Accessibility and the journey to work through the lens of equity

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ABSTRACT
Inequality in transport provision is an area of growing concern among transport professionals, as it results in low-income individuals travelling at lower speeds while covering smaller distances. Accessibility, the ease of reaching destinations, may hold the key in correcting these inequalities through providing a means to evaluate land use and transport interventions. This article examines the relationship between accessibility and commute duration for low-income individuals compared to the higher-income, in three major Canadian metropolitan regions, Toronto, Montreal, and Vancouver using separate multilevel mixed effects statistical models for car and public transport commuters. 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 show that the impacts of accessibility on commute duration are present and in many cases stronger for low-income individuals 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. 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 bridge the inequality gap that exists in commuting behavior.

Keywords: accessibility, equity, journey to work, commute duration

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 (Carroll, 1949; Kain, 1962), 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 (Ericksen, 1977; Quarmby, 1967) such as the evolution of commute times and distances (Wales, 1978). 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 (Banister, 2012). Some researchers in the 1990s (Cervero et al., 1999; Levinson, 1998) 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 (Banister, 2018). The conclusion from contemporary research in this area is that as the result of these inequalities, the less well-off groups of society are travelling slower and covering smaller distances (Banister, 2018). On the other hand, transport researchers have also recognized the need for a more equitable way of planning and policymaking (Fan et al., 2012; Golub and Martens, 2014; Levinson, 2002; Manaugh et al., 2015; Martens et al., 2012; Pereira et al., 2016); 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 (El-Geneidy et al., 2016; Manaugh and El-Geneidy, 2012), the ease of reaching destinations (Levinson and Krizek, 2007), to evaluate the distribution of opportunities in a region (Foth et al., 2013) 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 have 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, 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. 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 (Pooley and Turnbull, 1999). 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 (Gordon et al., 1991). Some researchers sought to explain this phenomenon from the perspective of mutual co-location between jobs and housing (a proxy for the labor market) (Giuliano and Small, 1993; Levinson, 1998; Levinson and Kumar, 1994). Levinson (1998), 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 (Hansen, 1959). Geurs and van Wee (2004) 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 constraint function (time, distance or cost) (Geurs and van Wee, 2004). 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 (El-Geneidy and Levinson, 2006). In measuring accessibility impacts on the journey to work, there is a need to account for the effect of competition (Shen, 1998). Previous research has incorporated the effects of competition by including accessibility to workers and accessibility to jobs at both ends of the trip (Levinson, 1998). 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 (Grengs, 2010; Kawabata and Shen, 2007).

The result from Levinson’s (1998) research answers the question posited by Giuliano and Small (1993): 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 be valid for the region as a whole, the same results may not hold true for the more disadvantaged groups as the housing pattern may deviate substantially from the status quo.

The term spatial mismatch was introduced by Kain (1968) 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 et al. (1989) found that low-income American automobile commuters did not have higher commute times. Similarly, Canadian researchers found that in Toronto (Foth et al., 2013), the most socially disadvantaged areas have shorter public transport commute times than the general population. In contrast, Shen (2000) 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 (2018) 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.

3. DATA & METHDOLOGY

3.1 Accessibility and Travel Time

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 includes the three largest Canadian metropolitan regions in Canada (Toronto, Montreal and Vancouver) to uncover potential geographical differences of the impacts of accessibility on the journey to work. Context maps comparing the three cities are shown in Figure 1. 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 (Statistics Canada, 2016b, c, d) at the census tract level of analysis. The total number of jobs in a census tract sums the total number of commuters arriving to work in that census tract, by individual income group. The total number of workers residing in a census tract sums those leaving a census tract.

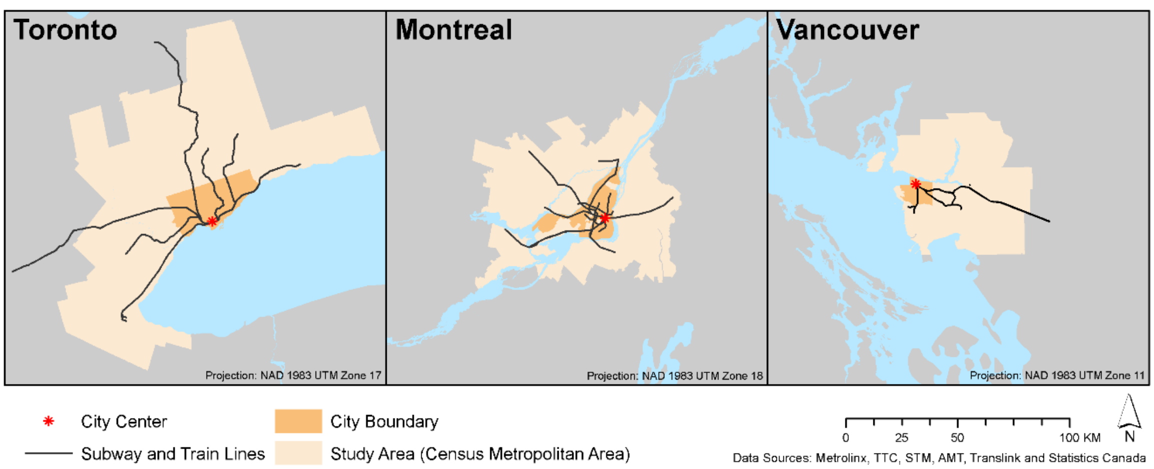

FIGURE 1: Context map of the three cities under consideration

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 (Statistics Canada, 2016e). Thus, the total low-income threshold for a one-person household is calculated to be \$25,516 in 2015 (Statistics Canada, 2017). 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 region, \$17.12 (Dinca-

