Travelling Fair: Low-wage commuting in the Greater Toronto and Hamilton Area

A supervised research project in two parts,
by

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Abstract

In order for transportation investment to be equitable those with little disposable income should receive an equitable share of transit service. Low-wage workers already experiencing limited choices in residential location and struggling to meet daily necessities require access to affordable and efficient transportation. The purpose of this project is to discover when low-wage workers and higher-wage workers in the Greater Toronto and Hamilton Area use transit and how variations in worker needs and transit service impact ridership. We then investigate how occupational sector relates to low-wage ridership and use these findings to propose a novel method for targeting policies, infrastructure, and marketing to areas and sectors of low-wage employment that require help. We find that low-wage workers use transit less than their higher-wage counterparts and that factors that increase transit use among higher-wage workers decrease transit use among low-wage workers. We also find that certain sectors of low-wage employment have a negative pull on transit use. By discovering areas of low-wage employment concentration in the GTHA, we can pinpoint areas where investment would be most beneficial for this vulnerable population. For practitioners and researchers, the findings and methods of this project can be replicated in other jurisdictions. In particular, we demonstrate that focusing research and interventions on employment locations may be a novel way to efficiently target transit investment.

Résumé

Pour que les investissements en transport soient équitables, ceux dont le revenu disponible est plus faible devraient bénéficier d'une part équitable de service de transport en commun (TC). En raison de leur situation économique, les travailleurs à faibles revenus disposent d'un choix limité concernant le lieu de leur résidence et ils ont souvent de la difficulté à subvenir à leurs besoins quotients qui, par ailleurs, requièrent un accès abordable et efficace au transport. Ce projet a d'abord pour objectif de découvrir à quel moment de la journée les travailleurs à faible revenu et les travailleurs à revenu plus élevé ont besoin et utilisent les services de TC dans la grande région de Toronto et Hamilton tout en identifiant comment les variations entre la demande des travailleurs en TC et l'offre de service affectent l'achalandage. Le lien entre les secteurs professionnels et l'achalandage des travailleurs à faibles revenus dans les TC est ensuite examiné afin de proposer la mise en œuvre de politiques, l'ajout d'infrastructures et de nouvelles stratégies de marketing ciblant des zones géographiques et secteurs professionnels à faible revenu nécessitant une aide. Les résultats montrent que les travailleurs à faible revenu utilisent moins les services de TC que leurs homologues à revenu plus élevé et que les facteurs augmentant l'utilisation des TC parmi les travailleurs à revenu plus élevé diminuent l'utilisation des TC pour les travailleurs à plus faible revenu. Nos résultats montrent aussi que certains secteurs professionnels à faible revenu ont un effet négatif sur l'utilisation des TC. La découverte de zones d'emploi à faible revenu permet d'identification géographiquement où les investissements en TC seraient le plus bénéfiques pour les populations les plus vulnérables. Les résultats et les méthodes utilisées dans cette recherche sont d'un intérêt particulier pour les praticiens et les chercheurs puisqu'elles peuvent être reproduites dans d'autres juridictions. Cette étude démontre notamment qu'orienter la recherche et les interventions vers les lieux d'emploi plutôt que de résidence constitue une nouvelle manière efficace de cibler les zones où de nouveaux investissements en TC devraient être alloués.

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Table of Contents

List of figures

List of tables

Preface: Equity and transit planning

Public transit services are designed to help people get to where they need to go affordably, efficiently, and sustainably. However, a transit system cannot be equally distributed to every resident. Residents of suburban locations have less access to transit services than residents of dense urban neighbourhoods. Commuters working downtown will often find transit service convenient for their needs, but workers commuting to the periphery of cities will often find transit service inefficient or non-existent. People who travel at peak periods may have wide range of transit options, but workers of third or overnight shifts may find little or no service for their needs. Inequalities in a city's transit system are unavoidable. Agencies must choose how to invest limited resources. Often, we hope that this investment is guided by a simple promise: that a transit system is serving the most people for the least expense. This explains why more services are run during peak hours, why more buses run in downtown cores, and why suburban transit service is often lacking in major North American cities. It is a simple application of supply and demand: More riders demanding transit leads to more service to meet that demand.

However, although a perfect equality of service is impossible, an equitable transit system should be achieved. Structural changes in the city may cause residents who rely on transit (the elderly, the poor, recent immigrants, or those who cannot drive or walk, to name a few) to be pushed away from transit rich areas. The processes of gentrification and a growing suburbanization of employment may cause disadvantaged residents to lose transit service, not gain it.

A transportation network's infrastructure and benefits should be equitably provided. Why? Simply put, it is because these infrastructure and benefits are almost always a publically provided good, and should be equitably distributed to that public. The problem is that there is little to no consensus on what equity is, and how to go about assessing equity. Transit planning authorities are increasingly being required to assess equity before any new intervention is accepted or as part of their regular assessment procedures. It has been shown that public transportation systems can work towards diminishing economic disparities between social groups within a region (Grengs, 2010; Jones & Lucas, 2012). It has also been shown that transportation resources, if equitably distributed, provide more travel options and shorter travel times to those with less transportation choices (Krumholz & Forester, 1990). The fair distribution of transportation resources matter because people with little transportation choice have subsequently limited choices for jobs, shopping (Grengs, 2015), or housing location (Glaeser, Kahn, & Rappaport, 2008). Since almost all transportation infrastructure (roads, subway tunnels) and services (bus service, traffic lights) are provided publically, the equitable distribution of these goods is, ethically, necessary.

The main inspiration for this project is to study how changing circumstances (both on a daily and also geographic basis) influence disadvantaged population's use and access to transit in Canada's largest metropolis, the Greater Toronto and Hamilton Area. Divided into two chapters, the methods used in this project can inspire planners to conduct similar studies. More importantly, this project will hopefully bring to the table the pressing travel needs of disadvantaged residents. Precise and targeted interventions, which this project's findings can help guide, could have the most impact on those who are increasingly isolated in today's metropolis.

In the first chapter, this project explores how low-wage workers (defined as those earning under the living wage in the GTHA) react to daily fluctuations in transit service, and compares these fluctuations to the travel habits of higher-wage workers. We discover that low-wage workers use transit less than higher earners. We also find that they react differently to service changes or characteristics of their residential built environment. This means that investment and additional services may help only higher-wage workers and offer little to low-wage workers.

In the second chapter, we move our focus to *where* low-wage workers travel to in the region and how different occupational sector relates to transit use. Low-wage workers may find it difficult to travel to their place of employment because of its location; similarly, their job duties may make transit an unappealing travel option. With the growing importance of suburban job centers in most North American cities, this difficulty may be growing. We use a novel approach to locate low-wage employment zones in the suburbs of the GTHA. We then see how different occupational sectors of low-wage employment spatially locate in the region. Finally, we see how these sectorial concentrations, both in and outside of suburban employment zones, relate to transit ridership. We find that some sectors have a positive influence on ridership, while others do not. Findings from this chapter can help target policies and infrastructure at different areas and towards different sectors of low-wage workers by addressing their specific needs.

Chapter 1: Are low-wage workers different: Daily variation in ridership for low- and high-wage workers.*

Abstract

Public transportation agencies are faced with the difficult task of providing adequate service during peak travel periods while maintaining adequate service for those travelling off-peak or travel outside a city or region's densest areas. The ability or inability of a transit system to meet these needs helps explain transit ridership rates. This research seeks to understand how daily fluctuations in transit service are related to ridership in the Greater Toronto and Hamilton Area (GTHA) for different segments of the labour force. Many variables have been linked to transit use in past research including: frequency and proximity of transit service, socio-economic status, the built environment, and accessibility to employment using transit. However, many previous studies focus only on travel during peak hours. This study investigates if fluctuations in service and demand are related to transit ridership rates. Using six time periods, we produce an improved understanding of daily variation in transit mode share for commuting trips. By further dividing the commuting population into two employment wage categories, we demonstrate that the common understanding of the causes of transit ridership is potentially misleading. Commuting transit mode share and the variables that influence it are intimately related to when travel is needed, and to what jobs people are traveling to. To encourage transit use, agencies and researchers need to take into account commuters' need to commute at a variety of time periods.

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Introduction

Why do people use public transit? Most answers mention socio-economic reasons, ease of use (proximity and frequency of transit), and perhaps culture or education. For example, those with a college education are more likely to take suburban commuter trains over other forms of transit (Limtanakool, Dijst, & Schwanen, 2006). However, these influences are secondary to a more fundamental question commuters may ask themselves before travelling; "Does transit work for me?"

There has been much research on determining what makes transit work and what does not. Many commuting studies look at transit mode share to all jobs, ignoring the potential effect job category or occupation class may have on transit mode share and accessibility (Moniruzzaman & Paez, 2004). Foth et al. (Foth, Manaugh, & El-Geneidy, 2014) found that job category does have an effect on transit mode share. However, they used broad categories that included a wide range of wage groups, potentially ignoring the effect wage has on transit ridership. This effect may be present because social deprivation and low income have long been linked to transit ridership (Giuliano, 2005). In addition, income has been linked to captive transit ridership, which is caused when income limits access to other modes (Giuliano, 2005). Yet, there has been little effort to study *when* transit works and *when* it does not. Although a person's economic situation stays fairly constant throughout the day, the ease of using public transit can fluctuate, sometimes with great volatility.

This study asks if there is a relationship between the transit mode share of two wage groups and daily fluctuations in transit service and job availability. The research setting is the Greater Toronto and Hamilton Area (GTHA), Canada. The answer to this question should be of particular importance to regional transportation authorities similar to Metrolinx (the regional transportation authority of the GTHA), which is tasked with both facilitating cooperation among local transportation operators and developing regional transit service. We incorporate transit service and job availability during different times of the day into statistical models that include spatial and temporal variables known to associate with, if not influence, transit mode share. We hypothesize that the availability of jobs and transit change throughout the day, and these changes affect the share of travellers who find public transit convenient enough to use for their commuting needs. We also expect that the independent variables' coefficients will vary daily as user's preferences and needs throughout the day.

This paper is organized into four sections. The first section briefly introduces the reader to transit mode share research, focusing on what has been reported as the typical variables that influence or associate with transit mode share. Next, the data and methodological framework are described, followed by a description of the study context. A presentation of the results follows, where the data is analyzed spatially, temporally, and by job category. Finally, the results are discussed and conclusions identified and summarized.

Literature review

Variables typically related to transit mode share can be divided into two main groups: those pertaining to the rider's personal situation (socio-economic and other demographic variables) and those dealing with the activities and connectivity that make up a rider's milieu (the built environment and transit availability). The following section will discuss these variables, their presence in the literature, and their expected impacts on transit mode share.

Socioeconomic indicators

The decision to take transit is influenced by a person's social situation and economic standing. A number of variables have been used to capture socio-economic effect. Income is often used as a variable to describe social exclusion, transport disadvantage and equity issues (Giuliano, 2005; Mercado, Paez, Farber, Roorda, & Morency, 2012; Roorda, Paez, Morency, Mercado, & Farber, 2005; Vasconcellos, 2005), and lower median income at a neighbourhood scale has been linked to higher transit use (Bento, Cropper, Mobarak, & Vinha, 2005; Giuliano, 2005; Hine, 2004; Moniruzzaman & Paez, 2004). Higher transit use among those with lower incomes is often described as "captive ridership", a situation where public transit is a person's only affordable travel option (Garrett & Taylor, 1999; Polzin, Chu, & Rey, 2000). In turn, captive ridership may lead to lower-income residents moving to areas that are more accessible by transit.(Blumenberg & Hess, 2003; Glaeser et al., 2008; Hess, 2005).

