Accessibility, equity, and the journey to work

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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 commuting duration for low-income individuals, compared to the general population, in three major Canadian metropolitan regions, Toronto, Montreal, and Vancouver using multilevel mixed effects statistical models for car and public transport commuters separately. 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 commuting duration are present and stronger for low-income individuals than for the general population, and the differences in impact are more visible for public transport commuters. 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

1. INTRODUCTION

Issues relating to the journey to work and associated congestion and inequalities have been present since the Roman empire (Levinson & Krizek, 2007, p. 1). Research on that topic flourished in the mid-20th century (Carroll, 1949; Kain, 1962) at the onset of motorization and suburbanization. Since then, transport researchers have monitored this field of study closely to uncover observable trends in people's commutes (Ericksen, 1977; Quarmby, 1967) including their commuting times (Wales, 1978). Researchers have also been noticing major differences over time in commuting 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 (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 can stabilize commuting 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. Presently, transport professionals are beginning to take notice of inequalities in the form 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, Guthrie, & Levinson, 2012; Golub & Martens, 2014; Levinson, 2002; Manaugh, Badami, & El-Geneidy, 2015; Martens, Golub, & Robinson, 2012; Pereira, Schwanen, & Banister, 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 & El-Geneidy, 2012), the ease of reaching destinations (Levinson & Krizek, 2007), to evaluate the distribution of opportunities in a region (Foth, Manaugh, & El-Geneidy, 2013) and especially for low-income groups.

Our research aims to connect these two streams of research, journey to work and equity planning, through accessibility analysis. In the process, we extend the former story to the low-income group and offer a new perspective for the latter to consider the impact of accessibility on commuting 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 the general population with respect to commuting 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 corrected and the appropriate policy actions that would facilitate this change.

2. LITERATURE REVIEW

Historically, prior to the popularization and commercialization of the private vehicle and mass transit, the commute to work was carried out on foot, resulting in considerable shorter commute distances (Pooley & Turnbull, 1999). In fact, within the century following 1890, the mean one-way commuting trip distance in Britain increased four-fold (Pooley & Turnbull, 1999). However, in uncovering this trend in commuting distances, the researchers found that commuting times have not increased at the same rate, as only a doubling of time was observed in the same period (Pooley & 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, Richardson, & Jun, 1991). Some researchers sought to explain this phenomenon from the perspective of mutual co-location between jobs and housing (proxy for the labor market) (Giuliano & Small, 1993; Levinson, 1998; Levinson & Kumar, 1994). Levinson (1998) used accessibility measures to quantify the jobs and housing balance and in assessing their impact on commuting times, he sought to determine whether mutual co-location is the underlying reason for the relatively steadying commuting times observed in Washington D.C.

Accessibility measures 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 & 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 & Levinson, 2006). In measuring accessibility impacts on the journey to work, there is a need to account for the effect of competition (Shen, 1998). Some researchers incorporate 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.

The term spatial mismatch was introduced by Kain (1968) in 1968; he argues that due to segregation of the housing market, disadvantaged groups who live in the inner city and lack access to private vehicles are at risk of unemployment as jobs shift towards the suburbs. Researchers in the realm of the journey to work have been evaluating this hypothesis to determine whether certain aspects of the commute are different for more disadvantaged groups in society, such as those belonging to the low-income or minorities (Gordon, Kumar, & Richardson, 1989; Mercado, Páez, Farber, Roorda, & Morency, 2012; Shen, 2000). As such, researchers ask whether commuting times are higher for these groups than the whole region due to spatial mismatch.

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. The results tap into the concept of modal mismatch (Grengs, 2010) which may help to explain differences in commuting times between income groups where spatial mismatch cannot be observed. More recently, transport researchers note the inequalities that exist in transport (Juan Pablo Bocarejo & Daniel Ricardo Oviedo, 2012; Lucas, 2004, 2012). Less well-off groups in the UK are travelling slower and covering smaller space as a result of the use of slower modes of transport such as buses, (2018) echoing the results from Shen (2000) but going one step further to identify the type of public transport being used by different income groups. Building on previous research, this study evaluates the impacts of accessibility on commuting times in three Canadian cities, from an equity perspective.

3. DATA & METHDOLOGY

3.1 Accessibility and Travel Time

The first step in determining the impact of accessibility on commuting 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. 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, 2016c, 2016d) 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 personal income group. The total number of workers residing in a census tract sums those leaving a census tract.

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 & 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.

To calculate travel time by car, we use Google 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 all and low-income jobs and workers are calculated for car and public transport commuters separately. Here, accessibility are calculated as percentage of the total number of jobs or workers in the region. In other words, the number of jobs or workers that can be reached within a specific travel time threshold 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 for all individuals and for the low-income group.

