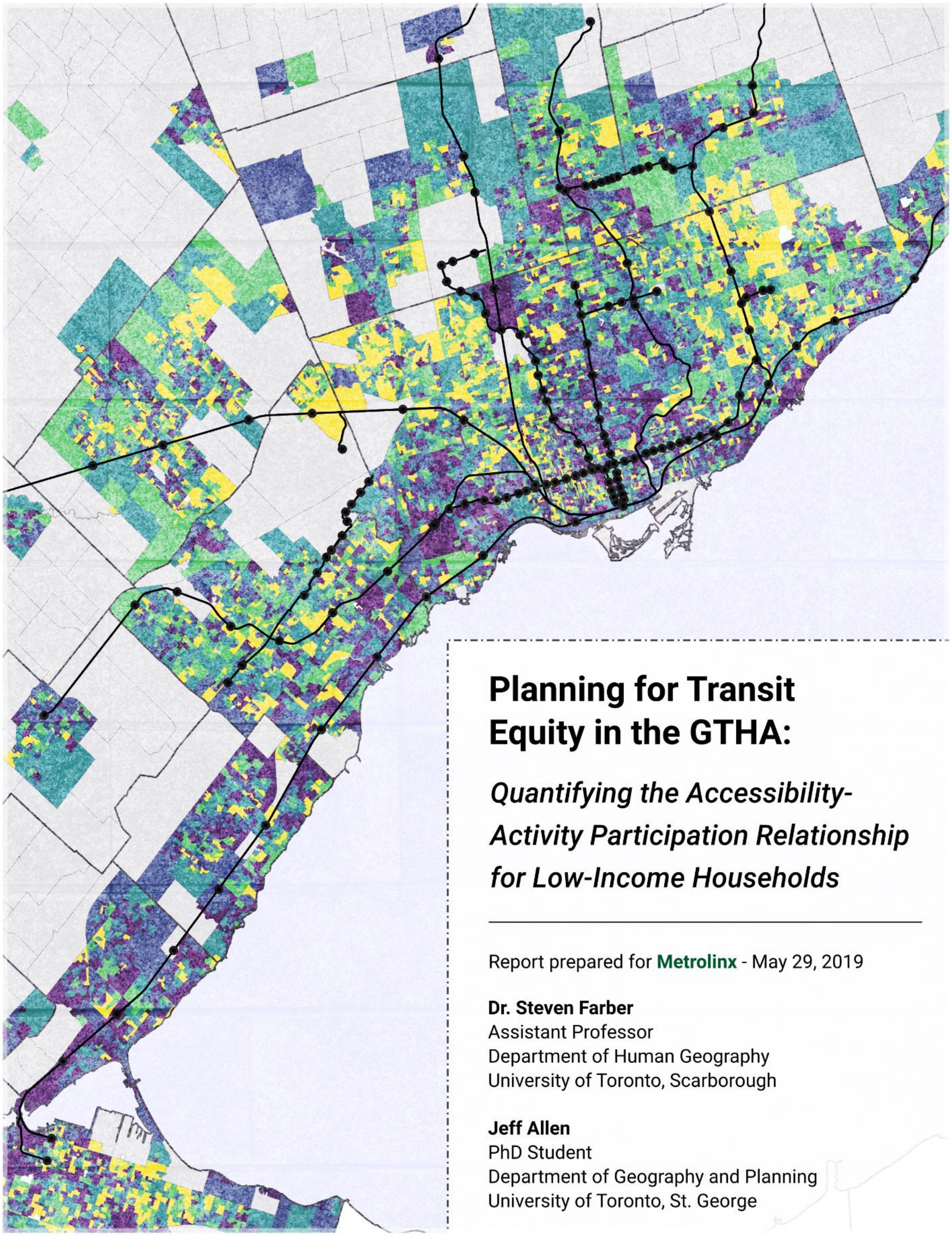

# Planning for Transit Equity in the GTHA:

## *Quantifying the Accessibility-Activity Participation Relationship for Low-Income Households*

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## Executive Summary

Across Canada, transportation agencies address social equity concerns in a plethora of diverse ways. However, there is little consensus on how equity should be measured, whether achieving equity through transport policy is a priority, or how equity measures can be incorporated into existing transport evaluation tools such as costs/benefits analysis. In this report, we argue for the importance in achieving social equity because of the relationship between transit accessibility and the risks of social exclusion, simply understood as the suppressed ability to conduct daily activities at normal levels. This study consists of several major contributions to our understanding of the state of transit equity in the Greater Toronto and Hamilton Area (GTHA).

- We produced an exhaustive set of equity-related benchmarks to assess the current state of equity in our transport system, and to be able to compare potential and real changes in the transport and social systems in our region to the current day state.
- We conducted a descriptive and spatial analysis of transit accessibility and activity participation rates in the GTHA and identified significant gaps between the socially derived demand for travel and the supply of public transit in the region, and illustrated where these gaps are associated with suppression of daily out-of-home activity participation.
- We quantified the accessibility/participation relationship using regression models that demonstrate a statistically significant positive relationship between the provision of transit and rates of participation in out of home activities. This relationship is shown to be strongest in carless households, and those households in the lowest categories of annual household income.

The research demonstrates that transit accessibility is highly concentrated and unevenly distributed across geographic and socioeconomic space. Low-income households tend to concentrate in areas with above average levels of transit accessibility, but there are still hundreds of thousands of low-income individuals living in places with low and very low levels of accessibility. For these households, automobile ownership rates are still quite high, but there is a large gap in daily participation rates between carless and car-owning households in areas of low transit supply or level of service. The differences in activity rates between car-owning and carless households evaporates in more central parts of the city where high rates of participation are achievable using alternative means of transport (i.e. public transit and active modes).

Consistent with theory, the regression models find a significant and positive relationship between transit accessibility and out-of-home activity participation. This relationship is strongest in low-income and carless households, suggesting that transport investments, either new infrastructure or increased levels of service, should result in larger increases in activity participation in neighbourhoods with high concentrations of poverty and low levels of car ownership. Sensitivity analysis indicates that investments in existing participation deserts are likely to generate high returns in new activity generations. We argue that such activity generations are not currently being predicted or valued in existing transport evaluation methodologies, but if they could be monetarily valued, there is great potential for using the value of new activity generation to capture benefits associated with increasing transit levels of service in currently underserved and socioeconomically deprived parts of the GTHA.

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# 1 Introduction

A basic function of urban transportation is to enable participation in daily activities. Nevertheless, transportation planning has historically focused on increasing mobility, reducing environmental impacts and improving congestion, in lieu of policies that directly foster widespread and equitable participation in the broad range of daily activities (Meyer & Miller, 2001; Benenson et al., 2011; Martens et al., 2012; Golub & Martens, 2014; Kaplan et al., 2014). As a result, recent qualitative evidence from the Greater Toronto and Hamilton Area (GTHA) suggests that poor transit accessibility is responsible for reduced satisfaction and participation in essential daily activities such as employment, medical appointments, and leisure (Toronto Public Health, 2013; Hertel et al., 2015; Premji, 2015). This is especially concerning given that income distributions are increasingly polarized, and many socioeconomically deprived neighbourhoods are now within suburban environments with low levels of transit provision (Hulchanski, 2010; Walks, 2013).

Although inequalities in the social distributions of accessibility have been identified in Toronto (Foth et al, 2013; El-Geneidy et al., 2016; Farber et al, 2017; Allen & Farber, 2019a) as well as in a number of other cities, there is little research that investigates whether increasing transport equity leads to increased activity participation (Roorda et al., 2010; Farber et al., 2011). It thus remains unclear whether increasing public transportation supply in the GTHA is likely to increase the social and economic participation of transport-poor people in the region (Kain, 1968; Smart & Klein, 2016). This is a key question that must be addressed if planners wish to capture the benefits of achieving a higher degree of transport equity in our region.

The overarching goal of this project is to develop capacity for incorporating equity within cost-benefits appraisals of transport projects in the GTHA. This is achieved through an investigation of the 2016 Transportation Tomorrow Survey, taking advantage of this being the first year that income is included in the questionnaire. This research has the following objectives designed to identify and measure the scale of transport inequality in the region, map and communicate specific areas of transit and participation deprivation, and estimate the benefits of increasing transit supply in low-income communities.

1 - Compute population benchmarks for the two-way relationships between income, transit accessibility, travel times, and activity participation. This allows us to understand the current state of transport inequality in the GTHA, and produce indicators which can be tracked over time or compared against in transportation scenario testing.

2 - Conduct exploratory spatial analysis to delineate clusters and corridors of transit need from the perspective of low-income residents. We identify locations in the region

suffering from transport poverty, a condition defined by jointly having poor socioeconomic status as well as poor access to activity destinations. From this we identify “participation deserts”, clusters of neighbourhoods where residents have lower than expected rates of daily activity participation.

3 - Quantify the accessibility-participation relationship through the estimation of activity-generation models in order to investigate the degree to which access to destinations is associated with participation levels in out-of-home activities, while controlling for other factors that affect participation, with particular focus on analyzing the relationships with income levels and number of vehicles per household.

4 – Use these models to predict future gains in activity participation stemming from improvements in transit accessibility. These predictions are stratified by car-ownership and income group, as well as by neighbourhood, to find where, and for whom, improvements in transit accessibility will have the greatest benefit in terms increases in activity participation. This also allows us to further understand whether, and to what extent, improvements in transit accessibility can reduce inequalities of activity participation and existing travel barriers.

Accomplishing these objectives will move Metrolinx towards the overarching goal of incorporating equity within cost-benefits analyses of transit project evaluations.

## 2 Literature Review

A primary function of an urban transport system is to provide people the opportunity to participate in daily activities, social interactions, and access to destinations necessary for their well-being. The concept of accessibility, commonly understood as the ease of reaching destinations, is often used to assess the distribution of benefits of urban transport systems (Hansen, 1959; Geurs & Van Wee, 2004; Páez et al., 2012). In modern cities, greater levels of accessibility have been significantly associated with benefits like shorter commuting times (Kawabata & Shen, 2007), increased employment rates (Sanchez, 1999), and higher activity participation rates (Paez et al., 2009). Transit access also reduces the risks of social isolation (Garrett & Taylor, 1999), and it can foster social inclusion (Lucas, 2012).

However, the distribution of land-use and transportation networks in cities is never spatially uniform. Therefore, access to destinations is never equal among different population groups. While some inequality is inevitable, particularly low levels of accessibility can potentially result in transport poverty. Transport poverty occurs when transport disadvantage (not having access to a car, poor public transit options, etc.) compounds with other forms of potential social disadvantage (unemployment or low income, disability or poor health, etc.) (Lucas, 2012). Transport poverty can limit trip making, result in low activity participation rates, and, in the worst cases, can result in the perpetuation of social exclusion (Casas, 2007; Preston & Rajé, 2007; Lucas, 2012).

Assessing the equity of transport systems is often approached by framing equity in terms of horizontal or vertical dimensions (Delbosc & Currie, 2011; Pereira et al., 2017). Horizontal equity is concerned with the distribution of a resource, like transit provision, equally among the overall population. Vertical equity pertains to the distribution of a resource with focus towards specific groups, often those who are more vulnerable to social or economic exclusion. As it pertains to transportation, vertical equity is often studied in relation to income and social class (Welch & Mishra, 2013). In other words, vertical equity is focused on analyzing the compounding factors that can result in transport poverty. A commonly cited goal of transport policy and planning is to reduce vulnerability to transport poverty and minimize wide-ranging inequalities in access, while increasing the overall accessibility of a region (Social Exclusion Unit, 2003; Martens et al., 2012; Martens, 2016), i.e. to make transport more equitable, both horizontally and vertically. There have been a number of academic reviews which have discussed how social equity, and in particular improving peoples access to destinations, should be further incorporated into transportation plans and policy to reduce inequalities and foster social and economic inclusion (Wee & Geurs, 2011; Karner & Niemeier, 2013; Papa et al., 2014; Manaugh et al., 2015; Martens, 2016; Pereira et al., 2017).

Within the Canadian context, several research projects have found that people living in areas with low accessibility have significantly lower activity participation rates, particularly focused on specific population groups that are socially disadvantaged in other ways. For example, McCray and Brais (2007) examined how transportation factors limit the daily activity patterns of low-income women in Quebec City. Spinney, Scott, and Newbold (2009) showed there is significant association between mobility and quality of life for elderly Canadians. Allen and Farber (2018) analyzed how commute times limit on-campus participation of University students. Farber et al., (2018) examined transport barriers to participation among Syrian refugees in Durham Region. A series of papers from a nationally funded research project used large-scale travel surveys and spatial econometric models of travel behaviour to identify how transport disadvantage for low-income, elderly, and single-parent families dissuaded participation in daily activities (Paez et al., 2009; Roorda et al., 2010; Páez et al., 2013). A report on social inclusion in transport planning in Canada estimated that a third or more of households in Canada have at least one member who is transport disadvantaged (Litman, 2003), while research by Allen & Farber (2019a) estimated that one million individuals in Canadian cities are at risk of transport poverty.

There has been some previous descriptive research in analyzing transit accessibility in Toronto. These existing studies have involved analyzing inequalities in accessibility by levels of socioeconomic status (Páez et al., 2013; Foth et al., 2013; El-Geneidy et al., 2016; Allen & Farber, 2019a) and comparing transit access before and after long-term changes in transportation infrastructure and land use patterns (Foth et al., 2013; Farber & Grandez, 2017), or examining fluctuations in accessibility over the course of a day due to shifts in levels-of-service (El-Geneidy et al., 2016; Wessel, Allen, & Farber, 2017, Widener et al., 2017). Overall, this existing work has indicated that lower income neighbourhoods generally have better transit accessibility than the overall population. However, these correlation results are likely skewed by the large number of affluent suburban neighbourhoods with poor transit access. Despite a general positive association between transit access and social disadvantage, there are still a substantial number of low-income households living in areas of low transit access (see Section 5.3 of this report).

Many have discussed the importance of including equity within evaluation of transportation plans (e.g. Karner & Niemeier 2013; Manaugh et al., 2015). Trip rates and activity participation, in particular, has been considered a key equity indicator (e.g. Martens, 2006; Martens, 2016), and has been highlighted as an important metric for evaluation during cost-benefit analysis (Litman, 2017). Some previous research has linked measures of accessibility and urban form with trip generation rates. Results have been mixed. Some have shown that measures of accessibility are associated with increased trip-making (Vickerman, 1974; Koenig, 1980; Thill and Kim, 2005), but other studies have also found that the association between accessibility and trip rates was weak or not statistically significant (Hanson & Schwab, 1987; Ewing et al., 1996, Kitamura et al. 2001). Research by Cordera et al. (2017) found that greater accessibility decreases trip rates in private vehicle for journey-to-work, whereas it increases trip rates via public transit. However, much of this existing research was primarily focused on improving the overall predictive capacity of travel demand models, rather than explicitly analyzing the benefits for equity seeking groups who are often reliant on public transit for daily travel (e.g. low-income or car-less households). Accordingly, the objective of this report is to map and communicate specific areas of transit and participation deprivation, examine how this aligns with the distribution of low-income households, and then estimate the benefits of improving transit supply in low-income communities, particularly with regards to increasing activity participation.

## 3 Data and Methods

### 3.1 Transportation Tomorrow Survey

The study area for this project consists of the six census divisions encompassing the Greater Toronto and Hamilton Area (GTHA). Primary data for this project is drawn from the Transportation Tomorrow Survey (TTS). Originating in 1986, the TTS is collected every five years. Its primary purpose is to provide estimates of travel demand that can then be incorporated into long-range planning models. Overall, the TTS aims to collect a 5% sample of households in the region, although sampling rates vary geographically, with Hamilton only consisting of a 3% sample, on the low end (see Figure 1 for the spatial distribution of sampling in the TTS). Importantly, the TTS survey includes a set of expansion factors that allow extrapolating the sample up to population level estimates. The weighting method takes into account dwelling type, household size, and the distribution of the population by age and gender matching the distributions with the 2016 Canadian census of population. Aggregations of Statistics Canada's Aggregated Dissemination Areas (ADAs) were used as the geographical basis for expansion zones.

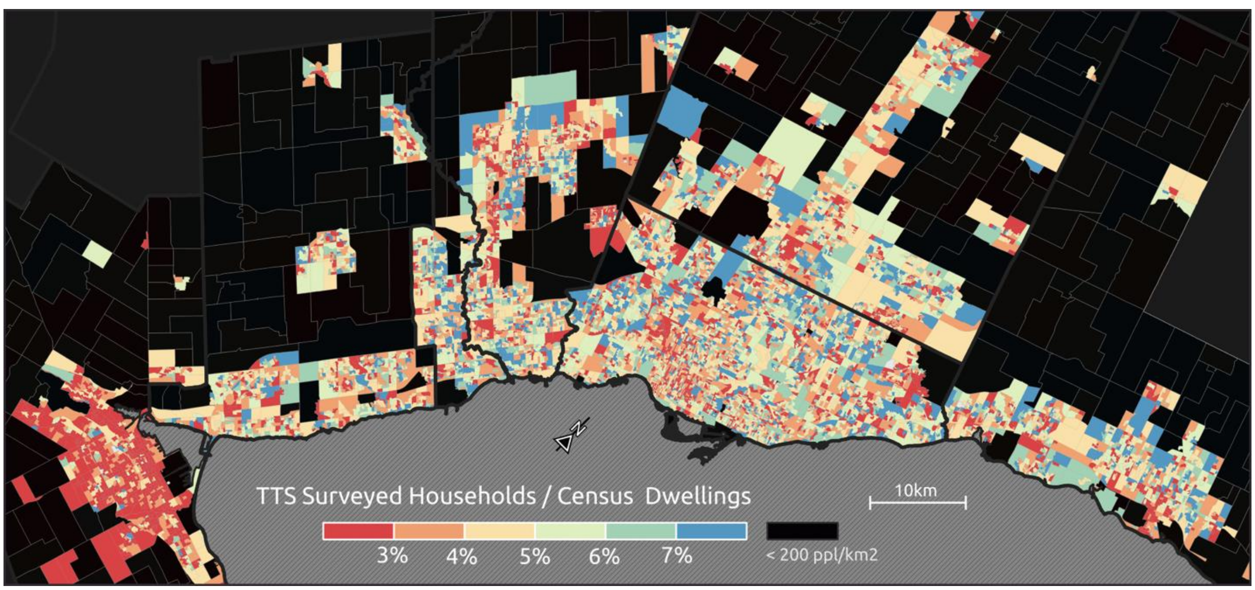


Figure 1 - Sampling rate of households per DA in the TTS

The TTS contains a 1-day travel diary for each member (aged 11 years and older) of a sampled household. One household member is required to report on all trips made by the entire household by proxy. This introduces reporting error as respondents have varying levels of knowledge of each and every trip made by all members of their household. This biases responses towards more complete information regarding mandatory trips (i.e. work and school), and likely some missing discretionary trips (shopping, errands, social, etc.). Notwithstanding this shortcoming, this is the most complete and largest sample dataset we have in the GTHA, and our results will be contextualized with cognisance of these and other TTS-related issues.

Another potential issue concerning the use of TTS is that the income question contains a high degree of non-response bias. Overall, 18% of households failed to provide an answer to the household income question. The two main ways to account for such levels of missing data are to remove the missing observations from the analysis, or to attempt to impute missing income values. Income imputation is outside the scope of this work, and instead we have opted to remove the missing income values or to control for missing income values using a "missing" factor level in our regression models. This decision was made after conducting a series of analyses that convince us that the missing responses are randomly distributed across households in the GTHA. To check this, we present Table 1, Figure 2 and Figure 3 which compare the missing-income respondents to the rest of the TTS sample (internal validation) as well as compare the neighbourhood level incomes of missing respondents (external validation).

We find that the missing responses have similar characteristics to other TTS respondents in the sample (except for a higher proportion of non-responses among elderly), and that the neighbourhood income patterns of missing income households matches the overall distribution of household incomes in the GTHA. This indicates to us that the decision not to respond to the income question is a function of personal tastes and preferences, and this does not result in disproportionate over/under representation of any specific population group. There is only a small observable difference indicating that higher income respondents were less likely on average to report their income level. Seeing as this study is largely concerning the behaviours of lower income groups, we do not anticipate the missing income responses to introduce an important bias into our analyses.

