Accessibility matters: Determinants of public transport use across income groups in Canada

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ABSTRACT

Planning for accessibility in increasingly considered in the development of equitable plans by transport agencies and it has also been shown to exert a positive influence on public transport use. However, this influence has not been examined across income groups and in different geographic regions of varying sizes. The present study measures the relationship between accessibility and mode choice for low- and higher-income groups in eleven Canadian metropolitan regions. Our results show that the impact of accessibility on public transport mode share is stronger and non-linear for the low-income group especially in the largest metropolitan areas, where increasing accessibility past a certain optimal value will lead to a decrease in public transport mode share. However, this point occurs at the 80th percentile of existing accessibility, so improvements in mode share are nonetheless expected with improved accessibility in most areas within these regions. Moreover, in regions where an optimal value is not readily observed, improved accessibility throughout the region would lead to increased uptake of public transport for both the higher- and to a greater extent, the low-income group. Findings from this paper can be of value to transport professionals working towards meeting ridership goals around the world as comparisons between groups and across regions highlight the variation in the impacts of accessibility on mode share.

Keywords: accessibility, equity, public transport, mode share

1. INTRODUCTION

In recent years, professionals have recognized that the environmental, social and economic benefits of public transport compared to personal vehicles are numerous. As such, governments in North America are promoting the use of public transport and often setting goals for ridership (*1*) or mode share (*2*) in their plans. In light of these goals, the use of public transport in Canada has risen slowly, from 10.1% in 1996 to 12.4% in 2016 with plateaus observed in recent years (*3*). In some areas, mode share has decreased over the same period (*4*). Considering that capital expenditure for public transport projects has been rising steadily at a much higher rate since the early 2000's (*5; 6*), one wonders if the costs of investing in public transport are appropriate to its use. Also, are these public transport investments going to serve those who would benefit and use it most? The response from researchers in the U.S. (*7*) and the U.K. to these questions is "no" (*8*) as they argue that there has been a trend of increasing investments in rail transport that is geared towards higher-income choice riders. As a result, captive riders, who generally have lower income and are less likely to own personal vehicles, tend to have a limited number of travel options (*9*) and find themselves stranded in the face of reduced public transport services (*10*).

For practitioners 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, the ease of reaching destinations (*11*), to be an appropriate measure to evaluate the social equity dimension of transport plans (*12; 13*) through comparing accessibility, as well as its impacts, across income groups. While accessibility to jobs is known to impact public transport mode share in general (*14*), the impacts of accessibility on public transport use among different groups, to our knowledge, has not been studied yet and should be undertaken from an equity perspective to help in the implementation of policies and projects targeting low-income groups. Previous research carried out in Canada was of an exploratory nature and relied on graphical bivariate analyses to highlight the relationship between accessibility and public transport use among different income groups and across different geographic regions in Canada (*15*). In this previous study, a non-linear relationship was identified between accessibility and mode share and was best modelled as a quadratic relationship. The aim of the present study is to build upon the bivariate analysis done previously to confirm and to quantify the impacts of accessibility to jobs on public transport mode share among low- and higher-income groups in these Canadian metropolitan regions, while controlling for other determinants of public transport use. This study will add to the conversation of planning for equitable transport system through accessibility by focusing on the outputs of doing so in regions of various sizes.

2. LITERATURE REVIEW

Whether or not cities in North America are experiencing a public transport renaissance, one thing is for certain - factors that drive public transport use have been of great interest to researchers for some time. These factors can be divided into two major categories: those related to the personal characteristics of the traveler and their attitudes and those related to the built environment. Mode choice is highly dependent on personal characteristics such as income (*16*), unemployment rate (*17*) and proportion of recent immigrants (*18*). Moreover, to capture the combined effects of these highly influential socio-demographic variables, researchers have started using composite variables such as the social deprivation index (*19*). In addition, there is consensus among researchers in Canada, the U.S. and Australia that personal vehicle ownership is a major deterrent of public transport use (*20-22*).