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

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

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

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

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

where:

A_{iEm} = accessibility to all-income jobs from census tract i by mode m
A_{iELIm} = accessibility to low-income jobs from census tract i by mode m
A_{iRm} = all-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
$\sum_{j=1}^{J} E_j$ = total number of jobs in the region
$\sum_{j=1}^{J} E_{LI,j}$ = total number of low-income jobs in the region
$\sum_{j=1}^{J} R_j$ = total number of 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: all-income car commuters (C_{AI}), low-income car commuters (C_{LI}), all-income public transport commuters (T_{AI}), 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 commuting 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 commuting 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 the 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 commuting times in the study area for the entire population. The average car commuting time is 33.62 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 commuting times and distances. Similar results are found for public transport commuters except for commuters in Toronto, where the average low-income commuting time is longer by five minutes. This general trend (with the exception of Toronto) corroborates previous research (Foth et al., 2013) but upon examination of the average commuting speeds, we can see that the low-income group is also travelling slower than the general population by car and public transport. This finding comports with Shen (2000) and Banister (2018).

TABLE 1: Summary Statistics - Car Commuters

	All Regions				Toronto				Montreal				Vancouver			
	All Income		Low Income		All Income		Low Income		All Income		Low Income		All Income		Low Income	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Average commuting time (minutes)	33.62	22.23	28.09	20.37	35.30	23.70	29.38	21.56	32.16	20.23	26.86	18.72	31.26	20.61	26.53	19.32
Average commuting distance (km)	17.25	14.48	14.06	12.79	18.80	16.06	15.16	14.08	16.24	12.83	13.35	11.62	14.52	11.46	12.14	10.28
Average commuting speed (km/h)	28.66	13.68	27.26	13.50	29.70	14.35	27.96	13.89	28.47	14.19	27.25	14.48	26.04	10.05	25.30	10.03
Accessibility Measures																
Jobs in 30 minutes @ origin (%)	10.28	8.05	10.57	7.51	7.84	5.51	8.20	5.35	10.22	7.75	10.60	7.35	17.23	10.21	17.21	8.89
Workers in 30 minutes @ origin (%)	11.34	6.57	11.81	7.13	8.23	3.39	8.66	3.91	11.89	5.97	12.04	6.52	19.20	7.40	20.34	8.03
Jobs in 30 minutes @ destination (%)	14.42	9.31	13.32	8.42	11.48	6.71	10.72	6.28	16.35	10.47	14.65	9.38	19.58	10.48	18.43	9.11
Workers in 30minutes @ destination (%)	12.02	6.54	12.40	7.11	9.04	4.24	9.39	4.94	12.69	5.90	13.16	6.69	19.30	6.83	19.63	7.45
Control Variables																
Median household income (thousand $)	84.31	26.24	81.22	25.08	91.21	27.06	88.16	25.92	74.32	24.56	70.69	22.61	81.11	20.05	79.36	19.47
Average age	40.01	4.02	39.98	3.97	39.61	4.13	39.56	4.09	40.29	4.01	40.34	3.95	40.68	3.54	40.54	3.49
Average household structure	2.77	0.55	2.80	0.57	2.96	0.59	3.00	0.59	2.48	0.36	2.46	0.35	2.72	0.51	2.78	0.51
Unemployment rate (%)	6.95	2.28	7.22	2.40	7.44	2.15	7.69	2.23	6.87	2.60	7.21	2.79	5.71	1.43	5.88	1.48
People spending >30% of income on housing (%)	26.80	9.46	27.45	9.51	29.39	9.08	30.18	9.15	20.64	8.16	21.45	8.31	29.50	7.70	29.81	7.67
Immigrants (%)	34.50	18.65	35.96	19.39	40.99	17.05	42.97	17.42	19.92	15.20	20.84	16.21	39.87	14.34	41.63	14.69
People with high school degree as highest education level (%)	22.33	6.09	23.04	5.89	23.19	6.08	23.95	5.84	18.99	4.43	19.61	4.16	25.36	6.05	26.25	5.80
Network distance to closest heavy rail public transport station (km)	6.15	6.56	6.12	6.55	5.83	6.27	5.81	6.17	6.38	6.94	6.44	7.20	6.66	6.67	6.43	6.43
Network distance to closest highway on ramp (km)	3.93	4.03	3.87	3.98	3.97	4.71	3.92	4.70	3.17	2.42	3.18	2.48	5.05	3.75	4.90	3.56
Network distance to city center (km)	30.36	17.77	30.55	17.32	36.44	19.14	36.66	18.44	23.91	13.12	23.97	13.27	23.71	13.82	24.36	13.37

