

Triggers of travel behavior change: From abrupt disruptions to lasting effects

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Abstract

Urban mobility patterns are constantly evolving through complex interactions between individual choices, policy interventions, and systemic disruptions. The COVID-19 pandemic has represented the most significant recent example of how quickly travel behaviors can transform. New challenges for understanding and predicting travel behavior dynamics have emerged in this era of increasing uncertainty and rapid urban change. Critical gaps exist in understanding how large-scale disruptions like pandemics and gradual life changes alter the relationships between built environments, people's perceptions, and travel behavior. Despite advances in panel data collection, significant methodological gaps remain in terms of capturing these dynamics across different temporal scales and population groups. In this context, the main goal of this dissertation is to contribute to the transport planning literature and practice by answering the following overarching research question: *What are the impacts of exogeneous disruptions and endogenous life decisions on travel behavior patterns and perceptions over time?* This main research question is addressed through four manuscripts, which, taken together, address the following research objectives:

1. To analyze the impact of the COVID-19 pandemic on workers' patterns of active-mode use mediated by telecommuting and the local built environment.
2. To analyze the changing impact of the built environment on transit-use patterns due to the COVID-19 pandemic.
3. To analyze the impacts of new transit infrastructure on quality of life and rising-cost concerns over time.
4. To analyze how home relocation, car ownership, and household structure changes reshape mode-use patterns.

To achieve these objectives, each of these manuscripts presents quantitative data-driven analyses using disaggregated panel data from the Montréal Mobility Survey (MMS). The MMS is a bilingual multi-period online survey that is advertised widely in the Greater Montreal region and has been collected yearly since 2019, except for 2020. The first five waves of the survey were analyzed based on responses from 4,579 participants from at least two survey waves between 2019 and 2024. This timespan enabled the analysis of

pre-, during-, and post-pandemic travel patterns, public-transport infrastructure impacts, and gradual behavioral shifts tied to life course changes.

The research presented in this thesis provides significant empirical insights while illustrating the value of employing disaggregated panel methods. In turn, these empirical findings provide relevant knowledge to appropriately intervene in public policies that better adapt to the post-pandemic context. These recommendations are likely to have lasting relevance given the persistence of habits like telecommuting in the post-pandemic era. More specifically, this thesis contributes to research and practice in the following ways:

- Advancing the understanding of how sudden disruptions and gradual life changes reshape travel behavior and perception patterns.
- Demonstrating the critical role of built environments in mediating dynamic post-pandemic travel behaviors.
- Showcasing the value of disaggregated panel data for capturing complex mobility transitions.
- Revealing recovery pathways for sustainable transport modes in a changing context.
- Proposing integrated policy approaches that combine infrastructure investments with behavioral interventions.

This research provides a better understanding of the current mobility landscape, and proposes potential frameworks to analyze evolving urban mobility within an uncertain and rapidly-changing context. By analyzing the interplay of individual choices, external shocks, and local environments, it shows that both sudden disruptions and gradual life changes require integrated planning approaches for sustainable mobility futures. These insights can equip policymakers and researchers to evaluate behavioral shifts, prioritize equitable interventions, and harness longitudinal methods to track evolving urban transitions.

Résumé

La mobilité urbaine évolue constamment à travers des interactions complexes entre les choix individuels, les interventions politiques et les perturbations systémiques. La pandémie de COVID-19 a été l'exemple récent le plus marquant de la rapidité avec laquelle les comportements de déplacement peuvent se transformer. De nouveaux défis pour comprendre et prédire la dynamique des comportements de déplacement ont émergé dans cette ère d'incertitude et de mutations urbaines rapides. Il existe des lacunes importantes dans la compréhension de la manière dont les perturbations à grande échelle (comme les pandémies) et les changements de vie graduels modifient les relations entre l'environnement bâti, les perceptions des individus et les comportements de déplacement. Malgré les progrès dans la collecte de données longitudinales, des lacunes méthodologiques subsistent quant à la façon de saisir ces dynamiques à différentes échelles temporelles et pour divers groupes de population. Dans ce contexte, l'objectif principal de cette thèse est de contribuer à la littérature et à la pratique en planification des transports en répondant à la question de recherche générale suivante : *Quels sont les impacts des perturbations exogènes et des décisions de vie endogènes sur les comportements de déplacement et les perceptions au fil du temps?* Cette question principale est abordée à travers quatre articles, qui répondent ensemble aux objectifs de recherche suivants :

1. Analyser l'impact de la pandémie de COVID-19 sur les modes de déplacement actifs des travailleurs, en tenant compte du rôle médiateur du télétravail et de l'environnement bâti local.
2. Étudier l'évolution de l'influence de l'environnement bâti sur l'utilisation des transports en commun suite à la pandémie de COVID-19.
3. Évaluer l'impact des nouvelles infrastructures de transport en commun sur la qualité de vie et les préoccupations liées à l'augmentation des coûts au fil du temps.
4. Examiner comment les déménagements, la motorisation et les changements dans la structure du ménage transforment les habitudes de déplacement.

Pour atteindre ces objectifs, chacun de ces articles présente des analyses basées sur des données quantitatives en utilisant des données panel désagrégées provenant du Sondage sur la mobilité à Montréal (SMM). L'SMM est une enquête en ligne bilingue et multi-période, largement diffusée dans la région du Grand Montréal et réalisée chaque année depuis 2019, à l'exception de 2020. Les cinq premières vagues de

l'enquête ont été analysées basées sur les réponses de 4 579 participants ayant pris part à au moins deux vagues entre 2019 et 2024. Ce délai a permis d'analyser les modes de déplacement avant, pendant et après la pandémie, les impacts des infrastructures de transport en commun, et les changements comportementaux liés aux évolutions des parcours de vie.

Les recherches présentées dans cette thèse fournissent des constats empiriques significatives tout en illustrant la valeur des méthodes panel désagrégées. À leur tour, ces résultats empiriques fournissent des connaissances pertinentes pour intervenir de manière appropriée dans les politiques publiques afin de mieux s'adapter au contexte post-pandémique. Ces recommandations devraient avoir une pertinence durable compte tenu de la persistance d'habitudes comme le télétravail dans l'ère post-pandémique. Plus spécifiquement, cette thèse contribue à la recherche et à la pratique de la manière suivante :

- Faire progresser la compréhension de la manière dont les perturbations soudaines et les changements de vie progressifs redéfinissent les comportements de mobilité et les perceptions des déplacements.
- Démontrer le rôle crucial des environnements bâtis dans la médiation des comportements de déplacement dynamiques post-pandémiques.
- Mettre en valeur l'utilité des données panel désagrégées pour saisir les transitions de mobilité complexes.
- Révéler les trajectoires de rétablissement des modes de transport durables dans un contexte en évolution.
- Proposer des approches politiques intégrées qui combinent des investissements infrastructurels et des interventions comportementales.

Cette recherche permet une meilleure compréhension du paysage actuel de la mobilité et propose des cadres potentiels pour analyser l'évolution de la mobilité urbaine dans un contexte incertain et en rapide mutation. En analysant l'interaction entre les choix individuels, les chocs externes et les environnements locaux, elle montre que les perturbations soudaines et les changements de vie graduels nécessitent des approches de planification intégrées pour des avens de mobilité durable. Ces insights peuvent équiper les décideurs politiques et les chercheurs pour évaluer les changements comportementaux, prioriser des interventions équitables et exploiter des méthodes longitudinales pour suivre l'évolution des transitions urbaines.

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Publication details and author contributions

This thesis consists of four manuscripts. Each of these manuscripts corresponds to a publication that has been submitted to peer-reviewed journals and presented at international conferences. All four manuscripts were co-authored by Rodrigo Victoriano-Habit and Ahmed El-Geneidy. Ahmed El-Geneidy contributed intellectually and provided comments and edits to the manuscript. Rodrigo Victoriano-Habit was the primary author of all four manuscripts. He performed all of the statistical analysis, interpretation of results, and writing. The publication details for each chapter are given below.

Chapter 2: “Studying the Interrelationship Between Telecommuting During COVID-19, Residential Local Accessibility, and Active Travel: A Panel Study in Montréal, Canada” by Rodrigo Victoriano-Habit and Ahmed El-Geneidy. Published in the journal *Transportation* and presented at the *102nd Transportation Research Board Annual Meeting* and the *16th International Conference on Travel Behaviour Research*.

Chapter 3: “Why are people leaving public transport? A panel study of changes in transit-use patterns between 2019, 2021, and 2022 in Montréal, Canada” by Rodrigo Victoriano-Habit and Ahmed El-Geneidy. Published in the *Journal of Public Transportation* and presented at the *103rd Transportation Research Board Annual Meeting* and the *17th International Conference on Travel Behaviour Research*.

Chapter 4: “Measuring the impacts of new Bus Rapid Transit (BRT) on quality of life and cost concerns: A natural experiment in Montréal, Canada” by Rodrigo Victoriano-Habit and Ahmed El-Geneidy. Under review for publication in the journal *Transportation Research Part A: Policy and Practice* and presented at the *5th World Symposium on Transport and Land Use Research*.

Chapter 5: “Evolving transport mode changes: A longitudinal analysis of built-environment exposure in Montréal, Canada” by Rodrigo Victoriano-Habit and Ahmed El-Geneidy. Under review for publication in the *Journal of Transport Geography*.

1. Chapter one: Introduction

1.1 Chapter overview

The constant evolution of people's travel patterns is a result of complex interactions between deliberate life choices, planned policy interventions, and unanticipated disruptions to transport systems. Grounded in the study of travel behavior dynamics, this research focuses on events, interventions, and individual life changes that result in short- and medium-term consequences on travel patterns. Undoubtedly, when focusing on widespread disruptions on travel patterns, the largest example in the last decades is the COVID-19 pandemic, being a prime example of an event leading to unprecedented changes in travel patterns due to the accelerated adoption of working from home (*telecommuting*). Moreover, such a widespread event does not only impact overall travel trends, it may also result in changes in individual-level relationships between built environments, lifestyles, and travel decisions. In the current globalized and rapidly changing world, it is expected to keep facing these types of disruptions in travel behavior at different spatial and temporal levels. Additionally, within this changing context, the study of planned interventions to land-use and transport systems remains relevant. Planning for the future within this rapidly shifting context involves the continuation of building large-scale transport projects, which disrupts the urban system locally in various ways.

Examining the complex evolution of travel patterns over time requires addressing unique methodological challenges. Collecting and analyzing disaggregated panel data (individual and repeated observations) may address many of these challenges. This research is aimed at studying the impacts of exogenous disruptions and endogenous life decisions on travel behavior through using disaggregated panel data. Thus, in addition to advancing the understanding around triggers in urban mobility changes, this study will provide insights into the methodological procedures that can be used to unravel complex trends associated with behavioral shifts and long-term adaptation.

To help in contextualizing this work, this introductory section will comprehensively present the background associated with the fundamentals of land-use and transport systems' interaction, and the role that accessibility plays as a central mediating concept influencing travel behavior. The temporal dynamics of travel behavior will then be discussed, followed by a discussion of the fundamental role disaggregated panel data plays in analyzing these patterns. The background section will end with a discussion around the study of the exogenous and endogenous triggers of travel behavior changes over time. After the background section, this chapter presents the thesis' research objectives and its overall design and structure. The contributions to original knowledge by this research are then explicitly stated, and this chapter closes with a thorough description of the main data sources used to achieve the objectives of this work.

1.2 Research background

1.2.1 Land use and transport fundamentals

Studies inquiring into the complexities of urban environments require solid theoretical and operational frameworks to systematically investigate these dynamics. In the case of human mobility dynamics within urban areas, the two major components in conceptualizing urban environments are: the land-use system, and the transport system. The land-use system refers to the patterns of urban development in terms of the spatial distribution of people and activities, mainly measured through their density and diversity (Ewing & Cervero, 2001). The transport system refers to the availability and quality of transport options, including infrastructure and operation (Ortúzar & Willumsen, 2011). Although it is easy to recognize that the urban transport system and the urban land-use system are closely related, it is difficult to examine the impacts of one on the other, given that they are mutually dependent (Giuliano & Agarwal, 2017).

In the context of these two major urban components, *the land use and transport feedback cycle*, shown in Figure 1.1, explains that these two systems are interdependent (Wegener & Fuerst, 2004). The cycle

describes how transport systems affect land use patterns through activity patterns, and land use affects travel behavior through a central concept in transport planning and research: Accessibility (Wegener, 2008).

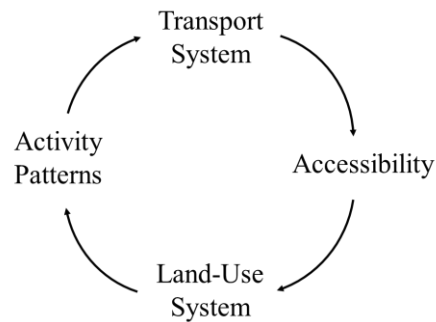


Figure 1.1. The land use and transport feedback cycle (Wegener, 2008).

Accessibility has been promoted as the most comprehensive land-use and transport measure (El-Geneidy & Levinson, 2022; Wachs & Kumagai, 1973). Defined as *the ease of reaching destinations* (Hansen, 1959), it is a measure that effectively reflects the relationship between land-use and transport systems (Geurs & van Wee, 2004). Geurs and van Wee (2004) provide four components to accessibility which influence the ease of reaching destinations: a land-use component, a transport component, a temporal component, and an individual component. The first two components are generally referred to as the main components of accessibility (Geurs & van Wee, 2004; Handy, 2020; Yan, 2021), while the latter two are more detailed specifications that need to be considered in its operationalization.

When operationalizing accessibility, a commonly used measure are cumulative opportunity indicators, which can simply be interpreted as the number of opportunities that are within reach in a given amount of time (El-Geneidy & Levinson, 2022). A common representation of opportunities in accessibility assessment is the number of jobs. This measure not only reflects the relevance of access to employment (Cui et al., 2019; Grengs, 2010), but also acts as a proxy of the quantity and diversity of services and products (El-Geneidy & Levinson, 2022). For these reasons, this measure is commonly proposed by some authors as one of the best ways to operationalize accessibility (COTAM, 2020; El-Geneidy & Levinson, 2022).

One reason why accessibility is an improved measure for understanding and predicting urban dynamics is the fact that it recognizes that demand for transport is largely derived and not an end in itself. Although more recently undirected travel (travel for the sake of travel) has been recognized as a relevant research subject (Cao et al., 2008; Mokhtarian & Salomon, 2001), it is still recognized that most urban travel is made with the purpose of reaching destinations for activity participation (Ortúzar & Willumsen, 2011). Moreover, accessibility recognizes that people are not interested necessarily in reaching destinations at a fast speed but rather at small travel times (Metz, 2008). That is, the land-use component of accessibility adds to the concept by recognizing the relevance of proximity (Levinson & Wu, 2019).

Perhaps the most relevant distinction that is necessary to make in order to understand the diverse impacts of accessibility is distinguishing between *regional accessibility* and *local accessibility* (Handy, 1993, 2020; Manaugh & El-Geneidy, 2012). These concepts relate directly to accessibility's two main components: the transport component, more related to mobility, and the land-use component, more related to proximity (Burns, 1981; Geurs & van Wee, 2004; Koenig, 1980). While local accessibility depends on the locality of activity centers, regional accessibility depends on transportation links, generally to larger regional activity concentrations (Handy, 1993).

Accessibility is a mode specific measure (El-Geneidy & Levinson, 2022), and its different components are more or less relevant depending on transport mode. As regional accessibility is more associated with speed, it is clear that it has a closer relationship to motorized modes: the private car and public transport (Lussier-Tomaszewski & Boisjoly, 2021; Silva & Altieri, 2022). On the other hand, local accessibility – shaped by density and proximity – is more related to active modes such as walking and cycling.

1.2.2 Travel behavior dynamics

While accessibility comprehensively summarizes the impact of the land-use and transport systems on people's behavior, travel patterns are broadly affected by other dimensions as well. This is particularly the

case when studying *travel behavior dynamics*. That is, the study of travel behavior which recognizes that patterns are not static in time (Clarke et al., 1982). For instance, the factors affecting a person's mode choice in a short-term context have been thoroughly explored in the literature, already showing to be highly complex and intricately dependent on multiple dimensions of daily behavior (Victoriano et al., 2020), as well as on people's historical mobility patterns (Grimsrud & El-Geneidy, 2013; Kitamura & van der Hoorn, 1987).

When considering *changing* travel behavior, behavioral processes related to dynamics come into play, increasing the complexity of the studied issue. These processes have been conceptualized to occur at three different levels (Clarke et al., 1982):

- *Microdynamics*, referring to the detailed scheduling within a day or a week
- *Macrodynamic modifiers*, related to changes in the medium- and long-term, generally linked to “life-shocks” (e.g., changes in life stage, the COVID-19 pandemic, introduction of urban infrastructure, etc.).
- *Macrodynamic processes*, which are related to overriding demographic processes of birth, ageing, and death.

While in the travel behavior literature, both microdynamics (Cherchi & Cirillo, 2014) and macrodynamic processes (Müggenburg et al., 2015) have been subjects of study, the macrodynamic-modifier level generally relates more to timespans and spatial extents that researchers and planners both have more control over. Dynamic behavioral processes at different levels aren't instant nor symmetrical (Clarke et al., 1982). History-dependence exists due to effects like habit and past behavior (Bamberg et al., 2003). For example, this means that the likelihood that a person will replace the use of a car by another mode, and the factors affecting this switch, are not the same for a long-time driver than for a recent one. These temporal complexities in travel behavior dynamics make the use of specialized data and methods essential for its appropriate measurement. One of the most relevant discussions in this context has been around the relevance of implementing disaggregated panel data.

1.2.3 Disaggregated panel data in travel behavior dynamics

The use of disaggregated panel data – that is, individual-level data collected at repeated points in time – is a key source to understand travel behavior changes. There are both theoretical reasons and broad empirical evidence showing that panel data is essential in unraveling complex problems in travel-behavior dynamics (Clarke et al., 1982; van de Coevering et al., 2015). Its use can also have an important role in solidly establishing causality, particularly when studying changes in travel behavior (van de Coevering et al., 2015).

As mentioned by Goodwin (1997), regarding urban-transport trends, “even apparently settled aggregated patterns are based on a very high degree of volatility, movement and turnover at the individual level”. This means that observed aggregated patterns may have hidden ‘sub-trends’ that are not observable at all in either aggregated or cross-sectional data. In fact, it is only disaggregated panel data that can reveal these ‘sub-trends’. In the case of travel behavior, this type of data is obtained by person- or household-level panel surveys. Multiple studies have shown the potential of disaggregated panel data in unraveling complexity and finding these hidden trends (Heinen et al., 2017; Song et al., 2017; Spears et al., 2017; Termida et al., 2016).

In terms of establishing causality, the most commonly cited requirements are (Bryman, 2012; van de Coevering et al., 2015):

- *Association (or correlation)*
- *Non-spuriousness*
- *Time precedence*
- *Plausibility (or mechanism)*

Given that plausibility is purely dependent on having a solid theoretical framework, the type of data used in an analysis – cross-sectional or panel – does not have a relevant relationship with this requirement. The

requirements of association, non-spuriousness, and time precedence highlight the need for using disaggregated panel data in the study of travel behavior changes.

There are no problems in establishing association between variables using cross-sectional data. For instance, it can be established that people living closer to a metro station have a higher frequency of metro use (Shen et al., 2016). However, causality is not necessarily established by this association, meaning that it is not necessarily living close to a station which *causes* more frequent metro use. In fact, residential self-selection can be a common confounding effect, for which the use of panel data is often recommended (Mokhtarian & Cao, 2008). In this sense, cross-sectional data is more likely to lead to spurious relationships by being more susceptible to confounding variables (van de Coevering et al., 2015).

Given that cross-sectional data is only a ‘snapshot’ of the state of subjects at one point in time, no temporal precedence can be established. To study and measure *changes* in behavior through time, such as changes in mode choices, multiple points in time need to be observed. Thus, while cross-sectional data is apt to unravel *differences* and establish *associations*, panel data is required to truly unravel *changes* and establish *causality* (Kitamura, 1990).

The triggers of changes in travel behavior can include both exogenous disruptions and endogenous changes in people’s life events (Müggenburg et al., 2015). Exogenous disruptions can include interventions and projects in urban environments that planners have control over, as well as exogenous widespread trends caused by events such as COVID-19. Endogenous changes, on the other hand, refer to events and decisions taken up by individuals or households that result in travel behavior change. The following subsections thoroughly describe the existing literature and research gaps around exogenous and endogenous triggers of travel behavior.

1.2.4 Exogenous triggers of travel behavior

The exogenous triggers of travel behavior can be conceptualized into spatially widespread disruptions and localized disruptions. The definition of these two groups can be understood through their relationship to the concept of a control group. That is, a reference group of people for which no effect can be assumed by the disruption. The first category is that for which no control group can be defined. This is the case for ubiquitous disruptions such as inflation, and spikes in gas prices, among others. Undoubtedly, the largest example of this type of disruption in the last decades is the COVID-19 pandemic. The pandemic has been a prime example of a widespread disruption in travel behavior and activity participation (Abduljabbar et al., 2022; Reuschke & Felstead, 2020), leading to unprecedented changes in mobility patterns across travel modes (Astroza et al., 2020; Melo, 2022; Nurse & Dunning, 2020; Tirachini & Cats, 2020).

Because there is no possibility for a control group, studies inquiring into the impact of widespread disruptions have three alternatives:

1. Assuming that the entirety of the observed change is due to the disruption.
2. Finding mediating explanatory factors that help analyze the impact of the disruption.
3. Measuring the changing impact of pre-existing explanatory factors due to the disruption.

The assumption in the first alternative may hold true only when the disruption is large enough and the timespan of analysis short enough. A good example of this was during the beginning stages of the pandemic, where studies could assume that most or all observed changes were due to COVID-19 (Hu & Chen, 2021; Tirachini & Cats, 2020). However, during later stages of the pandemic it is no longer reasonable to maintain this assumption, and studies moved accordingly to other alternatives. Examples of studies that find mediating explanatory factors include most of telecommuting related studies. Changes in telecommuting due to the pandemic are a concrete measurable factor to which many travel behavior changes can be attributed (Astroza et al., 2020; Reuschke & Felstead, 2020). Analyses using the third alternative include studies measuring the changing impact of factors that had consistently been proved to have a certain effect

in travel behavior. An example of this is analyzing how the pandemic has changed the relationship between the built environment and travel mode choices (Klapka et al., 2020).

Due to the changing context of the pandemic and the different manner in which changing habits like telecommuting affect several aspects of peoples' lives, there is still a significant gap in knowledge regarding the effects of the pandemic on travel and general wellbeing (Lunde et al., 2022). Telecommuting, in particular, has been linked to significant impacts on the likelihood of walking and cycling previous to the pandemic (Chakrabarti, 2018). However, a relevant gap remains in analyzing the impacts of telework on active travel in the context of its increased popularity during the pandemic. Similarly, the impacts of the pandemic on reducing public-transport ridership are highly relevant, 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 various efforts by governments and public transport agencies, a big percentage of former transit users switched towards driving and active transport as travel activities started to rebound (Abduljabbar et al., 2022). A relevant gap remains in studying the changing impacts on the factors affecting post-pandemic transit ridership. For instance, analyzing the changing impacts of the built environment characteristics in promoting public-transport use in this new context.

The case of localized disruptions differs largely due to the possibility of defining a control group. There are methodological designs that are apt to unravel conclusions from spatially localized disruptions, solidly establishing causality by avoiding multiple types of bias. In general, randomized experiments – before-and-after analyses with randomized control and treatment groups – are regarded as the ‘gold standard’ to infer causality in these types of interventions (van de Coevering et al., 2015). However, it is impossible for researchers to randomly assign the treatment and determine the exact time of its application when the ‘treatment’ is large transport infrastructure such as the construction of a metro line. Since the location of large transport infrastructure is carefully designed with different objectives than those of travel behavior research (Eliasson & Lundberg, 2012), treatment groups would likely be subject to spatial autocorrelation.

Moreover, since these interventions are built to last a timespan of decades, treatment cannot be applied and then removed in the timespan of a study design.

Due to the impossibility of applying randomized experiments, the closest alternative for research inquiring into the impacts of transport infrastructure are *natural experiments*. In spite of their name, natural experiments are not experimental but observational studies. They mainly differ from randomized experiments in that it cannot be decided by the researcher to whom or precisely when the treatment will be applied (van de Coevering et al., 2015). Few studies have taken advantage of the construction of large transport infrastructure in order to study the impacts *caused* by this infrastructure through natural experiments (Heinen et al., 2017; Spears et al., 2017; Sun & Du, 2023; Sun et al., 2020). This is done by designing a panel study where at least one of the survey waves is applied before the intervention, and at least one wave is applied after. Additionally, a control group must be defined and surveyed as well, which should in theory suffer no effect from the introduction of the intervention.

Despite an increasing popularity of natural experiments in transport research, most studies using these designs to measure the impact of new infrastructure 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 (Joseph et al., 2022; Song et al., 2023). A relevant research gap remains in using this type of robust design to analyze the impacts of new infrastructure on outcomes such as their perceived impacts on quality of life and wellbeing.

Although the conceptualization of widespread and localized disruptions may be useful to generate a framework to study these disruptions, they are not completely independent from each other. Despite the ubiquitous nature of widespread disruptions, their effect is not equal across all of space. For example, COVID-19 does not bare the same impact everywhere (Lizana et al., 2023; Long et al., 2023; Negm & El-Geneidy, 2024), and it is relevant for studies to use methodologies that can measure these spatially differing effects. On the other hand, the effects of spatially localized disruptions cannot be accurately measured if underlying trends are not accounted for (Goodwin, 1997). That is, when attempting to measure the impact

of new transport infrastructure, the effect of external trends such as those generated by COVID must be accounted for.

1.2.5 Endogenous triggers of travel behavior

The individual and household-level dynamics of travel behavior have been studied at widely differing temporal scales, with panel data and methods being central to their understanding (van de Coevering et al., 2015). For instance, microdynamics, as they relate to short-term variability, are more apt to be studied through multi-day or multi-week panels. These types of studies have shown that there is great variability in travel choices between days, suggesting the non-existence of a “typical” travel day (Fu, 2019). This high-degree of variability, described previously by Goodwin (1997), shows that traditional, one-day travel surveys can incur in large error by assuming static individual behavior. Although this variability exists, other studies have shown that these patterns are not random (Cherchi & Cirillo, 2014; Schlich & Axhausen, 2003). Thus, in the study of microdynamics, panel studies can not only reveal variability, but also the endogenous factors that determine it. This ‘repetitiveness’ effect is commonly referred to as *habit*, and is generally defined as the repeated performance of behavior sequences (Bamberg et al., 2003; Triandis, 1977). Since the concept of habit is directly tied to behavior through time, recognizing its importance in determining travel choices has been one more reason to promote the use of panel data in travel-behavior research (Gärling & Axhausen, 2003).