Table 1 - Comparison of survey statistics for those who did and did not respond to the income question

| | Responded to Income | Declined to respond or did not know their income |
|---|---|---|
| Survey n | 218,101 | 52,434 |
| Expanded N | 4,856,969 | 1,092,781 |
| Age | | |
| 11 to 18 | 11.2% | 10.3% |
| 19 to 64 | 74.2% | 68.3% |
| 65 and up | 14.6% | 21.4% |
| Gender | | |
| Female | 51.5% | 52.9% |
| Male | 48.5% | 47.1% |
| Percent who are Students | 19.1% | 17.8% |
| Percent who are Employed | 56.4% | 49.0% |
| Mean Cars per Household | 1.42 | 1.59 |
| Mean People per Household | 2.69 | 2.69 |
| Mean Transit Accessibility | 179,355 | 165,345 |
| Mean Auto Accessibility | 685,536 | 671,383 |

Note: all differences were statistically significant except for mean persons per household

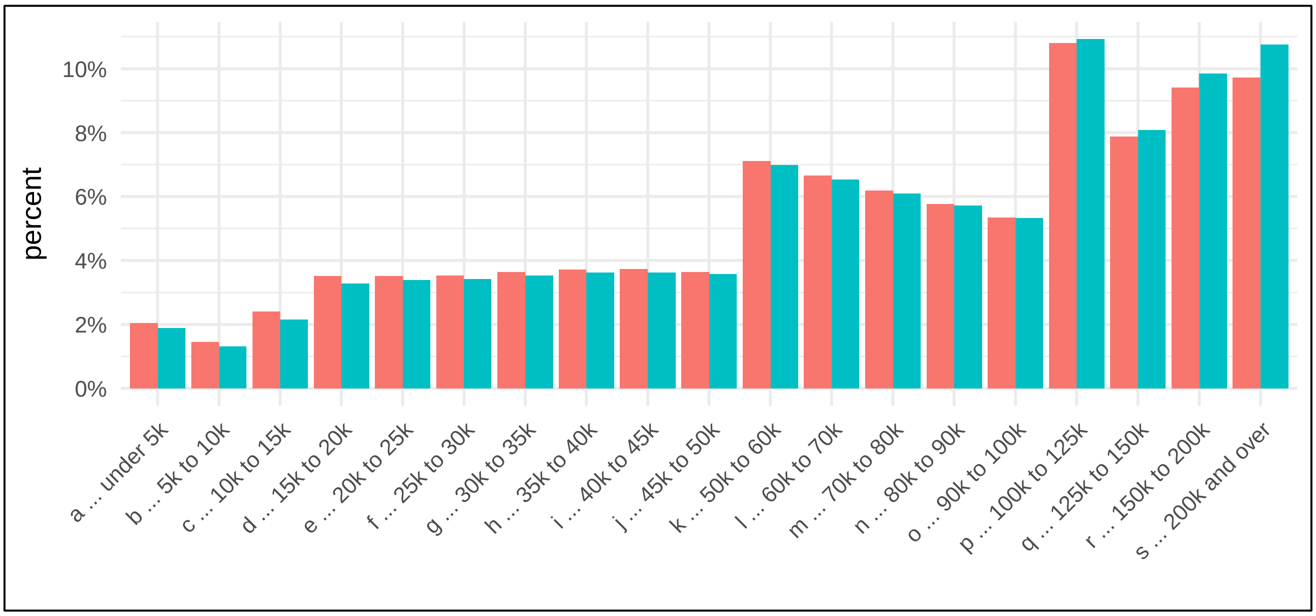


Figure 2 - Comparison of the distribution of household income from the 2016 census (red) and the probable household income of non-answers from the TTS based on their Dissemination Area (blue).

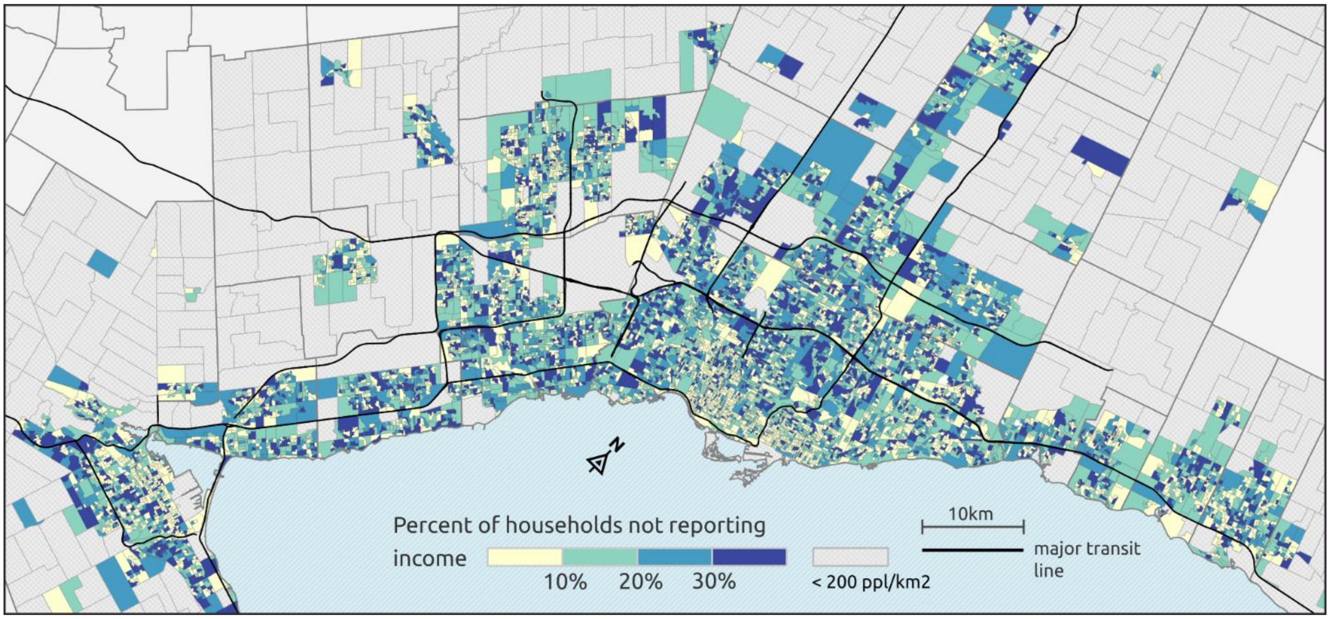

Figure 3 - Distribution of households not reporting income

## 3.2 Accessibility Measurements

Accessibility, from an urban geographic perspective pertains to the ease of reaching activity destinations (Hanson, 1959). Research has taken a wide array of approaches for measuring accessibility, with a full review outside the scope of this report. One very common, place-based approach is to sum the number of opportunities that are reachable from each location in a city, given a certain travel time threshold or distance-decay weighting function (i.e. a gravity model). It is also very common to limit measurements to access to employment, since the distributions of employment are theorized to proxy for many other potential destination types (e.g. services, shopping, etc.).

In this study, we compute access to employment by car and by transit as follows.

$$A_i = \sum_{j=1}^{J} O_j f\left(t_{i,j}\right)$$

Where $A_i$ is the accessibility measure for a zone $i$, $O_j$ is the number of job opportunities at zone $j$ and $t_{ij}$ is the travel time from $i$ to $j$. $f\left(t_{ij}\right)$ is a decreasing function which weights nearby job opportunities higher than those further away. For this analysis, we use an inverse-power function as it showed a greater correlation with transit mode share than other functional forms. This function returns a weight of 0.5 for a 30 minute trip, ranging from a weight of 1 at $t_{i,j} = 0$ and a weight of 0 at $t_{i,j} = 90$. 30 minutes is approximately the median commute time in the GTHA. This basis of returning a value of 0.5 for the median commute time has been used previously in the literature for its ease of interpretation (Östh et al., 2016; Allen & Farber, 2019b)

$$f\left(t_{i,j}\right) = 180\left(90 + t_{i,j}\right)^{-1} - 1$$

Transit accessibility is measured at the Dissemination Area (DA) level. DAs are the smallest areas for which socio-economic data are available from the Canadian census. DA's are designed to contain 400 to 700 persons. Specifically, we use the population weighted centroids of DAs snapped to the closest walking network segment to represent the home locations of residents. Larger, neighbourhood sized Census Tracts (CT), however, are used for the location of employment, as they are the smallest geography in which complete employment data was available for the 2016 census. The long-form census that we draw our employment location data from is based on a 25% representative sample of Canadian households.

For the above accessibility measures, travel times by transit were computed using OpenTripPlanner, an open-source trip-planning software. These travel times are inclusive of the time walking to and from stops, wait times, in-vehicle travels times, and transfers. These calculations require two sets of inputs. The first are the walking networks in each of these cities from OpenStreetMap. The second are transit schedules in the form of GTFS (General Transit Feed Specification) packages for every transit agency that serves the region, circa May 2016, in order to closely align with the collection dates of the 2016 census and TTS surveys. We compute transit travel time matrices of DAs (home locations) to CTs (employment locations) for the entire GTHA. Because of the inherent temporal variations in transit schedules, we follow the precedent in the literature to compute transit travel times for every minute of the morning commute period (e.g. Farber and Fu, 2017), which are subsequently averaged when computing accessibility metrics. Auto travel times were based on free flow travel times, multiplied by a factor of 1.7 to account for congestion. This factor is based on previous research on the costs of congestion in the region (Metrolinx, 2008). However, using a single congestion factor is likely under-estimating the effects of congestion in the core and over-estimating the effects of congestion in peripheral suburbs.

We present maps of access to jobs by transit and private automobile in Figure 4 and Figure 5 respectively. We also present a map of the ratio of transit to car access, which depicts the relative benefit of transit users to car users across the region (Figure 6). Generally, access to jobs follows a concentric pattern with a peak in the Toronto CBD, and in the case of transit, with heightened levels of accessibility tightly wrapped around the higher-order transit infrastructure in the region (e.g. major subway and GO rail lines). For automobile-based access, overall levels are orders of magnitudes higher, with a much less peaked distribution given the abundant and ubiquitous supply of road and highway infrastructure almost everywhere in the region.

The relative levels of accessibility by mode are depicted in Figure 6. Here we see that transit and car access are closest near the Bloor/Yonge subway interchange, reaching a peak ratio of 60%. This ratio drops precipitously with movement away from the downtown core, but local hotspots of high relative accessibility exist along transit corridors and within regional employment centres such as downtown Hamilton and Mississauga. Finally, the plot in

provides a comparison of access levels by auto and car, in terms of their frequency distributions. The overall higher levels of car-based access, as well as the more even levels of car-based access are evident in the figure. Similarly, the plot demonstrates the large number of people in the GTHA with extremely low levels of transit-based access to jobs, and the very small number of people with high access.

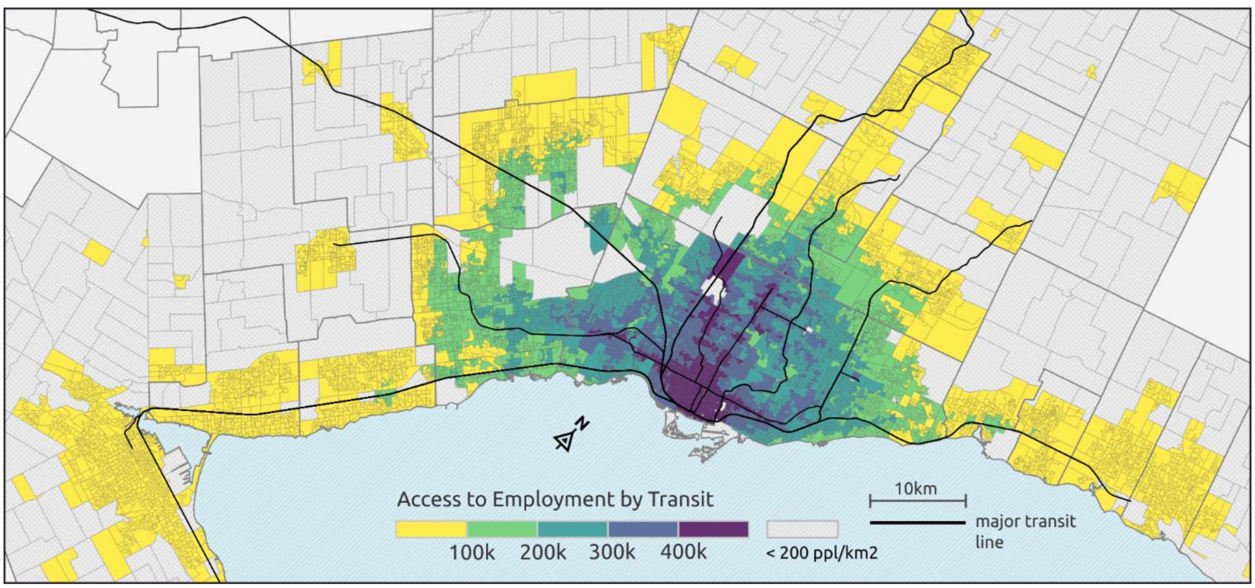


Figure 4 - Access to Jobs by Public Transportation in the GTHA

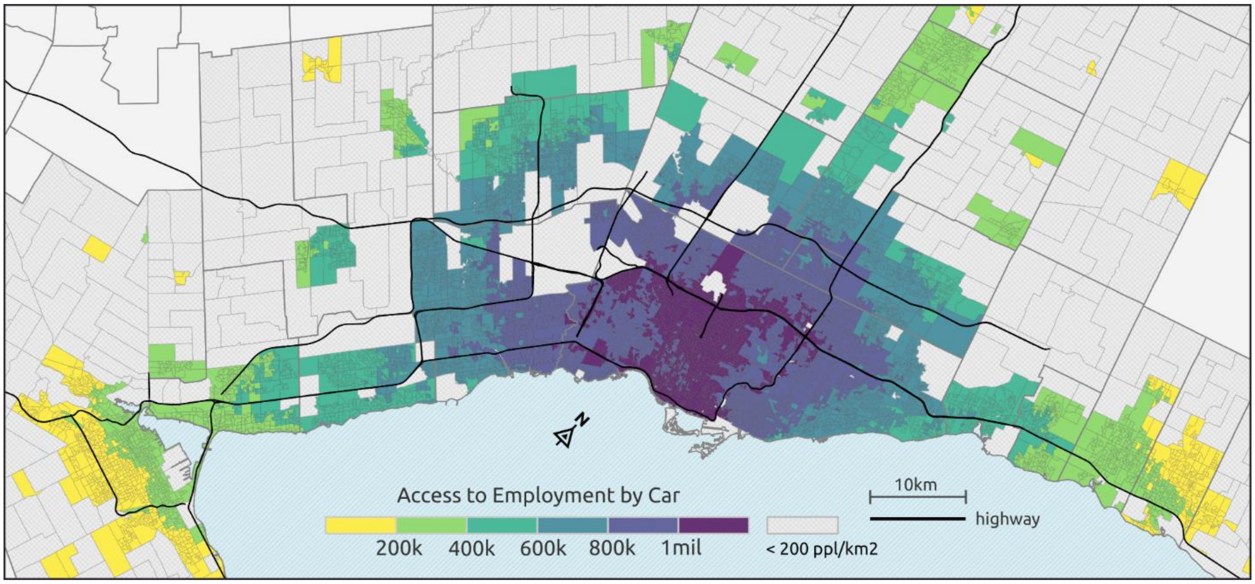


Figure 5 - Access to Jobs by Private Automobile in the GTHA

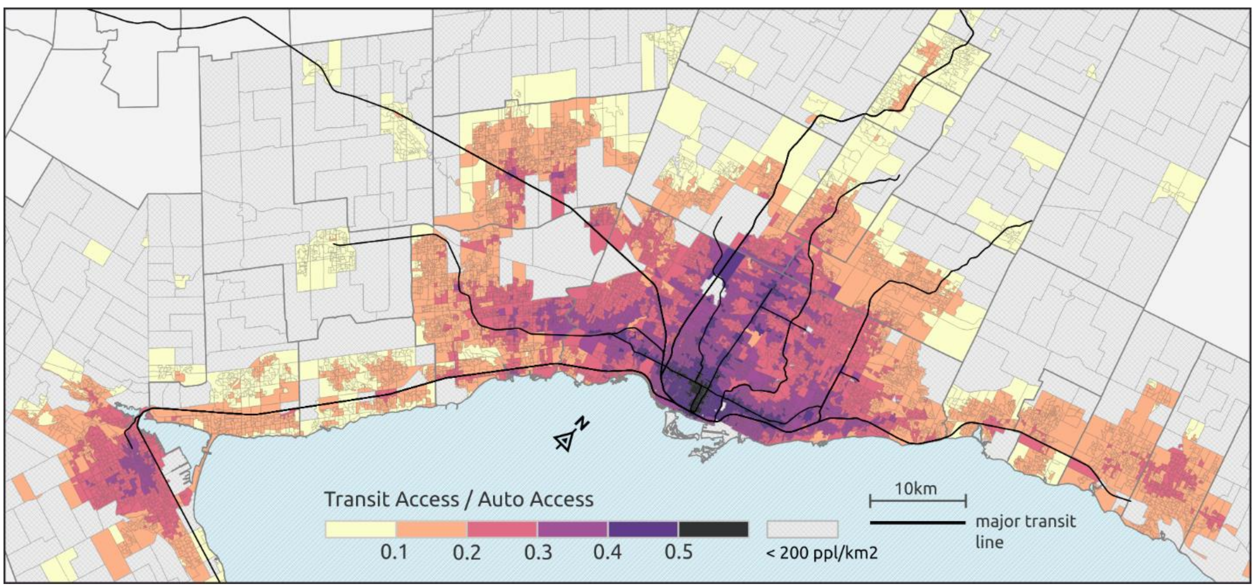


Figure 6 – Ratio of transit access by auto access to jobs in the GTHA

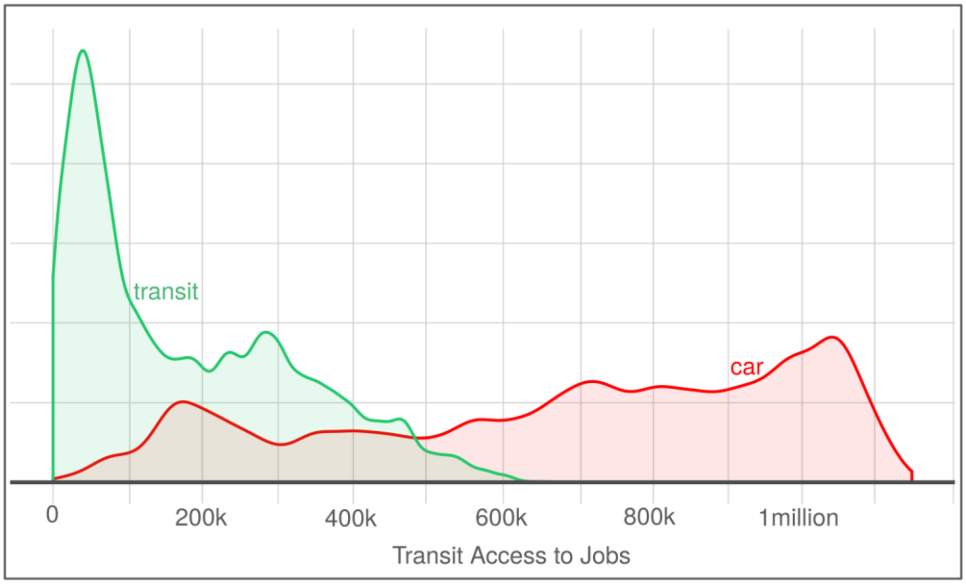

Figure 7 - Probability distribution of transit access compared to automobile access. (the total area under each curve = 1)

## 3.3 Quantifying Activity Participation using the TTS

Included in the TTS for each respondent is a one-day travel diary indicating origin, destination, travel mode, and purpose of each individual's daily trips.

The survey, including the travel diary, was only filled out by one member per household, so there could be some under-reporting of trips of those who did not fill out the survey. As well, there is no indication of trips that do not have an explicit distinct destination or that have the same origin and destination (e.g. going for a jog, taking a dog for a walk, etc.). For these reasons, we expect that trip and activity rates are modestly under-reported.

There are a number of ways in which trip diaries can be processed to quantify activity participation that produce slightly different results. For this study, we summarized diaries into three measures: (1) number of daily trips, (2) number of daily out-of-home activities, and (3) number of daily discretionary (non-work and non-school) out-of-home activities.

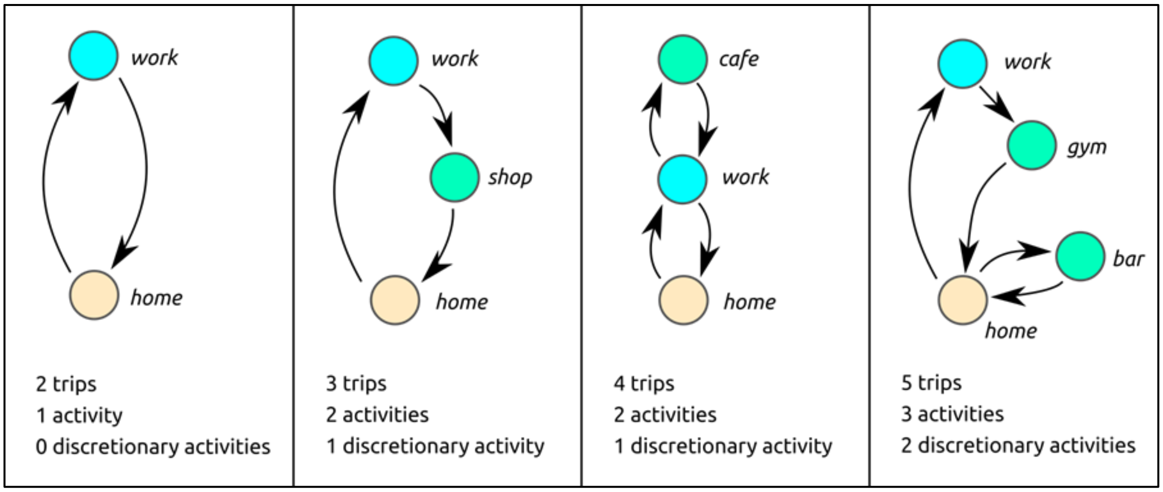


Figure 8 - Examples of how activity participation can be quantified using the TTS demonstrates how we counted these activities for four example respondents.