TABLE 2: Summary Statistics – Public Transport Commuters

	All Regions				**Toronto**				**Montreal**				**Vancouver**			
	All Income		Low Income		All Income		Low Income		All Income		Low Income		All Income		Low Income	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Average commuting time (minutes)	48.90	32.13	48.54	28.44	46.19	34.87	51.40	28.48	49.54	32.38	44.94	28.03	48.82	30.53	46.95	28.22
Average commuting distance (km)	14.00	12.42	12.76	11.14	15.08	20.61	14.03	12.69	13.90	10.82	11.11	88.66	13.77	10.73	12.13	96.28
Average commuting speed (km/h)	15.66	7.30	14.20	6.72	14.53	9.08	14.28	6.87	15.81	6.64	13.89	6.19	15.82	7.57	14.47	7.10
Accessibility Measures																
Jobs in 45 minutes @ origin (%)	22.65	16.28	15.64	13.61	19.03	8.98	8.96	7.24	22.03	17.11	21.47	15.07	25.10	16.59	23.34	15.14
Workers in 45 minutes @ origin (%)	15.67	11.01	13.04	10.54	11.59	5.63	7.71	4.76	14.14	10.81	16.97	11.94	19.85	11.62	20.28	11.67
Jobs in 45 minutes @ destination (%)	33.26	16.33	20.38	15.49	21.65	8.86	12.16	8.48	34.61	14.85	27.40	15.24	35.34	18.94	30.07	18.24
Workers in 45 minutes @ destination (%)	24.06	12.66	16.47	12.99	13.88	5.47	9.20	5.77	24.69	11.63	23.10	13.84	26.83	14.33	24.39	14.45
Control Variables																
Median household income (thousand $)	65.44	21.64	67.00	23.33	71.77	22.53	72.12	24.98	60.80	22.22	56.30	19.92	71.02	18.08	70.66	17.83
Average age	40.20	3.68	40.10	3.60	38.37	3.26	39.81	3.63	40.21	3.95	40.10	3.83	40.88	3.08	40.82	3.02
Average household structure	2.31	0.49	2.53	0.58	2.04	0.48	2.69	0.61	2.26	0.39	2.24	0.38	2.50	0.56	2.56	0.56
Unemployment rate (%)	7.45	2.79	8.18	2.75	7.21	2.44	8.53	2.44	8.38	3.06	9.01	3.15	5.94	1.40	6.03	1.42
People spending >30% of income on housing (%)	30.21	9.95	32.82	9.23	37.57	10.46	35.32	8.87	26.80	9.56	28.49	9.21	33.30	7.65	33.26	7.59
Immigrants (%)	33.84	15.39	41.93	16.17	31.53	9.48	47.30	14.69	28.70	15.02	31.45	15.35	43.53	13.05	44.67	12.95
People with high school degree as highest education level (%)	19.14	6.27	21.31	6.38	17.12	7.03	22.50	6.36	17.21	4.99	17.71	4.99	23.22	5.98	23.88	5.96
Network distance to closest heavy rail public transport station (km)	3.14	4.23	3.05	3.44	2.55	3.50	3.06	2.66	2.94	4.00	2.57	3.52	3.71	4.76	3.75	4.67
Network distance to closest highway on ramp (km)	3.05	2.37	2.92	2.13	2.16	1.96	2.71	1.90	2.43	1.58	2.33	1.49	4.45	2.95	4.33	2.80
Network distance to city center (km)	14.03	11.60	18.00	14.00	12.72	19.60	22.24	16.31	13.39	9.14	12.49	8.36	15.61	11.13	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 (commuting 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 all-income and low-income commuters.

After duplication, the sample size for each model exceeds 500,000 observations, reaching 3.5 million for the car commuters. It is expected that using this large sample size in modeling would lead to a bias in the statistical significance of the variables and generation of confidence intervals that do not represent the full sample. To mitigate these effects, a bootstrap technique was used to select 10,000 observations from each dataset (Montreal, Toronto and Vancouver) and the multilevel mixed effect model was then applied 100 times for each model. The bootstrap technique selects a random sample of 10,000 observations and conducts the statistical model on that sample in the first round, 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 until the 100th iteration. 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 the all-income public transport commuters (T_{AI}) model 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. First of all, our results corroborate the hypotheses of Levinson (Levinson, 1998) on the impact of accessibility on commuting times for all and 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 impact on it. Conversely, accessibility to workers at the origin is positively associated with commute times and has a negative association at the destination.