Although the microdynamics of travel behavior remain relevant for a comprehensive understanding of mobility patterns, medium- and long-term studies tend to present insights that are more relevant to the timescale of transport planning. The triggers of medium- and long-term travel behavior dynamics are generally linked to large “life shocks” (Goodwin, 1997), which are more apt to be studied by panels spanning over months or years. Multiple studies have inquired into the trajectories of travel-behavior changes of people and households over time at these scales, many of them under the concept of *mobility*

biographies (Scheiner, 2007). Through a systematic review, Müggenburg et al. (2015) found that the main key endogenous events discussed under this framework are: (i) private and professional life events such as changing jobs or birth of a child, (ii) adaptation of long-term mobility decisions such as purchasing a car, and (iii) long-term processes such as ageing and generational effects. Multiple studies have performed research surrounding these four points.

An example of a study that covers points (i) and (ii) is that by Lee et al. (2017), who studied the triggers of behavioral change within a household. Through this, they find that the evolution of a household's composition, particularly in terms of the number of children, is the main trigger of change. Similarly, Zhang et al. (2024) highlight how life events such as childbirth, changing jobs, and car ownership reshape travel attitudes and mode choices. Moreover, they find that there is a relevant impact of gender moderating these transitions. Khalil et al. (2024) showed the impact of demographic events to predict broad urban mobility impacts. These studies highlight that lifestyle transitions disrupt habitual travel patterns, particularly those related to mode choice and frequency of use (Adhikari et al., 2020). Moreover, these changing patterns often occur in highly mode-specific ways (Faber et al., 2025; Xu et al., 2024)

It is relevant to note that the mobility biographies framework is not limited to endogenous life shocks, as it includes exogenous interventions and disruptions such as those discussed in the previous subsection (Müggenburg et al., 2015). This highlights that, although the conceptualization of endogenous and exogenous factors results useful, they are deeply interconnected in determining triggers of travel behavior. Panel methods can contribute to the isolation of both effects in multiple ways (Goodwin, 1997). In this context, it is key for these types of study to not only measure endogenous triggers of changing behavior. They also require controlling for exogenous disruptions and trends such as changes in the built environment (Busch-Geertsema & Lanzendorf, 2015; Lee et al., 2017; Zhang et al., 2024) and broad overarching trends (Khalil et al., 2024).

Within the context of endogenous triggers of behavioral changes, residential relocations are particularly interesting, as they have the potential to combine relevant changes in lifestyle and life stage with changes

in the built environment. Studies have shown that these relocations gradually change both travel behavior and attitudes, especially when moving between areas with different built environments (De Vos et al., 2018; Wasfi et al., 2016). Moreover, the effects may vary broadly between different sociodemographic groups (Cheng et al., 2019), and impact transport modes in different ways over time (Schimohr et al., 2025).

Although multiple studies have contributed to understanding the endogenous triggers of evolving mobility patterns, significant gaps remain in the literature. First, most studies were done during the pre-pandemic times (De Vos et al., 2018; Wasfi et al., 2016) and there is a need for updating the analysis of these triggers when controlling for the new context. Secondly, many panel studies in this research topic perform simple before-after comparisons (Adhikari et al., 2020; Schimohr et al., 2025). Although this approach does provide longitudinal impacts of triggers in shifting behavior, it does not address more complex issues of time-lagged effects and the graduality of changes. Finally, many studies focus narrowly only on one mode of transport (Faber et al., 2025; Xu et al., 2024), which provides a partial view of changing behaviors but lacks a more comprehensive and multimodal approach.

1.3 Research objectives

Considering the research background and gaps presented, the ultimate purpose of this dissertation is to contribute to the transport literature by studying temporal shifts in travel behavior through the use of disaggregated panel data. In this context, this research will aim to answer the following overarching research question:

What are the impacts of exogeneous disruptions and endogenous life decisions on travel behavior patterns and perceptions over time?

This main research question is addressed through the following four research objectives:

1. To analyze the impact of the COVID-19 pandemic on workers' patterns of active-mode use mediated by telecommuting and the local built environment.

2. To analyze the changing impact of the built environment on transit-use patterns due to the COVID-19 pandemic.
3. To analyze the impacts of new transit infrastructure on quality of life and rising-cost concerns over time.
4. To analyze how home relocation, car ownership, and household structure changes reshape mode-use patterns.

Given that all the research included in this dissertation is contemporary, COVID-19 plays a role in studying temporal trends in travel, albeit at different levels. The first two objectives focus explicitly on aspects related to the pandemic. Objective 1 focuses on the impacts of increased frequency of telecommuting, which was a change in activity-travel patterns brought directly by the pandemic. In the case of Objective 2, the focus is on the changing impact of access to opportunities in promoting public transit use. In this sense, this objective addresses the changing impact of a factor that is well-known to impact travel patterns within the pandemic context.

While Objectives 3 and 4 are not explicitly centered on COVID-19, the pandemic's widespread influence on mobility trends needs its consideration as a contextual factor. Objective 3 examines the impacts of new public transit infrastructure on perceptions, a relationship potentially affected by pandemic-induced shifts in travel priorities and attitudes. Similarly, Objective 4 explores endogenous life decisions that may have been driven by, or whose effects may have been reshaped by, pandemic-era uncertainties. Thus, while these objectives prioritize other disruptions and gradual adaptations, the analysis within these objectives must control for pandemic-driven trends to isolate their distinct effects. This approach ensures robustness in attributing behavioral changes to their true triggers, whether exogenous shocks or endogenous choices, within the current post-pandemic context.

1.4 Thesis structure and overview

The body of this thesis is divided into four modular peer-reviewed articles, each of which is an individual chapter that relates to each of the previous objectives. As shown in Figure 1.2, objectives 1 to 4 are covered by chapters 2 to 5, respectively. They include a brief section positioning the study within the thesis prior to the manuscript, as well as distinct introduction, literature review, methodology, results and conclusion sections. To assemble the dissertation around these four key chapters, and in accordance to McGill University's guidelines, a discussion chapter (Chapter 6), and a conclusion chapter (Chapter 7) are included. Chapter 6 includes a comprehensive scholarly discussion of all the findings pertaining to the entirety of the thesis, linking the findings of the four manuscripts. Finally, Chapter 7 briefly summarizes and concludes on how the research objectives here presented were met.

1.5 Contributions to original knowledge

This research lies at the intersection of travel behavior dynamics, the analysis of shifting travel patterns, and the factors that trigger them. This topic is especially relevant considering the current globalized and rapidly changing world. The COVID-19 pandemic has shown how rapidly and widespread disruptions to travel can happen, revealing how critical it is to understand behavioral adaptation under changing conditions. In this context, transport planning needs be able to distinguish between temporary disruption and underlying trends. Within this context, this research contributes to understanding post-pandemic travel patterns through analyzing the impacts of telecommuting on active travel and the changing impacts of accessibility in promoting public transport use. Additionally, this work contributes to measuring the impacts of new transport infrastructure and individual decisions such as home relocation, even within these volatile conditions.

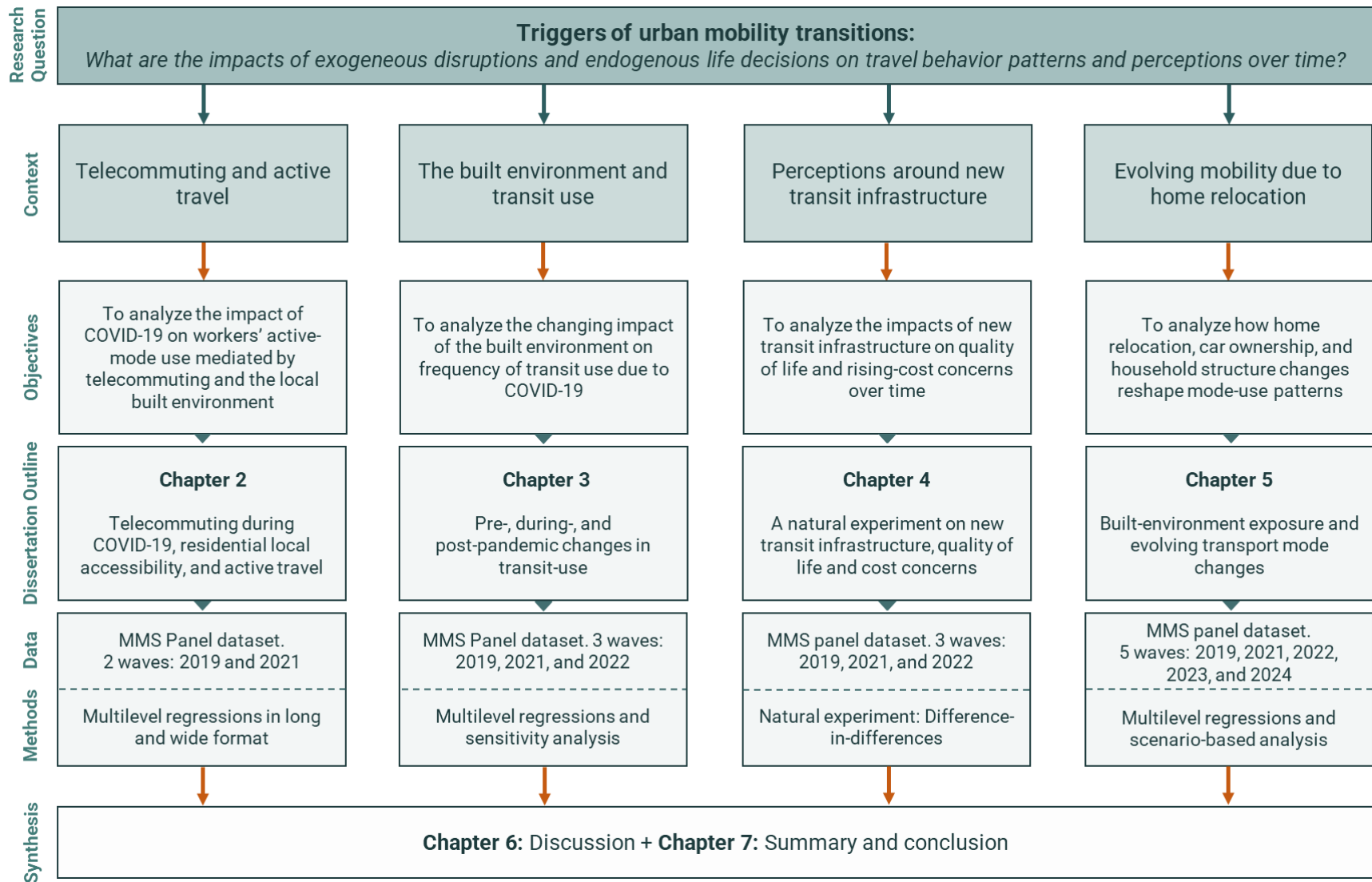


Figure 1.2. Dissertation outline.

Not only is it relevant to understand the new context due to the pandemic, but also to develop frameworks that capture how different triggers - from sudden policy interventions to gradual neighborhood changes - influence mobility patterns across varying time scales. This research provides findings regarding methodological decisions that harness the potential of disaggregated panel data for travel behavior analysis. This, in turn, aids in generating a framework that allows for effectively providing insights into how the impact of different triggers of urban mobility patterns change over time. A significant contribution of this research regards relevant methodological decisions in utilizing disaggregated panel data to study shifts in travel behavior and their driving factors. This will aid in understanding the specific complexities and biases that need addressing in analyzing different types of evolving and disrupting patterns, allowing for a deeper understanding of how they influence mobility over different time scales. Overall, this research will advance the understanding of how travel behavior transitions can be evaluated in time, providing essential insights for effective transport research and policy development in ever-changing urban landscapes.

1.6 Data sources

The four manuscripts included in this dissertation are data-driven analyses using quantitative data to achieve their respective objectives. This section details the common quantitative data sources for these four chapters: the Montréal Mobility Survey (MMS), regional, and local accessibility data.

1.6.1 Montréal Mobility Survey

The Montréal Mobility Survey (MMS) is a multi-period online bilingual survey administered in the Greater Montréal Area to participants aged 18 years or older. This survey collected by the Transportation Research at McGill team is composed of a cross-sectional and a panel dataset. That is, certain participants have responded to only one wave of the survey while others have participated in multiple points in time. The chapters of this dissertation which use the MMS data (chapters 2 to 5) exclusively use the panel dataset.

That is, individuals who participated in two or more waves. The sample sizes for these subsets of respondents are shown in Figure 1.3.

The studies in this dissertation use the first five waves of the MMS. The first wave of the survey collected 3,520 valid responses during the fall of 2019, the second wave collected 4,058 valid responses during the fall of 2021, the third wave collected 4,065 valid responses during the fall of 2022, the fourth wave collected 5,312 during the fall of 2023, and the fifth collected 7,428 during the fall of 2024. This multi-wave sample collects information at very distinct points in time. First, with regard to COVID-19, 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 posterior waves were collected when no travel restrictions remain. Thus, the multiple waves of the Montréal Mobility Survey, which start prior to the pandemic, represent a unique opportunity to study pre- and post-COVID travel behavior changes (chapters 2 and 3). Moreover, the multiple periods of the MMS are an opportunity to perform before-and-after studies the introduction of transport projects in the Montreal Region (chapter 4). It also represents an opportunity to analyze evolving individual travel trends while controlling for external overarching trends (Chapter 5).

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 residences and transport hubs, as well as targeted online recruitment through advertisements on 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 to help in recruiting part of the sample. All survey respondents who provided an email address received an invitation to participate in all subsequent waves. Through this process, the sample is composed of respondents who participated in only one wave (cross-sectional) and those who participated in two or more waves (panel).

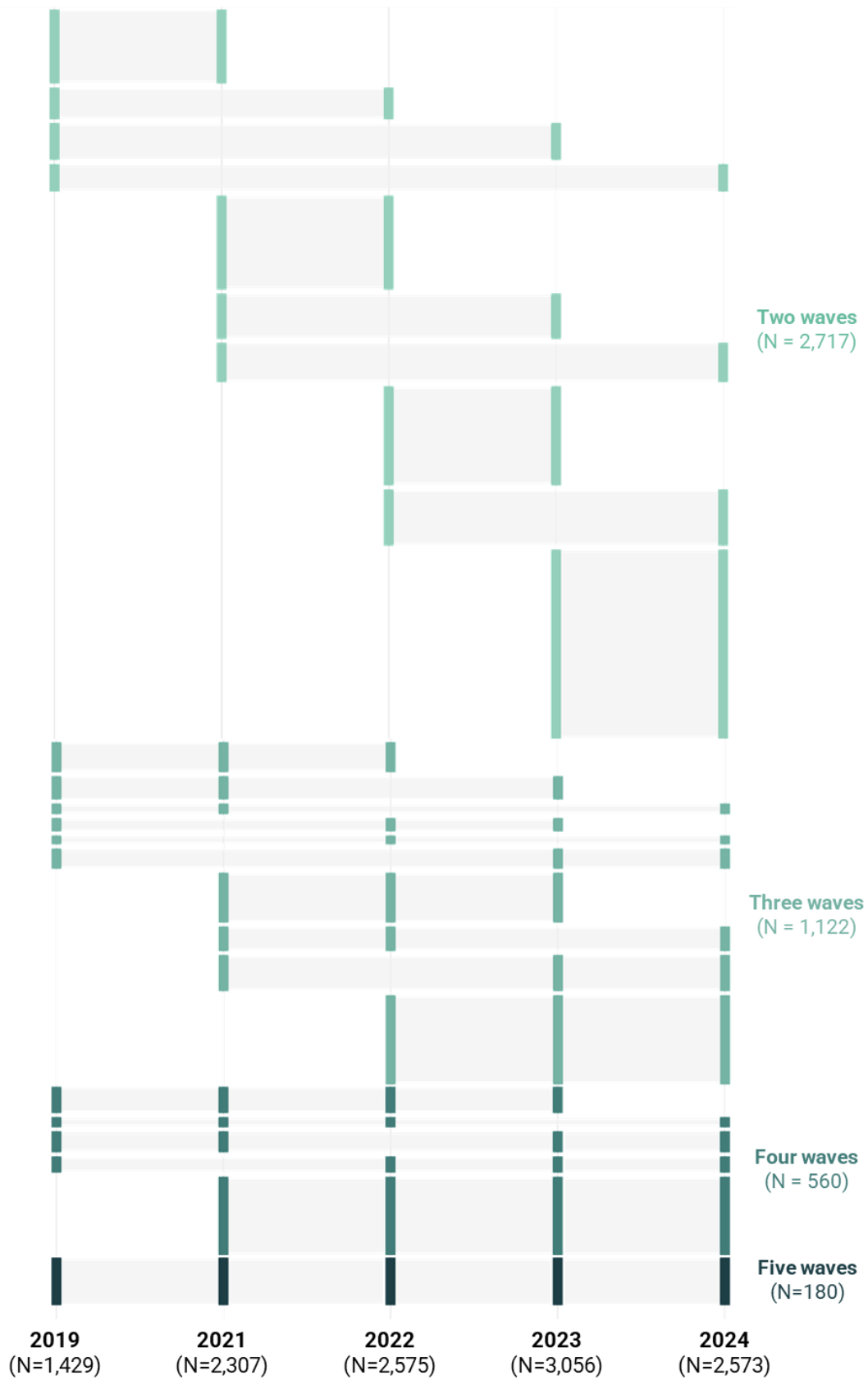


Figure 1.3. MMS panel sample sizes by wave participation

The same data-cleaning process was applied to all waves of the survey to ensure consistency in the exclusion criteria of unreliable responses. These criteria included removing multiple responses entered by the same e-mail or IP address, and invalid age and height changes between waves. Those who placed a pin representing their home, school and/or work location outside the Montréal metropolitan region or on bodies of water were excluded. 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. This cutoff was selected by analyzing the distribution of survey response times for each survey wave, as shown in Figure 1.4. Consistently across all survey waves, the fifth percentile was found to align with a break in the distribution of response times, as seen in Figure 1.4. This suggests that most responses below the 5% survey time cutoff represent anomalous responses, for which they were filtered.

All waves of the survey included the same questions pertaining to multiple dimensions of behavior, such as mode-choice patterns by purpose, telecommuting patterns, perceptions of the built environment, physical activity, and home location among others. The specifics of which data is used in each study is described in detail in each chapter. Most notably, since every question was answered by participants at all 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 Victoriano-Habit et al. (2024)

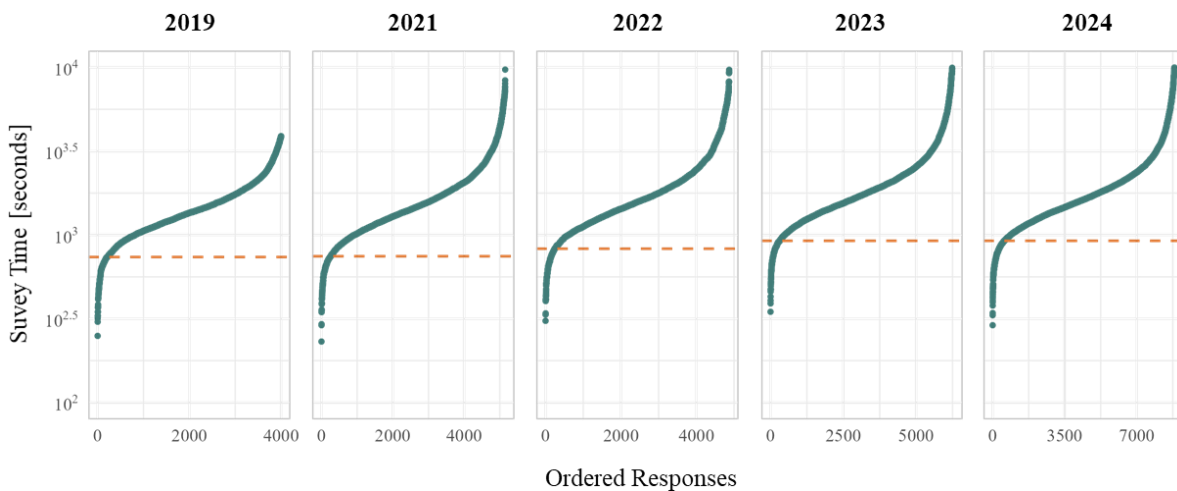


Figure 1.4. Survey speed 5th percentile cutoff for each survey wave.

1.6.1 Regional accessibility data

To comprehensively account for transit services and their changes over time, a measure of regional accessibility by transit is included. This measure is a cumulative-opportunities indicator to all jobs in the region within a 45-minute threshold. This indicator is widely used to measure accessibility mainly due to its direct interpretation (El-Geneidy & 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 (R. 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.

1.6.2 Local accessibility data

To account for residential local accessibility levels, WalkScore was retrieved for each respondent's home from *walkscore.com*. WalkScore is a popular measure of local accessibility which has been repeatedly tested in the land use and transport literature (Hall & Ram, 2018), and has shown reliability in predicting active travel patterns (Manaugh & El-Geneidy, 2011). The WalkScore index is produced through a gravity-based assessment of amenities within a 30-minute walk of a location, as described by Walk Score (2022). The index, which ranges from 0 to 100, integrates proximity to several types of amenities into a single composite score. These amenities include grocery stores, schools, parks, restaurants, and coffee shops (Walk Score, 2022). WalkScore was retrieved in each survey year. Thus, the data accounts for changes in residential local accessibility both in the case of respondents moving house and/or due to changes in time.

2. Chapter two – Telecommuting during COVID-19, residential local accessibility, and active travel.¹

2.1 Chapter positioning

The main objective of this chapter is to analyze the impact of COVID-19 on workers' patterns of active-mode use mediated by telecommuting and the local built environment. This objective contributes to answering the overarching research question of this dissertation by studying the role of an exogenous widespread disruption as a trigger of travel behavior change. Specifically, this chapter focuses on understanding the spatially differing effects of COVID-19 on workers' patterns of active travel. To do so, this study evaluates the effect of telecommuting during COVID-19 as the mediating factor that affects travel behavior. To assess the spatially differing effects of remote work, this chapter analyses the differing impact that telecommuting has had during the pandemic depending on the local accessibility levels around a worker's home. Moreover, this study contributes to understanding the implications of different panel modelling frameworks on analyzing widespread disruptions: long and wide format models. Results show that these types of models can yield complementary insights into the spatially differing effects of a widespread disruption in travel such as the COVID-19 pandemic. Most importantly, through the use of these methods, the effects of COVID-19 through a specific change in habits such as telecommuting can be accurately measured. This is done by controlling for changes in active travel trends that, while likely pandemic-driven, are unrelated to the increased popularity of telework.

¹ Victoriano-Habit, R. & El-Geneidy, A. (2024). Studying the Interrelationship between Telecommuting during COVID-19, residential local accessibility, and active travel: a panel study in Montréal, Canada. *Transportation*, 51(3), 1149-1166.

2.2 Abstract

The COVID-19 pandemic led to a substantial increase in the number of people working from home (*telecommuting*), in turn leading to unprecedented changes in mobility patterns worldwide. Due to the changing context of the pandemic, there is still a significant gap in knowledge regarding the effects of working from home on workers' travel patterns. The main goal of this work is to unravel the interrelationship between telecommuting during the COVID-19 pandemic, frequency of active travel for non-work utilitarian purposes, and local accessibility levels around workers' homes. This study uses a longitudinal approach by analyzing travel and telecommuting behavior data from a two-wave survey administered in the Greater Montreal in 2019, pre-pandemic, and 2021, during COVID-19 (n=452). Through a set of weighted multi-level linear regressions, we study the effects of telecommuting on the frequency of active travel for non-work utilitarian purposes, mediated by local accessibility around the household. Results show that the effect of telecommuting on non-work active travel for utilitarian purposes is highly dependent on local accessibility levels around the person's household. For workers living in high local accessibility areas, an increase in telecommuting during the pandemic has induced an increase in active trips for non-work utilitarian purposes. On the other hand, for workers residing in low local accessibility neighborhoods, the effect is the opposite. This research provides insights on the effects of telecommuting on non-work active travel, an area that is currently of interest to policy makers and practitioners working towards increasing the level of physical activity among individuals through travel.

2.3 Introduction

The COVID-19 pandemic has led to unprecedented changes in mobility patterns worldwide due to lockdowns and various health intervention measures. Almost all regions around the world experienced a substantial increase in the number of people working from home (*telecommuting*) and participating in various activities remotely (Reuschke & Felstead, 2020). Since the beginning of the pandemic, it has been

speculated that these large impacts on travel patterns can be a pivotal point for the renaissance of active modes of travel (Nurse & Dunning, 2020). Although nowadays there is considerably less travel to work, with many employers still encouraging telecommuting, the use of private vehicle for various purposes has nearly recovered compared to pre-pandemic levels (Melo, 2022). In this context, it is still not clear if the large increase in telecommuting during the lockdown periods has truly led to more use of active modes of travel for non-work purposes or the opposite.

Due to the changing context of the pandemic and the different manner in which telecommuting affects several dimensions of workers' lives, there is still a significant gap in knowledge regarding the effects of working from home on workers' general wellbeing (Lunde et al., 2022). While pre-COVID-19 studies have linked telecommuting to an increase in the likelihood of walking and cycling (Chakrabarti, 2018), it is not yet clear what the impact of telework on active travel is in the context of increased telecommuting during the pandemic. This is of particular relevance, since active travel has been shown to be a good way to increase people's physical activity and mental health (Kroesen & De Vos, 2020; Panik et al., 2019).

While some studies suggest that the higher levels of telecommuting during COVID-19 have increased active travel for leisure (Doubleday et al., 2021), to our knowledge there are no studies that focus on non-work utilitarian purposes. Moreover, since active travel has been shown to be highly dependent on local accessibility levels (Ewing & Cervero, 2010; Saelens & Handy, 2008), we hypothesize that residential local accessibility acts as a moderator variable in the effects of telecommuting on active mode use. In this context, the main goal of this work is to unravel the interrelationship between telecommuting, frequency of active travel for non-work utilitarian purposes, and local accessibility levels around workers' homes, specifically during the COVID-19 pandemic.

To achieve this goal, we take a panel approach using a two-wave survey administered in the Greater Montreal Area. To unravel the interrelationship between active travel, telecommuting, and local accessibility, while also taking the specific context of increased telecommuting during COVID-19 into account, we estimate three weighted multi-level linear regressions. With a first set of two models, we study

the frequency of travel for non-work utilitarian purposes as a response of (i) frequency of telecommuting, and (ii) the interrelated effect of telecommuting and local accessibility. Subsequently, we use a third model to study (iii) the interrelated effect of telecommuting and local accessibility on the frequency of travel for non-work utilitarian purposes, specifically in the context of increased telecommuting during the COVID-19 pandemic.

2.4 Literature review

In a matter of weeks, the spread of COVID-19 and imposition of non-pharmaceutical measures to combat the pandemic changed mobility patterns worldwide. One of the most relevant aspects in the evolution of mobility patterns throughout the pandemic is that reduction in travel has not been uniformly distributed across transport modes (R. H. M. Pereira et al., 2021). While public transit has suffered steep declines in ridership (Tirachini & Cats, 2020), the use of private vehicle for various purposes has nearly recovered compared to pre-pandemic levels (Melo, 2022). Within this context, since the beginning of the pandemic, it has been speculated that COVID's impacts on mode split can be an opportunity for increasing the use of active modes, such as walking and cycling (Nurse & Dunning, 2020).