Yet, social deprivation is not the result of income alone. To more accurately identify deprivation at the neighborhood level, a socioeconomic approach is often used (Foth, Manaugh, & El-Geneidy, 2013). Variables usually included are unemployment rate, immigration status, and housing affordability, as well as income. Unemployment is understood to be a suitable indicator of mitigated well-being in the Canadian context (Employment and Social Development Canada, 2014). Similarly, a high concentration of recent immigrants within a neighbourhood may indicate a site of possible social exclusion, or the presence of exclusionary processes or systemic discrimination in housing markets and/or housing policy within a city (Liu & Painter, 2011; Mercado et al., 2012; Taylor, Miller, Iseki, & Fink, 2009). In Canadian urban centers, recent immigrants are more likely to work for lower wages or be unemployed (Statistics Canada, 2004). Finally, high relative expenditure of individual or household budgets on rent, especially for tenants, could indicate locations where households are struggling to maintain a decent standard of living (Foth et al., 2013, 2014; Luffman, 2006). In this paper we apply an index of social deprivation that incorporates income, unemployment rate, immigrant share and housing affordability to identify socially deprived zones at the census tract (CT) level (Foth et al., 2013, 2014). Deprivation revealed using this indicator is positively linked to transit mode share in Toronto, Canada (Foth et al., 2014).

The built environment and accessibility

Socio-economic motivations for transit use are just one part of the picture. The built environment, including density, the diversity of land uses, and the urban design of the area (the three 'Ds'), have been shown to influence transit ridership, even when residential self-selection is controlled for (Cao, Mokhtarian, & Handy, 2009; Cervero & Kockelman, 1997). Residential proximity to transit stops and frequency of service have been shown to associate with higher levels of transit ridership (Ewing & Cervero, 2010; Foth et al., 2014; Mercado et al., 2012). In particular, short distances to rapid transit stations, such as subway stops, have some positive effect on transit ridership rates (Crowley, Shalaby, & Zarei, 2009). In contrast, proximity to controlled access highways has been shown to have a negative influence on transit mode share (Foth et al., 2014; Kawabata, 2009).

Accessibility's relationship with transit mode share has also been studied. Accessibility measures account for both the transit service people have as well as the opportunities that are reachable using those services (Geurs & Van Wee, 2004). Measuring transit accessibility can be as simple as measuring the distance to the nearest stop to more complex measures (for a review see, Polzin, Pendyala, & Navari, 2002). However, accessibility measures often make two basic assumptions, which this study avoids. First, there is an assumption that all opportunities attract equally. However, since measures of accessibility aim to take into account opportunities available to the traveler, the type of opportunities the traveler wants to reach should be taken into account (Geurs & Van Wee, 2004; Niemeier, 1997). For employment accessibility, different measures for different job categories may be used as better determinants of mode share for specific working populations. Employment type has been shown to influence travel behavior: managers are more likely to commute from the suburbs, whereas service workers, office workers, and professionals are more likely to reside in the urban core (Moos & Skaburskis, 2009). Calculating accessibility measures that take into account the jobs labour must reach affords researchers a better understanding of different working-groups' transport needs.

Foth et al. (Foth et al., 2014) divided the Toronto (Canada) labour force into three main job categories, based on National Occupation Classification (NOC), to study transit ridership and equitable access to employment opportunities. However, NOC categories do not fully capture the wide wage differences present within and across them. An inspection of average wages in Toronto by NOC subcategory shows that each major group has within it considerable variation in income (Statistics Canada, 2014). Since income, and thus wage, has an influence on transit ridership, separating jobs based on wage may be a more appropriate investigative method (Wang, 2003).

A second assumption is that accessibility to jobs remains constant over the day or that accessibility during peak travel hours is indicative of a transport system's overall performance. This is clearly not the case when regarding most transit services. Changing schedules and daily network closures (planned or otherwise) affect accessibility in non-trivial ways (Farber, Morang, & Widener, 2014). It is easy to imagine that employees who work non-regular or third-shift hours may find using transit impossible or untenable because of a lack of service when they need it.

Recently, a few studies have developed accessibility measures that take into account changing levels of transit service or changing levels of job availability. A first attempt involved generating a single accessibility score, which indicates accessibility at one time period, and combining it with a measure of service frequency (Dill, Schlossberg, Ma, & Meyer, 2013; Mavoa, Witten, McCreanor, & O'Sullivan, 2012). Lei et al. (Lei, Chen, & Goulias, 2012) devised a way to incorporate detailed transit schedules into a series of accessibility scores for different times of day. Fan et al. (Fan, Guthrie, & Levinson, 2012) followed a similar approach, measuring accessibility on an hourly interval. Owen and Levinson (Owen & Levinson, 2015) developed a continuous measure, where they measured accessibility by the minute, and use these measures to derive the maximum, mean, and minimum. They find that incorporating the maximum and mean in a model offers a better explanation of transit-mode choice than incorporating a single measure of accessibility. These attempts, however, fail to take into account that opportunities (for instance, job start times), not just transit service, also vary throughout the day. One paper, does point this out: Polzin et al. (Polzin et al., 2002) offer a good introduction to the nuances of daily variation of transit accessibility, and argue that demand for travel, in addition to transit travel times, also fluctuate throughout the day.

Methodology

In this section, we describe how we take into account both fluctuations in job availability and transit service to come to a better understanding of transit mode choice throughout the day for two different wage groups in the GTHA. There are three major steps. First, we divide our commuting population into two wage-based groups and calculate their transit mode share. Second, we gather variables pertinent to transit mode share. Third, we calculate accessibility to jobs for both groups. It should be noted that this all variables are measured at the census tract (CT) level.

For this study we divided the GTHA into three areas to explore differences in accessibility outcomes across a broad range of settlement typologies. We use the borders of the City of Toronto before it was politically amalgamated with surrounding inner suburban municipalities in 1998 as a base area representing the urban core of the region, including its downtown (Keil, 2000). Secondly, we take those areas that are part of the present (post-amalgamated) City of Toronto, excluding the urban core, as the City of Toronto's inner suburbs. The area within the core was often lauded before amalgamation as being a leading example of good public transit planning (Keil, 2000). To this day, the main rapid transit services (the subway and the Go-Train) are geared towards serving Toronto's urban core and inner suburbs. Including two dummy variables indicating if a CT is either in Toronto's urban core or inner suburbs controls for the benefit of residing in these locations. The area outside of the City of Toronto represents a diverse mix of semi-rural communities and distinct urban areas and cities, including Hamilton (population 0.5 million, (Statistics Canada, 2011b) and Mississauga, Canada's sixth largest city (population 0.7 million, (Statistics Canada, 2011b)). GO commuter trains and local regular and express bus services operate in the region's outer suburban places, and cities like

Hamilton and Mississauga envision a transit future that will include light rail services of some kind.

To test for the influence that variation in transit service and job availability have on transit mode share, we use a series of Ordinary Least Square regressions. First, we divide the working population into two study groups, based on hourly wage. Those jobs with a mean wage of $16.00 dollars an hour or less serve as our 'low-wage' category while jobs paying more than $16.00 dollars an hour serve as our higher-wage category. This threshold is used because it is the living wage for the Toronto region (Mackenzie & Stanford, 2008). Wage data by NOC subcategory is gathered from Statistics Canada's wage report for the Toronto census metropolitan area (Statistics Canada, 2014). We calculate transit mode share for these two groups to see what relationship typical variables have with each group's mode share. In addition, we estimate transit mode share for all workers in the region (both groups combined), to see if modeling transit mode share using wage categories improves our understanding.

Transit mode share for each job group at the CT level is the dependent variable for each model. We use two datasets from Statistics Canada, both of which come from the 2011 National Household Survey to perform this analysis (Statistics Canada, 2011b). The first dataset indicates origins and destinations for all workers at the CT level, organized by six departure times (5am, 6am, 7am, 8am, 9am to noon, and noon to 5am). The amount of trips on different modes, including transit, is reported for those times. The second dataset offers the same information restricted to workers employed in low-wage jobs. The difference between the data for all workers and low-wage workers gives us the same information for higher-wage workers. Collapsing the hours between 9am to noon and noon to 5am is necessary because of Statistics Canada's data suppression rules. A cell that contains less than five actual responses will be suppressed by Statistics Canada. Since departures at these hours are relatively infrequent, a large amount of suppression is to be expected, which would skew any analysis. By collapsing these hours together, data suppression can be lessened. Also note that 40 CTs (out of an original 1330 in our study area) are excluded because National Household Survey data is entirely suppressed for these locations, due to low response rates (Statistics Canada, 2011a).

For all model groups (all jobs, low-wage earners, and the comparison group), one regression is run for each time period, resulting in 18 models (six time periods for three job models). All models include the same variables, described below. These models help demonstrate that variable coefficients related to transit mode share fluctuate over the course of the day and by job category. A correlation matrix between all continuous variables was produced to determine if there are any multicollinearity problems. No relationship between variables significantly greater than $p>0.6$ was found. Also, some continuous variables demonstrate potentially non-normal distributions, namely “transit frequency”, “network distance to highway on-ramp”, and “Euclidian mean distance travelled to low-wage jobs.” For each of these variables, a natural log transformation was applied, and they were tested. However, sensitivity analysis using transformed variables produced little effect on regression results when compared to the results from models with untransformed variables. Thus, the original untransformed variables are included in our final models. The rest of this section explains the models we use and how variables were calculated. If variables required a specific point origin and destination in order to be calculated, CT centroids are used.

Socio-economic index

To test for the effect of socio-economic status, a social index developed in previous research is used. This index is a combination of z-scores of median income, unemployment, share of residents who have immigrated to Canada in the last five years, and share of households who pay rent that is greater than thirty percent of their income at the CT level (Foth et al., 2013). Data for this measure are taken from the 2011 National Household Survey (Statistics Canada, 2011a), and divided into deciles. CT membership in the 10^{th} decile is considered an indication of being the most socially deprived; in the 1^{st} decile, the least socially deprived. Figure 1 shows the spatial distribution of these deciles in the GTHA, with the borders of the urban core and inner suburbs super-imposed.

