DOES AN INCREASE IN POPULATION DENSITY INCREASES TRANSIT MODE SPLIT? GOING BEYOND THE CONTEMPORANEUOS CORRELATION BETWEEN BUILT FORM AND PUBLIC TRANSIT MODE SHARE

by
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MRP Title: Does an increase in population density increases transit mode split: Going beyond the contemporaneous correlation between built form and public transit mode share

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Abstract

This paper explores the relationship between public transit mode share and population density. It critically reviews the long-held belief that an increase in population density (compact built form) will result in an increase in public transit ridership. The research developed a longitudinal data set of travel behavior, transit supply, and proxies of built form for 1996 and 2016 for the City of Toronto. The data set is spatially disaggregated at the Traffic Analysis Zone (TAZ) level such that the TAZs that divide the City into 480 mutually exclusive and collectively exhaustive zones.

The paper found that a cross-sectional analysis of population density and transit mode share captures mostly the contemporaneous relationship between the two and does not, by default, lend credence to the argument that if the density increases over time at a place, it will subsequently result in higher public transit ridership. Such a question will require a longitudinal analysis where the impact of a change in public density over time is examined to determine its impact, if any, on transit ridership. Using Linear Mixed Models for longitudinal data, the paper found that the contemporaneous relation between density and transit mode share holds, but the change in population density over time does not automatically correlate with an increase in transit ridership.

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To my parents and to my brother

Table of Contents

List of Tables

List of Figures

List of Appendices

Introduction

Travel demand is increasing in many countries. Transportation sector accounts for 14% of the global greenhouse gas emissions produced in 2010 (United States Environmental Protection Agency, 2017) and plays part in world's climate change. In addition to climate change, issues such as congestion and sprawl results in attempts to moderate automobile use through urban policies, planning, and design. Many studies explored the impact of built environment on travel behavior and tried to identify the predictors of people's travel mode choice.

Cross-sectional empirical evidence and literature regarding the built environment impacts on travel behavior demonstrated urban population density is a predominant explanatory variable in the pattern of transit mode share and auto-dependency; these studies support that density is positively correlated with public transit mode split and/or indicate a negative correlation between density and auto-dependency (Cervero & Kockelman, 1997; Cervero, Murakami, & Miller, 2010; Chen, Gong, & Paaswell, 2008; Guerra, 2014; Johnson, 2003; Kenworthy & Laube, 1996; Moniruzzaman & Páez, 2012; Newman & Kenworthy, 1989, 1991; M. Zhang, 2004).

The famous studies by Newman and Kenworthy (1989, 1991), and Kenworthy and Laube (1996), which compared population densities and transit mode share across thirty-two world's major cities, indicated that cities with higher population densities reported higher transit mode share and less petrol use per capita. These correlations have been translated into sustainable urban planning guidelines and interpreted as suggesting increasing density would increase the public transit mode share (Kenworthy & Laube, 1996; Newman & Kenworthy, 1989, 1991; Polzin, Chu, & Rey, 2000). Newman and Kenworthy (1989, 1991), and Kenworthy and Laube (1996) concluded that increasing density in the low-density areas affects people travel behavior, increase use of public transit and reduce automobile dependencies. As an increase in population density correlates with an increase in population density; hence, the idea of increasing transit mode share through increasing population density has formed.

However, does this assumption hold true upon more rigorous analysis observing neighborhood level density and transit mode share over time?

The correlation between density and transit mode split does not imply that an increase in population density increases the public transit mode split (Bertaud & Richardson, 2004). A critique of the previous cross-sectional research is that the population density is a manifestation of a whole host of other influences and is not necessarily an outcome of public policy or urban design. Moreover, in European cities where population densities are high, the fuel taxes are also high, and the cities built form is from centuries old style that does not permit parking or enough street width for two-way traffic. In such circumstances, public transit has the natural enabling environment to service mobility needs. In addition, in other studies where researchers have looked at the relationship between transit mode share and population densities at the municipal level, they also ignored the temporal effects when they concluded that population density increases are correlated with higher transit use. In fact, a critical review of most studies of public transit use and population density confuse higher densities with increasing densities. To observe the impact of increasing densities, one need to observe population densities and the related transit mode share over two time periods. Although, higher population densities may be correlated with higher transit mode share, this is not enough evidence to suggest that an increase in population density will correlate with an increase in transit mode share.

Research objectives

This research compares population densities at the Transportation Analysis Zone level over a 20-year period in the City of Toronto to determine whether a change in population density from 1996 to 2016, while controlling for other relevant explanatory variables, is correlated with the commensurate increase in transit mode share. Equally important in the study is to control for the changes in supply of transit services over time.

Literature Review

A growing body of literature has explored the influential factors and determinants of people's travel behavior and studied the impacts of built environment characteristics and socioeconomic attributes of individuals on their travel mode choices. The influential attributes of built environment on travel behavior are known as "the Ds". The term "three Ds", coined by Cervero and Kockelman (1997), references density, diversity, and design as essential characteristics of transit-oriented development and attributes of built environment that affects travel behavior. Further studies identified two more attributes: destination accessibility and distance to transit (Ewing & Cervero, 2001). In addition to the built environment attributes, research indicated that individuals' socioeconomic characteristics also play a great role in people's travel mode choice (Ewing & Cervero, 2001, 2010), and need to be controlled in transportation studies (Ewing & Cervero, 2010).

This research reviewed previous studies focusing primarily on the North American cities. The reviewed literature focused on cities that were comparable to Toronto. This was done in recognition of the fact that the contextual and cultural aspects of a city affect people's travel behavior, especially travel mode choice.

Density

In transportation modeling and analysis, urban density indicates the amount of activity concentrated per unit of area (Garcia-Sierra & van den Bergh, 2014). To represent this definition, density is measured by a variable of interest; which generally is population, employment, dwelling units, or building floor area; per areal unit (Chatman, 2003; Ewing & Cervero, 2010; Garcia-Sierra

& van den Bergh, 2014). Some research use the sum of employment and population per unit to calculate an overall activity centered in each unit of area (Ewing & Cervero, 2010). Some studies calculate the total amount of density's variable of interest within a predefined area, for example 800m catchment area of station (Cardozo, García-Palomares, & Gutiérrez, 2012) or station's service area (Gutiérrez, Cardozo, & García-Palomares, 2011).

Higher density areas proved to have higher share of active and public transportation, and less use of private vehicles (Cervero, 1996; Cervero & Kockelman, 1997; Cervero et al., 2010; Chen et al., 2008; Guerra, 2014; Johnson, 2003; Moniruzzaman & Páez, 2012; M. Zhang, 2004).

Density at the origin and at the destination of a trip are of importance in studying people's travel behavior and can influence mode choice based upon trip's purpose. Zhang (2004) explored the influence of built environment at both origin and destination on work and non-work purpose trips. The study indicated that in a North American context (Boston) higher population density at origin is associated with higher probability of taking active and public transportation for work trips but it is not an influential factor for non-work trips; whereas higher population density at destination promotes taking non-driving modes for both work and non-work trips. In terms of job density, Zhang's (2004) research indicated that job density at origin is not significant influential factor for both work and non-work trips; while job density at the destination increases the probability of walking, biking, or taking public transportation only for work commutes and does not matter for non-work trips.

Diversity

Diversity or land-use mix is associated with the variety of land-use types and the degree to which they are balanced and are integrated in a given area (Ewing & Cervero, 2010; Garcia-Sierra & van den Bergh, 2014; Stoker, Petheram, & Ewing, 2015). Entropy and dissimilarity indices are two common measures of diversity (Boarnet, 2017; Cervero & Kockelman, 1997) which indicate the degree to which different types of land uses are intermixed in an area. The Entropy value ranges from 0 to 1, where values closer to 0 represents homogenous land use and values closer to 1 indicates diversified land use. A more diversified land-use encourages use of public transit and walking whereas reduces use of single-occupancy vehicle (SOV) (Frank & Pivo, 1994). Job-housing and job-population balances are other diversity measures that are not as common (Stoker et al., 2015). A more balanced distribution of job and housing reduces motorized travel (Cervero & Duncan, 2006). However, land use diversity at the origin or destination does not have a significant influence on mode choice for work trips (Badland, Schofield, & Garrett, 2008; M. Zhang, 2004). When getting to work is the only purpose of the trip, the extent to which the land use near workplace or near residence area is intermixed is irrelevant to the commute mode choice (M. Zhang, 2004). However, Land use mix is more relevant and significant in the all-purpose trips or nonwork trip purposes (Srinivasan & Ferreira, 2002).

Design

Design variable involves with street design and street network characteristics as well as measures determining where the study area, for example the neighborhood, stands on the spectrum of pedestrian- to auto-oriented environments (Ewing & Cervero, 2010; Garcia-Sierra & van den Bergh, 2014; Stoker et al., 2015).

Primary street network characteristics includes street connectivity, street network density, and street patterns (Marshall & Garrick, 2010), which all together are an indication of accessibility and availability of alternative routes in the network (Garcia-Sierra & van den Bergh, 2014; Surbin, 2015). Measures evaluating the route network characteristic are also known as site-level measures (Surbin, 2015). On the other hand, measures assessing the environment design in order to determine the degree to which it is pedestrian-friendly or auto-oriented are indication of the level of comfort for active transportation; and such measures are also known as street-level measures (Surbin, 2015).

Intersection density, dead-end density, centerline kilometer density, and average block size are common measures of street network density and the link-to-node ratio and the connected-node ratio are the usual measures of network connectivity (Marshall & Garrick, 2012). Among all the measures, intersection density is the strongest measure of network density and the link-to-node ratio is the strongest measure representing the network connectivity (Marshall & Garrick, 2012).

Street pattern varies from a grid-like to a curvilinear and mixed pattern to a cul-de-sac pattern (Marshall & Garrick, 2010, 2012; Pasha, Rifaat, Tay, & De Barros, 2016). A gridded street network tends to have a higher street connectivity and density, as the street pattern get closer to the cul-de-sac pattern the density and connectivity become low (Marshall & Garrick, 2010; Pasha et al., 2016).

Street network characteristics impact people mode choice. Generally, in areas with increased street network density and higher street network connectivity, people use more active and public transportation (Marshall & Garrick, 2010).

Measures such as planting strips, street trees, overhead streetlights, mid-block crossings, sidewalk length, slope, bicycle lanes (Surbin, 2015), average street widths, presence of amenities, traffic intensity, and safeness (Garcia-Sierra & van den Bergh, 2014) sidewalk width (Cervero & Kockelman, 1997) are the street-level measures, determining the degree to which environment is pedestrian-friendly or is auto-oriented. The street level measure influence active transportation mode share (Garcia-Sierra & van den Bergh, 2014).

Destination accessibility

Destination accessibility measures the ease of access and proximity to trip attractions and valued destinations (Ewing & Cervero, 2010) and (Garcia-Sierra & van den Bergh, 2014). Handy (1993) differentiates between local and regional accessibility. Central Business Districts, i.e. areas with job concertation (Bannon, 2013), downtown areas (Handy, 1993; Stoker et al., 2015) or other attractions such as regional shopping malls are considered as trip attractions at the regional level and contribute to regional accessibility; whereas the distance from home to the closest grocery store is defined as local accessibility (Handy, 1993). Regional accessibility depends upon transportation links to regional attractions and activities, while local accessibility relies on closeness to the local attractions and activities (Handy, 1993). Based on Handy's (1993) definition, it is the reginal accessibility which is important for public transportation planning. Distance to the central business district (CBD) is a proxy for accessibility and closeness to the employment, business and commercial opportunities (Li & Zhao, 2017; Yang et al., 2018), and is used as a measure of destination accessibility (Ewing & Cervero, 2010). Number of jobs or other important destinations that can be reached within a certain distance or travel time are other ways to measure the destination accessibility (Ewing & Cervero, 2010; Garcia-Sierra & van den Bergh, 2014).

Diversity promotes destination accessibility; as a diverse land use potentially reduces the need for travel long distances (Chen et al., 2008). Being close to mixed use areas, people are less likely to drive and more likely to use non-motorized modes (Cervero, 1996). For the same reason, proximity to city centers, where the land uses are intermingled is important in influencing people mode choice.

Distance to transit

Distance to transit is defined as the proximity to transit stops/stations and the level of transit service at the residences or workplaces (Garcia-Sierra & van den Bergh, 2014; Y. Zhang, Li, Liu, & Wu, 2018) and is measured by the distance from residence/workplace to the nearest transit stop based on the shortest street route (Ewing & Cervero, 2010; Stevens, 2017). For a given area this measure can be calculated as the average of the shortest street routes from the residences/workplaces in the area to the nearest transit stop (Ewing & Cervero, 2010).

Households living in suburban areas within 1 km of a subway station have an enhanced access to jobs and other destinations compared to the households living in the similar suburban setting that are not served by the subway system (Cervero & Day, 2008). Living near suburban subway stations influences commute mode choice; people living in such areas tend to commute by rail transit rather than active transportation and bus transit (Cervero & Day, 2008).

Regarding access to transit at origin Lund, Cervero, and Willson's (2004) study shows that in general, residents of a transit-oriented development are likely to commute by transit five times more than residents of the same city who live in other areas. In terms of access to transit at the destination, Dill (2003) found that employees working at locations within one-half mile of a rail station are more likely to use transit comparing to employees working at locations farther from the rail station. The research also indicated people working at job locations which are within one-quarter mile of a rail station are more likely to take transit for commute than employees working at locations between one-quarter and one-half mile from rail station (Dill, 2003). Being closer to a transit stop/station and having higher access to public transit is associated with choosing public transit as a way of commute.

Demographics

In transportation planning research it is important to control for the influence of demographic attributes. Several studies reveal how socioeconomic characteristics associate with travel mode choices.

In the spectrum of motorized travel modes there are two polarities: transit captive users and auto captive users; and the choice users are at the middle of the spectrum. The captive mode users are defined as individuals who have no other mobility mode option available to them than the mode they are captivated in and demographic, socioeconomic, and personal circumstances are of the underlying reasons for mode captivity (Jacques, Manaugh, & El-Geneidy, 2013). Transit captives are usually refer to those people who do not have an automobile available; i.e. people who do not own a car or cannot use a car due to their age limitation, not owning a driver’s license, or disability;

but must make daily trips, and therefore have no choice but to use transit (Beimborn, Greenwald, & Jin, 2003; Victoria Transport Policy Institute, 2014). Auto-captivity is due to the reasons such as: “lack of service connecting origins or destinations, scheduling limitations, or need to carry large objects” (Beimborn et al., 2003, p. 1) rather than being related to socioeconomic status of individual. Apart from socioeconomic attributes that can force using transit, there are other socioeconomic characteristics that affect people’s mode choice.

Family structure, which refers to household size and household having children proved to affect transit mode share. Households having children are less likely to take public transit and are more car-dependent (Farber, Bartholomew, Li, Páez, & Nurul Habib, 2014; Farber et al., 2014; Pasha et al., 2016). Larger size households are more likely to take public transit (Boisjoly et al., 2018; Farber et al., 2014) and higher number of household members is associated with higher public transit usage (Pasha et al., 2016). Age is another influential factor on transit use. Studies showed that elderly and children (below the ages of 14-18) have a lower tendency to use public transit (Farber et al., 2014; Pasha et al., 2016), while young people are more likely to take public transit (Farber et al., 2014). Immigrants, especially recent immigrants, the unemployed (Boisjoly et al., 2018; Pasha et al., 2016), students with full-time jobs (Farber et al., 2014) are among population segments relying more on public transit than private vehicle. In contrast, high income earners tend to not take public transit and are more likely to use private vehicles (Pasha et al., 2016). However, it should be noted that elderly, the unemployed, and high-income households are among populations that travel less and make less trips (Farber et al., 2014).

Transit service supply

The effect of built environment characteristics as well as demographic and socioeconomic attributes of individuals and the importance of controlling for them in the analysis have been explained. In addition, it is also important to control for transit service supply. Previous research indicated that higher transit accessibility was associated with higher share of public transit mode split (Pasha et al., 2016; Yao, 2007). Furthermore, auto-dependency and being automobile captives is more related to the level of transit service supply. Automobile captives are described as individuals who feel that they have left with no feasible transit option than to use their automobile in order to complete their trip in their preferred time (E. Beimborn, Greenwald, & Jin, 2003). Being automobile captive is due to reasons such as: “lack of service connecting origins or destinations, scheduling limitations, or need to carry large objects” (E. Beimborn et al., 2003, p. 1). Therefore, controlling for transit supply over time in the analysis is of great importance.

Level of transit service supply regarding its impact on mode splits can be evaluated by service frequency (Foth, Manaugh, & El-Geneidy, 2014; Jou & Chen, 2014; Legrain, Buliung, & El-Geneidy, 2015), number of transit routes and the total transit routes length (Jou & Chen, 2014). Frequent transit service is negatively associated with waiting times and is positively correlated with the likelihood of taking public transit (Foth et al., 2014; Jou & Chen, 2014; Legrain et al., 2015, 2015). Number of transit routes and the total length of transit service are indicative of the scope of transit service across the city and are a proxy for transit network coverage (Jou & Chen, 2014). However, these two variables are correlated with each other. Hence, use both variables in a regression type model should be prevented. More transit routes in the city increases the public transportation transit access and correlates with higher transit mode split as well as lower use of private vehicles (Jou & Chen, 2014).

Methodology

This study examines the effect of an increase in population density on public transportation mode share by addressing the following question "does increase in population density correlate with an increase in public transit mode share?"