Active modes of transport have been a relevant topic for travel behavior research and urban planning alike, as their use has shown to beget several benefits for people's general wellbeing. For instance, when compared to motorized mode use, the use of active modes is known to have a positive impact on physical health (Panik et al., 2019), mental health (Kroesen & De Vos, 2020), general quality of life (Fordham et al., 2018), and trip satisfaction levels (St-Louis et al., 2014). For these reasons, promoting active travel is widely seen as a desirable outcome of transport planning. However, there is still no general consensus on the effect of the pandemic over current and future mode share for active modes. For instance, Doubleday et al. (2021) have shown that the pandemic has had a reduction effect on walking and cycling, except for the purpose of leisure, for which active mode use has increased. On the other hand, Thombre and Agarwal

(2021) showed that, although active mode use has presented a relative decrease due to the pandemic, the effect hasn't been as steep due to mode switching as a result of public transport avoidance.

The changes in urban mobility patterns brought by the pandemic are largely related to changes in activity patterns, with an increase in the frequency of remote activities (S. M. Rahman et al., 2021; Reuschke & Felstead, 2020). In this context, the popularity of remote working (or *telecommuting*) has largely increased and is expected to persist even after the COVID-19 pandemic is over (Mohammadi et al., 2022). However, even before the pandemic there has been an interest in the effect of telecommuting on mobility patterns, as well as on mental and physical health (Mokhtarian, 1991). Previous research has shown that telecommuting has positive impacts on workers performing it, such as increased perceived quality of life (O'Keefe et al., 2016). On the other hand, other studies have shown that telecommuting can also result in negative impacts to physical health, as it increases time spent sitting and reduces performance of physical activities (Kooshari et al., 2021). Moreover, due to the changing context of the pandemic and the different manner in which telecommuting affects several dimensions of workers' lives, there is still a significant gap in knowledge regarding the effects of working from home on workers' physical activity and health (Lunde et al., 2022).

A relevant way in which telecommuting can affect workers' health is through its impact on the use of active modes of transport, given the multiple benefits that their use has been shown to beget (Fordham et al., 2018; Kroesen & De Vos, 2020; Panik et al., 2019). What past studies have shown in the pre-pandemic context, when telecommuting was restricted to a more limited fraction of workers (Mokhtarian, 2009; Reuschke & Felstead, 2020), is that teleworkers have a higher probability of using active modes (Chakrabarti, 2018), which is also linked to the performance of shorter trips (Elldér, 2020). While telecommuting eliminates the necessity to travel to work, it has been shown that teleworkers have an increased frequency of travel for non-work purposes (Caldarola & Sorrell, 2022). It is this context that has led to the speculation that the increasing frequency of telecommuting due to the COVID-19 pandemic can result in more frequent use of active modes of transport (Nurse & Dunning, 2020). However, studies during the COVID-19 pandemic have associated higher telework frequency to a potential increase in car use once the pandemic is over

(Javadinasr et al., 2022). Thus, given that the pandemic context may have changed the relationship between teleworking and mode choice, analyses of the relationship between active travel and telecommuting need to be revisited.

Previous analyses have shown that factors related to the built-environment are key predictors of active mode use frequency (Ewing & Cervero, 2010). Improving local accessibility of an urban area has been linked to increased likelihood of incurring in active travel (Saelens & Handy, 2008), as well as an increase in equity in active travel among genders and age groups (Althoff et al., 2017). One popular measure of local accessibility is WalkScore, which focuses on the number and diversity of activities that can be reached within walking distance, has been tested repeatedly in the land use and transport literature (Hall & Ram, 2018) showing reliability in predicting active travel behavior (Manaugh & El-Geneidy, 2011).

While local accessibility has been shown to be a highly relevant factor in predicting levels of active travel, to our knowledge no previous studies have inquired into the interaction between telecommuting and local accessibility, and its joint effect on active mode use. Additionally, since eliminating the commute to work changes peoples' activity spaces, then telework also has the potential to influence telecommuters' experienced accessibility levels throughout the day (Tribby et al., 2016). This can, in turn, affect their active travel behavior. For this reason, this work tests the hypothesis that the impact of telecommuting on active non-work utilitarian trips is mediated by residential local accessibility within the specific context of increased telecommuting due to the COVID-19 pandemic.

This paper contributes to the existing literature in several ways. First, given the large changes brought by the COVID-19 pandemic to activity participation and travel behavior, analyses of the relationship between telecommuting and mode choices need to be revisited. Specifically, this work focuses on active mode use for utilitarian purposes, as this can mitigate the sedentary lifestyle that teleworking may promote (Kooshari et al., 2021). In this way, this paper addresses the impacts of increased telecommuting during COVID-19 on both workers' travel behavior and physical health. Additionally, this work helps unravel the effect of telecommuting on active mode use while taking the effect of residential local accessibility into account as

a moderator variable. To the best of our knowledge, this has not yet been tested in the existing literature. Finally, this paper contributes to the literature by unraveling complex interrelationships in travel behavior through a longitudinal approach. This kind of approach has been strongly recommended for unraveling causal links in travel behavior but is seldomly used due to high costs and complexity (van de Coevering et al., 2015).

2.5 Data

This study uses data collected through a two-wave online survey administered in the Greater Montreal Area to participants of 18 years of age and older. The first wave of the survey collected 3,533 valid responses between October and November of 2019 (pre-pandemic), while the second wave collected 4,063 valid responses between October and November of 2021 (during the pandemic). All those who participated in wave 1 and provided their email address received an invitation to participate in wave 2. Through this process, we received 1,541 responses in wave 2 from participants who had previously answered wave 1.

To ensure the representativeness of the sample, in both waves we employed various recruitment techniques recommended by Dillman et al. (2014). These techniques 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 both waves to help in recruiting part of the sample.

The same data cleaning process was applied to both waves of the survey to ensure consistency in the exclusion criteria of unreliable responses. Some of these exclusion criteria were related to responders' time in filling the survey, multiple responses being filled by the same e-mail or IP address, and invalid age and height changes between 2019 and 2021. In terms of the time in which the respondent filled the survey, the fastest 5% were excluded from the sample depending on the number of questions answered in each wave.

It must be noted that 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 Montreal metropolitan region were also excluded. This led to a final sample of 870 valid and complete responses answering both waves, out of which 452 were working in both waves of the survey and indicated a valid primary work location.

The two waves of the survey included the same questions pertaining to travel behavior information such as frequency of travel, telecommuting, and mode choices. Respondents' sociodemographic and economic characteristics, as well as residential choice factors, which allow to control for residential self-selection, were collected in both waves. For each person in the sample we know their individual pre-pandemic behavior, as well as their current behavior (during the pandemic). This allows to assess the impacts of new telecommuting that respondents adopted due to the pandemic on travel behavior for non-work utilitarian purposes, namely grocery shopping and attending healthcare facilities. Since this work focuses on the effect of telecommuting, we only analyze and model the responses of the 452 workers in the sample with a valid primary work location, excluding students and retirees.

To account for residential local accessibility levels, we retrieved the WalkScore for each respondent's home from *walkscore.com*. WalkScore is a popular measure of local accessibility which has been repeatedly tested in the land use and transport literature (Hall & Ram, 2018), and has shown reliability in predicting active travel patterns (Manaugh & 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, restaurants, and coffee shops. The value of WalkScore ranges from 0 to 100, and is typically classified into one of four categories: car dependent (0-49), somewhat walkable (50-69), very walkable (70-89), and walker's paradise (90-100) (Walk Score, 2022). For the first-wave sample, WalkScore was retrieved in 2019, while for the second-wave sample it was retrieved in 2021. Thus, our data accounts for changes in residential local accessibility both in the case of respondents moving house or due to changes in time.

2.6 Methods

To achieve this work's main goal of unraveling the interrelationship between active travel for non-work utilitarian purposes, telecommuting, and local accessibility in the context of increased telecommuting during COVID-19, we estimate three weighted multi-level linear regressions. The methodological framework followed in this work is summarized by Figure 2.1. In our first model, we use a panel three-level linear regression with the number of weekly trips conducted by an active mode for non-work utilitarian purposes. In this context, active modes include walking and cycling, and non-work utilitarian purposes include grocery shopping and going to healthcare facilities. The main independent variables of Model 1 are frequency of telecommuting and the home-location local accessibility measured through WalkScore. Since Model 1 assumes that the effects of telecommuting frequency and home-location local accessibility are independent, in Model 2 we consider the interaction between these two effects. In this context, Model 2 is identical to Model 1 except for the inclusion of the interaction variable constructed from multiplying weekly telecommuting frequency by home-location WalkScore.

Model 1 and Model 2 use a three-level approach in which we use the census tract of the home location as the higher level. This allows to control for characteristics shared by a neighborhood that are otherwise unaccounted for. The second and lowest levels of the models, person-level and person-wave-level respectively, give the model its longitudinal component. That is to say, this model takes the dataset in long format (i.e., each row is one time point per person) and the second-level random effects control for the fact that observations in different waves can correspond to a same respondent. However, it must be noted that when using this three-level panel format, we assume that the effect of telecommuting on non-work utilitarian active travel frequency is the same in 2019 as it is in 2021.

To study the effect of frequency of telecommuting on non-work utilitarian active travel specifically in the context of COVID-19, our third model uses a different modeling approach. In this third model, we use the number of weekly trips conducted for non-work utilitarian purposes by an active mode in 2021 as the dependent variable. In this context, the model is specified as a two-level weighted linear regression, where

the higher-level is the census tract of the home location and the dataset is introduced in its wide format (i.e., each row consists of a person’s repeated responses). Here, the longitudinal component is considered by predicting behavior in 2021 by factors from both 2019 and 2021.

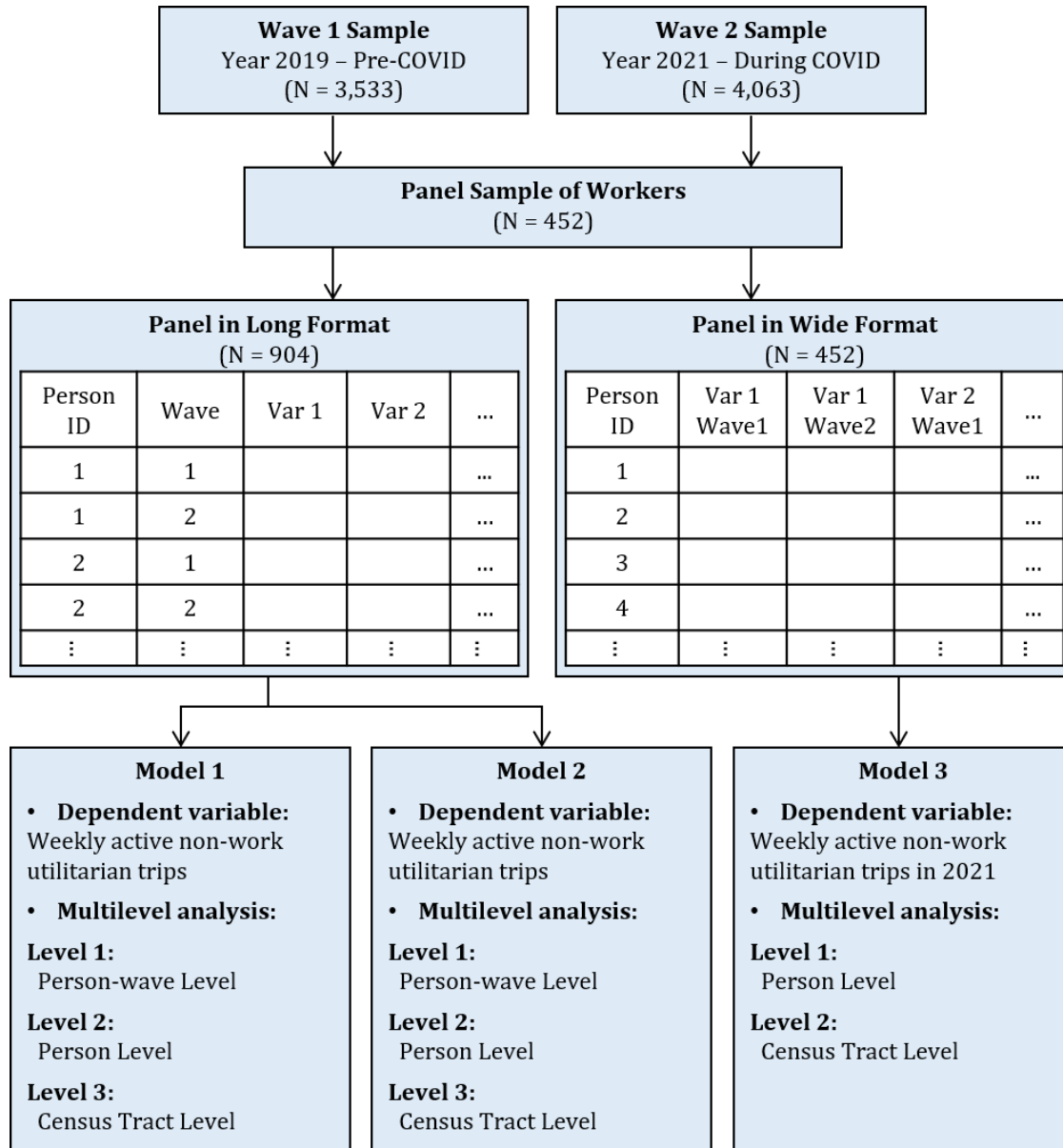


Figure 2.1. Methodological framework

To evaluate the effect of increased telecommuting during the pandemic, we used the difference in weekly telecommuting between 2021 and 2019 to measure its impacts on the non-work utilitarian active travel. The relevance of using this difference in telecommuting between the two survey waves is that it allows us to

measure the impact of telecommuting specifically during the COVID-19 pandemic, as opposed to most previous research on telecommuting (e.g., Caldarola & Sorrell, 2022; Elldér, 2020). Since, in this third model, the dependent variable relates to behavior in 2021 and is being predicted by factors that relate to both current and pre-pandemic behavior, in order to control for past active mode use, we also introduced the number of weekly non-work utilitarian active trips reported in 2019.

Each model considered additional independent variables to control for sociodemographic characteristics and residential self-selection. In the case of sociodemographic characteristics, gender, age, and household income were tested but were not statistically significant in any of the models. Car ownership at the household level was also tested and included in the models in which it had statistical significance. To control for residential self-selection, we incorporate respondent's reported importance factors for neighborhood choice. These factors were reported in a five-level likert scale and are also described in Table 2.1. Moreover, to assess non-linear effects of local accessibility, we tested the squared value of the home-location WalkScore as an independent variable. This variable was only included in model 3 as it was not statistically significant for other models.

The weighted multilevel linear regression was the method selected for all three models estimated as it responds to several requirements of this work's objective. First, for models 1 and 2, the second level of the random-effects' structure (person level) accounts for the longitudinal component of the dataset when it is taken in its long format (Figure 2.1). Second, for all three models, the highest level (census-tract level) allows to control for common characteristics shared in a neighborhood that are otherwise unaccounted for such as the quality of active transport infrastructure and frequency of crime. Third, the weighting process is key to ensure that the resulting effects of telecommuting and local accessibility on active travel are not biased by the sampling of the survey. Lastly, the coefficients of this type of model are easily interpretable as the marginal effect of independent variables on the explained variable, reason for which this method has been widely used in the travel behavior literature (El-Assi et al., 2017; El-Geneidy et al., 2014; Faghih-Imani et al., 2014; Grisé & El-Geneidy, 2017).

All of the weighted multilevel linear 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). The weights were calculated to match our sample to census tract information of age, income, and gender from Statistics Canada 2016 census (Statistics Canada, 2016), retrieved through the cancensus R package (von Bergmann et al., 2021).

2.7 Results and discussion

2.7.1 Data description

Table 2.1 includes the description of the sample in terms of their sociodemographic characteristics and modelling variables, and Figure 2.2 presents the geographical location of the respondents' households within the Greater Montreal Area in 2021. Our two-wave sample of 452 workers is composed of 53.3% of participants identifying as men. Because this sample focuses only on workers, it can be seen that most respondents are between 30 and 64 years of age. The sample presents variability among income groups, and there is a general tendency of income levels increasing from 2019 to 2021. Residential local accessibility presents large variability, with good representation of all WalkScore groups. This is also seen in Figure 2.2, showing that there is large spatial representation of the sample over the Greater Montreal Area. Moreover, the sample's local accessibility levels seem to have remained stable over time between 2019 and 2021.

As expected, telecommuting frequency suffered a large increase from the first to the second wave of the survey. While 78.7% of the sample did not telecommute in 2019, this percentage went down to 31.5% in 2021. Moreover, while only 4.9% of the sample were telecommuting 5 days per week in 2019, this number increased to 42.6% in 2021. In terms of non-work active trips for utilitarian purposes, the share of people with zero weekly trips suffered a slight decrease, from 54.3% in 2019 to 50.8% in 2021. However, there is also a slight decrease in the number of people doing five or more non-work active weekly trips, from 8.2%

in 2019 to 6.7% in 2021. Finally, it can be seen that attitudes towards residential selection remain stable over time between 2019 and 2021.

Table 2.1. Sample description by survey wave

Variable	Wave 1 (2019)	Wave 2 (2021)
	Mean (std. dev.)	Mean (std. dev.)
N		452
Sociodemographic		
Gender	<i>[1=man]</i>	53.3%
Age	<i>[years]</i>	
<i>[18 - 29]</i>	16.2%	10.0%
<i>[30 - 44]</i>	42.1%	42.6%
<i>[45 - 64]</i>	39.9%	45.2%
<i>[65 - 80]</i>	1.8%	2.2%
Household Income	<i>[\$/year]</i>	
<i>\$120,001 or more</i>	33.3%	40.1%
<i>\$60,001 - \$120,000</i>	42.4%	44.6%
<i>\$60,000 or less</i>	24.4%	15.3%
Local accessibility		
Neighborhood WalkScore	<i>[1-100]</i>	
<i>[0 - 49]</i>	37.9%	39.2%
<i>[50 - 69]</i>	23.1%	21.3%
<i>[70 - 89]</i>	28.2%	29.3%
<i>[90-100]</i>	10.9%	10.2%
Telecommuting		
Weekly days telecommuted	<i>[days/week]</i>	
<i>No telecommuting</i>	78.7%	31.5%
<i>1 to 4 days per week</i>	16.4%	25.9%
<i>5 days per week</i>	4.9%	42.6%
Non-work travel		
Non-work active trips	<i>[trips/week]</i>	
<i>None</i>	54.3%	50.8%
<i>1 to 2 trips per week</i>	23.3%	27.1%
<i>3 to 4 trips per week</i>	14.2%	15.5%
<i>5 or more trips per week</i>	8.2%	6.7%
Residential Self-Selection		
Neighborhood car-friendliness	<i>[5 levels]</i>	3.33 (1.42)
Familiarity with the neighborhood	<i>[5 levels]</i>	3.66 (1.13)
Near the work/school of HH member	<i>[5 levels]</i>	3.48 (1.28)
Being near family and friends	<i>[5 levels]</i>	3.25 (1.21)
Being near cycling infrastructure	<i>[5 levels]</i>	3.25 (1.22)

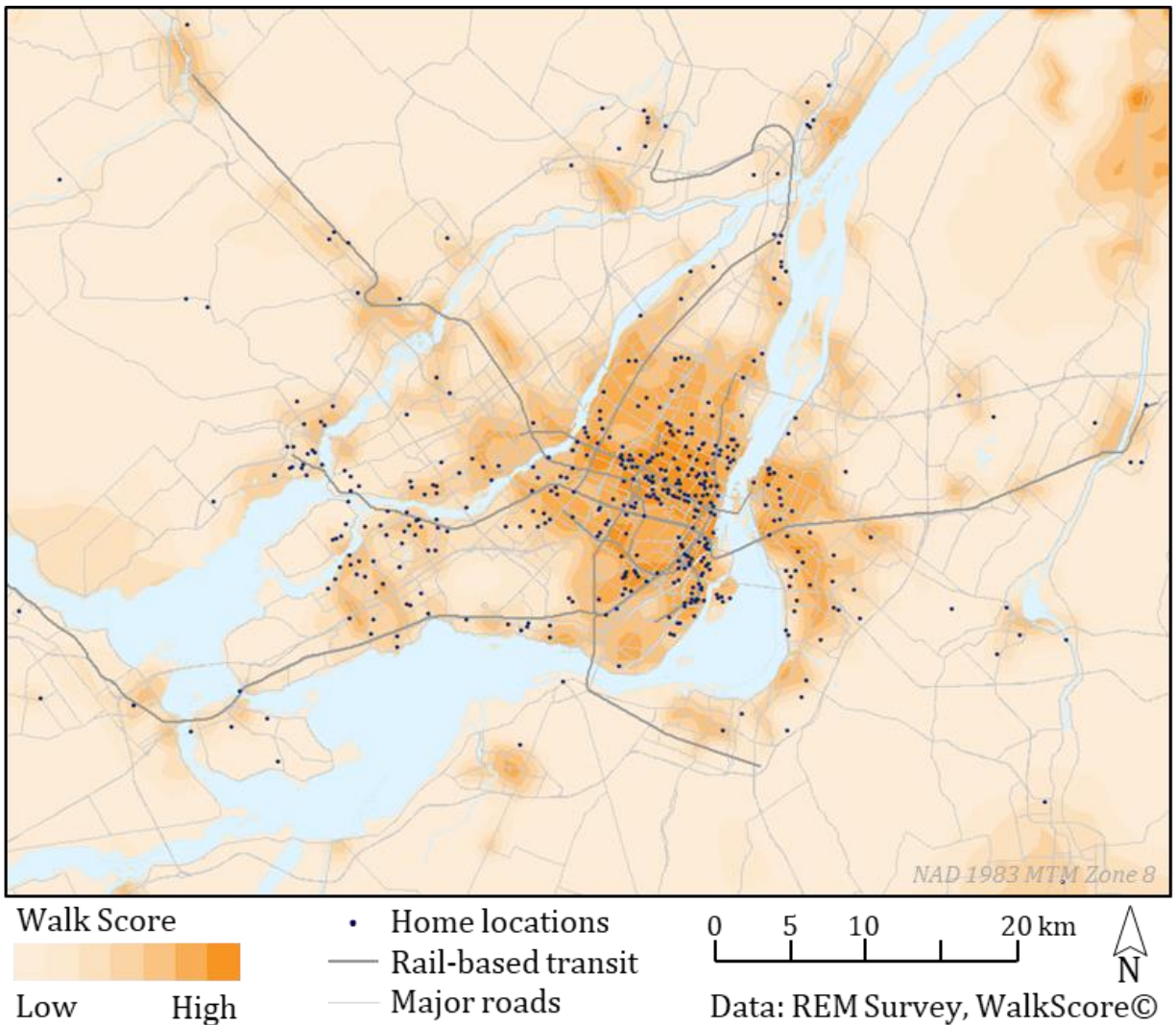


Figure 2.2. Home location of survey participants and WalkScore levels in 2021

2.7.2 Modelling results

The results for models 1 and 2 are presented in Table 2.2, in which the dependent variable is the weekly number of active trips for non-work utilitarian purposes. In Model 1, from the wave 2 coefficient we can conclude that, when keeping all else constant, people had a lower frequency of active travel for non-work utilitarian purposes, with 0.21 trips less in 2021 than in 2019. From this model we can also conclude that telecommuting has a small but statistically significant positive effect of 0.1 additional non-work utilitarian active trips for each additional day of telecommuting. In terms of the effect of local accessibility, for every

10-point increase in WalkScore, weekly active trips performed for non-work utilitarian purposes increase by 0.2 trips. Having at least one private vehicle in the household reduces the dependent variable in 0.4 weekly trips, ceteris paribus. The residential self-selection factors in Model 1 show that a preference for car-friendly environments decrease non-work utilitarian travel by 0.23 trips, while the preference for neighborhoods that are near to the respondent's family and friends increases the frequency of active travel for non-work utilitarian purposes. Similarly, a preference for proximity to cycling infrastructure also has a positive effect on our dependent variable.

Table 2.2. Models 1 and 2: Weekly non-work utilitarian active trips as dependent variable

Variable	Model 1		Model 2	
	Coefficient	95% C.I.	Coefficient	95% C.I.
Intercept	0.23	[-0.46; 0.92]	0.40	[-0.31; 1.11]
Wave 2 (Year 2021)	-0.21**	[-0.41; -0.01]	-0.22**	[-0.42; -0.02]
Telecommuting				
Weekly days telecommuted	0.10***	[0.04; 0.16]	-0.001	[-0.11; 0.11]
Local accessibility				
Home location WalkScore	0.02***	[0.02; 0.03]	0.02***	[0.01; 0.03]
Telecommuting-WalkScore interaction				
Telecommuting days * WalkScore	--	--	0.002**	[0.000; 0.003]
Car ownership				
At least 1 car in the household	-0.40**	[-0.72; -0.08]	-0.40**	[-0.72; -0.08]
Residential self-selection factors				
Neighborhood car-friendliness	-0.23***	[-0.33; -0.13]	-0.23***	[-0.32; -0.13]
Being near family and friends	0.14***	[0.04; 0.24]	0.14***	[0.04; 0.24]
Being near cycling infrastructure	0.13**	[0.03; 0.23]	0.13**	[0.03; 0.23]
Observations	904		904	
$N_{\text{PEOPLE}} / N_{\text{CT}}$	452 / 374		452 / 374	
$ICC_{\text{PEOPLE}} / ICC_{\text{CT}}$	0.45 / 0.15		0.45 / 0.15	
σ^2	1.15		1.14	
$\tau_{00 \text{ PEOPLE}} / \tau_{00 \text{ CT}}$	1.29 / 0.43		1.28 / 0.44	
AIC	3524.8		3534.8	
BIC	3577.6		3592.5	
Pseudo-R2 (fixed effects / total)	0.25 / 0.70		0.25 / 0.70	

** p < 0.05 *** p < 0.01

Model 2, which is identical to Model 1 except for the inclusion of the interaction between telecommuting frequency and local accessibility, shows nearly identical results to Model 1. The effect of telecommuting frequency is not statistically significant, yet the interaction term with local accessibility is statistically significant. The best way to understand these results is through a sensitivity analysis shown in Figure 2.3. We calculated the number of weekly non-work utilitarian active trips for 2019 and 2021 separately, by fixing every independent variable to the sample’s mean except for local accessibility and number of telecommuting days. We varied these two key variables within their possible ranges: 0 through 100 in the case of WalkScore, and 0 to 5 telecommuting days a week.

