One size does not fit all: Evaluating the impact of accessibility on commute duration and public transport mode share for different income groups in Canadian metropolitan regions

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September 2019

A thesis submitted to McGill University in partial fulfillment of the requirements of the degree of Master of Engineering

ABSTRACT

Accessibility, defined as the ease of reaching destinations, has been shown to be an influential determinant on commute travel outcomes and behaviors, such as commute duration and the mode selected for commuting. At the same time, researchers have also identified that accessibility is central in the development of sustainable and equitable transport plans. However, no existing research has considered the intersection of these two areas of research to evaluate the impact of accessibility as a determinant of commuting outcome and behavior from an equity perspective. The present thesis aims to do so specifically in the context of income, by examining the difference in the impact of accessibility on commute duration and public transport mode share for the low-income as well as the higher-income group.

In the first part of the research, I examine the relationship between accessibility, to jobs and workers by car or by public transport, and commute duration for low-income individuals as compared to higher-income individuals. This is carried out using data for three of the largest metropolitan areas in Canada: Toronto, Montreal, and Vancouver, using separate multilevel mixed effects statistical models for car and public transport commuters. In this study, accessibility measures are generated for jobs and workers both at the origin (home) and the destination (place of work) to account for the impact of competing labor and firms. Our models in this study show that the impacts of accessibility on commute duration are present and, in many cases, stronger for low-income group than for higher income groups. The results suggest that low-income individuals have more to gain (in terms of reduced commute time) from increased accessibility to low-income jobs at the origin and to workers at the destination. Similarly, they also have more to lose from increased accessibility to low-income workers at the origin and to low-income jobs at the destination, which are proxies for increased competition. As a result, policies targeting improvements in accessibility to jobs, especially low-income ones, by car and public transport while managing the presence of competition can serve to reduce the inequality gap observed for commuting outcomes.

The next part of the research examines the relationship between accessibility to jobs by public transport and public transport mode share at the origin for the low-income group in comparison to the higher-income using a series of linear regression models carried out at the census tract level. The geographic scope of this study is expanded from three to eleven Canadian metropolitan regions of varying sizes. Prior research has shown that there exists a non-linear

relationship between accessibility and mode share and as such, a quadratic relationship is used to approximate this relationship in this study. Our results show that the impact of accessibility on mode share are present for both income groups and the impacts are stronger for the low-income group. In addition, there is strong evidence for the low-income groups in the largest metropolitan areas that there is a point past which increasing accessibility will lead to a decrease in public transport mode share. However, this point occurs around when accessibility is at the 80^{th} percentile, so improvements in mode share are nonetheless expected in most areas of these metropolitan regions when accessibility is increased. Moreover, in regions where a linear relationship between accessibility and mode share is more applicable, accessibility can be improved throughout the region, which could lead to increased uptake of public transport for both the higher-income group and to a greater extent, the low-income group.

RÉSUMÉ

Le concept d'accessibilité, définie comme étant la facilité d'accès aux points de destinations, s'est révélé être un facteur influent sur les résultats et les comportements liés aux déplacements domicile-travail, comme par exemple le temps du trajet et le mode de transport choisi. Également, des chercheurs ont constaté que l'accessibilité s'avère être un élément essentiel à l'élaboration des plans de transport durables et équitables. Cependant, il n'existe actuellement aucune étude ayant examiné le croisement de ces domaines de recherche dans le cadre d'une optique axée sur l'équité et ayant pour but d'évaluer l'impact de l'accessibilité en tant que facteur agissant sur les résultats et les comportements de transport. Cette thèse vise à combler ce manque en examinant, dans un contexte salarial, l'impact que peut exercer l'accessibilité sur les temps de trajets et la part modale des transports en commun ainsi que la variation de cet impact entre les groupes à faible revenu et ceux à revenus élevés.

Dans la première partie de cette recherche, j'évalue la relation entre l'accessibilité, aux emplois et aux travailleurs en voiture ou en transports publiques, et le temps de trajet pour les personnes à faible revenu par rapport aux personnes à revenu plus élevé. Pour ce faire, des données provenant de trois des plus grandes régions métropolitaines au Canada, soit Toronto, Montréal et Vancouver, ont été utilisées tout en faisant appel à des modèles statistiques multiniveaux à effets mixtes distincts pour les automobilistes et usagers de transport en commun. Dans le cadre de cette étude, des mesures d'accessibilité ont été générées pour les emplois et employés à la fois au point d'origine (le domicile) et au point de destination (le lieu de travail) afin de prendre en considération l'impact des travailleurs et des entreprises en concurrence. Nos modèles dans cette étude démontrent que les impacts d'accessibilité sur le temps de trajet domicile-travail sont présents et, dans de nombreux cas, s'avère être plus importants pour les groupes à faible revenu que les groupes à revenu élevé. Les résultats suggèrent que les personnes à faible revenu ont plus à gagner (en termes d'une réduction du temps de trajet) d'une augmentation en accessibilité aux emplois à faible revenu au point d'origine et aux travailleurs à faible revenu au point de destination. De même, ils ont plus à perdre à la suite d'une augmentation en accessibilité des travailleurs à faible revenu au point d'origine et des emplois à faible revenu au point de destination, qui sont tous deux preuves d'une concurrence accrue. Par conséquent, les politiques visant à améliorer l'accessibilité aux emplois, en particulier pour ceux qui sont à faible revenu, en voiture et en transport en commun

tout en gérant la concurrence, peuvent servir à refermer le fossé d'inégalité qu'on observe dans les déplacements.

La suite de cette recherche examine la relation entre l'accessibilité aux emplois en transports collectifs et la part modale des transports en commun au point d'origine pour le groupe à faible revenu comparativement au groupe à revenu plus élevé en utilisant une série de modèles de régression linéaire effectués au niveau du secteur de recensement. L'ampleur géographique de cette étude est étendue de trois à onze régions métropolitaines canadiennes de taille variable. Des recherches antérieures ont démontré qu'il existe une relation non-linéaire entre l'accessibilité et la part modale des transports en commun et à ce titre, une relation quadratique est utilisée dans cette étude pour l'estimer. Nos résultats montrent que les impacts de l'accessibilité sur la part modale sont présents pour les deux groupes de revenus et que les impacts sont plus importants pour le groupe à faible revenu. De plus, il a été prouvé que pour les groupes à faible revenu dans les régions métropolitaines, il existe un point au-delà duquel une amélioration d'accessibilité entraînera une diminution de la part modale des transports en commun. Toutefois, ce point se produit lorsque l'accessibilité se situe au 80^{e} centile, de sorte que des améliorations dans la part modale sont néanmoins attendues dans la plupart des zones de ces régions métropolitaines lorsque l'accessibilité s'améliore. En outre, dans les régions où une relation linéaire entre l'accessibilité et la part modale est plus pertinent, l'accessibilité peut être améliorée dans l'ensemble de la région, ce qui pourrait entraîner une augmentation de l'utilisation du transport en commun pour le groupe à revenu élevé et, dans une plus grande mesure, pour le groupe à faible revenu.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank Prof. Luis Miranda-Moreno and Prof. Ahmed El-Geneidy for their guidance throughout my time at McGill. I have learned a great deal from them. Special thanks goes out to Prof. Geneviève Boisjoly who is now an assistant professor at Polytechnique Montreal for helping me in developing the methodology for carrying out the models in Chapters 2 and 3 as well as continuous support during the research process. As well, thanks to Prof. David Levinson at the University of Sydney for providing us with the inspiration for carrying out the study in Chapter 2 as well as providing feedback on the manuscript. I would also like to acknowledge Prof. Owen Waygood who took the time to thoroughly review the initial draft of this thesis and provided numerous comments to improve its content and writing.

Thanks are in order for the Social Sciences and Humanities Research Council of Canada (SSHRC) for partially funding the research carried out in this thesis as well as McGill University for granting me with the Grad Excellence Award which helped to cover some of the costs associated with this Master's degree.

I would also like to thank the people whom I've worked with at the Transportation Research at McGill (TRAM) lab as well as those at the Integrated Mobility and Transportation Safety (IMATS) lab who've made the journey a lot more enjoyable. Finally, I would like to thank my family and my boyfriend Jordy, who encouraged me to pursue a master's degree and supported me throughout my time at McGill.

CONTRIBUTION OF AUTHORS

Chapters 2 and 3 of this thesis are based on manuscripts that have been submitted, or being prepared for, presentation or publication for which I am the primary author. Chapter 2 is based on the manuscript titled *Accessibility and the journey to work through the lens of equity* which was published in the Journal of Transport Geography in 2019 for which the secondary authors are Prof. Geneviève Boisjoly, my co-supervisor Prof. Ahmed El-Geneidy, as well as Prof. David Levinson, who provided the inspiration for this manuscript. For this study, I carried out the data cleaning, analysis as well as preparation of the article for submission. Chapter 3 will be submitted for presentation at the 99th Meeting of the Transportation Research Board in 2020 as well as for publication in a peer-reviewed journal. In this study, the secondary authors are Prof. Boisjoly, Prof. El-Geneidy as well as my supervisor Prof. Luis Miranda-Moreno, who provided guidance on the development of the research objectives as well as revisions of the manuscript. In both studies, Prof. Boisjoly and Prof. El-Geneidy provided guidance and feedback on the methodology employed in the study as well as revisions of the manuscript. In addition, the accessibility measures used in both studies were generated using R scripts adapted from those developed by Robbin Deboosere, a former Graduate Research Assistant at the Transportation Research at McGill group, who generated the public transport travel time matrices used in both studies. As well, car travel time matrices used in the study in Chapter 2 were obtained with the help of Gillaume Barreau.

Under the direction of my supervisors, I have prepared all sections of this document.

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CHAPTER 1: INTRODUCTION

1.1 THE ACCESSIBILITY CONCEPT

The concept of accessibility for many people may be related to the design of objects, services and environments for people with disabilities. While this is certainly an essential consideration in the planning of transport services and infrastructure, accessibility takes on a different meaning in transport planning to indicate the ease with which people can reach opportunities *(1)*. This notion of accessibility has been gaining traction among transport planning agencies as it has been incorporated into the objectives of many transport plans *(2-5)*, albeit perhaps not with a full comprehension of what accessibility really means *(6)*. Nonetheless, the intention of using accessibility as an indicator is to identify not only where gaps in access are located, but also who, or which groups in society, benefit from good access to opportunities and who are hindered socially or economically from a lack thereof.

Traditional transport planning has been focused on mobility, or the potential for movement or the ability to move from one place to another *(7)*. On the other hand, planning for accessibility rather than mobility is born out of an awareness for the interactions that occur between transport systems and land use. Trips are made as a result of a need to reach destinations where daily activities take place, for work and for leisure. Land use policies are what governs the distribution of these opportunities in space. As such, planning for accessibility makes up for what planning for mobility lacks, shifting the focus away from increasing the supply of transport infrastructure, which has been proven to be ineffective at resolving the problems that it was meant to solve (i.e. congestion) *(8)*, to consider long-term solutions to manage the externalities of travel with regards to time and distance as well as costs to the individual and society.

Accessibility has been studied by researchers in transport from both methodological and practical perspectives. On the theoretical side, researchers have developed various measures of accessibility to reflect the "true" or "experienced" accessibility. It is important to first discuss the fundamental components of accessibility, i.e. the land use and the transportation components as well as the individual and temporal components which are also influential *(9)*.

Specifically, the land use component reflects the spatial distribution of opportunities at the destination, such as jobs *(10)*, grocery stores *(11)*, and healthcare facilities *(12; 13)*, as well as the demand for these opportunities (i.e. where travelers are living). The transportation component, as mentioned before, includes the disutility from using a specific mode to make trips as well as the supply of infrastructure for that mode. For example, for public transport, the transport component would include the waiting and travel times, fare, level of comfort and other factors related to the service itself such as frequency, reliability and network design. It is important to mention that there will be factors that can be categorized under both components such as the location of public transport stops which is part of land use as well as being a crucial component of the transport system.

The individual component reflects the need, abilities and opportunities of the individual to access the services and goods that are available to them. It is necessary to consider this component as it may be the case that certain individuals have very good access to jobs by car, but if they cannot afford personal vehicles or if the jobs are not appropriate for their educational level, their "experienced" accessibility would be much lower than expected. For example, the term spatial mismatch was introduced by Kain *(14)* to explain that due to the segregation of the housing market, disadvantaged groups, who lived in the inner city and in theory have good access to jobs, were at risk of unemployment because the jobs suitable to their skills were suburbanizing. Certain researchers have found that accessibility is considerably lower when occupational matching is considered, i.e. access to low-income jobs for low-income, vulnerable commuters *(15)*. In addition, when car ownership is taken into account, accessibility for low-wage workers decreases for the reason that a greater proportion of them do not own personal vehicles *(16)*.

The temporal component reflects the constraints set by public transport time schedules for when the services will be available as well as the availability of opportunities at different times of the day due to different starting times for jobs and opening time for services. Various researchers have measured accessibility to reflect variability in the number of jobs, using dynamic job data for different start times *(17)*, as well as the public transport service, using variable departure times taken at small intervals during the commute period *(18)* or throughout the day *(19)*. Some researchers posit that fixed-time accessibility (i.e. accessibility examined at only one time period during the day) is not realistic as it fluctuates depending on when transport services are operational and when opportunities are available. On the other hand, other researchers indicate that a balance between accuracy and simplicity is needed for practitioners who do not wish to be bogged down by data when attempting to compute and use accessibility *(17)*.

Furthermore, different measures of accessibility have been developed to capture the interactions of these components. Firstly, accessibility can be measured either at the individual level or at the location level *(20)*. While person-based measures consider the individual components of accessibility whereas the location-based does not, they can be incorporated in location-based studies by segmenting the population into groups based on socio-demographic characteristics or by specifying the destination being studied. Two examples of location-based accessibility measures are the cumulative-opportunity measure, which counts the number of opportunities that be reached within a given cost threshold (such as time, distance or out-of-pocket cost), and the gravity-based measure, which weights the opportunities using a gravity-based function of the travel cost *(21)*. Since the cumulative-opportunity measure is easier to generate and interpret and is highly correlated with gravity-based measures *(22)*, its use may be preferred to communicate accessibility to policy-makers.

The application of accessibility in research has been used in studies addressing equity issues that exist in transport where it was found that accessibility plays an important role in the delivery of equitable transport policies and projects *(23)*. More specifically, transport planners and engineers should be concerned with the equitable distribution of benefits provided by transport system and researchers have made the argument that the distribution should be just, which is related to political philosopher John Rawls's Theory of Justice *(24)*. The argument has been made that accessibility, as a measure of the ease of reaching destinations that meet the needs of citizens, is a primary good which is essential to everyone *(25)*. As well, transport planning as an institution should ensure that the distribution of accessibility as a primary good is equal among citizens, in accordance with the principles of justice *(25)*. Furthermore, equity has been evaluated on two axes, horizontal and vertical, whereby horizontal equity refers to the equal distribution of benefits and costs among individuals in society with the same level of need, i.e. accessibility should be equally divided across the entire region to all individuals who have the same need for employment. On the other hand, researchers emphasize that it is equality of opportunities that ultimately counts but since there are personal and institutional barriers that prevents a true equal distribution of opportunities, i.e. a job is not a job for those who are not qualified, those who suffer from limited opportunities should be provided with higher levels of accessibility *(25; 26)*. Such is the goal of vertical equity and is deemed fair by those who follow this school of thought *(27)*.

1.2 RESEARCH OBJECTIVES

Many researchers have measured the level of accessibility between different socio-economic groups to evaluate the equity of existing transport systems as well as future plans to identify locations where accessibility should be increased. However, fewer research is concerned with the impact of accessibility, which in essence is a measure of the need for travel, on actual or realized travel outcomes such as commute duration and mode share. This field of research is also important as it addresses how accessibility could be used as a tool to achieve the goals of equity planning for more disadvantaged individuals in society who stand to gain the most from better travel outcomes.

As such, my research aims to contribute to the aforementioned field by examining the impact of accessibility, to jobs and workers by car and by public transport, on commute duration in addition to the impact of accessibility to jobs by public transport on public transport mode share for the low-income group as compared to the higher-income group. Specifically, I wish to examine whether the degree to which accessibility impacts commute duration and mode share is different between the income groups, i.e. whether the travel outcomes of the low-income group is more sensitive to the changes in accessibility. The goal is not to examine how accessibility can be increased for the low-income group, but rather how an improvement in accessibility could minimize travel time as a disutility and increase public transport use as a suitable means of travel. In addition, I will be extending the geographic scope of this research to multiple Canadian metropolitan regions to offer a fuller picture of the range of impacts that can be expected in regions of various size and structure.

1.3 THESIS STRUCTURE

Chapter 2 explores the impact of accessibility, by car and by public transport, on commute duration for the low-income group compared to the higher-income group in three major Canadian metropolitan regions (Toronto-Hamilton, Montreal and Vancouver). Chapter 3 explores the impact of accessibility by public transport on public transport mode share for the same income groups in Chapter 2 but in the expanded geographic context of eleven regions. Each individual chapter contains its own introduction, literature review, data and methodology, results and discussion sections as well as a conclusion specific to the chapter. Chapter 4 summarizes the important findings and policy implications from both studies, as well as directions for future research.

1.4 GENERAL METHODOLOGY

The general methodology followed by both studies is shown in **Figure 1**. The land use and travel time data was first obtained as inputs to the accessibility measures. Then the accessibility measures as well as a set of control variables enter into a series of regression models to model the impact of these explanatory variables on the travel outcome, commute time in Chapter 2 and public transport mode share in Chapter 3. The results are then compared between the low and higher-income groups as well as between regions.