In particular, income is a widely used indicator of social exclusion, transport disadvantage and social inequity (*23; 24*). With respect to mode choice, it has been shown that nationally, low-income groups exhibit higher public transport use than higher-income groups in the U.S. (*10*). In some cases, lower-income users have been termed captive users as they have no choice but to use public transport (*25*). On the other hand, a study that examined public transport use of low- and higher-wage workers in Toronto-Hamilton found that low-wage workers as a group had lower public transport mode share than higher-wage workers (*14*). However, this contradictory finding could be attributed to the methodology employed to segment workers into wage categories by job sector. The determinants of public transport use specific to lower-income populations has also been explored by researchers such as Mercado et al. (*23)* where they found that among low-income workers, immigration status, place of work, age, and employment status were significant predictors.

Aside from personal characteristics, aspects of land use and characteristics of the public transport system play a role in explaining mode share. Many researchers have found that even when self-selection is accounted for, density, diversity, and design of the urban milieu influence ridership (*26*). In particular, researchers (*27*) have found that higher densities support public transport use better than low-densities whereas Chen, Gong and Paaswell (*28)* found that in the case of the New York Metropolitan Region, employment density is more influential than residential density. Easy access to a public transport system also impacts mode choice, where being closer to public transport infrastructure, such as stations or stops, increases the odds of its use (*29*). Accessibility, as the ease of reaching destinations, is used to measure the ease of accessing opportunities using the transport system, thus internalizing aspects of both the built environment, namely density and location of opportunities, as well as availability and quality of transport infrastructure.

Accessibility has also been shown to influence public transport mode share positively (*30*). For example, researchers Owen and Levinson (*31)* found, using continuous accessibility to jobs, higher mode share is associated with higher average public transport accessibility in the

Minneapolis-Saint Paul area. Moniruzzaman and Páez (*32)* found, using data from Hamilton, Ontario that mode share increases as accessibility increases but the relationship is not linear due their use of logit regression models. With this in consideration, and based on the shift we have seen in the past years towards incorporating accessibility as an objective in transport plans (*33*), we identified a need to study accessibility and mode share from an equity perspective to enable a comparison between its impact on public transport mode share at different geographic scales and among different income groups.

Moreover, there have been empirical studies done specifically on the distributional impacts of existing transport systems (*34; 35*) as well as future projects (*36*) using accessibility. Some researchers sought to compare accessibility of low-income jobs for socially vulnerable residents against accessibility to all jobs for the entire population in eleven Canadian metropolitan regions (*37*). They identified that while there are geographic differences in 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 research done on the impact of accessibility on the journey to work (*38*). In particular, Canadian researchers (*39*), using data for Toronto-Hamilton, Montreal and Vancouver, found that the influence of accessibility to jobs as well as the presence of worker competition impacts commute duration and is stronger for low-income compared to higher-income groups. In addition, the distributional impact of accessibility on employment outcomes were examined for the Los Angeles area where researchers identified that accessibility to jobs by car positively affected the employment status of medium- to low-income groups but not for the lowest income group (*40*).

3. DATA AND METHODOLOGY

3.1 Study context

The geographic scope of the present study concerns eleven Canadian metropolitan regions extending from coast to coast as shown in Figure 1. These regions, shown in detail in Figure 2, were selected due to differences in city size, city structure, public transport system maturity, and other socio-demographic factors. As a result, we hope that their inclusion would offer some insight as to how the impact of accessibility differs between regions and among different income groups.