To answer this question a longitudinal has been conducted, which takes into consideration the changes in the two main variables, i.e. population density and public transit mode share. Cross-sectional data are used to determine whether density (or other built form attributes) are associated with travel mode shares; however, longitudinal data, i.e. panel data are used to determine whether changes in density over time changes the travel mode shares (Kamruzzaman et al., 2016).

Hence, this study investigates the changes in population density and public transit mode share at the traffic analysis zone (TAZ) level over a twenty-year old period in the City of Toronto to determine whether a change in population density is correlated with a commensurate change in public transit mode share. It is equally important in this study to control for the changes in other relevant explanatory variables, i.e. diversity, design, destination accessibility, and distance to the transit; as well as the changes in supply of public transit services over time. The outcome of the analysis tests the assumption of a relationship between population density and public transit mode share. The study's dataset has been gathered from 3 main sources: Transportation Tomorrow Survey (TTS), Statistics Canada, and the Toronto Transit Commission (TTC).

Geographic unit of analysis

The main geographic unit of analysis in this study is the Traffic Analysis Zone (TAZ). TAZs are the most common geographical division used in conventional transportation models. Selection of

TAZ as the unit of analysis was based on both availability of data and statistical reasons. Both TAZ and dissemination areas (DA) are small geographic units that aggregate socioeconomic and travel data. Both levels are relatively stable and provide the most detailed data at the aggregate level. Using larger units of analysis higher the chance of losing spatial variations in aggregation. The study's dataset includes data both from TTS and Canadian Census. TTS data are available at TAZ level and Census data are available at DA level. Since data collected from one source needed to be aggregated to the other unit of analysis and the study's dataset uses more data from the TTS database TAZ was selected as the main unit of analysis. The data collected from the Canadian Census was gathered at the DA level and then aggregated into TAZ level. In this way the errors from aggregating the data from one geographic unit to another would be minimized.

Time period selection

The data were collected for two years: 1996 and 2016. The year 2016 was selected as it was the latest year that the TTS and census data were available. As this study take into consideration changes over time, the time period of the analysis cannot be short to ensure that changes occurred during the selected time period. The TTS data are available for every five years and the earliest available data dates back to 1986 (Data Management Group, 2014). However, this study needs data on transit supply, which were gathered from TTC. The earliest data available from TTC were from 1996. Therefore, the availability of data was a determinant in the choice of the time period duration. Still, a twenty-year period allows for behavioral and built form changes to happen in a growing city.

Data and sources

Transportation Tomorrow Survey (TTS) database

TTS collects comprehensive information about urban travel in southern Ontario (Data Management Group, 2014). Data regarding built environment attributes, public transit mode split, and part of socioeconomic data were collected from the TTS database for both 1996 and 2016. The data list from the TTS data center can be found in the Appendix 1.

All the data collected from the TTS database, for both 1996 and 2016, have been aggregated at the TAZ geographic unit for 2001 TAZ boundaries. Having the same geographic boundaries in both years allows considering the developments and changes of each variable based on the same geographic unit area.

This study used data from the Transportation Tomorrow Survey (TTS) for the years 1996 and 2016. TTS data was preferred because the transportation data available from the census covered only trips made to work. Whereas the TTS data is available for all types of trips. Although the present study focuses on only work trips, TTS data allow for the future more comprehensive follow up studies that may analyze the transit mode split for different trip purposes and not necessarily trips destined to work.

Canadian Census database

A part of socioeconomic data, which complements the socioeconomic characteristics of people were collected from the Canadian Census in 1996 and 2016. The data collected at the DA-level were aggregated to 2001 TAZ boundaries using Maptitude software. If a DA's centroid was within a TAZ boundary, then the DA data were assigned to that specific TAZ. In this way no double counting of the DA data will occur.

Toronto Transit Commission (TTC) database

The transit supply data were collected from the TTC database. TTC is the major public transit agency that operates subway, streetcars, and buses in the City of Toronto. In order to capture the indicators of the public transit service supply for the analysis, the author contacted Reuben Briggs, senior transportation analyst at University of Toronto and held meetings with Conor Adami, senior planner of procedures and system development at TTC. After meeting with TTC's senior planner, the authors were given the access to the scheduled service summary reports of 1996 and 2016 in PDF format, and TTC route network of 1996 and 2016 in shapefile format.

The summary reports show the service intervals scheduled for each TTC route, which includes subway, streetcar, and bus route and all their branches. For each route, the service frequency per hour has been calculated based on its service interval. The service frequency per hour sets a base to compare the supply of public transit service in different locations of the city along the two time periods.

The service summary reports are for different months of year. This study used public transit routes' schedule for October-November due to more stability in individual's travel behavior and consistency with other data sources. The most significant reason for this selection is that the TTS data are collected in these periods as well and we want to rebuild a scenario which is closest to the time of other data collection. Furthermore, there are other reasons for this choice. Service in April is almost the same as services in September, October, and November, however there is lower ridership especially on routes serving colleges and universities as classes have ended. As the summer begins in May and June, these routes will receive seasonal service reductions, which will then be reverted in the following September. Due to inclement weather in January to March, the public transit ridership might not be as stable as it is in October to November. In addition, December is the month with long holidays which affects the individuals' travel behavior.

It should be noted that some of the routes' schedule changed due to TTC construction. If the construction was going on for a period less than a year, service frequency for months without construction were considered. But if the construction for going on for a year, the schedule for October to November was considered.

The service interval data are provided for different times of the day, i.e. morning peak period, midday, afternoon peak period, early evening, late evening, and overnight for different days of the week, i.e. Monday-Friday, Saturday, and Sunday. Table 1 shows the definition of each time period based on the weekdays.

Table 1. TTC definition of time periods based on the weekdays; Extracted from Toronto Transit Commission (2019)

Time period	**Time period definition**
Monday to Friday	
Morning peak period	6:00 a.m. to 9:00 a.m.
Midday	9:00 a.m. to 3:00 p.m.
Afternoon peak period	3:00 p.m. to 7:00 p.m.
Early evening	7:00 p.m. to 10:00 p.m.
Late evening	10:00 p.m. to 1:00 a.m.
Overnight	1:30 a.m. to 5:30 a.m.
Saturday and Sunday	
Morning peak period	6:00 a.m. to 8:00 a.m.
Midday	8:00 a.m. to 12:00 noon
Afternoon peak period	12:00 noon to 7:00 p.m.
Early evening	7:00 p.m. to 10:00 p.m.
Late evening	10:00 p.m. to 1:00 a.m.
Overnight	1:30 a.m. to 5:30 a.m. (8:00 a.m. Sundays)

This study considers only the work trip data, as the work commutes include a significant portion of weekly and daily trips in a city. Hence, to assess and compare the transit supply data the study used the public transit frequency for weekdays which is scheduled based upon people's need for travel to work.

Furthermore, the most significant difference in public transit service supply during a day is the difference between provision of service in peak and off-peak hours. Hence, this study considers both the service frequency for morning peak period and midday for each route in its analysis to take into account the public transit service supply for both peak and off-peak periods in the analysis. The route network GIS format file needed minor changes to be fully conformed with the routes mentioned in the summary reports. Also, the service summary reports were entered in tabular format from PDF files in and linked to the TTC route in GIS format.

Figure 1 and Figure 2 show the public transit surface routes and subway lines in 1996 and 2016 respectively. The most evident difference between the two figure is the Line 4 Sheppard, which opened in 2002 and is was not constructed in 1996.

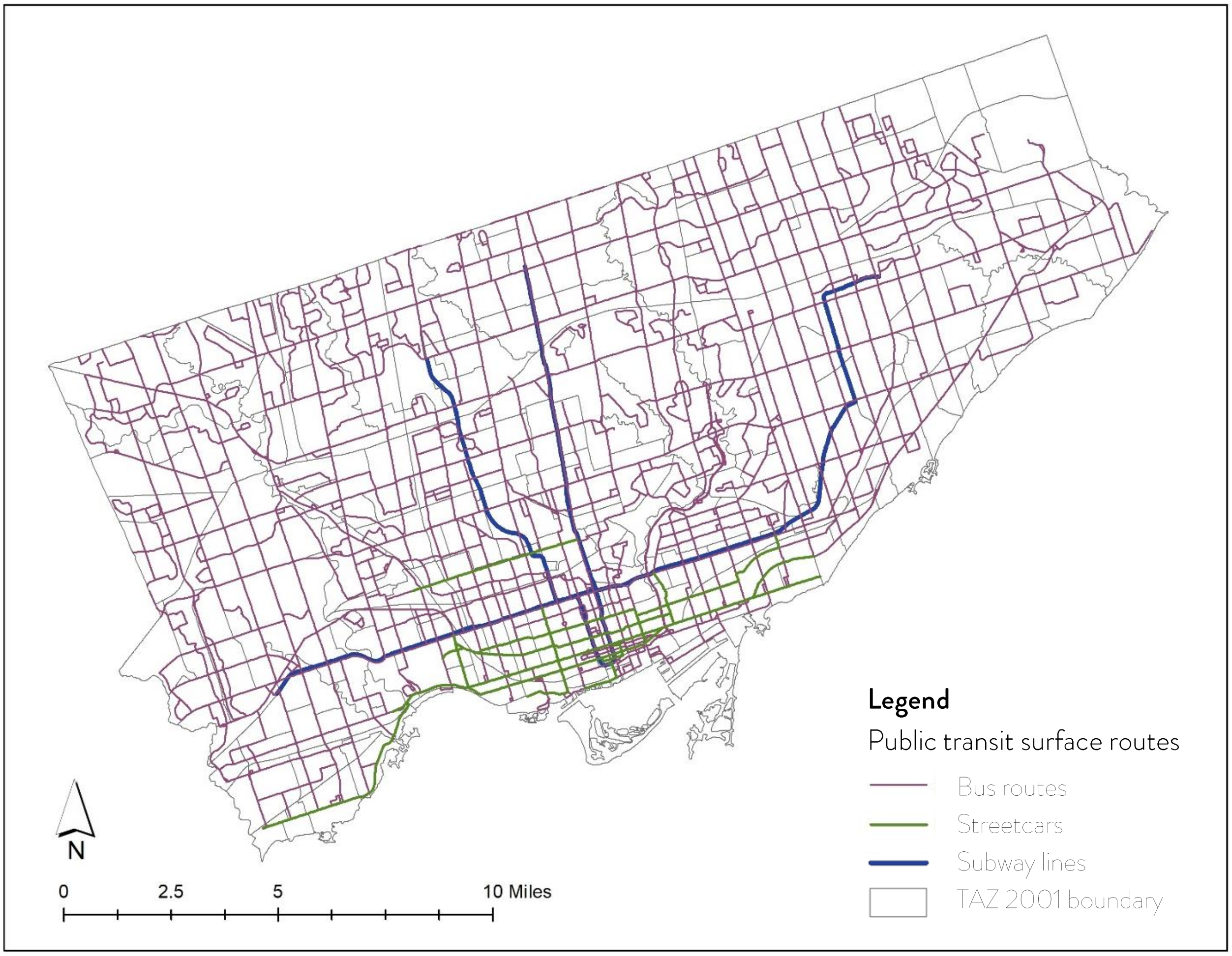

Figure 1. Public transit surface routes and subway line in 1996

Figure 2. Public transit surface routes and subway lines in 2016

To evaluate the supply of public transit at the TAZ level, the highest frequency among all the accessible transit surface routes within a TAZ boundary was used as a proxy of the level of transit supply in that TAZ. For each TAZ the highest frequency of the routes within the TAZ and a 400-meter buffer around has been assigned as the frequency of public transit service to that TAZ. The 400-meter walkable distance around the TAZ was selected so that the transit routes that are at the border of the TAZ can be considered.

The surface transit stops are usually located at every 400 meters. So, if a transit route is crossing a TAZ and 400-meter buffer around it there is high chance that at least one stop of those routes will be located within the TAZ or the walkable distance around it.

Dataset

Data used in this study were selected based on their importance and use in other research. Table 2 lists the data, their definition and the data source they are gathered from.

Table 2. Variables used in the study and their definition

	Variable label	Variable description	Variable formula	Data source
	transmode	Transit mode split	public transportation trips / total trips	Based on TTS
	year	Year of data collection		
Relevant built-environment variables	popdens	Population density	total population / area ($miles^2$)	TTS
	densdelta	Percentage change in population density	(increase in population denisty$_{2016-1996}$ / population density$_{1996}$) $\times$ 100	Based on TTS
	distcbd	Distance to downtown Toronto	Euclidean distance from the TAZ centroid to King and Bay intersection (miles)	TTS
	dist_stn	Distance to the nearest subway station	Euclidean distance from TAZ centroid to the nearest subway station (miles)	TTS
	intden	Intersection density	Number of intersetions/area ($miles^2$)	Caliper
Relevant socioeconomic variables	hhld_inc	Average household income		Census Canada
	hhld_size	Average household size		Census Canada
	per_1519	Percentage of population between 15 – 19		Census Canada
	per_imm	Percentage of immigrants		Census Canada
Relevant transit service supply variables	am_freq	Highest frequency of transit surface routes during morning peak period accessible to TAZ and a 400-meter buffer around it		Based on TTC
	mid_feq	Highest frequency of transit surface routes during midday (off-peak) period accessible to TAZ and a 400-meter buffer around		Based on TTC
	am_routes	Highest number of accessible transit surface routes active during morning period to TAZ and a 400-meter buffer around		Based on TTC
	mid_routes	Highest number of accessible transit surface routes active during midday (off-peak) period to TAZ and a 400-meter buffer around		Based on TTC

Empirical models

This study uses regression models to analyze data. As regression models allow to control for the impact of other predictors while studying the effect of a particular predictor (Haider, 2015). This helps determine the impact of a particular predictor on the variable of the interest when all else (all other explanatory variables), is equal (Haider, 2015).

To analyze and determine the effect of density and changes in density on transit mode split, controlling for explanatory variable explained in the dataset section the following models have been estimated:

In all the regression models y denotes the dependent variable, i.e. transit mode share; p denotes population density; t denotes transit mode share; δ denotes the percentage change in population density; and x denotes other explanatory variables.

- **Contemporaneous model for 2016: Linear Regression Model (OLS)**

  In the contemporaneous regression models the transit mode split of 2016 is a function of 2016 population density and other predictors in the model which follows the equation 1:

$$y = f\ (p, \text{other explanatory variables}) = \beta_0 + \beta_1 p + \sum_{i=2}^{n} \beta_i X_i + \epsilon$$

- **Revised contemporaneous model for 2016: Linear Regression Model (OLS)**

  In the revised model the effect of percentage change in population density from 1996-2016 were added to the model to determine the impact of population density changes from 1996-

2016 on the transit modal share in 2016, when all else is equal. Equation 2 presents the revised contemporaneous model.

$$y = f\ (p, \delta, \text{other explanatory variables}) = \beta_0 + \beta_1 p + \beta_2 \delta + \sum_{i=3}^{n} \beta_i X_i + \epsilon$$

- **Final model: Linear Mixed Effect Regression Model**

The previous models are appropriate for contemporaneous data, while our data is longitudinal. Longitudinal studies are a method to study longitudinal differences. In other words, longitudinal studies allow to study changes in each unit of analysis (within-subject change) and to identify factors associate with that change; while allowing to compare between units of analysis and to study the cross-sectional differences, that are the variations between units of analysis (between-subject variation). Mixed-effect models handle both between-subject variation and within-subject variation. In order to consider the within-subject changes on population density, a new variable have to be added, which is the interaction between population density and time. This variable represents the changes in population density over time in each unit of analysis, i.e. TAZ. Equation 3 formulated this model, where i_{pt} denotes the interaction between population density and time and t denotes the categorical time variable:

$$y = f\ \left(p, t, i_{pt}, \text{other explanatory variables}\right) = \beta_0 + \beta_1 p + \beta_2 t + \beta_3 i_{pt} + \sum_{i=4}^{n} \beta_i X_i + \epsilon$$

Limitations

Every study, no matter how well it is conducted, has limitations. Time and data availability are of the most limiting constraints of the present study.

This study collected a large set of explanatory variables for the transit mode split from TTS, Statistics Canada, and TTC. However, it was not possible to analyze all the variables due to time limitation. Hence, the study only selected the most significant predictors based on previous research and predictors that likely to have changed over the 20-year period in the City of Toronto. Land use entropy was not immediately available in the data sources and needs to be included in the future research. Moreover, in order to evaluate the public transit supply in each TAZ, the study was compelled to use transit routes instead of the transit stations/stops. As the transit stops/stations were not available in GIS format for 1996 time period.

Additionally, one could include the afternoon peak and off-peak public transit services for transit supply measures. However, the summary reports data of transit service characteristics were not available in tabular form. The process of entering the PDF files into a tabular format was time consuming an did not allow for analyzing all available data. Another time-consuming part of data cleaning was the process of editing transit routes network GIS file. The transit routes network GIS file needed edits and manipulation to be fully consistent with the routes mentioned in the summary reports.

Case study: City of Toronto

This study analyzes the City of Toronto for its case study. The choice was motivated by the fact that the demographic and travel behavior data were available for Toronto. The City of Toronto offers a great mix of public transit modes, i.e. buses, streetcars, and subway, which makes it a good travel laboratory for studying travel behavior. In addition, the City also has a reasonable size of 2.7 million people and its average population density has increased by 2894.8 from 1996 to 2016. Hence, the lessons learned in this study are relevant to other large North American cities.