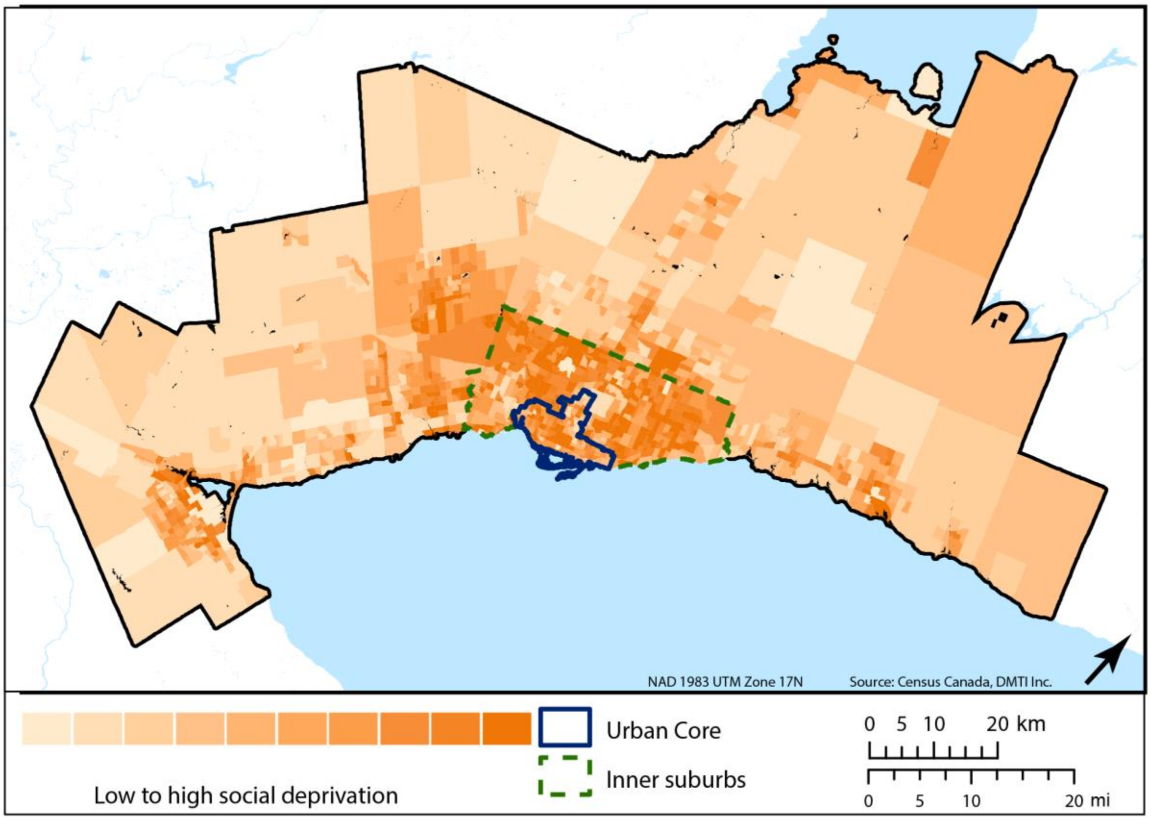

Figure 1: Social deprivation in the GTHA

Built environment and transit proximity

Mean straight-line distance travelled to work from each census tract is included. This variable is calculated by determining the straight-line distances of all trips originating at a census tract during a day, and weighting these trips by the number of commuters who take each trip. This number divided by the total number of commuters at each CT provides the mean distance travelled from each CT during a day. It is generally acceptable to use straight line distances when studying relations at the regional level since the ratio between this distance and network distance is generally stable across a region (Levinson & El-Geneidy, 2009).

Two dummy variables, indicating whether or not a CT's centroid is within one kilometer of a subway and whether or not it is within one kilometer of a GO (commuter) train station, are included to test for transit proximity. Distances are gathered using a pedestrian network. One kilometer is used as a buffer because previous research indicates that most people are willing to walk 900 meters but never more than 1750 meters to a rapid transit station (O'Sullivan &

Morrall, 1996). Distance to the nearest controlled-access highway on-ramp is also measured, using automobile network distances.

A variable indicating transit frequency is included as well. Using General Transit Feed Specification (GTFS) data for the entire GTHA region, a frequency analysis is run using the 'Better Bus Buffers' toolset developed by M. Morang and ESRI (for more information see, Farber et al., 2014). We measure how many transit trips stop within one kilometer of each CT centroid at each hour between 5am and noon, on a typical Monday. The mean of these frequencies (by hour) is used to approximate morning service frequency at each CT. Table 1 shows summary statistics for all independent variables. Three of the continuous variables display potentially skewed distributions ("transit frequency", "network distance to highway on-ramp", and "Euclidian mean distance travelled to low-wage jobs"), where their standard deviations are greater than their means. Potential transformations were tested (discussed above).

Table 1: Summary statistics: Variables relating to daily variation in transit use

(N=1290)	Mean	Median	SD	Min	Max
Transit frequency (trips per hour)	36.09	20.40	44.36	0.00	339.20
Located in city center	0.12	0.00	0.03	0.00	1.00
Located in inner suburbs	0.30	0.00	0.05	0.00	1.00
Network distance to nearest subway station (km)	24.19	18.74	22.73	0.00	83.97
Network distance to nearest GO station (km)	5.29	4.09	5.00	0.36	53.37
Network distance to nearest highway on-ramp (km)	4.02	3.00	4.72	0.02	53.00
Euclidian mean distance travelled to all jobs (km)	10.21	9.53	4.58	1.32	38.62
Euclidian mean distance travelled to low-wage jobs (km)	11.78	6.63	12.15	0.46	35.42
Euclidian mean distance travelled to higher-wage jobs (km)	9.57	8.79	4.45	0.83	35.35

Accessibility and travel time

Accessibility to jobs is calculated using a gravity-based measure (Hansen, 1959):

$$A_i^{\text{pub}} = \sum_{j=1}^{n} D_{e^{-\beta cij}}$$

Where A_i^{pub} is the accessibility at point *i* to all jobs at zone *j* using public transit. C_{ij} is the travel cost (measured in time) between census tract *i* and census tract *j*, and β is a negative exponential cost function. This cost function is derived from reported work trips in the 2011 National Household Survey linked to a transit travel time matrix. Travel time from each CT centroid to every other CT centroid at each departure time period is calculated using current GTFS data for all eight public transit agencies serving the GTHA. These calculations provide a travel time matrix for each departure time period, including travel times from each CT to every other CT. These transit times are estimated using the OpenTripPlanner Analyst, provided by Conveyal ("OpenTripPlanner," 2014), which uses GTFS data to determine which route is the fastest option between two points at a certain departure time, and records the time it would take. For the collapsed time periods (9am to noon and noon to 5am) an average travel time is calculated. However, for the noon to 5am period, travel time at noon is used because of misleadingly long transit times measured during the early morning hours (when most transit systems are closed).

Job availability data during each time period is gathered from the Statistics Canada dataset discussed above (Statistics Canada, 2011b): the number of jobs available at each time period at a CT is the sum of all trips departing during that time period, ending at the CT in question. The gravity approach to accessibility discounts jobs based on how far they are from a trip origin. The underlying assumption is that jobs farther away are less attractive than those closer. We can calculate accessibility at each time period to all jobs, to low-wage jobs, and to higher-wage jobs. In the regression models, the accessibility measure included is the one pertinent to the job and time period under question. For instance, in the 6am model for low-wage jobs, the measure included is accessibility to low-wage jobs at 6am.

Note that raw accessibility scores are divided by 10,000 to increase their resolution. Also note that upon initial testing, we chose to exclude the models for the 5am time period, for two reasons: each model at this time period has an R^2 value less than 0.300. Also, these model's findings may be circumspect because of a high level of data suppression in the 2011 National Household Survey and misleading travel times generation, due to it being so early in the morning.

Findings

The data suggests that, as expected, transit mode share fluctuates over the day depending on which job category is under inspection (see Figure 2). This indicates that daily fluctuations of some set of factors are influencing transit ridership. Low-wage worker transit mode share has different peaks when compared to higher-wage workers (Figure 2). Figure 3 shows transit mode share fluctuations for these two groups spatially. Transit mode share for those working in low-wage jobs grows throughout the day, peaking between noon and 5am. In contrast, transit mode share for higher-wage workers peaks in the early morning (6am). Their share declines at 8am, only to rise again in the afternoon. It is surprising to find that transit mode share is highest outside of usual commuting to work peak hours (7am-9am) for the low-wage group. This may indicate that low-wage workers use transit service later than better-paid workers. It should also be noted that those working in low-wage jobs always have a lower transit mode share than higher-wage earners. This runs counter to findings that hold that those with lower incomes are more likely to use transit than others (Garrett & Taylor, 1999; Polzin et al., 2000). This lower transit ridership rate may indicate that commuting transit services are not adequately meeting low-wage worker needs.

The regression findings (Table 2) indicate that the relationship variables have with transit mode share fluctuates throughout the day, possibly explaining why fluctuations in transit mode share, seen in Figure 2, occur . The changing effect of these variables highlights where fluctuating levels of service and travel need impact transit ridership for our wage groups.