FIGURE 1 Context map of the eleven Canadian metropolitan areas being studied

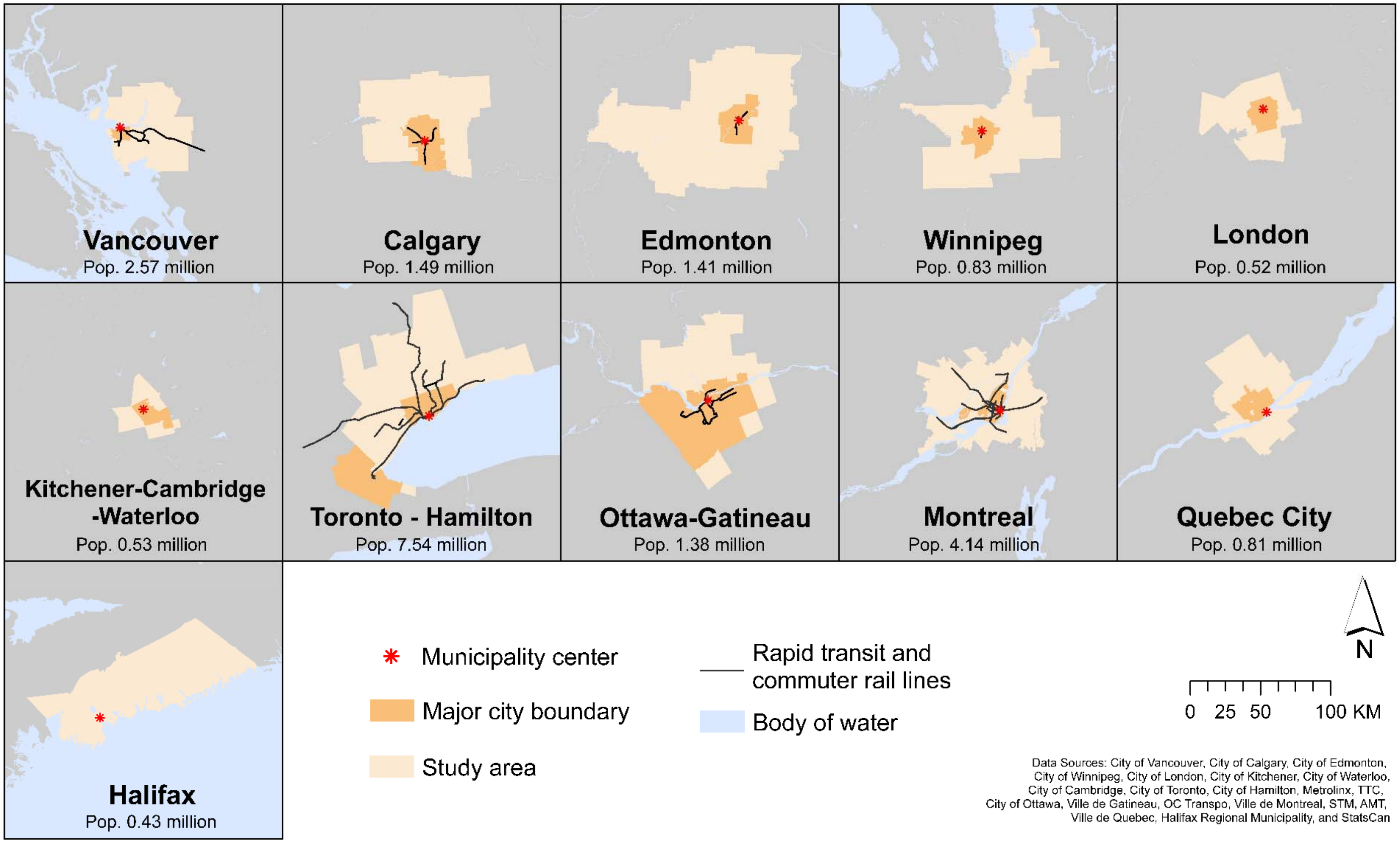

FIGURE 2 Detailed comparison of the eleven metropolitan areas

3.2 Accessibility and public transport mode share

Accessibility measures used in this study are cumulative-opportunity measures which evaluate the number of opportunities that can be reached from an origin point within a fixed cost, e.g.travel time. As such, the generation of such accessibility measures requires two data inputs: number of low- and higher-income jobs available in each census tract across the eleven regions and public transport travel time between census tracts within each region.

The number of jobs available in each census tract was obtained from the Statistics Canada 2016 Commuting Flow tables (*41*) which summarize number of work commuters, by mode of transport and income bracket, commuting between the their home census tract and the census tract of their place of work. The total number of workers working in a census tract is taken as a proxy for the total number of jobs, excluding unfilled positions which we do not have information about using the Flow tables. A limitation associated with the Commuting Flow tables is that the data has been suppressed for confidentiality purposes. As such, this could lead to some inconsistencies in the results especially where there are low numbers of commuters observed. As we do not know the distribution of the jobs within the census tracts, jobs were assumed to be located at the census tract centroids for which travel time information was also calculated for.