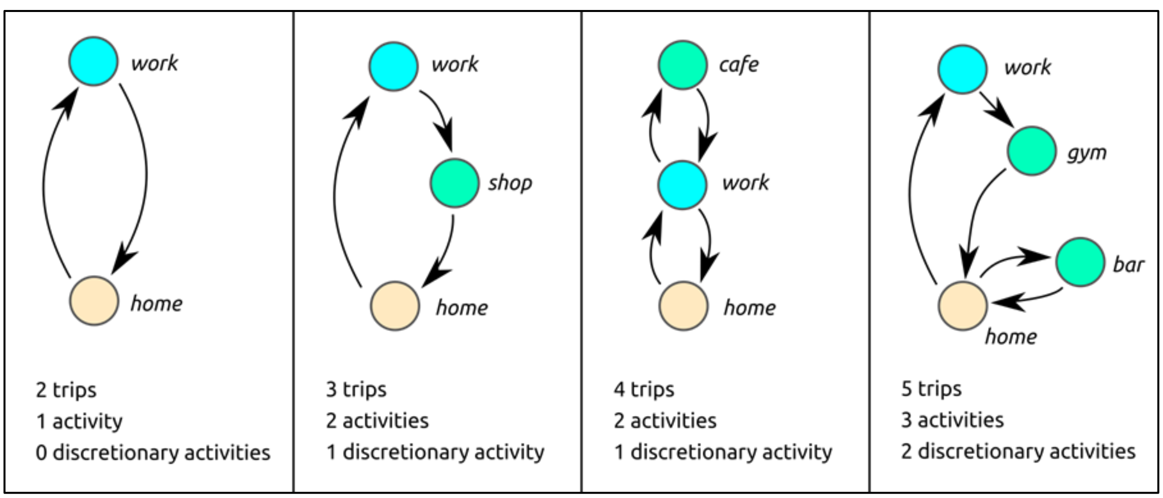


Figure 8 - Examples of how activity participation can be quantified using the TTS

# 4 Descriptive Statistics

In this section, we provide descriptive statistical results that achieve objectives 1 and 2 of this project: namely, the benchmarking of univariate distributions (4.1-4.5) and bivariate relationships (4.6-4.8) between the key variables of interest pertinent to this study. These variables of interest include, but are not limited to household income, accessibility, and levels of trip making and participation. Following the presentation of these simple statistics, we highlight particular benchmarks that may be useful in the development of equity performance benchmarks (in Section 5).

## 4.1 Sample Characteristics

We begin by providing descriptive summaries of household and individual level characteristics collected by the TTS for respondents in the GTHA in Table 2 and Table 3. These tables contain a description of the variables outside of the focus of this report, but provide the context of the population under study. Tables for our prime variables of interest (income, access, participation, etc.) follow in more detailed breakdowns.

## 4.2 Income Distributions

2016 is the first year that income is included in the TTS. For this analysis, we use household income as the primary variable explaining socio-economic status. The TTS collected income with a more detailed breakdown of lower incomes to enable poverty and equity related research. The weighted income distribution of households and individuals are presented in Table 4. According to these figures, 20% of households and 15.5% of individuals live in households with annual income less than $40,000, placing them near or below commonly used poverty lines in the GTHA.

Figure 9 presents the spatial distribution of low-income households in the TTS (household income < $40,000 per year) as a percent of all households in each Dissemination Area. The spatial patterns align with similar maps made from census data (e.g. Hulchanski, 2010). Poverty is most prevalent in parts of downtown Toronto, the inner suburbs of Toronto, Hamilton and Oshawa. Germane to this report are the pockets of suburban poverty that are not well served by public transportation options (e.g. Malvern, Rexdale, Morningside & Kingston, etc.).

Table 2 - Household level characteristics of weighted TTS responses in the GTHA

| | Households (1000s) | Percent | Descriptive Statistics | |
|---|---|---|---|---|
| **Household Size** | | | | |
| 1 person | 622 | 24.6 | Mean | 2.69 |
| 2 people | 727 | 28.7 | Median | 2.00 |
| 3 people | 439 | 17.3 | Std. Dev. | 1.47 |
| 4 people | 442 | 17.4 | | |
| 5 people | 205 | 8.1 | | |
| 6 or more people | 97 | 3.8 | | |
| Total Households | 2,532 | | | |
| **Cars per Household** | | | | |
| 0 cars | 404 | 16.0 | Mean | 1.44 |
| 1 car | 1,005 | 39.7 | Median | 1.00 |
| 2 cars | 837 | 33.1 | Std. Dev. | 1.02 |
| 3 or more cars | 287 | 11.3 | | |
| Total Households | 2,532 | | | |
| **Households per Census Division** | | | | |
| Toronto | 1,113 | 44.0 | | |
| Durham | 228 | 9.0 | | |
| York | 357 | 14.0 | | |
| Peel | 430 | 17.0 | | |
| Halton | 194 | 7.7 | | |
| Hamilton | 212 | 8.4 | | |

Table 3 - Individual level characteristics of weighted TTS responses in the GTHA

| | Individuals (1000s) | Percent |
|---|---|---|
| **Total Pop** | 5,950 | 100 |
| **Age** | | |
| 11 to 18 | 659 | 11.1 |
| 19 to 64 | 4,351 | 73.1 |
| 65 and up | 941 | 15.8 |
| **Gender** | | |
| Female | 3,081 | 51.8 |
| Male | 2,868 | 48.2 |
| **Employment Status** | | |
| Full time | 2,684 | 45.1 |
| Work at home full time | 183 | 3.1 |
| Work at home part time | 72 | 1.2 |
| Not employed | 2,418 | 40.6 |
| Part time | 590 | 9.9 |
| **Occupation Category** | | |
| General Office / Clerical | 481 | 8.1 |
| Manufacturing / Construction / Trades | 468 | 7.9 |
| Not employed | 2,421 | 40.7 |
| Professional / MGMT / Technical | 1,624 | 27.3 |
| Retail Sales and Service | 931 | 15.7 |
| **Student** Status | | |
| Not a student | 4,830 | 81.2 |
| Full time student | 980 | 16.5 |
| Part time student | 139 | 2.3 |
| **Has Transit Pass** | | |
| No | 4,588 | 77.1 |
| Presto | 783 | 13.2 |
| Monthly Pass | 579 | 9.7 |
| **Has Driver's Licence** | | |
| No | 1,480 | 24.9 |
| Yes | 4,469 | 75.1 |

Table 4 - Household and Individual-level Income Distributions of Weighted TTS Respondents

| | Household Summary | | Individual Summary | |
|---|---|---|---|---|
| Household Income | Households (1000s) | Percent | Individuals (1000s) | Percent |
| $0 to $14,999 | 124 | 5.3 | 207 | 3.5 |
| $15,000 to $39,999 | 365 | 14.4 | 715 | 12.0 |
| $40,000 to $59,999 | 352 | 13.9 | 785 | 13.2 |
| $60,000 to $99,999 | 538 | 21.2 | 1,259 | 21.2 |
| $100,000 to $124,999 | 255 | 10.1 | 663 | 11.1 |
| $125,000 and above | 448 | 17.7 | 1,229 | 20.7 |
| Decline / don't know | 452 | 17.9 | 1,093 | 18.4 |
| Total | 2,532 | | 5,950 | |

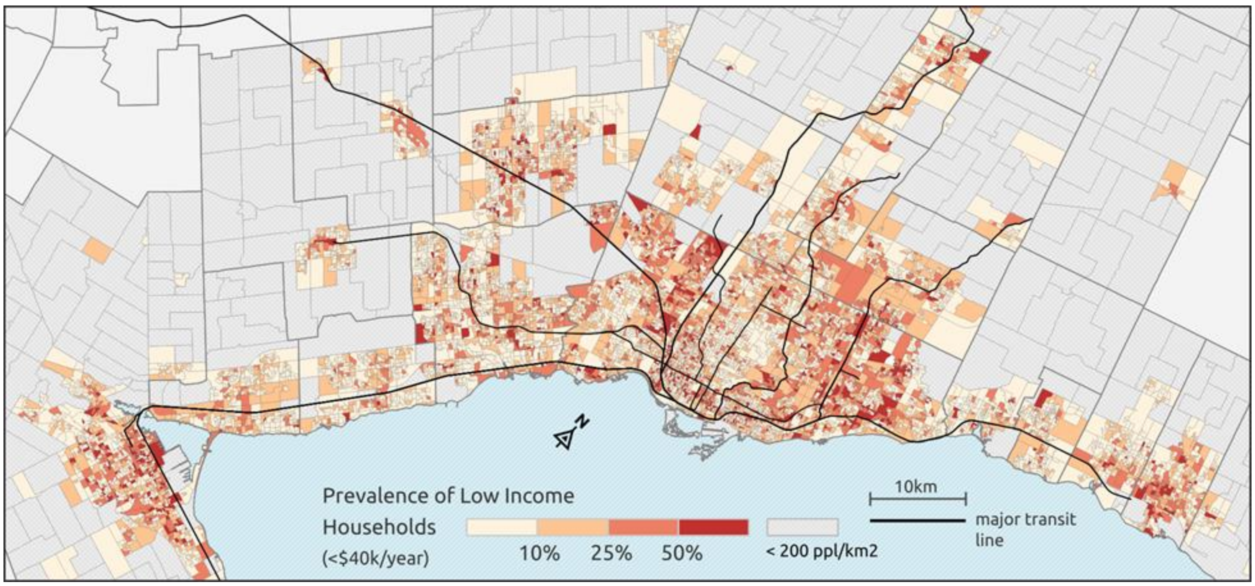


Figure 9 - Map of Low Income Prevalence in the GTHA based on TTS Responses

## 4.3 Participation Distributions

As previously mentioned, we enumerate participation in three different ways: total daily trips, out-of-home activities, and daily discretionary activities. The frequency distributions of these variables are presented in Table 5. Quite strikingly, captured out-of-home participation is low overall, with 22% of individuals participating in no trips or out-of-home activities. About half the population conducts two trips, consisting of a single out-of-home activity (i.e. mostly work and school), while very few participate at higher rates. On a typical survey weekday, 62% of respondents reported no discretionary activities.

Table 5 - Frequency Distributions of Daily Rates of Participation

| Daily Trips | Thousands of People | Percent | Daily Activities | Thousands of People | Percent | Daily Discretionary Activities | Thousands of People | Percent |
|---|---|---|---|---|---|---|---|---|
| 0 | 1,295 | 21.8 | 0 | 1,329 | 22.3% | 0 | 3,665 | 61.6% |
| 1 | 77 | 1.3 | 1 | 2,991 | 50.3% | 1 | 1,403 | 23.6% |
| 2 | 2,909 | 48.9 | 2 | 1,040 | 17.5% | 2 | 541 | 9.1% |
| 3 | 504 | 8.5 | 3 or more | 590 | 9.9% | 3 ore more | 341 | 5.7% |
| 4 | 673 | 11.3 | | | | | | |
| 5 or more | 492 | 8.3 | | | | | | |
| | | | | | | | | |
| mean | 2.22 | | mean | 1.21 | | mean | 0.63 | |
| median | 2.00 | | median | 1.00 | | median | 0.00 | |
| standard deviation | 1.77 | | standard deviation | 1.07 | | standard deviation | 1.02 | |

It should be noted that the travel diary was collected only for a weekday and therefore could be a downwardly biased indicator of overall participation in discretionary activities. Another source of potential downward bias is the use of proxy responses, when a single household member reports trips made by all members. Work and school related trips are likely known to the proxy respondent, but discretionary trips are more likely to go unreported, particularly if they are done by active modes of travel not requiring the negotiation of household resources.

Next, we provide maps that illustrate the spatial patterns of participation rates in the GTHA. Here we can see that the three types of participation are, by definition, tightly correlated with each other over space (Figure 10, Figure 11, and Figure 12). More importantly, however, is that the patterns of participation very much resemble the income patterns presented in Figure 9. However, it is not possible at this scale of analysis to determine whether low-income neighbourhoods with higher levels of accessibility participate in more activities than those living in areas with worse transit accessibility. This is because of there are a number of other factors (e.g. employment status, household characteristics, etc.) that also impact daily activity participation that should be controlled for.

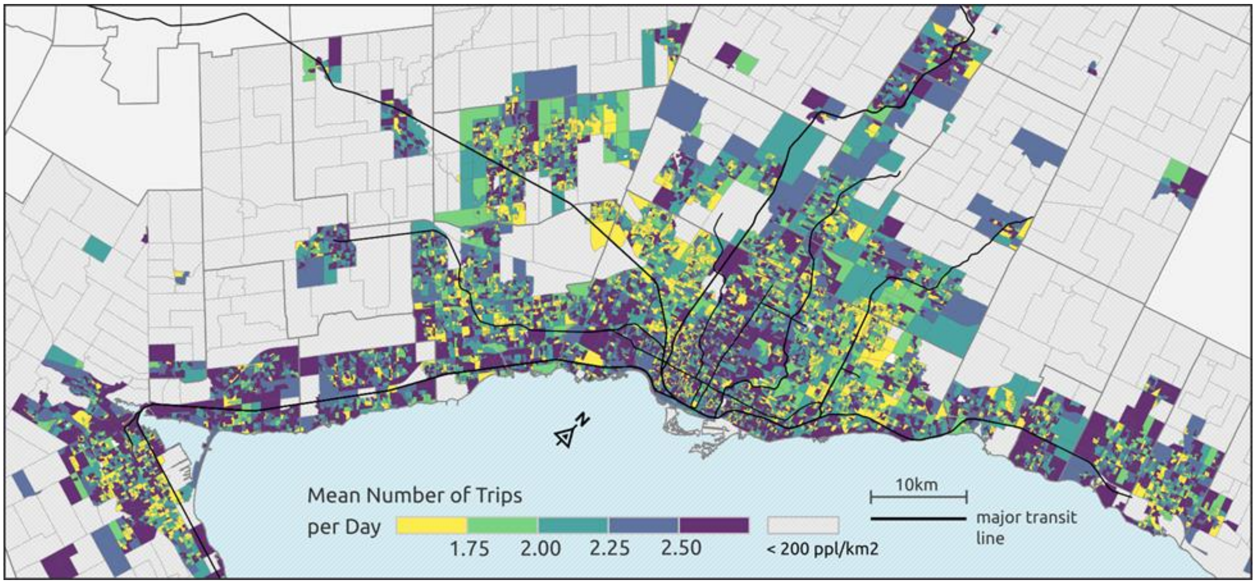

Figure 10 - Trip rates per dissemination area

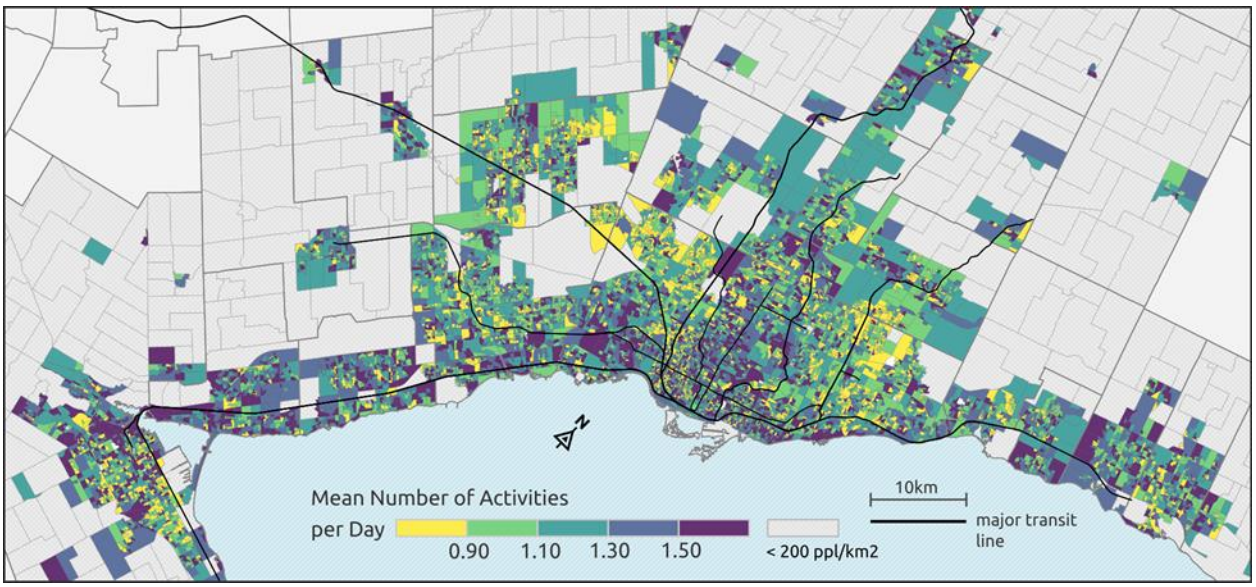

Figure 11 - Activity rates per dissemination area

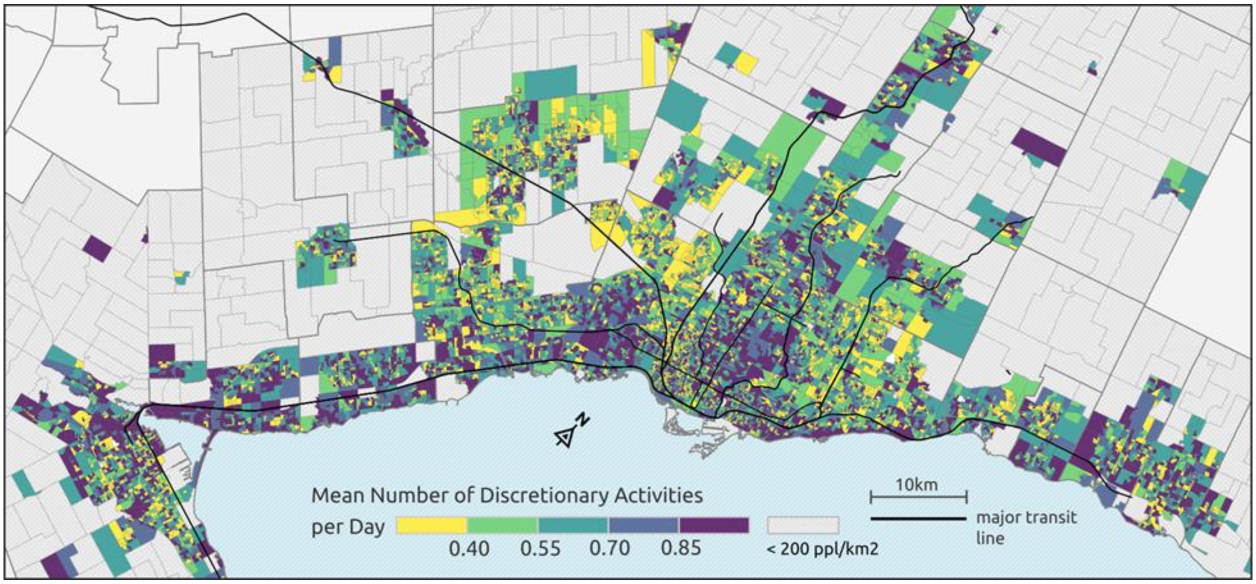


Figure 12 - Discretionary activity rates per dissemination area

## 4.4 Identifying Participation Deserts

To extend the previous section, we conduct exploratory spatial analysis in order to detect clusters (i.e. hotspots) of high and low levels of participation in the region. We compute two commonly used measures, the Local Moran's I and Local Getis-Ord $G_i^*$ statistic, for the average number of trips per person in each Dissemination Area, *i*, in the region. These statistics compare the values in the local neighbourhood of a DA to those across the region. What counts as a neighbourhood is encoded within a spatial weights matrix *W* (i.e. for each row, this counts what other zones, *j*, are in the neighbourhood of *i*). For this study, we assume that zones sharing and edge or corner form a neighbourhood (i.e. Queen connectivity), and that each row is normalized to sum to 1.

First we compute $G_i^*$ where *x* is the mean activity participation rate:

$$G_i^* = \frac{\sum_j w_{ij} x_j}{\sum_j x_j}$$

$G_i^*$ is essentially the percentage of the total sum of participation in the region that is found in the local neighbourhood of *i*. For $G_i^*$, the neighbourhood *i* is included in the numerator of the equation. We can test whether the observed $G_i^*$ values are significantly different to those we would expect to see under an assumption of a spatially random distribution of daily activity participation rates.

Second, we compute Local Moran's I as follows:

$$I_i = Z_i \sum_j Z_j w_{ij}$$

Where $Z_i$ is the normalized value of mean participation rate at $i$ and $j$. Local Moran's I is also able to highlight so-called spatial outliers (low value zones surrounded by high value zones as well as high value zones surrounded by low value zones). Statistically significant clusters for these two statistics are presented in Figures 13 and 14.[1] It should be noted these statistics do not consider attribute uncertainty within each areal unit from using survey data. The statistics assume that the values being compared are population values without error.

Both of these figures indicate that there are pockets of low participation within Toronto's "inner suburbs" in parts of Scarborough and northern Etobicoke. These areas were typically built in the post-war period and currently have moderate levels of transit accessibility combined with declining rates of socioeconomic affluence (Ades et al., 2012; Breau et al., 2018). There are also pockets of low-participation in more suburban areas in south and eastern Brampton, southern Markham, central Mississauga, and eastern Hamilton.