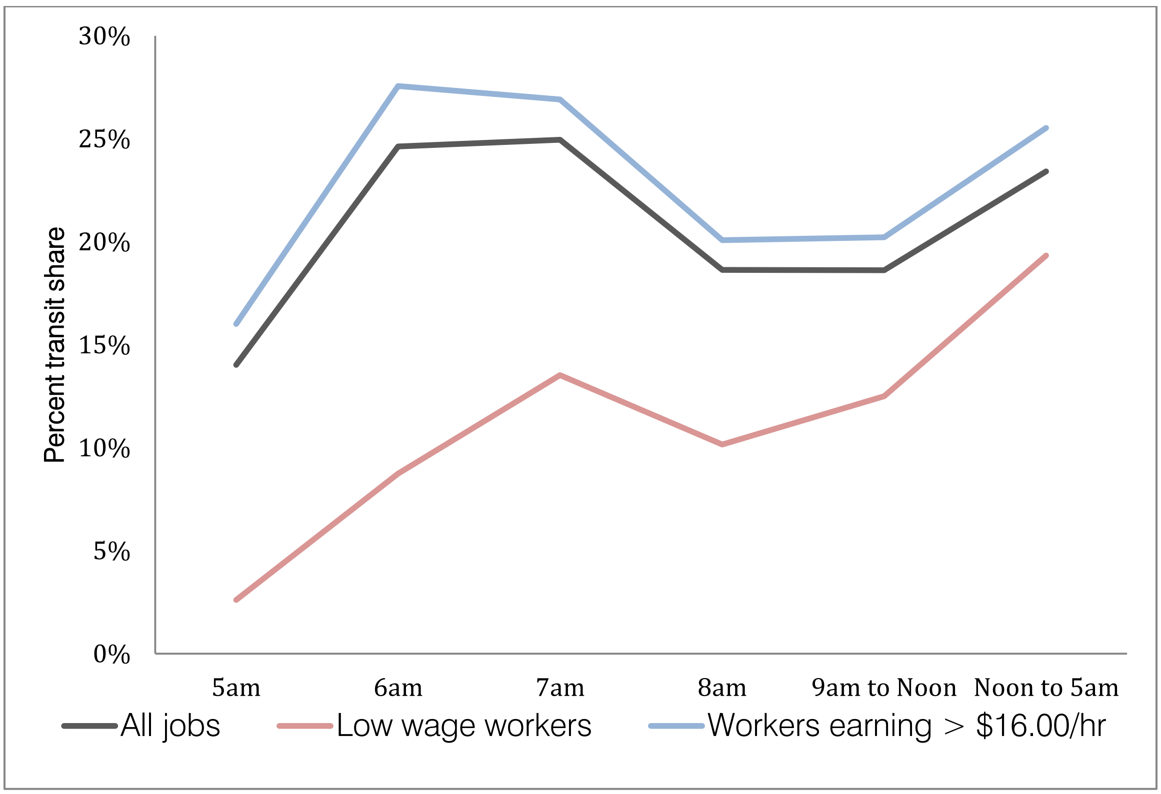

Figure 2: Transit mode share during the day

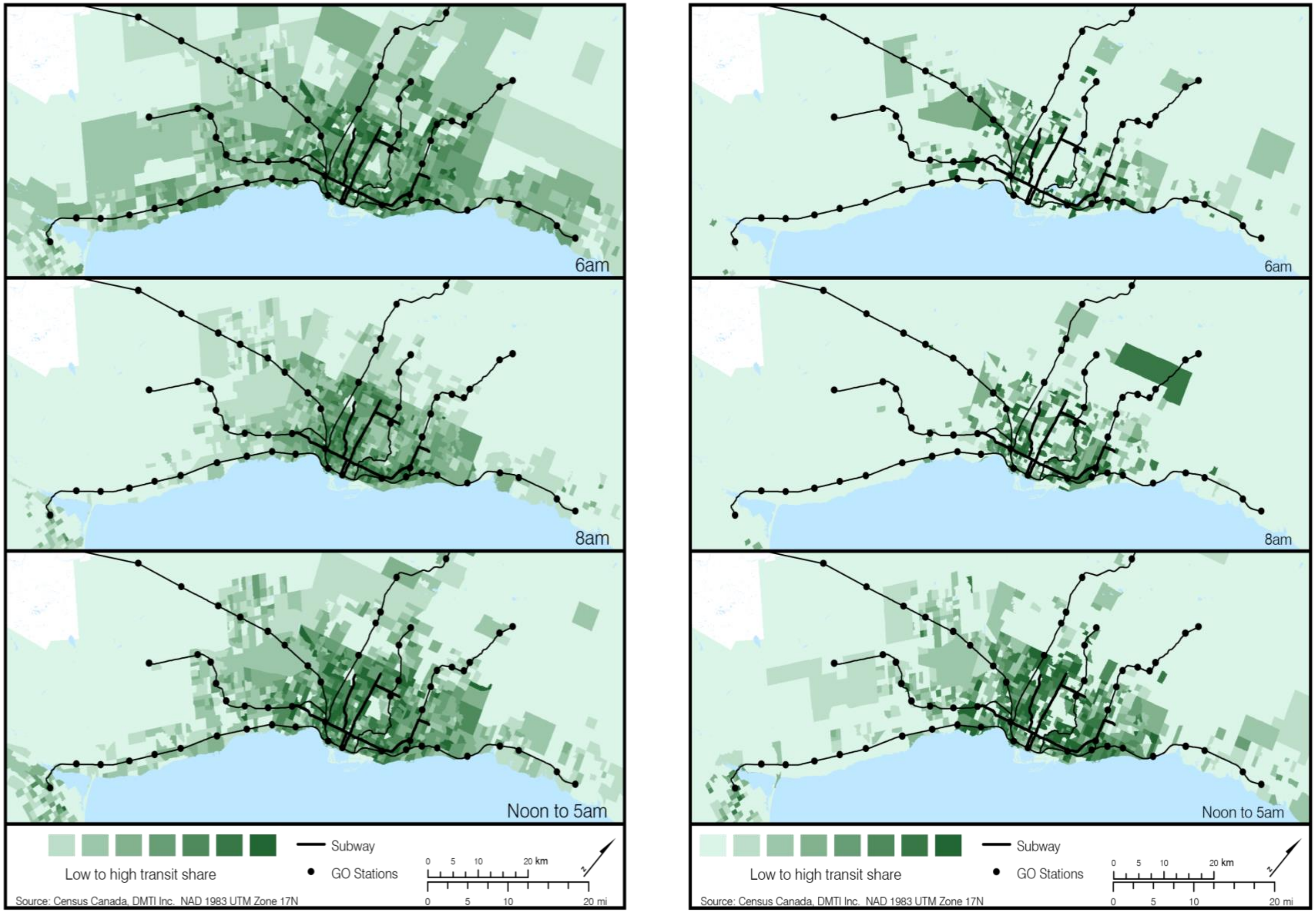

Figure 3: Transit mode share for higher-wage workers (left) and transit mode share for low-wage workers (right)

Table 2: Regression results: Variation in transit use for low-wage and higher-wage workers

	6am			7am			8am		
	Total jobs	Low-wage	Higher-wage	Total jobs	Low-wage	Higher-wage	Total jobs	Low-wage	Higher-wage
Transit frequency[b]	0.003	0.035*	-0.005	0.012	0.048**	0.006	0.017*	-0.021	0.023**
In urban core	0.171***	0.078***	0.167***	0.134***	0.175***	0.111***	0.200***	0.217***	0.190***
In inner suburbs	0.120***	0.140***	0.119***	0.123***	0.190***	0.117***	0.154***	0.164***	0.149***
1km to subway station	0.385**	0.25	0.089	0.254*	-0.002	0.218	0.633***	0.692**	0.498***
1km to GO station	-0.027	0.447	-0.193	-0.144	0.371	-0.226	-0.04	0.292	-0.054
Distance to highway on-ramp†	-0.022**	-0.005	-0.022**	-0.015**	-0.018	-0.013*	-0.003	-0.009	-0.003
Social indicator decile	0.008***	0.014***	0.010***	0.014***	0.010***	0.015***	0.011***	0.008***	0.013***
Mean distance†	0.069***	-0.017***	0.049***	0.068***	-0.023***	0.045***	0.020**	-0.007	0.019**
Accessibility to jobs by transit[a]	0.019***	-0.014	0.024***	0.013***	0.013	0.015***	0.011***	0.018	0.013***
Constant	-0.027	-0.019	0.017	-0.077***	-0.001	-0.028*	-0.071***	-0.03	-0.067***
R^2	0.529	0.234	0.463	0.731	0.338	0.674	0.78	0.319	0.753
AIC	-2008.354	-821.513	-1577.426	-2736.932	-696.775	-2379.064	-2771.349	-897.782	-2516.496

	9am to Noon			Noon to 5am		
	Total jobs	Low-wage	Higher-wage	Total jobs	Low-wage	Higher-wage
Transit frequency[b]	0.019	-0.007	0.029*	0.029**	0.018	0.041**
In urban core	0.198***	0.191***	0.179***	0.206***	0.273***	0.183***
In inner suburbs	0.165***	0.165***	0.156***	0.192***	0.243***	0.170***
1km to subway station	0.299*	0.035	0.181	-0.017	-0.603**	0.231
1km to GO station	0.11	-0.787*	0.387	0.185	0.196	0.235
Distance to highway on-ramp†	0.003	0.008	0.002	0.001	-0.005	-0.006
Social indicator decile	0.018***	0.019***	0.018***	0.014***	0.020***	0.013***
Mean distance†	0.011	-0.018***	0	0.008	-0.018***	0.018
Accessibility to jobs by transit[a]	0.011***	0.015	0.015***	0.017***	-0.002	0.033***
Constant	-0.053**	-0.046**	-0.028	-0.018	0.001	-0.008
R^2	0.639	0.304	0.556	0.684	0.457	0.57
AIC	-2037.444	-601.848	-1571.55	-2108.392	-865.694	-1489.261

* p<0.05
**p<0.01
***p<0.001
† Variable/10
[a]: Accessibility /10,000
[b]: Frequency/1,000

A comparison of Akaike's Information Criterion (AIC) for each model shows that modeling transit mode share by wage offers a better analysis than without such a division. A lower AIC indicates that the low-wage and high-wage models improve our understanding of transit mode share.

Three variables are significantly and positively related to transit mode share across all job categories and time periods. If a CT is located in either the urban core or inner suburbs, transit mode share increases compared to other parts of the region. Furthermore, having a higher social indicator decile (meaning a CT is more socially deprived) is linked to higher rates of transit ridership. This confirms previous findings linking social deprivation with transit ridership (Bento et al., 2005; Foth et al., 2014; Giuliano, 2005; Liu & Painter, 2011; Mercado et al., 2012; Moniruzzaman & Paez, 2004; Taylor et al., 2009). What follows is a discussion of each variable's relationship to transit mode share. Highway proximity is not discussed because of its inconclusive effect.

Transit frequency is statistically significant and has a positive relationship with transit mode share for low-wage workers in the early morning (6am and 7am). For higher-wage workers, transit frequency is statistically significant and positive from 8am onwards. This may indicate a number of things: low-wage workers who have an early morning departure time are influenced to take transit if transit service is frequent at this time, perhaps because those low-wage workers with early start-times work in areas served by transit. For higher-wage workers, departing early while using transit seems not to be a concern, thus transit frequency is only significant after 8am.

We see a similar change when considering transit proximity. Being close to a subway station is significant for total jobs up until noon. This confirms previous findings regarding rapid transit proximity (Crowley et al., 2009; Foth et al., 2014; Mercado et al., 2012). However, by wage category, subway influence is much more complicated. It is positively related to transit mode share for both low-wage workers and higher-wage workers at 8am. Yet, it is negatively related to transit mode share for low-wage workers between noon and 5am. In other words, at 8am, proximity to the subway is an important factor potentially influencing transit mode share. However, for low-wage workers with afternoon or evening jobs, other factors, such as little transit service to their destinations at these times or for their return journey (which is most likely in the early morning) may dissuade these workers from using transit, even if they live close to a subway.

Proximity to a Go-Train station has little demonstrated relation to transit mode share, and where it does, this relationship is negative (between 9am and noon for low-wage workers). This may indicate a mismatch between where Go-Trains serve and where low-wage workers need to travel to at this time. The majority of GO stations are located outside of the urban core of the City of Toronto. Also, this regional service is geared towards ferrying commuters between suburban locations and downtown Toronto. For low-wage workers, being close to a GO station at this time may simply indicate that they live outside of the urban core, and this type of residential location has a negative relationship with their transit use.

Furthermore, the effect of mean commuting distance switches with job category. Cervero and Kockleman found that mean distance between home and work locations has a negative effect on non-personal vehicle ridership, meaning it has a potential negative effect on transit mode share (Cervero & Kockelman, 1997). This finding is partially supported in our results. In our case, mean distance has a negative effect on transit ridership for low-wage workers at all time periods except at 8am. However, for higher-wage workers, an increase in mean distance is linked to greater transit ridership up until 8am. Afterwards this variable is insignificant. These findings further substantiate the claim that it may be difficult for low-wage workers to commute using transit at certain times. For low-wage workers, an increase in distance between their home and job may make a commuting trip by transit more inconvenient compared to other modes. For higher-wage workers, an increase in distance may make a commuting trip by transit more convenient in the morning compared to other modes, especially if it ends downtown.

The most unexpected finding from this study is that transit accessibility at any time period has no statistically significant relationship with ridership for low-wage workers, a finding which is somewhat contrary to common conceptions of the relationship between income, transit use, and accessibility (Blumenberg & Hess, 2003; Fan et al., 2012; Foth et al., 2013; Glaeser et al., 2008; Hess, 2005). Foth et al. (Foth et al., 2014) showed that accessibility has the smallest transit mode share effect for those working in manufacturing, construction, and transport. However, income variation in this NOC category is quite broad, which means conclusions made between income and accessibility are limited in their case (Statistics Canada, 2014). One possible explanation for our results is that low-wage workers are captive riders. They will take transit whether they have high accessibility or not. This possibility seems less likely considering that other factors (proximity and frequency of transit, mean distance travelled) have an influence on their transit mode share, indicating that they may have some choice when it comes to transit use.

In contrast, accessibility is positively associated with transit ridership for higher-wage workers at every time period. By looking at the change in influence over time we see a pattern emerge. An additional 10,000 jobs accessible at 6am increases their ridership by 2.4%. This influence then declines, reaching its nadir at 8am. Afterwards it starts to increase, reaching its peak between noon and 5am, where an additional 10,000 accessible jobs results in a 3.3% increase in transit mode share. This finding may be of particular interest to local transportation and planning agencies. Increasing accessibility in the afternoon and evening may have the most effect on increasing ridership for higher-wage workers.

Conclusion

This study investigates how variables have a fluctuating relationship with transit mode share during the day. Many transit mode share studies use data that represent one time period, usually the morning travel peak, combined with job data that represent the entire day. This study looks at transit mode share at six time periods to demonstrate that different departure times have different transit mode share rates, and that variables' relationship with transit mode share also vary according to time period and job category. Understanding these daily fluctuations in travel behavior will allow researchers and transit agencies to more adeptly predict demand and need in transit service. Two important findings from this study are (1), that low-wage workers always have a lower transit share than higher-wage workers, and (2), that accessibility has no effect on transit mode share for low-wage workers, at any time period.