Panaitescu et al., 2017) averaged for the Durham, Hamilton and Metro Toronto regions, and Vancouver at \$20.68 (Ivanova and Klein, 2015). These hourly wages translate to a total personal income of \$35,600 in Toronto 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 to obtain a congested car travel time matrix at 8 AM on a Tuesday in all three regions. At the same time, the public transport travel time matrix is generated in ArcGIS using the 'Add GTFS to a network dataset' toolbox. The General Transit Feed Specification (GTFS) data is obtained from all public transport agencies in each of the three cities and the travel time matrix is calculated for departing home at 8 AM on a Tuesday using the fastest route calculations. The public transport travel time includes access/egress, waiting, in-vehicle, and transfer times, when 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.

Proportional accessibility at each trip end and by income group is measured using the equations below:

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

$$A_{iELIm} = \frac{1}{\sum_{j=1}^{J} E_{LI,j}} \sum_{j=1}^{J} E_{LI,j} f(t_{ijm}) \text{ and } f(t_{ijm}) = \begin{cases} 1 \text{ if } t_{ijm} \leq t_{threshold,m} \\ 0 \text{ if } t_{ijm} > t_{threshold,m} \end{cases} \quad (2)$$

$$A_{iRHm} = \frac{1}{\sum_{j=1}^{J} R_j} \sum_{j=1}^{J} R_{H,j} f(t_{ijm}) \text{ and } f(t_{ijm}) = \begin{cases} 1 \text{ if } t_{ijm} \leq t_{threshold,m} \\ 0 \text{ if } t_{ijm} > t_{threshold,m} \end{cases} \quad (3)$$

$$A_{iRLIm} = \frac{1}{\sum_{j=1}^{J} R_{LI,j}} \sum_{j=1}^{J} R_{LI,j} f(t_{ijm}) \text{ and } f(t_{ijm}) = \begin{cases} 1 \text{ if } t_{ijm} \leq t_{threshold,m} \\ 0 \text{ if } t_{ijm} > t_{threshold,m} \end{cases} \quad (4)$$

where:

A_{iEHm} = accessibility to higher-income jobs from census tract i by mode m
A_{iELIm} = accessibility to low-income jobs from census tract i by mode m
A_{iRHm} = higher-income workers that are able to access census tract i by mode m = accessibility to workers in census tract i

A_{iRLIm} = low-income workers that are able to access census tract i by mode m = accessibility to workers in census tract i
E_j = number of jobs in census tract j
R_j = number of workers in census tract j
t_{ijm} = commute time between census tracts i and j by mode m
$t_{threshold, m}$ = average commute time by mode m
$\sum_{j=1}^{J} E_{H,j}$ = total number of higher-income jobs in the region
$\sum_{j=1}^{J} E_{LI,j}$ = total number of low-income jobs in the region
$\sum_{j=1}^{J} R_{H,j}$ = total number of higher-income workers in the region
$\sum_{j=1}^{J} R_{LI,j}$ = total number of low-income workers in the region

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) 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 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 (Foth et al., 2013). Socio-demographic variables are obtained from the Census Profile Tables from the 2016 Canada Census (Statistics Canada, 2016a).

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.

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 (Foth et al., 2013) but upon examination of the average commute speeds, we can see that the low-income group is also travelling slower than the general population by car and public transport where the difference is more pronounced for public transport users. This finding is consistent with the conclusions from Shen (2000) and Banister (2018) 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				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
People 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 transit 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				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
People 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 transit 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

3.3 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 certain models experienced difficulty with convergence. 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 variables in all models to be consistent.

4. RESULTS AND DISCUSSION

Tables 3 and 4 summarize the results of the regression models by the two different modes and by income group. 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 (Levinson, 1998) 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 shows negative relation with 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, removing this variable from the model did not affect other coefficients, demonstrating the stability of the model. The variable was, therefore, kept in the results as it is one of the main variables of interest and for comparative purposes (Levinson, 1998).

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
People 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 transit 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	-0.212	***	-0.271	-0.154	-0.187	***	-0.271	-0.102
Dummy = 1 if in Vancouver	-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-squared 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<0.05 ** p<0.01 *** p<0.001

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
People 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 transit 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	0.225	***	0.188	0.262	0.202	***	0.147	0.256
Dummy = 1 if in Vancouver	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-squared 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<0.05   ** p<0.01   *** p<0.001

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 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.

For the public transport models, an increase of one percentage point 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 (Hu and Giuliano, 2017), 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 (Coffey and Shearmur, 2002) and providing frequent and reliable public transport services to these concentrations of low-income jobs.

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. 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 region is both larger and more spread out than both Montreal and Vancouver (which can be seen in Figure 1), 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 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, illustrated in Figure 1, 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 distance to heavy rail public transit stations and commute duration for car commuters.

Table 5: Summary table 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 transit 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	*

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 Tables 1 and 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 Tables 6 and 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	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	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 (8).

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 (Banister, 2018; Shen, 2000). 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 transit 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 (Foth et al., 2013). Multiple measures of the distribution of access may be tested across many different cities, as in Palmateer and Levinson (2018). 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.

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