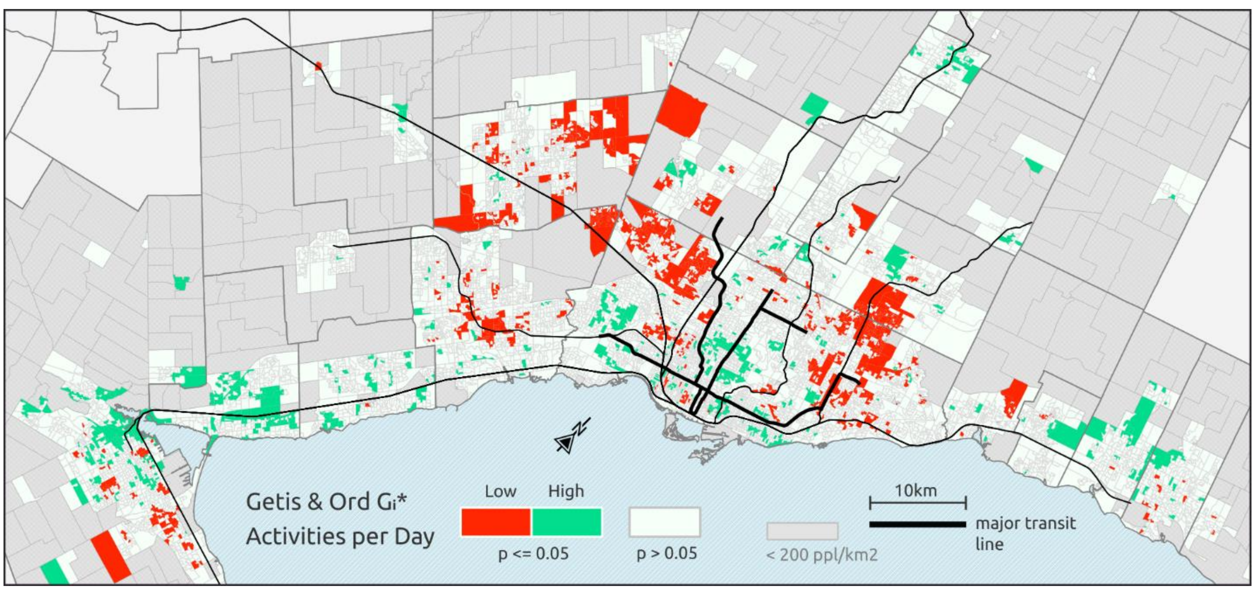


Figure 13 - Clusters of low and high participation using the $G_i^*$ statistic

[1]These were computed using PySal (python spatial analysis library) https://pysal.readthedocs.io/en/latest/

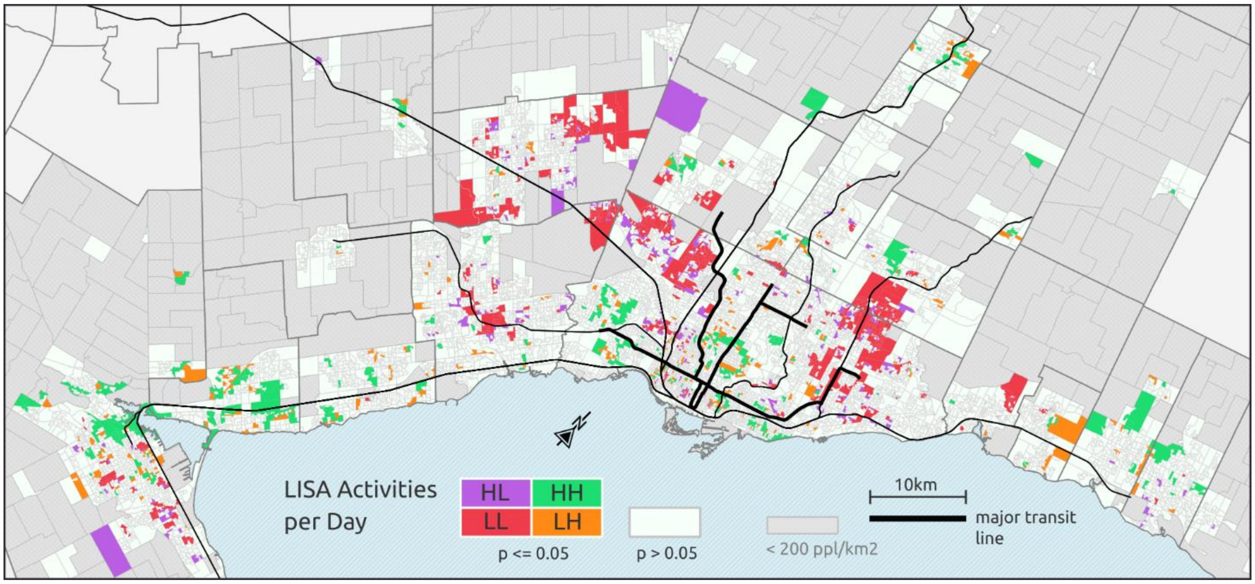

Figure 14 - Clusters of low and high participation using Local Moran's I

## 4.5 Trip Lengths and Durations

In this section, we present the distributions of distances and durations, reported on per trip and per day bases. Table 6 summarizes the distance travelled by individuals, for each trip and for each day in the travel diary. This is a simple Euclidean (as the crow flies) distance and thus does not consider transport networks. The results indicate a positive skew, with mean distance being pulled away from the median due to the presence of some very long distance trips.

Table 6 - Travel distances per trip and per day for weighted TTS respondents

| | Trip Distance (km) | Daily Travel Distance (km) |
|---|---|---|
| mean | 11.45 | 33.28 |
| median | 5.00 | 20.00 |
| standard deviation | 22.98 | 49.31 |
| 25th percentile | 2.00 | 8.00 |
| 50th percentile (median) | 5.00 | 20.00 |
| 75th percentile | 13.00 | 42.00 |

Table 7 displays the distribution of trip durations. The TTS does not include travel times for each trip, so we had to compute these ourselves. Trip times for transit, cycling, and walking were computed using OpenTripPlanner (the same software used in the accessibility measures) by inputting the centroid of the origin DA and destination DA of each trip encoded in the TTS. Transit travel times were computed for the specific trip time reported in the TTS. Trip times for driving were estimated using the GTHA V4.0

Model[2] which accounts for congestion at different times of day. A similar pattern is evident in trip and daily travel times; while median travel times are quite low, 25% of the population still travels 89 minutes or more per day. The extent to which high or low-income households perform these longer distance trips, and how this relates to mode choice and travel durations, needs to be further investigated

Table 7 - Travel times per trip and per day for weighted TTS responses

| | Trip Time (min) | Daily Travel Time (min) |
|---|---|---|
| mean | 24.6 | 68.0 |
| median | 15.9 | 52.5 |
| standard deviation | 29.0 | 64.8 |
| 25th percentile | 8.5 | 29.0 |
| 50th percentile (median) | 15.9 | 52.5 |
| 75th percentile | 31.4 | 89.1 |

Table 8 - Mode share percentage by income category

| Household Income | Car | Transit | Walk | Bike | Other |
|---|---|---|---|---|---|
| $0 to $14,999 | 51.3 | 28.2 | 14.5 | 2.4 | 3.5 |
| $15,000 to $39,999 | 69.0 | 18.3 | 8.3 | 1.6 | 2.8 |
| $40,000 to $59,999 | 75.4 | 13.8 | 6.8 | 1.4 | 2.6 |
| $60,000 to $99,999 | 77.8 | 11.8 | 6.4 | 1.5 | 2.5 |
| $100,000 to $124,999 | 79.9 | 10.5 | 5.7 | 1.3 | 2.6 |
| $125,000 and above | 80.3 | 9.4 | 5.9 | 1.5 | 3.0 |
| Decline / don't know | 79.4 | 11.1 | 5.9 | 0.8 | 2.8 |
| Total | 77.0 | 12.3 | 6.6 | 1.4 | 2.7 |

## 4.6 The Relationship between Income and Transit Accessibility

Here we look at the relationship between transit accessibility and household income. Table 9 shows the distribution of transit-based access to jobs for individuals within each income category. Overall, we see that lower income households have the highest levels of accessibility, and that accessibility smoothly declines as incomes rise. This is an indication that lower-income households prefer neighbourhoods with good transit access, and that many of the densest apartment neighbourhoods that attract low-income households are located centrally or on major arterials with high levels of transit service. Additionally, the table shows a preference among higher income families for suburban, automobile dependent locales.

[2]https://tmg.utoronto.ca/documents/

We next provide the same cross-tabulation but restrict the sample to carless households (Table 10). In this table, we can observe higher levels of transit access among all income groups, indicating that car-free households try to locate in high-access neighbourhoods. Importantly, the increase in access by low-income households pales in comparison to the increase among wealthier households, resulting in a stark reversal of the access/income trend. Among carless households, accessibility increases in tandem with wealth.

One explanation is that among low-income households, car ownership can be quite high and the desire to pay for transit accessibility can therefore be quite low. Among the carless poor households, we only see modest increases in transit access, indicating that the wealth required to pay to live near rapid-transit is not there. For wealthier households, the ability to pay for higher levels of accessibility is present, and among carless wealthy households, we observe a clear preference for locating near higher order transit.

Table 9 - Bivariate relationship between household income and transit-based access to jobs for all individuals in the GTHA

| | Transit Accessibility | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Household Income** | **<-- 95%** | **Mean** | **95% -->** | **Sdev** | **Q25** | **Q50 (med)** | **Q75** | **survey n** | **expf N** |
| $0 to $14,999 | 239,648 | 243,001 | 246,355 | 152,189 | 107,081 | 239,576 | 350,314 | 7,830 | 206,551 |
| $15,000 to $39,999 | 203,137 | 204,691 | 206,244 | 140,093 | 72,001 | 192,793 | 305,116 | 30,925 | 714,877 |
| $40,000 to $59,999 | 181,309 | 182,779 | 184,250 | 140,112 | 57,767 | 154,588 | 286,372 | 34,531 | 784,770 |
| $60,000 to $99,999 | 174,398 | 175,607 | 176,817 | 146,954 | 50,747 | 130,106 | 279,840 | 56,136 | 1,258,849 |
| $100,000 to $124,999 | 159,625 | 161,301 | 162,976 | 149,357 | 39,328 | 97,285 | 272,762 | 30,213 | 662,722 |
| $125,000 and above | 164,037 | 165,311 | 166,585 | 157,996 | 36,469 | 93,215 | 288,943 | 58,466 | 1,229,199 |
| Decline / don't know | 164,142 | 165,345 | 166,548 | 141,275 | 46,880 | 117,021 | 269,941 | 52,434 | 1,092,781 |

Table 10 - Bivariate relationship between household income and transit-based access to jobs for individuals in zero-car households

| | **Transit Accessibility (for car-free households)** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Household Income** | **<-- 95%** | **Mean** | **95% -->** | **Sdev** | **Q25** | **Q50 (med)** | **Q75** | **survey n** | **expf N** |
| $0 to $14,999 | 283,802 | 288,995 | 294,188 | 154,156 | 169,722 | 304,182 | 401,624 | 3,351 | 97,527 |
| $15,000 to $39,999 | 279,554 | 282,940 | 286,325 | 145,495 | 174,897 | 295,591 | 381,114 | 7,021 | 183,417 |
| $40,000 to $59,999 | 328,965 | 333,489 | 338,014 | 140,131 | 245,898 | 349,557 | 444,112 | 3,648 | 91,310 |
| $60,000 to $99,999 | 382,134 | 386,137 | 390,140 | 129,342 | 308,753 | 404,364 | 477,686 | 3,970 | 95,936 |
| $100,000 to $124,999 | 414,050 | 419,985 | 425,919 | 112,767 | 368,933 | 436,124 | 498,097 | 1,373 | 28,499 |
| $125,000 and above | 440,529 | 445,736 | 450,943 | 104,613 | 397,011 | 460,420 | 518,595 | 1,535 | 27,830 |
| Decline / don't know | 292,655 | 297,067 | 301,479 | 153,937 | 185,354 | 306,247 | 414,848 | 4,629 | 104,412 |

The above statistical patterns can also be visualized using maps. The three maps below display accessibility as the underlying surface, and use an overlay of dots that represent low-income households (Figure 15), carless households (Figure 16), and low-income, carless households (Figure 17). Low-income households are defined as households with a before tax household income of less than $40,000 per year. Areas where clusters of dots align with low transit access are at the greatest risk of experiencing transport poverty.

Figure 15 - Map of accessibility and low-income households

Figure 15 shows that low-income households are distributed evenly across many accessibility levels, from high concentrations in downtown Toronto, through the inner suburbs, and well into some of the suburban cities in outlying regions of the GTHA. Carless households, however, as seen in Figure 16, are far more concentrated along rapid transit lines, and to some extent, in downtown Hamilton.  Finally, looking at Figure 17, the low-income carless households, despite having a centralized distribution, are less clustered around Toronto's subway lines, indicating lower access to subways, and this could be responsible for only attaining a moderate overall level of accessibility via transit. There is also a large cluster of carless, low-income households in Hamilton, which requires further examination.

Figure 15 - Map of accessibility and low-income households

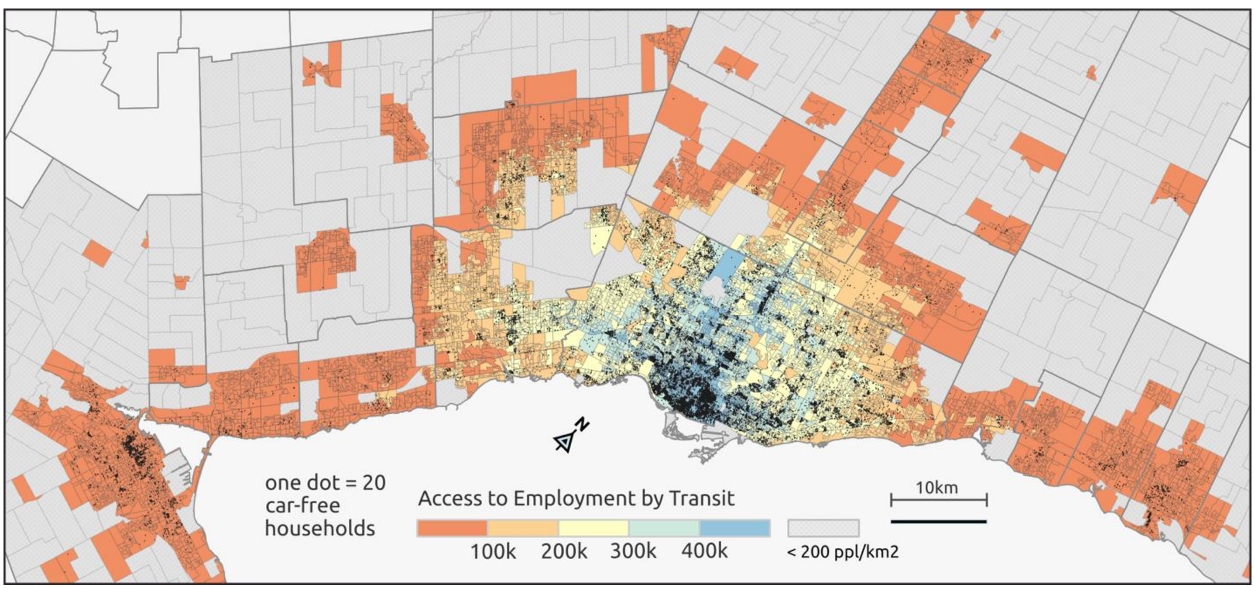

Figure 16 - Map of accessibility and carless households

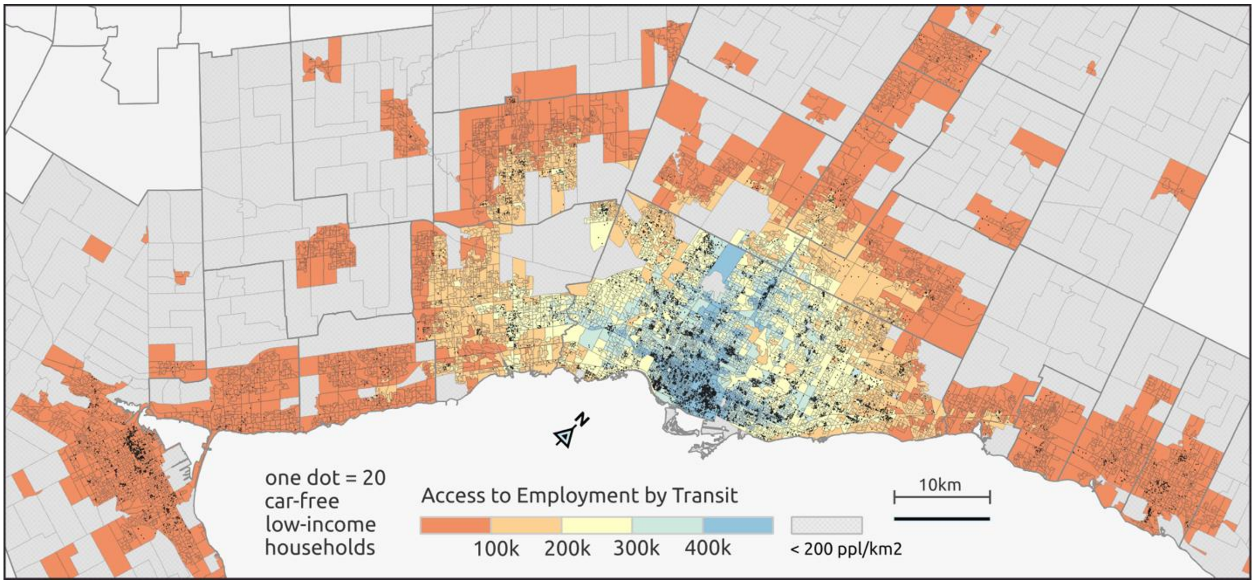

Figure 17 - Map of accessibility and carless, low-income households

## 4.7 The Relationship between Income and Activity Participation

We next investigate the two-way association between income and activity participation. Again, we divide this up by first looking at the full population (Table 11), and then looking for differences with the car-free households (Table 12). In both population groups, trip rates increase smoothly with income levels. Trip rates tend to be 0.2 trips per day lower in carless households, indicating the positive impact of car ownership on activity participation. However, this difference is greater, in percentage terms, for low-income households, indicating that the returns of car-ownership on participation are higher among low-income groups compared to high-income groups. This is consistent with theory regarding transport poverty; those with higher income are able to achieve their desired levels of trip making, despite not owning a vehicle.

Table 11 - Activities per day by level of household income

| | | | Activities per Day | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Household Income** | **survey n** | **expf N** | **0** | **1** | **2** | **3up** | **<-- 95%** | **Mean** | **95% -->** |
| $0 to $14,999 | 7,830 | 206,551 | 5.7% | 3.1% | 2.5% | 2.0% | 0.89 | 0.91 | 0.93 |
| $15,000 to $39,999 | 30,925 | 714,877 | 16.8% | 11.4% | 9.6% | 8.5% | 1.00 | 1.01 | 1.03 |
| $40,000 to $59,999 | 34,531 | 784,770 | 14.2% | 13.6% | 11.8% | 11.0% | 1.12 | 1.13 | 1.14 |
| $60,000 to $99,999 | 56,136 | 1,258,849 | 19.0% | 21.9% | 21.8% | 21.2% | 1.23 | 1.24 | 1.25 |
| $100,000 to $124,999 | 30,213 | 662,722 | 8.5% | 11.4% | 12.4% | 13.4% | 1.33 | 1.34 | 1.35 |
| $125,000 and above | 58,466 | 1,229,199 | 13.5% | 20.3% | 26.2% | 28.6% | 1.43 | 1.44 | 1.45 |
| Decline / don't know | 52,434 | 1,092,781 | 22.3% | 18.2% | 15.6% | 15.3% | 1.09 | 1.09 | 1.10 |

Table 12 - Activities per day by level of household income among carless households

| | | | Activities per Day (car-free households) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Household Income** | **survey n** | **expf N** | **0** | **1** | **2** | **3up** | **<-- 95%** | **Mean** | **95% -->** |
| $0 to $14,999 | 3,351 | 97,527 | 20.2% | 13.6% | 12.5% | 12.8% | 0.78 | 0.81 | 0.84 |
| $15,000 to $39,999 | 7,021 | 183,417 | 34.4% | 28.0% | 24.1% | 22.7% | 0.83 | 0.86 | 0.88 |
| $40,000 to $59,999 | 3,648 | 91,310 | 10.3% | 16.0% | 17.8% | 16.4% | 1.07 | 1.10 | 1.13 |
| $60,000 to $99,999 | 3,970 | 95,936 | 8.1% | 17.6% | 20.2% | 22.2% | 1.18 | 1.21 | 1.24 |
| $100,000 to $124,999 | 1,373 | 28,499 | 2.3% | 5.1% | 6.4% | 7.5% | 1.20 | 1.25 | 1.30 |
| $125,000 and above | 1,535 | 27,830 | 1.7% | 4.9% | 7.5% | 8.1% | 1.31 | 1.36 | 1.41 |
| Decline / don't know | 4,629 | 104,412 | 22.9% | 14.8% | 11.3% | 10.3% | 0.72 | 0.74 | 0.77 |

## 4.8 The Relationship between Accessibility and Activity Participation

Lastly, in this subsection we compare the relationship between transit access and activity participation. The detailed enumeration of accessibility distributions appears in Table 13, and a summary plot clarifying the trends is in Figure 18. There are several findings to take away:

1) When averaged across the entire population, activity participation does not seem to be very closely related with accessibility. In fact, it appears that most individuals with high levels of activity participation tend to live in low-access parts of the city, presumably achieving these high rates through automobile use.