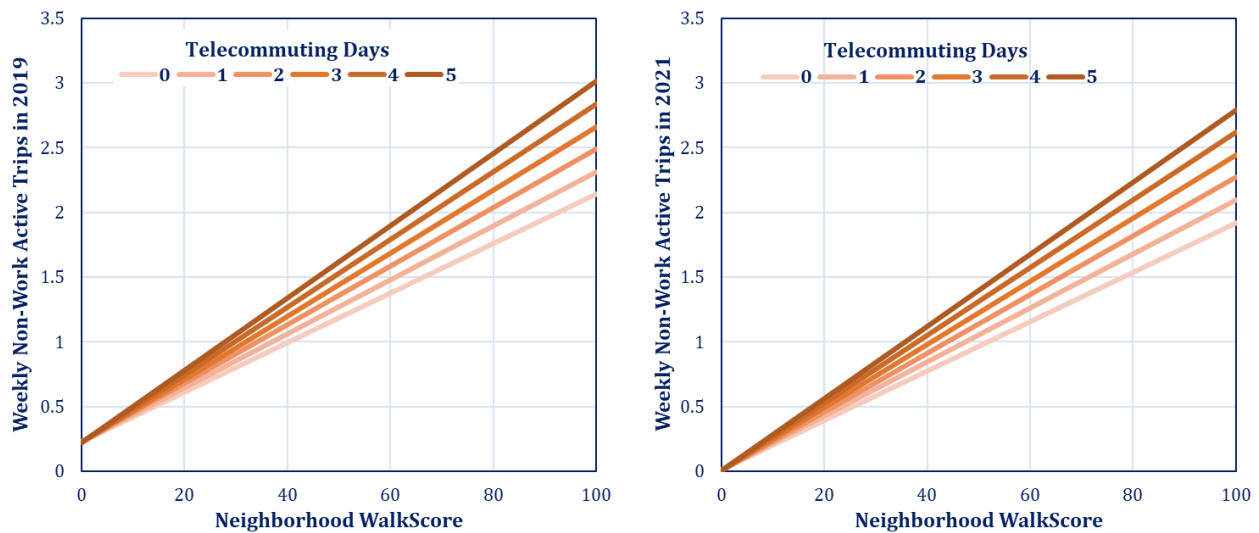


Figure 2.3. Model 2 telecommuting-WalkScore sensitivity analysis for 2019 and 2021

The analysis in Figure 2.3 shows that the effect of increasing telecommuting frequency on the number of active trips for non-work utilitarian purposes depends strongly on the worker’s home-location local accessibility levels. For workers living in higher local accessibility areas, the effect of telecommuting is positive and larger than that predicted by Model 1. In fact, for workers living in an area with the maximum WalkScore of 100, each additional telecommuting day results in 0.2 additional weekly active trips for non-work utilitarian purposes, assuming all else remains constant. This is double the value predicted by Model 1. For workers in low local accessibility areas, the effect of increasing telecommuting frequency is almost negligible.

Table 2.3 presents the results of Model 3, with weekly non-work utilitarian active trips in 2021, during COVID-19, as dependent variable. Similar to results in Model 2, while the effect of change in telecommuting from 2019 to 2021 is not statistically significant, other coefficients in the model allow to understand the effect of telecommuting on active travel. In this model, both home-location WalkScore and WalkScore squared are statistically significant, indicating a non-linear effect of local accessibility on non-work utilitarian active trips during COVID-19. Additionally, the interaction between telecommuting and local accessibility implies that the effect of telecommuting is strongly dependent on the worker's home-location local accessibility levels in the pandemic context.

Table 2.3. Model 3: Weekly non-work utilitarian active trips in 2021 as dependent variable

Variable	Model 3	
	Coefficient	95% C.I.
Intercept	0.65	[-0.22; 1.52]
Telecommuting		
Changes in telecommuting	-0.06	[-0.19; 0.08]
Local accessibility		
Home location WalkScore	-0.02**	[-0.04; 0.00]
WalkScore squared	0.0003***	[0.0000;0.0005]
Telecommuting-WalkScore interaction		
Change in telecommuting * WalkScore	0.002**	[0.000; 0.004]
Pre-pandemic travel behavior		
2019 Non-work active trips	0.40***	[0.34; 0.47]
Residential self-selection factors		
Neighborhood car-friendliness	-0.24***	[-0.35; -0.14]
Familiarity with the neighborhood	0.11**	[0.02; 0.28]
Near the work/school of HH member	0.15**	[0.00; 0.22]
Observations	452	
N_{CT}	315	
ICC_{CT}	0.10	
σ^2	1.58	
$\tau_{00 CT}$	0.17	
AIC	1711.5	
BIC	1756.8	
Pseudo-R2 (fixed effects / total)	0.47 / 0.53	

** p < 0.05 *** p < 0.01

A good way to illustrate these interrelated effects and how they differ from the results from Model 2 is through the sensitivity analysis shown in Figure 2.4. We calculated the number of weekly non-work utilitarian active trips in 2021 by fixing every independent variable to the sample's mean, except for local accessibility and number of additional telecommuting days during the pandemic, which we varied within their respective ranges. Through the results in Figure 2.4, we can conclude that home-location local accessibility acts as an important moderator variable in the effect of increased telecommuting due to COVID-19 on active travel. Workers living in high local accessibility areas experienced an increase in active trips for non-work utilitarian purposes during the COVID-19 period. The results show that the effect is the opposite for workers in the lowest local accessibility areas, who decrease their active travel for non-work utilitarian purposes. Thus, while Model 2 showed that telecommuting has no statistically significant effect on the active mode use of workers in the lowest local accessibility areas, Model 3 shows that additional telecommuting days during COVID-19 has had a negative effect for the active mobility of these workers.

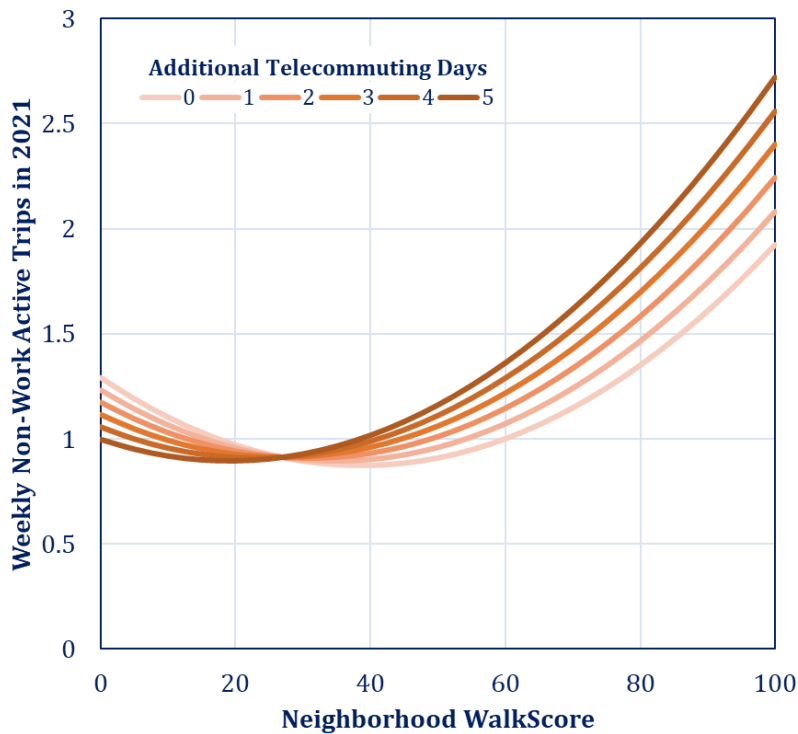


Figure 2.4. Model 3 telecommuting-local accessibility sensitivity analysis

Model 3 also controls for residential self-selection, showing that a preference for car-friendly environments has a negative and statistically significant effect on non-work utilitarian travel, *ceteris paribus*. A preference for neighborhoods which were previously familiar to the respondent increases the frequency of active travel for non-work utilitarian purposes, similar to preference for proximity to workplace or school of a household member.

It is relevant to note that, while there is no explicit control of sociodemographic variables in the models, we estimated versions of all three regressions which included several sociodemographic characteristics as independent variables, none of which showed to be statistically significant. Among the tested variables were age, income, number of children in the household, marital status, and environment while growing up (urban, suburban, or rural), all of which showed no significant effects. A binary variable indicating if a worker was employed full time or part time was tested as well, showing no significant effect.

2.8 Discussion and policy implication

The results from this work allow to draw relevant conclusions regarding travel behavior during the pandemic through a multi-period design. In turn, many of these conclusions can help policy-making in a post-pandemic context, as well as provide methodological insights for longitudinal analyses of travel behavior in the future.

Our results from models 1 and 2 yield interesting results with respect to the effects of telecommuting on active non-work trips. First, both of these models allow to conclude that active trips for non-work utilitarian purposes have suffered a small decrease which is not related to telecommuting. This suggests that a renaissance of active modes due to the pandemic (Nurse & Dunning, 2020) may not be the case, at least for workers in the Canadian context. Moreover, this result highlights the necessity of promoting public policies that encourage active-mode use which are specifically designed for the post-pandemic context.

The results from Model 2 show that the effect of telecommuting is strongly dependent on the worker's home-location local accessibility levels. This means that eliminating the necessity of commuting to a workplace only results in more non-work utilitarian active travel when there is a potential for reaching a destination within a small distance from home. From this, it can be concluded that ignoring the interrelated effect of telecommuting and local accessibility results in an inaccurate estimation of non-work utilitarian active trips. More specifically, ignoring the effect of local accessibility as a moderator variable results in an underestimation of non-work utilitarian active trips for workers in high local accessibility areas, and an overestimation for workers in low local accessibility areas.

The results of Model 3 provide an interesting complement to models 1 and 2. While this model's specification does not allow the conclusion that, keeping all else constant, there has been a reduction in non-work active utilitarian trips, it allows for other relevant insights. First, this model specification does not assume that the effect of telecommuting on active travel was the same pre-pandemic as it was during the pandemic. With this specification, active-travel behavior in 2021 is considered a result of active-travel behavior in 2019, as well as a result of the change in telecommuting frequency. Most importantly, this allows to unravel that the effect of increased telecommuting frequency during the pandemic results in less active trips for non-work purposes for workers living in the most car-dependent areas.

In the long-term, these results suggest that the best intervention for increasing active mobility for non-work purpose can be achieved through increasing local accessibility in car-dependent areas. That is, increasing the number and diversity of amenities that can be reached from residential areas within walking or cycling distance. While the importance of local accessibility in promoting active travel has been widely shown by previous literature (Ewing & Cervero, 2010; Saelens & Handy, 2008), to our knowledge, this is the first study that shows the effect of local accessibility as a moderator variable in the effect of telecommuting on active travel. In this context, this study shows that local accessibility has taken a heightened role during the pandemic given the increase in telecommuting frequency. Moreover, this heightened relevance of local

accessibility can be expected to remain, at least partially, once the pandemic is over, as post-pandemic frequency of telecommuting are expected to be higher than pre-pandemic levels (Javadinasr et al., 2022).

This work complements past studies which have concluded that teleworkers have a higher frequency of active travel (Chakrabarti, 2018; Elldér, 2020). As these previous studies, our results suggest that telecommuting may be encouraged as a public policy to increase active mode use. However, our results also show that, if policies are designed by analyzing the effect of telecommuting on active mobility on its own, ignoring the mediating effect of local accessibility, the expected positive outcomes in active mobility could be largely overestimated. In this context, this work highlights the relevance of designing transport policy that correctly adapts to the post-pandemic context. Considering the interaction between the increase in telecommuting due to the pandemic with local accessibility is key for effective policy design, which clearly shows the relevance of local accessibility and its positive impacts on active travel.

In our model estimations, we found that no individual or household sociodemographic characteristics of the respondent are significant to explain workers' active mode use when accounting for telecommuting and local accessibility. This indicates that the effect of telecommuting is influenced significantly more by the worker's neighborhood characteristics than their personal characteristics. This goes against the results of Elldér (2017), which suggested that telework would decouple travel behavior from urban form, making only personal characteristics relevant.

2.9 Conclusions

In this work, we inquired into the interrelationship between telecommuting during the COVID-19 pandemic, frequency of active travel for non-work utilitarian purposes, and local accessibility levels around workers' homes. Using a set of weighted multi-level linear regressions, we analyze a two-wave survey administered in the Greater Montreal Area in the years 2019 and 2021, allowing us to study the specific context of increased telecommuting frequency due to the COVID-19 pandemic.

Through our first model, we conclude that increasing telecommuting frequency has a positive average effect on the frequency of active travel for non-work utilitarian purposes. However, through our second model, we conclude that this positive effect is strongly dependent on the local accessibility levels of workers' home locations. More specifically, we conclude that this effect increases with higher local accessibility levels, and that there is no effect of telecommuting on non-work utilitarian active trip frequency for workers living in the lowest local accessibility areas. The results of these two models lead us to conclude that ignoring the interrelationship between telecommuting frequency and local accessibility levels result in an overestimation of the effect of telecommute on active travel for workers in low local accessibility areas, and an underestimation for workers in high local accessibility areas.

Through our third and final model we study the interrelated effect of change in telecommuting during the COVID-19 period and local accessibility levels on active travel. For this specific context, we corroborate that the effect of telecommuting on non-work active travel for utilitarian purposes is highly dependent on workers' home-location local accessibility levels. More specifically, for workers living in high local accessibility areas, our modelling results suggest that an increase in telecommuting during the pandemic has also induced an increase in the number of active trips for non-work utilitarian purposes. On the other hand, for workers who live in low local accessibility neighborhoods, results suggest that the effect is the opposite. We speculate that, for workers living in higher local accessibility areas, not having to travel to work gave them more time to interact with their local context

Our results can be of value for the travel behavior literature. To our knowledge, these are the first results to incorporate local accessibility as a moderating variable of the effect of telecommuting on active travel. This work shows that, for the case of utilitarian purposes, telecommuting increases active mode use when the worker's home has available destinations by active modes. Additionally, these results' conclusions suggest that, at least for active non-work utilitarian purposes, neighborhood local accessibility showed to be more relevant than sociodemographic characteristics.

In terms of policymaking, the two main implications of our results are that, first, if telecommuting is meant to be promoted with a goal of increasing active travel, then it should be mostly incentivized for people living in higher local accessibility areas, while for people living in lower local accessibility areas it should be accompanied by land-use policies that encourage positive changes in local accessibility. Secondly, improving neighborhood local accessibility increases the likelihood that people will incur in active travel, which goes in line with past results (Ewing & Cervero, 2010; Saelens & Handy, 2008). Our results suggest that this is especially the case in a context of increased telecommuting. Thus, our results additionally suggest that the benefits of increasing local accessibility in the COVID-19 context are larger than in pre-pandemic years.

One limitation of this work is that we assume a linear effect of every telecommuted day on non-work utilitarian active trips. However, previous works have shown that there could be an exponential effect, as more telecommuting allows for larger changes in mobility strategies and lifestyle (Asgari et al., 2019). Another limitation is that we don't take into account trip-chaining behavior, which has been shown to be more prevalent in workers living in lower accessibility areas (T. Chowdhury & D. M. Scott, 2020).

As a future line of work, it would be interesting to inquire into a similar analysis for active trips for non-utilitarian purposes, *i.e.*, recreation and socialization. The effects of telecommuting and the moderating effect of local accessibility on these purposes is not intuitive, since walking and cycling for recreation is not as dependent on availability of destinations as utilitarian purposes, or even socializing. Another possibility for future work would be to corroborate the effects found in this work in the future, as COVID-19's effect on daily behavior starts to decrease, including a wider time gap and potentially more survey waves in future studies. Future results will depend on the prevalence of telecommuting in a post-COVID world, as well as on workers' adjustments towards voluntary telecommuting.

3. Chapter three: Pre-, during-, and post-pandemic changes in transit-use.²

3.1 Chapter positioning

This chapter's objective is to analyze the changing impact of the built environment on transit-use patterns due to COVID-19. Similarly to the previous chapter, this study contributes to the dissertation by analyzing an exogenous widespread disruption as a trigger of change in travel patterns with an application on the pandemic. Building on this approach, this study complements Chapter 2 by analyzing the spatially differing effects of this disruption through measuring the changing impact of a dimension that has previously been established to influence travel behavior. In this case, this dimension is the built environment's characteristics. More specifically, this chapter investigates the post-pandemic utilitarian (non-leisure) transit behavior of workers and non-workers, and the changing impacts of accessibility in this process in Montréal Canada. As opposed to active travel, which is mostly affected by local accessibility, transit use may be impacted both by local and regional accessibility levels. This adds a layer of complexity to this work compared to Chapter 2, as the interrelated impact of local and regional accessibility is evaluated. Additionally, this study makes use of three waves of data, assessing the evolution of these effects over time before, during, and after the pandemic. To accurately isolate the changing impacts of accessibility, this work also evaluates the changing impact of other factors on the frequency of transit use. These include the frequency of telecommuting, changes in attitudes and sociodemographic characteristics, commuting time by transit, and pandemic-driven trends unrelated to the measured factors.

² Victoriano-Habit, R. & El-Geneidy, A. (2024). Why are people leaving public transport? A panel study of changes in transit-use patterns between 2019, 2021, and 2022 in Montréal, Canada. *Journal of Public Transportation*, 26, 100087.

3.2 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 to 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.

3.3 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 & 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 & 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 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).

3.4 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 & 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 & 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 & 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; S. 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 & Levinson, 2022; Wachs & 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 & van Wee, 2004). Accessibility is a mode specific tool (El-Geneidy & 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 & 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 (T. Chowdhury & D. 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 & 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.

3.5 Data and methods

3.5.1 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 3,520 valid responses during the fall of 2019, the second wave collected 4,058 valid responses during the fall of 2021, and the third wave collected 4,065 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 Figure 3.1.

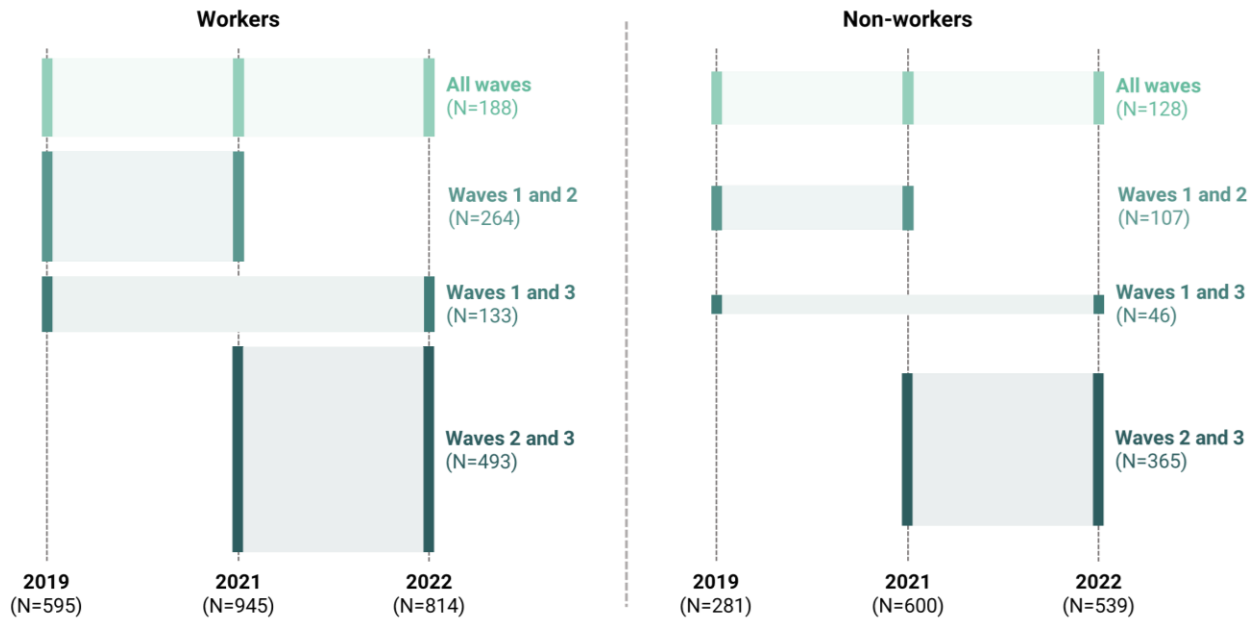


Figure 3.1. Sample size by wave participation.

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 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).

3.5.2 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 & 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 (R. 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 & Ram, 2018), and has shown reliability in predicting active travel patterns (Manaugh & 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.

3.5.3 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 & 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).

3.5.4 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.

3.6 Results

3.6.1 Descriptive statistics

The panel sample description is presented in Table 3.1 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.

Table 3.1. 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 to 29)	19.3%	17.5%	15.6%	8.2%	6.2%	5.0%
(30 to 49)	54.4%	55.1%	55.5%	9.3%	7.5%	7.6%
(50 to 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 to 15 min)	24.1%	6.3%	8.2%	-	-	-
(15 to 30 min)	41.0%	19.9%	21.0%	-	-	-
(30 to 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%

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. Figure 3.2 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.



Figure 3.2. Workers' and non-workers' home location at baseline.

The number of weekly utilitarian transit trips, the dependent variable of this study, varies both between subsamples 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 Figure 3.3, 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 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%.

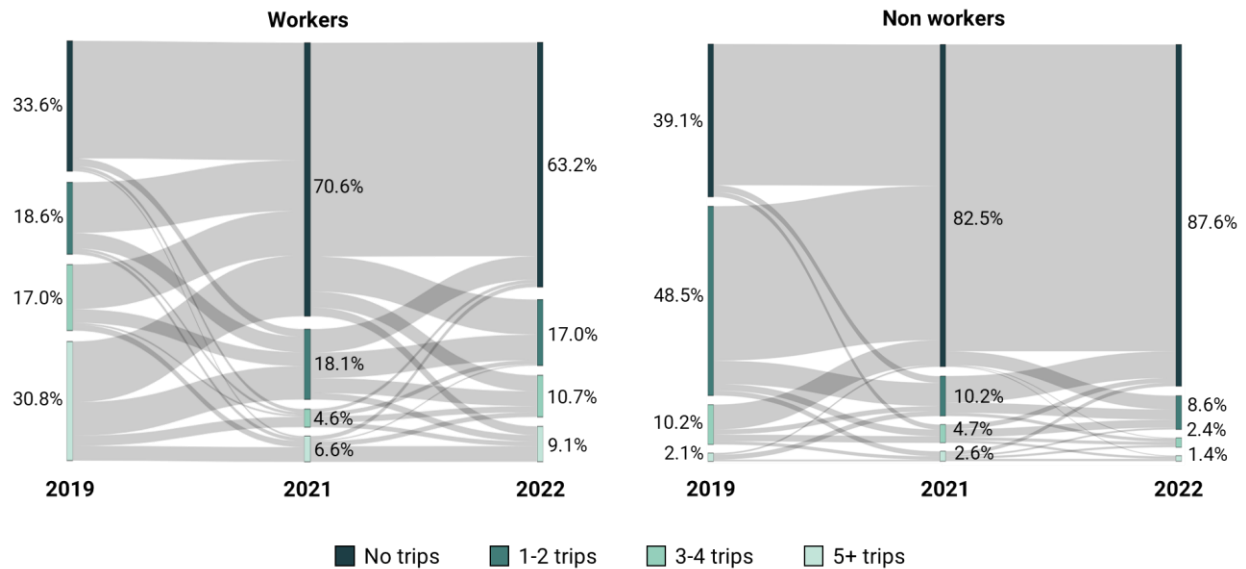


Figure 3.3. Changes in weekly frequency of transit use between survey waves.

Workers' commuting and telecommuting patterns presented drastic changes after the occurrence of the pandemic. The share of people exclusively telecommuting (represented in Table 3.1 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.

3.6.1 Modeling results

Results for the two estimated models are presented in Table 3.2. 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 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 (w_2 and w_3 , 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 (w_2) and 2022 (w_3), the non-interacted coefficient must be added to the interacted term of each respective wave. Thus, the interaction term between w_2 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 w_3 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.

Table 3.2. 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 to 29)				
(30 to 49)	-0.16	-0.44 – 0.12	-0.86***	-1.30 – -0.41
(50 to 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 to 15 min)	-0.48***	-0.83 – -0.13	-	-
(15 to 30 min)	0.49***	0.21 – 0.77	-	-
(30 to 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	
τ_{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

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 to 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 1,000 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.

3.6.2 Sensitivity analysis

The first sensitivity analysis illustrates the importance of different factors in explaining the decrease in frequency of transit use after 2019. Figure 3.4 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 4.1, but largely due to the decrease in the relevance of transit accessibility as shown in Table 4.2. Changes in 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%.



Figure 3.4. Factors affecting decline in transit use for workers with respect to 2019.

In the case of non-workers (Figure 3.5), 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.

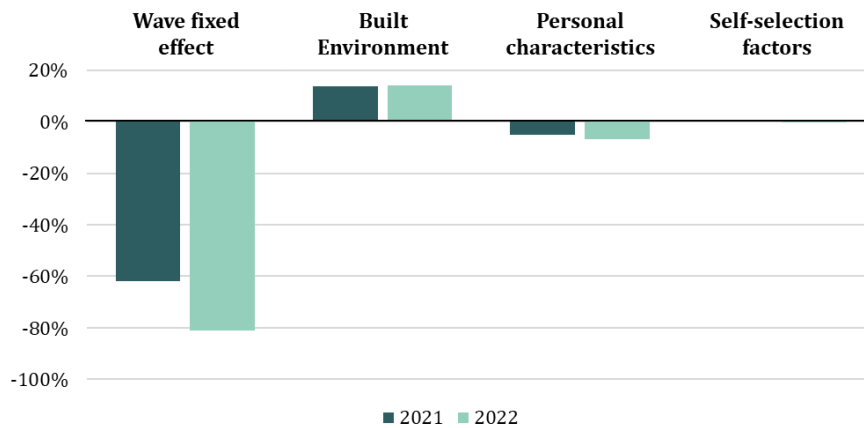


Figure 3.5. Factors affecting decline in transit use for non-workers with respect to 2019.

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 Figure 3.6 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 300k to 500k-jobs range of accessibility by transit, after the pandemic this peak moved to the 500k to 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.