The City of Toronto has 480 TAZs based on the TAZ boundaries of 2001. After filtering for missing data, 433 out of 480 TAZs, and 452 out of 480 TAZs remained respectively for 1996 and 2016 data collection.

The average population density increased by 2894.84 in the course of 20 years and the average of transit mode split increased by roughly 4%. Both minimum and maximum of transit mode split decreased from 1996 -2016. The average population density and the average transit mode split for 1996 and 2016 are reported in Table 3.

Table 3. Descriptive analysis for transit mode share and population density in 1996 and 2016

-> t = y1996

Variable	Obs	Mean	Std. Dev.	Min	Max
transmode	433	.2258588	.0938607	.0394551	.75
popdens	433	14340.98	12207.53	24.51028	122519.9

-> t = y2016

Variable	Obs	Mean	Std. Dev.	Min	Max
transmode	452	.2632291	.1001945	.0175439	.6641791
popdens	452	17234.84	17209.63	67.64298	152583

Analysis and results

This section provides a geographical and statistical analysis of transit, socioeconomic, and built form trends in the City of Toronto for the years 1996 and 2016 using Traffic Analysis Zones (TAZs) as the basic geographical unit.

Descriptive Analysis

In this section the distribution of built environment characteristics and level of transit supply as well as the changes in socioeconomic characteristics will be discussed across the TAZs in the City of Toronto.

Figure 3 illustrates TAZs in the City of Toronto in 2001 (the study's geographic unit of analysis) and overlaid with the geographical position of subway lines in 2016: Line 1 – Yonge-University, Line 2 Bloor-Danforth, Line 3 Scarborough, and Line 4 Sheppard. Line 4 – Sheppard opened in 2002 and is the difference between subway service provision in 1996 and 2016.

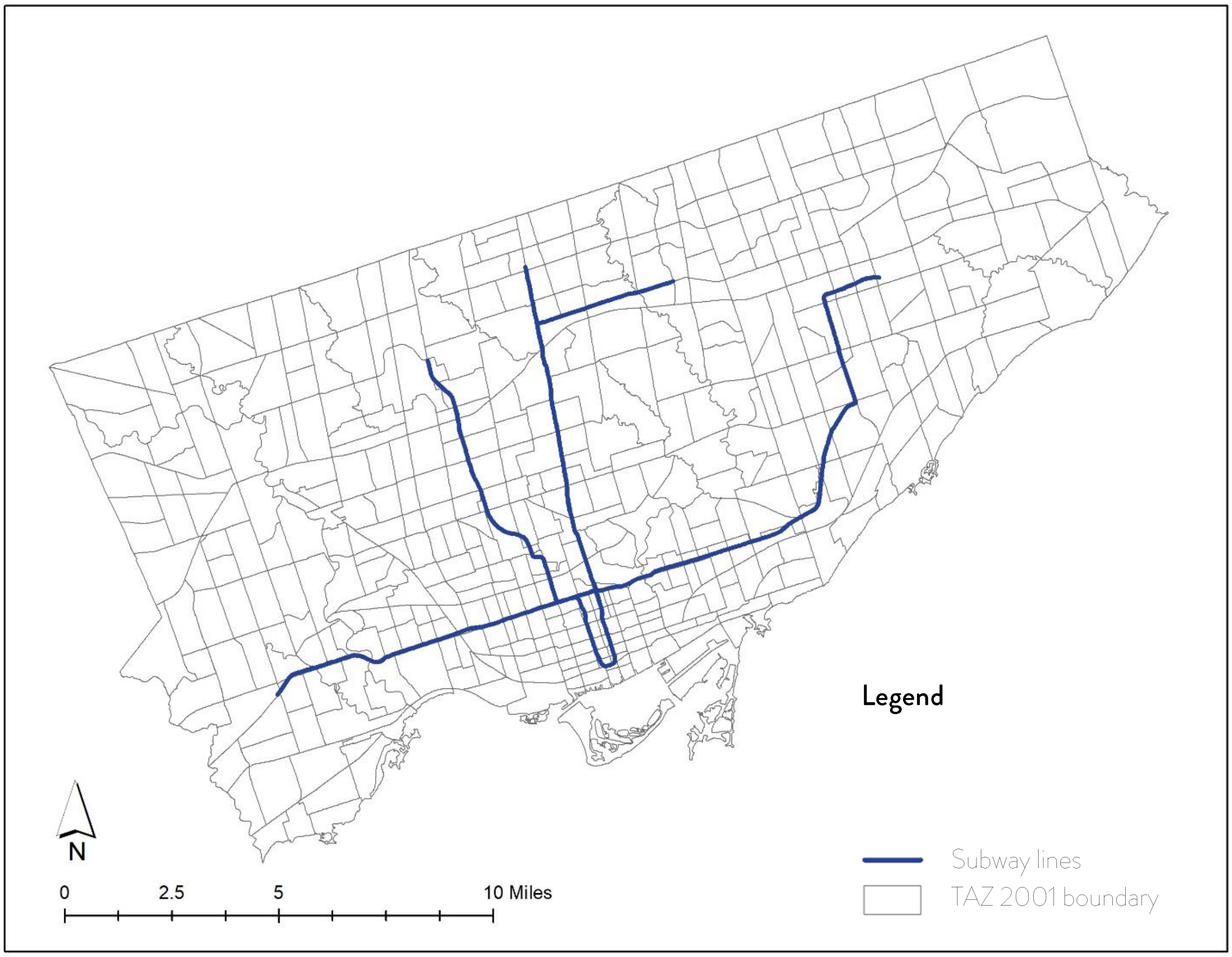

Figure 3. Subway lines in 2016 overlaid with TAZ boundaries in 2001

Figure 4 and Figure 5 display cartograms that TAZs geography have been distorted by transit mode share in 1996 and 2016 respectively. The larger the TAZ area gets compared to its original size, the higher is the TAZ transit mode share; and the smaller the TAZ area gets in comparison to its original size, the lower is the TAZ transit mode share. As the maps' colors are indicative of population density, both figures clearly show the positive correlation between population density and transit mode share.

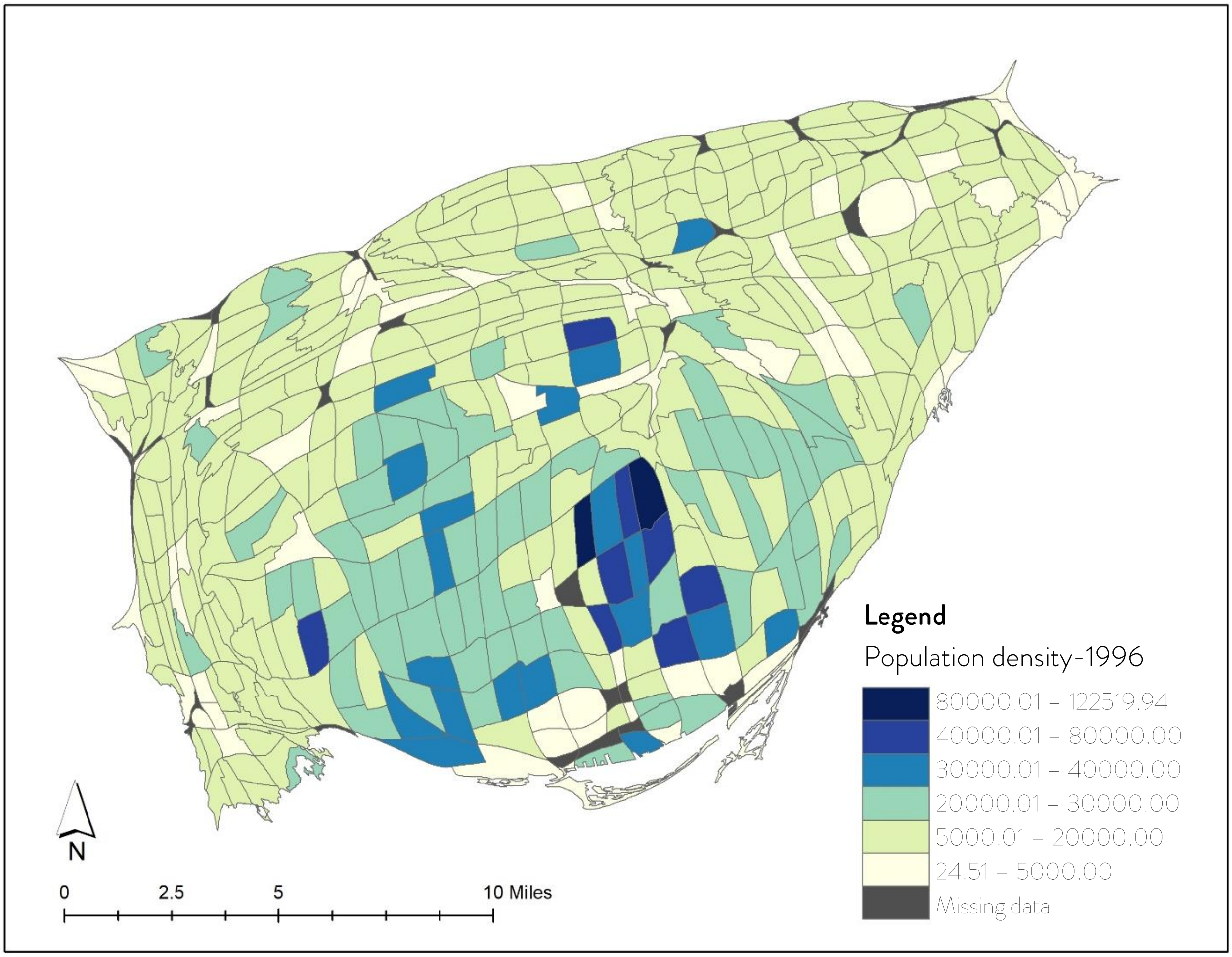

Figure 4. Cartogram distorting TAZ geography by transit mode share in 1996 and displaying population density in 1996

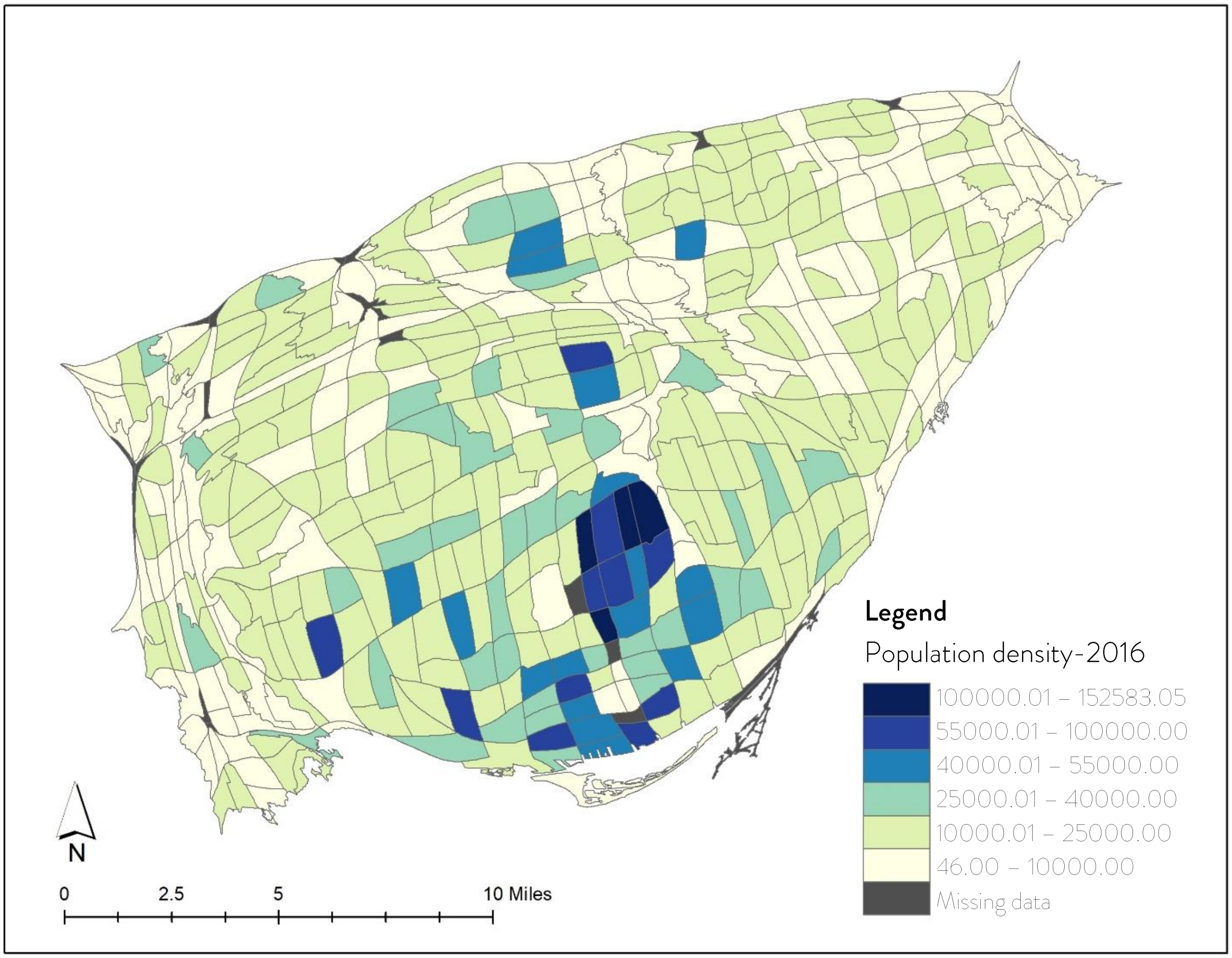

Figure 5. Cartogram distorting TAZ geography by transit mode share in 2016 and displaying population density in 2016

Figure 6 shows percentage change in population density. Blue TAZs decreased in population density between 1996 and 2016, while TAZs shown in light, medium, and dark red experienced increase in population density. Areas that saw increase in population density between 1996 and 2016 are in the section of the Yonge-University Line south of Bloor street, along Lake Ontario in Downtown Toronto, in the northern part of Scarborough, near Kipling Station in Etobicoke, along the northern terminus of the Yonge Line, and along the Sheppard Line. Areas that saw a decrease in population density are located in Etobicoke adjacent to and north of Highway 401 and west of Downtown near the Bloor Line.

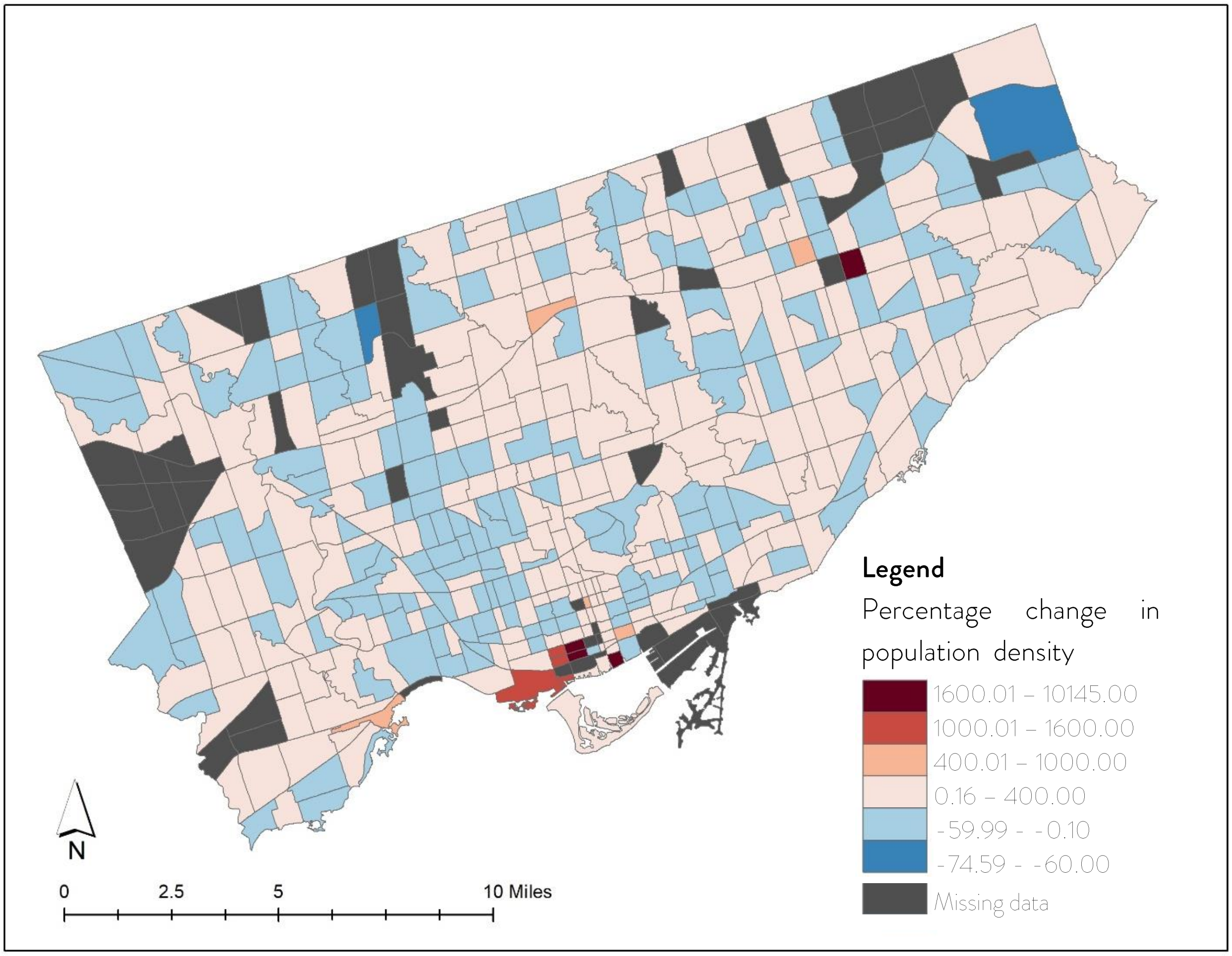

Figure 6. Percentage change in population density from 1996 - 2016

Figure 7 and Figure 8 illustrate intersection density in 1996 and 2016 respectively. Intersection density denotes the number of road intersections per square mile in each TAZ. In 1996, TAZs with higher intersection densities were concentrated mostly around the downtown core spreading both east and west along Lake Ontario. There were also pockets of high intersection density adjacent to the Yonge subway line in midtown, northwest of downtown, and in Etobicoke. Areas with low intersection density occur in the extreme northeast of the city in the Rouge neighborhood in Scarborough and in the extreme northwest of the city in the West Humber-Clairville neighborhood