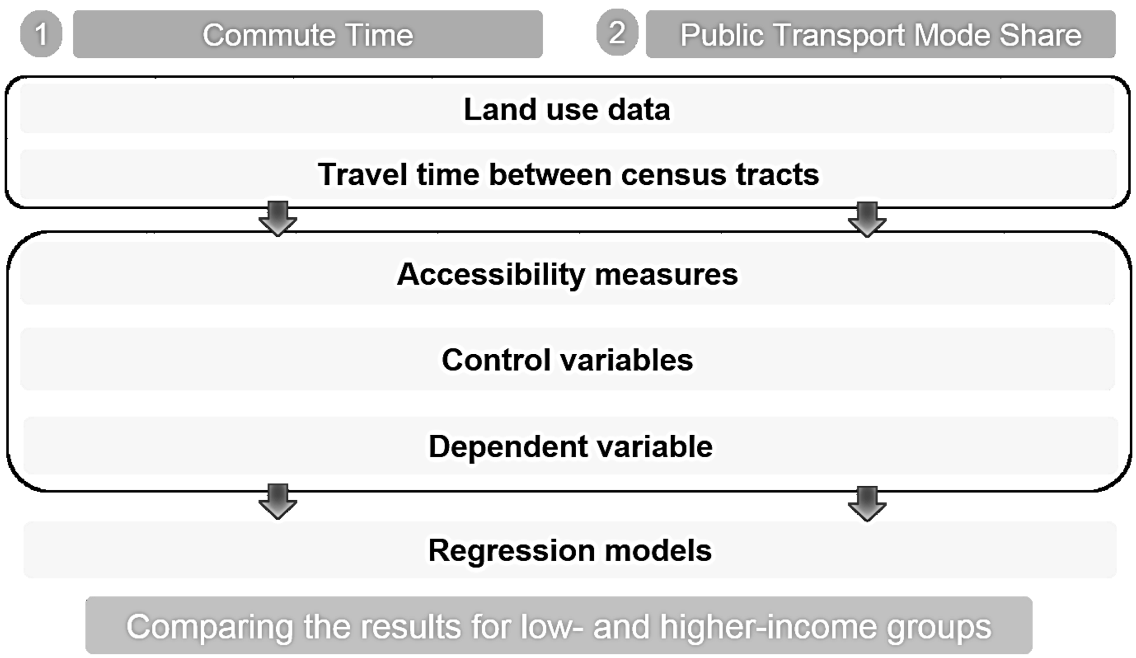

Figure 1 General methodology of the studies carried out in the thesis

CHAPTER 2: ACCESSIBILITY AND THE JOURNEY TO WORK THROUGH THE LENS OF EQUITY

2.1 INTRODUCTION

Issues relating to the journey to work and associated congestion and inequality considerations were closely examined by researchers in the mid-20th century *(28; 29)*, during a time of intense motorization and suburbanization. Since then, transport researchers have monitored this field of study continuously to uncover observable trends in people's commutes *(30; 31)* such as the evolution of commute times and distances *(32)*. Researchers have noticed major increases over time in commute distances, which can be related partially to technology developments, income changes, and decentralization, when compared to changes in commute time, which can be seen as relatively constant *(33)*. Some researchers in the 1990s *(34; 35)* sought to explain this phenomenon through the use of accessibility measures to quantify the state of job-housing balance in a region. The resulting conclusion is that a balance in accessibility at both the home and work end of trips contributes to stable commute times. However, the story of accessibility and the journey to work does not have to end here.

Inequality is a topic of extensive discussion amongst researchers across all domains, including transport. Presently, certain transport professionals have posited that transport inequalities could be the result of unequal investments in the provision of transport services *(36)*. The conclusion from contemporary research in this area is that as a result of these inequalities, the less well-off groups of society are travelling slower and covering smaller distances *(36)*. On the other hand, transport researchers have also recognized the need for a more equitable way of planning and policymaking *(26; 37-41)*; that resources should be allocated to those who stand to benefit from it the most, an example being low-income individuals. An existing way of approaching equity in this domain is through using accessibility *(42; 43)*, the ease of reaching destinations *(44)*, to evaluate the distribution of opportunities in a region *(45)* and especially for low-income groups.

Our research aims to connect the following streams of research, journey to work and equity planning, through accessibility analysis. While there has been extensive research done in each of these topics, and even in certain combinations (i.e. journey to work and equity; journey to work and accessibility; equity and accessibility), our approach is unique in that we are addressing all three topics in one place. In the process, we extend the story of accessibility and the journey to work to the low-income group and offer a new perspective for equity planning to consider the impact of accessibility on commute times. Using the existing body of research on accessibility and the journey to work as a stepping-stone, our research will focus on the question: does accessibility impact low income groups differently than higher-income groups with respect to commute travel times? We answer this question in a contemporary Canadian context, looking specifically at Toronto-Hamilton, Montreal and Vancouver. In answering this question, we aim to offer a new perspective on how inequalities in transport can be addressed and the appropriate policy actions that would facilitate this change.

2.2 LITERATURE REVIEW

The rate at which commute distances have been increasing compared to commute durations have been studied by various researchers worldwide. In the period between the late 19th and 20th centuries, researchers in Britain recorded a four-fold increase in the mean one-way commute trip distances. However, commute times have not increased at the same rate, as only a doubling of time was observed in the same period *(46)*. Similar findings were realized by researchers in the United States: in many major cities, commute times have decreased or at the very least stayed relatively stable *(47)*. Some researchers sought to explain this phenomenon from the perspective of mutual co-location between jobs and housing (a proxy for the labor market) *(34; 48; 49)*. Levinson *(34)*, in quantifying the job and housing balance, used accessibility to jobs and workers at the home as well as place of work, to assess its impact on commute times for car and public transport users in in Washington, D.C.

Accessibility is in essence a measure of potential opportunities *(21)*. Geurs and van Wee *(9)* summarized the four components that interact to affect accessibility: transport, the availability of infrastructure which enables movement as well as the associated travel disutility; land-use, the availability of opportunities at the destination; individual, the needs and abilities of people travelling; and time, the temporal factors constraining availability of opportunities. The two main accessibility methods commonly employed include cumulative opportunities and gravity-based measures. The first counts the number of opportunities that can be reached within a given cost threshold (time, distance or monetary cost) *(9)*. The benefit of this approach lies in the ease of interpretation and analysis. A gravity-based model on the other hand, while perhaps more realistic, requires the estimation of a cost function using recent empirical data of travel behavior in a region, but both measures were found in the past to be highly correlated *(22)*. In measuring accessibility impacts on the journey to work, there is a need to account for the effect of competition *(16)*. Previous research has incorporated the effects of competition by including accessibility to workers and accessibility to jobs at both ends of the trip *(34)*. At the origin (home-end), more houses indicate more workers competing for jobs; at the destination (place of work), more jobs indicate more competing firms. Accessibility has often been evaluated in the context of different transport modes, notably the difference in accessibility by car and public transport. In terms of employment, researchers generally find that in car-centric regions like North America, the number of jobs that can be accessed within a certain time threshold is higher with the use of a car than public transport *(50; 51)*.

The result from Levinson's research *(34)* answers the question posited by Giuliano and Small *(48)*: is the journey to work explained by urban structure? As urban structure can be measured by the jobs and housing available in a region, Levinson concludes that as a significant portion of the variation in travel time in his data can be explained by urban structure, that it certainly, from the perspective of accessibility, can help to explain the journey to work. Lastly, he concludes that in an auto-dominated society, the stabilizing commute duration despite increasing commute distances is the result of the polycentric urban form created by the suburbanization of jobs instead of housing. However, while this conclusion may have been be valid for the region as a whole, this same pattern was not necessarily observed for more disadvantaged groups in society.

The term spatial mismatch was introduced by Kain *(14)* in 1968 where he argued that due to segregation of the housing market, disadvantaged groups who lived in the inner city were at risk of unemployment as jobs shifted towards the suburbs. Researchers studying the journey to work have also been evaluating this hypothesis to determine whether certain aspects of the commute are different for more disadvantaged individuals in society, particularly those belonging to low-income groups or minorities. There have been some opposing results from researchers in this field as Gordon, Kumar and Richardson *(52)* found that low-income American automobile commuters did not have higher commute times. Similarly, Canadian researchers found that in Toronto *(45)*, the most socially disadvantaged areas have shorter public transport commute times than the general population. In contrast, Shen *(53)* found that, when focusing on the area within the central city region, there is an identifiable trend across major US cities that people living in low-income census blocks tend to have longer commute times than the entire central city region, attributable to higher dependence on public transport, resulting in slower travel speeds. More recent research done by Banister *(36)* echoes these results where he concluded that less well-off groups in the UK are travelling slower and covering shorter distances as a result of the use of slower modes of transport, particularly buses as opposed to high-speed rail.

2.3 DATA & METHDOLOGY

2.3.1 Generation of accessibility and determination of commute duration

The first step in determining the impact of accessibility on commute time is to obtain the appropriate data to be evaluated at a reasonable level of analysis. The analysis scope includes the three largest Canadian metropolitan regions in Canada (Toronto-Hamilton, Montreal and Vancouver) to provide richness to the results while uncovering potential geographical differences of the impacts of accessibility on the journey to work. Context maps comparing the three cities are shown in **Figure 2**. Land use (location of jobs and workers) and travel time are the two main components required to calculate accessibility in a region. The job and worker locations are obtained for every individual residing in all three regions, categorized by income bracket and selected commute mode, from the Statistics Canada Census Flow tables (54-56) for 2016 at the census tract level, which is the spatial level of analysis that is available for this source of data. The Census Flow tables shows the commuting flows for the employed labor force aged 15 years and over with a usual place of work. The mode of transport refers to the main mode that a person uses to travel between his or her home and his or her place of work. The data assumes that the commute originates from the usual place of residence but understandably in some cases, this is not true where respondents may have been on business trips and reported their place of residence as the place they were staying in. This and other exceptional cases are included in the data and cannot be identified. The total number of jobs in a census tract sums the total number of commuters arriving to work from everywhere in Canada, include that census tract itself, to that census tract, by individual income group. Similarly, the total number of workers residing in a census tract sums those leaving a census tract.

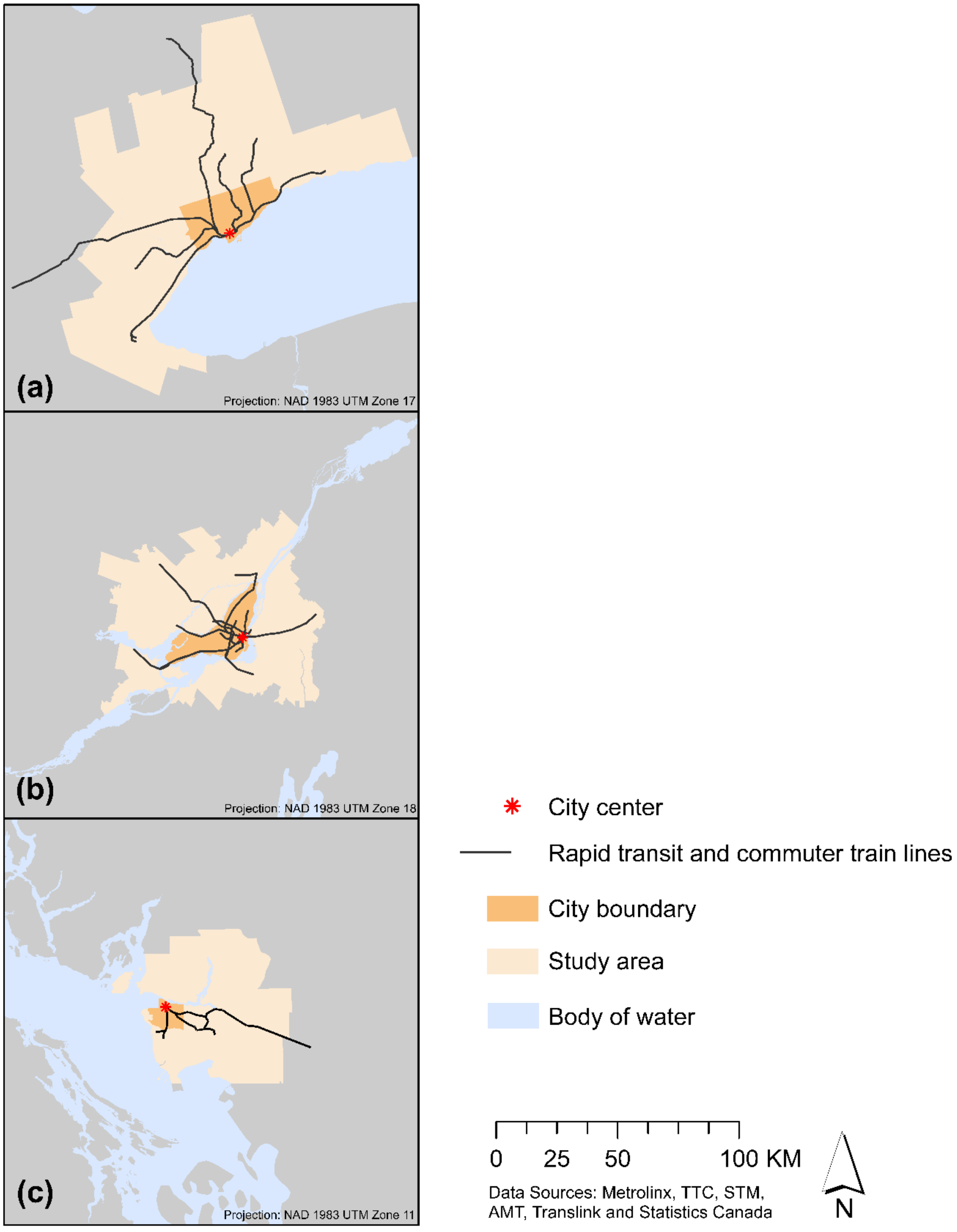

Figure 2 Context map of the three cities under consideration: (a) Toronto-Hamilton, (b) Montreal, and (c) Vancouver. The public transport lines illustrated in the figure include commuter train lines and rapid rail lines.

The benefit of using these Census Flow tables is that it allows us to accurately determine the number of low-income jobs and workers better than previous definitions. In order to calculate accessibility to low-income jobs and workers, an income threshold is established. Statistics Canada uses the low-income line (LIL), which is calculated through the Low-Income Cut-Offs (LICOs). LICOs measure the income threshold below which a household of a certain size will likely devote a larger share of its income on necessities than the average family *(57)*. Thus, the total low-income threshold for a one-person household is calculated to be $25,516 in 2015 *(58)*. However, as a result of increasing living costs in Canada, the definition of low-income can be widened to incorporate the actual costs of living in a city. So far, living wages have been calculated for the Toronto-Hamilton region, $17.12 *(59)* averaged for the Durham, Hamilton and Metro Toronto regions, and Vancouver at $20.68 *(60)*. These hourly wages translate to a total personal income of $35,600 in Toronto-Hamilton and $43,000 in Vancouver in 2015 assuming a 40-hour work week. The living wage information was not available for Montreal. Therefore, we adopt a threshold of $40,000 personal household income for consistency and to enable direct comparisons between cities. Subsequently, higher-income jobs and workers are defined as everyone above the low-income threshold.

To calculate travel time by car, we use Google Maps Distance Matrix API[1] to obtain a pessimistic congested car travel time matrix at 8 AM on a typical Tuesday in all three regions. To compute the public transport travel time between census tracts within each metropolitan region at the census tract centroid, the General Transit Feed Specification (GTFS) data[2] was first obtained from all public transport agencies operating in each of the three regions. Then a joint network between the public transport network and the streets was created using the "Add GTFS to network dataset" toolbox[3] in ArcGIS and subsequently the travel time matrix for departure times at 8 AM on a Tuesday was generated using the fastest route calculations. The public transport travel times

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[1] The Google Maps Distance Matrix API is a service that provides developers and other users with travel distance and time for a matrix of origins and destinations based on the recommended route between origin and destination points.

[2] The GTFS data is based on scheduled transit service information, which is determined and in theory, optimized by the transit agencies. As such, effects of congestion is incorporated implicitly to some degree into the schedules but not to the degree that real-time data would. The structure of the GTFS data is fairly standardized among all public transport agencies.

[3] A joint network between the public transport network and streets was created which meant that the fastest route did not necessarily have to be done using public transport: when a route between census tract centroids is fastest by walking, walking route was designated as the fastest.

include access, egress, waiting, in-vehicle and transfer times as applicable. Car and public transport travel times are then assigned to each commuting flow obtained from the census by income group. In addition, the generated travel time matrices are used as inputs in the accessibility calculations.

Accessibility measures to higher and low-income jobs and workers are calculated for car and public transport commuters separately. Here, accessibility values are calculated as percentage of the total number of jobs or workers in the region (referred to as proportional accessibility). In other words, the number of jobs or workers that can be reached within a specific travel time threshold in a particular census tract is divided by the total number of jobs or workers in the region. Accessibility measures are calculated at both the origin and destination for jobs and workers in the higher-income group as well as the low-income.

A location-based accessibility measure is the most suitable for the purpose of our analysis. More specifically, a cumulative accessibility measure is used as the data that we have is not suitable for the development of a cost function required in the gravity model using recent estimations of travel behavior data. The operative description of a cumulative accessibility measure is the determination of the number or density of travel opportunities of particular types within certain time distance or travel-cost ranges from the residential locations of groups of interest *(61)*. An earlier set-up of this measure is shown in **Equation (1)** from the research done by Wang and Chen *(61)* where they used a GIS approach to determine the accessibility to jobs by public transport:

$$A_i^T = O_i + \sum_{j=1}^{J} B_j O_j S_i \quad \textbf{Equation (1)}$$

where A_i^T is the job accessibility by public transport for census block I, O_i is the number of jobs in census block I, B_j is a binary parameter which equals 1 if centroid of census block j is within the 30-minute buffer of census block i; equals 0 if otherwise, and S_i is a binary parameters equals 1 if centroid of census block i has at least one bus stop within a ¼ miles buffer; equals 0 if otherwise.

However, for this study, accessibility measures do not enter into the regression models as the actual number of jobs or workers that can be accessed, but rather they are taken as percentages of the total number of jobs or workers at the two income levels available in each of the cities. If the actual number of jobs or workers is used, it is expected that the travel time would be significantly shorter in Vancouver when accessibility is controlled for due its compactness compared to Toronto. The proportional accessibility should overcome this bias.