2) The above trend appears to hold when considering low-income households in isolation. As a general rule, accessibility and activity participation are not closely related, even among low-income households. This may be because many low-income households still own and rely on their automobile for daily travel. Activity participation rates among the general population are higher than those for the low-income population across all levels of access.

3) For carless households, there is a strong positive relationship between transit accessibility and activity participation.

4) The trend among carless households extends to those that are specifically low-income.

5) At the highest levels of accessibility, activity participation among carless, low-income and all households equalizes. High levels of transit accessibility therefore diminishes the participation-disadvantage of being low-income and not owning a vehicle.

Importantly, these tables and plots suggest that increasing access for carless households should result in participation increases. However, participation is only equalized at the highest levels of access, so eliminating the participation gap through transit investments will likely require significant investments in the highest-order transit options, and in locations relatively close to the centre of the region. These findings indicate that further examination using multivariate models is certainly warranted.

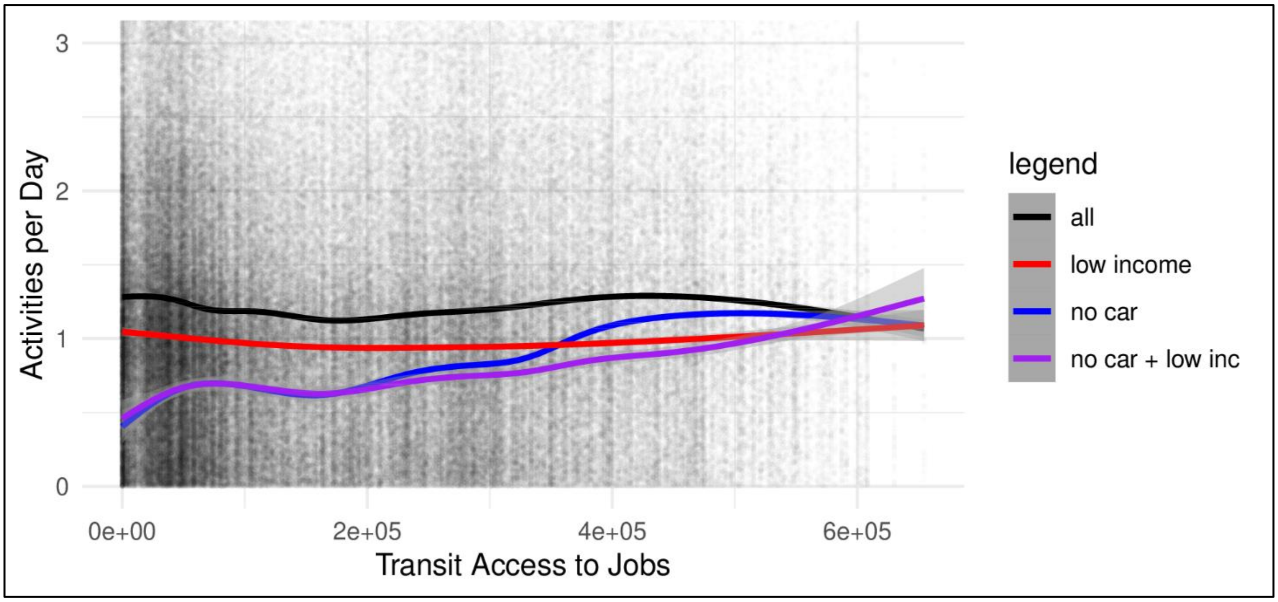


Figure 18 - Relationship between Transit Accessibility and Activities per Day

Table 13 - Distribution of Transit Accessibility by Number of Activities per Day

| **All** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Activities per Day** | **<-- 95%** | **Mean** | **95% -->** | **Sdev** | **Q25** | **Q50 (med)** | **Q75** | **survey n** | **expf N** |
| 0 | 176,271 | 177,385 | 178,499 | 143,021 | 52,616 | 138,727 | 283,562 | 62,647 | 1,329,121 |
| 1 | 177,425 | 178,222 | 179,019 | 148,478 | 49,576 | 133,109 | 288,437 | 131,943 | 2,991,382 |
| 2 | 173,313 | 174,669 | 176,025 | 152,083 | 45,255 | 118,779 | 289,030 | 47,840 | 1,039,498 |
| 3up | 170,084 | 171,840 | 173,595 | 150,947 | 42,753 | 116,059 | 288,309 | 28,105 | 589,749 |
| **Car-free households** | | | | | | | | | |
| **Activities per Day** | **<-- 95%** | **Mean** | **95% -->** | **Sdev** | **Q25** | **Q50 (med)** | **Q75** | **survey n** | **expf N** |
| 0 | 277,875 | 281,006 | 284,138 | 151,318 | 163,050 | 293,573 | 391,055 | 8,880 | 197,175 |
| 1 | 330,460 | 333,097 | 335,734 | 146,707 | 239,771 | 347,565 | 448,978 | 11,767 | 310,372 |
| 2 | 356,335 | 361,106 | 365,877 | 144,583 | 277,039 | 384,955 | 469,777 | 3,492 | 87,211 |
| 3up | 363,704 | 371,160 | 378,615 | 142,442 | 296,251 | 397,487 | 473,219 | 1,388 | 34,172 |
| **Low-income households <$40k per year** | | | | | | | | | |
| **Activities per Day** | **<-- 95%** | **Mean** | **95% -->** | **Sdev** | **Q25** | **Q50 (med)** | **Q75** | **survey n** | **expf N** |
| 0 | 208,394 | 210,769 | 213,143 | 141,496 | 76,678 | 197,879 | 316,280 | 13,500 | 299,111 |
| 1 | 214,437 | 216,568 | 218,698 | 143,310 | 80,465 | 210,373 | 319,773 | 17,203 | 433,969 |
| 2 | 208,848 | 212,759 | 216,670 | 147,323 | 72,131 | 203,403 | 318,697 | 5,395 | 126,348 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 3up | 197,754 | 203,425 | 209,096 | 149,908 | 58,830 | 186,502 | 308,597 | 2,657 | 62,000 |
| | | | **Car-free & Low-income households <$40k per year** | | | | | | |
| **Activities per Day** | **<-- 95%** | **Mean** | **95% -->** | **Sdev** | **Q25** | **Q50 (med)** | **Q75** | **survey n** | **expf N** |
| 0 | 260,807 | 265,077 | 269,346 | 147,000 | 143,808 | 281,366 | 369,307 | 4,508 | 107,743 |
| 1 | 289,280 | 293,581 | 297,881 | 145,240 | 190,944 | 304,246 | 395,955 | 4,337 | 129,078 |
| 2 | 294,833 | 303,900 | 312,967 | 156,164 | 183,238 | 317,959 | 425,989 | 1,128 | 31,987 |
| 3up | 306,632 | 321,762 | 336,892 | 154,984 | 219,954 | 343,753 | 443,714 | 399 | 12,136 |

Figure 19 contains a plot of accessibility versus activity generation for different income categories. The plot reveals a clear striation of participation by income groups for lower levels of accessibility (i.e. below 300,000 jobs). At 300,000 jobs, the highest income group converges downward, and at 500,000 the lowest income group converges upwards towards a mean participation rate. It is unclear whether these inflections in the trend are caused by sampling error alone or if they are statistically significant. Figure 20 displays a contour map of transit accessibility in the GTHA with the same breaks in the plots. The area for 300,000 jobs is the majority of the old City of Toronto, York, and East York as well as neighbourhoods near the major subway lines that extend into North York, Scarborough, and Etobicoke.  The area for 500,000 jobs only covers downtown Toronto and a few major transit stations outside this area (north to St. Clair and St. Clair West, east to Pape, and west to Dundas West).

While the upward movement of the low-income curves are predicted by transport poverty theory, it is not clear why higher income groups see declining participation rates inside the City of Toronto. It is important to keep in mind that while $125,000 is the highest income category in the TTS, more than 14% of households reported higher than $125,000 in the 2016 Census in the Toronto CMA, so this is a pattern pertaining to a large number of households, and not just the ultra-wealthy.  There may be age and household-structure variables at play, some of which can be controlled for in the multivariate models that follow.

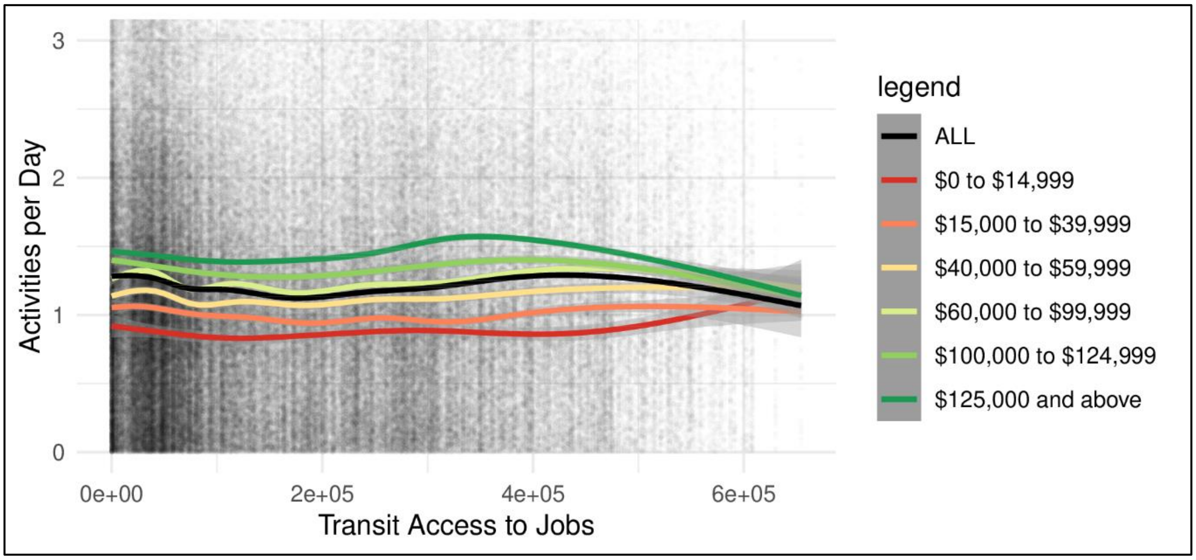


Figure 19 - Relationship between Transit Accessibility and Activities per Day by Income Categories

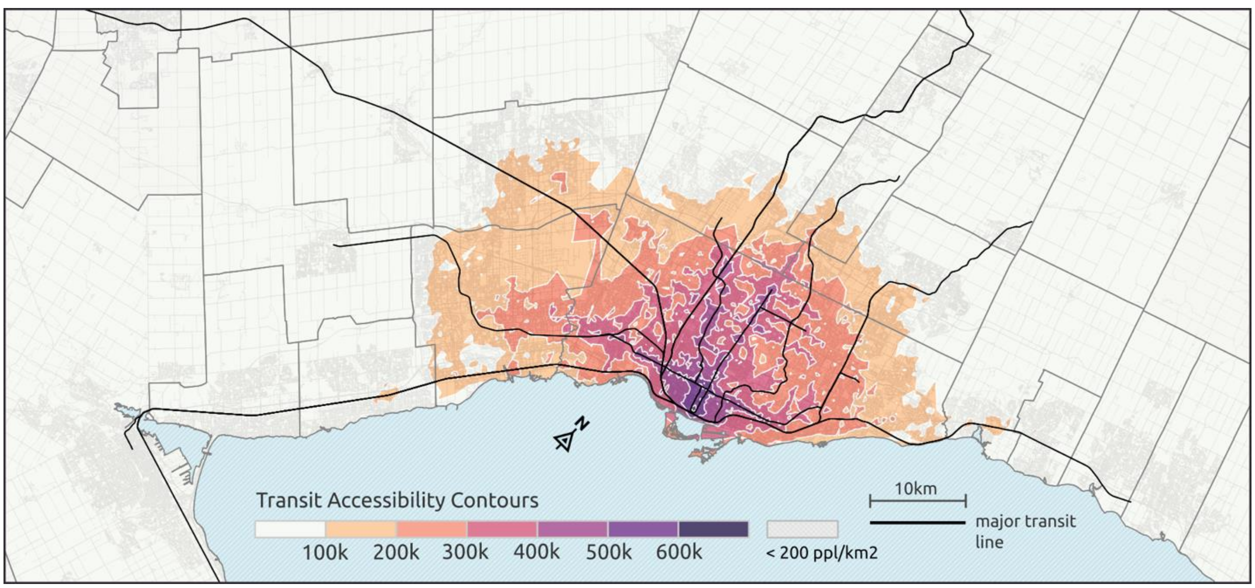


Figure 20 - Contour map of transit access to employment

# 5 Benchmarks and Key Performance Indicators

One objective of this phase of the research project is to develop benchmarks and KPIs that can be recorded now and used later to evaluate change in transport equity over time. Such measures should therefore be easy to calculate, repeatable at a later date, and capture a meaningful measure of "performance" with a clear normative interpretation (i.e. higher is better, or lower is better).

## 5.1 Measures of Evenness

Horizontal equity pertains to how evenly transportation costs and benefits are meted out across the population. It is difficult to ascribe a normative interpretation of such measures since it is unclear whether evenness in distribution is attainable, or even if there should be a goal to attain evenness. It suffices to say that evenness is only desirable if overall levels of benefits are high, or some minimum threshold is met for the region. Also, evenness can be achieved through the removal of benefits at the high-end of accessibility, which makes little policy sense.

Nevertheless, for the sake of posterity, we identify two measures of horizontal equity that can describe and keep track of evenness of transport provision based on the Gini coefficient. The two measures are identical except in the first case, the Gini is applied to the distribution of accessibility across individuals, and in the second, it is applied to the distribution of accessibility across dissemination areas. The latter is a special case of evenness that captures the notion of spatial equity, or how even the distribution of transit benefits is over space.

We can also compute the Gini coefficient to measure the evenness of trip and activity participation. Again, evenness is not really a goal we should be striving for blindly, as it can be achieved by reducing high levels of participation. But if evenness is attained by uplifting those on the lowest end of the spectrum, then achieving evenness can be interpreted positively.

The Gini coefficient ranges between 0 and 1, where 0 expresses perfect equality when all values are the same, and 1 expresses maximal unevenness when one individual (or zone) has all of the good being distributed.

Table 14 provides Gini coefficients for Transit Accessibility, and participation in trips, activities and discretionary activities. Overall, accessibility, trips, and activities display moderate levels of unevenness, while participation in discretionary activities is highly uneven. It will be imperative to explore further how this unevenness transcends population groups using measures of vertical equity.

Table 14 - Gini Coefficients as Measures of Evenness

| Variable | Gini Index |
|---|---|
| Transit Accessibility (spatial) | 0.53 |
| Transit Accessibility (individual) | 0.46 |
| Trips per Day | 0.41 |
| Activities per Day | 0.44 |
| Discretionary Activities per Day | 0.70 |

## 5.2 Measures of Vertical Equity

Vertical equity pertains to the fairness of the benefits distribution according to income and class. Again, there are many ways to measure this notion of equity, but perhaps the simplest is achieved by comparing between social groups with a ratio (Bannister, 2018). For example, the ratio of mean participation of high-income households to low-income households, is a telling measure of how unfairly participation is achieved by income levels. Extrapolating from this simple logic, we provide ratios for accessibility and participation (measured 3 ways) according to household income, household car-ownership, and individual age (Table 15). There are several notable findings:

1) Discretionary activities are more equitable across income than trips and all activities overall.
2) Despite trips and overall activities being quite equal between youth and middle-aged respondents, youth perform only half the number of discretionary trips compared to adults.
3) Middle-aged individuals conduct more trips and more overall activities compared to the elderly, but only about ¾ the number of discretionary activities.
4) Carless households have twice the typical access level compared to those with cars, but in general conduct 70-75% the number of trips and activities.

Table 15 - Table of Vertical Equity Measures

| Variable | High-Income / Low-Income | Middle-Aged / Youth | Middle-Aged / Elderly | Car / No Car |
|---|---|---|---|---|
| Transit Accessibility | 0.78 | 1.23 | 1.02 | 0.49 |
| Trips per Day | 1.42 | 1.01 | 1.41 | 1.31 |
| Activities per Day | 1.44 | 1.05 | 1.38 | 1.31 |
| Discretionary Activities per Day | 1.24 | 2.09 | 0.76 | 1.38 |

High Income = $125k and up; Low Income = $40k and under
Youth = 18 and under; Middle-aged = 19 to 64; Elderly = 65 and up

## 5.3 Accounting for the Transport Poor

Yet another benchmark to keep track of in the planning process is the accounting of how many transport poor households and individuals there are in the region. This can be achieved by estimating the number of low-income and/or carless households that are living in poor-access neighbourhoods of the GTHA. In this case, it is not clear how to define “poor-access” neighbourhoods in such a way that can be easily compared over time. If we choose a threshold based on percentile, for example the 20% level, in ten years, even if accessibility improves dramatically, there will still be a bottom 20th percentile, and it may be irrelevant how many low-income people live below that line of accessibility. On the other hand, if we choose an accessibility line that is fixed, at say, 150,000 jobs, there is no set precedent for how to choose a meaningful level, and it is difficult to know how this level need be shifted to accommodate for overall growth or decline in the region’s population or economy. In order not to limit the future use of this benchmark due to these issues, we present the number and percent of low-income and carless households living below each decile of transit accessibility, and each category of absolute accessibility by 100,000 job intervals. These measures can be used to track performance, in terms of the concentration of low-income and carless households within low-access neighbourhoods.

Table 16 - Counts of population groups by deciles of transit access to jobs

| Transit Accessibility Deciles | Overall Population | Car-Free Households | Persons 18 & under | Persons 65 & older | Persons in Low-Income Households | Persons in households not responding to income |
|---|---|---|---|---|---|---|
| 1 (low) | 575 | 6 | 79 | 79 | 23 | 44 |
| 2 | 575 | 11 | 71 | 91 | 35 | 44 |
| 3 | 576 | 17 | 73 | 93 | 40 | 45 |
| 4 | 574 | 19 | 76 | 77 | 36 | 39 |
| 5 | 576 | 13 | 69 | 91 | 36 | 41 |
| 6 | 575 | 24 | 63 | 98 | 51 | 41 |
| 7 | 575 | 40 | 59 | 105 | 61 | 47 |
| 8 | 575 | 47 | 58 | 102 | 61 | 44 |
| 9 | 575 | 82 | 54 | 89 | 68 | 44 |
| 10 (high) | 574 | 142 | 32 | 80 | 66 | 45 |
| Total | 5,748 | 401 | 635 | 906 | 478 | 433 |

Note: All population counts represented in 1000’s of individuals.

Table 17 - Counts of population groups by 100k intervals of transit access to jobs

| Transit Accessibility Equal Intervals | Overall Population | Car-Free Households | Persons 18 & under | Persons 65 & older | Persons in Low-Income Households | Persons in households not responding to income |
|---|---|---|---|---|---|---|
| 0 to 100k | 2,411 | 55 | 312 | 356 | 140 | 179 |
| 100k to 200k | 1,017 | 35 | 117 | 169 | 80 | 73 |
| 200k to 300k | 973 | 70 | 100 | 177 | 103 | 77 |
| 300k to 400k | 775 | 100 | 74 | 124 | 90 | 59 |
| 400k to 500k | 416 | 89 | 27 | 59 | 47 | 32 |
| 500k to 600k | 147 | 50 | 4 | 19 | 18 | 12 |
| 600k to 700k | 12 | 3 | 1 | 2 | 1 | 1 |
| Total | 5,748 | 401 | 635 | 906 | 478 | 433 |

Note: All population counts represented in 1000's of individuals.

## 5.4 Modal Equity

Finally, it is also meaningful to compare the degree to which destinations are accessible by different modes of transportation, so-called modal equity (Golub & Martens, 2014). The ratio of transit to car-based access to jobs can be used to keep track of the relative benefits afforded to each mode user. We present the mean, standard deviation, and deciles of this ratio across individuals, households, and neighbourhoods in the GTHA. As with the accounting in the previous section, it is not clear exactly which statistic will prove to be the most meaningful, so we provide representative cut-offs across the entire distribution.

Table 18 - Ratios of Transit Access to Auto Access

| | Neighbourhood | Household | Individual |
|---|---|---|---|
| Mean | 0.23 | 0.24 | 0.22 |
| Standard deviation | 0.11 | 0.13 | 0.13 |
| minimum | 0.00 | 0.00 | 0.00 |
| 10th percentile | 0.09 | 0.07 | 0.07 |
| 20th percentile | 0.13 | 0.11 | 0.11 |
| 30th percentile | 0.16 | 0.15 | 0.14 |
| 40th percentile | 0.18 | 0.19 | 0.17 |
| 50th percentile (median) | 0.22 | 0.23 | 0.21 |
| 60th percentile | 0.25 | 0.27 | 0.25 |
| 70th percentile | 0.29 | 0.31 | 0.29 |
| 80th percentile | 0.33 | 0.35 | 0.33 |
| 90th percentile | 0.38 | 0.43 | 0.39 |
| maximum | 0.60 | 0.60 | 0.60 |

# 6 Activity Participation Models

We now quantify the accessibility-participation relationship through the estimation of activity-generation models. These models estimate the marginal effect of transit accessibility on the number of daily activities, both for the overall population as well as disaggregated for different income groups and cars per household (classified as vehicles per adult in each household). These models investigate the degree to which transit access to employment is associated with participation levels in out-of-home activities, while controlling for other factors that effect participation such as age, household structure, and employment status.