The GTHA is a vast region, containing a large share of Canada's entire population. If transit mode share is to grow in this region then adequate transit availability during non-peak hours may be the key. It is also important to realize that low-wage workers may be having a difficult time using transit to reach their jobs at certain times. Noticing that low-wage workers demonstrate a number of key differences from their higher-wage counterparts substantiates this finding: In addition to accessibility's lack of effect, being close to a subway station has a negative effect during non-peak hours; potentially indicating that although transit service may be close to their homes, the destinations they can reach using transit at these times may not be satisfactory. Finally, low-wage workers are less likely to take transit because of lengthy distances between their home and work, indicating that as distance increases the ease of covering that distance using transit may decrease. In contrast, for higher-wage workers, an increase in distance is positively related to transit ridership in the morning (from 6am to 8am), demonstrating that an increase in distance may, in some instances, mean an increase in the ease of using transit for that trip. This may also indicate that higher-wage workers are much more likely to travel to the downtown area, which is easily accessible by transit, versus low-wage earners, whose employment locations are perhaps more evenly dispersed throughout the region. Future research into the spatial locations of different wage groups' homes and employment could help elucidate this point, the lack of which is a limitation of this study. Also, the division into two wage groups could be expanded to include other wage groups.

Metrolinx is tasked with coordinating and planning transportation investment and service in the GTHA. The agency's most recent transportation plan, the Big Move, predicts that transit ridership will double over the next two decades in this area. Understanding the non-peak travel needs of different working groups will be important to both local and regional transit service providers. Scheduling during non-peak hours and providing transit service to destinations not frequently served (e.g. outside the urban core) may have more or less of an influence on ridership depending on variables studied in this paper, a topic worthy of more investigation. The ability to provide convenient transport to a diverse set of areas at a variety of times will be the challenge faced by Metrolinx and its regional partners in the future. The Big Move recognizes this challenge, noting that transit trips crossing intra-regional boundaries are inconvenient, frustrating, and unattractive, not to mention costly (Metrolinx, 2008, p. 7). Research into the most cost effective and beneficial approach to this challenge is needed. The most important finding of this study, however, is that people's need to travel to work throughout the day, not just between 6am and 9am, is important. These needs also fluctuate depending on one's wage. These finding should be taken seriously when assessing which level of transit service is adequate, and to whom. By more accurately understanding daily transit needs, agencies can adequately and efficiently serve these needs

Chapter 2: Targeting equitable transit: Job location, sectorial concentration and low-wage transit use

Abstract

Low-wage workers have a pressing need for adequate and affordable transportation services for their commuting. However, the growing polycentricity of North American metropolises means transit providers face the difficult task of serving ever more dispersed employment centers. Deciding where limited project resources would provide the most benefit for vulnerable populations is a persistent concern for transit planners and elected officials. The purpose of this research is to determine where low-wage employment zones are, where different sectors of low-wage jobs concentrate, and determine if sectorial concentration and suburban location have an effect on transit ridership for this disadvantaged group. We use a previously proposed method to find low-wage employment zones in the Greater Toronto Hamilton Area, Canada and measure occupational sector concentration using a gravity approach. We then test to see if sector concentration relates to ridership, both in and outside of suburban employment zones, while controlling for other factors that influence mode share. Our results indicate significant differences in transit-use for different sectorial concentrations of low-wage employment. Employment zones that have very low transit mode share should be the focus of investment, and these investments can be tailored to the needs of the occupations in these zones. This project demonstrates that focusing study on transit use at the place of employment, characterized by its job makeup and relative location in an urban area, offers significant insight into travel use. By focusing on employment location, transportation planners can efficiently and equitably target resources and policies towards vulnerable sectors of low-wage workers.

Introduction

There is a recent and growing need to considering social equity when planning transportation infrastructure and policies (Manaugh, Badami, & El-Geneidy, 2015; Martens, Golub, & Robinson, 2012). Limited transportation resources should be fairly distributed, especially considering that almost all transportation infrastructure is paid for and managed by public agencies. Social equity concerns are particularly important for proponents of public transit. Arguments for continued or expanded investment into public transit often point out that those who cannot drive are reliant on transit for their daily needs. It would be unfair to limit the mobility of these individuals by cutting back transit services. In addition, a growing concern is that public transit agencies are directing new service and resources to choice commuters rather than to transit dependents, who are often poor and reside in areas of social exclusion (Garrett & Taylor, 1999). Even when equity is mentioned as a goal in transportation plans, clear objectives and benchmarks are often lacking in them, which results in plans that contain a veneer of fairness without the necessary bite to enforce it (Manaugh et al., 2015).

For this reason, many researchers have attempted to develop easily applicable methods to assess the equitable distribution of transportation services in a region (Currie, 2010; Delbosc & Currie, 2011; Hay, 1993; Ramjerdi, 2006). As a word of warning, however, some scholars have pointed out that equity goals are diverse. There is no clear consensus on what a fair or equitable distribution of transportation goods actually looks like, and equity may vary for different neighbourhoods, cities, or even countries (Martens et al., 2012). Nevertheless, recent work has used regional accessibility measures to compare transit provisions in areas of social disadvantage to advantaged areas (El-Geneidy et al., 2015; Foth et al., 2013; Grengs, 2010, 2015; Manaugh & El-Geneidy, 2012). The idea behind this approach is that areas of poverty should have equal or greater accessibility to employment opportunities when compared to the rest of the region. Somewhat surprisingly, these studies find that poorer areas, which are most often found in the centre of cities, often have above average access to employment and other opportunities. These findings confirm the arguments of Glaeser et al. (2008), who argued that the poor live in inner-city neighbourhoods precisely because transit access is high in those locations.

Although poor residents may have more transit accessibility to jobs, this benefit may not result in higher transit mode share among this population. Indeed, a possible disconnect between transit provisioning and transit use may exist for low-wage workers. A recent study has shown that low-wage workers in the Greater Toronto and Hamilton Area (GHTA) use transit less than their higher-wage counterparts during both the peak and off-peak travel periods (Legrain, El-Geneidy, & Buliung, 2015). This study also demonstrated that transit accessibility to employment is not related to increases in ridership for low-wage workers. These findings may indicate that transit, typically an affordable transportation mode, often does not work for low-wage workers even though they are struggling to afford many of their other daily needs. Simple equity assessments that compare accessibility between poor and other areas may suggest that transit is being provided equitably. Yet, at least in the GTHA, the fact that low-wage workers use transit less than higher-earners calls into question the relationship between transit service and transit usage among this population.

One possible explanation for low transit ridership among low-wage workers is the growth in suburban employment in North American cities, which has been well documented (Coffey & Shearmur, 2001; Giuliano & Small, 1991). Growing suburban employment coupled with the inability of transit agencies to both efficiently and effectively serve these suburban locations results in poorer residents being unable to reach suburban jobs using transit. In this research we argue that areas of significant low-wage employment that are experiencing the lowest levels of transit ridership should be the focus of transit investments. Focusing on low-wage job centres, whether they are in the suburbs or in the urban core, that have low levels of transit mode share would be an efficient way to target equitable transportation investments. The purpose of this study is to propose a novel method for discovering areas low-wage job centres that have low transit use, but would be good candidates for increased transit service or policies. Although somewhat obvious, most literature looking at the variables impacting mode share has focused on the home and factors surrounding that location. Instead, we focus on where the job is and the factors in the job's surrounding area, including the occupations concentrating there, to see what relates to transit mode share. By discovering how different low-wage occupations relate to transit use, policies targeted to these low ridership areas can be tailored to the occupations in them.

In what follows, we situate this paper in the literature by arguing that understanding mode choice through studying job location variables is necessary and important. We then briefly present the literature on the growing importance of suburban job locations and how this relates to spatial mismatch theory. From this, we demonstrate that modeling low-wage transit mode share that takes into account job location and occupational concentrations can lead to targeted and equitable transit planning. After the literature review we present the data and methodology used. We then present our findings and conclude with some future research directions.

Literature review

Most literature uses residential location as the starting point for an investigation into travel behavior, including investigations into commuting mode choice (Schwanen & Mokhtarian, 2005). Typically, studies on commuting habits focus on the individual's or household's socio-economic status and their surrounding built environment. In particular, lower income or higher social disadvantage has been linked to more transit use (Giuliano, 2005). Studies investigating built environment factors often approach the topic through the three 'Ds' of density, diversity and design, first proposed by Cervero and Kockelman (1997). To complicate matters further, the built-environment's role in travel behavior has been related back to socio-demographic factors and personal preferences. This relationship, understood as a result of residential self-selection, questions the view that environmental factors, independent of personal preferences and socio-demographic variables, have any effect on mode choice (Cao et al., 2009).

Studies focusing on transit mode share find that transit availability, reliability, or frequency are related to it (Ewing & Cervero, 2010; Foth et al., 2014; Mercado et al., 2012). Also, proximity to rapid transit stations has been linked to higher transit use (Crowley et al., 2009). In contrast, availability or proximity to other transportation infrastructure, such as controlled access highways, has been related to less transit use (Foth et al., 2014; Kawabata, 2009).

It should be remembered that the primary focus of most of these studies, whether they are on transit use or travel behavior in general, has been on factors surrounding home locations. Little work has been done on the factors at the other end of the commuting trip, at employment locations. This preponderant focus on the home may be partially explained by academic discipline. Shearmur, (2006) in a study on commuting distance, notes the lack of focus on employment type and location. Quoting Hanson and Pratt (1988), he argues that the focus on the home and socio-demographic variables, instead of a focus on job location and occupational sector, can be explained by a difference in academic focus, with human geographers, and in part urban planners, focusing on the home and the person, and economic geographers focusing on the workplace. Furthermore, Shearmur (2006) demonstrates that occupation sector and job location have an influence on commuting distance. This finding partially grounds this study's focus. Although residential variables have been shown to be important, employment location variables should also be of interest to transportation planners and scholars.

The growing dominance of polycentric urban form makes studying a job location's influence on commuting behavior an even more compelling research direction. Studies have shown that an employment center's location in a region (urban vs. suburban), the occupations in them (professional vs. blue collar), and the socio-demographic makeup of workers travelling to them all have an influence on commuting behavior. Sultana (2000), in a study on Atlanta's mean commuting distance, demonstrates that a more dispersed employment pattern (a polycentric metropolis) leads to shorter mean commute times. In addition, her study also found that employment centers with a high percentage of Black workers have, on average, longer mean commute times. Cervero and Wu (1997), looking at the San Francisco Bay area, demonstrate that employment centre location and job density have an effect on the mode used to reach them. Peripheral locations with low job density have significantly higher automobile use and a corresponding lack of transit use. A more recent study, focusing on three metropolitan areas in France, demonstrated that a growth in employment sub-centers leads to an increase in commuting distance (Aguilera, 2005). This growth, the author notes, is due to a growing division between employment location and residential location. In their study, suburban employment centers saw a growth in the number of jobs and a loss in residents from 1990 to 1999. This growing division between suburban workplaces and residential neighbourhoods implies a growing mismatch between job location and housing availability, forcing workers to go farther and farther afield to find homes.

The occupations at employment centers has also been linked to commuting distance and behavior. In a study on Montreal, areas with high-tech manufacturing, transport and warehousing, and higher order services often experienced the longest commute distances (Shearmur, 2006). One recent study in Toronto demonstrated that manufacturing, construction, and transport workers have lower transit use compared to other occupational categories (Foth et al., 2014). Shen (2007), when modeling commuting distance, found that executives and managers as well as workers providing household services travel longer than average commute times.

The suburbanization of employment and the rise of the polycentric city have also been linked to important equity concerns. Spatial mismatch theory contends that the increasing importance of suburban job centers causes disadvantaged residents, predominantly residing in the inner-city and heavily reliant on public transit, to be disconnected from job opportunities (Gobillon & Selod, 2014). Although racial prejudice is often the defining factor in spatial mismatch theory, recent studies have shown that spatial mismatch, independent of race or ethnicity, does occur (Houston, 2005). The primary problem here, Houston (2005) contends, is one of spatial, not racial, inequality. Those with little means to move to job rich areas suffer from a lack of job opportunities.