Accessibility measures to higher and low-income jobs and workers are calculated for car and public transport commuters separately because we expect that the resulting impact on the two modes should be different and worthy of examination. Furthermore, accessibility is calculated at both the origin and destination as per Levinson's set up. Proportional accessibility as described here is measured using the equations below. Note that O_i from **Equation (1)** is captured in these equations with the inclusion of census tract i in J.

$$A_{iEHm} = \frac{1}{\sum_{j=1}^{J} E_j} \sum_{j=1}^{J} E_{H,j} f(t_{ijm}) \text{ and } f(t_{ijm}) = \begin{cases} 1 \text{ if } t_{ijm} \le t_{threshold,m} \\ 0 \text{ if } t_{ijm} > t_{threshold,m} \end{cases} \quad \textbf{Equation (2)}$$

$$A_{iELIm} = \frac{1}{\sum_{j=1}^{J} E_{LI,j}} \sum_{j=1}^{J} E_{LI,j} f(t_{ijm}) \text{ and } f(t_{ijm}) = \begin{cases} 1 \text{ if } t_{ijm} \le t_{threshold,m} \\ 0 \text{ if } t_{ijm} > t_{threshold,m} \end{cases} \quad \textbf{Equation (3)}$$

$$A_{iRHm} = \frac{1}{\sum_{j=1}^{J} R_j} \sum_{j=1}^{J} R_{H,j} f(t_{ijm}) \text{ and } f(t_{ijm}) = \begin{cases} 1 \text{ if } t_{ijm} \le t_{threshold,m} \\ 0 \text{ if } t_{ijm} > t_{threshold,m} \end{cases} \quad \textbf{Equation (4)}$$

$$A_{iRLIm} = \frac{1}{\sum_{j=1}^{J} R_{LI,j}} \sum_{j=1}^{J} R_{LI,j} f(t_{ijm}) \text{ and } f(t_{ijm}) = \begin{cases} 1 \text{ if } t_{ijm} \le t_{threshold,m} \\ 0 \text{ if } t_{ijm} > t_{threshold,m} \end{cases} \quad \textbf{Equation (5)}$$

where A_{iEHm} is the accessibility to higher-income jobs from census tract i by mode m, A_{iELIm} is the accessibility to low-income jobs from census tract i by mode m, A_{iRHm} is the number of higher-income workers that are able to access census tract i by mode m (accessibility to higher-income workers in census tract i), A_{iRLIm} is the number of low-income workers that are able to access census tract i by mode m (accessibility to low-income workers in census tract i), E_j is the number of jobs in census tract j, R_j is the number of workers in census tract j, $f(t_{ijm})$ is a dichotomous function to determine if jobs or workers in census tract j are reachable by census tract i based on t_{ijm} compared to $t_{threshold,\,m}$ by mode m, t_{ijm} is the commute time between census tracts i and j by mode m, $t_{threshold,\,m}$ is the average commute time by mode m, $\sum_{j=1}^{J} E_{H,j}$ is the total number of higher-income jobs in the region, $\sum_{j=1}^{J} E_{LI,j}$ is the total number of low-income jobs in the region, $\sum_{j=1}^{J} R_{H,j}$ is the total number of higher-income workers in the region, and $\sum_{j=1}^{J} R_{LI,j}$ is the total number of low-income workers in the region

2.3.2 Model inputs

Four separate commute time models are developed for the analysis: higher-income car commuters (C_{HI}), low-income car commuters (C_{LI}), higher-income public transport commuters (T_{HI}), and low-income public transport commuters (T_{LI}). Accessibility measures are used according to the model in which they enter, i.e. accessibility to jobs and workers by public transport do not enter into the car commuter models.

In addition to the four accessibility variables presented above, control variables related to the built environment and the presence of transport infrastructure are introduced in the models. Network proximity to heavy rail public transport stations (excluding streetcars for Toronto-Hamilton) and highway on-ramp from the home census tract centroids are used to control for the influence of existing transport infrastructure on commute times to work. Proximity to the city center, measured from the home census tract centroids to the center of downtown (defined with the tallest structure in each city), can strongly impact commute times and is accordingly introduced in the models. Since the dataset that was used to generate the models is the combined observations from all three cities, dummy variables are also included in reference to Toronto-Hamilton to account for spatial and cultural differences not accounted for in the models.

Moreover, a variety of socio-demographic variables at the home census tract are also included the regression models. While we have a separate model for low-income individuals, differences in socio-demographic characteristics at the census tract level may exert another dimension of influence for this income group. These variables are generic and some have been used to determine social indicators in previous studies on social equity and accessibility (*45*). Socio-demographic variables are obtained from the Census Profile Tables from the 2016 Canada Census (*62*) and are taken at the census tract level (i.e. *Average age* indicates the average age of individuals living in a particular census tract).

2.3.3 Summary statistics

The summary statistics for the four models, split by income groups, are presented in **Table 1** for car commuters and **Table 2** for public transport commuters, for the combined dataset and for each city. At first glance, it would seem that the accessibility by public transport is higher than by car but it is important to note the difference in accessibility time thresholds renders this comparison across mode inappropriate. The time thresholds used in the accessibility measures differ for the car and public transport models as they reflect the mode-specific average commute times in the study area for the entire population (combining higher and low-income groups). The average car commute time is 33.6 minutes, which is rounded down to a 30-minute threshold to ease interpretation and understanding. Similarly, public transport commuters had an average commute time of 48.9 minutes which is rounded down to a 45-minute threshold. The same thresholds for car and public transport commuters were used for the three metropolitan regions.

In comparing commute attributes, we find the car commuters in the low-income group, across all regions, have shorter commute times and distances. Similar results are found for public transport commuters. This general trend corroborates the results from previous research (*45*) but upon examination of the average commute speeds, we can see that the low-income group is also travelling slower than the higher-income group by car and public transport where the difference is more pronounced for public transport users. This finding is consistent with the conclusions from Shen (*53)* and Banister (*36)* that the low-income public transport users may be commuting using slower forms of public transport, resulting in lower commute speeds compared to higher-income individuals who have better access to higher quality public transport.

Table 1 Summary statistics – Car commuters

	All Regions				**Toronto-Hamilton**				**Montreal**				**Vancouver**			
	Higher-income		Low-income		Higher-income		Low-income		Higher-income		Low-income		Higher-income		Low-income	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Average commuting time (minutes)	37.02	22.64	28.09	20.37	38.88	24.20	29.38	21.56	35.64	20.48	26.86	18.72	33.99	20.81	26.53	19.32
Average commuting distance (km)	19.21	15.05	14.06	12.79	20.99	16.69	15.16	14.08	18.13	13.26	13.35	11.62	15.88	11.78	12.14	10.28
Average commuting speed (km/h)	29.52	13.71	27.26	13.50	30.76	14.51	27.96	13.89	29.24	13.95	27.25	14.48	26.50	10.04	25.30	10.03
Accessibility Measures																
Jobs in 30 minutes @ origin (%)	10.13	8.58	10.57	7.51	7.67	5.80	8.20	5.35	9.93	8.19	10.60	7.35	17.33	11.29	17.21	8.89
Workers in 30 minutes @ origin (%)	11.11	6.27	11.81	7.13	8.03	3.10	8.66	3.91	11.82	5.66	12.04	6.52	18.65	7.06	20.34	8.03
Jobs in 30 minutes @ destination (%)	15.33	10.09	13.32	8.42	12.13	7.25	10.72	6.28	17.79	11.35	14.65	9.38	20.43	11.53	18.43	9.11
Workers in 30minutes @ destination (%)	11.73	6.24	12.40	7.11	8.84	3.85	9.39	4.94	12.21	5.45	13.16	6.69	19.10	6.56	19.63	7.45
Control Variables																
Median household income (thousand $)	86.23	26.73	81.22	25.08	93.07	27.44	88.16	25.92	76.66	25.55	70.69	22.61	82.17	20.29	79.36	19.47
Average age	40.05	4.05	39.98	3.97	39.66	4.17	39.56	4.09	40.27	4.04	40.34	3.95	40.77	3.59	40.54	3.49
Average household structure	2.76	0.55	2.80	0.57	2.93	0.58	3.00	0.59	2.49	0.36	2.46	0.35	2.69	0.50	2.78	0.51
Unemployment rate (%)	6.78	2.17	7.22	2.40	7.27	2.07	7.69	2.23	6.64	2.44	7.21	2.79	5.62	1.39	5.88	1.48
Households spending >30% of income on housing (%)	9.97	4.89	10.17	4.72	10.33	4.83	10.49	4.66	8.41	4.47	9.01	4.54	11.44	5.05	11.22	4.81
Recent immigrants (%)	4.28	3.61	4.81	4.01	4.62	3.68	5.20	4.01	3.07	3.51	3.55	4.08	5.26	3.04	5.82	3.32
People with high school degree as highest education level (%)	11.98	3.41	12.57	3.27	12.39	3.35	13.03	3.20	10.06	2.55	10.59	2.30	13.90	3.31	14.61	3.13
Network distance to closest heavy rail public transport station (km)	6.18	6.59	6.12	6.55	5.85	6.35	5.81	6.17	6.36	6.80	6.44	7.20	6.84	6.82	6.43	6.43
Network distance to closest highway on ramp (km)	3.97	4.07	3.87	3.98	4.02	4.74	3.92	4.70	3.17	2.39	3.18	2.48	5.11	3.84	4.90	3.56
Network distance to city center (km)	30.22	18.05	30.55	17.32	36.24	19.57	36.66	18.44	23.87	13.07	23.97	13.27	23.38	14.03	24.36	13.37

Table 2 Summary statistics – Public transport commuters

	All Regions				Toronto-Hamilton				Montreal				Vancouver			
	Higher-income		Low-income		Higher-income		Low-income		Higher-income		Low-income		Higher-income		Low-income	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Average commuting time (minutes)	58.19	35.44	48.54	28.44	62.19	35.09	51.40	28.48	54.42	36.01	44.94	28.03	51.75	33.77	46.95	28.22
Average commuting distance (km)	19.73	15.75	12.76	11.14	22.42	18.00	14.03	12.69	16.84	11.92	11.11	88.66	16.08	11.72	12.13	96.28
Average commuting speed (km/h)	18.46	7.67	14.20	6.72	19.04	8.19	14.28	6.87	17.82	6.52	13.89	6.19	17.71	7.73	14.47	7.10
Accessibility Measures																
Jobs in 45 minutes @ origin (%)	17.35	16.13	15.64	13.61	12.22	11.49	8.96	7.24	21.68	18.67	21.47	15.07	26.64	17.81	23.34	15.14
Workers in 45 minutes @ origin (%)	11.08	9.34	13.04	10.54	8.16	6.08	7.71	4.76	11.83	9.84	16.97	11.94	19.65	11.73	20.28	11.67
Jobs in 45 minutes @ destination (%)	32.66	14.60	20.38	15.49	24.72	9.67	12.16	8.48	42.07	11.32	27.40	15.24	41.74	17.83	30.07	18.24
Workers in 45 minutes @ destination (%)	23.70	9.93	16.47	12.99	17.32	5.78	9.20	5.77	28.04	5.45	23.10	13.84	37.18	9.91	24.39	14.45
Control Variables																
Median household income (thousand $)	75.82	27.49	67.00	23.33	82.69	29.47	72.12	24.98	65.59	23.88	56.30	19.92	72.00	18.57	70.66	17.83
Average age	40.19	3.82	40.10	3.60	39.89	3.86	39.81	3.63	40.33	4.02	40.10	3.83	40.93	3.12	40.82	3.02
Average household structure	2.49	0.58	2.53	0.58	2.62	0.63	2.69	0.61	2.28	0.40	2.24	0.38	2.41	0.55	2.56	0.56
Unemployment rate (%)	7.39	2.39	8.18	2.75	7.66	2.17	8.53	2.44	7.72	2.81	9.01	3.15	5.81	1.39	6.03	1.42
Households spending >30% of income on housing (%)	13.31	6.47	13.71	5.91	13.89	6.62	13.98	5.92	11.51	5.88	13.16	5.86	14.78	6.32	13.89	5.91
Recent immigrants (%)	5.81	4.16	6.93	4.53	6.04	4.32	7.09	4.69	5.22	4.25	6.91	4.92	6.17	3.13	6.58	3.30
People with high school degree as highest education level (%)	10.89	3.35	11.95	3.40	11.13	3.34	12.55	3.27	9.29	2.67	9.79	2.60	13.14	3.06	13.79	3.12
Network distance to closest heavy rail public transport station (km)	3.14	3.79	3.05	3.44	2.86	2.82	3.06	2.66	3.35	4.46	2.57	3.52	3.72	5.01	3.75	4.67
Network distance to closest highway on ramp (km)	3.03	2.31	2.92	2.13	2.83	2.08	2.71	1.90	2.53	1.66	2.33	1.49	4.71	3.22	4.33	2.80
Network distance to city center (km)	18.09	13.98	18.00	14.00	20.98	15.86	22.24	16.31	14.39	9.81	12.49	8.36	15.29	11.48	15.91	10.89

2.3.4 Model development, processing, and validation

Since applying a regular regression to a dataset with a number of commuters leaving the same origin census tract would impose estimation biases, multilevel mixed effects regression models are more appropriate to carry out the analysis, as individual observations (commute trips) are nested within a census tract. Moreover, as applying the statistical analysis directly on the census flows will impose an additional error when high-occurrence commute flows are weighted equally to flows with lower occurrences (i.e. less commuters), a duplication process is carried out for each census flow pair based on the number of commuters moving between each pair. Since the census flow tables also express the flows by mode used, we can duplicate the observations based on the number of people using a car for the car models and public transport for the public transport models. This process is carried out for higher-income and low-income commuters.

After duplication, the sample size for each model exceeds 500,000 observations, which contains the combined observations of all three cities. It is expected that using this large sample size in modeling would lead to a bias in the statistical significance of the variables. Additionally, taking smaller samples from the complete dataset may yield in the generation of coefficients and confidence intervals that do not represent the full sample. To mitigate these effects, a bootstrap technique was used where a random sample of 10,000 observations was selected and the statistical model was conducted on that sample in the first round, then the outputs of the model are saved, and a second random sample is pulled from the data to generate a second model to be compared to the first model. This process is repeated 100 times. Essentially, through bootstrapping, the confidence interval and statistical significance of the regression coefficients that are produced by the models are stable and representative of our datasets.

After modifying the model to incorporate the bootstrapping method, we found that earlier iterations of some models could not converge. Upon review, it was determined that the distribution of the public transport commute time exhibited non-normal behavior (i.e. it was positively skewed due to the presence of zero travel times for commute within census tracts). To overcome this, a natural-log transformation was done on the dependent variable of commute duration in all models to be consistent.

2.4 RESULTS AND DISCUSSION

2.4.1 Accessibility and commute duration

Table 3 and **Table 4** summarize the results of the regression models by the two different modes and by income group where the dependent variable in all models is commute duration in minutes. Overall, our results corroborate with existing research with respect to the socio-economic variables where for example, an increase in household size is correlated with increase in commute duration. For the accessibility measures, our results confirm the hypotheses of Levinson (*34*) on the impact of accessibility on commute times for higher as well as low-income commuters by car and low-income public transport commuters. Accessibility to jobs at the origin is negatively associated with commute times while at the destination it has a statistically significant positive association. Conversely, accessibility to workers at the origin is positively associated with commute times and has a negative association at the destination. The T_{HI} model shows some inconsistencies as accessibility to workers at the origin is negatively related to commute time where a positive one was expected. Yet, this variable is not significant in the model, which may be attributed to a high correlation with other accessibility variables, particularly accessibility to jobs at the origin. However, the model was stable after removing this variable from the model as this did not affect other coefficients. The variable was therefore kept in the results as it is one of the main variables and for comparison purposes (*34*).

Table 5 summarizes the coefficients from the four models of main variables of interest that are discussed in further detail. First and foremost, for both car and public transport commuters, the association between accessibility and commute time, no matter the direction, is higher for low-income groups. We see that the impact of accessibility measures for the two income groups is statistically different as coefficients of the accessibility measures associated with the higher-income models are not located within the confidence interval of the low-income model for the same variables and vice versa, with the exception of the non-significant variable in the $\boldsymbol{T_{HI}}$ model and the number of workers accessible at the destination measure. However, the magnitude of this difference in impact between the two income groups is similar between the two modes.

Table 3 Regression results – Car commuters: Dependent Variable = Commute Time (minutes)

	Higher-income (C_{HI})				Low-income (C_{LI})			
	Coefficient		95% confidence interval		Coefficient		95% confidence interval	
Accessibility Measures								
Jobs in 30 minutes @ origin (%)	-0.022	***	-0.025	-0.019	-0.030	***	-0.034	-0.025
Workers in 30 minutes @ origin (%)	0.016	***	0.011	0.021	0.022	***	0.018	0.027
Jobs in 30 minutes @ destination (%)	0.037	***	0.035	0.039	0.051	***	0.048	0.053
Workers in 30 minutes @ destination (%)	-0.023	***	-0.026	-0.020	-0.026	***	-0.030	-0.023
Control Variables								
Median household income (thousand $)	-0.001		-0.002	0.001	-0.001		-0.003	0.001
Average age	-0.013	***	-0.018	-0.008	-0.013	***	-0.019	-0.008
Average household structure	0.056	*	-0.0004	0.112	0.053	*	-0.010	0.115
Unemployment rate (%)	-0.001		-0.011	0.009	0.002		-0.009	0.013
Households spending >30% of income on housing (%)	0.004		-0.002	0.010	0.004		-0.004	0.013
Recent immigrants (%)	-0.007	**	-0.015	-0.0001	0.001		-0.007	0.009
People with high school degree as highest level of education (%)	-0.004		-0.012	0.004	-0.004		-0.014	0.005
Network distance to closest heavy rail public transport station (km)	-0.002		-0.006	0.001	-0.003		-0.006	0.001
Network distance to closest highway on ramp (km)	0.014	***	0.008	0.020	0.010	***	0.003	0.017
Network distance to city center (km)	-0.0004		-0.002	0.001	-0.002	**	-0.003	0.000001
Dummy = 1 if in Montreal (*ref. = Toronto*)	-0.212	***	-0.271	-0.154	-0.187	***	-0.271	-0.102
Dummy = 1 if in Vancouver (*ref. = Toronto*)	-0.177	***	-0.265	-0.089	-0.250	***	-0.343	-0.158
Constant	3.645		3.473	3.818	3.279		3.048	3.511
Number of observations	1,963,735				1,224,210			
Log likelihood | Intraclass correlation	-2268030 | 0.062				-1631267 | 0.076			
Akaike's information criterion | Bayesian information criterion	4536098 | 4536335				3262572 | 3262801			
Snijders/Bosker R^2 Level 1 | Level 2	0.146 | 0.288				0.113 | 0.261			
Random effects parameters @ home census tract	Estimate	Std. Err.	95% confidence interval		Estimate	Std. Err.	95% confidence interval	
Standard deviation of level-two errors	0.198	0.003	0.192	0.203	0.262	0.004	0.254	0.270
Standard deviation of level-one errors (residuals)	0.766	0.0004	0.765	0.767	0.914	0.001	0.913	0.915

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

Table 4 Regression results – Public transport commuters: Dependent Variable = Commute Time (minutes)