We 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 results for the low-income group rather than exploring the impacts across an entire income distribution. The low-income threshold is defined in this study as the bottom 30% of low paying jobs in each metropolitan region to reflect the local wage distribution. As the Commuting 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 apart from 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.

To compute public transport travel time between census tracts centroids within each metropolitan region, General Transit Feed Specification (GTFS) data was first obtained from all public transport agencies operating in each of the eleven regions. Then a joint network between the public transport network and the streets was created using the "Add GTFS to network dataset" toolbox in ArcGIS and a travel time matrix for an 8 a.m. departure on a Tuesday was generated using fastest route calculations. Public transport travel time includes access, egress, waiting, in-vehicle and transfer times as applicable. In this research we opted to calculate accessibility using one departure time and at the census tract level as the imposed errors from using this method are minor and value added from going into more detail by averaging multiple departures or using smaller geographic areas is minor (*42*) and would generally harm the transferability of the findings to practitioners.

Separate accessibility measures were generated in this study for the two income groups being studied in each metropolitan region. We chose to represent the number of jobs that are accessible by individuals in a census tract as a percentage of the total number of jobs that are available in the metropolitan region (i.e. proportional accessibility). This ensures that comparisons can be made between different metropolitan regions. Furthermore, we believe that the use of median travel times (as travel time thresholds) specific to each income group in each metropolitan area would further ensure a fair comparison and more realistically reflect the activity spheres and travel times for each group. In addition, the median as opposed to the average would minimize the effects of extreme travel times between census tracts in large regions such as Edmonton. Median travel time thresholds are presented in Table 1 and are rounded to the nearest 5-minute interval for use in accessibility measures.

Cumulative accessibility measures for the two income groups was calculated separately the jobs and median travel times specific to each group in each region. The measures are formulated as follows:

$$A_{jobs,i} = \frac{1}{\sum_{j=1}^{J} E_j} \sum_{j=1}^{J} E_j f(t_{ij}) \; and \; f(t_{ij}) = \begin{cases} 1 \; if \; t_{ij} \leq t_{median} \\ 0 \; if \; t_{ij} > t_{median} \end{cases} \quad (1)$$

where

$A_{jobs,i}$ = accessibility to jobs from census tract i;

$\sum_{j=1}^{J} E_j$ = total number of jobs in a metropolitan region;

E_j = number of jobs in census tract j;

$f(t_{ij})$ = a dichotomous function to determine if jobs in census tract j are reachable by census tract i;

t_{ij} = commute time by public transport at 8 a.m. between census tracts i and j; and

$t_{,median}$ = median commute time used as the travel time threshold.

Lastly, the dependent variable is the percentage of commuters leaving each census tract using public transport out of all commuters. This was computed for low- and higher-income commuters separately. Public transport mode share was obtained from the Commuting Flow tables mentioned previously where public transport includes bus, subway, elevated and light rail, streetcar, commuter train, and passenger ferry.

3.3 Model inputs and development

The regression model is formulated as follows:

$$PT_i = \beta_0 + \beta_1 Access_i + \beta_2 Access^2{}_i + \beta_3 Density_i + \beta_4 Age_i + \beta_5 HHstructure_i \quad (2)$$
$$+ \beta_6 Index_i + \beta_7 Station_i + \beta_8 Highway_i$$

where

PT = predicted public transport mode share of commuters leaving census tract i;

Access = accessibility to jobs by public transport of census tract i;

Access² = squared value of accessibility to jobs by public transport in census tract i;

Density = population density in census tract i;

HHstructure = average household structure in census tract i;

Index = decile ranking of census tract i in terms of social deprivation;

Station = network distance to the nearest rapid public transport station from centroid of census tract i;

Highway = network distance to the nearest highway ramp from centroid of census tract i; and

$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$ = parameters to be estimated.