Furthermore, a reliance on public transit has led to a preponderance of poorer residents residing in inner-city areas, where public transit provisions are available (Glaeser et al., 2008). Indeed, one recent study found that most U.S. metropolitan regions experienced poverty growth in dense residential areas between 1990-2007 (Cooke & Denton, 2015). In the Toronto context, another study found that socially disadvantaged areas are heavily located in the urban core of the region (El-Geneidy et al., 2015). However, the concentration of poverty in the centre of cities may be changing. A study looking at Canada’s eight largest cities over a twenty year period demonstrated that poverty, although predominantly found adjacent to downtown cores, has increased in the suburbs (Ades, Apparicio, & Séguin, 2012). Even more worrisome is their finding that poverty has become more spatially concentrated, increasing the isolation experienced by residents of these areas.

Most worrisome is the effect that a growing concentration of poverty coupled with the growth of polycentric urban form can have on vulnerable populations. Although heavily reliant on public transportation, the urban poor may nevertheless need to use private automobiles to reach suburban jobs that are increasingly located in the suburbs, whether they live downtown or in suburban fringes. Indeed, Cervero and Wu (1997) find that the growth in suburban employment centres in San Francisco led to blue-collar and non-professional residential displacement: Lower-wage workers were pushed away from new employment centers in their search for housing. The authors further demonstrate that employment suburbanization was linked to a rise in automobile usage.

To put it succinctly, a combination of factors may be squeezing low-income residences away from transit services while at the same time a growing share of low-wage employment is found in suburban locations, where transit service is lacking. In particular, this process may be one where the ‘in-between’ city, locations between the downtown core and the outer suburbs, suffer from an almost complete lack of transportation investment (Young & Keil, 2010). Instead, transportation investment is focused on ferrying commuters back and forth from suburban locations to the downtown core at peak periods, and not focused on serving isolated and socially excluded areas (Garrett & Taylor, 1999).

Data and methodology

This study determines where low-wage employment zones are, determines where sectors of low-wage employment concentrate, and then models low-wage transit mode share using location and sectorial concentrations. Using this methodology will allow us to highlight areas where transit investment would benefit significant numbers of low-wage workers and where this investment would most likely succeed. Model findings can also help guide research into the way different occupations relate to transit use. Most of the methods used here have been developed in previous research, and can be easily applied in many jurisdictions. The innovative approach this paper offers is to combine various methods to test how suburban employment location and occupational sector influences transit use among low-wage workers, and then use differences in predicted and actual levels of ridership to discover areas in need of attention. This study is also a powerful argument for further study on employment sector’s and location’s relationship with travel behaviour.

Our area of study is the Greater Toronto and Hamilton Area (GTHA), Canada, excluding two western census subdivisions (see Figure 4). The GTHA has a total population of over 6 million people, and is comprised of Canada’s largest city (Toronto, population 2.6 million), significant peripheral cities (Mississauga and Hamilton, both with populations over 500,000), and a wide array of suburban communities and rural hinterland. In addition, previous research has shown that this region has important employment centers outside of its urban core, and that these suburban employment locations are growing both in number and size (Charney, 2005; Shearmur, Coffey, Dube, & Barbonne, 2007). Thus, the region is a suitable place to study the interaction between suburban employment location and low-wage worker travel behaviour.

Figure 4 Study Area

We use data from the 2011 National Household Survey, aggregated to the census tract level. The custom tabulations used include home and work locations, times of departure, and modes used for two-wage groups defined by us. For this study, we focus on the lower-wage group, defined as individuals working in one of 75 four-digit NOC sub-categories that have an average wage under $16.00 an hour in the region. Two related studies have used the same method to define low-wage workers (El-Geneidy et al., 2015; Legrain et al., 2015). Average wage data by NOC subcategory was gathered from Statistics Canada's wage report for the Toronto census metropolitan area (Statistics Canada, 2014). $16.00 an hour is used as a cut-off because it has been cited as the living-wage for the region (Mackenzie & Stanford, 2008). Those earning less than $16.00 an hour are more likely to be struggling to pay for basic necessities, including transportation. It should be noted that the use of this data has its caveats: It does not contain actual money earned, which can fluctuate based on hours worked and the individual job. Also, it is certainly possible that some higher-earning individuals are included, since individuals working in these low-wage subcategories may be earning more than the subcategory's average. For those interested, the full list of low-wage sub-categories is available upon request.

Table 3: Low-wage occupational sectors

NOC	Short Name	Description	Total	In Urban Core	Outside Urban Core
0	Management	Management Occupations	7,695	2,880	4,815
			1.26%	37.43%	62.57%
1	Administration	Business, Finance, and Admin.	145,440	31,105	114,335
			23.84%	21.39%	78.61%
5	Cultural Prod.	Occupations in Art, Culture, Rec. and Sport	8,950	2,900	6,050
			1.47%	32.40%	67.60%
6	Sales & Service	Sales and Service	332,785	71,360	261,425
			54.55%	21.44%	78.56%
7	Trades & Trans.	Trades, Transport, and Equipment Operations	8,090	100	7,990
			1.33%	1.24%	98.76%
8	Primary	Agriculture, Landscaping, Natural Resources	7,100	130	6,970
			1.16%	1.83%	98.17%
3	Health	Health Occupations	1,425	355	1,070
			0.23%	24.91%	75.09%
4	Edu.& Gov't	Occupations in Education and Gov't Services	12,830	3,325	9,505
			2.10%	25.92%	74.08%
9	Mfg.	Manufacturing and Utilities	85,710	2,195	83,515
			14.05%	2.56%	97.44%
		Total Low-Wage Jobs	**610,025**	**114,350**	**495,675**
			100%	19%	81%

Our final dataset contains home and work locations (at the CT level), modes used, and time of departure for low-wage workers aggregated into nine (out of a possible ten) NOC major categories (see Table 3). The missing category (NOC 2, natural and applied sciences and related occupations) has no subcategories earning, on average, below $16.00 an hour in the GTHA.

Table 3 shows that these nine categories demonstrate key differences in how they locate in the region. To demonstrate these differences, we define the "urban core" of the region as the City of Toronto before it was amalgamated with surrounding municipalities in 1993 (see Figure

4). Trades and transport, primary, and manufacturing jobs are all overwhelmingly located outside of the urban core, whereas management occupations tend to be in the urban core (with 37% in that area). It is also interesting to note that sales and service jobs make up over 54% of all low-wage jobs in the region, whereas health occupations make-up less than one percent. In order to understand how suburban employment patterns affect ridership for each of these sectors we determine where, irrespective of sector, low-wage employment zones are, and second, use a gravity approach to determine where each of these sectors is concentrating.

Our methodology is as follows: First, we determine where low-wage employment zones are in the region using a method proposed in previous research. Second, we measure occupational sector concentration for all nine NOC categories. Third, we use OLS regression techniques to model transit mode share at the CT level and incorporate our employment zones and sector concentrations in addition to typical variables associated with transit use. Fourth, and finally, we discover employment zones that have high predicted ridership rates but low actual ridership rates. We argue that these areas have all the right ingredients for high transit mode share, but low-wage workers are not actually using transit to get to them. Transit policies and investment to these areas have a greater likelihood of success in increasing ridership and would further the equitable distribution of transportation resources in the region.

Low-wage employment zones

Debate around how to locate and define employment zones has generated a substantial literature. Typical methods involve classifying geographic areas based on employment density (Gardner & Marlay, 2013; Giuliano & Small, 1991; McDonald, 1987). However, the use of employment density when using CTs, where boundaries are designed to keep population levels, not employment levels, consistent, would be potentially misleading (Coffey & Shearmur, 2001). This is especially the case for suburban areas, where residential density is often low and, correspondingly, CTs can be quite large in area. Instead, we first calculate a ratio of low-wage employment to low-wage employed residents (E/R). An E/R > 1 indicates an area that has more low-wage jobs than low-wage workers. It follows that these areas are a commuting destination for low-wage workers in the region (Forstall & Greene, 1997; Shearmur & Coffey, 2002b). We then determine a threshold that keeps the majority of low-wage jobs in employment zones while holding the number of employment zones to a minimum. This threshold was determined by first cumulatively plotting the distribution of low-wage jobs in the region. An inspection of this plot made apparent that a significant break occurs in the distribution of jobs per CT at 1,000. A similar method is commonly used in traffic flow analysis to identify bottlenecks and the time when they occur (Bertini & Leal, 2005). Using threshold of 1,000 jobs per CT combined with a restriction to CTs with an E/R > 1 results in 131 CTs (out of 1328 CTs in the region) being defined as low-wage employment zones. These employment zones contain 59% of low-wage jobs in the region while only representing ten percent of all CTs. We validated our results by comparing our findings to those of Shearmur and Coffey (2002a), who defined employment zones for the Toronto CMA using a similar method. Their categorization resulted in comparable findings to ours, with their employment zones containing 53% of employment in the area, while representing twelve percent of all CTs.

Figure 5 shows our low-wage employment zones. It should come as no surprise that a concentration of employment zones occurs in the urban core of the region. These areas represent 17% (25 out of 145 CTs) of the urban core. Outside of the urban core, low-wage employment zones represent 8%. In our models, we separate employment zones outside of the urban core from those within, using those outside as our suburban employment zones (106 in total). In the final step of our analysis, we use all employment zones (irrespective of suburban/urban location) to pinpoint areas of significant low-wage employment with low levels of transit mode share.

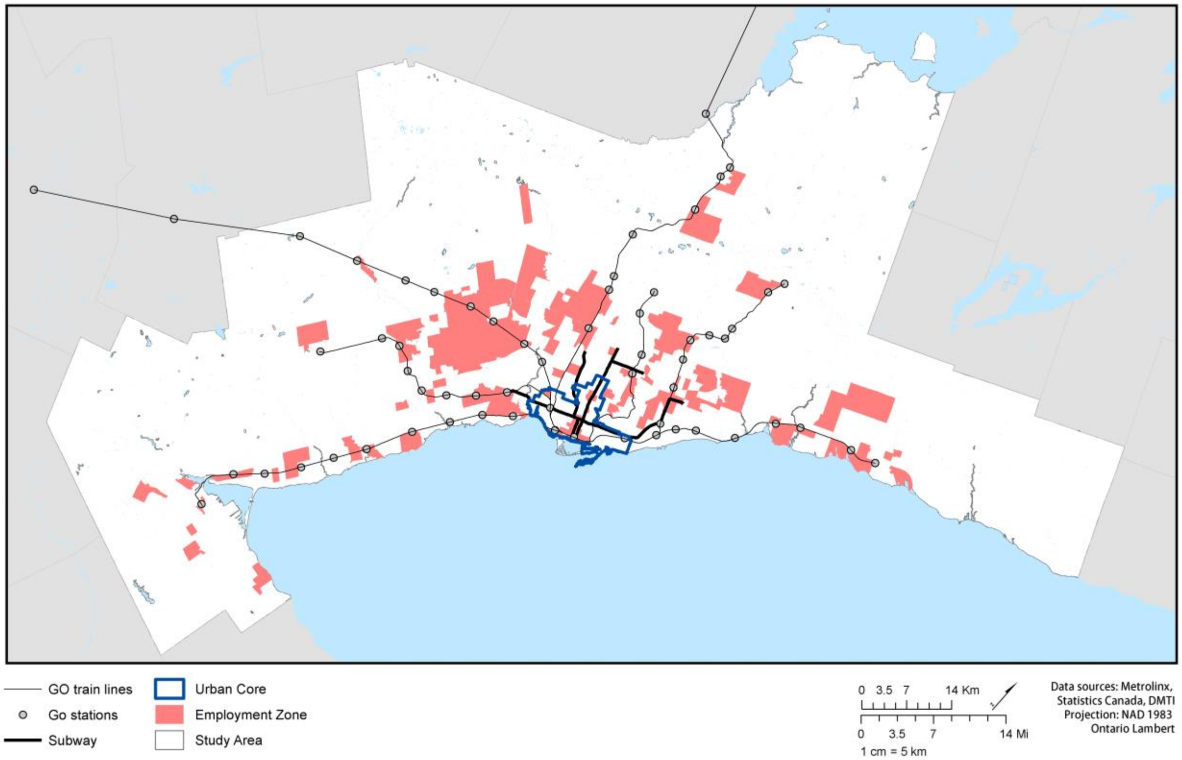

Figure 5: Low-wage employment zones

Low-wage occupational sectors and their concentration

Our next step is to determine where low-wage sectors are concentrating and determine if any of these concentrations tend to collocate. Inspired by Shearmur and Coffey (2002b), we use a gravity approach to measure the potential of each sector present at each CT. This potential is measured using the following formula:

$$P_{ix} = \sum_{j=1ton} \left(\frac{E_{ij}}{D_{jx}^2}\right)$$

Where P_{ix} = potential of sector i in tract x; E_{ij} = employment in sector i in tract j; D_{jx} = Euclidian distance between tract j and x, if j = x, $D_{xx} = 1/2\sqrt{(a_x/\pi)}$; a_x = area of tract x; n = number of census tracts.