	Higher-income (T_{HI})				Low-income (T_{LI})			
	Coefficient		95% confidence interval		Coefficient		95% confidence interval	
Accessibility Measures								
Jobs in 45 minutes @ origin (%)	-0.014	***	-0.016	-0.013	-0.021	***	-0.024	-0.018
Workers in 45 minutes @ origin (%)	-0.0004		-0.004	0.003	0.010	***	0.006	0.014
Jobs in 45 minutes @ destination (%)	0.011	***	0.008	0.015	0.021	***	0.017	0.024
Workers in 45 minutes @ destination (%)	-0.023	***	-0.027	-0.019	-0.027	***	-0.031	-0.023
Control Variables								
Median household income (thousand $)	0.001	***	0.001	0.002	0.0003		-0.001	0.002
Average age	-0.002		-0.005	0.0004	-0.006	**	-0.010	-0.001
Average household structure	0.141	***	0.103	0.179	0.111	***	0.050	0.172
Unemployment rate (%)	-0.010	***	-0.015	-0.005	-0.011	***	-0.017	-0.004
Households spending >30% of income on housing (%)	0.004	**	0.0004	0.008	-0.002		-0.008	0.003
Recent immigrants (%)	-0.003	*	-0.007	0.0002	0.004	*	-0.001	0.008
People with high school degree as highest level of education (%)	0.002		-0.002	0.007	-0.0001		-0.007	0.007
Network distance to closest heavy rail public transport station (km)	0.024	***	0.021	0.028	0.016	***	0.009	0.023
Network distance to closest highway on ramp (km)	0.018	***	0.013	0.023	0.023	***	0.012	0.034
Network distance to city center (km)	0.008	***	0.006	0.010	0.002	***	0.001	0.004
Dummy = 1 if in Montreal (*ref. = Toronto*)	0.225	***	0.188	0.262	0.202	***	0.147	0.256
Dummy = 1 if in Vancouver (*ref. = Toronto*)	0.135	***	0.091	0.179	0.040		-0.019	0.100
Constant	3.532		3.292	3.772	3.700		3.422	3.978
Number of observations	539,775				570,275			
Log likelihood | Intraclass correlation	-267157 | 0.309				-547710 | 0.192			
Akaike's information criterion | Bayesian information criterion	534351 | 534552				1095459 | 1095673			
Snijders/Bosker R^2 Level 1 | Level 2	0.530 | 0.777				0.194 | 0.528			
Random effects parameters @ home census tract level	Estimate	Std. Err.	95% confidence interval		Estimate	Std. Err.	95% confidence interval	
Standard deviation of level-two errors	0.262	0.004	0.255	0.270	0.306	0.005	0.297	0.315
Standard deviation of level-one errors (residuals)	0.393	0.000	0.392	0.393	0.627	0.001	0.626	0.628

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

For the public transport models, an increase of one percentage point (an absolute increase of one percent) in accessibility to jobs by public transport at the origin is expected to reduce public transport commute time by 2.1 percent for low-income commuters compared to 1.4 percent for higher-income commuters. In contrast, an increase of one percentage point in accessibility to jobs at the destination increases the commute time by 2.1 percent compared to 1.1 percent for higher-income individuals. Also, living in places with high accessibility to low-income workers increases the commute times of low-income workers by public transport while this is not significant in the higher-income model. For car commuters, similar differences in the impact of accessibility on commute times is observed but in these two models, accessibility to workers at the origin is significant in the positive direction for individuals in both income groups. The implication of these results is that commute times for low-income groups will be reduced by a larger magnitude by an increase in the accessibility of jobs at the origin census tract. However, the influence of competition due to higher accessibility to jobs at the destination (i.e. more competing firms) on commute duration is greater for individuals in low-income groups. Furthermore, looking specifically at the public transport model where a non-significant coefficient for the accessibility to workers at the origin measure is observed in the higher-income model but is significant in the low-income model, this result implies that a concentration of low-income workers near low-income individuals tend to increase their commute times by public transport but the same cannot be said for higher-income individuals. In contrast, this trend is observed for car commuters in both income groups.

These results offer some insights as to how inequalities in transport, specifically with regards to the significantly slower commute speeds experienced by low-income public transport users as opposed to higher-income users, can be addressed by achieving an equitable distribution of transport services using accessibility measures. Our results suggest that specific improvements in accessibility can lead to lower commute duration for low-income individuals. One is to improve accessibility to low-income jobs at the origin through a mix of land use, to bring low-income jobs closer to low-income workers. The second is to mitigate the more intensive effects of competitors (workers at the origin and jobs at the destination) for low-income car and public transport users, through a mix of low-income and other-income workers at the origin and jobs at the destination. This can be done through dispersing affordable housing in a region and also introducing different types of employment at the place of work (rather than having a concentrated area of high-paying jobs). This strategy can also mitigate the negative aspects of concentration of poverty that researchers have been noticing in several regions (*63*), which we have also alluded to previously.

In addition to land use changes, accessibility can also be directly improved through an improvement in public transport services between low-income workers and low-income jobs. A first step in determining where this policy can be implemented is through an examination of where low-income jobs are concentrated in a region similar to earlier research on high-order employment in the Montreal region (*64*) and providing frequent and reliable public transport services to these concentrations of low-income jobs.

Table 5 Summary of key variables

	Car				Public Transport			
	Higher-income		Low-income		Higher-income		Low-income	
Accessibility Measures								
Jobs in 45 minutes @ origin (%)	-0.022	***	-0.030	***	-0.014	***	-0.021	***
Workers in 45 minutes @ origin (%)	0.016	***	0.022	***	-0.0004		0.010	***
Jobs in 45 minutes @ destination (%)	0.037	***	0.051	***	0.011	***	0.021	***
Workers in 45 minutes @ destination (%)	-0.023	***	-0.026	***	-0.023	***	-0.027	***
Selected Control Variables								
Network distance to closest heavy rail public transport station (km)	-0.002	**	-0.003	**	0.024	***	0.016	***
Network distance to closest highway on ramp (km)	0.014	***	0.010	***	0.018	***	0.023	***
Network distance to city center (km)	-0.0004		-0.002	***	0.008	***	0.002	***
Dummy = 1 if in Montreal	-0.212	***	-0.187	***	0.225	***	0.202	***
Dummy = 1 if in Vancouver	-0.177	***	-0.250	***	0.135	***	0.040	

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

2.4.2 Other variables

With respect to the dummy variables for the different metropolitan regions, we see that, for car commuters, being in Montreal decreases commute time by 18.7 percent for the low-income and by 21.2 percent for higher-income compared to being in Toronto-Hamilton. Being in Vancouver reduces commute time by 25.0 percent for the low-income and 17.7 percent for the higher-income group. The reason for this may be attributed to the different city structures between the three cities. Also, since the Toronto-Hamilton region is both larger and more spread out than both Montreal and Vancouver in terms of the dispersion of people's homes as well as jobs (which can be seen in **Figure 2**), this could mean higher average commute times by car in general. In contrast, Montreal public transport users experience an around 20 percent increase in commute times compared to Toronto-Hamilton commuters for both income groups. This difference is smaller for public transport users in Vancouver, especially for low-income individuals. This seems to suggest a faster and well-connected public transport network in Toronto-Hamilton, illustrated in **Figure 2**, compared to Montreal and Vancouver.

For variables related to transport infrastructure, longer distance to a highway ramp is positively correlated to higher commute duration for car commuters but public transport commuters as well. This is expected as car commuters who are closer to the highway are more likely to use it and would experience faster speeds and shorter travel times. In the public transport models, proximity to rail stations is positive and statistically significant, which is expected as access/egress times are reduced the closer someone is to a station. Distance to city center is significant in the public transport models as public transport services in Canadian cities are designed with a mono-centric pattern originating from the city core. Interestingly, this variable is also significant for low-income car users but is negative which may illustrate the presence of congestion for car commuters closer to the city center. This may also help to explain the negative correlation between the distance to heavy rail public transport stations and commute duration for car commuters.

2.4.3 Sensitivity analysis

It is important to address the practical significance of the aforementioned differences between higher and low-income groups, in terms of commute duration. We want to first point out that the differences in the coefficients of the accessibility variables translate in important differences in commute time. As such, a sensitivity analysis is carried out to relate the changes in accessibility to the associated changes in commute time predicted by the regression models in minutes. Holding all variables at the mean values (see **Table 1** and **Table 2**), we predict commute time for different values of accessibility to jobs at origins. For illustrative purposes, we chose to double the mean percentage of jobs that can be accessed at the origin census tract for each of the four models as part of the sensitivity analysis. The results are presented in **Table 6** and **Table 7** for the car and public transport commuters in the three cities. These results confirm that increasing job accessibility at the origin is associated with greater decreases in commute duration for the low-income group than higher-income. For example, a 27.3 percent decrease in commute time is observed for low-income car commuters, compared to a 20.2 percent decrease for high-income commuters. Similar trends can be observed for the other accessibility measures to varying degrees.

Table 6 Change in predicted travel time as a result of doubling the mean percentage of jobs accessible at the origin census tract of car commuters

	Higher-income			Low-income		
City	Predicted travel time @ mean value = 10.1% jobs accessible (min)	Predicted travel time @ x2 mean value = 20.2% jobs accessible (min)	Difference (%)	Predicted travel time @ mean value = 10.6% jobs accessible (min)	Predicted travel time @ x2 mean value = 21.2% jobs accessible (min)	Difference (%)
Toronto-Hamilton	31.3	25.0		21.9	15.9	
Montreal	25.3	20.2	-20.2	18.1	13.2	-27.3
Vancouver	26.2	20.9		17.0	12.4	

Table 7 Change in predicted travel time as a result of doubling the mean percentage of jobs accessible at the origin census tract of public transport commuters

	Higher-income			Low-income		
City	Predicted travel time @ mean value = 17.4% jobs accessible (min)	Predicted travel time @ x2 mean value = 34.7% jobs accessible (min)	Difference (%)	Predicted travel time @ mean value = 15.6% jobs accessible (min)	Predicted travel time @ x2 mean value = 27.2% jobs accessible (min)	Difference (%)
Toronto-Hamilton	41.9	32.7		37.6	27.1	
Montreal	52.5	40.9	-22.1	46.0	33.2	-27.9
Vancouver	48.0	37.4		39.2	28.2	

Lastly, the goodness-of-fits of the models are discussed in the context of the Snijders/Bosker R^2 values. From this, we can see that the explanatory power of the public transport models are significantly higher than the car models at the home census tract level (level 2). This result is also similar to previous research in comparing the impact of accessibility between car and public transport users for commuting (*34*).

2.5 CONCLUSION

In this research, we introduce a dimension of equity to the existing body of research on the journey to work and accessibility as we ask the question: does accessibility impact low-income groups differently than higher-income groups with respect to commute times? While research has shown that low-income individuals experience shorter commute durations, researchers have also observed that at the same time, they are travelling slower than their higher-income counterparts (*36; 53*). Our results confirm these results as our data indicates that low-income commuters are travelling slower compared to their higher-income counterparts by public transport, and by car to a smaller extent.

The results from this study demonstrates that accessibility can be a key factor in reducing the commute time experienced by low-income groups. We find that the effect of increased accessibility to jobs at the origin is observably stronger for low-income compared to higher-income car and public transport users. Therefore, introducing a mix of land-use at both the home and work locations would effectively reduce commute times by bringing low-income jobs closer to low-income workers. On the other hand, the influence of competition at the origin in the form of accessibility to workers and at the destination in the form of accessibility to jobs is also greater for the low-income group. Taking this into account, an alternative way to reduce low-income public transport users' commute times is to introduce a mix of housing at the origin, through the implementation of social housing in places with traditionally higher-income housing options, and a mix of employment type offered at the destination to avoid a concentration of low-paying job sectors.

Future research can build on this research by increasing the geographical extent of this analysis to include mid and small-sized cities where land use distribution differs significantly from the large metropolitan regions analyzed here. In addition, the accessibility approach to the journey to work in an equity context can be extended to other disadvantaged groups, perhaps through the use of social indicators (*45*). Multiple measures of the distribution of access may be tested across many different cities, as in Palmateer and Levinson (*65)*. Moreover, the aggregation of control variables to the census tract level may result in loss of detail and accuracy in the models, therefore, the use of a household travel survey for the analysis in future studies is recommended.

CHAPTER 3 ACCESSIBILITY AND MODE SHARE

3.1 INTRODUCTION

In recent years, we have a seen a shift in the planning paradigm from planning for the automobile to planning for active modes of transport. Planners have recognized that the benefits of these modes, compared to the use of personal vehicles, are numerous (*66*) and are applicable to everyone not only on a personal level in terms of improved health outcomes, but also on a global scale through the reduction of transport-related emissions. While walking and cycling are certainly viable in many cities around the world, their use in the North American context has largely been limited to dense city centers, a legacy of car-centric planning practices. As such, governments in North America tend to promote the use of public transport and often set targets for ridership (*67*) or mode share (*68*) in their transport plans.

In light of these goals, the use of public transport in Canada has been increasing steadily, albeit slowly, from 10.1% in 1996 to 12.4% in 2016. However, in some areas such as Winnipeg, mode share decreased in the same period (*69*). Furthermore, public transport ridership in recent years has been plateauing across cities in Canada (*70*). Similar trends have also been observed in cities in the U.S. (*71*). Considering that capital expenditure for public transport projects has been rising steadily at a much higher rate since the 2000's (*72; 73*), one wonders if the costs of investing in public transport are commensurate with its use.

An important question asked by those advocating for equitable transport policies is this: are public transport investments going towards groups of people who need it and are they the ones who are using it the most? The response from certain researchers in the U.S. (*74*) and the U.K. is "no"(*36*) as they argue that there has been a trend of increasing investments in rail transport geared towards higher-income choice riders. As a result, captive riders, who generally have lower income, are less likely to own personal vehicles and therefore are limited in their travel options (*75*), find themselves stranded in the face of reduced public transport services for which they are more frequent users of (*71*).

For planners to begin tackling this inequality in transport, a metric must be defined for which objectives can be set and progress can be tracked against. Researchers have deemed accessibility to be appropriate in evaluating the social equity dimension of transport plans (*23; 50; 76; 77*). The effectiveness of accessibility lies in its characterization of land use, namely the availability of opportunities in space and time, as well as the transportation system, such as public transport frequency and reliability (*9*). The level of accessibility can then be evaluated for more disadvantaged groups in society to gauge whether the current network is equitable and/or if future plans and policies will be.

At the same time, researchers and planners are also concerned about the potential barriers that transport may pose regarding labor outcomes. While some argue that policies should be implemented to put more private automobiles in the hands of the lower-income to improve their accessibility (*78*), many argue that programs to increase car accessibility not only work against environmentally sustainable objectives set by agencies, but also lead to reduced funding for public transport and a further decline in quality of service (*79*).

Ideally, transport policies should aim to maximize the number of opportunities that people who stand to benefit the most from it can reach while minimizing unnecessary travel time and out-of-pocket costs. For the low-income group, to be able to do so using public transport is even more important for the reason of minimizing the financial burden of personal vehicle ownership. We can test whether this goal is being realized through an examination of the relationship between accessibility and public transport mode share for the low-income group across metropolitan regions of varying sizes in Canada, which to our knowledge has not been done before. We also examine this relationship for the higher-income group to serve as a point of comparison. In addition, we are using a wide geographic lens to carry out this analysis, to view these relationships in the context of eleven Canadian metropolitan regions of varying size, structure and other characteristics.

This research builds upon the existing exploratory research that we have carried out to examine the impact of accessibility on public transport mode share in the eleven regions (*80*). In this exploratory study, we observed visually that there are differences in the relationship between accessibility and mode share between income groups and in various geographic regions. The next logical step is to quantify these differences through a series of regression models while controlling for other explanatory variables – leading us to carry out the present study. Specifically, we aim to answer the following question: to what extent does accessibility have an impact on public transport mode share in a particular census tract, how does the relationship differ between the low and higher-income groups in various Canadian metropolitan regions and whether low-income commuters are captive to public transport or does accessibility still matter to them? In answering these questions, we hope to demonstrate that accessibility is a suitable means to improve public transport mode share for the low-income group and to further emphasize its role in meeting the social equity objectives set by planning agencies.

3.2 LITERATURE REVIEW

Whether or not metropolitan regions in North America are experiencing a public transport renaissance, one thing is clear - the factors that drive public transport use has been of great interest to researchers for some time. These drivers can be divided into two major groups: those related to the personal characteristics of the traveler and those related to the built environment including the public transport infrastructure. Mode choice is highly dependent on personal characteristics, where income (*81; 82*), unemployment rate (*83*) and the proportion of recent immigrants (*84*) have been shown to be highly influential. Moreover, to capture the combined effects of these highly influential socio-demographic variables, researchers have started using composite variables such as social deprivation indices (*85-87*). In addition, there is consensus among researchers in Canada, the U.S. and Australia that personal vehicle ownership, irrespective of income, is a major deterrent of public transport use (*88-90*).

Income is a widely used indicator of social exclusion, transport disadvantage and social inequity (*71; 91; 92*). With respect to mode choice, it has been shown that nationally, the low-income group exhibit higher public transport use than higher-income groups in the U.S. (*71*). In some cases, lower-income users have been termed captive users of public transport as they have no choice but to use public transport (*93*). On the other hand, a study that examined the public transport use of low and higher-wage workers in the Toronto-Hamilton area found that low-wage workers as a group had lower public transport mode share than higher-wage workers (*94*). However, this contradictory finding could be attributed to the methodology employed to segment the workers into wage categories. The determinants of public transport use specific to the lower-income has also been explored by researchers such Mercado et al. (*91)* where they found that among low-income workers, immigration status, place of work, age and employment status were significant predictors.

Aside from personal characteristics that could motivate a traveler to use public transport, aspects of the built environment and the characteristics of the public transport system do play a role in explaining mode share. Many researchers have found that even when self-selection bias is accounted for, characteristics of the built environment such as the density, diversity and design of the urban milieu does influence public transport ridership (*95; 96*). In particular, researchers (*97; 98*) have found that higher densities support public transport use better than low-densities whereas Chen, Gong and Paaswell (*99)* found that for the New York Metropolitan Region, employment density is more influential than residential density to explain public transport use. The accessibility to public transport infrastructure also impacts mode choice where being closer to public transport infrastructure, such as stations or stops, increases the odds of its use (*87; 94; 100; 101*).