Separate models for each income group in each metropolitan region are generated since different median travel times serve as thresholds to calculate accessibility. To capture the non-linear relationship between accessibility and mode share that we have observed in previous research (*15*), we have decided to model this non-linearity as a quadratic function between accessibility and mode share by generating a squared accessibility term (higher-order term) by taking the square of the existing proportional accessibility values (lower-order term).

The road network distance to the closest rapid public transport station (including Bus Rapid Transit stops as well as light, heavy and commuter rail stations) from the centroid of the origin census tract is used to control for the influence of higher quality transport infrastructure on mode share. We defined BRTs based on the presence of dedicated right-of-way and off-board fare payment systems. In addition, network proximity to the nearest highway ramp is also included as the presence of car-oriented infrastructure could impact public transport use negatively (*43*).

Moreover, socio-demographic variables at the origin census tracts, obtained from the 2016 Canadian Census, are also included in the regression models. These variables have been studied in previous studies as determinants of public transport use (*3*).We have also elected to use a social deprivation index (in the model) which combines normalized values of household income, unemployment rate, housing affordability, and recent immigration status which has been used previously in studies (*43*). The social deprivation index of each census tract within a metropolitan region is then divided into deciles and entered into the models, with one being least socially deprived to ten being most socially deprived. As we do not have information on the travel attitudes for each commuter, we were not able to control for this in this study.

Furthermore, while household vehicle ownership has been found to be influential on public transport use (*3*), this was not available at the census tract level at time of the study. As such, its inclusion in future studies of a similar nature may be beneficial. As well, early trials of the models included the network distance to the city centre as a variable to correct for the effects of spatial autocorrelation by controlling for similarities between census tracts at the same distance from the city centre. However, it was removed from the final model as it was found to be highly correlated with accessibility.

3.4 Summary statistics

The mean values for the input variables (including variables that make up the social deprivation index) and relevant summary statistics are presented in Table 1.

For the majority of the areas being studied, with the exception of London and Kitchener-Cambridge-Waterloo, both average and median commuting times by public transport are lower for low-income groups. Public transport mode share is nonetheless much higher for low-income groups across the country, as observed in past research (*10*). As expected, average mode share is highest in the three largest metropolitan regions with the most developed rapid public transport systems. However, the difference in mode share between other 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. This confirms that the presence of high-quality public transport infrastructure is not the sole predictor of public transport use. Interestingly, active modes are also used by a greater proportion of low-income commuters across all regions. However, when considering higher-income commuters in Halifax, Kitchener-Cambridge-Waterloo, and London, we observe that when averaged across each region, a greater proportion of commuters use active modes compared to public transport, which is indicative of either a lack of high-quality public transport infrastructure or dense city structures that facilitates the use of active modes.

Furthermore, across regions, with exceptions being Kitchener-Cambridge-Waterloo and London, average accessibility to low-income jobs is lower than average accessibility to higher-income jobs for each metropolitan region. This is in contrast to previous research (*37*) and illustrates the effect of segmenting the population into low- and higher-income groups as well as using time thresholds specific to each income group.

TABLE 1 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
PT (%)	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
Car (%)	75.7	62.4	74.0	59.9	68.5	58.0	75.1	58.1	80.9	71.9	86.6	73.4	79.7	67.2	91.1	74.6	90.1	71.3	74.2	63.4	79.9	65.3	82.3	66.7
Active (%)	6.6	11.5	5.0	10.6	8.1	12.5	7.9	12.7	5.6	8.7	3.8	8.3	10.2	14.8	5.3	11.1	5.5	12.7	8.8	12.6	9.4	15.6	6.4	10.5
Commute time (min)																								
Average	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 threshold	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	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 threshold	50	45	55	45	45	40	45	40	55	50	50	45	45	45	40	40	40	45	45	45	45	40	40	40
Accessibility																								
Total jobs (10,000)	604.9	269.9	205.4	88.1	122.9	52.2	68.9	31.5	39.0	19.6	36.3	18.8	12.6	5.5	16.1	6.6	13.6	6.3	39.2	21.3	27.6	9.9	24.3	10.1
Access (%)	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
Access (thous. jobs)	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																								
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	
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	
HH structure	2.6		2.8		2.3		2.7		2.7		2.6		2.3		2.6		2.4		2.4		2.1		2.5	
HH 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	
Unemployment (%)	7.5		7.8		7.7		5.8		9.5		8.9		7.6		6.5		7.6		7.4		4.9		6.6	
% of HHs 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	
% of recent immigrant (%)	5.1		4.9		4.5		5.6		6.1		5.7		2.2		2.6		2.3		2.8		1.8		6.1	
Distance to 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	
Distance to 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	
Distance to city centre (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	