This equation allows for the number of jobs in a certain sector at a census tract to be taken into account while factoring in the number of jobs in the same sector in the surrounding area. For example, a CT with a high number of health-related jobs surrounded by CTs with health-related jobs themselves will have a high health-sector potential. Although a nearest neighbour analysis could result in similar findings, the use of a potential gravity model is beneficial for a number of reasons. First, the measure blurs CT boundaries. This fuzziness is beneficial for a study focused on employment sectors that uses CTs boundaries, since these boundaries are based primarily on population and socio-demographic rules and pay little attention to economic activity. Second, this measure highlights areas of sectorial concentration by allowing CTs with similar sector make-up to influence one another, even if they are not strictly neighbours. In addition, the formula gives all CTs a share of what surrounds them, meaning areas with little employment are partly defined by their surrounding sectorial milieu. Concentrations of each sector are defined as areas with a high potential score in that sector.

Potential scores for each occupational sector were calculated for every CT in the area. To simplify the data we use a principal component analysis (PCA) to determine if any sectorial potentials tend to co-locate. Determining sector co-location will simplify our understanding of the relationship between sectorial concentration and mode use. The assumption we make is that sectors that have co-locating concentrations will have a similar relationship to transit use because spatial, environmental, and social factors are similar. PCA allows the researcher to reduce a set of variables (in this case our potential scores) to a smaller set, all the while maintaining the variability present in the original data.

As a first step, a pairwise correlation matrix was generated between all nine potential scores. This matrix showed that significant and influential correlations were present (nine correlations where $r>0.5$, $p<0.05$), which indicates that a PCA is appropriate. Initially, all nine potential scores were included in the PCA. This first round indicated that two components, both with eigenvalues greater than one, accounted for 66% of the variation in the data. However, an inspection of the rotated component loadings (Varimax rotation with Kaiser normalization) indicated that three sector potential scores (the health, education and government, and primary categories) had communalities below 0.5. Such low communalities imply that these variables have a great amount of uniqueness and are not being sufficiently captured by the suggested components. We then reran a series of PCAs, each time eliminating the potential score with the lowest communality, before arriving at a PCA with every communality greater than 0.5. Table 4 shows component loadings and communalities for the final PCA, which, as expected, does not include the health, education and government, and primary sectors. This final solution has two components, both with eigenvalues greater than one. Together, these components account for

87% of the included potentials' variation. It should be noted that an addition of a third component (with an eigenvalue of 0.3) would only increase variation accounted for by 5.7%.

Table 4: Sector colocation: Component loadings & communalities

		Component Loadings		
NOC	**Category**	**Higher-Order Services**	**Trades, Trans. & Mfg.**	**Communalities**
0	Management	**.950**	.117	.917
1	Administration	**.955**	.094	.920
5	Cultural Prod.	**.895**	.119	.815
6	Sales & Service	**.963**	.079	.934
7	Trades & Trans.	.062	**.912**	.835
9	Mfg.	.136	**.899**	.826
3	Health	Excluded		
4	Edu.& Gov't	Excluded		
8	Primary	Excluded		
	Eigenvalue	3.72	1.53	
	Cum. % of Variance			87%

As can be seen in Table 4, component loadings are all greater than 0.89, and communalities are all greater than 0.80, which indicates that at least 80% of the variation of each score is accounted for by these two components. In addition, our findings are corroborated by previous studies on sectorial co-location in Canadian cities that do not take into account wage. These studies found that trades, manufacturing, and warehousing jobs often co-locate, similar to our "trades, transport, and manufacturing" component, and find that higher order services and sales tend to co-locate, similar to our "higher-order services" component (Shearmur, 2007; Shearmur & Coffey, 2002b). Intuitively, it is not surprising that low-wage sectorial co-location would be similar to co-locations that do not take into account wage since businesses tend to pay a wide range of wages and rarely spatially segregate their locations by wage, although further research could substantiate this claim. Since the variation, loadings, and components are so high component scores were calculated by summing, for each component, the sector potential scores that are part of it. In Figure 6 we map our two components and our three remaining sectors to show how each category spatially concentrates in the region.

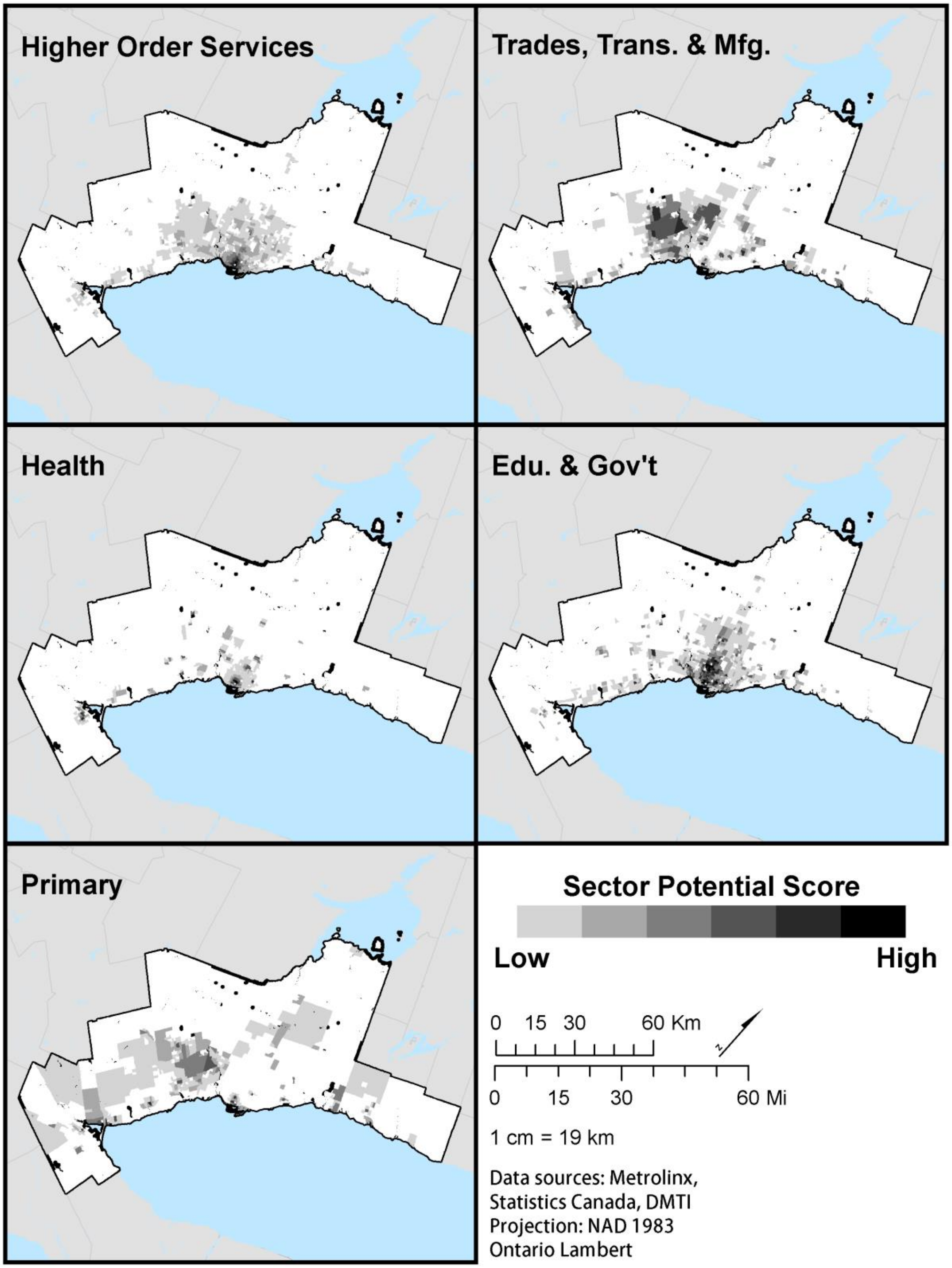

Figure 6: Sector potential concentrations

These maps (Figure 6) demonstrate that sectors show differences in how they concentrate in the GTHA. Higher order services, health occupations, and education and government services are, for the most part, centrally located. The health sector also shows clear concentrations outside of the urban core, especially in Hamilton (south-west of the center of the region). Also unique for the health sector is how ‘spotty’ its concentrations are compared to other sectors. In contrast, the trades, transport, and manufacturing sectors are clearly concentrated to the west of the urban core. Finally, primary occupations (extraction and horticulture) are more diffuse throughout the area, but are more generally found in the west of the region, with some notable activity to the east as well.

The findings from Figure 6 are substantiated in Table 5, which shows summary statistics for each sector potential in the entire region, in suburban employment zones, and in the urban core. An inspection of each potential’s mean depending on location shows clear divisions in where sectors locate. Trades, transport, and manufacturing occupations are more heavily located in suburban employment zones than elsewhere in the region. Corroborating what is shown in Figure 6, higher order services, health occupations, and education and government services all have higher means in the urban core, indicating a tendency for these sectors to centrally concentrate.

Table 5: Sector potentials: summary statistics

		Higher-Order Services	Trades, Trans. & Mfg.	Health	Edu. & Gov't	Primary
Entire Study Area (N=1067)						
	Mean	10,343.05	94.98	36.56	281.80	33.05
	SD	21,530.02	127.35	200.03	456.91	72.01
	Min	119.97	4.50	0.23	2.67	2.72
	Max	274,337.59	1,975.50	4,064.78	3,307.35	1,407.34
Inside Suburban Employment Zone (n=106)						
	Mean	10,476.39	**218.02**	37.31	160.38	**49.62**
	SD	13,307.14	209.55	138.51	170.97	67.47
	Min	1,380.57	21.81	0.93	7.62	7.98
	Max	120,717.46	1,019.78	1,279.71	1,254.09	418.99
Inside Urban Core (n=145)						
	Mean	**38,126.54**	91.20	**147.69**	**979.17**	38.49
	SD	47,259.29	171.59	502.06	733.03	87.49
	Min	5,811.71	28.88	11.08	153.94	7.86
	Max	274,337.59	1,975.50	4,064.78	3,307.35	860.79

Relating sectorial concentration to transit mode share

We use OLS regressions to determine how each low-wage sector relates to transit mode share for commuters arriving at each CT. The inclusion of sector potential scores, which measure the level of concentration of each low-wage sector at every CT, demonstrates if a change in a sector's concentration relates to transit use. Through these models we can see how different sectors, while controlling for other variables, relate to transit use, and discover if this relationship changes depending on a CT's location. As noted in the literature review, most studies on commuting behaviour focus their analysis on the origin of the trip, a commuter's home. In contrast, this study is focuses on the destination of commuting, a commuter's job location. In this way the coefficients in the models are indicating how variables relate to the transit mode share of low-wage workers *coming to* the CT.