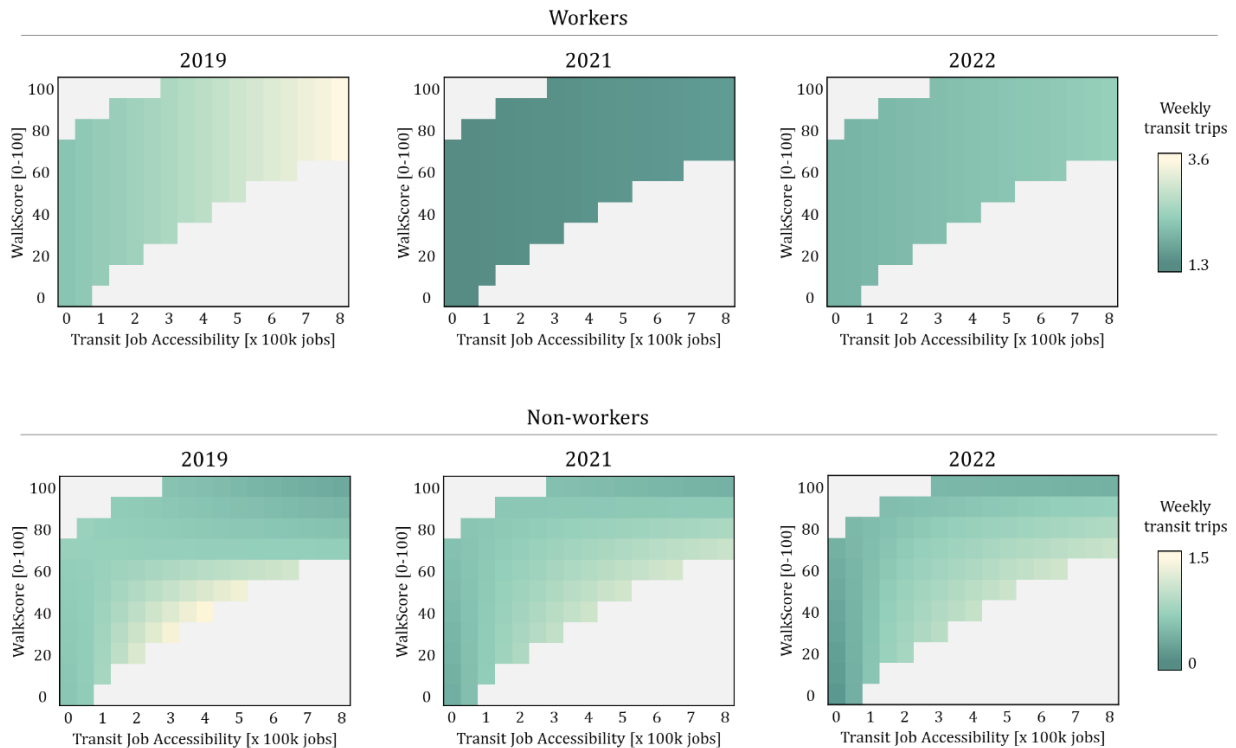


Figure 3.6. Local/regional accessibility sensitivity analysis.

3.7 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 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.

4. Chapter four: A natural experiment on new transit infrastructure, quality of life and cost concerns.³

4.1 Chapter positioning

This chapter aims to achieve the objective of analyzing the impacts of new transit infrastructure on quality of life and rising-cost concerns over time. Thus, this study focuses on the context of an exogenous disruption applied to the case of new transit infrastructure. However, as opposed to Chapters 2 and 3, this disruption is planned and localized, which requires different methodological approaches. More specifically, this chapter evaluates the perceived impacts of the new Pie-IX Bus Rapid Transit (BRT) implemented in 2022. The main impacts being measured are related to surrounding residents' perceptions around quality of life and increasing costs of living. To appropriately isolate the impacts of this intervention, this chapter applies a natural experiment framework. That is, the implementation of treatment and control groups within a before-and-after panel design. Two control groups are defined spatially with respect to their distance to the BRT: a higher dose group, and a lower dose group. In order to accurately isolate the impacts of the introduced project, this implies the use of models that control for observed pre-existing spatial differences among these analyzed groups. Although this chapter does not focus specifically on COVID-19 like Chapters 2 and 3, unobserved trends in time not related to the project need to be measured to effectively isolate the effects of the BRT, which include pandemic-driven trends. This study evaluates the changing impacts of these projects over two points in time: when the project was newly opened, and after one year in operation. Temporally, this is a similar approach to that used in Chapter 3, although applied to a localized trigger of travel behavior change.

³ Victoriano-Habit, R. & El-Geneidy, A. (Under review). Measuring the impacts of new Bus Rapid Transit (BRT) on quality of life and cost concerns: A natural experiment in Montréal, Canada. Transportation Research Part A.

4.2 Abstract

Investments in major infrastructure projects such as Bus Rapid Transit systems (BRT) are always accompanied by fears of gentrification and displacing residents. The fear of being priced out of a neighborhood can cause major mental stress to those residing near the new infrastructure, which can have major 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 0.5km 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.

4.3 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 increase 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 due to the anticipated increase in demand for housing, which is always accompanied by increases in 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 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.

4.4 Literature review

4.4.1 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 shown to be positive. 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.

4.4.2 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 are needed 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), 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.

4.5 Data

4.5.1 Panel dataset

The primary dataset of this study is composed of panel responses from the first four waves of the Montréal Mobility Survey (MMS) (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 ensure sample representativeness, various recruitment techniques recommended by Dillman et al. (2014) were employed in all waves. 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. However, only a portion of these samples were panel observations.

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).

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 are 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 in 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).

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).

4.6 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 \$523M 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 are more prevalent than in the rest of the island of Montréal (Statistics Canada, 2016). As seen in Figure 4.1, the study area is defined around 2 to 3 km at 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 away from an operating BRT stations 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. Moreover, the neighborhoods encompassed by the control group present similar population and built-environment characteristics to the treatment areas. For these reasons, this treatment/control design is effective in isolating the impacts of the new BRT.

4.7 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 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).



Figure 4.1. Home location of respondents by treatment/control group.

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), which is most simply defined as follows (Craig et al., 2017):

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

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. The variable X_i represents a confounding effect. For simplicity, Equation 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.

In this study, we employ two sets of DiD models; one set for each dependent variable: 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). 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). 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 (<0.5km and 0.5 to 1.0km), which are evaluated in each model. The confounding variables included in each model are yearly household income, number of people in the household, and the respondent's gender.

The DiD models were estimated through a multilevel binary logistic regression. With this modelling framework, the higher level of the random-effects' structure (person level) accounts for the longitudinal component of the dataset. The statistical framework recognizes that there are repeated observations of the same individual over time. All regressions were estimated using the lme4 R package (Bates et al., 2015).

4.8 Results

4.8.1 Descriptive statistics

The descriptive statistics of the studied sample are presented in Table 4.1. This description is presented by survey time and by treatment/control group. In terms of trends in time, there is a general trend of decreasing perception of quality of life due to neighborhood concerns, except for Treatment group 1 (<0.5km). In terms of the differences at baseline in this variable, although Treatment group 2 (0.5 to 1.0km) 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).

Table 4.1. Descriptive statistics by survey time and treatment group.

Variable	Before opening			Newly opened			1 year after opening		
	N = 175			N = 322			N = 401		
	[2019 / 2021]			[2022]			[2023]		
	<0.5km	0.5-1.0km	Control	<0.5km	0.5-1.0km	Control	<0.5km	0.5-1.0km	Control
Dependent Variables									
Quality of Life [Binary]	47.8%	75.0%	73.4%	51.8%	43.3%	51.9%	52.9%	50.7%	55.3%
Cost Concerns [Binary]	21.7%	20.8%	49.2%	35.7%	26.7%	31.6%	23.5%	22.5%	36.3%
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									
[\$150k or more]	43.5%	20.8%	28.1%	25.0%	21.7%	20.9%	30.9%	28.2%	24.4%
[\$60k to \$150k]	60.9%	33.3%	48.4%	33.9%	41.7%	35.0%	33.8%	36.6%	34.7%
[\$60k 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%
N	23	24	128	56	60	206	68	71	262

A general trend of decreasing cost concerns over time can be observed, except for Treatment group 1 (<0.5km), for which it increased temporarily in 2022 and decreased again in 2023. 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. Finally, the percentage of women in each sub-sample varies between 35% and 60%.

4.8.2 Quality of life modeling results

The first set of models, presented in the first two columns of Table 4.2, 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 (<0.5km), indicating that the DiD framework is correcting for observed biases at baseline. These coefficients show that, keeping all else constant, the first treatment group has 73% lower odds of perceiving higher quality of life in 2022 and 82% lower odds in 2023 compared to the control. No observed biases can be seen for Treatment group 2 (0.5 to 1.0km).

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 (<0.5km) but no significant effects for Treatment group 2 (0.5 to 1.0km). The first model 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 3.74 times what it would have been with no intervention. The second

model shows that, after 1 year of operation of the BRT, this effect became even stronger. The odds of perceiving increased quality of life are 4.26 times larger after one year than what they would have been without the BRT in Treatment group 1. However, the BRT had no significant effect on perceived quality of life in Treatment group 2.

Table 4.2. BRT impacts DiD modeling results (odds ratios).

Variable	Quality of life		Cost concerns	
	Newly opened (2022)	1 year after (2023)	Newly opened (2022)	1 year after (2023)
Intercept	2.06*	2.55**	0.20***	0.24***
Temporal Effects [ref: 2019/2021]				
Newly opened [2022]	0.71		0.58*	
1 year after [2023]		0.81		0.85
Spatial Effects [ref: >1.0km]				
[<0.5km]	0.27**	0.18***	0.33*	0.42
[0.5km-1.0km]	1.40	1.38	0.30*	0.36
Treatment Effects				
[2022] * [<0.5km]	3.74**		3.82*	
[2022] * [0.5km-1.0km]	0.50		2.81	
[2023] * [<0.5km]		4.26**		2.90
[2023] * [0.5km-1.0km]		0.55		1.23
Confounding Variables				
Household Size [ref: One person]				
[Two people]	0.95	0.79	1.53	1.08
[Three or more]	1.09	1.47	1.24	1.08
Yearly Income [ref: \$150k or more]				
[\$60k to \$150k]	0.68	0.64	2.29**	1.96*
[\$60k or less]	0.66	0.41**	4.80***	4.53***
Gender [1 = woman]	1.02	1.12	1.20	1.17
N _{person}	402	398	402	398
σ^2	3.29	3.29	3.29	3.29
τ_{00} _{person}	1.46	3.56	1.55	3.43
ICC	0.31	0.52	0.32	0.51

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

In both quality of life models, all confounding variables present expected tendencies, although most of them are not statistically significant. The only significant effect controlled for was the lowest income group (\$60k

per year or less) having 59% less odds of perceiving improvements in quality of life due to neighborhood change. This effect is measured with regard to the highest income bracket (\$150k per year or more).

4.8.3 Cost concerns modeling results

The third and fourth columns of Table 4.2 present the models measuring changes in odds of having financial concerns about raising costs of life in the neighborhood. The temporal effects in these two models show an overall 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 42% lower than at baseline. 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. The first model, however, is controlling for observed effects for both treatment groups. The Treatment 1 group (<0.5km) has 67% less odds, and Treatment 2 (0.5 to 1.0 km) has 70% less 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). The first model shows that, when it was newly inaugurated, the new BRT had a statistically significant impact in the odds of perceiving raising-costs concerns of Treatment 1 (<0.5km). The magnitude of this increase in odds is 3.82 times what it would have been with no intervention. However, the second model 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 (\$60k to \$150k per year) are 1.96 to 2.29 times more likely to have financial concerns compared to high-income households (\$150k per year or more). For low-income households the effect is even larger, with 4.53 to 4.80 more odds to perceive cost concerns than high-income households.

4.9 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 verified 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 is similar to what has been observed in Canada due to the COVID-19 pandemic (Wen et al., 2022). This general trend shows how the implementation of the BRT is helping sustain levels of perceived quality of life in an area that would otherwise be on the decline. 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, and not only limited to those who may use the system regularly. 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.

Our results show a general increase in the concerns regarding the cost of living. This trend is consistent with the Canadian high increase in inflation rates that has been noticed in the past couple of years during the study period (Chen & Tombe, 2023). Moreover, 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 effects are particularly relevant for lower-income populations. 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. These results suggest that there is no significant potential of gentrification due to the BRT, at least after only one year. For more conclusive long-term conclusions about gentrification, a larger timespan needs to be analyzed.

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.

However, it is relevant to note that for this type of transit service, service areas of 0.8 to 1.0 km are commonly considered (El-Geneidy et al., 2014; 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 (<0.5km) 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 is otherwise 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 need to provide campaigns that aim to enhance the positive perceptions of the BRT and decrease unfounded concerns about increasing costs of living. 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 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).

4.10 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. 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.

5. Chapter five: Built-environment exposure and evolving transport mode changes.⁴

5.1 Chapter positioning

This chapter, corresponding to the last manuscript, has the objective of analyzing how home relocation, car ownership, and household structure changes reshape mode-use patterns. While previous chapters focused on different types of exogenous disruptions, this study contributes to the dissertation by focusing on endogenous life changes as triggers of changing travel behavior. Specifically, this chapter examines how gradual, individual-level decisions cumulatively alter travel habits over time. Unlike the widespread disruption studied in Chapters 2 and 3 or the localized intervention in Chapter 4, this work captures slower behavioral transitions through five waves of panel data between 2019 and 2024. This achieves the goal of assessing the gradual changes in mode use due to relocation-induced changes in local and regional accessibility. Methodologically, this chapter advances the use of longitudinal exposure measures to disentangle these gradual relocation effects. This chapter shows how personal decisions, when combined with neighborhood design, trigger changes in travel behavior. Unraveling these interactions is a key contribution, as endogenous life changes are not as directly impacted by planners as changing the built environment. While this chapter focuses on endogenous life changes rather than exogenous pandemic-related disruptions, the analysis requires controlling for unobserved temporal trends, including COVID-19's broader impacts on travel behavior. This ensures an accurate measurement of the changes in mode use due to the studied triggers.

⁴ Victoriano-Habit, R. & El-Geneidy, A. (Under review). Evolving transport mode changes: A longitudinal analysis of built-environment exposure in Montréal, Canada. *Journal of Transport Geography*.

5.2 Abstract

Understanding the impacts of exposure to local and regional accessibility on travel behavior is essential to develop long-term effective land-use and transport policies. Previous research concentrating on accessibility impacts were mostly of cross-sectional nature and were conducted using pre-pandemic data. This study examines the longitudinal relationships between exposure to different levels of local and regional accessibility and mode use, focusing on how home relocation affects the frequency of use of the three major transport modes: active transport, driving, and public transit. The study uses five waves (2019–2024) of the Montréal Mobility Survey, to analyze 4,550 panel respondents, split into worker ($N = 3,067$) and non-worker ($N = 1,483$) subsamples. Using a set of multilevel linear regressions and a cumulative exposure measure, this work analyzes the gradual impacts of home relocation and changes in exposure levels to regional and local accessibility on weekly mode use frequency over time while controlling for car ownership and household structure. The study provides robust longitudinal evidence on how residential relocation, built-environment exposure, and concurrent life decisions collectively reshape urban travel behavior in the post-pandemic era across different transport modes. The multilevel modeling approach reveals three key insights: (1) regional and local accessibility changes (through relocation) exert gradual and mode-specific effects, with active transport showing the strongest response; (2) while workers and non-workers show varying baseline travel patterns, both groups respond similarly to local and regional accessibility improvements and changes in car ownership; and (3) car ownership decisions can significantly moderate the effects of home relocation. These findings advance the methodological integration of longitudinal exposure measures to levels of accessibility in mobility research.

5.3 Introduction

Urban mobility systems face unprecedented challenges, from climate commitments to post-pandemic behavioral shifts. Understanding how and why people travel, and how these patterns change over time, is

essential for long-term land use and transport policies. Given the complexity of studying the temporal dynamics of travel behavior, most studies focus on cross-sectional framings, failing to capture the dynamic interplay between life transitions, changing built environments, and transport decisions. This gap is particularly critical today in the rapidly changing context of the post-pandemic world.

Longitudinal approaches that disentangle gradual adaptations are essential to designing policies that align with current behavioral trajectories. Previous studies have focused deeply on evolving travel behavior through the lens of changing lifestyles and mobility biographies (Müggenburg et al., 2015), analyzing how travel patterns vary for individuals over time. Key triggers have been found to correlate with changes in these dynamics, such as home relocation, mobility decisions such as buying a car, and changes in household structure (Adhikari et al., 2020; Lee et al., 2017; Wasfi et al., 2016). However, existing longitudinal studies were either done in the pre-pandemic context (De Vos et al., 2018; Wasfi et al., 2016); performed simple before-after comparisons ignoring gradual temporal adaptation (Adhikari et al., 2020; Schimohr et al., 2025); or focused narrowly only on one mode of transport (Faber et al., 2025; Xu et al., 2024). Addressing these three gaps is critical because pre-pandemic findings may not reflect current mobility trends, simple before-after comparisons overlook gradual adaptations essential for policy timing, and a single-mode focus ignores substitution effects which are relevant for integrated transport planning.

This study aims to advance longitudinal mobility research by analyzing how key behavioral triggers - particularly residential relocation, car ownership changes, and changes in household structure - reshape mode use patterns in the post-pandemic context. Using a five-wave longitudinal survey between 2019 and 2024 in Montréal, Canada, this work analyzes the dynamics of mode-use patterns across all major transport modes: active transport, driving, and public transit. Through a set of multilevel linear regressions, this study analyzes the factors affecting the frequency of use for the three stated modes of transport while tracking gradual adaptations to local and regional accessibility changes through an exposure measure. By allowing the decay rate of past exposures to vary by transport mode, the models capture distinct temporal patterns in behavioral adaptation across active, transit, and car travel. This approach explicitly accommodates potential

differences in the temporal evolution between modes. Moreover, these models disentangle pandemic-related disruptions from lasting behavioral shifts and compare how these dynamics differ between workers (N = 3,067) and non-workers (N = 1,483).

Findings in this work provide actionable insights for planners and policymakers navigating post-pandemic mobility challenges. By quantifying how relocations between built environments interact with life-stage decisions across population groups, the results suggest priorities to local and regional accessibility improvements through land-use and transport measures.

5.4 Literature review

The study of travel behavior dynamics refers to the analysis of how and why individuals' mobility patterns evolve over time. Multiple dimensions have been shown to affect these dynamics, such as lifecycle events (Lee et al., 2017; Zhang et al., 2024), exogenous trends and events (Khalil et al., 2024; Victoriano-Habit & El-Geneidy, 2024), and changes in the built environment and transport systems (Heinen et al., 2017; Spears et al., 2017; Sun & Du, 2023). These dynamics have been conceptualized to occur at different timeframes, from daily and weekly scheduling to life-long aging processes (Clarke et al., 1982). Changes in the medium-long term, which this study concerns with, are generally linked to large “life shocks” (Goodwin, 1997). Many studies have inquired into the trajectories of travel-behavior changes over time using *mobility biographies* (Scheiner, 2007, 2018). Through a systematic review, Müggenburg et al. (2015) found that the main key events discussed under this framework are: (i) private and professional life events such as changing jobs or birth of a child, (ii) adaptation of long-term mobility decisions such as purchasing a car, (iii) exogenous interventions such as new infrastructure, and (iv) long-term processes such as ageing and generational effects.

In order to understand temporal trends of travel behavior and their direction, repeated observations of the same individuals through time are required (Clarke et al., 1982; van de Coevering et al., 2015). As

mentioned by Goodwin (1997) regarding urban-transport temporal trends, “*even apparently settled aggregate patterns are based on a very high degree of volatility, movement and turnover at the individual level*”. This means that observed aggregate patterns may have hidden ‘sub-trends’ that are not observable by aggregate, cross-sectional, or repeated cross-sectional data. This is particularly relevant in the post-COVID context, where emerging mobility trends (Wang et al., 2022; Zhao & Gao, 2022) and evolving relationships with the built environment (Negm & El-Geneidy, 2024; Victoriano-Habit & El-Geneidy, 2024) highlight the need for disaggregated longitudinal data to unravel behavioral shifts.

Studies using panel data to analyze travel behavior dynamics have shown that shifts are deeply intertwined with life stage and household structure changes. Lee et al. (2017), using ten waves of panel mobility data, studied the triggers of behavioral change within a household. They found that the evolution of a household’s composition, particularly in terms of the number of children, is the main trigger of change. Similarly, Zhang et al. (2024) highlight how life events reshape travel attitudes and mode choices, with gender moderating these transitions. Khalil et al. (2024) showed the impact of demographic events to predict broad urban mobility impacts. These studies highlight that lifestyle transitions disrupt habitual travel patterns, particularly those related to mode choice and frequency of use (Adhikari et al., 2020). Moreover, these changing patterns often occur in highly mode-specific ways (Faber et al., 2025; Xu et al., 2024)

The contribution of exogenous components has shown to be significant in shaping travel behavior through time. The concept of accessibility, central in transport discussions for more than four decades, has been effective in reflecting the impacts of changing land-use and transport systems (El-Geneidy & Levinson, 2022; Geurs & van Wee, 2004; Hansen, 1959). Reflecting exogeneous conditions through accessibility has been thoroughly incorporated into longitudinal travel behavior studies (Busch-Geertsema & Lanzendorf, 2015). Within this context, residential relocations are particularly interesting, as they have the potential to combine relevant changes in lifestyle and life stage with changes in the residential accessibility levels. Studies have shown that these relocations gradually change both travel behavior and attitudes, especially when moving between different built environments (De Vos et al., 2018). Moreover, the effects may vary

between different sociodemographic groups (Cheng et al., 2019), and impact transport modes in different ways over time (Schimohr et al., 2025). To properly capture these complex temporal dynamics, exposure measures have proven valuable in revealing the gradual, long-term behavioral adaptations that occur after relocation between different built environments (Wasfi et al., 2016).

A relevant distinction in the use of accessibility within travel behavior studies is that between *local accessibility* and *regional accessibility* (Handy, 1993, 2020; Manaugh & El-Geneidy, 2012). Local accessibility is more related to density and proximity, and thus is more related to active modes such as walking and cycling (Manaugh & El-Geneidy, 2011). As regional accessibility is related to speed, it is clear that it has a closer relationship to motorized modes: the private car and public transport (Lussier-Tomaszewski & Boisjoly, 2021; Silva & Altieri, 2022). This distinction has shown to be useful when evaluating travel behavior dynamics and the effect of residential relocations (Lee et al., 2017; Wasfi et al., 2016).

Although multiple longitudinal studies have contributed to understanding evolving mobility patterns, particularly those related to mode use and home relocation, significant gaps remain. Existing studies either (1) were done in the pre-COVID context (De Vos et al., 2018; Wasfi et al., 2016), (2) perform simple before-after comparisons ignoring gradual temporal adaptation (Adhikari et al., 2020; Schimohr et al., 2025), or (3) focus narrowly only on one mode of transport (Faber et al., 2025; Xu et al., 2024). These research gaps are critical to address both for research and policymaking. First, pre-pandemic studies risk offering outdated insights, as COVID-19 has reshaped fundamental relationships, including that between travel behavior and the built environment (Negm & El-Geneidy, 2024; Victoriano-Habit & El-Geneidy, 2024). Second, reliance on simple before-and-after comparisons overlooks potential gradual adaptations such as delayed mode shifts (Chang et al., 2010; Chatterjee & Ma, 2007, 2009). Third, a narrow focus on a single transport mode ignores the potential substitution dynamics between different transport modes (Sun & Du, 2023; Sun et al., 2020). This study addresses these three limitations by analyzing five waves of panel

data, spanning the pandemic period, and employing exposure measures to track gradual behavioral change across active, driving, and transit modes.

5.5 Data

5.5.1 Montreal Mobility Survey

The primary dataset of this study is composed of the panel responses from the first five waves of the Montréal Mobility Survey (MMS) (Negm et al., 2023; Victoriano-Habit et al., 2024). These five waves were collected in 2019, 2021, 2022, 2023, and 2024 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. These included the distribution of flyers at various residences and 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 hired during all waves to help in recruiting part of the sample. All survey respondents who provided an email address received an invitation to participate in all subsequent waves. Through this process, the survey sample was composed of both respondents who participated in only one wave (cross-sectional) and those who participated in two or more waves (panel), which are the interest of this study.

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 several sequential filters. Repeated responses entered by the same e-mail or IP address were removed. Invalid age and height changes between waves were also filtered. 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. The 5% threshold was determined by plotting response times in

ascending order and identifying a natural break point in the distribution, which consistently appeared around the fastest 5% of responses. Spatial filters were also applied. Those who placed a pin representing their home, school and/or work location outside the Montréal metropolitan region were excluded. Participants who reported no weekly trips were removed from the sample. This thorough validation process resulted in a final sample size of 4,550 respondents who participated in at least two of the five survey waves. This work separates the panel sample into two sub-samples (Figure 5.1). The sub-sample of workers (N = 3,067) is composed only of those employed full- or part-time in all waves of the survey with a valid work trip. Similarly, the sub-sample of non-workers (N = 1,483) are respondents with no employment in every wave they responded to.

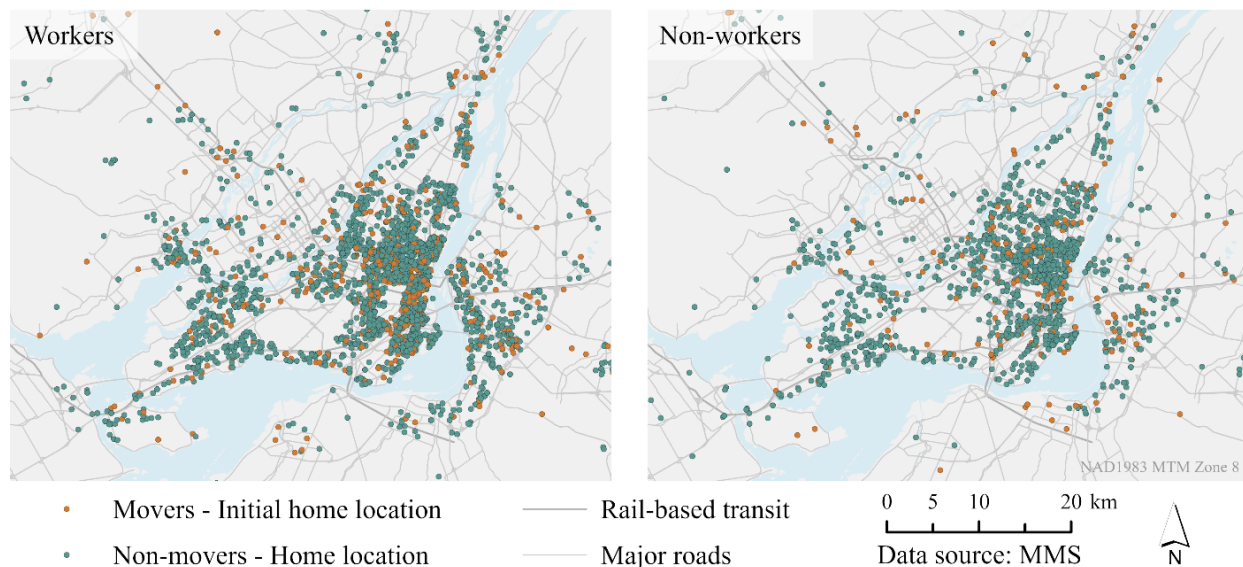


Figure 5.1. MMS panel subsamples of workers and non-workers.

All waves of the survey included the same questions pertaining to weekly mode-use frequency. Trips by active modes of transport, driving, and public transit were 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. Each travel mode and purpose combination were measured consistently. Respondents reported the number of trips made in the last week on a discrete scale from 0 to 10 for each trip purpose by each mode. The uniform measurement structure across modes helps ensure comparability and minimizes

the risk of measurement sensitivity. To reduce the influence of extreme values in the dependent variable, respondents reporting zero total trips or more than 40 total trips per week were excluded. Additionally, a more conservative filter was tested, capping total trips per mode at 10 across all purposes. Results remained substantively unchanged, indicating that findings are robust to outlier treatment. For workers, each survey wave collected information pertaining to weekly commuting and telecommuting behavior. Commuting time by driving and public transit was extracted from Google Maps API for the time and day reported by the participant. Respondents' sociodemographic characteristics were collected in all waves. Most importantly, since every question was answered by participants at least in two points in time, changes in all variables can be measured through time. Because the analysis uses panel data which tracks the same individuals over time, residential self-selection becomes less of a concern than in cross-sectional studies (van de Coevering et al., 2015). Individuals carry their attitudes towards travel in their residential relocations. This allows for behavioral changes to be more accurately assumed as a response to the changes in surrounding built environment rather than a product of attitudes toward residential selection.