## 6.1 Model Definitions

The dependent variables are count data and are modelled best using negative binomial regression. This type of model assumes the natural logarithm of the expected value can be modeled by a linear combination of independent variables with unknown coefficients. Negative binomial regression is chosen over Poisson regression because of over-dispersion of the dependent variable (the variance of activities per day is significantly greater than the mean). The data are not over-abundant in zero observations, so zero-inflated models were not necessary. During estimation, the model assumes that the dependent variable has a negative binomial distribution. This is similar to a Poisson distribution, but has an additional parameter to account for over-dispersion (a Poisson distribution assumes that the mean and variance are equal). The model is estimated via maximum likelihood estimation using the `glm.nb` function from the MASS package in R (see Venables & Ripley (2002) for more detail about this type of model and its estimation in R).

Of the three potential variables measuring activity participation, we choose to focus on activities per day. Models for trips per day produced very similar results, so we chose not to duplicate for the sake of brevity. For discretionary activities per day, previous studies have noted that they are better modelled with space-time accessibility metrics (Fransen et al., 2018), which were not within the scope of our study. Using place-based measures of accessibility resulted in substantially lower model fit when predicting discretionary activities per day than all trips or all activities per day. Moreover, since the TTS only surveys respondents about their weekday travel, there is likely under-reporting of discretionary activities which are more likely to occur on weekends. Despite not directly modelling activity counts by purpose, we make use of activity purpose distributions in our estimates of activity generations through a post hoc analysis described in Section 7.3.

Variables in the TTS included in the models were chosen via step-wise regression. We also use the TTS to derive and include in the model a variable pertaining to household type. This is generated via categorizing households based on the ages of their members. Categories include single-person households, single-generation households (2 or more people within 18 years of each other living together), two-generation households (2 or more people, in which there is at least a 18 year gap between two members, after being ranked in order according to age). If there are two or more of these 18 year gaps, then the household is classified as multi-generational. All other households are grouped into a fifth category. Secondly, in addition to the TTS data, we also include a variable in the model to control for urban form within the home Dissemination Area of each survey respondent. This variable captures the density of activity in a DA, which is derived as the weighted sum of standardized values of population density, business density, and employment density in each Dissemination Area. Similar localized density measures have been used in previous studies to examine their relationship with travel behaviour (e.g. Cervero & Kockelman, 1997), and specifically on trip and activity generation (e.g. Zhang et al., 2019).

Goodness of fit was examined via the Akaike information criterion (AIC) and the $\rho^2$ parameter. AIC is based on information theory. It measures the relative amount of information lost by a given model during the model estimation process. The lower the AIC, the less information lost, and the higher quality of the model. The $\rho^2$ is defined as one minus the ratio of the maximum log-likelihood of the entire model, divided by the maximum log-likelihood of the model which only contains the intercept (i.e. the least informative model) (Ben-Akiva and Lerman, 1985). The greater the $\rho^2$ the better the fit of the model as there is a greater relative difference between the maximum log-likelihood of the full model and least informative model. The same goodness of fit statistics have been used in other studies in the GTHA examining trip generation and activity participation rates (e.g. Roorda et al., 2010, Allen & Farber 2018).

In negative binomial regression, each independent variable is associated with a single regression coefficient, implying, for example, that impacts of accessibility on activity generation are homogenous for all levels of access. This is theoretically unlikely to be true in reality, as similarly sized gains in access will have different effects on activity generation for those with very low levels of access, medium levels of access, or high levels of access (Martens 2006; Martens 2016). We do not know, a priori, where the various inflections in the curve may occur, so we adopt a modelling strategy that tests various transformations of accessibility that enter into our activity generation models. Assuming the following generalized form of an activity generation model:

$$\ln(y) = \alpha + f(A) + \beta X + \epsilon$$

We proceed by varying how accessibility is transformed before entering into the model in three different ways. The first transformation of accessibility, $f(A)$, is linear, which assumes that each change in accessibility has the same effect on activity participation, regardless of the starting point:

$$f(A) = \beta_A A$$

The second is a quadratic function (i.e. second order polynomial) in which the rate of change of increase in activity participation increases with greater levels of accessibility (e.g. moving from 400k jobs to 500k jobs will have a greater effect on activity participation than moving from 100k jobs to 200k jobs).

$$f(A) = \beta_A A + \beta_{A^2} A^2$$

Third, we examine a sigmoidal function, which assumes that effects are largest in the middle of the accessibility distribution but are relatively flat in the upper and lower tails. Specifically, we transform accessibility based on the logistic function as follows where $\beta_A$ can be interpreted as the height of the sigmoidal curve, $k$ is the steepness of the curve, and $A_o$ is the value at the curve's midpoint (i.e. the value of $A$ where the slope is at its maximum). A brute-force parameter sweep is used to cycle through values of $A_o$ and $k$, allowing $\beta_A$ to be estimated by maximum likelihood, returning the model where $\rho^2$ is maximized.

$$f(A) = \beta_A \frac{1}{1 + \exp(-k(A - A_o))}$$

## 6.2 Model Results

Model results for the three accessibility transformations are displayed in Table 19, while the shapes of the implied relationships to participation are plotted in Figure 21 to better visualize and compare their effects. In general, the three models achieve very similar goodness-of-fit, with only minor differences in coefficients for non-accessibility variables. Estimated model parameters ($\beta$) as well as incident rate ratios (IRR) are displayed in the tables below. The estimates ($\beta$) can be interpreted as the difference between the log of expected counts given a 1 unit increase (for numerical variables) or for being in a different group than the reference group (for categorical variables). The IRR for an independent variable is computed as IRR = $e^{\beta}$. It can be interpreted as the multiplicative increase or decrease in daily activity participation rate caused a 1 unit increase for numerical variables or by changing groups for categorical variables. For example, someone who is a full-time student is expected to have an activity participation rate 1.27 times greater than a non-student, holding all other variables constant. A model estimate greater than 0 and an IRR greater than 1 indicate that the variable has a positive effect on activity participation.

From the three models, we find that transit accessibility has a small, but significant, effect on activity participation. Importantly, this indicates that improvements in transit accessibility can lead to people participating in a greater number of daily activities. These findings align with some previous research that has found similar results (Vickerman, 1974; Koenig, 1980; Thill and Kim, 2005). Figure 21 shows the fitted curve of accessibility for each transformation. The three accessibility specifications behave similarly for low levels of accessibility (<150k jobs), but the quadratic and sigmoidal transformations show steeper rates of increase in the range (200k to 500k jobs), at which point the sigmoidal curve begins to level off, while the quadratic continues to increase. Despite theory predicting that the effect of accessibility should level off (e.g. Martens, 2016), the quadratic curve obtains a very similar statistical level of fit than the sigmoidal function when accounting for all of the other variables in the model. This is likely due to there being very few observations at the highest end of the accessibility domain, and therefore only a very slight penalty for any estimation in the quadratic function.

With regards to household income, those in higher income brackets are more likely to participate in more daily activities than in those in low-income households (<$40k per year), all else being equal. Relative to low-income households, middle income households ($40k-$60 per year) participate in 1.05 times as many daily activities, while those in the highest income bracket ($125k+ per year) participate in 1.19 times as many daily activities as the lowest income bracket, all else being equal. Zero-car households also have lower probability of participating in daily activities. Indeed, individuals in households with at least one car per adult are predicted to have 1.3 times the level of daily activity participation than households without cars, all else being equal. These results corroborate the descriptive findings in Section 4.7.

Table 19 – Activity participation global model results (full sample)

| | Linear Accessibility | | Quadratic Accessibility | | Sigmoidal Accessibility | |
|---|---|---|---|---|---|---|
| | n<br>rho<br>AIC | 247,452<br>0.1064<br>659822 | n<br>rho<br>AIC | 247,452<br>0.1066<br>659761 | n<br>rho<br>AIC | 247,452<br>0.1066<br>659769 |
| **Independent Variables** | ***β*** | **IRR** | ***β*** | **IRR** | ***β*** | **IRR** |
| Variables of Interest | | | | | | |
| Accessibility | 0.0018 | 1.0018 | -0.0016 | 0.9984 | - | - |
| Accessibility squared | - | - | 0.0001 | 1.0001 | - | - |
| Accessibility (sigmoid, k = 0.13, Ao = 42) | - | - | - | - | 0.1748 | 1.1910 |
| Household income (ref < 40k per year) | | | | | | |
| 40k-60k per year | 0.0516 | 1.0529 | 0.0501 | 1.0514 | 0.0501 | 1.0514 |
| 60k-100k per year | 0.0953 | 1.1000 | 0.0924 | 1.0968 | 0.0925 | 1.0969 |
| 100k-125k per year | 0.1479 | 1.1594 | 0.1437 | 1.1545 | 0.1439 | 1.1548 |
| 125k+ per year | 0.1822 | 1.1999 | 0.1765 | 1.1930 | 0.1769 | 1.1935 |
| decline / don't know | 0.0317 | 1.0322 | 0.0289 | 1.0293 | 0.0291 | 1.0295 |
| Vehicles per household (ref = 0) | | | | | | |
| 0 < vehicles per adult < 0.5 | 0.1315 | 1.1405 | 0.1400 | 1.1503 | 0.1394 | 1.1495 |
| 0.5 vehicles per adult | 0.1867 | 1.2052 | 0.1948 | 1.2151 | 0.1940 | 1.2141 |
| 0.5 < vehicles per adult < 1 | 0.2009 | 1.2225 | 0.2086 | 1.2319 | 0.2078 | 1.2310 |
| 1 or more vehicles per adult | 0.2664 | 1.3052 | 0.2719 | 1.3125 | 0.2720 | 1.3125 |
| Control Variables | | | | | | |
| Constant | 0.0668 | 1.0691 | 0.0815 | 1.0849 | 0.0752 | 1.0781 |
| Sex (ref female) | | | | | | |
| male† | -0.0044 | 0.9956 | -0.0045 | 0.9955 | -0.0045 | 0.9955 |
| Persons per hhld | -0.0450 | 0.9560 | -0.0448 | 0.9562 | -0.0449 | 0.9561 |
| Hhld type (ref two generation family) | | | | | | |
| one generation | 0.0994 | 1.1045 | 0.0958 | 1.1005 | 0.0959 | 1.1007 |
| multi generation | -0.1426 | 0.8671 | -0.1423 | 0.8673 | -0.1426 | 0.8671 |
| single person | 0.2336 | 1.2631 | 0.2301 | 1.2588 | 0.2299 | 1.2585 |
| other / complex | -0.1010 | 0.9039 | -0.1000 | 0.9048 | -0.1002 | 0.9046 |
| Percent hhld under 18 | 0.0058 | 1.0059 | 0.0058 | 1.0058 | 0.0058 | 1.0058 |
| Age (ref 31-65) | | | | | | |
| 18-30 | -0.1380 | 0.8711 | -0.1391 | 0.8701 | -0.1391 | 0.8702 |
| 66-75 | 0.0416 | 1.0425 | 0.0413 | 1.0422 | 0.0416 | 1.0425 |
| 76+ | -0.2155 | 0.8062 | -0.2154 | 0.8062 | -0.2150 | 0.8066 |
| Employment status (ref full-time) | | | | | | |
| tele-work | -0.2586 | 0.7721 | -0.2603 | 0.7708 | -0.2599 | 0.7711 |
| part-time | -0.0401 | 0.9607 | -0.0406 | 0.9602 | -0.0405 | 0.9604 |
| not employed | -0.4286 | 0.6514 | -0.4282 | 0.6517 | -0.4281 | 0.6517 |
| Student status (ref not a student) | | | | | | |
| full-time | 0.2385 | 1.2693 | 0.2378 | 1.2685 | 0.2382 | 1.2690 |
| part-time | 0.1636 | 1.1777 | 0.1631 | 1.1772 | 0.1632 | 1.1773 |
| Dwelling type (ref detached home) | | | | | | |
| townhouse | -0.0500 | 0.9512 | -0.0439 | 0.9571 | -0.0450 | 0.9560 |
| apartment† | -0.0085 | 0.9916 | -0.0066 | 0.9935 | -0.0071 | 0.9929 |
| Neighbourhood activity density | -0.0087 | 0.9914 | -0.0161 | 0.9841 | -0.0144 | 0.9857 |

† All variables were significant at the 0.001 level except for those indicated with a †, which were not significant at the 0.1 level

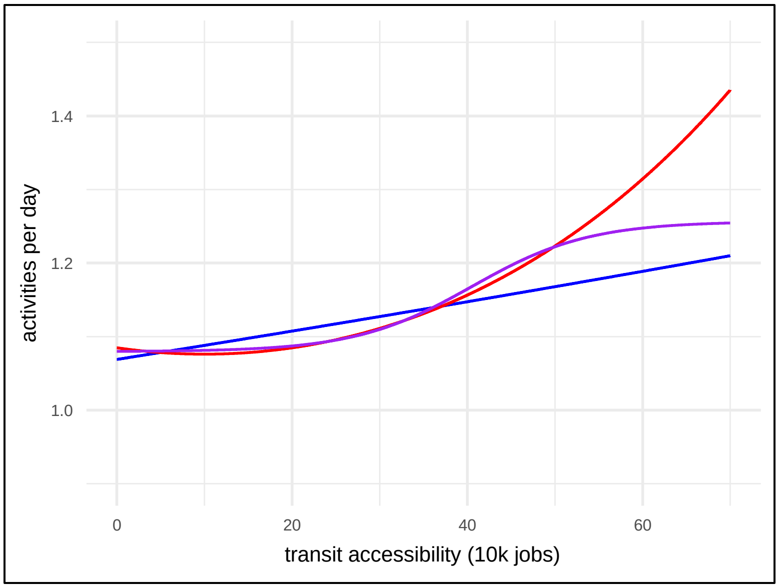


Figure 21 – Estimated effects of transit accessibility on activity participation (blue = linear, red = quadratic, purple = sigmoidal) based on all other variables at their reference levels.

## 6.3 Stratified Models

To further understand the effects of transit accessibility for those groups who are more vulnerable to transport poverty, we stratify the models by income and car-ownership. This results in 30 separate models (six income groups times five groups of car-ownership) from which we examine the magnitude and statistical significance of the accessibility coefficients to understand how they vary by group. The sign (positive or negative) and significance of the effects of accessibility for each sub-model is displayed in Table 20 (complete model parameters are included in the Appendix). The quadratic and sigmoidal models were better fitting than the linear models, but we focus on the sigmoidal in particular because of the desirable property of diminishing marginal effects of accessibility on participation.

Table 20 – Effects of accessibility on activity participation for different SES groups*

| Vehicles per Adult (VA) | Household Income | | | | | |
|---|---|---|---|---|---|---|
| | < $40k | $40k - $60k | $60k - $100k | $100k - $125k | $125k + | decline |
| VA = 0 | + | + | + | + | + | + |
| 0 < VA < 0.5 | + | - | - | + | + | - |
| VA = 0.5 | - | - | + | + | + | + |
| 0.5 < VA < 1 | - | + | + | - | + | + |
| VA >= 1 | + | + | + | + | + | + |

| | | | |
|---|---|---|---|
| p <= 0.001 | 0.001 < p <= 0.01 | 0.01 < p <= 0.05 | p > 0.05 |

*from the best-fitting sigmoidal transformation of accessibility

Table 20 shows that for car-less households, transit accessibly has a significant and positive effect on activity participation rates, regardless of income level. However, there are substantially more lower-income households without cars than there are zero-car households in the higher-income brackets. Low-income households with at least 0.5 cars per adult do not see a significant effect of accessibility on activity participation. These results are in-line with the bivariate results found in Section 4.8. Interesting as well is that some higher income groups and households with cars are also more likely to experience gains in activity participation if they live in accessible areas. This could be because living in more active urban environments encourages more out-of-home activities, which wealthier households are more able to afford to participate in, regardless of travel-related barriers.

## 7 Scenario Testing: Estimating Activity Gains from Improvements in Accessibility

We use the coefficients from the stratified models with sigmoidal accessibility functions to forecast how individuals living in different types of households are likely to respond to transit accessibility improvements, conditional on their household income, automobile ownership, and current levels of transit accessibility. We aggregate these activity generations by SES group, neighbourhood and geographic region to explore where and for whom changes in transit accessibility are likely to result in the highest levels of activity gains.

For each observation in our sample, we can use the stratified model specific to their class of income and car-ownership to estimate their current $(\hat{y}_{i,o})$ and projected $(\hat{y}_{i,p})$ levels of activity participation given their current $(A_o)$ and projected $(A_p)$ levels of accessibility, respectfully.

The predicted change in activity participation due to a change accessibility (from the observed state, *o*, to a potential future state, *p*), is provided as follows:

$$\Delta\hat{y}_i = \hat{y}_{i,p} - \hat{y}_{i,o}.$$

We compute $\Delta\hat{y}_i$ for each individual in our sample for five different scenarios representing different levels of change in accessibility:

- 10% increase
- 25% increase
- 50,000 job increase
- 100,000 job increase
- 200,000 job increase.

The sizes of these accessibility increases are informed by previous work that estimated changes in accessibility for a number of GTHA rapid transit expansions (Farber & Marino, 2017). The smaller gains in accessibility (10% or 50k jobs) are roughly the gains that would be achieved via moderate improvements in existing transit service (e.g. adding dedicated bus lanes, more frequent service), while the larger scenarios could be achieved from investments in higher-order transit infrastructure (e.g. well-connected rapid transit running on separated grades). The map in Figure 20 can be used to understand the spatial context for the hypothesized changes in accessibility.

For each scenario, we apply the accessibility change uniformly across the entire region. This allows us to evaluate the differences in sensitivity to accessibility different social groups have, and how individual-level changes in activity participation aggregate to social groups or neighbourhood boundaries.

### 7.1 Activity Gains by Household Income and Car-Ownership

Given the overall small effect of accessibility on activity participation, and the small numbers of activities being conducted by each person per day, the estimated values of $\Delta y_i$ are quite small for each person $i$, measured typically in small fractions of a daily activity. However, when aggregated by social group, neighbourhood or to the overall region, the results indicate that improvements in accessibility have substantial benefits in terms of increased activity participation in the region.

First, we aggregate potential accessibility gains by household income and car-ownership levels (Table 21). This is focused on low-income and car-free households, who theoretically have the greatest mobility-based barriers to activity participation. The cells on the right indicate the number of overall new activities gained for each scenario. The rows with 0s pertain to cases when the accessibility coefficient did not achieve statistical significance for a particular strata (i.e. where $p < 0.05$). The table shows that zero-car households in particular are likely to achieve substantial gains in activity participation. The effects are greatest for low-income households in the lowest two levels of automobile ownership.

We next examine how the total gain in activity participation is distributed across each group of household income and car ownership (see Table 22). For example, those in the low-income and car-less households make up less than 5% of the overall population, and currently only 3.37% of the current levels of activity participation in the region, but would achieve from 9% to 15% of the total benefit in terms of activity participation, depending on the scenario. Improvements in transit accessibility result in gains in activity participation for these low SES groups, those who currently have the lowest levels of activity participation, and therefore, has the ability to reduce inequalities between SES groups.

