies showing that post-pandemic teleworking patterns are moving towards hybrid schedules (Javadinasr et al., 2022), the total effect in reducing workers' transit use maintains in 2022 compared to 2021. However, even if telecommuting habits are maintained in following years, it is important to promote workers' public-transport use through providing good workplace access given that workers are propelling the post-pandemic transit recovery.

In both models, the wave fixed effects remain comparatively large, which reflects that much of the decrease in transit use after 2019 remains unexplained by the factors in our models. This can have multiple interpretations. First, there are certain factors not available in this work's panel data that may be relevant for future studies to account for, such as changing attitudes and frequency of virtual activities other than work. However, even for future studies with more data availability, there is an unavoidable challenge in studying the post-pandemic context given its global nature. That is, there is no control group that did not experience COVID-19 with which to contrast travel behavior trends. In this sense, it is likely that any study following this work's panel modelling approach will deal with relatively large wave fixed effects.

Future studies may also build on this work's results by explicitly incorporating specific interventions to the transport system, such as new walking or cycling infrastructure. This would allow assessing the direct impact of each type of intervention, as opposed to this work's results which use comprehensive accessibility measures to capture the impacts of such interventions. Another future line of work that would complement this study is analyzing mode switching and the impacts of other substitutes such as ride-hailing services.

CRediT authorship contribution statement

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

Declaration of Competing Interest

The authors declare no conflict of interest.

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