[*] Kit-Cam-Wat stands for Kitchener-Cambridge-Waterloo region

4. RESULTS

The final model outputs are shown in Tables 2, 3 and 4 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 findings are explained in further detail. In terms of the model goodness-of-fit, a range of R^2 values is observed 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 for models segmented by income as well as by region size.

4.1 Accessibility to jobs by public transport

The lower-order term of percentage of jobs (*Access*) accessible by public transport is positively associated with mode share in most regions except for the higher-income groups in Halifax and Kitchener-Cambridge-Waterloo and the higher-order term of the same variable (*Access squared*) has a negative impact. This result indicates a relationship demonstrated by a concave parabola, where mode share increases in response to increasing accessibility at a non-constant rate up until the optimal accessibility value, where a further increase in accessibility has a negative effect on 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) to 7% for the low-income group in Toronto-Hamilton will result in a mode share improvement of 2.7 percentage points (an absolute increase of 2.7%, not a relative increase) compared to an improvement of 1.1 percentage points when accessibility is increased from 13% (one standard deviation above the mean) to 14% in the same region. Moreover, the optimal value for this model is reached when the percentage of jobs that are accessible is 18% (89^{th} percentile) where maximum public transport mode share is expected but any further increase in accessibility would cause the mode share to decrease. It is important to note that 18% may seem low, but this is three times greater than the mean value of 6% for the low-income Toronto-Hamilton model. The optimal values for the low-income models in Montreal and Vancouver are also much higher than the mean and occurs when accessibility is at the 87^{th} and 81^{th} percentiles respectively.

The lower-order accessibility term is statistically significant at 95% 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. The average value of the lower-order accessibility term for the low-income group 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 -0.004. In the higher-income models, the coefficients of the lower order term are also highest for these three regions with an average of 0.645 compared to the others with an average value of 0.148. This may suggest that the non-linear relationship as modelled by a quadratic relationship between accessibility and mode share is most profound in the largest metropolitan areas. In contrast, the quadratic relationship between accessibility to jobs by public transport and public transport mode share is not strongly observable for either income groups in Calgary, Halifax, Kitchener-Cambridge-Waterloo and Winnipeg as indicated by the insignificance of the two variables.

TABLE 2 Model results using accessibility as percentage of jobs accessible for 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																		
Access (%)	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
Access^2 (%^{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/km^2)	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
HHstructure	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
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		
R-squared value	0.757			0.738			0.739			0.781			0.702			0.649		

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

TABLE 3 Model results using accessibility as percentage of jobs accessible for 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																		
Access (%)	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
$Access^2$ ($\%^2$)	-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/km^2)	-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
HHstructure	-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
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		
R-squared value	0.497			0.668			0.674			0.710			0.432			0.641		

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

TABLE 4 Model results using accessibility as percentage of jobs accessible for 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																		
Access (%)	-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
Access² (%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/km²)	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
HHstructure	-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
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-squared 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												
Access (%)	0.28 ***	0.17	0.40	0.48 ***	0.16	0.80	0.06	-0.05	0.16	0.16	-0.07	0.39
Access² (%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/km²)	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
HHstructure	-2.91	-7.24	1.42	10.13 ***	2.77	17.49	-2.37 ***	-4.08	-0.66	-4.40 ***	-7.75	-1.06
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-squared value	0.740			0.643			0.762			0.750		

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

In addition, we observe that the coefficients for accessibility 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 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.