The T_{AI} model shows some inconsistencies as accessibility to workers at the origin shows negative impact on 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)

	All income (C_{AI})				Low Income (C_{LI})			
	Coefficient		95% confidence interval		Coefficient		95% confidence interval	
Accessibility Measures								
Jobs in 30 minutes @ origin (%)	-0.025	***	-0.029	-0.022	-0.030	***	-0.034	-0.026
Workers in 30 minutes @ origin (%)	0.018	***	0.014	0.022	0.022	***	0.017	0.027
Jobs in 30 minutes @ destination (%)	0.044	***	0.042	0.046	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	-0.014	***	-0.019	-0.008	-0.015	***	-0.022	-0.008
Average household structure	-0.003		-0.080	0.073	-0.017		-0.099	0.065
Unemployment rate (%)	-0.003		-0.015	0.008	0.002		-0.009	0.013
People spending >30% of income on housing (%)	-0.002		-0.005	0.002	-0.001		-0.005	0.003
Immigrants (%)	0.0005		-0.002	0.003	0.002	*	0.000	0.005
People with high school degree as highest level of education (%)	-0.005	*	-0.010	0.000	-0.003		-0.009	0.002
Network distance to closest heavy rail public transport station (km)	-0.002		-0.007	0.003	-0.002		-0.006	0.002
Network distance to closest highway on ramp (km)	0.013	***	0.007	0.020	0.010	**	0.003	0.017
Network distance to city center (km)	-0.001		-0.002	0.001	-0.001		-0.003	0.001
Dummy = 1 if in Montreal	-0.264	***	-0.343	-0.186	-0.176	***	-0.263	-0.089
Dummy = 1 if in Vancouver	-0.227	***	-0.319	-0.134	-0.239	***	-0.325	-0.153
Constant	3.808		3.665	3.951	3.527		3.322	3.733
Number of observations	3,189,945				1,224,210			
Log likelihood | Intraclass correlation	-3136092.4 | 0.045				-1631259.4 | 0.076			
Akaike's information criterion | Bayesian information criterion	6272223 | 6272465				3262557 | 3262785			
Snijders/Bosker R-squared Level 1 | Level 2	0.139 | 0.335				0.114 | 0.265			
Random effects parameters @ home census tract	Estimate	Std. Err.	95% confidence interval		Estimate	Std. Err.	95% confidence interval	
Standard deviation of level-two errors	0.183	0.003	0.178	0.188	0.261	0.004	0.254	0.269
Standard deviation of level-one errors (residuals)	0.847	0.0004	0.846	0.847	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)

	All income (T_{AI})				Low Income (T_{LI})			
	Coefficient		95% confidence interval		Coefficient		95% confidence interval	
Accessibility Measures								
Jobs in 45 minutes @ origin (%)	-0.010	***	-0.012	-0.007	-0.021	***	-0.024	-0.017
Workers in 45 minutes @ origin (%)	-0.0003		-0.004	0.003	0.009	***	0.005	0.013
Jobs in 45 minutes @ destination (%)	0.006	***	0.004	0.009	0.021	***	0.020	0.021
Workers in 45 minutes @ destination (%)	-0.012	***	-0.015	-0.008	-0.027	***	-0.027	-0.026
Control Variables								
Median household income (thousand $)	-0.001		-0.002	0.001	0.0003		-0.001	0.001
Average age	-0.008	***	-0.012	-0.004	-0.008	***	-0.012	-0.004
Average household structure	0.054		-0.017	0.126	0.072	**	0.019	0.124
Unemployment rate (%)	-0.014	***	-0.021	-0.007	-0.010	**	-0.016	-0.004
People spending >30% of income on housing (%)	-0.004	*	-0.007	-0.001	-0.003	*	-0.005	-0.001
Immigrants (%)	0.001		0.000	0.003	0.003	***	0.001	0.004
People with high school degree as highest level of education (%)	-0.004		-0.008	0.000	-0.001		-0.004	0.002
Network distance to closest heavy rail public transport station (km)	0.021	***	0.016	0.026	0.017	***	0.014	0.020
Network distance to closest highway on ramp (km)	0.019	***	0.012	0.027	0.024	***	0.019	0.028
Network distance to city center (km)	0.013	***	0.011	0.015	0.003	***	0.002	0.004
Dummy = 1 if in Montreal	0.210	***	0.148	0.272	0.216	***	0.171	0.261
Dummy = 1 if in Vancouver	0.078	*	0.009	0.146	0.050	*	0.008	0.092
Constant	4.018		3.785	4.250	3.879		3.628	4.129
Number of observations	607,999				570,275			
Log likelihood | Intraclass correlation	-488208.9 | 0.144				-547704 | 0.192			
Akaike's information criterion | Bayesian information criterion	976455.8 | 976670.9				1095446 | 1095660			
Snijders/Bosker R-squared Level 1 | Level 2	0.404 | 0.818				0.195 | 0.531			
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	0.221	0.004	0.212	0.229	0.305	0.005	0.296	0.314
Standard deviation of level-one errors (residuals)	0.537	0.000	0.536	0.538	0.627	0.001	0.626	0.628