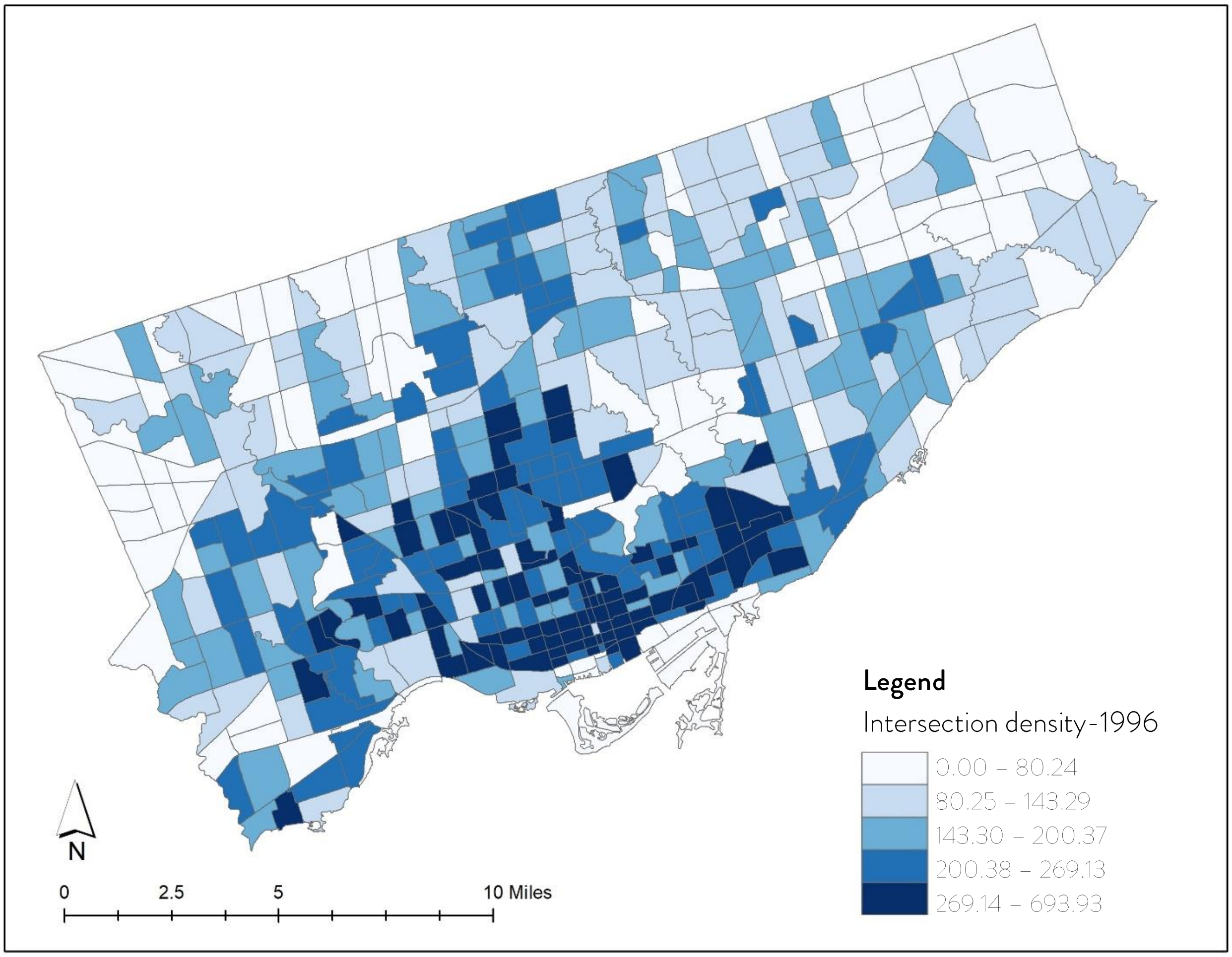

Figure 7. Intersection density - 1996

in Etobicoke. There are also several TAZs with low intersection density along the Don Valley Parkway in central Toronto.

Figure 8 illustrates the intersection density in 2016 time period. High levels of intersection density in 2016 are located primarily in Downtown Toronto and in the TAZs to the immediate east and west along Lake Ontario. TAZs with the lowest intersection densities are more spread out than in 1996, with pockets of low-density present in Scarborough (especially in the east along the municipal border), North York (mostly along Yonge, Finch, and Steeles) and throughout Etobicoke.

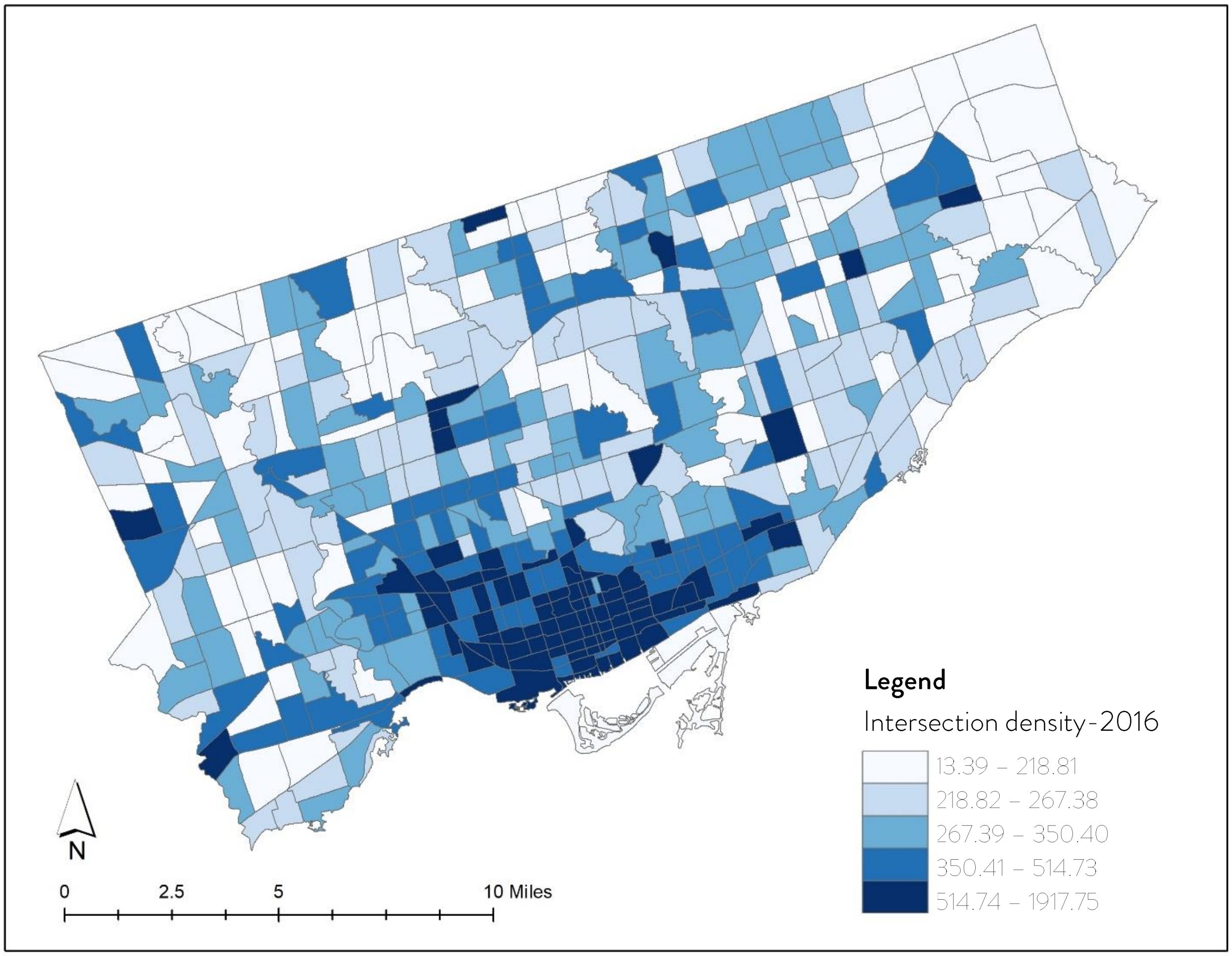

Figure 8. Intersection density - 2016

Figure 9 and Figure 10 respectively highlight how far the center point of each TAZ is from the nearest subway station in 1996 and 2016. TAZs closest to subway stations are located in the downtown core, along Yonge Street, Bloor Street, and Danforth Avenue, along the University Line, and along the Scarborough Line. Areas that are furthest from subway stations include the northeast and northwest portions of the city, in Scarborough and Etobicoke respectively, and the southwest neighborhoods of Long Branch, New Toronto, and Mimico, along Lake Ontario. The improved access to access to subway around Sheppard East is evident by visually comparing Figure 9 and Figure 10.

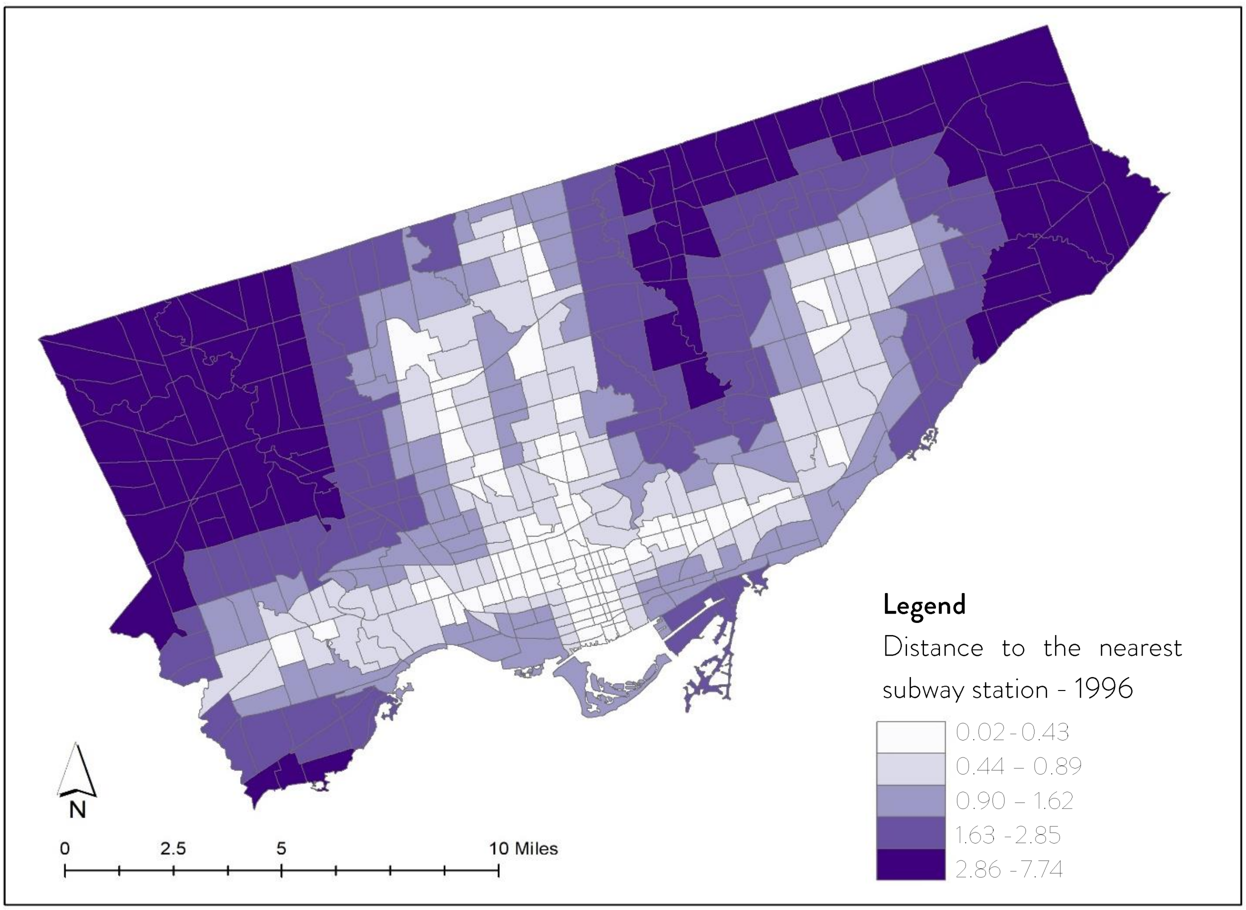

Figure 9. Distance to the nearest subway station-1996

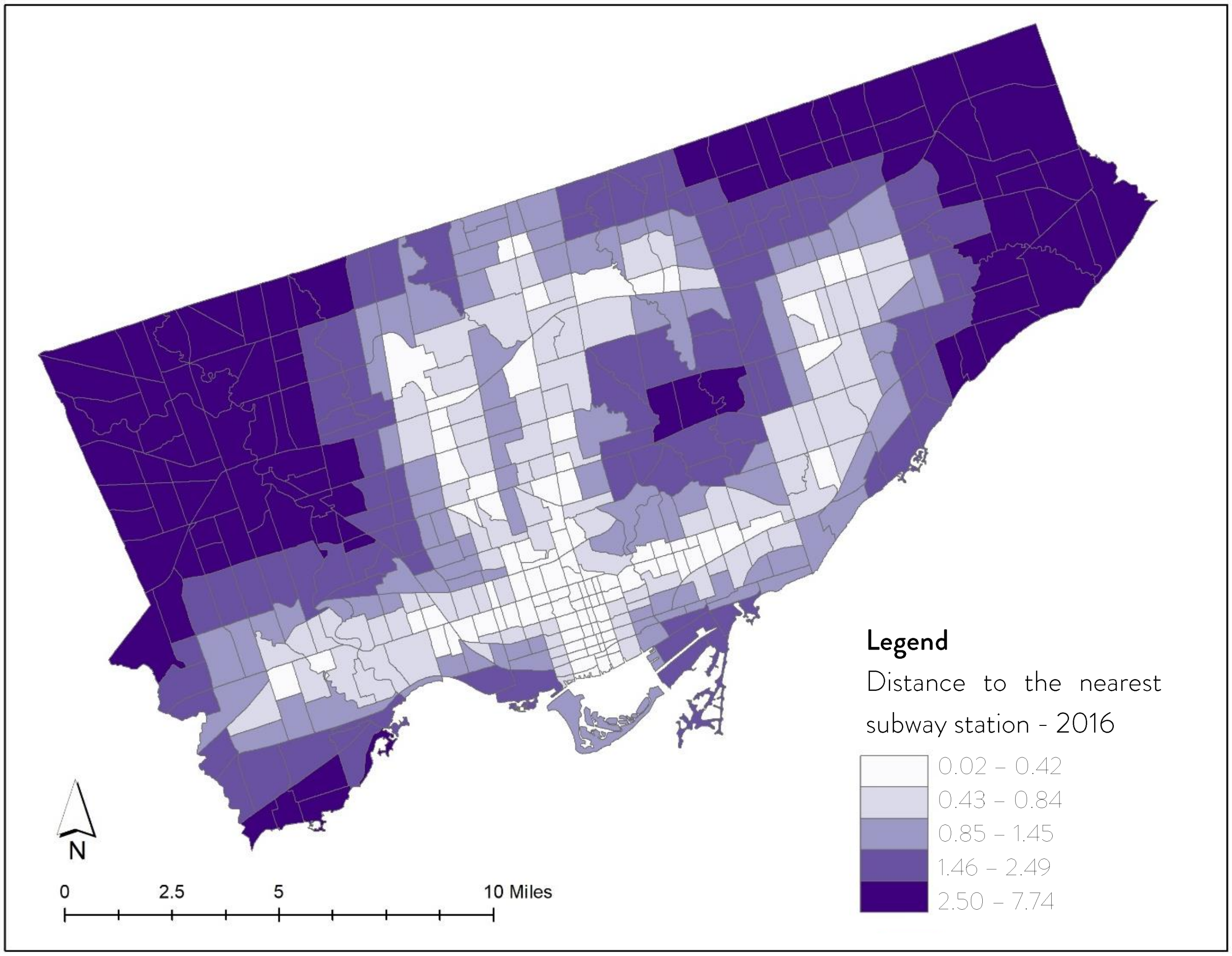

Figure 10. Distance to the nearest subway station-2016

Surface transit frequency measures the highest frequency of the bus and streetcar vehicles that passthrough a given TAZ and a 400-meter buffer around it in an hour during the morning commute (AM-peak frequency) and during morning off-peak hours (Midday frequency). Figure 11 displays the AM-peak frequency in 1996. The highest AM peak surface transit frequency in 1996 could be found in the downtown core and the areas immediately east and west, specifically south of Bloor Street and Danforth Avenue. The next highest AM peak surface transit frequency in 1996 can be found along Kipling Avenue, the Don Valley Parkway, and in north-central Scarborough.