Furthermore, it is important to note that a one percent increase in job accessibility in Toronto-Hamilton is not equal to the same percent increase 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 equates to 600 jobs, which is unlikely to have 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 5), 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. For example, an increase in accessibility from a mean of 13,942 low-income jobs to 23,942 in London results in a 5.1 percentage point 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 in mode share.

TABLE 5 Model results using accessibility as number of jobs accessible for all metropolitan regions

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																		
Access (ten thousand)	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
Access^2 (ten thousand^2)	-0.001	-0.002	0.0003	-0.15 ***	-0.17	-0.14	-0.003 ***	-0.01	-0.001	-0.08 ***	-0.10	-0.06	-0.01 **	-0.01	-0.001	-0.29 ***	-0.36	-0.21

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																		
Access (ten thousand)	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
Access^2 (ten thousand^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

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																		
Access (ten thousand)	-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
Access^2 (ten thousand^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												
Access (ten thousand)	1.02 ***	0.61	1.44	4.87 ***	1.65	8.10	0.23	-0.20	0.66	1.61	-0.66	3.87
Access^2 (ten thousand^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

4.2 Other control variables

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 results from past research (*43*). It is clear that low-income individuals living in more socially deprived census tracts are more likely to use public transport rather than high-income individuals in a similarly socially deprived census tract.

As expected, as distance from a rapid rail station increases, public transport mode share is likely to decrease for both income groups (*44*). The relationship between network distance to the 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 negative for both income groups in Vancouver, Halifax and Quebec City, and would require further investigation.

5. 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 regression models using accessibility to jobs by public transport while accounting for other control variables to model public transport mode share for departing commuters at the census tract level. The results confirm the importance of planning for accessibility to impact mode share, particularly for the low-income group, while demonstrating discrepancies between metropolitan regions.

Firstly, we confirm that a greater proportion of people in the low-income group use public transport as their main commute mode in all study areas, similar to past research (*10*). Next, more socially deprived census tracts exhibit higher public transport use and shorter distances to rapid public transport stations positively influence mode share. Most importantly, we find that accessibility is a predictor of mode share as previous researchers have shown (*32*), 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 income does moderate the relationship between accessibility and mode share in that it has a higher predicting power of mode share for the low-income group than higher-income groups in the majority of the studied 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, increasing accessibility is not expected to lead to a substantial increase in use due the non-linear relationship observed between accessibility and mode share. However, since the percentage of jobs accessible in a census tract would have to be in at least the 80th percentile in these regions 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 this value. Moreover, for metropolitan regions where the quadratic relationship is not strongly observed and there is no optimal value, we can expect an increase in mode share for the low-income, and to a lesser extent, the higher-income groups with improved accessibility throughout the region.

With these findings in mind, policies that would greatly improve the accessibility for low-income groups would bring about a greater increase in public transport use. As a first step, ridership profiles can be created for the public transport network in a region to identify routes that are mostly frequently used by low-income commuters. These can be targeted for service improvements to improve accessibility and potentially result in more public transport use based on our findings. In addition, a return on public transport investments can be expected when they are aimed at improving accessibility in areas of low existing accessibility rather than highly accessible ones. Furthermore, the findings of our research can help policy-makers determine the approximate optimal accessibility value at which public transit use may be maximized based on the values of the input variables specific to a census tract and the results of the regression analysis in this study.

Further examination of the relationship between accessibility by active modes and public transport mode share is necessary to confirm our hypothesis that the decline in mode share at very high levels of accessibility is attributed to the uptake of walking and cycling. Doing so could also help explain the inconsistent results that were observed in the higher-income Halifax, Kitchener-Cambridge-Waterloo models. In addition, the effects of temporal variability of public transport on accessibility can be addressed in the future studies by using an average accessibility value to be entered in the models described in this study. As well, other regressions models may be employed to model public transport use such as a binomial regression model for the proportion of commuters that use public transport.

This study 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. Furthermore, while income is one indicator of socio-economic status, similar comparisons to what was done in this study can be made for groups in society based on other attributes of socio-economic status to reveal the travel preferences of these groups change with respect to accessibility. These analyses can offer new insight to help practitioners approach transport planning in a more equitable manner.

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AUTHOR CONTRIBUTION STATEMENT

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

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