## Table 21 - Gains in activity participation for different accessibility improvement scenarios[3]

| Hhld. Income | Vehicles per Adult (VA) | n | N | Observed total daily activities | Increase in Activities for each scenario | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | 10 percent | 25 percent | 50k jobs | 100k jobs | 200k jobs |
| < $40k | VA = 0 | 9,934 | 264,475 | 217,867 | 3,859 | 9,141 | 5,494 | 11,319 | 21,949 |
| < $40k | 0 < VA < 0.5 | 3,688 | 109,122 | 92,225 | 1,784 | 6,914 | 1,752 | 5,327 | 24,702 |
| < $40k | VA = 0.5 | 10,320 | 217,567 | 216,610 | 0 | 0 | 0 | 0 | 0 |
| < $40k | 0.5 < VA < 1 | 2,081 | 52,502 | 47,554 | 0 | 0 | 0 | 0 | 0 |
| < $40k | VA >= 1 | 9,888 | 189,582 | 240,964 | 0 | 0 | 0 | 0 | 0 |
| $40k - $60k | VA = 0 | 3,492 | 85,983 | 94,397 | 1,753 | 3,916 | 2,623 | 4,970 | 8,645 |
| $60k - $100k | VA = 0 | 3,868 | 92,831 | 112,578 | 2,466 | 4,996 | 3,361 | 5,960 | 9,199 |
| $100k - $125k | VA = 0 | 1,338 | 27,407 | 34,533 | 797 | 1,661 | 1,049 | 1,864 | 2,921 |
| $125k + | VA = 0 | 1,500 | 27,034 | 37,000 | 342 | 596 | 489 | 727 | 1,013 |
| decline | VA = 0 | 4,405 | 97,645 | 70,984 | 399 | 825 | 755 | 1,344 | 2,329 |
| all others | all others | 196,939 | 4,181,271 | 5,295,963 | 14,656 | 36,377 | 28,383 | 64,884 | 175,911 |
| Total | | 247,453 | 5,345,419 | 6,460,674 | 26,056 | 64,426 | 43,906 | 96,394 | 246,669 |

## Table 22 - Distribution of gains in activity participation by SES group

| Hhld Income | Vehicles per Adult (VA) | n | N | Total activities | Increase in Activities for each scenario | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | 10 percent | 25 percent | 50k jobs | 100k jobs | 200k jobs |
| < $40k | VA = 0 | 4.01% | 4.95% | 3.37% | 14.81% | 14.19% | 12.51% | 11.74% | 8.90% |
| < $40k | 0 < VA < 0.5 | 1.49% | 2.04% | 1.43% | 6.85% | 10.73% | 3.99% | 5.53% | 10.01% |
| < $40k | VA = 0.5 | 4.17% | 4.07% | 3.35% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| < $40k | 0.5 < VA < 1 | 0.84% | 0.98% | 0.74% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| < $40k | VA >= 1 | 4.00% | 3.55% | 3.73% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| $40k - $60k | VA = 0 | 1.41% | 1.61% | 1.46% | 6.73% | 6.08% | 5.97% | 5.16% | 3.50% |
| $60k - $100k | VA = 0 | 1.56% | 1.74% | 1.74% | 9.46% | 7.75% | 7.65% | 6.18% | 3.73% |
| $100k - $125k | VA = 0 | 0.54% | 0.51% | 0.53% | 3.06% | 2.58% | 2.39% | 1.93% | 1.18% |
| $125k + | VA = 0 | 0.61% | 0.51% | 0.57% | 1.31% | 0.93% | 1.11% | 0.75% | 0.41% |
| decline | VA = 0 | 1.78% | 1.83% | 1.10% | 1.53% | 1.28% | 1.72% | 1.39% | 0.94% |
| all others | all others | 79.59% | 78.22% | 81.97% | 56.25% | 56.46% | 64.65% | 67.31% | 71.31% |
| Total | | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% |

[3] These results are based on the sigmoidal accessibility functions. Results for linear, quadratic, and best-fitting function were also computed. Linear models were rarely best fitting, and deemed inaccurate. Quadratic models overemphasized activity gains, especially for populations living in already high-accessibility neighbourhoods. This resulted in overestimation of the effect of accessibility on carless, low-income households living in and near downtown Toronto.

## 7.2 Activity Gains by Neighbourhood

We next aggregate potential gains in activity participation by neighbourhood, in this case study by Dissemination Areas (DA). For example, if accessibility improves by X amount in a DA, either due to improved transit or intensification of urban form, we can estimate the predicted gain in activity participation in the DA. Doing this for each DA in the region, and then mapping the results, allows us to highlight where improvements in accessibility will have the greatest benefit in terms of activity participation.

Figure 22 displays the estimated gain in activity participation in each DA from a hypothetical increase of 100k jobs applied to the current level of accessibility. The darker the blue on the map, the greater the gains in activity participation. This pattern is largely governed by three factors: the number of low-income households, the number of carless households, and the baseline levels of accessibility in the DA. The latter is a result of the sigmoidal shape of the access-participation relationship, which predicts that the biggest effect of accessibility will occur in areas with already moderate levels of access. We see that accessibility increases activity rates most in the City of Toronto, and especially in low-income areas and those not served by the subway. These are places with moderate levels of accessibility and so are located near the steep part of the sigmoidal curve. Conversely, there are many light-blue areas in the GTHA's outer suburbs. These are places where accessibility currently is low, and so an increase in access moves neighbourhoods along the flattest part of the sigmoidal curve. These are also places with relatively high levels of automobile ownership, leading to an insensitivity to transit improvements, from the perspective of net change in overall activity generations.

In general, this emphasizes that accessibility improvements in inner-suburban areas, those that are closer to the midpoint of the sigmoidal curve, would likely have greater impacts in terms of increases in activity participation.

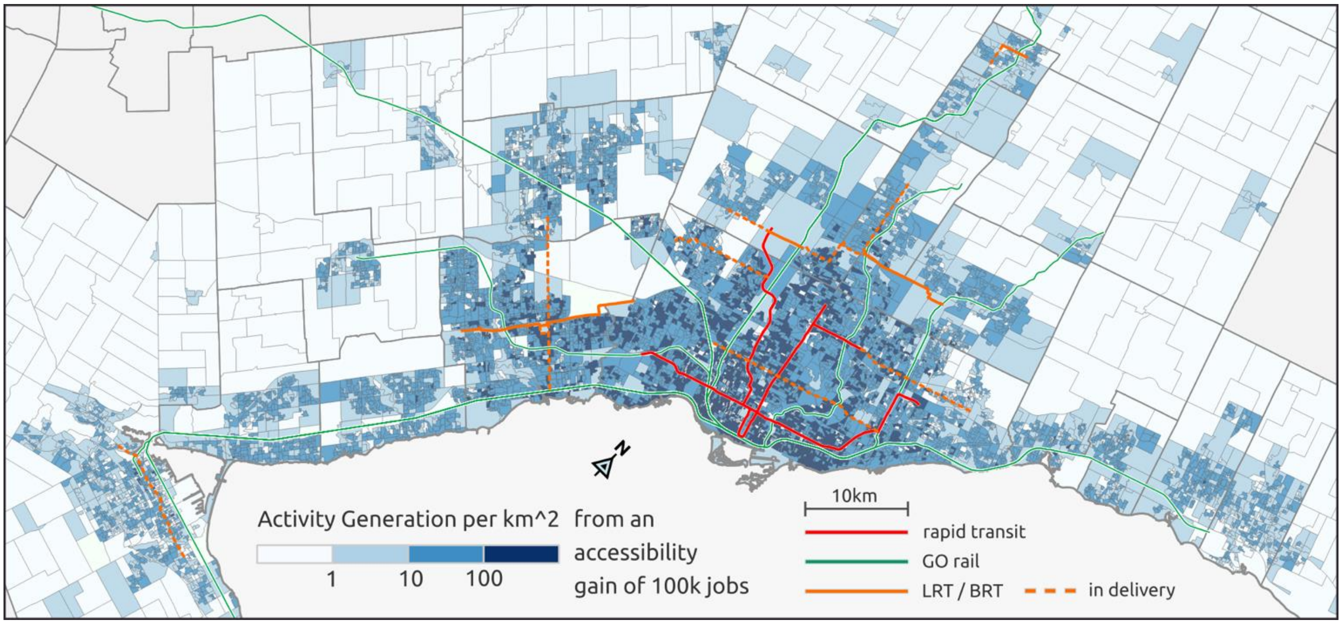

Figure 22 - Density in activity generation resulting from an improvement in accessibility of 100k jobs

Figure 23 masks out areas that already have moderate to high levels of activity participation, and only displays neighbourhoods with low levels of activity participation (where the mean level of activity participation per person is less than one out-of-home activity per day). The dark blue areas on this map can be thought of as high priority neighbourhoods for improving transit accessibility, as they currently have low-levels of activity participation, and would likely see some of the highest returns activity gains. Focusing on these areas could therefore reduce existing socio-spatial inequalities of activity participation, and result in increases in overall levels of transit equity in the region. On this map, the dark blue areas cluster more within the inner-ring suburbs where there are moderate levels of accessibility already as well as higher numbers of low-income and/or car-less households which currently participate in fewer daily activities relative to other areas. On the other hand, the light blue areas in Figure 23 are those where there are currently low levels of activity participation, but improvements in transit accessibility would only have a minor impact, and short-term mobility strategies for improving activity participation would have to include other potential solutions (e.g. subsidizing taxis or ride-hailing).

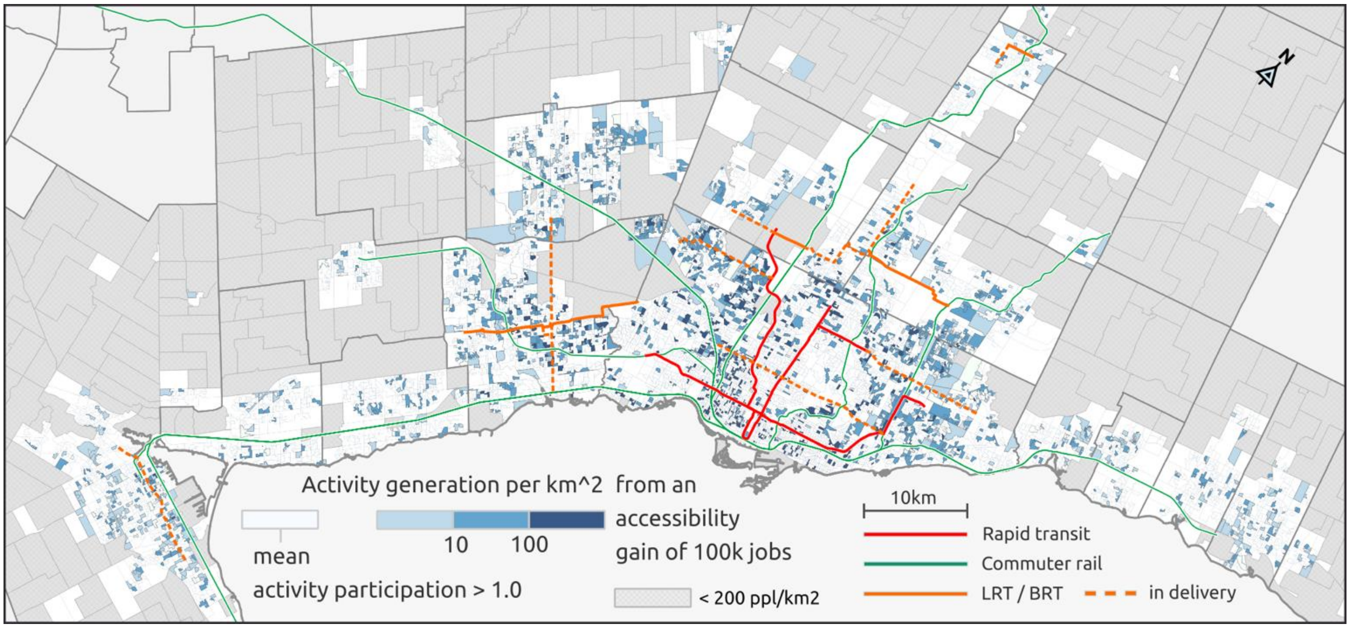


Figure 23 - Density in activity generation resulting from an improvement in accessibility of 100k jobs for neighbourhoods with low levels of activity participation (mean individual activity participation < 1)

Overlaid on Figures 22 and 23 are existing major transit lines, as well as transit lines which are in-delivery (either currently under-construction or are in the planning stage with secured funding, as of April 2019). The in-delivery lines do appear to reach some neighbourhoods that are projected to witness gains in activity participation. However, there are still a number of neighbourhoods within inner-suburban areas that would benefit greatly from improvements in accessibility, that are not slated to be reached by higher-order transit in the near future. These include, but are not limited to, neighbourhoods in eastern Mississauga, northern Etobicoke (parts of Rexdale), central Etobicoke (e.g. Eglinton West), Thorncliffe, Flemingdon Park, in North York along Steeles Ave as well as along Jane Street, and parts of Scarborough (e.g. along Victoria Park, Finch East, and Eglinton East).

## 7.3 Activity Gains by Purpose

In this section, we attempt to disaggregate potential gains in activity participation by purpose (e.g. work, school, shopping, etc.) for the five accessibility improvement scenarios analyzed above. This allows us to examine which types of additional activities will be conducted if accessibility improves in the region. These estimates are based on the data in Table 23, which shows the distribution of activity types for individuals who recorded 1 activity per day, 2 activities per day, and so on.

Table 23 - Observed distribution of activity types by number of daily activities

| Number of Activities | n | N | Percent of Activities by Purpose | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Work | School | Shopping | Facilitating | Other | Total |
| 0 | 61,057 | 1,286,795 | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| 1 | 116,003 | 2,570,020 | 65.51% | 8.09% | 9.85% | 3.85% | 12.69% | 100.00% |
| 2 | 43,538 | 930,993 | 31.06% | 3.57% | 18.01% | 16.52% | 30.84% | 100.00% |
| 3 | 16,559 | 344,726 | 23.36% | 1.64% | 21.82% | 21.02% | 32.16% | 100.00% |
| 4 | 6,252 | 128,307 | 20.08% | 0.84% | 24.99% | 24.03% | 30.07% | 100.00% |
| 5+ | 4,044 | 84,577 | 15.99% | 0.46% | 28.61% | 28.99% | 25.95% | 100.00% |

We use this table, and the observed number of activities for each individual, to estimate the probability that each new activity (or partial activity as the case may be) will be of each type. Specifically, we use the previously computed predicted gain in activities per day ($\Delta\hat{y}_i$) and multiply this by the row in the table corresponding to each individual's observed number of daily activities plus one additional activity. This distributes the estimated gross gain in activity participation across the distribution of types of activities for their new level of activity participation. For example, if someone does not record doing an activity in the survey, then we multiply $\Delta\hat{y}_i$ by each of the percents in the row pertaining to 1 activity. The aggregated results for each scenario are presented in Table 24. If we were able to attach an average dollar value to each type of trip, we could begin to establish the value of transit investments through the lens of induced activity generation.

It should be noted, however, that the results in Table 24 are somewhat crude estimates designed to get a sense of the overall distributions of types of activities. These estimates do not consider other individual and household factors likely to influence certain activities that have more structure (e.g. whether the individual is already employed, their student status, etc.). Future work in this domain should likely utilize models that are specific to different types of activities that take into account a set of activity-specific variables.

Table 24 - Estimated activity gains by purpose of activity

| Accessibility Improvement Scenario | New Activities by Purpose | | | | | |
|---|---|---|---|---|---|---|
| | Work | School | Shopping | Facilitating | Other | Total |
| 10 percent | 8,767 | 933 | 4,808 | 4,298 | 7,249 | 26,056 |
| 25 percent | 22,000 | 2,358 | 11,779 | 10,478 | 17,812 | 64,426 |
| 50k jobs | 14,773 | 1,570 | 8,108 | 7,247 | 12,208 | 43,906 |
| 100k jobs | 32,655 | 3,482 | 17,726 | 15,808 | 26,723 | 96,394 |
| 200k jobs | 84,191 | 8,995 | 45,174 | 40,185 | 68,124 | 246,668 |

# 8 Conclusions

## 8.1 Summary of Findings

The first objective of this project was to compute a set of benchmarks regarding the state of transit equity in the GTHA, including an accounting of transport poverty in the region. These findings highlight that low-income households are more likely to be located in areas with better transit accessibility, but they participate in substantially fewer daily activities than wealthier households. As well, even though the relationship between transit accessibility and household income is negative, there are still 17,000 zero-car households and 58,000 people living in low-income households in the lowest quintile (20%) of transit accessibility. It will be imperative to track these statistics (presented in Section 5) using future survey waves to examine whether the state of transit equity improves or worsens over time, and for whom.

Our study also included exploratory spatial analysis to identify “participation deserts”, clusters of neighbourhoods where residents have lower than expected rates of daily activity participation. We find that these areas of low activity participation tend to concentrate in the automobile oriented “inner-suburbs”, poorer, post-war neighbourhoods where existing levels of transit service are assumed to not be sufficient for meeting the needs of residents. This hypothesis was further explored in a series of descriptive data explorations, where the links between accessibility, income, car-ownership and activity participation were unpacked further. The data show quite clearly that participation rates in out-of-home activities for carless households are dependent on high levels of transit accessibility. There were large gaps in participation among those with and without cars inside transit-poor neighbourhoods, and these gaps grew smaller with increasing levels of transit access. Parallel to this, we find that carless households tend to be located in higher access neighbourhoods, but among the carless, there are big differences in accessibility between wealthier and poorer households.

Following the descriptive analyses, accessibility-activity participation relationships were examined using multivariate negative binomial models. These models showed that after controlling for other individual and household characteristics, transit accessibility had a small, but significant positive effect on daily activity participation rates. Car ownership and household income also had positive effects (i.e. low-income and zero-car household were more likely to participate in fewer daily activities). We also generated models stratified for different subsets of household income and car-ownership. These indicated that equity seeking groups, like low-income households, and particularly, zero-car households, are the most sensitive to transit accessibility in terms of its effects on increasing activity participation. Carless households also tend to be poor households, so increases in transit accessibility are more likely to result in gains in a low-income activity generation, compared to other income groups. These benefits are the greatest in central and inner-ring suburbs, where there are high concentrations of low-income residents, and where increases in accessibility are most likely to affect activity generation.

## 8.2 Study Limitations

This study had several limitations which could be improved upon in future work. There are several unavoidable issues related to the nature and sampling characteristics of the Transportation Tomorrow Survey. One issue is that sampling rates were very low in some neighbourhoods (<3%) compared to the overall sampling rate of 5%. While this does not pose a serious challenge to the use of descriptive statistics and multivariate models, largely due to the use of individual-level analyses, the unevenness in sampling will cast a shadow of uncertainty over neighbourhood-level averages, such as those used to delineate participation deserts. There is a tension here between using low-levels of geography like DAs to find detailed spatial patterns, and using larger aggregation units, like TAZs, that would allow for tighter margins of error. In the end, given the exploratory nature of the participation deserts, we opted for the former, but a case could be made that larger units should be investigated before policies directed participation deserts are designed.

A second issue with the TTS is that it likely under-reports discretionary activities, trips made by youth, short trips or activities, or trips conducted by active modes. The reasons for underreporting include the collection via proxy, the difficulty in travel history recall, the lack of collection of recreational trips (e.g. trips for exercise, dog-walking, etc.), and the focus of collection on weekday activities, when arguable, more discretionary activities occur on the weekends. In all cases, it is uncertain whether this under-reporting is related to income, transit accessibility, or car ownership – the key variables we have used to analyze activity participation. So it may be the case that while our values used to benchmark activity rates, such as number of activities per day, are biased downwards, the relationships quantified in our models, are likely to hold true. We use the same logic to assume that the 18% non-response rate to the income question does not have a major bearing on the robustness of our model results.

The focus of this research was on transit accessibility and it's effects on activity generation. Despite this, it was not feasible to conduct an exhaustive study of the numerous ways in which accessibility has been quantified in the literature. We used a single gravity-based access to jobs measure, to model activity generation. While in general, there are high levels of correlation between different place-based measures of accessibility, it might be better to use different types of destinations to predict different types of activity generation (e.g. use measures of transit access to retail to examine its effects on shopping trips). Moreover, participation in discretionary activities may be better modeled using space-time accessibility measures, rather than the place-based measures employed here (Fransen et al., 2018). Generating separate models for participation in different activity types (e.g. work, shopping, etc.) could also result in more nuanced understandings, and eventual valuations, of the how accessibility is converted into participation benefits for different types of households. Along these lines, future modelling could also focus more efforts to estimate the monetary value of activity generation, since dollar values are predominant in cost-benefit analyses used to decide where to build new transport infrastructure (Litman, 2017). This line of research could expand upon work by Stanley et al. (2011) who outline an approach using an ordinal choice model of social exclusion. However, this may be difficult using categorical, self-reported, groupings of income that are currently in the TTS. One alternative in the short-term is to assign reasonable values to activities of different types.

Lastly, conducting a cross-sectional analysis (i.e. using data from a single time period) is limited in terms of deciphering causality and directionality. Similarly, due to the cross-sectional nature of the analysis, it is difficult to ascertain the degree to which self-section is responsible for the findings. It could be that those low-income and carless households who have a preference for higher activity levels, choose to pay higher rents to live in the inner city, while those with a preference for less activity, chose to locate in the suburbs. Without a set of attitudinal and preference questions in the TTS, we are unable to control for this type of self-selection in a cross-sectional analysis.

It would be worthwhile to research these questions longitudinally, either empirically or within a simulation framework. There has been some descriptive research analyzing changes in transit accessibility with respect to socio-economic status over time (e.g. Foth et al., 2013), but no research to date has examined this at a more in-depth level with variables pertaining to car-ownership and activity participation rates. Indeed a fruitful direction for future research would be to conduct a longitudinal analysis of changes in the effects of activity participation, partly in relation to increasing socio-spatial inequalities in the city (e.g. suburbanization of poverty). This could be conducted historically (using previous waves of the TTS), as well as continuing to track changes into the future via analyzing ongoing shifts in population distributions and urban form.

## 8.3 Policy Implications

Given our findings, this research provides ample evidence in support of transport policies that are directed towards improving the participation rates of low-income and carless households, those who we consider to be transport-poor, such as improving public transit in areas where these households concentrate. We contend that existing methods for evaluating transport investments under-value the benefits derived from unlocking suppressed demand for out-of-home activity participation among the transport poor.

Moreover, because these benefits are likely to concentrate among the poor and carless households in the region, our evaluation frameworks are not currently suited to the task of achieving improved levels of equity in the GTHA's transportation system. We think the major contribution of this research project is to demonstrate that participation benefits matter, that they are likely very valuable, that they occur when investments are made in low-income neighbourhoods, and that these benefits should be captured when evaluating transportation infrastructure projects in the region.