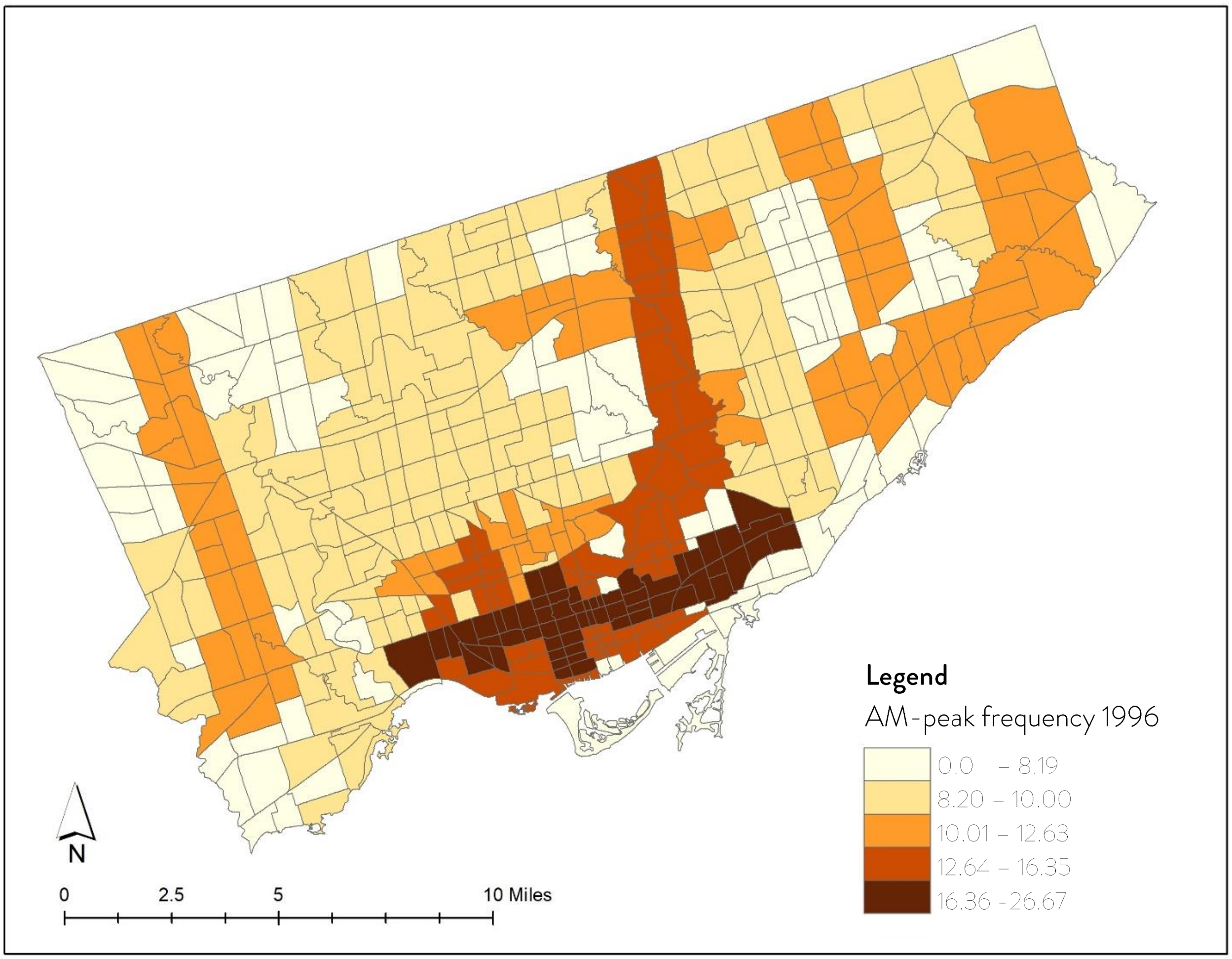

Figure 11. AM-peak surface transit frequency in 1996

As shown in Figure 11 the lowest AM peak surface transit frequency in 1996 occurs primarily along the municipal border in the northeast, northwest, and southwest edges of the city – areas that have traditionally been underserved by transit. Clusters of low AM peak surface transit frequency also occur in central Scarborough and in North York near the Yonge and Sheppard Lines.

AM-peak surface transit frequency in 2016, illustrated in Figure 12, differs significantly from 1996.

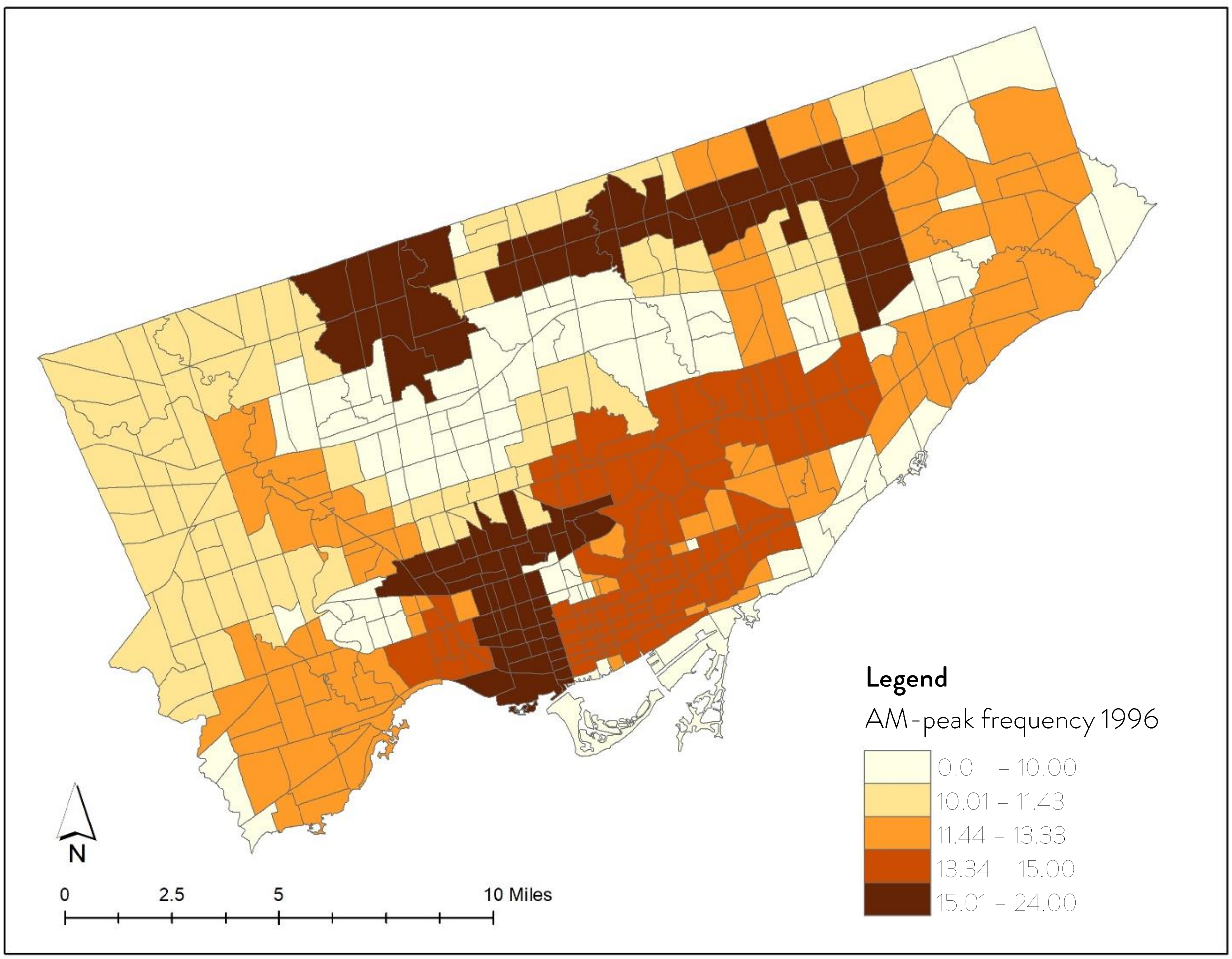

Figure 12. AM-peak surface transit frequency in 2016

The highest concentration of high frequent surface transit can be found along Finch and Steeles Avenues in North York and Scarborough and immediately west and northwest of the downtown core. The downtown core itself has the second highest frequency of AM surface transit as most of the transit demand in the area is served by the Yonge-University and Bloor-Danforth Lines. There are also significant areas of frequent AM surface transit north and northeast of the downtown core. Areas with the lowest AM surface transit frequency are clustered in the north-central part of the city near the 401, in south-central and southeast Etobicoke, in southwest Scarborough along Lake Ontario, and scattered throughout the rest of Scarborough.

Figure 13 illustrates the midday surface transit frequency of in 1996. The highest frequency of midday surface transit in 1996 occurred along Dufferin Street, Spadina Avenue, St. Clair Avenue, and the Don Valley Parkway. The second highest frequency occurred in the downtown core east of Spadina Avenue, the area just east of the Don Valley Parkway near Lake Ontario, and along Bathurst Street. The largest cluster of low frequency mid-day surface transit is found primarily in Etobicoke. Smaller clusters of low frequency AM surface transit are found in southwest, central, and northeast Scarborough.

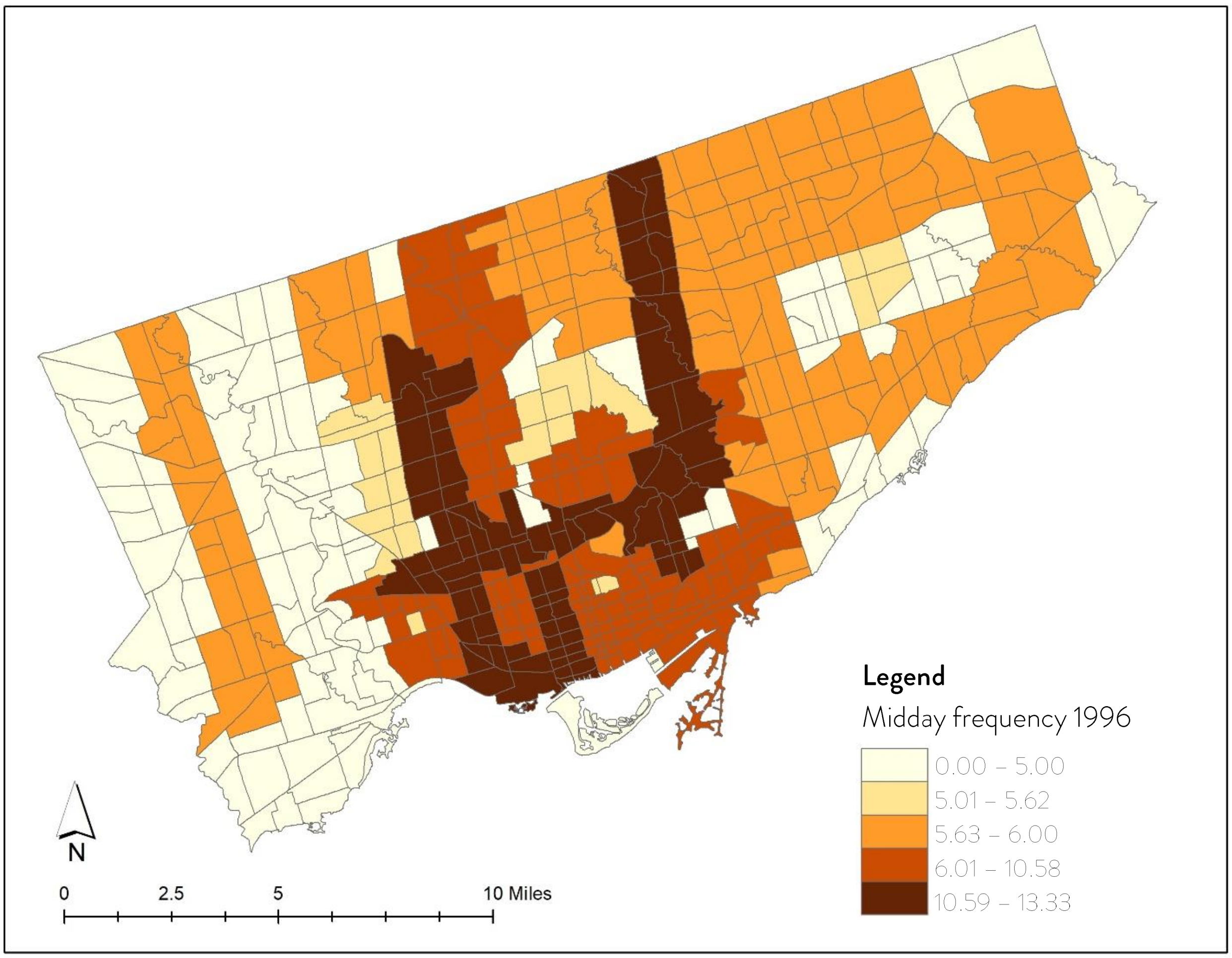

Figure 13. Midday surface transit frequency in 1996

Midday surface transit frequency in 2016, displayed in Figure 14, differs significantly from that found in 1996. The highest frequency can be found along Dufferin Street from Lake Ontario to the northern edge of the city at Steeles Avenue. Other stretches of high frequency midday surface transit can be found along Bathurst Avenue in the Downtown core, Finch Avenue, and north of Scarborough City Centre along McCowan Road. The second highest frequency can be found mainly in and around the downtown core to the north and east of Bathurst Street and at the norther edge of the city along Finch Avenue and Steeles Avenue. The lowest midday surface transit frequency is scattered throughout central and south Etobicoke, North York, and much of Scarborough.

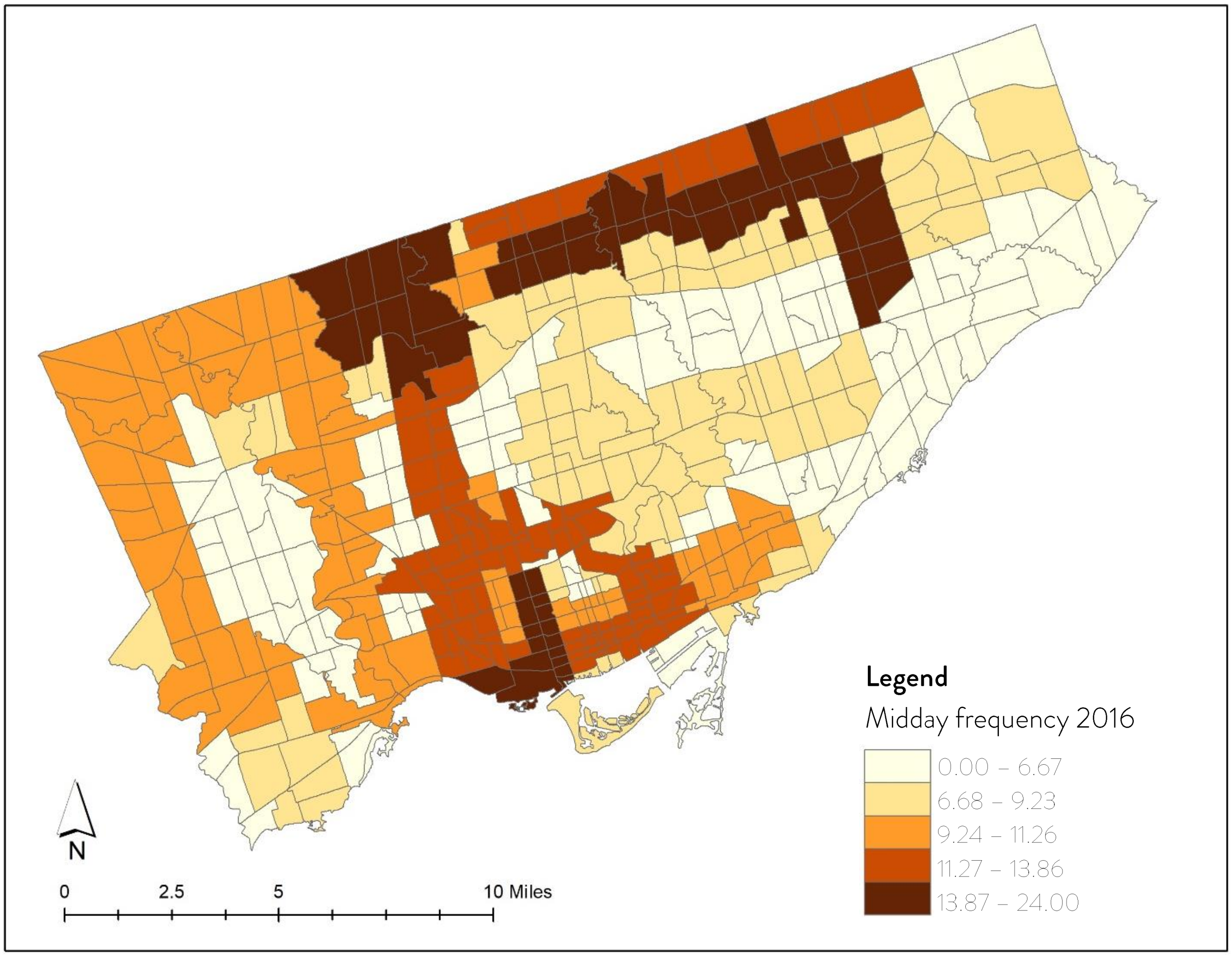

Figure 14. Midday surface transit frequency in 2016

Changes in the percentage of people between 15 -19 years old is shown in Figure 15. Purple shades show decrease while green shade displays increase in percentage of 15 – 19 years old peoples. The largest increase in percentage of 15 – 19 years old people can be found in the middle-center of the Toronto, west, northwest, east and southeast areas of the city. The areas around the junction neighborhood, northern areas along Steeles Avenue are of the areas that experienced large decrease in the percentage of 15 -19 years old.