Accessibility not only applies to the ease of accessing transport infrastructure, it can also be used in the context of transport to measure the ease of accessing opportunities that exist in time and space that motivate trip-making. In this sense, a measure of accessibility internalizes aspects of both the built environment, namely the density and location of opportunities, as well as the available transport infrastructure. Here, a distinction is made between locational accessibility and individual accessibility where the former is concerned with the attractiveness of places within the urban system relative to one another (*102*) and the latter considers the ability of individuals to reach places (*103*). A place's attractiveness could be impacted by factors such as the density of available jobs as well as the ease of reaching it (i.e. time and cost).

The research on accessibility is extensive that include both approaches to refine the data and methodology used to generate accessibility as well as empirical evidence on the impact of accessibility on various aspects of travel. On the theoretical side, researchers are interested in generating measures that reflect more closely the "true" or "experienced" accessibility in a region. Gravity-based measures, in contrast to cumulative-opportunity measures, weights the potential opportunities using a gravity-based function of the cost (such as distance or time) to access it and then summed (*21*). Despite being more difficult to use and interpret, the gravity measure is sometimes preferred due to its theoretical soundness. However, researchers have found that accessibility results generated using the cumulative and the gravity measures are highly correlated (*22*) and as a result, the cumulative measure is used in contemporary studies that aim to communicate accessibility to policy-makers (*104*). In addition, measures have also been generated using less idealized data inputs to account for the variability in the provision of transport services (*18; 19*) and in the availability of jobs at different periods of the day (*17*).

Empirically, there have been studies done specifically on the distributional impacts of both the existing transport system (*105-107*) as well as future projects (*41*) in terms of the accessibility to opportunities. Some researchers sought to do this on a large geographic scale, by comparing the accessibility of low-income jobs for socially vulnerable residents against the accessibility to all jobs for the entire population in eleven Canadian metropolitan regions (*15*). They identified that while there are geographic differences in the accessibility of the two groups, the vulnerable tend to experience higher accessibility when compared to the entire population in each region. Furthermore, accessibility has also been studied as a predictor of travel, such as the research done on the impact of accessibility on the journey to work (*34*). In particular, Canadian researchers (*108*), using data for Toronto-Hamilton, Montreal and Vancouver, found that the influence of accessibility to jobs as well as the presence of competition at home on commute duration is stronger for the low-income compared to higher-income groups.

Accessibility has also been shown to influence public transport mode share positively (*87; 109; 110*). For example, researchers Owen and Levinson (*18)* found, using continuous accessibility to jobs, higher public transport mode share is associated with higher average public transport accessibility in the Minneapolis-Saint Paul area. Moniruzzaman and Páez (*111)* found, using data from Hamilton, Ontario that public transport mode share increases as accessibility increases but the relationship is not linear through their use of logit regression models. With this in consideration, we identified a need to study accessibility and mode share from an equity perspective to examine how this impact between accessibility change for more disadvantaged groups in society such as such as the low-income group. Furthermore, to do so in the context of multiple metropolitan regions would provide results that can be applied to different geographical contexts rather than focusing on one area with a specific set of characteristics.

3.3 STUDY CONTEXT

The geographic scope of the present study concerns eleven Canadian metropolitan regions extending from coast to coast as shown in **Figure 3**. These regions, shown in detail in **Figure 4**, were selected due to differences in city size, city structure, public transport system maturity, and other potential socio-demographic factors. As a result, we hope that their inclusion would offer some insight as to how the impacts of accessibility would differ between regions. The key characteristics of each metropolitan area is presented in **Table 8**. Note that the Kitchener-Cambridge-Waterloo is shortened as Kit-Cam-Wat in the tables presented in this thesis.

Figure 3 Context map of the eleven Canadian metropolitan areas being studied

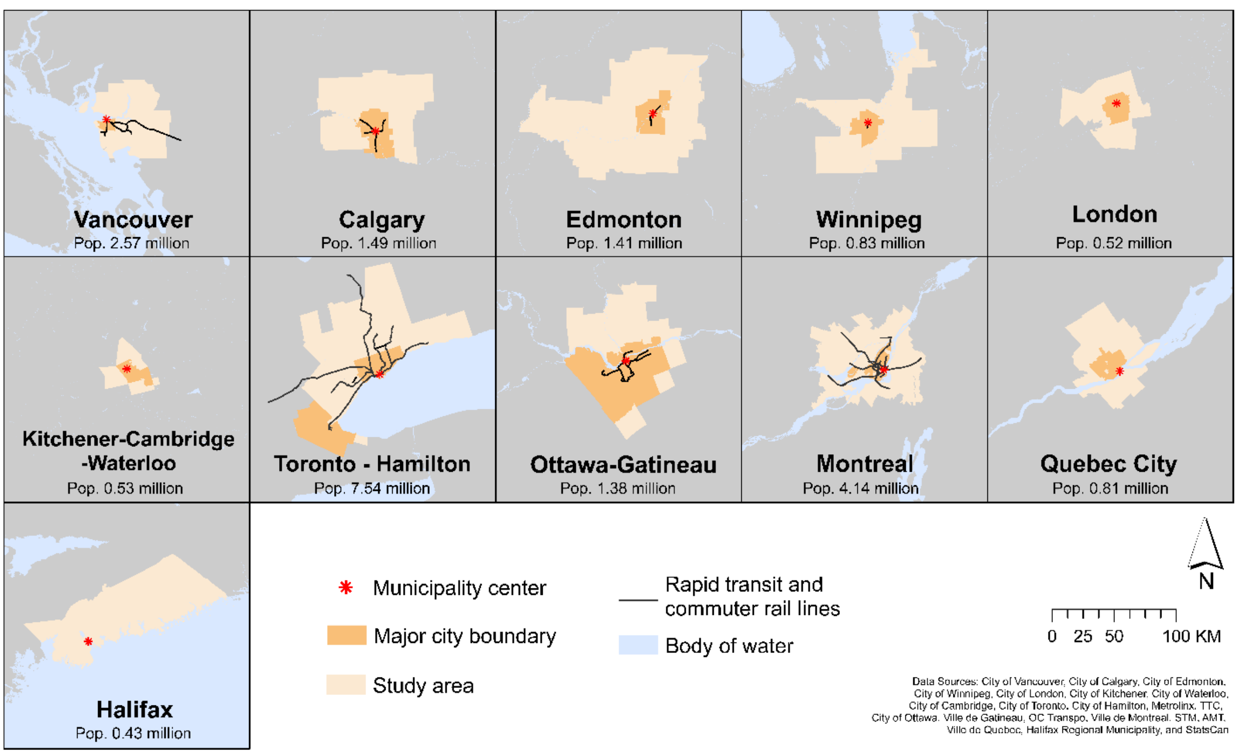

Figure 4 Detailed maps of the eleven metropolitan areas

Table 8 Key characteristics of the eleven Canadian metropolitan areas (2016 values)

Metropolitan region	Population (millions)	Density (pop/km^2)	Low-income jobs[1]	Higher-income jobs[1]	Median household income (CAD)	Rapid public transport systems (excluding bus)
Vancouver	2.46	854.6	315,190	689,185	70,795	Rapid rail, commuter train
Calgary	1.39	272.5	196,035	389,825	99,583	Light rail
Edmonton	1.32	140.0	188,260	362,880	94,447	Light rail
Winnipeg	0.78	147.0	100,785	242,580	70,795	BRT
London	0.49	185.6	62,990	136,100	64,743	N/A
Kit-Cam-Wat	0.52	480.1	66,345	161,155	77,229	N/A
Toronto-Hamilton[2]	7.06	862.4	881,435	2,054,495	78,437	Subway, commuter train, BRT[3]
Ottawa-Gatineau	1.32	195.6	212,805	381,940	82,053	Light rail, BRT
Montreal	4.10	890.2	521,840	1,228,765	61,790	Subway, commuter train
Quebec City	0.80	234.8	99,055	275,625	65,359	N/A
Halifax	0.40	73.4	54,520	126,340	69,522	N/A

[1] The definition of low- and higher-income groups are explained in detail in Section 3.4.1

[2] Refers to the Greater Toronto and Hamilton Area and includes the Toronto, Hamilton and Oshawa census metropolitan areas

[3] The Toronto streetcar system is excluded from our definition of rapid public transport system

3.4 DATA AND METHODOLOGY

3.4.1 Generation of accessibility measures and calculation of mode share

The accessibility measures used in this study, similar to Chapter 2, are cumulative-opportunity measures. Once again, the generation of such accessibility measures requires two data inputs: the number of low and higher-income employment opportunities available in each census tract across the eleven regions and the public transport travel time between census tracts within each region.

The number of jobs available in each census tract was also obtained from the Statistics Canada 2016 Census Flow tables which summarize the number of work commuters, by mode of transport and income bracket, commuting between a home census tract and the census tract in which their place of work is located. A limitation associated with the use of the Census Flow tables is that the data has undergone a series of data suppression processes for confidentiality purposes. As such, this could lead to some inconsistencies in the results especially when there are few commuters between certain census tract pairs.

We also chose to define the two income groups in this study as low and higher-income rather than further defining categories such as medium and high-income groups because we wanted to focus on the difference in the results for the low-income compared to everyone else rather than exploring the impact across an entire income distribution. However, we have experimented with using three income groups for the Montreal region for which the results are discussed later in Section 3.5.3. The low-income threshold is defined differently in this study compared to Chapter 2 where the low-income threshold is defined in this study as the 30% lowest paying of jobs in each metropolitan region, which reflects the wage distribution pertaining to each region. As the Census Flow tables categorize commuters by income brackets, the bracket closest to having 30% of the lowest paying jobs is selected as the threshold. A threshold bracket of 30,000 CAD is used for all regions with the exception of Calgary, Edmonton and Ottawa-Gatineau where 40,000 CAD is used. Subsequently, the higher-income group includes commuters from all other income groups higher than the low-income threshold bracket. Therefore, the number of low-income jobs in a census tract is taken as the sum of all commuters belonging to or below the low-income threshold bracket arriving at that census tract. This was similarly done for the higher-income group. It is worth noting that future research can adopt the idea of a "living wage" to delineate the threshold between low and higher-income for regions such as Toronto-Hamilton and Vancouver where living costs are incredibly high.

The travel time matrix by public transport between census tracts is calculated in the same way as Chapter 2, by first obtaining the GTFS data from the all the public transport agencies operating in the eleven metropolitan regions and then using the "Add GTFS to a network dataset" tool in ArcGIS. The travel times were also used as inputs to determine the median travel time for the low and higher-income groups in each metropolitan area separately.

Two accessibility measures are generated in this study for the two income groups being studied. Proportional accessibility is also used in this study, similar to Chapter 2. This measure ensures that a comparison can be made between the different metropolitan regions which places for example a high access census tract in Halifax on level ground with a high-access census tract in Toronto-Hamilton. Furthermore, we believe that the use of median travel times (as the travel time threshold) specific to each income group in each metropolitan area would further ensure a fair comparison between the segmented groups. The reason being that the median travel time would reflect most accurately the activity spheres of each group and its use in the accessibility measure would represent what's accessible within an acceptable travel time for them. In addition, using the median as opposed to the average travel time (used in Chapter 2) would minimize the effects of extreme travel times for large metropolitan regions (in terms of area) such as Edmonton. The median travel time thresholds are presented in the summary statistics in **Table 9** and are rounded to the nearest 5-minute interval for use in the accessibility measures.

The cumulative proportional accessibility measure used in the study is formulated as follows for the low-income group:

$$A_{LI,i} = \frac{1}{\sum_{j=1}^{J} E_{LI,j}} \sum_{j=1}^{J} E_{LI,j} f(t_{ij}) \text{ and } f(t_{ij}) = \begin{cases} 1 \text{ if } t_{ij} \leq t_{LI,median} \\ 0 \text{ if } t_{ij} > t_{LI,median} \end{cases} \quad \textbf{Equation (6)}$$

where $A_{LI,i}$ is the accessibility to low-income jobs from census tract i, $\sum_{j=1}^{J} E_{LI,j}$ is the total number of low-income jobs in a metropolitan region, $E_{LI,j}$ is the number of jobs in census tract j, $f(t_{ij})$ is a dichotomous function to determine if jobs in census tract j are reachable by census tract i based on t_{ij} compared to $t_{LI,\ median}$, t_{ij} is the commute time between census tracts i and j, and $t_{LI,,median}$ is the median commute time for the low-income group in the region that is used as the travel time threshold.

The cumulative proportional accessibility measure used in the study is formulated as the following for the higher-income group:

$$A_{HI,i} = \frac{1}{\sum_{j=1}^{J} E_{HI,j}} \sum_{j=1}^{J} E_{HI,j} f(t_{ij}) \text{ and } f(t_{ij}) = \begin{cases} 1 \text{ if } t_{ij} \leq t_{HI,median} \\ 0 \text{ if } t_{ij} > t_{HI,median} \end{cases} \quad \textbf{Equation (7)}$$

where $A_{HI,i}$ is the accessibility to higher-income jobs from census tract i, $\sum_{j=1}^{J} E_{HI,j}$ is the total number of higher-income jobs in a metropolitan region, $E_{HI,j}$ is the number of jobs in census tract j, $f(t_{ij})$ is a dichotomous function to determine if jobs in census tract j are reachable by census tract i based on t_{ij} compared to $t_{LI,\ median}$, t_{ij} is the commute time between census tracts i and j, and $t_{HI,,median}$ is the median commute time for the higher-income group in the region that is used as the travel time threshold.

We experimented with incorporating the ratio of car accessibility to public transport accessibility in the models but found high correlations between accessibility by the two modes and as a result, removed it from the models. However, we recognize that the car is more attractive than public transport in areas where accessibility is much higher by car than by public transport and by not including the impact of this scenario, we may be overestimating the "experienced" accessibility by public transport for a particular census tract.

Lastly, the dependent variable used in the study is the percentage of commuters leaving each census tract who used public transport out of all commuters. This was done for low and higher-income commuters separately, i.e. the percentage of commuters who used public transport out of all low-income commuters who left that census tract and the percentage of commuters who used public transport out of all higher-income commuters who left that census tract. From the Census Flow tables, we determine the percentage of commuters using public transport including bus, subway or elevated rail, light rail, streetcar, commuter train, and passenger ferry, as their main mode of transport compared to using a car (as driver or passenger) or using an active mode such as walking or cycling.

3.4.2 Relationship between public transport mode share and accessibility

While researchers have found that there exists a relationship between public transport mode share and accessibility by public transport (*18; 111*), fewer research attempted to characterize this relationship. As a precursor to this present study (*80*), we carried out an introductory examination of this relationship for the low and higher-income groups where we first used a series of best-fit curves to determine the function that best represented the relationship. Data obtained for accessibility and public transport mode share are as described in the previous section. However, the travel time threshold used in this precursor study is the average commute time for the reason that prior to the present study, we were working with the average travel time before improving the methodology through the use of the median.

The curve-fitting process was applied to the Toronto-Hamilton dataset for the two income groups to determine the best function. We included three functions: 1) exponential function, 2) linear function, and 3) second order polynomial (quadratic) function. A visual comparison of the best-fit curves against the scatterplots of the data points for the two income groups is shown in **Figure 5**. Understandably, the quadratic function is not the one that yielded the best R^2 values for all income groups across all regions (the linear relationship is more applicable in certain cases) but for the sake of comparison, we decided to move forward with the quadratic because we would be able to observe indirectly, through the coefficients, where the quadratic is not strongly observable.

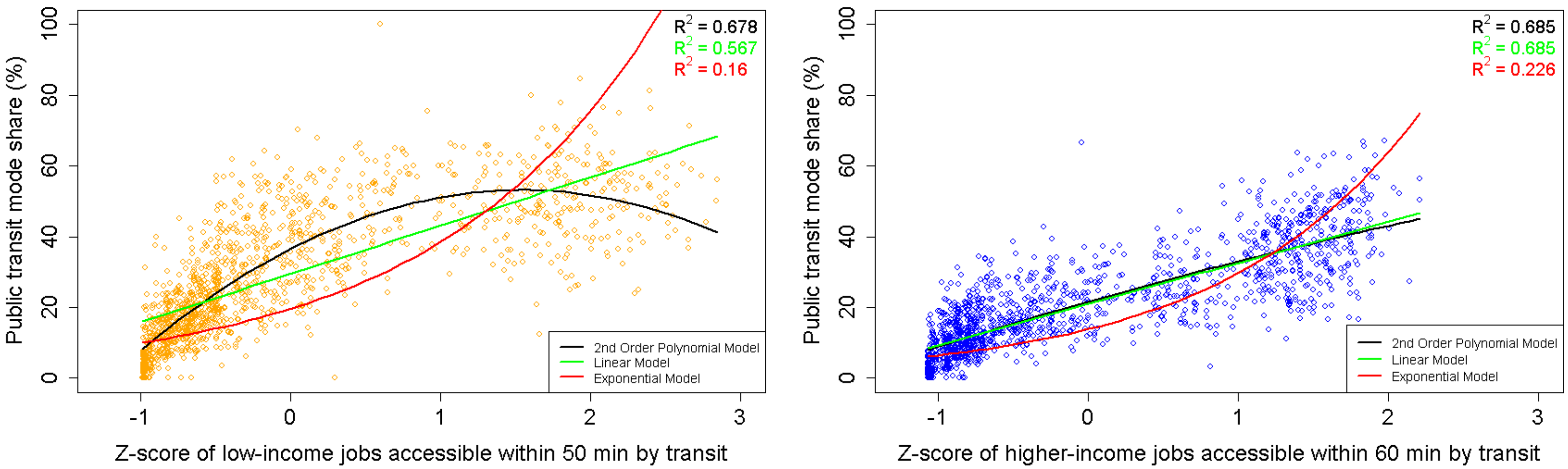

Figure 5 Comparison of curve fitting models for the Toronto-Hamilton dataset for low-income (left) and higher-income (right) groups

3.4.3 Model inputs and development

Separate models for each income group in each metropolitan area are generated for the reason that different median travel times are used as the travel time threshold to calculate accessibility. To capture the non-linear relationship between accessibility and mode share that was discussed in the previous section, a squared accessibility term ("higher-order term") was generated and entered in to the models which is equal to the existing accessibility value ("lower-order term") squared. In addition to the two accessibility variables, control variables related to the presence of transport infrastructure and socio-demographic characteristics at the origin census tract are included. These variables are evaluated for the census tract and so are not differentiated by income group.