Participants' home locations were reported through one of two methods, by the respondent's choice: through placing a pin on a map or by providing the postcode of their home location. Since Canadian postal code is defined at the block-level, centroids are generally precise to within 100 meters of the true home location. Rates of residential moving were assessed first only for respondents who provided their home location through postal codes, assuming that a move occurs only when there is a change in postal code. Given the high level of precision, this postal-code-based approach served as the benchmark for determining an equivalent distance threshold for map-pin respondents. Through a comparative analysis, a 1,600-meter threshold for pin placements produced moving rates equivalent to those observed in the postal code group, ensuring consistent mobility detection across both reporting methods. Thus, for respondents using a pin on a map, a residential move was deemed to happen if the distance between two reported locations collected in two surveys was at a distance of 1,600 meters or more.

An attrition analysis was conducted to assess the representativeness of the panel sample across waves. Models predicting panel retention were estimated for each subsequent wave. No consistent patterns emerged from this analysis, indicating no significant issues with attrition. For this study, all responses included in the analysis were complete, with the exception of income. For this variable, missing values were imputed using Multivariate Imputation by Chained Equations (MICE) using the *mice* package in R (van Buuren & Groothuis-Oudshoorn, 2011). Imputation was based on respondents' age, employment status, homeownership, household size, and education level. The Montréal Mobility Survey dataset has been widely used in travel behavior research (Carvalho & El-Geneidy, 2024; Negm & El-Geneidy, 2025; Victoriano-Habit & El-Geneidy, 2023, 2024), supporting its relevance and applicability for longitudinal transport studies. More details on its collection, data cleaning, and description can be found in Negm et al. (2023) and Victoriano-Habit et al. (2024).

5.5.2 Accessibility exposure measures

To evaluate the impacts of exposure to different built environments, access to opportunity measures are used in this work as they are the most comprehensive land use and transport measures (Wachs & Kumagai, 1973). Accessibility is a mode specific tool (El-Geneidy & Levinson, 2022) that reflects the built-environment characteristics in a unique way (Geurs & van Wee, 2004). To assess the impacts of access to opportunities at different urban scales and by different transport modes, measures are typically subdivided into *local accessibility* and *regional accessibility* (Handy, 2020). Accordingly, this work uses measures that separately evaluate exposure to different local and regional accessibility environments.

In this work, regional accessibility by public transport is measured using a cumulative-opportunities indicator, which considers access to all jobs within the region within a 45-minute threshold. This indicator is commonly used in accessibility measurement, primarily because of its straightforward interpretation (El-Geneidy & Levinson, 2022). The 45-minute threshold was chosen as it aligns closely with the median transit

travel time in the Montréal region, as suggested by Kapatsila et al. (2023). To calculate this measure, transit travel times were computed between the centroids of census tracts (CTs) for a typical weekday during the morning peak period from 8:00 to 9:00 AM, using the “r5r” package (Pereira et al., 2021). While this work uses morning peak accessibility, previous works have shown that this measure strongly correlates with accessibility throughout the day and performs similarly in mode choice models (Boisjoly & El-Geneidy, 2016). CTs were selected as the unit of analysis since job data from the 2016 census commute flows (Statistics Canada, 2018) was available at this level. The calculation of transit travel times required the use of Global Transit Feed Specification (GTFS) data and the OpenStreetMap (OSM) street network, which were collected for each wave's respective year. This approach ensures that changes in public transport services are reflected in the variations of accessibility over time throughout the five survey waves.

The WalkScore index is used to measure local accessibility levels, which 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 & Ram, 2018), and has shown reliability in predicting active travel patterns (Manaugh & El-Geneidy, 2011). This 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. This data was collected yearly with each survey wave to represent the most recent local accessibility measure.

To measure exposure to different built environments, this work builds on the Proportional Cumulative Exposure measure (PCET) developed by Wasfi et al. (2016). In this work, the proportional cumulative exposure measure $PCETrk_{it}$ for accessibility range i at time point t is defined as:

$$PCETrk_{it} = \frac{\sum_{s=1}^t (rk_{is} \cdot \Delta T_{is})}{(T_{it})^\alpha} \quad (\text{Eq. 5.1})$$

Where:

- rk_{is} : binary variable indicating if the person lives within accessibility range i at time point s .
- ΔT_{is} : time elapsed between time point s and the previous survey wave in which the respondent participated.
- $T_{it} = \sum_{s=1}^t (\Delta T_{is})$: cumulative time of the participant in the study until time point t .
- α : time decay exponent controlling how sharply the impact of past exposures decays over time.

A time decay exponent of $\alpha = 1$ results in the original measure proposed by Wasfi et al. (2016), simply representing the proportion between (1) the cumulative number of years that a respondent has lived in a certain built environment category, and (2) the number of years that the respondent has participated in the study. In this work, the addition of a decay exponent allows for the measurement of how steeply the effect of past exposure decays. Higher values of α correspond to a faster response to current exposure, with a lesser impact of past exposures. Conversely, lower values of α correspond to a greater importance of past exposure and a slower adaptation to new environments. The estimation of α is done separately for each transport mode to assess the potentially different decay rates of different transport modes.

PCET enables more accurate comparisons of how sustained exposure to specific environments influences mobility behaviors, overcoming limitations of simple binary or snapshot exposure measures that fail to capture duration effects (Wasfi et al., 2016). To evaluate exposure to different accessibility levels, four groups (rk_{it}) are defined for each accessibility measure: low, mid-low, mid-high, and high. For exposure to local accessibility, PCET is calculated for the four groups defined by Walk Score (2022): car dependent (0 to 49), somewhat walkable (50-69), very walkable (70-89), and walker's paradise (90-100). In the case of regional accessibility by public transit, PCET is calculated for the four quartiles of accessibility by public transit for the entire Greater Montreal Area by census tract. The use of these ranges is consistent with previous works both in the case of WalkScore (Victoriano-Habit & El-Geneidy, 2023; Wasfi et al., 2016)

and accessibility by transit (Boisjoly et al., 2020; Chia & Lee, 2020). Alternative specifications for these ranges were tried, including different thresholds and a greater number of ranges. These alternative specifications offered similar results. Thus, the ranges described above were chosen in this study for their consistency with the literature and parsimony.

5.6 Methods

5.6.1 Multilevel linear regressions

To achieve the goal of modelling evolving mode-use patterns, a set of multilevel longitudinal linear regressions is used. Each model estimates an individual's weekly frequency of use for a specific transport mode. Moreover, the panel sample is subdivided into workers' and non-workers' subsamples, as they exhibit markedly different patterns and levels of complexity of travel (Chowdhury & Scott, 2020; Dharmowijoyo et al., 2018). Furthermore, analyzing these two groups separately has become particularly relevant in the current context of increased popularity of telecommuting. These changes in working patterns have shown to beget large changes in travel patterns (Javadinasr et al., 2022; Victoriano-Habit & El-Geneidy, 2023). Three models are estimated for each of these two subsamples, one for each of the transport modes analyzed: active modes, driving, and public transport.

The data is coded in its long format, meaning that a respondent is represented in the database in as many rows as valid responses they provided. Therefore, the models estimate the frequency of weekly mode use for a specific survey wave. The multilevel structure of the model considers the fact that multiple observations correspond to the same respondent, where person is the higher level and person-wave is the lower level. Through dummy variables representing wave fixed effects, temporal shocks affecting all respondents are measured. This includes variations between survey waves, for example, due to COVID-19 and other broader trends. Alternative model specifications were tested including interactions between wave fixed effects and key predictors such as exposure measures and car ownership. These interactions assessed

whether the pandemic significantly affected the effect of such predictors. None of the interaction terms ultimately showed statistically significant effects, for which they were not included in the final models.

The explanatory variables included in each model relate to personal characteristics and exposure measures to different accessibility levels. The estimation of separate worker/non-worker models allows for the evaluation of the impact of commuting and telecommuting patterns on workers' evolving travel dynamics. For all models, personal characteristics include yearly household income, gender, number of people in the household, and number of cars in the household. Exposure to different accessibility environments is included through an indicator that builds on the Proportional Cumulative Exposure measure (PCET) developed by Wasfi et al. (2016). As explained in the previous section, a time-decay exponent (α) is added to the original PCET measure. This exponent controls how rapidly the influence of past exposures diminishes over time. Higher values of α indicate faster rate of adaptation. Each transport mode (active, transit, driving) was allowed to have a unique exponent value for each worker and non-worker subsamples. This reflects potential differences in adaptation speeds across modes and subgroups. All models were estimated multiple times for different values of α , in values ranging from 0 to 5. The value that maximizes the model's marginal R^2 was chosen as the final decay exponent for each mode. In all cases, a value of α that produces a global maximum was found. Thus, the best decay is chosen for each mode and subsample, representing different adaptation rates to different environments.

All models take the form of standard multilevel linear equations, where the dependent variable (weekly mode-use frequency) is modeled as a linear function of fixed-effect predictors (personal characteristics, exposure measures, etc.) and random intercepts by individual. The random effects structure accounts for unobserved heterogeneity between individuals. In other words, taking into account that travel behaviors are strongly person-specific. This specification aligns with various longitudinal travel behavior research in the existing literature (El-Assi et al., 2017; Faghieh-Imani et al., 2014; Victoriano-Habit & El-Geneidy, 2023, 2024). This method simultaneously: (1) captures within-person evolution of mode use over time, (2)

controls for stable individual differences that could bias estimates, and (3) the coefficients of this type of model are easily interpretable as the marginal effect of independent variables on the explained variable.

For the active-transport model, PCET to local accessibility levels (WalkScore) is included. On the other hand, for the driving and public transit models, PCET to regional accessibility (cumulative opportunities by public transit in 45 minutes) is included. For the worker subsample, commuting characteristics are included in the model through two variables. First, commuting time by car is used as a measure of the person's proximity to their workplace. The second variable is the number of days per week that the respondent reported to work from home to capture the effects of telecommuting.

5.6.2 Scenario-based analysis

To clearly illustrate the time-evolving effects of exposure to different built environments when moving home, a scenario-based analysis is performed. In this analysis, the models are used to predict weekly mode use for several proposed profiles of people, evaluating their mode-use trajectories over time. The main goal of this analysis is to demonstrate how the estimated models are capable of representing travel behavior trajectories using the PCET framework described in Section 3. This is achieved by simulating a set of proposed profiles that isolate the effects of changing accessibility levels by home relocation while holding other sociodemographic and temporal factors fixed at proposed values. In this sense, the goal of this scenario analysis is not to predict absolute mode-share values for specific populations, but rather to elucidate the relationships between accessibility changes, mode-specific adaptation rates (α), and resulting behavioral trajectories.

First, a set of four profiles are defined, all of which are analyzed as workers and non-workers. For these profiles, all characteristics are set fixed at one level, only varying exposure to accessibility, simulating a residential relocation:

- **Profile 1 (P1):** Moving *low* to *high* accessibility
- **Profile 2 (P2):** Moving *low* to *mid-high* accessibility
- **Profile 3 (P3):** Moving *mid-high* to *low* accessibility
- **Profile 4 (P4):** Moving *high* to *low* accessibility

All other variables are fixed in the models, as follows. First, the wave fixed effects are set for wave 5 (2024) as this is the latest wave in the study. Given that the largest changes between waves that are encompassed within the fixed effects are related to the pandemic and its recovery, this is similar to assuming no further post-COVID recovery in mode shares. The household structure is set at the median size, with no children. All profiles are set to be women, with average income, average age at baseline, and no cars. Additionally, when performing this analysis with the workers' models, commuting time by car is set at the range of 30 to 60 minutes, and no days working from home. Most importantly, none of the particular values fixed for the profiles carry major relevance. This is because the main goal is to isolate the effect of the residential move, and the conclusions extracted from this analysis would be analogous even when changing any of these fixed variables.

To illustrate the joint effect of home relocation with other changes in lifestyle and mobility decisions, another set of four profiles is proposed. The following profiles are identical to the previous four, with the addition of either (1) getting a car if the move happens towards a lower accessibility level or (2) selling (get rid of) a car if the move is towards higher accessibility:

- **Profile 5 (P5):** Moving *low* to *high* accessibility + selling car
- **Profile 6 (P6):** Moving *low* to *mid-high* accessibility + selling car
- **Profile 7 (P7):** Moving *mid-high* to *low* accessibility + getting car
- **Profile 8 (P8):** Moving *high* to *low* accessibility + getting car

All other characteristics are set fixed in these profiles at the same values as profiles P1 through P4, with the exception of car ownership. For profiles selling a car (P5 and P6), the number of cars in the household is initially set at one (pre-move). For profiles getting a car (P7 and P8), the initial number of cars is zero.

5.7 Results

5.7.1 Descriptive statistics

Both panel subsamples used in this work are described through summary statistics in Table 5.1 for each of the five survey waves. First, it is important to note that sample sizes between waves vary due to different wave participation by respondents. Although all participants in the analyzed samples are repeated observations, they may not have participated in all waves. The workers' sample is composed of 7,219 observations from 3,067 respondents, whereas the non-workers' sample is composed of 3,443 observations from 1,483 respondents. For the purposes of this work, people relocating within the same accessibility range are not treated as movers. Within workers, between 10% and 20% of the respondents relocated home at any given survey wave. For non-workers, this share is slightly lower than 10%, most likely due to the higher age of this subsample compared to employed respondents. Figure 5.2 shows the detailed distribution of all movers in terms of their accessibility levels before and after their home relocation. For both subsamples, most personal characteristics remain largely stable over time. The only characteristic for which there is a slight trend is yearly income, which slightly increases each wave for both workers and non-workers, consistent with inflation over the years. For each subsample, residential accessibility levels, both local and regional, remain largely stable over the five waves. This, together with the information shown in Figure 5.2, indicates that home relocations don't take place majorly in one direction. Although there is a larger representation of people living in higher accessibility areas, all accessibility groups are represented by at least 10% of the sample at any point in time for both subsamples.

Mode-use patterns, on the other hand, do display larger variations over time for both subsamples. These effects are consistent with pandemic-related trends: a reduction in the use of active modes and public transit, particularly large for the latter, and an increase in driving. For workers, COVID-related effects can be seen on commuting patterns, with an increase in the frequency of telecommuting and a reduction in the share of longer commuting times.

Table 5.1. Descriptive statistics by subsample and survey wave.

Variable	<u>Workers</u>					<u>Non-workers</u>				
	N = 3,067					N = 1,483				
	Mean (std dev.)					Mean (std dev.)				
	2019	2021	2022	2023	2024	2019	2021	2022	2023	2024
Sample size										
Movers	0	186	160	204	178	0	50	61	61	66
Non movers	941	1184	1356	1680	1330	309	644	772	804	676
Total sample	941	1370	1516	1884	1508	309	694	833	865	742
Personal characteristics										
Age in 2019	40.70 (12.64)	41.10 (12.45)	41.92 (12.37)	40.11 (12.83)	39.27 (12.72)	60.20 (12.88)	62.35 (11.15)	62.28 (10.73)	61.64 (11.28)	60.96 (11.06)
Yearly income (\$10k CAD)	9.42 (5.04)	10.55 (5.03)	10.67 (5.12)	11.20 (5.95)	12.28 (6.06)	6.56 (3.94)	7.43 (4.41)	7.34 (4.41)	7.63 (4.75)	8.51 (5.44)
Household size	2.60 (1.25)	2.53 (1.24)	2.45 (1.23)	2.45 (1.25)	2.54 (1.26)	1.99 (0.97)	1.92 (0.88)	1.82 (0.80)	1.85 (0.85)	1.87 (0.89)
Children in the household	0.43 (0.83)	0.43 (1.04)	0.37 (0.84)	0.35 (0.74)	0.37 (0.74)	0.13 (0.54)	0.08 (0.38)	0.06 (0.34)	0.08 (0.43)	0.09 (0.45)
Cars in the household	1.09 (0.90)	1.09 (0.89)	1.08 (0.88)	1.07 (0.86)	1.04 (0.85)	1.00 (0.73)	1.05 (0.74)	0.99 (0.71)	0.97 (0.68)	0.98 (0.74)
Accessibility metrics										
WalkScore										
<i>Low (0 to 50)</i>	13%	12%	12%	13%	13%	16%	18%	17%	13%	14%
<i>Medium-low (50 to 70)</i>	18%	17%	17%	16%	16%	19%	19%	18%	19%	18%
<i>Medium-high (70 to 90)</i>	23%	26%	28%	30%	30%	32%	29%	33%	35%	34%
<i>High (90 to 100)</i>	46%	45%	43%	42%	41%	34%	34%	32%	34%	34%
Transit accessibility										
<i>Low (Quartile 1)</i>	16%	14%	13%	11%	11%	12%	14%	14%	11%	14%
<i>Medium-low (Quartile 2)</i>	20%	19%	19%	21%	22%	25%	26%	24%	23%	23%
<i>Medium-high (Quartile 3)</i>	22%	26%	28%	29%	27%	30%	28%	30%	32%	30%
<i>High (Quartile 4)</i>	42%	42%	41%	40%	40%	33%	32%	32%	34%	34%
Mode use - weekly trips										
Active transport	2.65 (2.74)	2.10 (2.53)	2.09 (2.43)	2.34 (2.56)	2.79 (2.90)	3.85 (2.82)	1.87 (2.41)	1.89 (2.26)	1.92 (2.24)	2.17 (2.58)
Driving	2.06 (2.69)	2.81 (2.92)	2.67 (2.76)	2.48 (2.66)	2.61 (2.80)	1.08 (2.07)	2.44 (2.20)	2.13 (2.02)	2.12 (2.04)	2.17 (2.07)
Public transport	3.03 (2.64)	1.01 (1.92)	1.25 (2.00)	1.37 (2.13)	1.48 (2.29)	1.73 (1.89)	0.53 (1.47)	0.26 (0.87)	0.37 (1.07)	0.52 (1.29)
Commuting patterns										
Commute time by driving										
<i>(Under 15 min)</i>	31.2%	60.5%	51.2%	44.8%	47.0%	–	–	–	–	–
<i>(15 to 30 min)</i>	22.4%	27.6%	31.5%	31.9%	30.5%	–	–	–	–	–
<i>(30 to 60 min)</i>	30.6%	11.8%	16.2%	21.5%	21.2%	–	–	–	–	–
<i>(60+ min)</i>	15.7%	0.1%	1.1%	1.8%	1.3%	–	–	–	–	–
Weekly telecommuting days	0.55 (1.26)	2.39 (2.25)	2.10 (1.99)	1.97 (1.90)	1.93 (1.84)	–	–	–	–	–



Figure 5.2. Accessibility levels of movers before and after relocation.

5.2 Frequency of mode-use modeling

Results for the two sets of estimated models are presented in Table 5.2. Each of these models presents, for workers and non-workers respectively, the impact of different factors on the weekly frequency of use of each mode of transport. Through wave fixed effects, each model measures the change in weekly trips for each transport mode compared to 2019 while keeping other factors fixed. These fixed effects reveal clear pandemic-related shifts in travel behavior for both workers and non-workers. Transit suffered the steepest declines in 2021, with a reduction of -1.27 trips per week for workers, and -1.16 trips per week for non-workers, keeping all else constant at their mean. Moreover, both groups showed only a partial recovery through 2024. Active modes dropped but rebounded fully for workers by 2024, while remaining depressed for non-workers by -1.39 trips per week, ceteris paribus. Driving frequency increased and stayed elevated, confirming a lasting pandemic-induced shift toward car reliance. These wave fixed effects not only describe but also control for the underlying pandemic-related trends shown in the descriptive analysis. Most importantly, these effects allow the isolation of the effects of the remaining independent variables.

Table 5.2. Weekly mode use – workers and non-workers model results.

	Workers			Non-Workers		
	Active	Driving	Transit	Active	Driving	Transit
Time-decay exponent	$\alpha = 0.73$	$\alpha = 0.83$	$\alpha = 1.09$	$\alpha = 0.81$	$\alpha = 0.73$	$\alpha = 1.13$
Intercept	2.56 ***	0.01	3.31 ***	2.73 ***	-1.66 ***	1.49 ***
w2 (2021)	-0.53 ***	1.24 ***	-1.27 ***	-1.96 ***	1.21 ***	-1.16 ***
w3 (2022)	-0.43 ***	0.99 ***	-1.13 ***	-1.86 ***	1.01 ***	-1.39 ***
w4 (2023)	-0.21 *	0.86 ***	-1.11 ***	-1.81 ***	1.11 ***	-1.28 ***
w5 (2024)	0.17	1.09 ***	-1.00 ***	-1.39 ***	1.19 ***	-1.05 ***
Personal characteristics						
Yearly income	0.01	0.01	-0.02 ***	-0.01	0.02 **	-0.02 ***
Age in 2019	-0.01 **	0.03 ***	-0.02 ***	0.00	0.03 ***	0.00
Gender [1 = woman]	-0.13 *	-0.06	0.08	-0.31 ***	0.01	0.06
Household size	0.11 ***	-0.04	0.15 ***	0.08	0.13 **	0.02
Children in the household	-0.04	0.15 ***	-0.17 ***	-0.03	0.05	-0.04
Cars in the household	-0.56 ***	0.84 ***	-0.47 ***	-0.54 ***	0.75 ***	-0.36 ***
Commuting characteristics						
Transit commute time (ref.: under 15 min)						
(15 to 30 min)	-0.29 ***	-0.22 ***	-0.24 ***	–	–	–
(30 to 60 min)	-0.43 ***	0.41 ***	0.49 ***	–	–	–
(60+ min)	-0.50 **	0.38 ***	0.62 ***	–	–	–
Weekly telecommuting days	-0.10 ***	0.20	0.42 **	–	–	–
Accessibility exposure measures						
WalkScore						
PCET to Low (0-50)	-1.14 ***	–	–	-0.99 ***	–	–
PCET to Mid-low (50-70)	-1.05 ***	–	–	-0.50 **	–	–
PCET to Mid-high (70-90)	0.04	–	–	0.64 ***	–	–
PCET to High (90-100)	3.02 ***	–	–	3.22 ***	–	–
Transit accessibility						
PCET to Low (Q1)	–	1.32 ***	-0.22	–	0.74 **	0.07
PCET to Mid-low (Q2)	–	1.02 ***	0.48 ***	–	0.87 ***	0.13
PCET to Mid-high (Q3)	–	-0.04	0.48 ***	–	0.14	0.39 ***
PCET to High (Q4)	–	-2.00 ***	0.28 **	–	-1.49 ***	0.24 **
σ^2	3.17	2.78	2.18	2.37	1.69	0.95
τ_{00} person	1.99	2.21	1.92	2.16	1.61	0.54
ICC	0.39	0.44	0.47	0.48	0.49	0.36
N person	3067	3067	3067	1483	1483	1483
Observations	7219	7219	7219	3443	3443	3443
Marginal R2	0.25	0.32	0.19	0.27	0.25	0.15
Conditional R2	0.54	0.62	0.57	0.62	0.62	0.46

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

The effects of income and age present expected results, with higher-income groups using transit less, while older adults tend to drive more. Small gender differences are found only for active modes, with women having -0.13 active trips per week in the workers group, and -0.31 active trips per week in the non-workers group, when keeping all else constant. Among workers, each additional household member was associated with small but statistically significant increases in active transport use (+0.11 trips/week) and transit use (+0.15 trips/week), while having children under the age of 12 showed offsetting effects, slightly increasing driving (+0.15 trips/week). Notably, these patterns were either weaker or non-significant for non-workers, suggesting household structure plays a more limited role for this group. On the other hand, the effect of each car in the household has marked effects in expected directions: increasing driving (workers: +0.84 trips/week; non-workers: +0.75 trips/week), and decreasing use of active modes (workers: -0.55 trips/week; non-workers: -0.52 trips/week) and public transit (workers: -0.47 trips/week; non-workers: -0.36 trips/week), *ceteris paribus*.

The effects of exposure to different accessibility environments are the main results of interest from these models. First, the value of the time-decay exponent (α) reveal mode-specific adaptation rates to changes in the built environment. For workers, transit use adapts fastest to accessibility changes ($\alpha = 1.09$), followed by driving ($\alpha = 0.83$) and active modes ($\alpha = 0.73$). Non-workers show a similar hierarchy but with transit levels adapting even faster ($\alpha = 1.13$) and driving levels slower ($\alpha = 0.73$). Given that the proportional cumulative indicator PCET is a measure constructed based on an individual's history, the interpretation of the marginal effects is not direct, and is better understood through the scenario-based analysis provided in the next section. However, the direction and magnitude of these coefficients can be analyzed comparatively. Figure 5.3 illustrates this for both subsamples, showing that the effects of exposure have expected directions for both subsamples. Exposure to higher local and regional accessibility areas has a direct impact on promoting higher use of active modes and decrease driving, whereas the opposite happens with exposure to lower local and regional accessibility areas. The differing effects of exposure to local accessibility environments on active mode are slightly larger in magnitude than those of regional accessibility on the

frequency of driving. In the case of transit, for both subgroups the effect is not only comparatively smaller, but it displays a non-linear effect. Whereas in other modes higher accessibility levels correspond to higher usage, the highest accessibility levels don't correspond to the highest positive impact on the use of public transport.