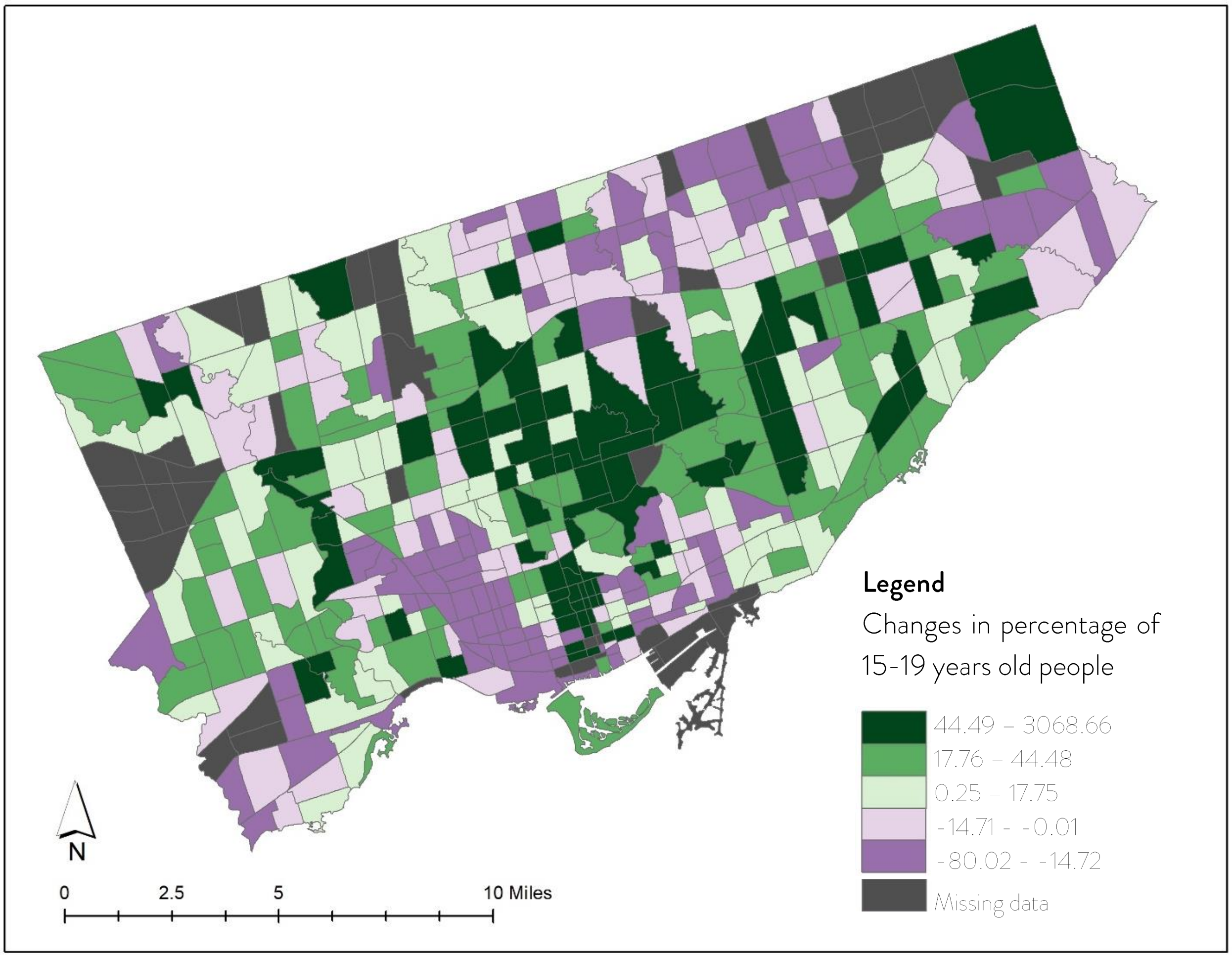

Figure 15. Changes in percentage of 15 - 19 years old people from 1996 to 2016

Figure 16 illustrates changes in immigrants' population over the course of 20 years. TAZs with increase in their percentage of immigrants' population are mapped by orange shades and areas with decrease in the percentage of immigrants are mapped by purple shades. The highest increases in immigrant population from 1996 to 2016 can be found in the downtown core near the Yonge-University Line, throughout Scarborough especially in the northeast, in neighborhoods near Yonge Street in the northern part of the city, around Downsview Park and York University, and in pockets throughout Etobicoke. The lowest increases in immigrants' population occurred primarily east and west of downtown south of Eglinton Avenue and in the West Humber-Clairville neighborhood.

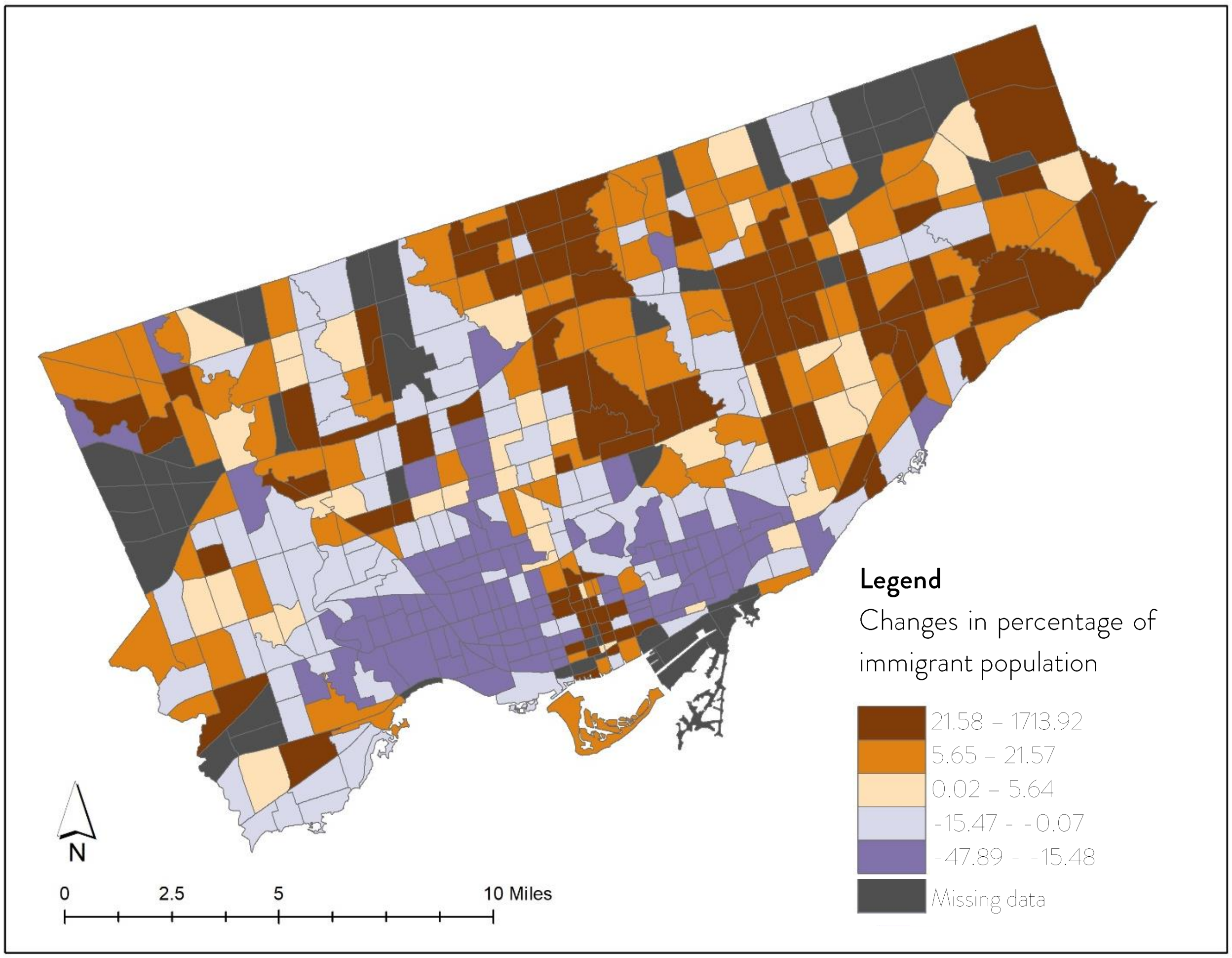

Figure 16. Changes in percentage of immigrant population from 1996 to 2016

Figure 17 details changes in average household income in each TAZ from 1996 to 2016. The largest increases occurred along the Yonge-University Line in the downtown core, in the Rosedale, Annex, Casa Loma, and Yonge-St. Clair neighborhoods just north of downtown, in areas near the Yonge Line in Midtown Toronto including Lawrence Park, and in the northeast section of Scarborough. Areas that saw the smallest increases in household income are scattered primarily across the northern third of the city throughout the former municipalities of Etobicoke, North York, and Scarborough. Many of these areas have been earmarked as priority neighborhoods by the City of Toronto as they have long been some of the most underprivileged neighborhoods in the city.

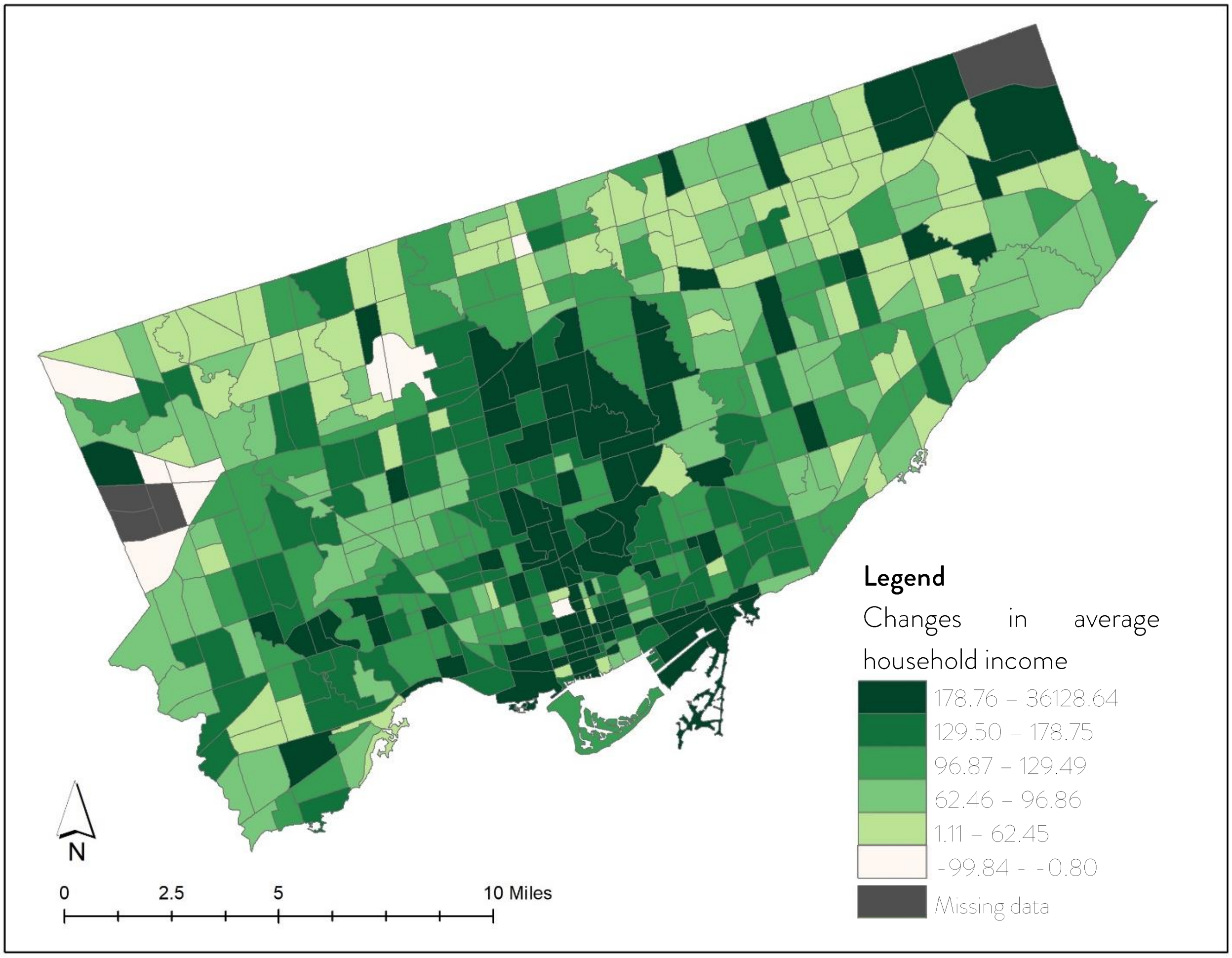

Figure 17. Changes in average household income from 1996 to 2016

According to Figure 18, which displays the changes in average household size, the largest increases in household size from 1996 to 2016 occur in the downtown core near the Yonge-University Line, in Midtown Toronto east of Yonge and Eglinton, around Yorkdale Mall adjacent to Highway 401, near Downsview Park and York University, and scattered throughout Etobicoke, North York, and Scarborough.

TAZs with the lowest increases in household size are concentrated west of downtown, in the western half of Etobicoke, and in the northern part of the city, particularly in Scarborough.

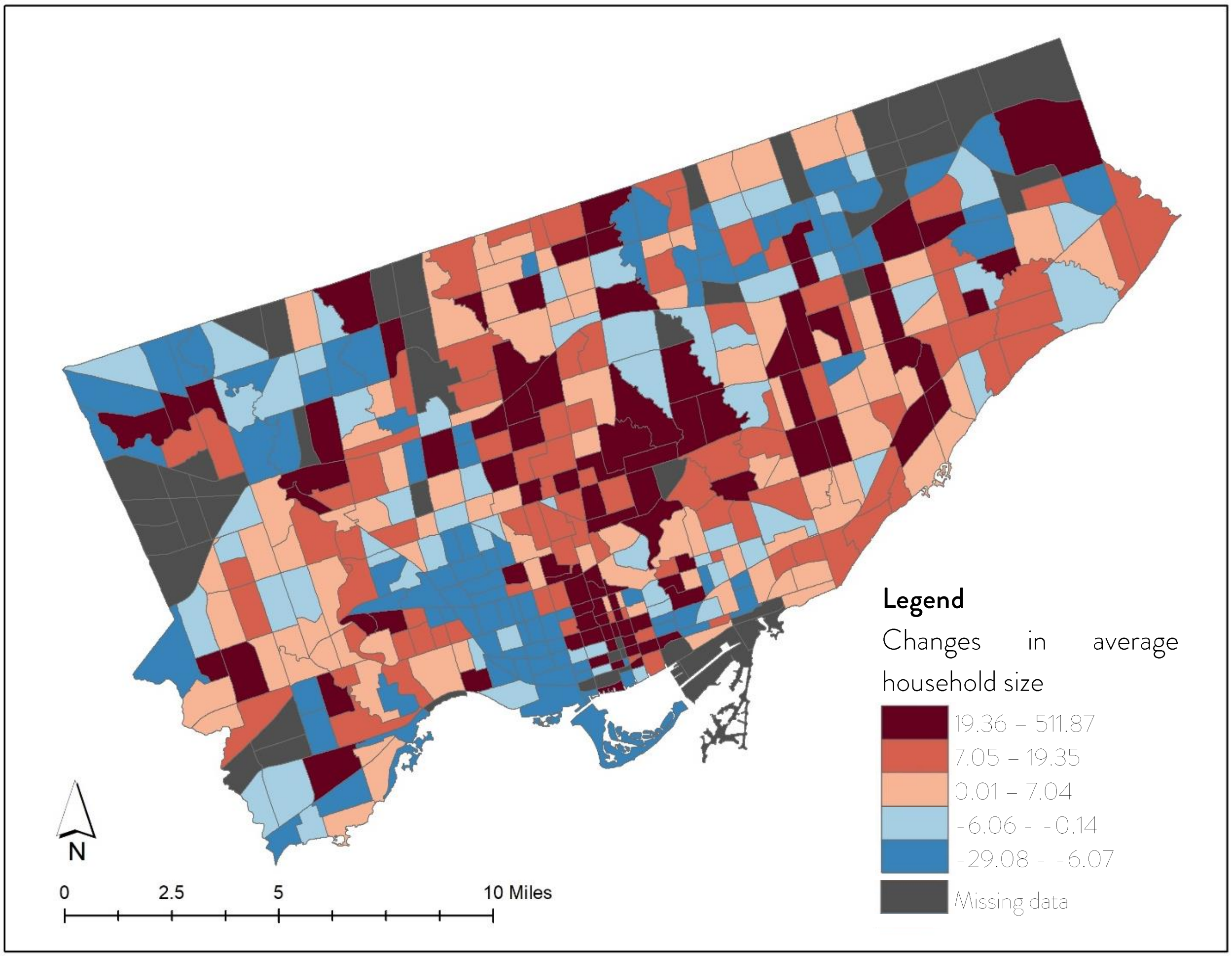

Figure 18. Changes in average household size from 1996 to 2016

This section concludes with scatterplot analysis of the relationship between transit mode split, population density, and intersection density for the 1996 and 2016 time periods. Figure 19 highlights the relationship between transit mode split and population density. Transit mode split denotes the percentage of trips in a TAZ made by transit (rather than by car, bicycle, walking, etc.) and can range from 0 to 100 percent. Population density denotes the number of people per square mile that live in a particular TAZ.