Non-highway network proximity to rapid public transport stations (including Bus Rapid Transit stops as well as light, heavy and commuter rail stations) from the origin census tract centroid is used to control for the influence of transport infrastructure on mode share. While certain bus systems operated by various Canadian transport agencies are termed as Bus Rapid Transit systems (BRTs), we find that not all meet the basic criteria of a BRT as outlined by the Institute for Transportation and Development Policy (*112)*. Based on a quick evaluation, we conclude that the Ottawa Transitway, Gatineau Rapibus, Mississauga Transitway, Winnipeg Southwest Transitway and the York Region Viva Rapidway qualify as BRTs due to the presence of dedicated rights-of-way and off-board fare payment systems. As well, the public transport infrastructure identified in this step reflect the state of the systems in 2016 to match the accessibility and mode share data.

In addition, the network proximity to the nearest highway ramp is also included as the presence of car-oriented infrastructure could impact public transport mode share negatively (*87*). Furthermore, while information on household vehicle ownership and travel expenditure would be relevant explanatory variables to include, they were not available at the appropriate geographic level at the time of the study. As such, their inclusion in future studies of a similar nature may be beneficial as they have been found to be influential on public transport use (*70*). Early trials of the models included the network distance to the city center as a variable. However, we removed this variable from the final model as it was highly correlated with accessibility.

Moreover, socio-demographic variables at the origin census tracts, obtained from the 2016 Census, are also included the regression models. We've elected to use a social deprivation index which combines normalized values of household income, unemployment rate, housing affordability and recent immigration status which has been used previously in studies on mode share (*87*). The social deprivation index of each census tract within a metropolitan region are then divided into deciles, with one being the least socially deprived to ten being the most socially deprived. The rankings are then entered as inputs into the models.

3.4.4 Summary statistics

The mean values for the input variables are presented in **Table 9**. In the majority of the areas being studied, with the only exceptions being London and Kitchener-Cambridge-Waterloo, both the average and the median commuting times of low-income public transport commuters are lower than higher-income public transport commuters. The public transport mode share is nonetheless much higher for the low-income group compared to the higher income group across the country, i.e. a greater proportion of low-income commuters use public transport. This has been observed in past research (*71*). As expected, the average public transport mode share is highest in the three largest metropolitan regions with the most developed rapid public transport systems. However, the difference in public transport mode share between the other large metropolitan regions seems to be unrelated to the existence of rapid public transport systems. For example, in Quebec City, a city without an LRT system, both income groups exhibit higher public transport use when compared with Edmonton, one with an LRT. On the other hand, Halifax is less dense than Edmonton but nonetheless both income groups in the two areas exhibit similar levels of public transport use. This confirms past researchers' hypothesis that the presence of public transport infrastructure is not the sole predictor of public transport use.

Furthermore, the statistics on accessibility indicate that across regions, with the exception of Kitchener-Cambridge-Waterloo and London, accessibility is lower for the low-income group even when the difference in the number of low and higher-income jobs available is adjusted through the use of proportional accessibility. This is in contrast to previous research (*15*) and illustrates the effect of segmenting the population into low and higher-income as well as using time thresholds specific to each income group. For example, the median travel time is longer for the higher-income group in all regions except in Kitchener-Cambridge-Waterloo where the median travel time is the same between groups and in London where it is longer for the low-income group; the result in these two regions is higher accessibility for the low-income group.

An illustration of the difference in accessibility to jobs by public transport and mode share between the low- and higher-income groups in Montreal are shown in **Figure 6** and **Figure 7**, respectively. As expected, both accessibility and mode share is higher on the denser Island of Montreal and around the locations of metro stations.

Table 9 Summary statistics

	All Regions		Toronto-Hamilton		Montreal		Vancouver		Calgary		Edmonton		Halifax		Kit-Cam-Wat		London		Ottawa-Gatineau		Quebec City		Winnipeg	
	Higher	Low	Higher	Low	Higher	Low	Higher	Low	Higher	Low	Higher	Low	Higher	Low	Higher	Low	Higher	Low	Higher	Low	Higher	Low	Higher	Low
Average commute time (min)	58.0	49.8	62.0	52.4	53.7	45.9	52.1	47.4	58.7	56.8	73.2	53.6	61.5	54.2	47.1	45.9	44.3	51.4	60.6	50.0	53.5	45.5	43.0	42.4
Average commute time threshold (min)	60	50	60	50	55	45	50	45	60	55	70	55	60	55	45	45	45	50	60	50	55	45	45	40
Median commute time (min)	49.5	43.5	54.6	47.0	45.4	39.4	44.5	40.8	53.9	52.1	49.7	44.4	47.4	44.7	42.3	42.3	41.9	44.2	47.2	43.7	46.5	40.1	39.7	38.6
Median commute time threshold (min)	50	45	55	45	45	40	45	40	55	50	50	45	45	45	40	40	40	45	45	45	45	40	40	40
Average public transport mode share (%)	17.8	26.1	21.0	29.5	23.4	29.4	17.1	29.2	13.4	19.4	9.5	18.3	10.1	18.0	3.7	14.3	4.4	16.0	16.9	23.9	10.7	19.1	11.3	22.9
Accessibility Measures																								
Average accessibility to jobs by public transport (%)	19.3	11.9	11.8	6.0	17.2	11.8	17.4	12.5	28.8	17.3	20.3	13.3	23.4	20.9	14.8	15.4	18.4	22.1	22.3	17.3	22.7	15.4	25.7	23.4
Average accessibility to jobs by public transport (thous.)	18.8	4.4	24.2	5.3	21.2	6.2	12.0	3.9	11.2	3.4	7.4	2.5	3.0	1.1	2.4	1.0	2.5	1.4	8.5	3.7	6.2	1.5	6.2	2.4
Control Variables																								
Average population density (thous. persons/km^2)	4.3		5.0		5.6		4.8		2.7		2.3		1.9		2.1		2.1		2.6		2.8		2.7	
Average age	40.5		40.6		40.6		41.3		38.3		38.8		41.1		39.8		41.0		40.9		43.1		40.1	
Average number of persons per household	2.6		2.8		2.3		2.7		2.7		2.6		2.3		2.6		2.4		2.4		2.1		2.5	
Average household income (thous. $)	80.1		84.8		66.1		78.8		106.2		95.9		73.3		81.1		68.4		86.0		67.0		74.4	
Average unemployment rate (%)	7.5		7.8		7.7		5.8		9.5		8.9		7.6		6.5		7.6		7.4		4.9		6.6	
Average percentage of households spending >30% of income on housing (%)	26.2		30.6		24.7		30.7		20.9		21.5		24.5		23.5		24.7		22.1		18.1		20.2	
Average recent immigrant population (%)	5.1		4.9		4.5		5.6		6.1		5.7		2.2		2.6		2.3		2.8		1.8		6.1	
Average network distance to closest rapid public transport station (km)	5.8		4.8		4.8		6.2		6.0		11.7		N/A		N/A		N/A		6.4		N/A		8.5	
Average network distance to closest highway on ramp (km)	4.0		3.5		2.8		5.0		3.8		4.8		5.6		3.5		6.1		5.4		3.4		7.6	
Average network distance to city center (km)	21.5		32.2		18.0		21.6		13.8		15.3		14.5		10.4		10.7		15.9		11.4		9.6	

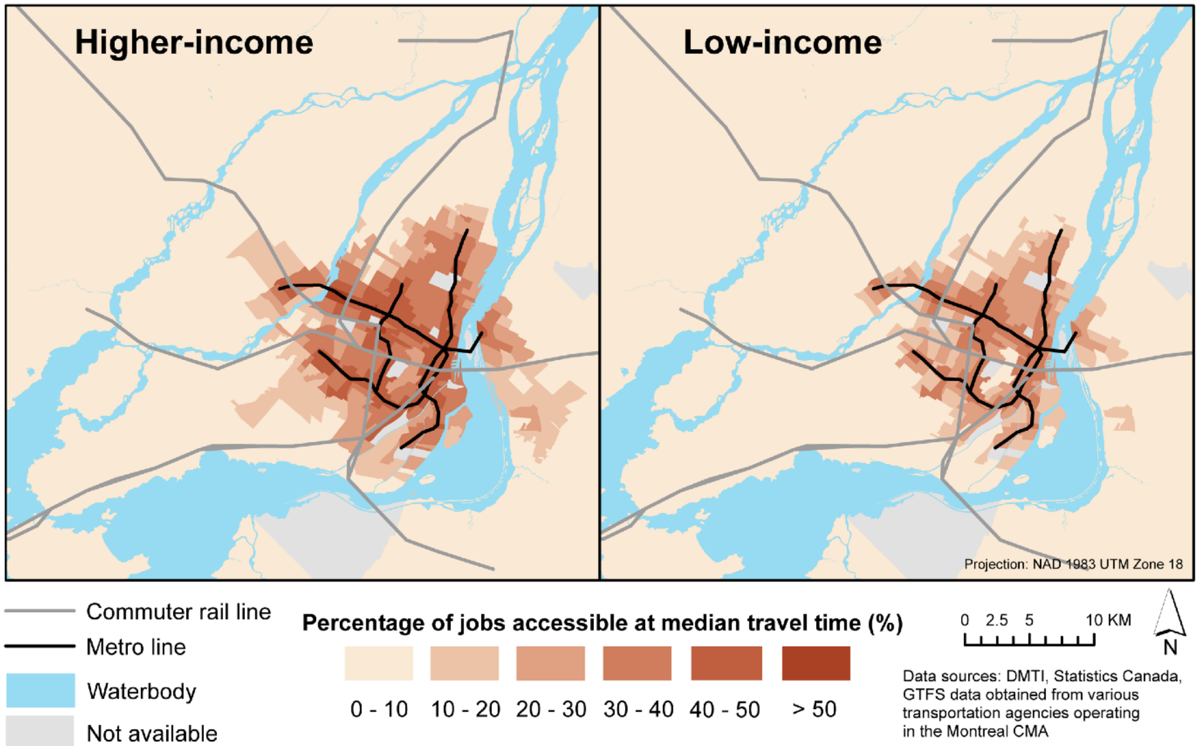

Figure 6 Comparison of job accessibility at median travel time for higher and low-income groups in Montreal

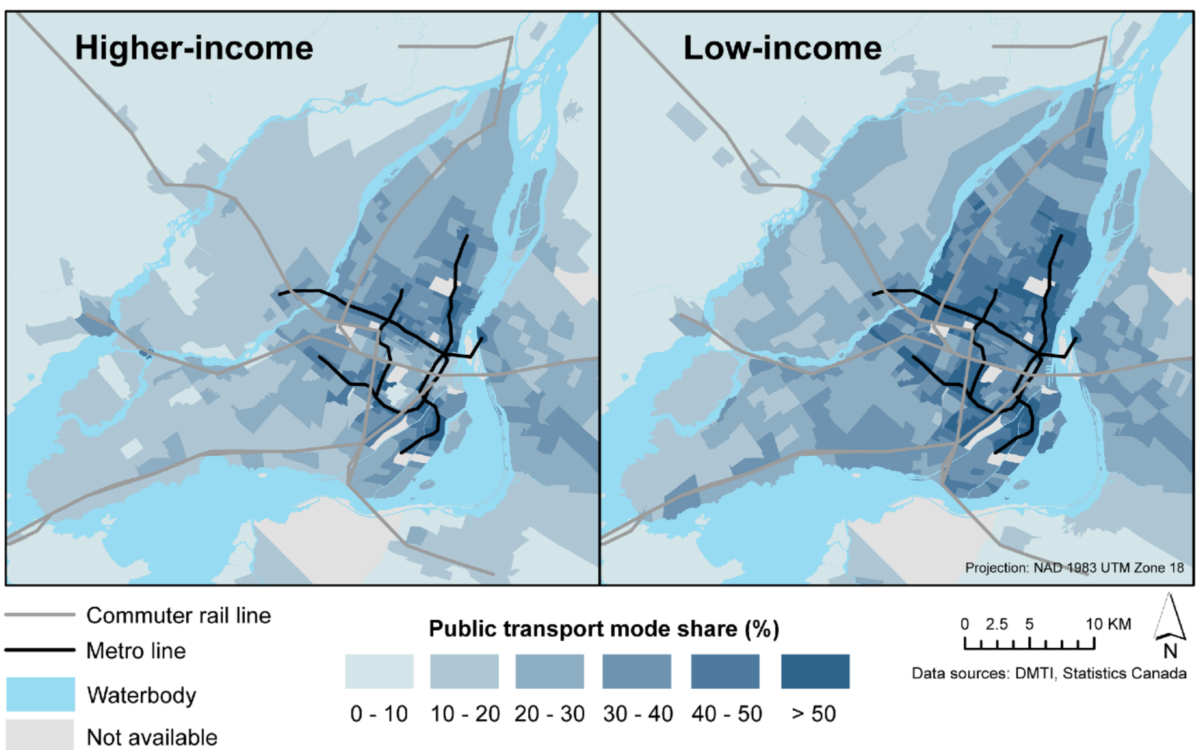

Figure 7 Comparison of public transport mode share for higher and low-income groups in Montreal

3.5 RESULTS AND DISCUSSION

The final model outputs are shown in **Table 10** where regions are grouped based on population and presented as largest, medium and smaller-sized metropolitan areas. Since there are many models to contend with, the most prominent trends are explained in further detail but researchers interested in the results for a specific region can refer to the results shown in this table. In terms of the model goodness-of-fit, we see a range of R^2 values from 0.432 in the higher-income Ottawa-Gatineau model to 0.781 in the low-income Montreal model. There are no observable differences between the goodness-of-fits between models segmented by income as well as the models segmented by region size. The variance inflation factor (VIF) for the majority of the models are within reason with the exception of the Quebec City models.

3.5.1 Accessibility to jobs by public transport

The lower-order term of percentage of jobs (*Accessibility)* accessible by public transport is positively associated with mode share in most regions (except for the higher-income group in Halifax and Kitchener-Cambridge-Waterloo) and the higher-order term of the same variable (*Accessibility^2*) has a negative impact. This result indicates a relationship demonstrated by a concave parabola, where public transport mode share increases, albeit at a non-constant rate of change, in response to increasing accessibility up until a certain point, the vertex, where increasing accessibility past it has a negative effect on public transport mode share. It is possible that the uptake of active modes at locations of very high accessibility by public transport, which can be correlated to high accessibility by active modes, could explain this pattern. A quadratic relationship also means that improvements in mode share due to a one percent point increase in accessibility is different depending on the starting accessibility level. For example, an increase in accessibility from 6%, the mean value the low-income group in Toronto-Hamilton, to 7%, results in a mode share improvement of 2.7 percentage points (in other words, an absolute increase of 2.7 percent, not a relative increase) compared to an improvement of 1.1 percentage point when accessibility is increased from 13%, one standard deviation above the mean, to 14%. Moreover, the vertex for this model is reached when the percentage of jobs that are accessible is 18% (where the highest transport mode share is expected to occur) but any increase in accessibility would cause the mode share to decrease from this point. It is important to note that 18% may seem low, but this is three times greater than the mean value of 6%.

In terms of statistical significance, the lower-order accessibility term is significantly different from zero (at 95% confidence interval) in most models but the higher-order term is significant in fewer models. In addition, the magnitudes of both of these coefficients in the low-income models are highest in the three largest metropolitan areas where accessibility is an important, if not the most, influential determinant of public transport mode share as compared to the other variables. The average value of the lower-order accessibility term in these three regions is 2.470 compared to 0.383 in the others; the average value of the higher-order term is -0.057 compared to -0.00438. The coefficient for the lower order term is also highest in the higher-income models for these three regions (an average of 0.645) compared to the others (average value of 0.148). This may suggest that the non-linear relationship between accessibility and mode share is most profound in the largest metropolitan areas. In contrast, a quadratic relationship (used to estimate a non-linear relationship) between accessibility to jobs by public transport and public transport mode share is not strongly observable for either income group in Calgary, Halifax, Kitchener-Cambridge-Waterloo and Winnipeg as indicated by the significance levels of the two variables.

In addition, we observe that the coefficients for the accessibility measures are always higher (in terms of magnitude) in the low-income models compared to the higher-income ones, with the exception of Halifax where the effects are similar and Kitchener-Cambridge-Waterloo where the pattern is inversed. This pattern implies that accessibility by public transport influences mode share more strongly for the low-income group compared to the higher-income group while controlling for the same socio-demographic and spatial variables. Specifically, this result indicates that every percentage point increase in accessibility results in a greater increase in public transport mode share for the low-income group than the higher-income. This finding confirms the hypothesis that the impact of accessibility on mode share is different between income groups.

The contrary result that we observe for Halifax and Kitchener-Cambridge-Waterloo could be attributed to a few factors. First, the small number of census tracts which are used as the individual observations to be entered into the regression models can result in inconsistent and unclear results (also can be seen by the lack of significance for the coefficients). As well, the low public transport mode share for the higher income group in Kitchener-Cambridge-Waterloo could have caused the inconsistencies in the signs of the coefficients. Furthermore, the distribution of accessibility across Halifax and Kitchener-Cambridge-Waterloo where very low accessibility is observed throughout the region with higher accessibility concentrated in certain areas, for example around downtown Halifax and University of Waterloo in the Waterloo region, may result in a relationship that may resemble more like an exponential curve which in this case is estimated by a convex parabola.

Furthermore, it is important to note that a one percent increase in job accessibility in Toronto-Hamilton is not equal to one percent in a smaller city. For example, a one percent increase of low-income jobs accessible in Toronto-Hamilton is equivalent to an increase of 8,000 jobs whereas in London, this number is 600, which is unlikely to have an impact on public transport mode share. However, when the same models are run with all other variables held constant but using the number of jobs accessible rather than the percentage (shown in **Table 11**), we see that the magnitudes of the coefficients are higher in smaller regions like London where a 10,000 increase in jobs accessible by public transport would have a greater impact on mode share. An illustration of this difference is such: an increase from a mean of 13,942 low-income jobs accessible to 23,942 in London results in a 5.1 percentage points increase in low-income mode share whereas in Toronto-Hamilton, an increase from a mean of 53,268 low-income jobs to 63,268 results in an increase of 3 percentage points. Therefore, there is value in investing in projects that would greatly improve accessibility in these smaller regions like London.