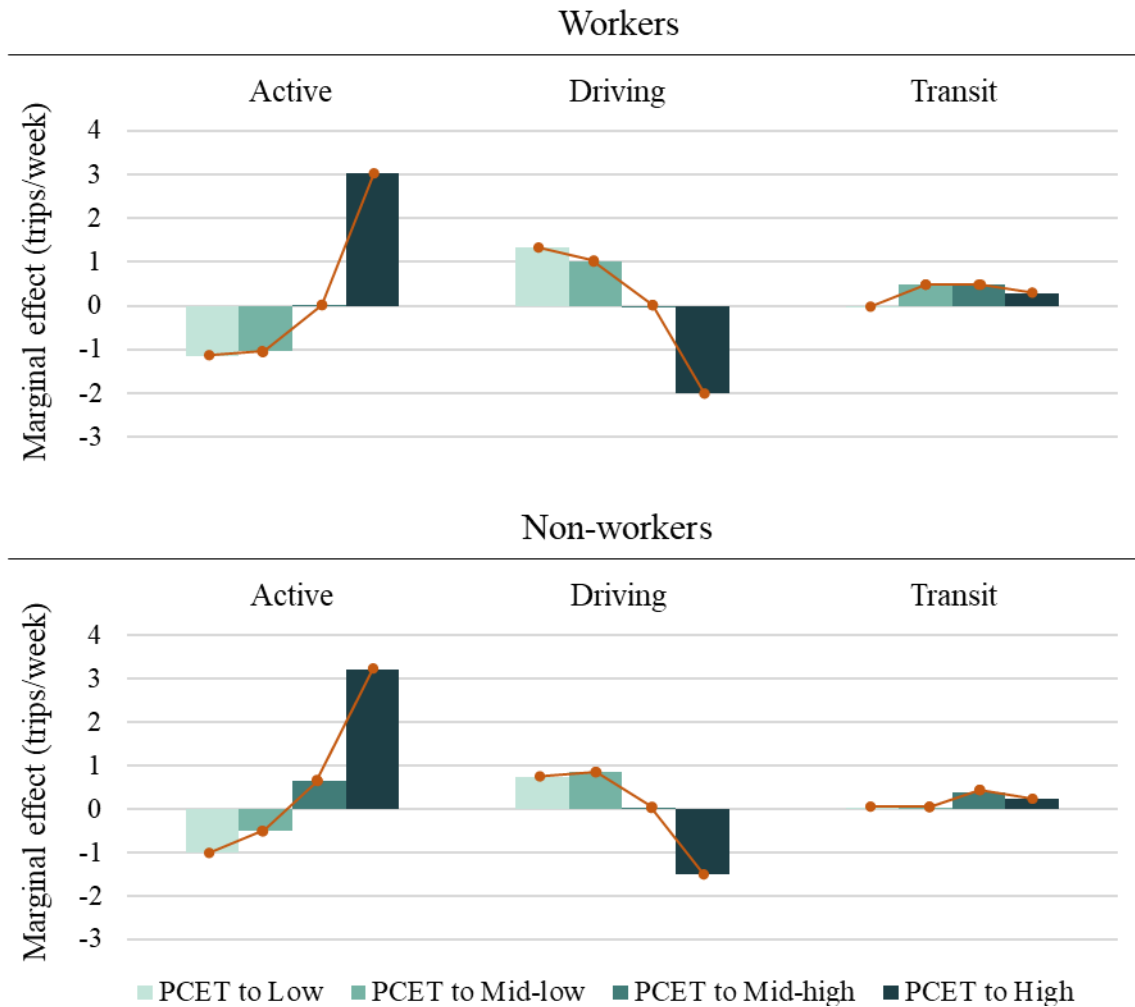


Figure 5.3. Effects of proportional cumulative exposure (PCET) to accessibility levels on mode use frequency. Non-significant coefficients are displayed as zero.

The random-effects structure reveals substantial between-person heterogeneity across all models, with intraclass correlation coefficients (ICCs) ranging from 0.36 to 0.49. This indicates that 36-49% of the variance in mode use frequencies is due to individual differences rather than measured predictors. Workers and non-workers show comparable ICC magnitudes, though non-workers exhibit slightly lower person-

level variance (τ_{00}) in transit use. To evaluate goodness of fit of the multilevel models, the marginal R^2 value represents the variance explained solely by fixed effects (i.e. time-varying predictors like relocation or car ownership). The conditional R^2 , on the other hand, reflects the model's total explanatory power including both fixed effects and random effects (i.e. individual heterogeneity). The conditional R^2 values (0.46-0.62) suggest the combined fixed and random effects explain nearly half to two-thirds of variance. On the other hand, the marginal R^2 values (0.15-0.32) confirm a substantive role of time-varying predictors. These results justify the multilevel approach while highlighting unexplained individual-specific factors shaping travel patterns, which is expected for an individual-level travel behavior model.

5.7.2 Scenario-based analysis

This scenario analysis has the goal of illustrating how the estimated models may represent the temporal evolution mode-use trajectories. By fixing all variables except for PCET, as described in Section 4, this analysis shows how home relocation may reshape mode-use behavior over time. In the first scenario-based analysis, four profiles of people are proposed, all of which are assumed to maintain all characteristics constant except for a home relocation that corresponds with a change in accessibility levels (Figure 5.4). Profiles P1 and P2 relocate from a lower to a higher accessibility level, while profiles P3 and P4 do the opposite. The weekly trips for each profile at years -2 and -1 (pre-move years) represent what the models predict for any person who has been living long term in each profile's initial built environment. For example, P4 initially in a high local and regional accessibility, as a worker is predicted to perform 5.3 trips/week by active modes, 0.6 trips/week by driving, and 2.5 trips/week by public transport. It is important to note that, although these absolute values may appear modest at the individual level, they reflect population-level averages that include both frequent and non-users of each mode. A more actionable interpretation is that for every 1,000 workers in high-accessibility environments, we'd expect ~5,300 weekly active trips and ~2,500 transit trips, compared to just ~600 driving trips, a ratio strongly favoring sustainable modes.

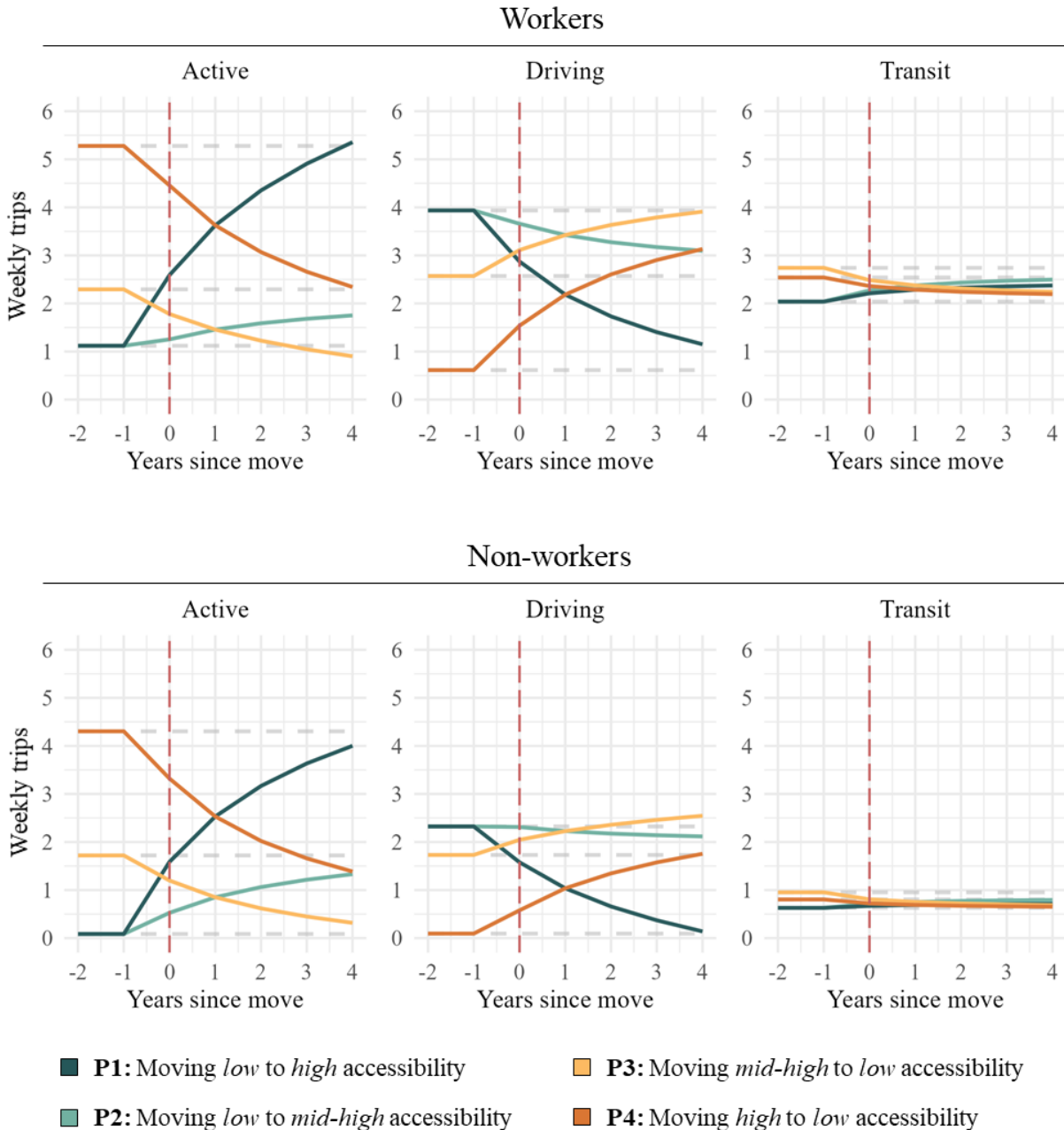


Figure 5.4. Home relocation impacts on mode-use frequency.

The residential relocation for all profiles occurs at year zero, and the gradual evolution of the frequency of travel by each transport mode is seen in following years. This gradual evolution is the main goal of this illustrative analysis and showcases the potential of this modelling approach. The impacts of built-environment exposure are consistently largest for active transport and smallest for public transport. Workers and non-workers present small response patterns in their mode use. Non-workers exhibit lower baseline

travel frequencies, particularly for driving and public transport. Additionally, they present slightly smaller responses to regional accessibility changes, especially for driving. The impacts of built-environment exposure are largest for active transport and smallest for public transport.

Building on the first relocation scenarios, the influence of combined changes in built environment and car ownership are analyzed. Four additional profiles (P5–P8) mirror the accessibility transitions of P1–P4 but incorporate realistic vehicle adjustments: selling a car when moving to higher-accessibility areas (P5, P6) or acquiring one when moving to lower-accessibility zones (P7, P8). All other characteristics remain fixed as in the initial analysis, ensuring isolation of these joint effects. The results from this analysis are shown in Figure 5.5, illustrating the joint effects of relocation and car ownership changes and how they differ between modes.

It is clear how the effect of car ownership decisions add to the effects of the built environment during a home relocation. These effects differ by mode both in absolute contribution as well as in the share that this contribution represents compared to the effects of exposure to local and regional accessibility levels. Expectedly, the largest impacts of car ownership are on the frequency of driving. This is followed by the frequency of active trips, which is reduced by car ownership. However, although car ownership has the smallest absolute impact on the frequency of transit use, it represents a considerable contribution compared to the impact of changes in local and regional accessibility levels. Again, differences between workers and non-workers exist, but the overall trends are the same. The findings from these scenarios make it clear that when people relocate, both the new neighborhood and whether they change their car ownership work together to shape their mobility patterns.

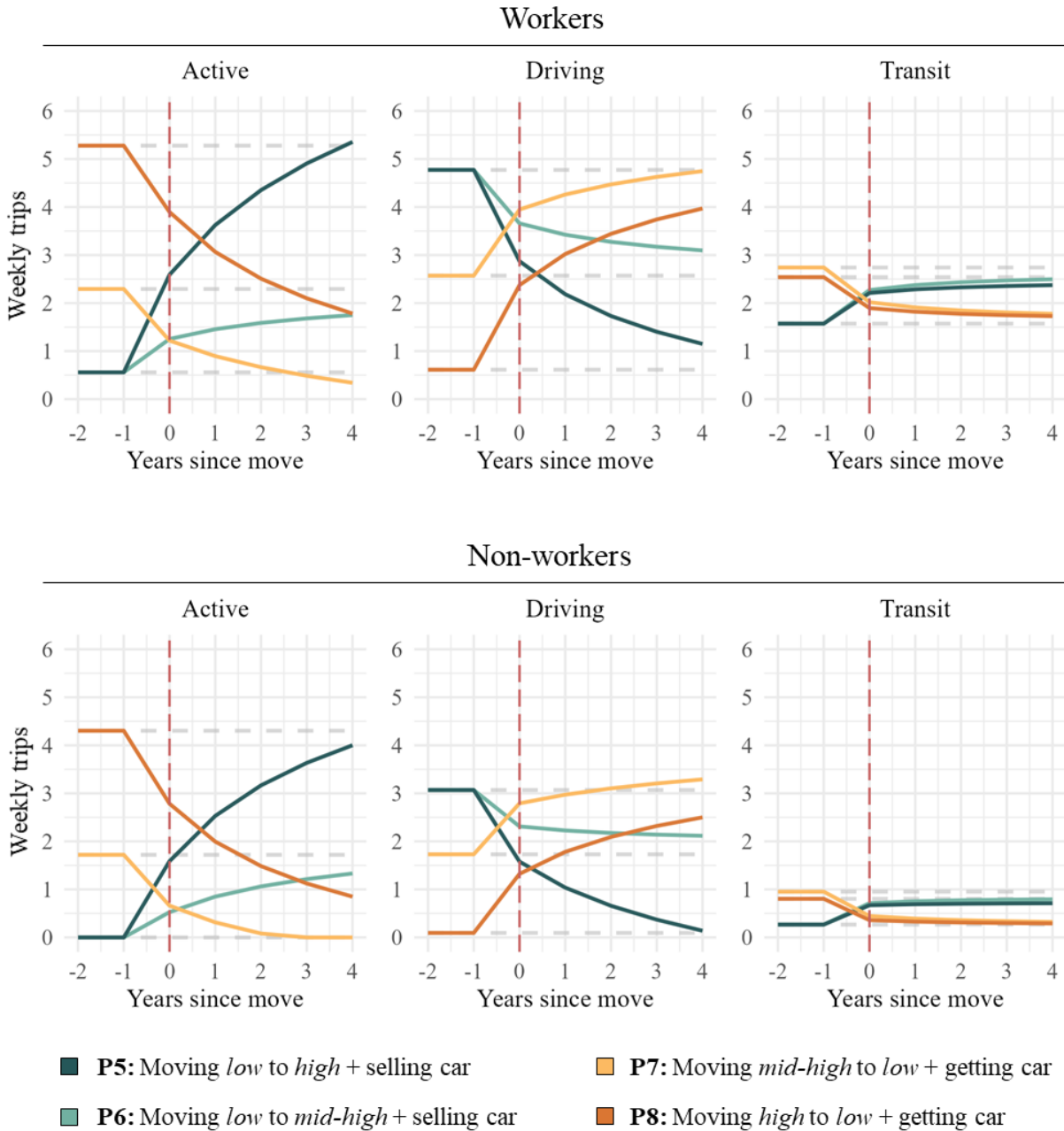


Figure 5.5. Home relocation and changes in car ownership impacts on mode-use frequency.

5.8 Discussion

The longitudinal modeling approach presented in this work reveals how residential mobility – shaped by built-environment exposure, mobility decisions such as buying a car, and pandemic-related disruptions – reconfigures urban travel behavior. The results not only provide valuable knowledge into changes in mode-

use patterns over time and the factors that mediate them. They also provide actionable insights toward land-use and transport policy.

The exposure measures and longitudinal models in this work are able to reflect a critical insight: behavior adapts gradually to built-environment changes. This contributes to the existing literature in longitudinal travel behavior changes after home relocation (De Vos et al., 2018; Lee et al., 2017; Wasfi et al., 2016), while providing a multimodal view of the current post-pandemic context. The scenario-based analysis effectively isolates these temporal effects, showing that mode-shift responses unfold over years, not immediately post-relocation. This graduality highlights a key challenge for short-term policy evaluations. Interventions like zoning reforms or transit investments, which already require spans of years to implement, may require even longer timelines to manifest their full impacts after implementation. These challenges could be addressed by pairing infrastructure and service changes with measures of soft policies aimed at behavioral changes during transition periods. These could include temporary car-use disincentives and public transport incentives. These gradual results in this work recognize that a focus on the turning point after which behavior becomes more consistent is essential to assess long-term efficacy.

Results confirm that distinct built environments, reflected through distinct local and regional accessibility levels, exert different effects across transport modes. These findings underscore the importance of disentangling local and regional accessibility effects, a distinction emphasized by the literature (Handy, 1993, 2020; Manaugh & El-Geneidy, 2012), as their divergent impacts on travel behavior require targeted policy interventions. Active transport shows the strongest response, reinforcing the centrality of local accessibility in sustainable urban mobility. Driving also presents a direct response, where areas with higher regional accessibility by public transit result in decreasing frequency of car use over time. Public transport, on the other hand, reveals more complex dynamics. Its responsiveness to regional accessibility is weaker, and results align with previous evidence of non-linear effects (Negm & El-Geneidy, 2024; Schimohr et al., 2025; Victoriano-Habit & El-Geneidy, 2024). That is, frequency of public transport use is not highest where regional accessibility is highest, and transit gains are most viable in moderate-accessibility areas. Further,

results explicitly suggest that there is replacement in mode use, where people relocating in the highest accessibility areas replace both driving and transit trips by active transport.

The exposure measure used in this work revealed distinct adaptation patterns across transport modes. For both workers and non-workers, public transport use adjusts most quickly to built environment changes due to home relocation. This rapid transit adaptation for both subgroups suggests this mode has less behavioral inertia post-relocation compared to other modes. This makes residential moves a short-term potential window for transit agencies to capture new users. Interestingly, workers adapt faster to changes in the built environment when it comes to driving patterns, while non-workers adapt faster to active mode changes. Notably, the estimated time-decay exponents for all modes and subgroups present values close to $\alpha = 1.0$ (from 0.73 to 1.13). Although the mode-specific exponents yield better model fits than the original PCET formulation by Wasfi et al. (2016), the increases in marginal R^2 values compared to the original measure were modest ($\Delta \leq 0.01$). This suggests that, despite the original PCET measure not capturing certain mode-specific differences, it may still provide reasonable approximations of travel behavior trajectories.

Results support the relevance of improving local accessibility, that is higher diversity and proximity of activities, around residential areas. These neighborhood-scale measures, although seemingly the most effective in promoting sustainable mode shifts, require a larger effort and time span to implement than purely transport measures. This highlights the importance of shorter-term measures such as enhancing regional mobility in low accessibility areas through public transport. Given the non-linear relationship between regional accessibility and transit use, it particularly highlights the need to improve transit services in moderate-accessibility areas. This supports recommendations by previous studies, as supporting these areas through transit-system improvements can have highest impact on ridership by promoting access where active modes cannot (Negm & El-Geneidy, 2024; Victoriano-Habit & El-Geneidy, 2024).

Residential relocation and car ownership changes often coincide, compounding their impacts on travel behavior. Our results indicate that acquiring a car significantly shifts mode use from both active transport and transit toward driving. This underscores the need for policy interventions that pair local and regional

accessibility improvements with car-reduction incentives. However, strategies like this should be anchored by affordability and equity. Lower-income populations, shown by the results to be more reliant on transit and less likely to own cars, are particularly prone to displacement from walkable neighborhoods (Bereitschaft, 2023). Results from this study suggest that such displacement not only exacerbates housing inequities but actively undermines sustainable transport goals.

Conversely, household structure and presence of children showed limited influence, particularly for non-workers. These results diverge from previous studies suggesting these factors to be some of the most relevant triggers of behavioral change (Lee et al., 2017). However modest, there was a consistent reduction in transit use among workers with children, as well as a small increase in the frequency of driving. This suggests that current transit systems may inadequately serve mobility needs related to childcare, consistent with previous studies (Soukhov et al., 2025). Though the magnitude of these effects is smaller than built environment or car ownership factors, these results may still highlight an equity gap. Families with young children may face constrained mobility options, even in high-accessibility areas.

Workers and non-workers exhibited significant differences in travel frequencies, mode usage, and responses to built environments. This is consistent with previous studies (Chowdhury & Scott, 2020; Dharmowijoyo et al., 2018; Victoriano-Habit & El-Geneidy, 2024) and confirms the need to analyze both samples separately. However, the direction and relative responsiveness to changes in accessibility levels remain aligned across groups. This suggests that policies targeting accessibility improvements, car-reduction incentives, or transit upgrades would yield benefits for both groups, even if absolute impacts differ.

The longitudinal data in this work showed mode-dependent trends in frequency of travel that are consistent with previous studies (Abduljabbar et al., 2022; Long et al., 2023; Wang et al., 2022). Namely, a movement towards more car mobility with a declining use of active and public transport modes, particularly steep on the latter. Results showed a relative stabilization of post-covid trends in mode use. It is relevant to note that the inclusion of these pre-, during-, and post-pandemic trends in this study is itself noteworthy. They

underscore how the pandemic reshaped the context in which mode-choice decisions are now made. This evolving context is central to this study's relevance.

Crucially, these changing trends highlight why longitudinal data and modeling are required: they simultaneously control for pandemic-era disruptions while unraveling the underlying effects of built-environment exposure and life-stage decisions. In this context, the contribution of a random effects structure is consistent with prior longitudinal work (Victoriano-Habit & El-Geneidy, 2023; Wasfi et al., 2016). Together, these findings demonstrate both the potential of this modeling approach for capturing behavioral adaptation and the nuanced ways different population segments adjust their travel patterns following residential moves.

5.9 Conclusion

This study advances our understanding of how urban travel behavior evolves in response to built-environment changes and other lifestyle changes in the post-pandemic era. Through longitudinal analysis of Montréal residents, results demonstrate that residential relocation, car ownership decisions, and local and regional accessibility exposure collectively reshape mode choices. Distinct patterns arise across the three major transport modes: active transport, driving, and public transit. The multilevel modeling approach reveals three key insights: (1) accessibility changes exert gradual but mode-specific effects, with active transport showing the strongest response; (2) while workers and non-workers show varying baseline travel patterns, both groups exhibit comparable directional responses and similar relative effect magnitudes in their mode use frequency as a response to local and regional accessibility improvements and changes in car ownership; and (3) car ownership decisions significantly mediate these effects, potentially generating compounding effects with relocating to different built environments. These findings advance the methodological integration of longitudinal exposure measures in mobility research.

Potential limitations from this study warrant future research. The scenarios presented here, while illustrative, point to the need for deeper analyses that explicitly capture individual paths of change in lifestyle and how they result in changing travel behavior. Future studies could address this in multiple ways. This work assumes symmetric effects when moving between different accessibility levels, yet future studies may assess potential directional differences (e.g., low-to-high versus high-to-low accessibility transitions). The worker/non-worker dichotomy presented in this study, although meaningful, could be refined in future works. This could be achieved through latent class analysis to identify subgroups with distinct adaptation patterns. The use of discrete accessibility ranges, though policy-relevant, may simplify more continuous environmental relationships on which future research could focus. Additional granularity could be gained by disaggregating active modes (walking versus cycling), examining further trip purposes, or considering temporal variations in accessibility levels throughout the day. While this work tested but found no significant pandemic interaction effects, comparative analyses with pre-pandemic data could reveal evolving behavioral norms. This study's modeling approach, while robust to individual heterogeneity through random effects, cannot fully resolve the inherent endogeneity in built environment-travel behavior relationships. Methodological extensions such as structural equation modeling, random coefficient specifications, or quasi-experimental designs could provide stronger causal identification in future work, as well as more explicitly address potential residential self-selection concerns. Nevertheless, this work establishes a replicable framework for studying mobility transitions amid evolving urban contexts.

6. Chapter six: Discussion

6.1 Chapter overview

This dissertation, through the four presented manuscripts, has thoroughly addressed the main research question of “What are the impacts of exogeneous disruptions and endogenous life decisions on travel behavior patterns and perceptions over time?”. Each chapter presented findings that not only contribute to the knowledge around the triggers of travel behavior change. They also provide actionable recommendations for policymaking. Moreover, the insights extracted from each chapter are not only valuable in isolation, as presented within each manuscript. These insights interrelate at different levels, with the potential of providing a broader view of the issue of triggers of travel behavior change, the measurement of their impacts, and the extraction of valuable learnings for real world applications. This discussion presents a synthesis of the main findings and contributions with regard to this dissertation’s, theoretical discussions, empirical findings, methodological advances, and policy recommendations. The section ends by discussing this work’s limitations and the future research directions that arise from them.

6.2 Theoretical discussion

6.2.1 Conceptualizing exogenous and endogenous triggers

The findings in this dissertation present an opportunity to discuss the usefulness of conceptualizing triggers of behavior and perception changes around the concepts of exogenous disruptions and endogenous life changes. Through studying different triggers of changes in travel behavior and perceptions, the four manuscripts present relevant insights into the ways in which these different types of triggers interrelate. Despite each of these chapters having a different specific focus, all of them show how none of these types of triggers can be assumed to act in isolation. There is an evident interrelation between them in all studied cases. Results reinforce the need to consider exogenous disruptions as a potential trigger of endogenous

change (Lee et al., 2017; Muggenburg et al., 2015), as well as to consider the impacts of endogenous characteristics on the differing impacts of exogenous triggers (Heinen et al., 2017; Spears et al., 2017; Sun & Du, 2023; Sun et al., 2020).

Chapters 2 and 3 studied the widespread effects of the COVID-19 pandemic on the use of different transport modes over time, although through different approaches. Chapter 2 analyzed the impacts of the COVID-19 pandemic through the changes in telecommuting habits, while Chapter 3 analyzed the changing impacts of the built environment after the COVID-19 pandemic. In both of these studies, an explicitly spatial dimension is incorporated by evaluating the effects of built environment characteristics. The inclusion of this dimension is key, both towards unraveling the spatially differing impacts of a widespread disruption like COVID-19, as well as pointing towards the localized interventions that are required to address urban mobility issues in the post-pandemic context. Additionally, the models in these two chapters required controlling for endogenous characteristics. Although the results surrounding characteristics like income, gender, and age are not particularly novel within the models in Chapters 2 and 3, they were essential control variables to effectively study the impacts of the COVID-19 pandemic.

In the case of Chapter 4, studying the perceived effects of introducing transit infrastructure corresponds to an exogenous intervention whose impacts can be evaluated locally. One of the reasons for which the use of natural experiments is supported in the literature is their capability of measuring treatment effects while controlling for unobserved and observed trends using a control group (Craig et al., 2017; Humphreys et al., 2016). In the context of analyzing a transit project as a trigger of perceived changes, this means that the framework explicitly shows the need for controlling for pre-existing endogenous differences between treatment and control groups, as well as for exogenous temporal trends unrelated to the introduction of the project. More specifically, pre-existing sociodemographic differences and pandemic-driven temporal trends are controlled for in order to isolate the effect of new transit infrastructure. Similar to the cases of Chapters 2 and 3, endogenous characteristics such as income, gender, and age do not present novel results, but are key control variables to unravel the effects of new infrastructure.

Finally, Chapter 5 studies the evolving impact of endogenous life changes such as home relocation, car ownership, and household structure. Again, although the focus of the study is on endogenous changes, this manuscript shows the importance of explicitly recognizing the existence of exogenous trends, most of which are related to the pandemic in the timespan of this study. Similar to the case of Chapters 2 and 3, a spatial component is explicitly added by accounting for characteristics of the built environment. The case study of home relocation results particularly interesting in this context, as it consists of a shift in a person's surrounding built environment due to an endogenous decision. The results from this analysis give insights into how to turn knowledge about endogenous decisions, which are not as directly intervenable by planners, to planned localized interventions that effectively address urban issues.

6.2.2 The role of accessibility within the triggers' framework

The theoretical framework of the land use and transport cycle – including accessibility as a central term – is not one that requires particular reinforcement. This is because, at this point, the role of the concept of accessibility in land use and transport analyses is hardly questionable, being accepted and promoted for decades (El-Geneidy & Levinson, 2022; Geurs & van Wee, 2004; Wachs & Kumagai, 1973). However, this dissertation does provide a relevant discussion in the use of accessibility within a dynamic framework, and particularly within the context of triggers of travel behavior change.