* p<0.05 ** p<0.01 *** p<0.001

It is clear that for both car and public transport commuters, the impact of accessibility, no matter the direction, is higher for low-income groups. The difference in impact is more visible for public transport commuters: the coefficients of accessibility measures associated with the T_{AI} model (excluding the one that is not significant) differ statistically from the coefficients of T_{LI} model (no overlap between the confidence intervals). A high accessibility to jobs by public transport at the origin is expected to reduce public transport commute time by two percent for low-income commuters compared to one percent for all commuters. At the destination, the decrease in commute time by public transport due to higher accessibility to workers for low-income individuals is 1.5 percent more than for all-income groups. 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 all-income model. For car commuters, there are overlaps in the confidence intervals for three of the accessibility coefficients (jobs and workers at origin; workers at destination), which does not suggest a statistically significant difference. Yet, the coefficients of accessibility to jobs at the destination are statistically different. Therefore, we can be more certain in saying that the difference in impact between the two models is greater for this particular measure. Put simply, low-income car commuters working at places with high accessibility to jobs will increase their commute times more than the general population.

To mitigate the more intensive effects of competitors for low-income individuals both for car and public transport commuters, a mix of low-income and other-income workers (i.e. housing) at the origin and jobs at the destination would decrease commute times for low-income workers, thereby decreasing the observed inequality in commute times. 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 & Giuliano, 2017). A different approach to reducing commuting times for low-income groups is to improve accessibility to low-income jobs at the origin and to workers at the destination by a mix of land use, to bring low-income jobs closer to low-income workers, or vice versa. Improving public transport services between low-income workers and low-income jobs can also increase accessibility in that sense. 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 & Shearmur, 2002) and providing frequent and reliable public transport services to these low-income job concentrations.

Regarding other socio-demographic variables in the models, the average age of the home census tract is significant in all models and is associated with shorter commute times, which can be related to life stages and career progression. Obviously, cities cannot now construct old homes, but they can preserve the existing affordable housing stock, which tend to be more centrally located in areas with higher than average job access. Average household size is only significant in the T_{LI} model and exhibits a positive impact on public transport commute time. The significance of this variable is more visible for low-income public transport commuters: as the number of people in a household increase by one, commute time is predicted to increase by 7.2 percent. Low-income households with more children are more likely pushed to the suburbs in areas with poor public transport service (Cooke & Denton, 2015).

In the car models, the significant variable related to the availability of transport infrastructure is proximity to highway on ramp. As the distance to highway on-ramp increases by one kilometer, car commute time is expected to increase by 1.3 percent for all-income and one percent for the low-income. 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. Surprisingly, this variable is also statistically significant in the public transport models. In the public transport models, proximity to rail stations is also 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 only 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.

Looking now at the dummy variables for the metropolitan regions, we see that, for car commuters, being in Montreal decreases commute time by 17.6 percent for the low-income and by 26.4 percent for all-income compared to being in Toronto. Being in Vancouver reduces commute time by about a quarter for both groups. The reason for this may be attributed to the different city structures between the three cities. Also, since the Toronto region is both large and more spread out than both Montreal and Vancouver, this could mean higher average commute times by car. In contrast, Montreal public transport commuters experience a 21 percent increase in commute time compared to Toronto commuters for both income groups. This increase is less than ten percent in Vancouver. This seems to suggest a faster and well connected public transport network in Toronto compared to Montreal and Vancouver.

5. CONCLUSION

In this research, we introduce a new dimension of equity to the existing body of research on the journey to work and accessibility. This study contributes to a better understanding of whether accessibility impacts the low-income group differently than the general population. Equity is framed in this research through the principle of vertical equity where a fair distribution is present where more is allocated to the most disadvantaged as they stand to benefit the most. For transport professionals interested in developing long-term plans for cities in an equitable way, our results offer some potential policy interventions that can help them realize these goals through planning for accessibility to low-wage jobs. Higher accessibility to jobs at the home and higher accessibility to workers at the workplace have a greater effect on low-income public transport commuting times than the overall population.

Future research can extend 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 & 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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