Table 10 Model results using proportional accessibility

Largest-sized metropolitan regions																								
	Toronto-Hamilton								Montreal								Vancouver							
	Higher-income				Low-income				Higher-income				Low-income				Higher-income				Low-income			
	Coefficient		95% CI		Coefficient		95% CI		Coefficient		95% CI		Coefficient		95% CI		Coefficient		95% CI		Coefficient		95% CI	
Accessibility Measures																								
Accessibility (%)	0.88	***	0.72	1.03	4.24	***	3.92	4.55	0.63	***	0.49	0.76	1.48	***	1.27	1.68	0.43	***	0.29	0.58	1.70	***	1.40	1.99
Accessibility² (%²)	-0.003		-0.01	0.001	-0.12	***	-0.13	-0.11	-0.01	***	-0.01	-0.002	-0.02	***	-0.03	-0.02	-0.003	**	-0.01	-0.0003	-0.03	***	-0.04	-0.02
Control Variables																								
Density (thous. persons/km²)	0.22	***	0.14	0.30	-0.15	***	-0.26	-0.04	0.38	***	0.24	0.53	0.29	***	0.12	0.45	-0.06		-0.20	0.09	-0.37	***	-0.60	-0.15
Age	0.02		-0.09	0.12	-0.30	***	-0.45	-0.15	-0.19	***	-0.32	-0.06	0.10		-0.05	0.25	-0.35	***	-0.52	-0.18	-0.40	***	-0.65	-0.15
HH structure	0.81	*	-0.07	1.69	-0.95		-2.12	0.22	-2.05	**	-3.80	-0.30	2.98	***	0.92	5.04	-4.95	***	-6.27	-3.62	-1.80	*	-3.79	0.19
Social index (decile)	0.93	***	0.77	1.09	1.86	***	1.65	2.07	0.66	***	0.42	0.91	1.89	***	1.62	2.17	0.73	***	0.50	0.97	0.68	***	0.33	1.04
Station (km)	-0.48	***	-0.58	-0.38	-0.26	***	-0.40	-0.13	-0.36	***	-0.45	-0.27	-0.49	***	-0.60	-0.39	-0.20	***	-0.31	-0.09	-0.28	***	-0.44	-0.12
Highway (km)	0.28	***	0.15	0.40	0.12		-0.05	0.29	0.09		-0.16	0.33	0.05		-0.23	0.34	-0.27	***	-0.42	-0.11	-0.42	***	-0.65	-0.18
Constant	3.68		-2.77	10.13	19.77	***	11.04	28.49	24.01	***	15.14	32.88	-1.32		-11.74	9.10	37.89	***	28.24	47.54	40.32	***	25.86	54.78
Number of observations	1,416				1,416				951				951				458				458			
R² value	0.757				0.738				0.739				0.781				0.702				0.649			

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

Medium-sized metropolitan regions																								
	Calgary								Edmonton								Ottawa-Gatineau							
	Higher-income				Low-income				Higher-income				Low-income				Higher-income				Low-income			
	Coefficient		95% CI		Coefficient		95% CI		Coefficient		95% CI		Coefficient		95% CI		Coefficient		95% CI		Coefficient		95% CI	
Accessibility Measures																								
Accessibility (%)	0.05		-0.06	0.16	0.20	**	0.02	0.38	0.16	***	0.05	0.28	0.60	***	0.32	0.89	0.18	***	0.05	0.31	0.53	***	0.27	0.80
Accessibility² (%²)	-0.001		-0.003	0.001	-0.002		-0.01	0.002	-0.002		-0.004	0.001	-0.01	***	-0.02	-0.002	-0.003	**	-0.01	-0.001	-0.005		-0.01	0.001
Control Variables																								
Density (thous. persons/km²)	-0.05		-0.40	0.31	0.08		-0.39	0.55	0.55	***	0.18	0.93	-0.03		-0.69	0.64	0.39		-0.02	0.79	0.40		-0.18	0.98
Age	-0.21	**	-0.38	-0.04	-0.12		-0.33	0.09	-0.19	***	-0.31	-0.06	-0.14		-0.36	0.09	-0.01		-0.21	0.20	0.19		-0.10	0.49
HH structure	-0.61		-2.20	0.99	0.25		-1.88	2.38	-2.37	***	-4.07	-0.67	-0.69		-3.77	2.38	1.43		-1.51	4.38	9.04	***	4.79	13.30
Social index (decile)	0.29	***	0.08	0.51	1.40	***	1.13	1.68	0.45	***	0.25	0.65	1.32	***	0.95	1.69	0.70	***	0.36	1.04	2.19	***	1.69	2.68
Station (km)	-0.66	***	-0.77	-0.55	-0.64	***	-0.79	-0.50	-0.20	***	-0.27	-0.14	-0.35	***	-0.46	-0.23	-0.36	***	-0.50	-0.22	-0.45	***	-0.66	-0.23
Highway (km)	0.38	***	0.22	0.55	0.17		-0.05	0.38	0.16	***	0.07	0.26	0.04		-0.13	0.21	0.13		-0.05	0.31	0.14		-0.13	0.41
Constant	23.75	***	13.81	33.70	16.27	**	3.41	29.12	18.65	***	10.02	27.28	16.93		1.29	32.58	9.11		-5.94	24.15	-23.65	**	-45.36	-1.95
Number of observations	252				252				257				257				275				275			
R² value	0.497				0.668				0.674				0.710				0.432				0.641			

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

Smaller-sized metropolitan regions																		
	Halifax						Kit-Cam-Wat						London					
	Higher-income			Low-income			Higher-income			Low-income			Higher-income			Low-income		
	Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI	
Accessibility Measures																		
Accessibility (%)	-0.13	-0.32	0.06	0.13	-0.24	0.51	-0.02	-0.14	0.10	0.13	-0.18	0.45	0.15 **	0.03	0.27	0.80 ***	0.54	1.07
Accessibility^2 (%^{2})	0.002	-0.001	0.005	-0.002	-0.01	0.004	0.004 **	0.001	0.01	-0.00003	-0.01	0.01	-0.002	-0.004	0.001	-0.01 ***	-0.01	-0.003
Control Variables																		
Density (thous. persons/km^2)	0.22	-0.48	0.93	-0.48	-1.70	0.73	0.20	-0.12	0.51	1.03 **	0.19	1.87	0.22	-0.20	0.64	-0.73	-1.72	0.26
Age	0.03	-0.24	0.31	-0.40	-0.86	0.07	-0.23 ***	-0.36	-0.11	-0.30 *	-0.61	0.02	-0.16	-0.33	0.01	-0.51 ***	-0.89	-0.13
HH structure	-2.92	-8.62	2.78	-9.58	19.21	0.04	-2.51 ***	-4.09	-0.93	-1.63	-5.71	2.45	-3.33 ***	-5.60	-1.05	-2.95	-7.86	1.97
Social index (decile)	0.84 **	0.16	1.53	1.64 ***	0.49	2.80	0.27 ***	0.07	0.47	1.35***	0.83	1.87	0.36 **	0.07	0.65	0.82 **	0.19	1.45
Station (km)	N/A			N/A			N/A			N/A			N/A			N/A		
Highway (km)	-0.20 ***	-0.29	-0.11	-0.32 ***	-0.47	-0.17	0.04	-0.11	0.18	-0.25	-0.62	0.12	0.08	-0.04	0.20	0.19	-0.07	0.46
Constant	12.23	-11.12	35.59	49.01 **	9.62	88.40	16.30 ***	7.46	25.15	19.44 *	-3.40	42.28	14.35 **	1.90	26.80	28.00 **	0.61	55.39
Number of observations	92			92			106			106			109			109		
R^2 value	0.472			0.588			0.725			0.680			0.627			0.756		

	Quebec City						Winnipeg					
	Higher-income			Low-income			Higher-income			Low-income		
	Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI	
Accessibility Measures												
Accessibility (%)	0.28 ***	0.17	0.40	0.48 ***	0.16	0.80	0.06	-0.05	0.16	0.16	-0.07	0.39
Accessibility^2 (%^{2})	-0.003 ***	-0.01	-0.001	-0.005	-0.01	0.003	-0.0003	-0.002	0.001	-0.003	-0.01	0.001
Control Variables												
Density (thous. persons/km^2)	0.54 ***	0.24	0.83	0.53 **	0.03	1.03	0.82 ***	0.51	1.13	1.32 ***	0.74	1.91
Age	-0.13	-0.29	0.03	0.26 *	-0.02	0.53	-0.23 ***	-0.41	-0.06	-0.11	-0.44	0.21
HH structure	-2.91	-7.24	1.42	10.13 ***	2.77	17.49	-2.37 ***	-4.08	-0.66	-4.40 ***	-7.75	-1.06
Social index (decile)	0.64 ***	0.20	1.08	1.80 ***	1.05	2.56	0.82 ***	0.59	1.05	1.73 ***	1.28	2.17
Station (km)	N/A			N/A			-0.13 *	-0.26	0.01	-0.40 ***	-0.65	-0.15
Highway (km)	-0.16 **	-0.30	-0.01	-0.54 ***	-0.79	-0.28	-0.05	-0.21	0.10	0.08	-0.21	0.37
Constant	14.62 *	-1.58	30.82	-28.57 **	56.10	-1.03	20.22 ***	9.25	31.19	26.71 **	5.46	47.97
Number of observations	179			179			171			171		
R^2 value	0.740			0.643			0.762			0.750		

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

Table 11 Model results using accessibility as number of jobs accessible

Largest-sized metropolitan regions

	Toronto-Hamilton						Montreal						Vancouver					
	Higher-income			Low-income			Higher-income			Low-income			Higher-income			Low-income		
	Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI	
Accessibility Measures																		
Accessibility (10,000)	0.43 ***	0.35	0.50	4.81 ***	4.45	5.17	0.51 ***	0.40	0.62	2.83 ***	2.43	3.22	0.63 ***	0.42	0.84	5.38 ***	4.45	6.31
Accessibility^2 (10,000^2)	-0.001	-0.002	0.0003	-0.15 ***	-0.17	-0.14	0.00 ***	-0.01	-0.001	-0.08 ***	-0.10	-0.06	-0.01 **	-0.01	-0.001	-0.29 ***	-0.36	-0.21

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

Medium-sized metropolitan regions

	Calgary						Edmonton						Ottawa-Gatineau					
	Higher-income			Low-income			Higher-income			Low-income			Higher-income			Low-income		
	Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI	
Accessibility Measures																		
Accessibility (10,000)	0.12	-0.15	0.40	1.00 **	0.09	1.92	0.45 ***	0.14	0.76	3.21 ***	1.69	4.73	0.47 ***	0.13	0.82	2.51 ***	1.26	3.77
Accessibility^2 (10,000^2)	-0.01	-0.02	0.01	-0.06	-0.16	0.04	-0.01	-0.03	0.004	-0.26 **	-0.47	-0.06	-0.02 **	-0.04	-0.004	-0.10	-0.23	0.02

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

Smaller-sized metropolitan regions

	Halifax						Kit-Cam-Wat						London					
	Higher-income			Low-income			Higher-income			Low-income			Higher-income			Low-income		
	Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI	
Accessibility Measures																		
Accessibility (10,000)	-1.04	-2.52	0.45	2.46	-4.39	9.31	-0.11	-0.84	0.62	2.00	-2.73	6.72	1.10 **	0.25	1.95	12.74 ***	8.54	16.94
Accessibility^2 (10,000^2)	0.13	-0.04	0.29	-0.72	-2.66	1.23	0.14 **	0.03	0.26	-0.01	-1.72	1.71	-0.09	-0.23	0.04	-2.01 ***	-3.30	-0.73

	Quebec City						Winnipeg					
	Higher-income			Low-income			Higher-income			Low-income		
	Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI	
Accessibility Measures												
Accessibility (10,000)	1.02 ***	0.61	1.44	4.87 ***	1.65	8.10	0.23	-0.20	0.66	1.61	-0.66	3.87
Accessibility^2 (10,000^2)	-0.04 ***	-0.07	-0.02	-0.48	-1.27	0.31	-0.005	-0.03	0.02	-0.30	-0.65	0.06

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

To illustrate visually the results being described here, the curves in **Figure 8** and **Figure 9**, which are generated using the model coefficients, show the predicted mode share with respect to the percentage and the number of jobs that are accessible, respectively, using the regression coefficients while holding the control variables at their means (refer to **Table 9**). Higher-income models are presented together on the top row and the low-income models are on the bottom. With the quadratic curves shown in these figures, we can observe clearly that perhaps there is an optimal value of accessibility (the vertex) at which public transport mode share is maximized.

The optimal value of accessibility (accessibility at the vertex) for each model where the quadratic is representative is presented in **Table 12** along with the maximum accessibility value observed for the dataset. This value can be treated as the target accessibility for census tracts where existing accessibility is less than the optimal value. This has practical implications where we can evaluate public transport projects on the basis of how well the increase in accessibility for the impacted census tracts meets the targeted optimal value. This finding is subject to the following caveats: the optimal value is specific to each income group in each metropolitan region, they are only applicable to each group and should not be applied to different regions. In addition, the interpretation of the vertices is only valuable in models where the quadratic is representative (i.e. both the *Accessibility* and *Accessibility*^{2} terms are significant) of the data. As we can see in **Table 12** in the higher-income models for Montreal and Vancouver, the number of jobs accessible at the vertex are extrapolations from the models as they exceed the maximum observable values, implying that increases in accessibility in any area is associated with increased mode share for higher-income individuals. In addition, while public transport mode share is expected to decrease past the optimal value, it is expected that use of active modes become more prevalent which is also desirable in the scheme of sustainable and equitable transport plans and projects.

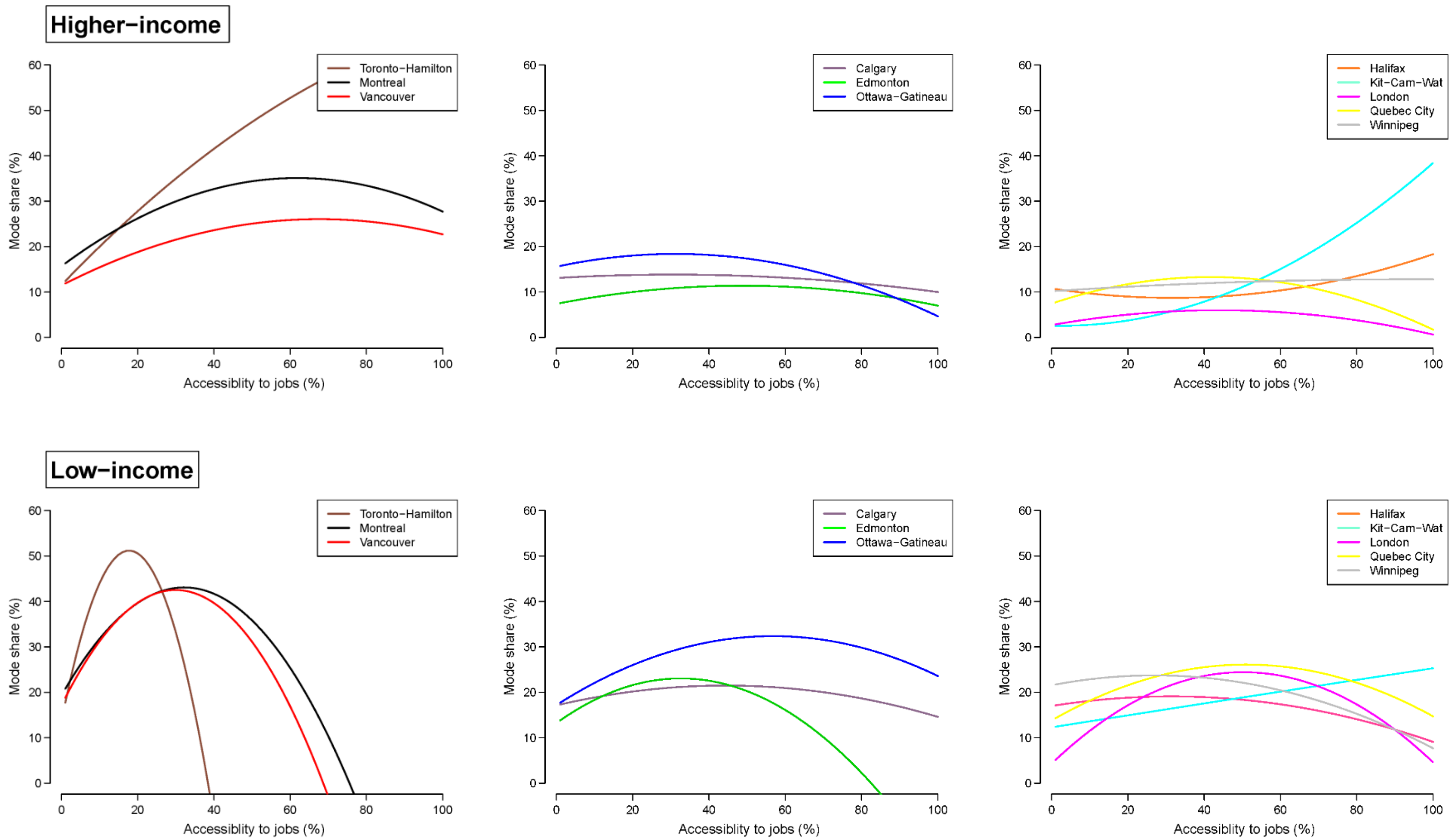

Figure 8 Visual comparison of the relationship between accessibility in terms of the percentage of jobs accessible and mode share