For the study of a widespread disruption like COVID-19, the concept of accessibility proved particularly useful in disentangling the spatially differing effects of the pandemic. Given the solid theoretical basis for using accessibility as an effective measure of the land-use and transport systems, Chapters 2 and 3 were able to incorporate the mediating role of the built environment on the impacts of the pandemic. Particularly, leveraging the local and regional distinction of accessibility measurements (Handy, 1993, 2020; Manaugh & El-Geneidy, 2012) allowed disentangling the effects of proximity and mobility on sustainable mode use in Chapters 2, 3, and 5.

In the dynamic contexts being studied longitudinally in this dissertation, the inclusion of accessibility does not only incorporate a static spatial component to the analyses. A dynamic spatial effect is incorporated through providing longitudinal accessibility *changes*. It is well known that accessibility levels by public transit were affected by the pandemic due to reductions in service (Nikolaidou et al., 2023). Chapters 2 and 5 implicitly incorporate these changes in accessibility within the analysis, resulting in more accurate estimations of mode-use factors. Additionally, by having yearly data of accessibility levels, Chapter 3 was able to explicitly distinguish the effects of reduced transit service from the effect of a diminishing influence of accessibility on ridership (Negm & El-Geneidy, 2024). In this way, these chapters illustrate the relevant role of accessibility within dynamic frameworks.

6.3 Empirical findings

Some of the main contributions of this dissertation arise from the empirical findings from each manuscript, and the way in which they interrelate. The three main themes around these empirical findings relate to: (1) the abrupt effects and the lasting legacy of the COVID-19 pandemic as a widespread disruption that has resulted in complex changes in mode-use patterns, (2) the effects of the built-environment on affecting travel patterns, particularly in a context of home relocation, and (3) the simultaneous benefits and risks that can arise from introducing new transit infrastructure in the post-pandemic context.

6.3.1 The pandemic's shock and legacy

Albeit for different purposes, as discussed previously, all four manuscripts in this thesis explicitly consider the impacts of the pandemic over time. Because of this, there are many empirical findings within them that interrelate and provide interesting insights for understanding post-pandemic travel behavior.

In terms of active-travel patterns, Chapter 2 showed that the “renaissance of active travel” that was hypothesized due to pandemic-related changes (Nurse & Dunning, 2020) was not observed at an aggregate level. In fact, the opposite was observed, with a small decrease in active-mode use overall. Results from Chapter 5 showed that a full recovery of pre-pandemic frequency of active-mode use only happened for workers, and it did not occur until 2024. However, when evaluating the overall effect of telecommuting specifically, Chapter 2 concluded that the aggregate effect of telework was positive on the frequency of active-mode usage, in line with previous studies (Chakrabarti, 2018; Elldér, 2020). This suggests that, at an aggregate level, the increased time budget provided by telework is partially used in active travel for purposes other than work. Most importantly, Chapter 2 added to this knowledge by clarifying that this aggregate effect is not the same for everyone, but is spatially distributed. Workers living in high local accessibility levels considerably increased their active-mode use when telecommuting, but those living in the lowest local-accessibility areas were less active when engaging in telework. These results highlight that the role of local accessibility levels in promoting active travel was heightened by the pandemic through the increased popularity of telework.

The results are highly contrasting when it comes to the post-pandemic frequency of public-transit use. Results from Chapter 3 showed that the role of regional accessibility by public transport in promoting its use considerably decreased during and after the physical restrictions of the pandemic. Previous to the increase in the popularity of telecommuting, there was already an expectation that virtual activities had the potential to decouple travel behavior from the urban form (Elldér, 2017). This expectation was confirmed by the results in Chapter 3, as well as by other studies in the literature (Negm & El-Geneidy, 2024). The reduction in the effect of regional accessibility was particularly strong for workers. For this subgroup, these changes had a similar contribution to the reduction in transit use as that by the increased popularity of telework.

The longer timespan of Chapter 5 provided further insights on post-pandemic mode-use trends, suggesting that many trends are stabilizing. In terms of mode usage, active modes, driving, and transit all show relative

stability in the 2022 – 2024 period compared to previous years. The results suggest a general post-pandemic trend of increased car mobility, and decrease active-mode and transit use compared to pre-pandemic times. Additionally, results showed that the frequency of telecommuting has maintained considerably higher than at pre-pandemic levels. This confirmed the expectation that the popularity of telework would maintain far beyond the pandemic restrictions (Javadinasr et al., 2022). Chapter 5 confirms a maintained effect of telecommuting in reducing the frequency of all modes of transport, although with the largest effect on transit and the lowest effect on active travel. These findings suggest that the relationships found in Chapter 2 and 3 could remain largely stable over time.

6.3.2 Abrupt relocation, gradual change

Within the life changes studied in Chapter 5, home relocation resulted particularly interesting, as it combines the endogenous decision of residential location with a potential change in the exogenous characteristics of the built environment. A first result from this study was that relocation within the sample did not occur primarily in one direction (*e.g.*, predominantly from higher to lower accessibility levels). This result is highly relevant, as there has been an expectation for telecommuting and other virtual activities to result in a decoupling between home location and access to activities (Asadieh & Neisch, 2025; Elldér, 2017). Although previous studies have concluded that home-location preferences have shifted away from dense urban areas (Ilham et al., 2024), results in this study suggest that these preferences haven't resulted in an overall trend of actual relocation from higher to lower density and diversity.

The lack of an overall direction in home relocation implies that aggregate trends in post-pandemic mode usage observed across studies cannot be attributed to moving patterns. However, at an individual level, multiple effects of changing built environments through home relocation can be observed on mode-use patterns. Results showed that changing built environments can have the largest overall impact on active-mode use. This could be consistent to the results of Chapter 2, where it was shown that the relevance of

local accessibility around a person's home is heightened after the pandemic. On the other hand, results show that the impacts of relocating between different accessibility levels have the smallest impacts on public transport use, which is consistent with Chapter 3 and other studies (Negm & El-Geneidy, 2024). Additionally, results in Chapter 5 regarding transit usage are also consistent with results from Chapter 3 and previous research in showing a non-linear effect of accessibility (Cui et al., 2020; Schimohr et al., 2025). These results show that the largest effect in promoting transit occurs in areas with intermediate regional accessibility levels. Most importantly, Chapter 5 illustrates how these patterns do not only reflect a static pattern, they give rise through gradual and dynamic processes, where people relocating take time to adapt to their environments.

6.3.3 Transit infrastructure: a double-edged sword

The context of a lower-income corridor studied in Chapter 4 showed overall trends of decreasing perceptions of quality of life and increasing concerns regarding costs of living and displacement. These overall trends were consistent with observed perceptions in Canada within the context of the COVID-19 pandemic and increased inflation (Chen & Tombe, 2023; Wen et al., 2022). In this context, the analysis in Chapter 4 showed that the introduction of a new Bus Rapid Transit system (BRT) helped mitigate the decreasing trends in perception of the impact of neighborhood changes on quality of life. Notably, this result was sustained in time after a year of operations of the BRT, and was not limited to users of the new system. These positive results supporting the introduction of this type of infrastructure represent valuable evidence, as BRT systems have particular political and practical challenges in their implementation (Allanson et al., 2023). Moreover, in the post-pandemic context of reduced transit ridership, promoting new transit projects like BRT systems may face heightened political and economic challenges. However, it is imperative to sustain transit improvements even in this context given that not doing so would ensue a vicious cycle that further promotes car mobility and deteriorates public transport (Ortúzar & Willumsen, 2011).

Generally, the introduction of this type of infrastructure has the goal of promoting public transit use through reducing travel times, (Hoang-Tung et al., 2021; Venter et al., 2017), increasing performance and reliability (Deng & Nelson, 2011; Hoang-Tung et al., 2021), and improving regional accessibility (Pereira, 2019; Singh et al., 2022). All of these aspects become more relevant in areas with a higher share of lower-income residents, as they rely more heavily on public transit, as shown consistently by Chapters 3 and 5. However, the implementation of transit infrastructure projects also carries more risk in these areas, as lower income households are more prone to displacement (Bereitschaft, 2023).

Results from Chapter 4 indicated that the introduction of the project produced significant concerns regarding displacement due to rising costs. However, these effects disappeared after one year of operation. These positive results could be attributed to the relative affordability of the city of Montréal compared to most other medium and large Canadian cities (Urbanation, 2023; Wright & Hogue, 2019). Despite these positive results, 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).

The issue of the potential for residential displacement that BRT and other transit projects have (Brown, 2016; Heres et al., 2014; Qi, 2023) becomes particularly relevant in the post-pandemic context discussed in previous subsections. First, the displacement of lower income individuals who rely most on public transport is likely to push them towards lower accessibility areas (Bereitschaft, 2023). Additionally, given the manner in which car mobility restructures people's activity-travel patterns, getting a car in car-dependent areas might improve ease of access to the workplace but not necessarily to non-work activities (Farber & Paez, 2011). This results in a high potential for social exclusion among lower-income populations (Farber & Paez, 2009). These effects might be highlighted in the post-pandemic context, as moving towards less walkable areas is linked with less frequent travel than in pre-pandemic contexts, as discussed previously.

6.4 Methodological findings

Beyond the empirical findings within the manuscripts in this dissertation, multiple themes with respect to methodological advances can be distinguished. These include: (1) the use of disaggregated panel data within the study of triggers of behavioral and perception changes, (2) the contribution of different panel modelling frameworks and specifications, and (3) the contribution of illustrative analyses beyond the estimation of a panel model in obtaining valuable insights for research and policymaking.

6.4.1 Disaggregated panel data

The use of individual-level repeated observations, or disaggregated panel data, has clearly shown its usefulness in the studies presented in this dissertation. None of the analyses performed in this thesis can be exactly replicated through cross-sectional or repeated cross-sectional data. While pseudo-panel frameworks could partially achieve the objectives in this thesis, these results would not allow for the individual-level observation of sub-trends (Goodwin, 1997), and would not provide evidence with the same level of confidence than that presented here (van de Coevering et al., 2015).

In the case of Chapter 2, the use of this type of data allowed for a disentangling of the effect of telecommuting at an individual level specifically during the pandemic, and the mediating effect of local accessibility. In Chapter 4, the natural experiment design, which is inherently a longitudinal framework, provides considerably more solid evidence than a cross-sectional design (Craig et al., 2017). As discussed previously, this is due to the explicit consideration of exogenous trends and pre-existing endogenous differences. In this way, the inclusion of individual-level trajectories within the data can confidently provide the relevant insights here provided. The disentanglement of individual-level effects is only fully achievable through repeated disaggregated observations (Raimond & Hensher, 1997).

The use of more than two waves of data in longitudinal studies is particularly relevant given the existence of time-lagged effects in perceptions and behavior (Chang et al., 2010). Understandably, few studies in the

literature engage in the use of three or more waves of panel data (Chatterjee & Ma, 2007, 2009; Heinen et al., 2017), as it is costly and complex to collect (Raimond & Hensher, 1997). In Chapter 3, the use of data from before, during, and after the pandemic provided valuable insights into the shock of the pandemic on transit usage and its gradual recovery. In Chapter 4, it allowed for the evaluation of the effects of introducing transit infrastructure at the moment of inauguration and one year after. The results from Chapter 5, through the use of five waves of data, can illustrate the gradual changes that come about from endogenous changes such as home relocation.

These manuscripts illustrate that two-wave studies on triggers of travel behavior and perception change have to accept one of two pragmatic options. The first is to measure a shorter-term impact, in which the “shock” effect of a trigger may be measured while ignoring the gradual evolution that may lead to a stable outcome in time. In the case of Chapter 5, for example, this would ignore the gradual evolution that occurs over the years after relocation. The second alternative is to evaluate only the longer term, potentially skipping over shorter-term “shock” effects. In the case of Chapter 4, this would have meant ignoring the short-term concerns caused by the introduction of transit infrastructure. Although these limitations of two-waves studies may be inevitable for many longitudinal studies, they must be taken into consideration.

6.4.2 Panel model specifications

As mentioned previously, the study of a specific trigger of changes in travel behaviors and perceptions must consider the presence of any other factors potentially affecting that change. In terms of model specification, this is illustrated explicitly in each chapter by the decisions in variable selection and modeling framework. In the case of Chapters 2 and 3, the inclusion of endogenous characteristics such as age, income, and gender within the models’ independent variables was key for an accurate measurement of the pandemic’s effects. In Chapter 4, the differences in differences framework explicitly accounts for pandemic-related trends by

defining a coefficient linked to these purely temporal effects. In Chapter 5, the inclusion of the exogenous effects of the built environment is explicit through the use of accessibility measures.

Regardless of the specific focus of each study, the inclusion of temporal trends through the use of wave fixed effects was key in isolating these effects over time. In each of these models, the temporal effects on the dependent variable, which are unrelated to the measured covariates, were captured through these fixed effects. These correspond to unrelated trends having an effect on frequency of mode use (Chapters 2, 3, and 5) and perceptions around quality of life and costs of living (Chapter 4). Moreover, the multilevel structure in each of these models was responsible for recognizing that multiple observations may come from the same individual. The random-effect results in each of these models provided insights into the proportions of within-person and between-person effects. The use of linear multilevel models in Chapters 2, 3, and 5, and the use of binomial multilevel models in Chapter 4, adds to the numerous studies using these random-effect specifications (El-Assi et al., 2017; El-Geneidy et al., 2014; Faghih-Imani et al., 2014; Grisé & El-Geneidy, 2017; Wasfi et al., 2016).

6.4.3 Beyond modelling: illustrating results

Although most articles that include statistical modeling limit themselves to presenting results as model coefficients, some previous studies have shown how using these models to predict illustrative scenarios can provide relevant insights (Birkenfeld et al., 2023; Villafuerte-Diaz et al., 2023). The sensitivity analyses presented in Chapters 2 and 3, and the scenario-based analysis presented in Chapter 5 represent additional support for these types of illustrative analyses, particularly within the use of panel models.

The sensitivity analyses in Chapter 2 were fundamental in illustrating the mediating effect of local accessibility within the impacts of telework on active-mode use. While the use of interactions between independent variables provides a tool for disentangling complex interrelationships, the coefficients associated to them are not directly interpretable. Similarly, in Chapter 3, the use of sensitivity analyses

illustrated the interactions between local and regional accessibility effects in promoting transit use, while also showing the temporal evolution of these effects. Finally, the scenario-based analysis in Chapter 5 used the resulting models to predict illustrative scenarios. Through these, the use of more complex measures as independent variables, such as proportional exposure measures to the built environment, can be explained in simple and direct terms. In these ways, utilizing the resulting models beyond presenting the estimators as final results can be a powerful tool for both research and planning. The insights from the application of these tools in research communication are strongly related to the extraction and support for the public policy recommendations provided by the work within this dissertation.

6.5 Policy implications

All the studies in this dissertation were designed to not only contribute to the research literature in the ways that have been described until now. Each of them provides relevant recommendations for transport planning in the post-pandemic context. The understanding of different types of triggers of travel behavior and perceptions provides multiple themes for these recommendations. These include: (1) How to promote active travel in a context of increased remote activities, (2) how to plan for transport services and infrastructure given the new relationships with the built environment, and (3) how to address the issues of relocation and gentrification after the pandemic.

6.5.1 Promoting active travel

Results from Chapter 2 showed that the aggregate impact of telework resulted in an increase in active-mode use, mitigating the overall pandemic effect. Additionally, results from this chapter indicate that this effect was highly dependent on a worker's local accessibility levels. Whereas people living in high local accessibility areas increased their use of active modes, those living in the most car-dependent areas had an opposite result. These results support the idea that local residential environments acquire a higher relevance

in this new context (Asadie & Neisch, 2025). Additionally, given the results from Chapter 5, which suggest that telecommuting levels have remained highly stable over time, it is likely that these impacts of the local built environment will remain relevant in the future.

The proximity and diversity of activities had been shown in the past to be a relevant trigger for changes in active-travel patterns (Lee et al., 2017), and have been promoted for decades as changes that will beget positive shifts in travel (Ewing & Cervero, 2010; Saelens & Handy, 2008). These aspects of planning for local proximity and diversity have a heightened role in the post-pandemic context, specifically within residential areas. In this sense, if the goal is to promote utilitarian active travel, it is sprawling areas with highest population and lowest local accessibility which should be prioritized through land-use changes in the post pandemic context.

6.5.2 Public transport planning

Results in Chapters 3 and 5 showed that the frequency of public transit usage was considerably affected by the pandemic, compounding to a decreasing tendency that was present in the North American context since before COVID-19 (Boisjoly et al., 2018; Erhardt et al., 2022). Additionally, results from these chapters show that the post-pandemic recovery has been partial and gradual. These trends are concerning for public transport planning in the post-COVID context, but results from this dissertation provide directions that help in addressing this issue.

The results from Chapter 3 showed a decreased role of regional accessibility in promoting public transport in the post-pandemic context, which is consistent with existing research (Negm & El-Geneidy, 2024). Particularly, for the case of workers, although ease of access to a diversity of opportunities does not hold its previous importance, travel time to work remains relevant in promoting transit usage. These results suggest, for employed individuals, an increased importance in planning for public transit for commuting. This can be addressed by providing improved transit services to major employment hubs. Complementarily,

employer-sponsored transit passes and increased parking fees at the workplace may help in bolstering workers' transit use. In the case of non-workers, results show that the largest impacts of public transit accessibility occur in comparatively lower accessibility areas. These results, consistent with Chapter 5 and other existing research (Cui et al., 2020; Schimohr et al., 2025), highlight the need for focusing on improving transit in lower- and middle- level local and regional accessibility areas.

Chapter 4 highlights the positive perceived impacts of introducing new transit infrastructure in areas with no pre-existing rapid transit. These results should serve as precedent to support these types of projects, particularly in lower income areas, where results from Chapters 3 and 5 have shown that public transit reliability is highest. In this sense, the implementation of Bus Rapid Transit (BRT) in areas with relatively low local and regional accessibility levels can be an effective solution for improving transit in the post-pandemic context.

6.5.3 Relocation and gentrification

Previous studies suggested that home-location preferences have shifted away from dense urban areas due to the increase in the popularity of remote activities (Ilham et al., 2024). Results from Chapter 5 showed that there is no overall trend in home relocation from higher to lower accessibility levels. However, as discussed previously, the post-pandemic context heightens the issues of increased relocating to lower accessibility areas, particularly when it regards gentrification and lower-income individuals. Because of this, housing policies that incentivize buying or renting homes in higher accessibility areas, and discourage moving to homes in lower accessibility areas, would have an increased positive effect in the post-pandemic context. These measures could include higher taxation or increased development fees in lower accessibility areas.

While results in Chapter 4 suggested that the increased concerns of displacement generated by a new BRT were short lived, there are still relevant implications for the introduction of transit infrastructure and

gentrification. First, a possible explanation for this effect can be that housing policies in the province of Québec already protect the surrounding residents from being displaced. In fact, these distinct housing regulations have resulted in Montréal having significantly higher levels of housing affordability than other comparable cities in Canada (Urbanation, 2023; Wright & Hogue, 2019). The results in this work highlight that, in the post-pandemic context, it is key to preserve and further these protective regulations.

The results in Chapter 5 showed that mode shifting responses to home relocations unfold over years. These gradual effects present an added challenge for public policymaking. Interventions such as zoning changes and the introduction of infrastructure already require spans of years to implement. Results from this dissertation suggest that the full impact of their implementation may require even longer. This gradualness of changes can be addressed by pairing these types of interventions with soft-policy measures aimed at the transition periods of project implementation. Potential solutions could include temporary car-use disincentives and public transport incentives.

6.6 Limitations and future research

6.6.1 General limitations

Regarding the analyses performed in the manuscripts in this thesis, there are some aspects that can be described as overall limitations which are applicable for the dissertation as a whole. A first limitation regards the observed stability in mode-use patterns and the relationships between travel and the built environment after the pandemic. Although a certain stability can be inferred towards the future, nothing guarantees that this will be the case. This limitation is intrinsic to any longitudinal study, and it highlights the relevance of continuously collecting panel data for travel behavior research. This inference of stability can only be monitored with time, and transport plans must be able to adapt to variability and uncertainty.

Another limitation regards the use of panel data collected in yearly intervals. Although collecting survey waves at the same time of year provides comparable points in time, seasonal effects cannot be measured.

Not only is this lack of seasonal measurements relevant to understanding the potentially different effects of triggers between seasons. This could affect the generalizability of results, particularly when it regards active modes of transport. Similarly, another general limitation that regards the generalizability of the empirical findings relates to the particular urban context being studied in this work, in Montréal, Canada. While performing all studies within the same spatial and temporal context provides an opportunity for directly connecting all obtained results, this also presents challenges for result transferability. While Montréal is denser and more diverse than many North American cities, it still encompasses a wide range of built environments, including suburban sprawl. Given the methodological approaches used in this work, many of the findings should retain reasonable transferability to other North American contexts. That said, no study can guarantee universal applicability, and further research in cities with differing urban forms would help validate and refine the generalizability of these results.

6.6.2 Specific limitations

Specific limitations for each chapter in this work can also be discussed. First, in Chapter 2, the focus on utilitarian trips disregards the effects of the pandemic on discretionary active travel. Chapter 3 incorporates the effects of localized interventions only partially through changing accessibility levels. However, further impacts of introducing new transport infrastructure could have localized impacts on transit ridership that are not reflected in accessibility changes. Additionally, the analyses in Chapters 2 and 3 focus individually on one mode of transport. Although this approach presents a focused view of the mechanisms for each specific mode, it lacks information regarding the results of changes in mode choice. That is, mode shifting effects are not analyzed. Similarly, Chapters 2, 3, and 5 ignore the possibility of trip chaining, which is a dimension that is potentially affected by all triggers studied in this work. The limitations in Chapter 4 are mostly methodological and due to restrictions in sample size. A larger panel dataset could enable more sophisticated threshold measures to determine the spatial extent of the impacts of new transit infrastructure, such as the use of geographically weighted regressions. Finally, although Chapter 5 generates interesting

insights resulting from home relocations, there is no explicit consideration of the reasons behind those relocations. Reasons which could result in different changes in mode use patterns over time.

6.6.3 Future lines of work

Multiple lines of future work can be identified from the gaps and limitations left from this dissertation. First, in general terms, it would be essential for future research to monitor the main findings in this work over time. This is particularly relevant given the possibility of further post-pandemic readjustments. Similarly, as a general line of work, future studies could focus on comparing the results in this thesis in different urban contexts. The effects of triggers of behavior and perception changes in cities of the Global South could be particularly interesting, as the dynamics around telework and travel can be significantly different. Urban mobility dynamics differ vastly in the Global South context due to factors like higher informality in transport systems, more constrained budgets, and different telework adoption patterns shaped by lower incomes and steeper inequality. Qualitative approaches like in-depth interviews could particularly help uncover lived experiences behind these structural differences in the Global South.

Future studies can build on Chapter 2 by addressing the post-pandemic patterns in active travel for non-working groups. Although telecommuting is not a dimension that directly concerns non-employed populations, other virtual activities becoming more popular due to the pandemic could have similar effects. The timespan of Chapter 3 only allowed a partial view of the recovery into the post-pandemic period. Future studies can extend this analysis in order to understand the recovery of the effects of accessibility (or lack thereof). Another line for future research could be to explicitly link the triggers of changes in perceptions – such as those measured in Chapter 4 – to triggers in actual behavioral change. This could include both daily travel patterns and home relocation. In this line, future studies could build on the results of Chapter 5 by incorporating the specific reasons for which people relocated. As discussed in this dissertation, it is essential to distinguish between those with the privilege of choosing when and where to relocate, and

potential gentrification effects. Mixed-method designs combining quantitative tracking with qualitative interviews would be particularly valuable, as they could reveal the subjective decision-making processes behind relocation choices and travel adaptations that surveys alone cannot capture.

There are multiple studies that could address the policy insights provided by the research in this thesis. In general, an interesting line of research would be to analyze public perceptions around the recommendations provided by this thesis. This is particularly relevant for potentially unpopular measures such as increased taxation and fees. Beyond public perceptions, further research could also focus on implementation-specific studies, such as identifying the high-population, low-accessibility areas to target in order to improve transit services in line with the recommendations from Chapter 3. Similarly, future works could identify the best interventions to the land use system in order to increase the local accessibility levels in low-diversity residential areas. This would aid in addressing the recommendations provided by Chapter 2. Finally, the role of housing policies in mitigating concerns of gentrification generated by transport projects could be explicitly analyzed by future research.

7. Chapter seven: Conclusion and summary

This dissertation examined how travel patterns evolve through the interplay of individual choices, policy interventions, and systemic disruptions. Through four interrelated studies, it revealed how pandemic-driven disruptions, new infrastructure, and life transitions interact with built-environment characteristics to alter travel behaviors and perceptions. Through studying this diverse arrangement of triggers of travel behavior and perceptions using panel data collected over five years, the manuscripts in this dissertation provide an overview of how these different triggers interact. The findings from this dissertation show that it is key for longitudinal studies on travel patterns at the individual level to acknowledge both endogenous (life decisions and personal characteristics) and exogenous disruptions (the pandemic and transport infrastructure). The inclusion of the built environment in this analysis highlighted its critical role in mediating how disruptions and life choices influence travel behavior and perception change. This, in turn, allows for the identification of elements that can be shaped by planners to shape these outcomes, such as transport infrastructure and zoning policies.

Research in this thesis provides empirical insights while illustrating the value of employing disaggregated panel methods. These empirical findings in the context of the COVID-19 pandemic may have lasting relevance given the persistence of habits like telecommuting. For instance, while telework increased active-mode use overall, its benefits were concentrated in high-access neighborhoods, reinforcing the critical role of local built environments. This finding underscores the need to prioritize accessibility improvements in low-diversity, car-dependent areas to sustain and increase active travel gains in the post-pandemic context. In the case of public-transit use, while the COVID-19 pandemic accelerated its decline, this research identifies targeted pathways for recovery. These include prioritizing commuter routes to employment hubs, expanding service in lower-access areas, and prioritizing investment in rapid transit infrastructure like BRT for transit-deprived neighborhoods. This research also revealed the critical need for housing policies that incentivize high-accessibility living, especially given the compounding risks of displacement and the slow yet significant mode shifts triggered by relocation. These results call for interventions that pair long-term

infrastructure with transitional soft policies to steer mobility transitions. The interrelated results of this thesis demand coordinated policy bundles: transit investments like BRT must address the finding of decreased impacts of accessibility by targeting employment hubs, while housing policies should prevent displacement in transit-improved areas. Simultaneously, telework incentives should target low-access residents to avoid compounding inequalities.

As future transport planning faces compounding large-scale changes due to climate crises, automation, and other disruptions, this research not only provides a better understanding of the current mobility landscape. It also provides potential frameworks to analyze evolving urban mobility within an uncertain and rapidly-changing context using panel data. By centering the interplay of choices, shocks, and place, it shows that both sudden disruptions and gradual life changes require integrated planning approaches for sustainable mobility futures. These insights can equip policymakers and researchers to anticipate behavioral shifts, prioritize equitable interventions, and harness longitudinal methods to track evolving urban transitions.

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