While the objective of this study was to examine how improvements in transit service would result in gains in activity participation, the same types of improvements in transit service could result in mode-switching from private car to public transit. This would have a number of environmental benefits, but also work towards improved levels of social equity in the region. In our analysis, we observe that there are many low-income drivers in the region. Understanding their mode choice elasticity to transit accessibility could help increase transit ridership while lowering their reliance on auto-based travel and subsequently their mobility costs; for example, reduce their need to take out loans, go into debt, etc. just to have access to a car, and therefore access urban destinations (e.g. Walks, 2018). This could result in more of their income going towards other necessities of daily life (e.g. housing, healthy food, etc.). To our knowledge, current infrastructure evaluations in the GTHA do not adequately differentiate the mode-choice elasticities with respect to income, largely because this data has not been available until the most recent version of the TTS. Coupled with our findings regarding activity generation, higher-elasticities of mode switching among low-income households, at least those who currently own vehicles, would only serve to enhance evaluation methods and increase the benefits associated with more progressive and fair provision of infrastructure.

Aside from the above implications for how we measure transport benefits and evaluate infrastructure projects, the detailed modelling efforts in this study give rise to a nuanced set of recommendations for how to unlock suppressed demand in different parts of the GTHA. These nuances stem from the spatial distributions of low-income and carless populations in the region, as well as the sigmoidal response function that describes how improvements in accessibility will not reap the same benefits everywhere in the region. In particular, we see that for most population groups, the steepest part of the sigmoid curve occurs in mid-range accessibility levels, signifying that investments in rural areas will see little impact on activity generation. At the same time, increases in extremely well served neighbourhoods will similarly have little impact on unlocking suppressed demand, as we do not see transportation service levels in these neighbourhoods acting as a barrier to participation. The challenge is to therefore find low-income neighbourhoods in areas our inner suburbs, as these are the places where we have high and growing concentrations of poverty, and where transit levels of service, if improved, would move people up the steepest part of the accessibility-participation sigmoid curve. In other words, this is where we see the greatest return on investment.  We therefore content that policies that extend the rapid transit network into transit-poor inner suburban neighbourhoods (the dark blue neighbourhoods appearing in Figure 23) should be pursued with priority.

In reality, very few rail expansions will occur over the short-term horizon. Because of this, we also turn our attention towards accessibility improvements achievable through increased provision of surface transit. In our inner suburbs in particular, the TTC has excellent coverage, and in most places, excellent frequencies of service. Despite this, we know that busses and streetcars do not reach desirable performance levels during peak-periods due to congestion and signal timing. We therefore recommend an overhaul of the City's surface-level transportation infrastructure, and a reallocation of street lanes to public transportation vehicles on a large number of arterials. A suburban network of bus and light-rail right-of-ways will extend high levels of service to a large number of priority neighbourhoods with the potential to greatly increase levels of activity participation and social inclusion. The Highway 7 BRT and King Streetcar project are examples of similar strategies that have been extremely successful in both the downtown core and in suburban environments.

As well, the maps in this report indicate that there are areas with low activity participation along the borders of municipalities, which in some cases operate separate local transit service on either side of political jurisdictions. Improving transit access in these areas should therefore also incorporate better connections between local transit agencies, both in terms of fare integration and better network connectivity.

The problem, and need for more solutions do not end there. Our research finds a large number of low-income, and some carless households live in far more dispersed suburbs, at overall populations densities and concentrations of poverty that make the provision of traditional public transit extremely costly and inefficient. Transit expansion in such places may rightly remain low on a priority list for a very long time. We see two avenues for cost-effective and immediate interventions on the horizon. The first is the adoption and delivery of new transit paradigms such as demand-responsive transit, where the abandonment of the fixed route, and sometimes the use of smaller vehicles, can achieve far greater levels of ridership, higher levels of user satisfaction, and efficiencies in delivery compared to traditional means of transit coverage. We see on-demand pilots, such as the night-bus pilot in Belleville, Ontario, as a very promising development that may extend much higher levels of service to those in need of transit on the urban/rural fringe. Alternatively, we must also consider policies that extend mobility and participation benefits to low-income families via enhanced access to automobility. While controversial, since car-based solutions do not scale well, are not environmentally efficient, and may further add to the divides between those who can and cannot drive, programs designed to provide automobile access to low-income households can be very successful at increasing levels of activity participation. These include government assistance for carpooling and car-sharing schemes, liability programs for offsetting the high costs of car insurance, and subsidizing taxi and ride-hailing trips. All of the above can be targeted for low-income individuals or low-income communities.

As a final note, our research found that low-income households travel less than high-income households, all else being equal. This indicates that the monetary costs of travel, as well as costs of participating in certain types of activities, could be deterring travel for low-income residents. At a higher level, this finding supports advocating for policy aimed at reducing overall levels of income inequality in the GTHA and beyond. Of course, this is not just an issue pertinent for transport planners, but across all disciplines aiming to reduce inequalities and improve well-being in society. From the transport planning perspective however, this points towards policy aimed at the reduction of transit fares to limit the monetary costs of travel. Certainly this would be difficult given the current funding climates and transit agencies needing to achieve certain revenue targets from fares to offset operational costs. However, policy could be designed in a progressive fashion; for example, by subsidizing low-income transit riders by taxing wealthy drivers through increased fuel taxes, increased taxes on luxury vehicles, or the deployment of congestion charges.

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# Appendix

Table 25 - Model parameters for linear transformation of accessibility for subsets of household income and car ownership

| hhld Income | Vehicles per Adult (VA) | N | n | Average Daily Activities | Estimated Model Parameters | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | intercept | β A | p | ρ |
| < \$40k | VA = 0 | 264,475 | 9,934 | 0.82 | 0.235 | 0.004 | 0.000 | 0.136 |
| < \$40k | 0 < VA < 0.5 | 109,122 | 3,688 | 0.85 | 0.373 | 0.001 | 0.580 | 0.116 |
| < \$40k | VA = 0.5 | 217,567 | 10,320 | 0.99 | 0.448 | -0.002 | 0.107 | 0.081 |
| < \$40k | 0.5 < VA < 1 | 52,502 | 2,081 | 0.91 | 0.411 | -0.002 | 0.330 | 0.143 |
| < \$40k | VA >= 1 | 189,582 | 9,888 | 1.27 | 0.307 | 0.000 | 0.852 | 0.043 |
| \$40k - \$60k | VA = 0 | 85,983 | 3,492 | 1.10 | -0.075 | 0.006 | 0.000 | 0.167 |
| \$40k - \$60k | 0 < VA < 0.5 | 115,998 | 3,997 | 0.89 | 0.455 | -0.003 | 0.021 | 0.175 |
| \$40k - \$60k | VA = 0.5 | 200,721 | 9,704 | 1.08 | 0.426 | -0.001 | 0.234 | 0.073 |
| \$40k - \$60k | 0.5 < VA < 1 | 93,395 | 3,768 | 0.97 | 0.321 | 0.001 | 0.596 | 0.087 |
| \$40k - \$60k | VA >= 1 | 213,946 | 10,928 | 1.36 | 0.256 | 0.000 | 0.888 | 0.051 |
| \$60k - \$100k | VA = 0 | 92,831 | 3,868 | 1.21 | -0.017 | 0.007 | 0.000 | 0.157 |
| \$60k - \$100k | 0 < VA < 0.5 | 148,083 | 5,547 | 0.97 | 0.518 | 0.000 | 0.684 | 0.183 |
| \$60k - \$100k | VA = 0.5 | 289,144 | 13,546 | 1.17 | 0.424 | 0.001 | 0.508 | 0.091 |
| \$60k - \$100k | 0.5 < VA < 1 | 182,766 | 7,383 | 1.05 | 0.446 | 0.000 | 0.781 | 0.112 |
| \$60k - \$100k | VA >= 1 | 428,974 | 21,237 | 1.47 | 0.432 | 0.001 | 0.276 | 0.042 |
| \$100k - \$125k | VA = 0 | 27,407 | 1,338 | 1.26 | 0.012 | 0.009 | 0.002 | 0.126 |
| \$100k - \$125k | 0 < VA < 0.5 | 58,579 | 2,244 | 1.04 | 0.490 | 0.004 | 0.006 | 0.169 |
| \$100k - \$125k | VA = 0.5 | 125,435 | 6,344 | 1.31 | 0.481 | -0.001 | 0.455 | 0.088 |
| \$100k - \$125k | 0.5 < VA < 1 | 116,076 | 4,546 | 1.14 | 0.504 | 0.002 | 0.237 | 0.123 |
| \$100k - \$125k | VA >= 1 | 267,324 | 13,033 | 1.52 | 0.406 | 0.002 | 0.039 | 0.046 |
| \$125k + | VA = 0 | 27,034 | 1,500 | 1.37 | 0.567 | 0.006 | 0.072 | 0.118 |
| \$125k + | 0 < VA < 0.5 | 62,544 | 2,568 | 1.11 | 0.316 | 0.002 | 0.137 | 0.165 |
| \$125k + | VA = 0.5 | 195,657 | 10,519 | 1.40 | 0.536 | 0.002 | 0.004 | 0.092 |
| \$125k + | 0.5 < VA < 1 | 211,944 | 8,507 | 1.23 | 0.463 | 0.003 | 0.001 | 0.098 |
| \$125k + | VA >= 1 | 584,354 | 29,240 | 1.58 | 0.348 | 0.004 | 0.000 | 0.050 |
| decline | VA = 0 | 97,645 | 4,405 | 0.73 | -0.156 | 0.003 | 0.050 | 0.169 |
| decline | 0 < VA < 0.5 | 115,399 | 4,320 | 0.84 | 0.251 | 0.001 | 0.312 | 0.107 |
| decline | VA = 0.5 | 209,902 | 11,298 | 1.03 | 0.396 | 0.000 | 0.582 | 0.061 |
| decline | 0.5 < VA < 1 | 174,770 | 7,167 | 1.03 | 0.231 | 0.002 | 0.046 | 0.077 |
| decline | VA >= 1 | 386,262 | 21,043 | 1.31 | 0.336 | 0.002 | 0.002 | 0.035 |

Table 26 - Model parameters for quadratic transformation of accessibility for subsets of household income and car ownership

| hhld Income | Vehicles per Adult (VA) | N | n | Average Daily Activities | Estimated Model Parameters | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | intercept | β A | *p* A | β $A^2$ | *p* $A^2$ | ρ |
| < $40k | VA = 0 | 264,475 | 9,934 | 0.82 | 0.3125 | -0.0039 | 0.1606 | 0.0002 | 0.0027 | 0.136 |
| < $40k | 0 < VA < 0.5 | 109,122 | 3,688 | 0.85 | 0.4544 | -0.0115 | 0.0077 | 0.0003 | 0.0019 | 0.117 |
| < $40k | VA = 0.5 | 217,567 | 10,320 | 0.99 | 0.4656 | -0.0048 | 0.0903 | 0.0001 | 0.2311 | 0.081 |
| < $40k | 0.5 < VA < 1 | 52,502 | 2,081 | 0.91 | 0.4573 | -0.0128 | 0.0605 | 0.0003 | 0.1015 | 0.144 |
| < $40k | VA >= 1 | 189,582 | 9,888 | 1.27 | 0.3309 | -0.0056 | 0.0259 | 0.0001 | 0.0195 | 0.044 |
| $40k - $60k | VA = 0 | 85,983 | 3,492 | 1.10 | -0.0632 | 0.0055 | 0.2653 | 0.0000 | 0.8358 | 0.167 |
| $40k - $60k | 0 < VA < 0.5 | 115,998 | 3,997 | 0.89 | 0.5182 | -0.0120 | 0.0072 | 0.0002 | 0.0407 | 0.176 |
| $40k - $60k | VA = 0.5 | 200,721 | 9,704 | 1.08 | 0.4282 | -0.0016 | 0.5696 | 0.0000 | 0.8796 | 0.073 |
| $40k - $60k | 0.5 < VA < 1 | 93,395 | 3,768 | 0.97 | 0.3099 | 0.0037 | 0.4377 | -0.0001 | 0.5375 | 0.087 |
| $40k - $60k | VA >= 1 | 213,946 | 10,928 | 1.36 | 0.2596 | -0.0007 | 0.7575 | 0.0000 | 0.6943 | 0.051 |
| $60k - $100k | VA = 0 | 92,831 | 3,868 | 1.21 | -0.0408 | 0.0089 | 0.0972 | 0.0000 | 0.7457 | 0.157 |
| $60k - $100k | 0 < VA < 0.5 | 148,083 | 5,547 | 0.97 | 0.5032 | 0.0018 | 0.5915 | -0.0001 | 0.4671 | 0.183 |
| $60k - $100k | VA = 0.5 | 289,144 | 13,546 | 1.17 | 0.4775 | -0.0077 | 0.0002 | 0.0002 | 0.0000 | 0.092 |
| $60k - $100k | 0.5 < VA < 1 | 182,766 | 7,383 | 1.05 | 0.4662 | -0.0043 | 0.1763 | 0.0001 | 0.1766 | 0.113 |
| $60k - $100k | VA >= 1 | 428,974 | 21,237 | 1.47 | 0.4412 | -0.0016 | 0.2867 | 0.0001 | 0.0966 | 0.042 |
| $100k - $125k | VA = 0 | 27,407 | 1,338 | 1.26 | -0.2374 | 0.0251 | 0.0413 | -0.0002 | 0.1868 | 0.128 |
| $100k - $125k | 0 < VA < 0.5 | 58,579 | 2,244 | 1.04 | 0.4896 | 0.0045 | 0.3792 | 0.0000 | 0.9931 | 0.169 |
| $100k - $125k | VA = 0.5 | 125,435 | 6,344 | 1.31 | 0.4964 | -0.0030 | 0.2955 | 0.0001 | 0.3999 | 0.088 |
| $100k - $125k | 0.5 < VA < 1 | 116,076 | 4,546 | 1.14 | 0.4918 | 0.0038 | 0.3079 | -0.0001 | 0.5259 | 0.123 |
| $100k - $125k | VA >= 1 | 267,324 | 13,033 | 1.52 | 0.4103 | 0.0008 | 0.6895 | 0.0000 | 0.6430 | 0.046 |
| $125k + | VA = 0 | 27,034 | 1,500 | 1.37 | -0.1796 | 0.0490 | 0.0002 | -0.0006 | 0.0006 | 0.133 |
| $125k + | 0 < VA < 0.5 | 62,544 | 2,568 | 1.11 | 0.3171 | 0.0021 | 0.6519 | 0.0000 | 0.9799 | 0.165 |
| $125k + | VA = 0.5 | 195,657 | 10,519 | 1.40 | 0.5301 | 0.0029 | 0.2146 | 0.0000 | 0.7246 | 0.092 |
| $125k + | 0.5 < VA < 1 | 211,944 | 8,507 | 1.23 | 0.4819 | -0.0015 | 0.5622 | 0.0001 | 0.0616 | 0.098 |
| $125k + | VA >= 1 | 584,354 | 29,240 | 1.58 | 0.3518 | 0.0028 | 0.0204 | 0.0000 | 0.4924 | 0.050 |
| decline | VA = 0 | 97,645 | 4,405 | 0.73 | -0.1722 | 0.0046 | 0.3500 | 0.0000 | 0.7350 | 0.169 |
| decline | 0 < VA < 0.5 | 115,399 | 4,320 | 0.84 | 0.1985 | 0.0079 | 0.0699 | -0.0001 | 0.1164 | 0.108 |
| decline | VA = 0.5 | 209,902 | 11,298 | 1.03 | 0.3952 | 0.0006 | 0.8163 | 0.0000 | 0.9588 | 0.061 |
| decline | 0.5 < VA < 1 | 174,770 | 7,167 | 1.03 | 0.2353 | 0.0013 | 0.6885 | 0.0000 | 0.7373 | 0.077 |
| decline | VA >= 1 | 386,262 | 21,043 | 1.31 | 0.3408 | 0.0007 | 0.6595 | 0.0000 | 0.4253 | 0.035 |

Table 27 - Model parameters for sigmoidal transformation of accessibility for subsets of household income and car ownership

| hhld Income | Vehicles per Adult (VA) | N | n | Average Daily Activities | Estimated Model Parameters | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | intercept | β A | k | $X_o$ | p | ρ |
| < $40k | VA = 0 | 264,475 | 9,934 | 0.82 | 0.292 | 0.238 | -0.175 | 40 | 0.000 | 0.136 |
| < $40k | 0 < VA < 0.5 | 109,122 | 3,688 | 0.85 | 0.375 | 1.735 | -0.250 | 60 | 0.000 | 0.120 |
| < $40k | VA = 0.5 | 217,567 | 10,320 | 0.99 | 3.647 | -6.478 | -0.001 | 25 | 0.107 | 0.081 |
| < $40k | 0.5 < VA < 1 | 52,502 | 2,081 | 0.91 | 5.178 | -9.654 | -0.001 | 25 | 0.330 | 0.143 |
| < $40k | VA >= 1 | 189,582 | 9,888 | 1.27 | 0.301 | 0.114 | -0.250 | 40 | 0.099 | 0.044 |
| $40k - $60k | VA = 0 | 85,983 | 3,492 | 1.10 | -0.055 | 0.334 | -0.100 | 30 | 0.000 | 0.167 |
| $40k - $60k | 0 < VA < 0.5 | 115,998 | 3,997 | 0.89 | 7.127 | -13.511 | -0.001 | 25 | 0.021 | 0.175 |
| $40k - $60k | VA = 0.5 | 200,721 | 9,704 | 1.08 | 0.414 | -0.397 | -0.125 | 60 | 0.204 | 0.073 |
| $40k - $60k | 0.5 < VA < 1 | 93,395 | 3,768 | 0.97 | 0.329 | 3.250 | -0.250 | 60 | 0.222 | 0.087 |
| $40k - $60k | VA >= 1 | 213,946 | 10,928 | 1.36 | 0.257 | 0.125 | -0.250 | 55 | 0.598 | 0.051 |
| $60k - $100k | VA = 0 | 92,831 | 3,868 | 1.21 | 0.087 | 0.291 | -0.200 | 35 | 0.000 | 0.159 |
| $60k - $100k | 0 < VA < 0.5 | 148,083 | 5,547 | 0.97 | 0.520 | -0.121 | -0.250 | 40 | 0.119 | 0.183 |
| $60k - $100k | VA = 0.5 | 289,144 | 13,546 | 1.17 | 0.425 | 0.215 | -0.250 | 45 | 0.000 | 0.091 |
| $60k - $100k | 0.5 < VA < 1 | 182,766 | 7,383 | 1.05 | 0.433 | 0.572 | -0.250 | 50 | 0.042 | 0.113 |
| $60k - $100k | VA >= 1 | 428,974 | 21,237 | 1.47 | 0.434 | 0.173 | -0.125 | 50 | 0.048 | 0.042 |
| $100k - $125k | VA = 0 | 27,407 | 1,338 | 1.26 | -0.054 | 0.564 | -0.100 | 25 | 0.002 | 0.127 |
| $100k - $125k | 0 < VA < 0.5 | 58,579 | 2,244 | 1.04 | 0.554 | 0.253 | -0.250 | 40 | 0.005 | 0.169 |
| $100k - $125k | VA = 0.5 | 125,435 | 6,344 | 1.31 | 0.467 | 0.325 | -0.250 | 60 | 0.304 | 0.088 |
| $100k - $125k | 0.5 < VA < 1 | 116,076 | 4,546 | 1.14 | 0.527 | -2.819 | -0.250 | 60 | 0.251 | 0.123 |
| $100k - $125k | VA >= 1 | 267,324 | 13,033 | 1.52 | 0.410 | 0.114 | -0.100 | 35 | 0.032 | 0.046 |
| $125k + | VA = 0 | 27,034 | 1,500 | 1.37 | 0.263 | 0.608 | -0.250 | 25 | 0.001 | 0.129 |
| $125k + | 0 < VA < 0.5 | 62,544 | 2,568 | 1.11 | 0.384 | 0.530 | -0.250 | 55 | 0.014 | 0.166 |
| $125k + | VA = 0.5 | 195,657 | 10,519 | 1.40 | 0.546 | 0.077 | -0.250 | 25 | 0.002 | 0.092 |
| $125k + | 0.5 < VA < 1 | 211,944 | 8,507 | 1.23 | 0.473 | 0.175 | -0.250 | 30 | 0.000 | 0.099 |
| $125k + | VA >= 1 | 584,354 | 29,240 | 1.58 | 0.367 | 0.139 | -0.225 | 25 | 0.000 | 0.050 |
| decline | VA = 0 | 97,645 | 4,405 | 0.73 | -0.157 | 0.127 | -0.250 | 25 | 0.018 | 0.169 |
| decline | 0 < VA < 0.5 | 115,399 | 4,320 | 0.84 | 0.268 | -2.169 | -0.250 | 60 | 0.050 | 0.108 |
| decline | VA = 0.5 | 209,902 | 11,298 | 1.03 | 0.398 | 0.020 | -0.250 | 25 | 0.501 | 0.061 |
| decline | 0.5 < VA < 1 | 174,770 | 7,167 | 1.03 | 0.246 | 0.177 | -0.250 | 35 | 0.013 | 0.078 |
| decline | VA >= 1 | 386,262 | 21,043 | 1.31 | 0.319 | 0.278 | -0.050 | 50 | 0.001 | 0.035 |