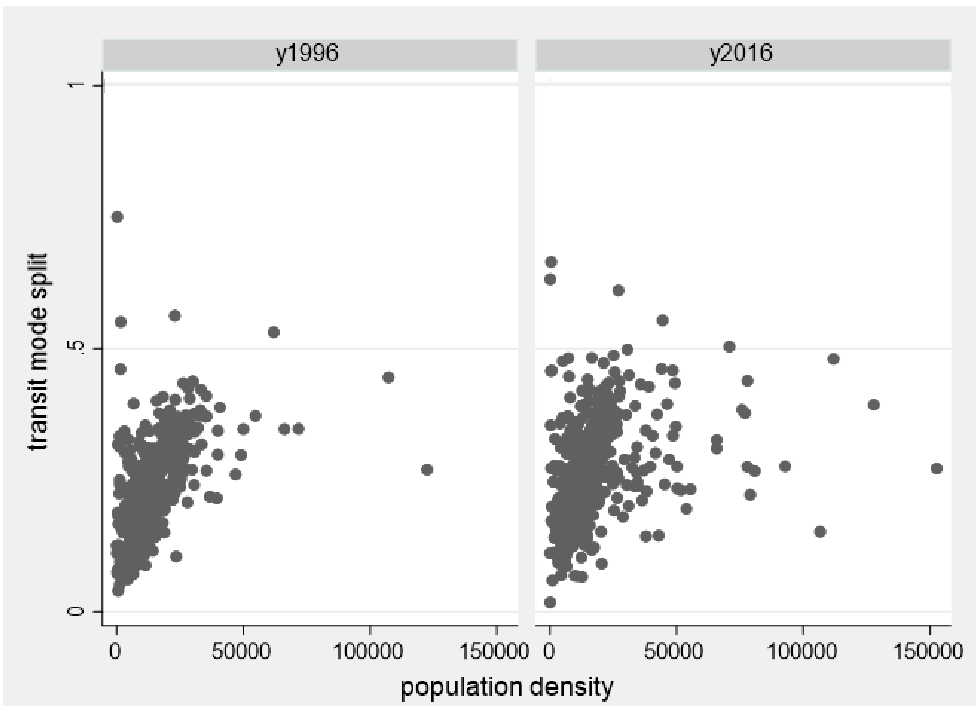

Figure 19. Relationship between transit mode split and population density in 1996 (left) and 2016 (right) time periods

From Figure 19 scatterplots we see that generally as population density increases so too does transit mode split. A conclusion which is also evident from Figure 4 and Figure 5. This is not surprising as areas with higher population densities are often better serviced by transit, especially higher order transit such as subways and commuter rail. Transit oriented development in the City of Toronto has also ensured that concentrations of high-density residential development are located in and around important transit hubs, affording residents of these areas easy access to higher order transit. Comparing the scatterplots from 1996 and 2016 we see that TAZs have higher population densities in 2016 than 1996. This is because the amount of land in the study area (around 630 square kilometers) has remained constant while the population of the area has increased. Transit mode split at the upper end has also increased as there appears to be a higher concentration of TAZs around 50 percent transit mode split in 2016 compared to 1996.

As discussed previously in this study, intersection density denotes the number of road intersections per square mile in a given TAZ. Intersection density can be thought of as a proxy for population density since the two are often highly correlated. Figure 20 shows the correlation of transit mode share and intersection density in this study. As with population density, when intersection density increases so too does transit mode split.

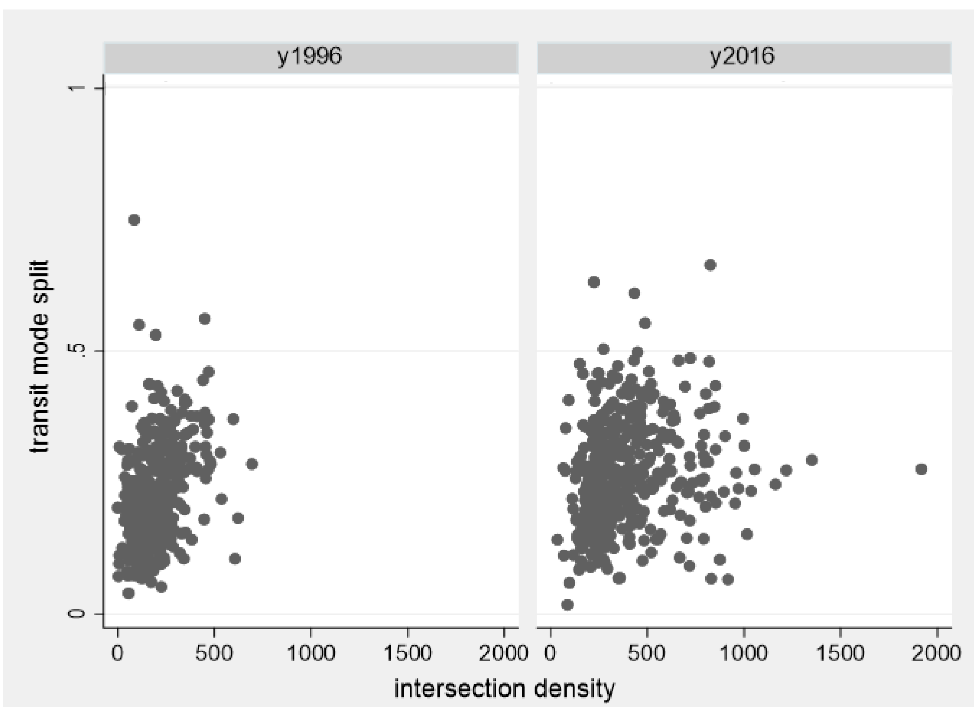

Figure 20. Relationship between transit mode split and intersection density in 1996 (left) and 2016 (right) time periods

In fact, the two sets of graphs (Figure 19 and Figure 20) look remarkably similar. This relationship is not surprising as higher density within a TAZ promotes and supports transit while necessitating a larger number of intersections. Because land in the study area has remained constant, intersection density throughout the city has increased dramatically to accommodate new residential, commercial, and industrial development. The highest intersection density for any TAZ in 1996 was around 700 intersections per square mile. By contrast, in 2016 there were dozens of TAZs with more than 700 intersections per square mile and several with over 1,000.

Model results

In the first step of the modelling and analysis, the study analyzed the impact of time, which changes from 1996 to 2016, on transit mode split by a linear regression model using ordinary least squares (OLS) method. The results, shown in Table 4, indicate that both population density and the time significantly (*p-value* < *0.05*) influence transit mode share. The average of transit mode share in 1996 is 19%. After the course of 20 years, transit ridership increased by 3.02% when we control for population density.

Table 4. Impacts of population density and time changing from 1996 to 2016 on the transit mode split in Toronto.

Source	SS	df	MS
Model	1.54012153	2	.770060767
Residual	7.102128	882	.008052299
Total	8.64224953	884	.0097763

Number of obs	=	885
F(2, 882)	=	95.63
Prob > F	=	0.0000
R-squared	=	0.1782
Adj R-squared	=	0.1763
Root MSE	=	.08973

transmode	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
popdens	2.49e-06	2.02e-07	12.37	0.000	2.10e-06	2.89e-06
t						
y2016	.030153	.0060623	4.97	0.000	.0182547	.0420513
_cons	.1900922	.0051925	36.61	0.000	.179901	.2002834

The next analysis determines the effect of percentage change in population density and the population density on transit mode split by a contemporaneous linear regression model for 2016 time period only. The results reveal a counterintuitive outcome. Changes in population density, presented by percentage change in population density, has no influence on transit mode share. As illustrated in Table 5, percentage change in population density from 1996 – 2016 is not statistically significant (*p-value* = *0.254* > *0.05*) for transit mode share. The results fail to reject the null hypothesis that the coefficient for percentage change in population density is equal to 0.

Table 5. Contemporaneous linear regression model for 2016 time period: Impacts of percentage change in population density from 1996-2016 and population density on transit mode split

Source	SS	df	MS			
Model	.439670905	2	.219835453	Number of obs	=	452
Residual	4.08789361	449	.00910444	F(2, 449)	=	24.15
				Prob > F	=	0.0000
Total	4.52756451	451	.010038946	R-squared	=	0.0971
				Adj R-squared	=	0.0931
				Root MSE	=	.09542

transmode	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
popdens	1.82e-06	2.63e-07	6.94	0.000	1.31e-06	2.34e-06
densdelta	-8.36e-06	7.31e-06	-1.14	0.254	-.0000227	6.01e-06
_cons	.2325252	.0063564	36.58	0.000	.2200332	.2450172

I introduced other relevant variables into the 2016 contemporaneous model in order to determine the impact of changes in density when controlling for the effect of other explanatory variables.

First, the explanatory variables related to the built environment were added into the model, which are distance to downtown, distance to nearest subway station, and intersection density. This model shows the impact of changes in population density on transit mode share while controlling for built environment explanatory variables. Based on the p-values presented in Table 6, the changes in population density from 1996 - 2016 does not affect the transit mode share in 2016 (*p-value > 0.05*) when controlling for relevant built environment variables. The model indicates that only the population density and distance to the nearest subway station are significant in influencing transit mode share. Based on Table 6, distance to downtown Toronto is negatively correlated with transit mode share. An Increase in population density is positively associated with increase in transit mode share. People living in TAZs closer to downtown tend to use public transit more.

Table 6. Contemporaneous linear regression model for 2016 time period: Impacts of percentage change in population density from 1996-2016 and relevant built environment variables on transit mode split

Source	SS	df	MS		
				Number of obs =	452
				F(5, 446) =	17.96
Model	.758914677	5	.151782935	Prob > F =	0.0000
Residual	3.76864984	446	.008449888	R-squared =	0.1676
				Adj R-squared =	0.1583
Total	4.52756451	451	.010038946	Root MSE =	.09192

transmode	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
popdens	1.35e-06	2.92e-07	4.63	0.000	7.78e-07	1.93e-06
densdelta	-.0000106	7.27e-06	-1.46	0.145	-.0000249	3.66e-06
distcbd	-.0002502	.0019302	-0.13	0.897	-.0040435	.0035432
dist_stn_16	-.0202179	.0042875	-4.72	0.000	-.0286441	-.0117916
intdens16	-.0000108	.0000266	-0.41	0.684	-.0000632	.0000415
_cons	.2769984	.0194679	14.23	0.000	.2387381	.3152586

The second contemporaneous model for 2016, which its results are presented in Table 7, controls for the impact of built environment variables as well as related socio-demographic attributes. In this model, changes in density do not have a statistically significant impact on transit mode share. When we control for the effect of socioeconomic variables, distance to downtown and intersection density become statistically significant factors in predicting the transit mode share and are negatively correlated with the dependent variable. All other variables have statistically significant influence on transit mode split except the average household size. Distance to the nearest subway station, distance to downtown, intersection density, and average household income have negative coefficients; hence, an increase in any of these variables is associated with a decline in the transit mode split. Contemporaneous population density, percentage of immigrants, and percentage of population between 15 – 19 are positively correlated with the dependent variable; an increase in any of these variables is correlated with increase in transit mode split.

Table 7. Contemporaneous linear regression model for 2016 time period: Impacts of percentage change in population density from 1996-2016, relevant built environment, and socioeconomic variables on transit mode split

Source	SS	df	MS			
				Number of obs	=	452
				F(9, 442)	=	20.39
Model	1.32825702	9	.147584113	Prob > F	=	0.0000
Residual	3.19930749	442	.007238252	R-squared	=	0.2934
				Adj R-squared	=	0.2790
Total	4.52756451	451	.010038946	Root MSE	=	.08508

transmode	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
popdens	8.50e-07	2.89e-07	2.94	0.003	2.83e-07	1.42e-06
densdelta	-6.61e-06	6.87e-06	-0.96	0.337	-.0000201	6.90e-06
distcbd	-.0085016	.0024226	-3.51	0.000	-.0132628	-.0037405
dist_stn_16	-.0199846	.0040246	-4.97	0.000	-.0278943	-.012075
intdens16	-.0000586	.0000259	-2.26	0.024	-.0001096	-7.67e-06
hhld_inc	-3.44e-07	5.02e-08	-6.85	0.000	-4.43e-07	-2.45e-07
per_imm	.0009982	.0004288	2.33	0.020	.0001554	.0018411
per_1519	.0103936	.0031531	3.30	0.001	.0041966	.0165907
hhld_size	-.0141542	.0146825	-0.96	0.336	-.0430104	.014702
_cons	.3374615	.0346711	9.73	0.000	.2693208	.4056022

The third contemporaneous model, controls for transit supply as well. The variables representing the level of transit supply data are highly correlated with each other so, to avoid multicollinearity in the model, adding all of them to the model at the same time should be prevented. The model was estimated 4 times and each time just one of the variables of transit supply were added to the model. However, none of these variables have a statistically significant impact on transit mode share.

Table 8 shows the model with the highest frequency of available transit service during morning peak period. The Models which include other transit supply indicators can be found in Appendix 2.

Table 8, presents the final contemporaneous regression model for transit mode split in 2016 time period. This model isolates the impact of change in density on transit mode share while we control for other explanatory variables; i.e. the relevant built-environment, socioeconomic, and level of transit service supply.

The results also indicate that TAZs with higher population density have higher transit mode split, all else is being equal. However, change in density over time have no impact on transit mode split when controlling for other explanatory variables. The results fail to reject the null hypothesis that the coefficient for percentage change in population density is equal to 0 ($p\text{-}value > 0.05$). This finding is not in consistent with previous research (Kenworthy & Laube, 1996; Newman & Kenworthy, 1989, 1991; Polzin et al., 2000) that concluded increasing population density would result in increased transit mode split based on the contemporaneous positive correlation between population density and transit mode share.

TAZs closer to downtown area tend to have higher transit mode split. TAZs that are closer to subway stations have higher transit mode splits. Higher intersection density is associated with lower transit mode split, which is not consistent with previous studies. This negative correlation between intersection density and transit mode share is likely due to multicollinearity in the data. The intersection density is correlated with other variables in the model. TAZs with higher average household income tend to have lower transit mode split, when all other variables are equal. Zones with higher percentage of immigrants are associated with greater transit mode split. Also, TAZs with higher portion of 15 – 19 years old population are having higher transit mode share. This positive correlation is also in contrast with previous studies that showed the 14-18 years old people are less likely to take public transit (Farber et al., 2014; Pasha et al., 2016). Additionally, in contrast to previous research, this study does not find average household size and transit service frequency, which is representing the level of transit service supply to have significant impact on transit mode share.

Table 8. Contemporaneous linear regression model for 2016 time period: Impacts of percentage change in population density from 1996-2016, relevant built environment, socioeconomic, and transit supply variables on transit mode split

Source	SS	df	MS		
				Number of obs =	452
				F(10, 441) =	18.31
Model	1.32844681	10	.132844681	Prob > F =	0.0000
Residual	3.1991177	441	.007254235	R-squared =	0.2934
				Adj R-squared =	0.2774
Total	4.52756451	451	.010038946	Root MSE =	.08517

transmode	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
popdens	8.49e-07	2.89e-07	2.94	0.003	2.82e-07	1.42e-06
densdelta	-6.56e-06	6.89e-06	-0.95	0.341	-.0000201	6.97e-06
distcbd	-.0085654	.0024571	-3.49	0.001	-.0133946	-.0037363
dist_stn_16	-.0198583	.004104	-4.84	0.000	-.0279241	-.0117925
intdens16	-.0000589	.000026	-2.26	0.024	-.0001099	-7.76e-06
hhld_inc	-3.44e-07	5.03e-08	-6.83	0.000	-4.43e-07	-2.45e-07
per_imm	.0010072	.0004329	2.33	0.020	.0001564	.001858
per_1519	.0104012	.003157	3.29	0.001	.0041966	.0166058
hhld_size	-.014083	.0147053	-0.96	0.339	-.0429842	.0148181
am_freq2	.0000609	.0003768	0.16	0.872	-.0006796	.0008014
_cons	.3361646	.0356234	9.44	0.000	.266152	.4061773

The next step is using mixed models in order to take into account the within-TAZ changes as well as the between-TAZ variation in the analysis. In the first attempt, the categorical time variable which has two categories 0 which represents year 1996 and 1 which represents year 2016 was added to the model. The result, presented in Table 9, indicates that change from 1996 to 2016 has a statistically positive effect on transit mode share.