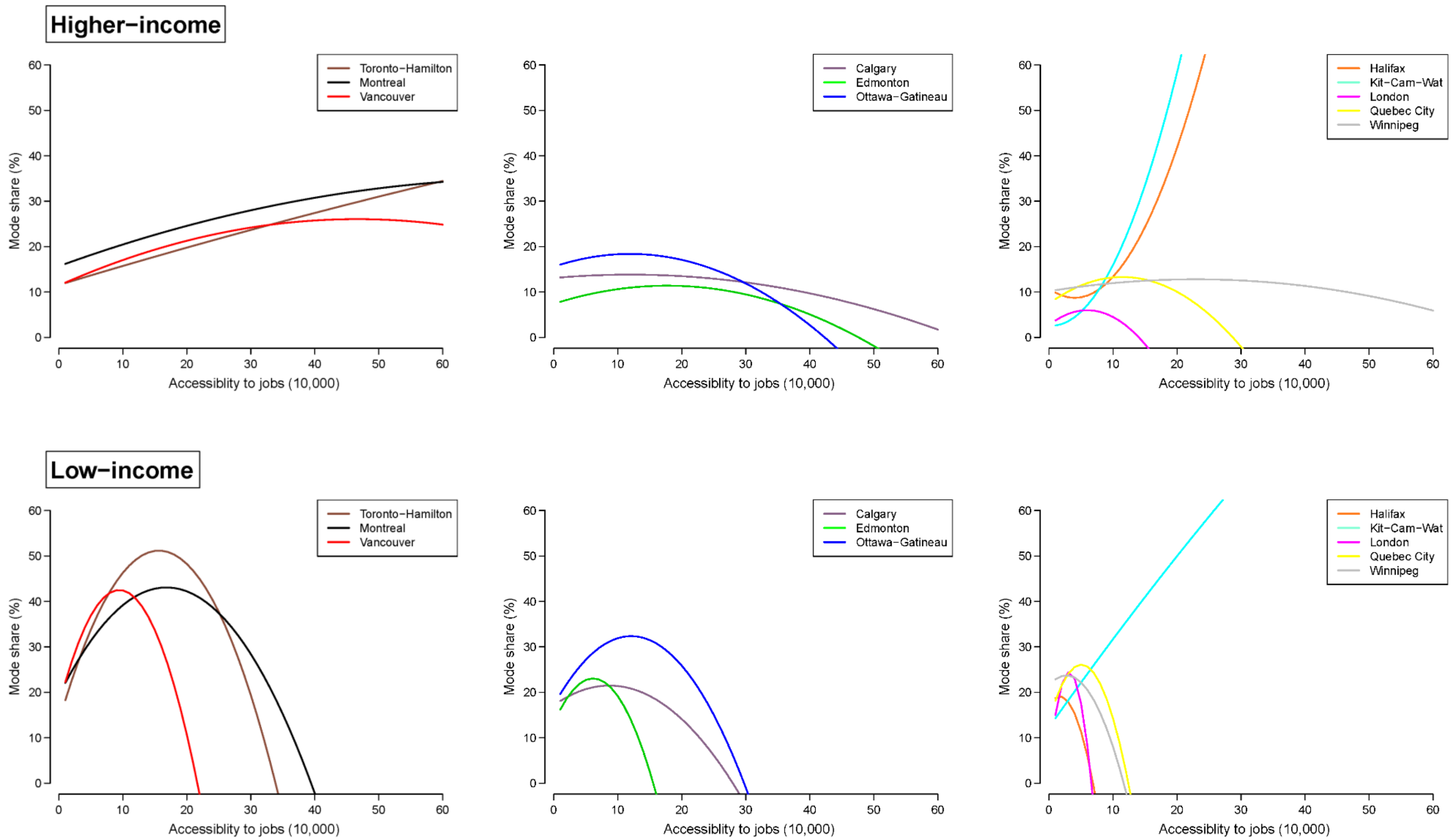

Figure 9 Visual comparison of the relationship between accessibility in terms of the number of jobs accessible and mode share

Table 12 Optimal accessibility value which would maximize public transport mode share for models where the quadratic relationship is observable

Model	Optimal accessibility (10,000 jobs)	Maximum accessibility in dataset (10,000 jobs)
Toronto-Hamilton *Low-income*	15.63	24.53
Montreal *Higher-income*	75.99	65.82
Montreal *Low-income*	16.80	22.72
Vancouver *Higher-income*	46.62	39.43
Vancouver *Low-income*	9.43	15.03
Edmonton *Low-income*	6.14	8.74
Ottawa *Higher-income*	11.91	25.82
London *Low-income*	3.16	3.46
Quebec City *Higher-income*	11.46	17.17

3.5.2 Other variables

From **Table 10**, we can see that the most influential control variables across all models include the social deprivation index (*Social Index*) and the network distance to a rapid public transport station (*Station*). The social deprivation index has a positive influence on public transport mode share (i.e. higher level of social deprivation is correlated with higher use) across all models, confirming the results from past research (*87*). The coefficients for this variable ranges from 0.273 in Kitchener-Cambridge-Waterloo to 0.929 in Toronto-Hamilton for the higher-income group and from 0.683 in Vancouver to 2.186 in Ottawa-Gatineau for the low-income group. It is clear that low-income individuals living in more socially deprived census tracts (based on the decile ranking where 10 is most socially deprived) are more likely to use public transport rather than high-income individuals in a similar socially deprived census tract.

As expected, as distance from a rapid rail station increases, the public transport mode share is likely to decrease for both income groups (*98*). The influence of this variable is similar for both income groups as it ranges from -0.656 in Calgary to -0.126 in Winnipeg for the higher-income group and from -0.644 in Calgary to -0.265 in Toronto-Hamilton for the low-income group. It is likely that this relationship is non-linear and the use of a binary variable for whether an area is located within a distance threshold may be explored in future research. The relationship between network distance to closest highway on ramp and mode share is mixed, as it is significant and positive for the higher-income group in Calgary, Edmonton and Toronto-Hamilton, but it is negative for both income groups in Vancouver, Halifax and Quebec City.

The average age (*Age*) of individuals in a census tract is significant in six out of eleven higher-income models and five of the low-income models. Census tracts with higher average age tend to have lower public transport use than younger census tracts. As the household size (*HH structure*) increases, it seems that public transport mode share for the higher-income group is expected to decrease in most of the regions whereas the pattern is less clear in the low-income models. This inconsistency in the influence of household size has been observed in previous research by Owen and Levinson (*18)*. In addition, while density tends to have a positive influence in areas where it is significant, the effect seems to be significant and negative for the low-income group in Toronto-Hamilton and Vancouver. A possible explanation for this could be the uptake of walking and cycling in very dense areas by the low-income group as a way to reduce their travel expenditure in these two areas with very high costs of living. This hypothesis could be further explored in future research.

3.5.3 Impact of using three income categories

As mentioned previously in the methodology section, we have experimented with carrying out the models with segmenting the population into low, middle and high-income groups. The definition of the low-income group is as described previously, based on the lowest paying 30% of jobs available in a region. A similar method was used for the high-income group but using the highest-paying 30% of jobs. The middle-income group is everyone that is left. While this may be a crude method of defining the groups, the results from the regression models are nonetheless as expected (refer to **Table 13**): the magnitudes for the accessibility variables are highest in the low-income model, lower in the middle-income model and lowest in the high-income model. Similarly, the change in mode share as a function of change in accessibility with other variables held at their means are shown in **Figure 10** for the three income groups. Moreover, it is interesting to see that household structure negatively influences mode share for the high- and middle-income groups but positively for the low-income.

Table 13 Model results using proportional accessibility generated for three income groups in the Montreal region

	High-income				Mid-income				Low-income			
	Coefficient		95% CI		Coefficient		95% CI		Coefficient		95% CI	
Accessibility Measures												
Accessibility (%)	0.40	***	0.28	0.53	0.98	***	0.82	1.13	1.48	***	1.27	1.68
Accessibility^2 (%^{2})	-0.002	*	-0.004	0.0001	-0.01	***	-0.01	-0.01	-0.02	***	-0.03	-0.02
Control Variables												
Density (thous. persons/km^2)	0.32	***	0.15	0.49	0.32	***	0.17	0.46	0.29	***	0.12	0.45
Age	-0.29	***	-0.45	-0.14	-0.10		-0.23	0.03	0.10		-0.05	0.25
HH structure	-3.35	***	-5.41	-1.30	-2.63	***	-4.40	-0.85	2.98	***	0.92	5.04
Social index (decile)	0.02		-0.27	0.32	0.63	***	0.38	0.88	1.89	***	1.62	2.17
Station (km)	-0.28	***	-0.38	-0.17	-0.35	***	-0.44	-0.26	-0.49	***	-0.60	-0.39
Highway (km)	0.04		-0.25	0.33	0.11		-0.14	0.36	0.05		-0.23	0.34
Constant	33.27	***	22.80	43.74	20.35	***	11.35	29.34	-1.32		-11.74	9.10
R^2 value	0.565				0.790				0.781			

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

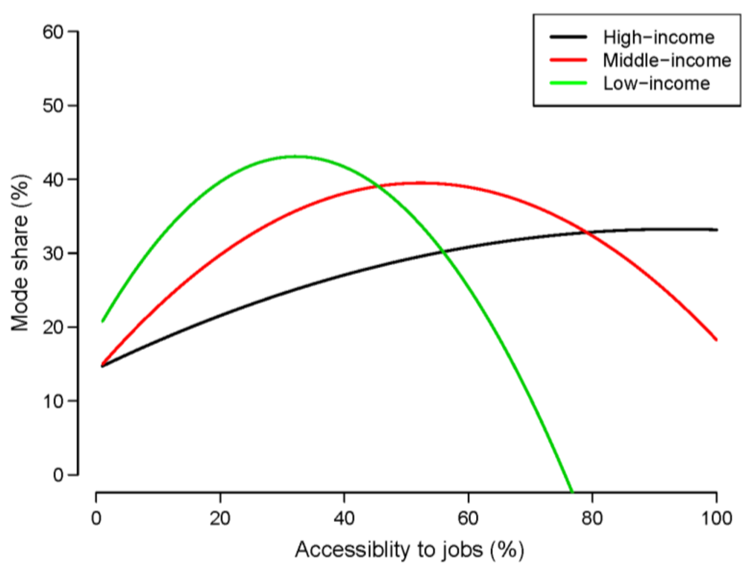

Figure 10 Visual comparison of the relationship between proportional accessibility and mode share for low, middle, and high-income groups in the Montreal region

3.6 CONCLUSION

To our knowledge, this is the first study to compare the impacts of accessibility on mode share between low and higher-income groups for numerous metropolitan regions of varying sizes. To do so, we carried out a series of linear regressions using accessibility to jobs by public transport, modelled as a quadratic, and other variables related to socio-demographics and the presence of transport infrastructure that have been found to be influential to model public transport mode share at the census tract level. The results confirm the importance of accessibility by public transport as a determinant of mode share, particularly for the low-income group, while demonstrating the discrepancies between the metropolitan regions.

Firstly, we confirm that a greater proportion of people in the low-income group use public transport as the main commute mode in all study areas, similar to past research (*71*). In addition, while public transport use is much more prevalent in regions with well-developed rapid public transport systems, this is not necessarily true in medium and smaller-sized regions. Next, more socially deprived census tracts exhibit higher public transport use and shorter distance to rapid public transport stations positively influence mode share. As well, through the use of linear regression models, we find that accessibility is a predictor of mode share as previous researchers have shown (*111*), although our characterization of this relationship as quadratic may not be applicable to all metropolitan regions. The relationship between the two variables is more strongly observed in the largest metropolitan regions. A notable result is that accessibility has a higher predicting power of mode share for the low-income group than higher income groups in the majority of the regions. In other words, public transport use by the low-income group is more sensitive to changes in accessibility than the higher-income group.

Furthermore, while these results imply that we would expect significant gains in public transport mode share for low-income groups in the largest metropolitan regions, we need to be mindful that at very high levels of accessibility (i.e. past the vertex), increasing accessibility is not expected to lead to an increase in public transport use. However, since the percentage of jobs accessible in a census tract would have to be in the 80th percentile at least for this to be applicable, improvements in mode share are still expected in the majority of the census tracts where the accessibility is currently below the optimal accessibility value at the vertex. The optimal value can be seen as a target for projects that would increase accessibility and maximize public transport use. Moreover, for metropolitan regions where the quadratic relationship is not strongly observed and there is no clear point where increasing accessibility will decrease mode share, accessibility can be improved throughout the region which would increase the mode share of the low-income group and to a lesser extent, the higher-income.

With these findings in mind, it's clear that projects and policies that would greatly improve the accessibility of the low-income group would bring about a greater increase in public transport use. Since the low-income group tend to be more dependent on, or captive to, public transport, it is paramount that public transport services are able to meet their needs and provide them with access to more opportunities as stipulated by the concept of vertical equity. In this way, we ensure that projects are carried out equitably while minimizing the environmental impact that increased car use would place on society.

Lastly, this research also highlights the importance of context-specific research. Namely, this study raises important questions, especially with respect to smaller metropolitan regions. Firstly, the quadratic relationship is not observed for all income groups and not in all the metropolitan regions. As such, other relationships can be explored between accessibility and mode share that may improve the model fit and yield more meaningful interpretations. In addition, the small number of census tracts in Halifax and Kitchener-Cambridge-Waterloo could explain the inconsistent results observed in the models for these two regions. Further investigations in these areas may benefit from using information at a smaller geographic scale than census tracts.

CHAPTER 4: SUMMARY AND CONCLUSIONS

4.1 SUMMARY OF CHAPTERS

While the body of research regarding accessibility is extensive, there has been a lack of research to incorporate the study of accessibility as a measure of equity and its ability to predict aspects of travel. The objective of this thesis is to identify whether the impact of accessibility, as a determinant of travel outcomes, differs between low- and higher-income groups and between geographic regions. Following the introduction chapter which outlines the need for accessibility in transport planning and how it has been measured and used, the two subsequent chapters present the studies that were carried out to explore this research question using commute duration and public transport mode share as the respective travel outcomes of interest.

Chapter 2 examines the impact of accessibility on commute duration, for car and public transport commuters in low and higher-income groups, using distinct multilevel mixed effects regression models for each group of commuters at the census tract level. Control variables that were shown in previous research to impact commute duration were also included in the regression models. This study was born out of a need to address the inequalities that exist in transport that contemporary researchers have identified (*36*) where the less well-off groups in society are found to travel a lot slower and covering much shorter distances than those who are better-off. As such, we wished to examine whether accessibility could be used as a tool to guide policies which would help to reduce travel times for the low-income group. The methodology used in this study is inspired from the work previously done by Levinson (*34)* to consider not just accessibility to jobs at the home census tract, but also accounting for the effect of accessibility to workers at the place of work as well as the impact of competition at both home and the place of work.

In this study, we confirm the original hypotheses originally posited by Levinson (*34)* where accessibility to jobs at the home census tract is negatively associated with commute duration (i.e. shorter duration is expected with better accessibility) while at the place of work, the association is positive. In addition, the association between accessibility to workers at home is positive with duration whereas it is negative at the place of work. When the impact of accessibility is compared between the two income groups, we observed that for both car and public transport commuters, the magnitude of association is consistently higher for the low-income group. These findings confirm that competition, in the form of workers at the home census tract and jobs at the place of work is present and more strongly observed for the low-income group. These findings imply that improvements made to accessibility can be more effective to lower commute durations for low-income individuals. In terms of the actions that policymakers can employ based on these findings, we suggest a mix of land uses at traditionally residential areas should be introduced which would bring low-income workers closer to low-income jobs. In addition, the effects of competition more strongly felt by the low-income group may be mitigated through a mix of housing stock (i.e. through the provision of affordable housing) in residential areas and job type in commercial areas respectively.

Chapter 3 examines the impact of accessibility to jobs by public transport on the public transport mode share of low and higher-income commuters leaving a census tract, using a series of linear regression models that include a similar set of control of variables as Chapter 2. The issue that is being considered in this study concerns the plateauing use of public transport across Canada which may be attributed to the unequal investments towards rail transport which tend to serve higher-income individuals rather than projects that benefit those who actually use public transport most often i.e. captive riders who tend to be more low-income and less likely to own personal vehicles. From a social justice perspective, it is paramount that planners provide them with services to improve their accessibility and these policies should target transport systems that they actually use. As a response, we examined whether improvements in accessibility would in turn lead to improvements in public transport use and more importantly, could we expect to see a faster uptake of public transport for the low-income group?

The results of this study, similar to Chapter 2, indicate that accessibility has a greater influence on mode share for the low-income group compared to the higher-income in the vast majority of the eleven study regions. However, we observed that in the largest metropolitan regions, increasing accessibility for the low-income group is not expected to lead to an increase in public transport use past when the existing accessibility level is at or greater than the 80th percentile, as a result of the curve-linear relationship that we modelled between accessibility and mode share. Nonetheless, gains in mode share is still expected in the majority of the areas within these regions as well as in the other metropolitan regions where the quadratic relationship was not representative. These findings reveal that projects and policies that would greatly improve the accessibility of the low-income group would bring about a greater increase in public transport use.

Since the low-income group tends to be more dependent on public transport, it is paramount that they have access to more opportunities using a mode that is less financially burdensome.

4.2 FUTURE RESEARCH

One limitation of the data and methodology employed in both studies is related to the use of aggregate data at the census tract level. As a result, there may not have been enough observations to be entered into the regression models for smaller regions being explored in Chapter 3 such as Halifax where there are only 96 census tracts. An additional limitation is present in Chapter 3 as variables regarding car ownership or travel expenditure (i.e. transit pass ownership) were not included in the models due to data not being available at the time of the study. For the reason that car ownership is a strong deterrent of public transport use as emphasized by previous research (*88*), its inclusion in future research of this kind could help to explain the inconsistencies observed in the results. In addition to the absence of car ownership data, the exclusion of a measure to reflect the influence of car accessibility on public transport mode share may also be a limitation as travelers may be dissuaded from using public transport if their accessibility to jobs by car at home is much greater than by public transport. However, from our experience, accessibility by car was highly correlated with accessibility by public transport so perhaps a different approach is needed to address this.

A recommendation for future research concerns the need for context-specific research. In Chapter 2, we found that commute duration by car is likely to be lower whereas it is likely to be higher by public transport in Montreal and Vancouver compared to Toronto-Hamilton, while controlling for all other variables used in the models. We attributed these differences to factors that we were not able to directly capture such as city structure and the connectedness of the public transport network. However, it became much more difficult to interpret the differences in results in Chapter 3 due to the inclusion of many medium- and smaller-sized cities. Subsequently, it may be beneficial for researchers to apply a similar research topic to medium- and smaller-sized regions separately to deliver more relevant recommendations specific to these regions (described as context specific research in Section 3.6. Furthermore, alternative ways of computing travel times may be used to generate the accessibility measures that would account for the impact of uncertainty. However, while this may mean that the accessibility measures may be in a sense more accurate, although the scheduled GTFS data is updated at least three times a year by the public transport agency which would account to some degree uncertainty, it is also uncertain that it will impact various travel outcomes differently in a significant way through the use of regression models.

Lastly, there seems to be a lack of research on accessibility by active modes such as walking and cycling. While the process of generating accessibility for active modes may be more difficult where for example, the generation of travel time by cycling is harder to predict as it is subject to numerous factors such as the route taken and the cyclist type (*113*), it would be worthwhile for researchers to study this topic further as active transport plays an important role in the planning of sustainable and equitable transport projects and policies.

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