Table 9. Impact of time changing from 1996-2016 on transit mode split based on mixed model regression

```
Performing EM optimization:

Performing gradient-based optimization:

Iteration 0:   log likelihood =   913.77403
Iteration 1:   log likelihood =   913.77403  (backed up)

Computing standard errors:

Mixed-effects ML regression                     Number of obs     =        885
Group variable: uid                                Number of groups  =        457

                                                Obs per group:
                                                              min =          1
                                                              avg =        1.9
                                                              max =          2

                                                   Wald chi2(1)      =      86.76
Log likelihood =   913.77403                       Prob > chi2       =     0.0000
```

transmode	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
tnew	.0375674	.0040332	9.31	0.000	.0296625	.0454723
_cons	.2249803	.00449	50.11	0.000	.2161801	.2337805

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
uid: Unstructured				
var(tnew)	.0046127	.1985289	1.07e-39	1.99e+34
var(_cons)	.0076887	.0992666	7.88e-14	7.51e+08
cov(tnew,_cons)	-.001752	.0992652	-.1963083	.1928043
var(Residual)	.0012251	.0992645	1.32e-72	1.14e+66

```
LR test vs. linear model: chi2(  3) = 210.27                 Prob > chi2 =  0.0000
```

In the second and final mixed model regression, relevant variables were added to the model. The final model shows the impact of changes in density over a course of 20 years on transit mode split, all else are being equal. This model includes an extra variable in addition to the explanatory variables presented before in this study. This variable takes into account the changes of population density over time; in statistical term, represents the interaction between population density and time.

The results, presented in Table 10, indicate that contemporaneously, population density has a positive statistically significant effect on transit mode share. The time change from 1996 - 2016 has a positive influence on transit mode share; that is if all the variables are the same for a TAZ, the transit mode share increases over a course of 20 years. However, the interaction variable is having a statistically significant impact on the transit mode share and it is negatively correlating with transit mode split. This means an increase in density does not have an even higher impact on the transit mode split, all else being equal. TAZs with increase in population density over time are associated with lower increase transit mode split.

The outcome also shows that contemporaneously TAZs closer to downtown area and/or are closer to subway station tend to have higher transit mode split, all else being equal. Intersection density, which takes account for the street network design, has statistically insignificant impact on transit mode split. Zones with higher average household income and/or with higher average household size tend to have lower transit mode split. Zones with higher percentage of immigrants are associated with higher transit mode split. Percentage of people between 15 – 19 years old is positively correlated with transit mode share, which is not consistent with previous studies that showed the 14-18 years old people are less likely to take public transit (Farber et al., 2014; Pasha et al., 2016). Transit service frequency during morning peak periods, which is an indicator of the level of transit supply, shows no statistically significant impact on transit mode share.

Two interesting findings are as follows: A unit increase in the average household size, the transit mode share increases by 4.02%. One percent increase in the percentage of 15-19 years old people, increases the transit mode split by 0.18%.

Table 10. Linear mixed-effect regression model: Impact of changes in density over time on transit mode split controlling for relevant built environment, socioeconomic, and transit supply variables on transit mode split

Variable	final
transmode	
population density	1.59e-06***
year 2016	.077***
tnew#c.popdens	
1	-1.17e-06**
distance to CBD	-.00875***
distance to subway in miles	-.0116***
intersection density	-.0000295
immigrants (%)	.00177***
population 15 to 19 (Census, %)	.00979***
average household size	-.0402***
average household income (nominal)	-3.11e-07***
AM peak surface transit frequency	.000196
Constant	.276***
lns1_1_1	
Constant	-2.65
lns1_1_2	
Constant	-2.29
atr1_1_1_2	
Constant	-1.33
lnsig_e	
Constant	-2.88
Statistics	
N	887

legend: * p<0.05; ** p<0.01; *** p<0.001

Discussion and Conclusion

The primary finding of this study is that population density has a contemporaneous correlation with public transit mode split, which is consistent with previous cross-sectional studies. However, this argument may not be readily stretched to infer that an increase in population density will automatically correlate with a commensurate increase in public transit mode share. Considering the longitudinal data and within-TAZ changes in population density over the course of 20 years, the results indicate that an increase in population density is associated with a slowing rate, and not a proportionate or higher, of increase in transit mode share.

In the case of Toronto, a bivariate comparison suggests that an increase of population density over time is correlated with an increase and a decline in transit mode share. This research brings new insights about the factors affecting people's travel behavior and how to study them in order to be able to better suggest principles and plans for increasing transit mode share in cities. The findings of this study provide context to other studies in transportation planning which suggest increasing transit mode split by means of increasing population density (Kenworthy & Laube, 1996; Newman & Kenworthy, 1989, 1991; Polzin et al., 2000).

This study suggests that Toronto Transit Commission or the planning authorities of the City of Toronto should be mindful of the diminishing returns to density. This means that density thresholds reached 20 years earlier or even sooner (density thresholds in 1996) establish the relationship between built form and how people travel. However, once such travel behaviors are established, the assumption that the relationship between the two variables will hold over time in marginal contexts, that is increasing densities always resulting in increasing transit mode splits, my not be true. Hence, for planning authorities, it might be prudent to focus on areas that may not necessarily have achieved those initial levels of population density that were observed in 1996.

Additionally, it should be noted that the results presented in this paper are more location specific. This implies that they are more relevant to Toronto in the sense that public transit mode share and built form characteristics of the city were already established by in the year 1996. Hence, from 1996 onwards, one does not see a strong relationship between the two variables of interest.

This study recommends that neighborhoods that have not yet attained the population densities observed earlier in 1996 in other parts of the city would be better candidates for targeted increase in densities or intensification to have a commensurate response in public transit ridership.

The study's conceptual framework and its methodology can be used in future research to take into account the changes of other travel behavior-relevant variables on transit mode share and identify factors associated with changes in transit mode share.

Appendices

Appendix 1. List of variables collected from TTS, TTC, and Census Canada data bases.

variable name	variable label
uid	unique TAZ id
zone	TAZ
temp	temp
intdens96	Intersection density (1996)
intdens16	Intersection density (2016)
dist_stn_96	Distance to subway station, 1996
dist_stn_16	Distance to subway station, 2016
hhlds	sampled households
hhlds_exp	hhlds expanded
pers	persons
pers_exp	persons expanded
trips	trips
trips_exp	total trips expanded
trans	transit trips
trans_exp	transit trips expanded
house	low-rise housing
apartment	apartments
townhouse	townhouses
pers_1	one person households
pers_2	two person households
pers_34	3 to 4 person households
pers_510	5 to 10 person households
vehs_0	zero vehicle households
vehs_1	vehs_1
vehs_2	two vehicle households
vehs_34	3 to 4 vehicle households

vehs_510	5 to 10 vehicle households
drv_0	zero driver households
drv_1	single driver households
drv_2	two driver households
drv_34	3 to 4 driver households
drv_510	5 to 10 driver households
ftw_0	zero FTW households
ftw_1	one FTW households
ftw_2	two FTW households
ftw_34	3 to 4 FTW households
ftw_510	5 to 10 FTW households
ptw_0	zero PTW households
ptw_1	one PTW households
ptw_2	two PTW households
ptw_34	3 to 4 PTW households
ptw_510	5 to 10 PTW households
stud_0	zero student households
stud_1	one student households
stud_2	two student households
stud_34	3 to 4 student households
stud_510	5 to 10 student households
trips_0	zero trip households
trips_1	one trip households
trips_2	two trip households
trips_34	3 to 4 trip households
trips_510	5 to 10 trip households
trips_1150	11 to 50 trip households
age_014	0 to 14 years old persons
age_1518	15 to 18 years old persons
age_1922	19 to 22 years old persons
age_2335	23 to 35 years old persons

age_3655	36 to 55 years old persons
age_5665	56 to 65 years old persons
age_65plus	65 and older persons
unknown_gender	unknown gender
female	female
male	male
nonrespondents	non respondents
respondents	respondents
unknown_licens	unknown driver license
doesnothavead~	does not have a driver's licen
hasadriversli~	has a driver's licence
unknown_pass	unknown pass status
combinationdu~	Combination/Dual Pass
metropass	Metro Pass
none	No pass
otheragencypas	Other Agency Pass
presto	Presto
gotransitpass	GO Transit Pass
unknown_emp_s~	Unknown employment status
fulltime	fulltime employed
homefulltime	Home / Full time
homeparttime	Home / Part time
notemployed	Not employed
parttime	parttime employed
unknown_emptyp	unknown employment type
generaloffice~	General Office/Clerica
manufacturing~int	%10.0g/Construction/Trades
notemployed_1	not employed
professionalm~	%10.0gManagement/Technical
retailsalesan~	Retail Sales and Service
unknown_homew~	Unknown homework

didnotworkfro~	Did not work from home on survey
notapplicable	Not applicable
workedfromhom~	Worked from home on survey day
unknown_parkin	Unknown parking status
nofreeparking	No free parking
notapp_parking	Not applicable
yesfreeparking	Yes, free parking
unknown_stud_~	Unknown student status
notastudent	Not a student
pt_stud	Part time
ft_stud	Full time
t400599	trips starting at 0400 - 0559
t600799	trips starting at 0600 - 0759
t800899	trips starting at 0800 - 0859
t900999	trips starting at 0900 - 0959
t10001599	trips starting at 1000 - 1559
t16001799	trips starting at 1600 - 1759
t18002200	trips starting at 1600 - 2200
unknown_trans~	Unknown transit pass
transitexclud~	Transit excluding GO rail
cycle	Cycle
autodriver	Auto driver
gorailonly	GO rail only
jointgorailan~	Joint GO rail and local transit
motorcycle	Motorcycle
other	Other
autopassenger	Auto passenger
schoolbus	School bus
taxipassenger	Taxi passenger
paidrideshare	Paid rideshare
walk	Walk

homebasedwork	Home-Based Work
homebasedschoo	Home-based School
homebaseddisc~	Home-based Discretionary
nonhomebased	Non Home-based
all_km_01	all trips b/w 0 and 1 km
all_km_2	all trips b/w 1 and 2 km
all_km_34	all trips b/w 3 and 4 km
all_km_510	all trips b/w 5 and 10 km
all_km_1115	all trips b/w 11 and 15 km
all_km_1620	all trips b/w 16 and 20 km
all_km_21200	all trips b/w 21 and 200 km
tran_km_01	transit trips b/w 0 and 1 km
tran_km_2	transit trips b/w 1 and 2 km
tran_km_34	transit trips b/w 3 and 4 km
tran_km_510	transit trips b/w 5 and 10 km
tran_km_1115	transit trips b/w 11 and 15 km
tran_km_1620	transit trips b/w 16 and 20 km
tran_km_21200	transit trips b/w 21 and 200 km
drvpass_km_01	driver+pass trips b/w 0 and 1 km
drvpass_km_2	driver+pass trips b/w 1 and 2 km
drvpass_km_34	driver+pass trips b/w 3 and 4 km
drvpass_km_510	driver+pass trips b/w 5 and 10 k
drvpass_km_111	driver+pass trips b/w 11 and 15
drvpass_km_162	driver+pass trips b/w 16 and 20
drvpass_k~2120	driver+pass trips b/w 21 and 200
hbw__km_01	home-based work_km_0-1
hbw__km_2	home-based work_km_1-2
hbw__km_34	home-based work_km_3-4
hbw__km_510	home-based work_km_5-10
hbw__km_1115	home-based work_km_11-15
hbw__km_1620	home-based work_km_16-20

hbw__km_21200	home-based work_km_21-200
hbd_km_01	home-based discretionary_
hbd_km_2	home-based discretionary_
hbd_km_34	home-based discretionary_
hbd_km_510	home-based discretionary_
hbd_km_1115	home-based discretionary_
hbd_km_1620	home-based discretionary_
hbd_km_21200	home-based discretionary_
year	year
popdens	population density
transmode	transit mode split
densdelta	change in density (%)
treated	density increase by > 10%
_est_fixede	esample() from estimates stor
_est_randome	esample() from estimates stor
cat_dens	change in density categories
area_sqkm	area (sq km)
area_miles	area (sq miles)
gta01	GTA01
pd	planning district
distcbd	distance to CBD
intersectdens	intersection density
dist_sway	distance to subway in miles
population	population
pop_dif_n	change in population (19
pop_chng	% change in population (19
am_freq	AM peak surface transit freque
mid_freq	mid-day surface transit freque
am_routes	AM peak surface transit routes
midday_rts	mid-day transit routes
per_1519	population 15 to 19 (Census, %)

per_2024	population 20 to 24 (Census, %)
hhld_inc	average household income (nomina
per_imm	immigrants (%)
rec_imm	recent immigrants (%)
hhld_size	average household size
_amfreq	AM peak surface transit frequency

Appendix 2. Outcome of contemporaneous linear regression model for 2016 using different indicators for level of transit supply

Source	SS	df	MS			
Model	1.32857326	10	.132857326			
Residual	3.19899125	441	.007253948			
Total	4.52756451	451	.010038946			

Number of obs	=	452
F(10, 441)	=	18.32
Prob > F	=	0.0000
R-squared	=	0.2934
Adj R-squared	=	0.2774
Root MSE	=	.08517

transmode	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
popdens	8.51e-07	2.89e-07	2.95	0.003	2.83e-07	1.42e-06
densdelta	-6.58e-06	6.88e-06	-0.96	0.339	-.0000201	6.94e-06
distcbd	-.0084682	.0024305	-3.48	0.001	-.0132449	-.0036915
dist_stn_16	-.0200177	.004032	-4.96	0.000	-.0279421	-.0120933
intdens16	-.0000599	.0000266	-2.25	0.025	-.0001122	-7.53e-06
hhld_inc	-3.44e-07	5.03e-08	-6.84	0.000	-4.43e-07	-2.45e-07
per_imm	.0009935	.0004299	2.31	0.021	.0001485	.0018384
per_1519	.0105028	.0031996	3.28	0.001	.0042145	.0167912
hhld_size	-.0145114	.0147976	-0.98	0.327	-.043594	.0145712
mid_freq2	-.0000631	.0003021	-0.21	0.835	-.0006567	.0005306
_cons	.3397222	.0363583	9.34	0.000	.2682652	.4111792

Contemporaneous linear regression model for 2016 time period showing Impacts of percentage change in population density from 1996-2016, relevant built environment, and socioeconomic variables on transit mode split, using highest frequency of available transit services during midday period as the indicator of level of transit supply.

Source	SS	df	MS		
Model	1.33803675	10	.133803675	Number of obs =	452
Residual	3.18952776	441	.007232489	F(10, 441) =	18.50
				Prob > F =	0.0000
Total	4.52756451	451	.010038946	R-squared =	0.2955
				Adj R-squared =	0.2796
				Root MSE =	.08504

transmode	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
popdens	8.79e-07	2.90e-07	3.04	0.003	3.10e-07	1.45e-06
densdelta	-7.67e-06	6.93e-06	-1.11	0.269	-.0000213	5.95e-06
distcbd	-.0086694	.0024259	-3.57	0.000	-.0134371	-.0039017
dist_stn_16	-.0193661	.004058	-4.77	0.000	-.0273415	-.0113908
intdens16	-.0000586	.0000259	-2.26	0.024	-.0001095	-7.63e-06
hhld_inc	-3.46e-07	5.02e-08	-6.90	0.000	-4.45e-07	-2.48e-07
per_imm	.0009338	.0004322	2.16	0.031	.0000843	.0017833
per_1519	.0102487	.0031543	3.25	0.001	.0040492	.0164481
hhld_size	-.0124602	.0147488	-0.84	0.399	-.0414468	.0165265
am_routes	.0010087	.0008675	1.16	0.246	-.0006962	.0027136
_cons	.32531	.0361984	8.99	0.000	.2541671	.3964529

Contemporaneous linear regression model for 2016 time period showing Impacts of percentage change in population density from 1996-2016, relevant built environment, and socioeconomic variables on transit mode split, using number of available transit services during morning peak period as the indicator of level of transit supply.

Source	SS	df	MS		
				Number of obs =	452
				F(10, 441) =	18.47
Model	1.33671174	10	.133671174	Prob > F =	0.0000
Residual	3.19085277	441	.007235494	R-squared =	0.2952
				Adj R-squared =	0.2793
Total	4.52756451	451	.010038946	Root MSE =	.08506

transmode	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
popdens	8.84e-07	2.90e-07	3.05	0.002	3.14e-07	1.45e-06
densdelta	-7.57e-06	6.93e-06	-1.09	0.275	-.0000212	6.05e-06
distcbd	-.0087922	.002437	-3.61	0.000	-.0135817	-.0040027
dist_stn_16	-.0192281	.0040842	-4.71	0.000	-.027255	-.0112012
intdens16	-.0000575	.000026	-2.21	0.027	-.0001085	-6.48e-06
hhld_inc	-3.43e-07	5.02e-08	-6.82	0.000	-4.41e-07	-2.44e-07
per_imm	.0009852	.0004289	2.30	0.022	.0001421	.0018282
per_1519	.0100242	.003171	3.16	0.002	.003792	.0162564
hhld_size	-.0131619	.0147084	-0.89	0.371	-.0420691	.0157453
midday_rts	.0010674	.0009874	1.08	0.280	-.0008732	.003008
_cons	.327395	.0358936	9.12	0.000	.2568512	.3979387

Contemporaneous linear regression model for 2016 time period showing Impacts of percentage change in population density from 1996-2016, relevant built environment, and socioeconomic variables on transit mode split, using number of available transit services during morning peak period as the indicator of level of transit supply.

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