Socio-demographic variables, also noted in the literature review, are often seen as important factors relating to mode-choice. Our models do not explicitly account for variation in these variables for two reasons: First, our sample is already restricted to a specific socio-demographic group. We are looking at mode used for those working in a job that, on average, earns less than the living wage in the region, or 'low-wage workers'. Findings related to variations in income within this group would be difficult to interpret, and would have little basis, to our knowledge, in the literature. Second, since the focus of our study is place of employment, the surrounding residential social milieu should not have an effect on the mode chosen to reach this area. Instead, what we are proposing is that occupational sector make-up at an employment location relates to the mode choice made for the trip to that location. It is also important to remember that this study is focused on the journey to work, not the return journey from the place of employment.

We generate two models to account for possible differences between peak travel (6am – 9am) and off-peak travel (9am – 5am) for the journey to work. The dependent variable in each model is the number of commuters arriving at a CT who use transit compared to the total number of commuters arriving at that CT: i.e., we measure transit share during the morning peak and outside of peak hours. Modeling for peak and off-peak travel periods will allow for efficiently targeted planning and policies that takes the time of travel into consideration.

It should be noted that the models' dataset is restricted to those CTs where low-wage employment is greater than zero (1,069 out of a possible 1,328 in the area). This restriction insures that transit share numbers are meaningful. Furthermore, areas with a transit mode share greater than 70% are excluded from each model. Their exclusion is warranted because of their small number (four cases in the peak model, nine cases in the off-peak model), and extremely high residuals. It is assumed that these areas either represent errors in measurement or a unique subset of the region.

Built environment

Built environment variables must be accounted for so that occupation sectorial influence on transit mode share is understood over and above differences in built environment. A dummy variable is included to indicate if a CT is within the urban core of the region (the City of Toronto before it was amalgamated with surrounding municipalities in 1993). This area is densely inhabited with a typical urban built environment, and it has been lauded as a good example of public transit planning (Keil, 2000). Furthermore, we include a dummy variable indicating if a CT is part of the City of Toronto's inner suburbs, those areas that were amalgamated with the City in 1993. Although less dense than the City of Toronto, these areas were also praised for their transportation planning before amalgamation (Keil, 2000). In addition, distance from each CT's centroid to the nearest controlled access highway on-ramp is included to account for the adverse influence this variable can have on transit mode share (Foth et al., 2014; Kawabata, 2009).

Transit service

In addition to built-environment variables, variables accounting for proximity of transit and accessibility using transit have been linked to transit mode share, and are controlled for in our two models (Ewing & Cervero, 2010; Foth et al., 2014; Mercado et al., 2012). Distances from a CT's centroid to the closest subway station and closet GO station (commuter rail) are included. Also, measures of accessibility to workers from each CT, one for the peak model and another for the off-peak model, are included. Using a gravity-based approach (Hansen, 1959), this measure discounts the number of low-wage workers accessible to each CT by the travel time between them, using the following formula:

$$A_i^{\text{pub}} = \sum_{j=1}^{n} D_{e^{-\beta cij}}$$

Where A_i^{pub} is the accessibility at CT *i* to all workers (at the time period in question) using public transit; D is the number of workers residing at CT *j*; C_{ij} is the travel cost (measured in time) between CT *i* and CT *j*, and β is a negative exponential cost function. This cost function is derived from reported work trips in the 2011 National Household Survey linked to a transit travel time matrix: Travel times from each CT centroid to every other CT centroid are calculated using current GTFS (Google transit feed specification) data for eight public transit agencies serving the GTHA. These calculations provide a travel time matrix for every hour of the day and were estimated using OpenTripPlanner Analyst, provided by Conveyal ("OpenTripPlanner," 2014), For C_{ij}, average travel times for the period in question (peak or off-peak) were used. Using multiple accessibility measures to capture variation in accessibility instead of a static measure to represent accessibility throughout the day has been shown to improve understanding of mode-choice behaviour (Owen & Levinson, 2015). It is also intuitive: transit service and the number of workers available fluctuate throughout the day. It follows that transit accessibility does as well.

Mean distance travelled

In Legrain et al., (2015), mean distance travelled to work was shown to have a negative influence on ridership for low-wage workers. We include mean Euclidian distance travelled to each CT to control for this effect. Previous research has shown that the ratio between network distance and Euclidian distance stays fairly constant in a metropolitan region. Thus, it is generally acceptable to use Euclidian distance in lieu of network distance (Apparicio, Shearmur, Brochu, & Dussault, 2003; Levinson & El-Geneidy, 2009).

Sector potentials & interactions

Our five sector potential scores (the two component scores created from our PCA plus the three remaining potentials) are included to determine the relationship that sectorial concentration has with transit use. Also included is a dummy variable indicating if a CT is in a suburban employment zone (an employment zone, determined above, that is outside the urban core). This allows us to test for the influence suburban employment zone has on transit use. In addition, we include two sets of interaction terms to test whether or not sectorial concentration has a different relationship to transit use depending on its location. Our first set of interaction terms occurs between each potential score and the dummy for suburban employment zone. This determines if being in a suburban employment zone changes the sector's relationship with transit mode use. Our second set of interaction terms occurs between each potential score and the dummy for being located in the urban core. This set determines if being in the urban core of the region changes a sector's relationship to transit mode use.

Regression modeling

Table 6 shows variable summary statistics and any transformations used (note that summary statistics for the sectorial potential scores can be found in Table 5). To minimize multicollinear relationships between sector potentials and interaction terms, potential sector scores were mean-centered (the mean was subtracted from each case's score) before interaction terms were calculated. This standardization method allows for score coefficients to be in the same scale as the original sector potential scores, easing coefficient interpretation. Models were initially run with all variables and interaction terms present. However, interaction terms that were not significant were removed from the final models. Although many variables show potentially non-normal distributions (means, in many cases, are less than standard deviations), linearity was inspected via augmented partial residual plots, which confirm that relationships are linear. Also, variance inflation factors for all included variables in both models are below ten, indicating that multicollinearity is not an issue.

Table 6: Summary statistics: transit use and sector concentration

(N=1067)	Transformations	Mean	SD	Min	Max
Same across models					
Sectorial Potential Scores	x /1000, mean-center		(See Table 3 Above)		
Suburban Employment Zone		0.10	0.30	0.00	1.00
Urban Core		0.14	0.34	0.00	1.00
Inner Suburbs		0.29	0.45	0.00	1.00
Distance to Highway (km)		3.98	4.26	0.02	52.69
Distance to GO (km)		5.28	4.93	0.36	41.83
Avg Distance Travelled (km)		17.64	13.06	0.36	30.00
Model specific variables					
Peak Transit Share*	x / 100	0.07	0.15	0.00	1.00
Off-Peak Transit Share*	x / 100	0.11	0.18	0.00	1.00
Peak Accessibility	x / 1000	33,086.63	15,359.40	234.26	61,821.60
Off-Peak Accessibility	x / 1000	19,416.31	12,093.05	111.31	45,293.84

* Max in model = 0.69, 4 cases excluded from Peak Model, 9 from Off-Peak Model

A major issue with datasets of this size is a persistent heteroscedasticity of residuals. Indeed, both models demonstrate heteroscedastic residual distribution. To overcome this issue we use the Huber-White sandwich estimator of standard errors, which has been shown to improve standard error estimation in the presence of heterogeneous variance (Huber, 1967; Maas

& Hox, 2004; White, 1982). While leaving coefficient estimates the same, the Huber-White estimator makes standard errors (and thus significance) more robust.

Model findings

Table 7 shows regression results for our two models. We include raw coefficients (b) to indicate what influence each variable has on transit mode share, and standardized coefficients (β) to note the strength of the variable's influence.

Table 7: Regression results: transit use and sector concentration

Transit Share of Commuting Trips To Work, Morning Peak					
	b	β	*t-stat*	95% Conf. Interval	
Sector Potentials & Interactions					
Higher-Order Services	0.31***	0.48	7.93	0.24	0.39
Trades, Trans. & Mfg.	-11.06*	-0.10	-2.22	-20.81	-1.30
Trades, Trans. & Mfg. x Suburban Emp. Zone	20.98***	0.11	3.45	9.05	32.92
Health	-6.59***	-0.09	-2.95	-10.98	-2.20
Edu. & Gov't	2.22	0.07	1.38	-0.94	5.38
Edu. & Gov't x Urban Core	7.51***	0.19	2.83	2.31	12.72
Primary	6.61	0.03	1.12	-4.94	18.17
Primary x Suburban Emp. Zone	-37.18*	-0.06	-2.43	-67.23	-7.13
Suburban Emp. Zone	7.05***	0.15	6.75	5.00	9.09
Control Variables					
Urban Core	3.80	0.09	1.77	-0.41	8.01
Inner Suburbs	4.62***	0.15	5.28	2.90	6.34
Proximity to Highway (km)	-0.04	-0.01	-0.92	-0.13	0.05
Proximity to GO (km)	0.19***	0.07	4.15	0.10	0.28
Avg Distance Travelled	-0.12***	-0.11	-4.75	-0.17	-0.07
Peak Accessibility	0.11***	0.12	3.42	0.05	0.17
Constant	1.27		1.09	-1.01	3.55
				r^2	0.55
* = *p*<0.05, ** = *p*<0.01, *** = *p*<0.001				N	1063

Transit Share of Commuting Trips to Work, Off-Peak					
	b	β	*t*-stat	95% Conf. Interval	
Sector Potentials & Interactions					
Higher-Order Services	0.27***	0.35	5.94	0.18	0.35
Trades, Trans. & Mfg.	-9.23	-0.07	-1.81	-19.25	0.79
Trades, Trans. & Mfg. x Suburban Emp. Zone	13.94*	0.06	2.54	3.16	24.72
Health	-7.20***	-0.09	-3.22	-11.58	-2.82
Health x Suburban Emp. Zone	16.40*	0.04	2.31	2.48	30.32
Edu. & Gov't	1.15	0.03	0.69	-2.11	4.41
Primary	-1.09	0.00	-0.18	-13.15	10.96
Suburban Emp. Zone	5.64***	0.10	4.99	3.42	7.86
Control Variables					
Urban Core	8.06***	0.17	2.92	2.64	13.48
Inner Suburbs	5.59***	0.15	3.42	2.39	8.80
Proximity to Highway (km)	-0.13*	-0.03	-2.18	-0.25	-0.01
Proximity to GO (km)	0.10	0.03	1.76	-0.01	0.22
Avg Distance Travelled	-0.27***	-0.22	-8.46	-0.34	-0.21
Off-Peak Accessibility	0.32***	0.23	4.00	0.16	0.47
Constant	6.04***		4.55	3.44	8.65
			r^2		0.44
* = *p*<0.05, ** = *p*<0.01, *** = *p*<0.001			N		1058

Sector potentials & interactions

Our models confirm that occupational sectors have statistically significant influences on transit mode share when interactions between sector and location (being in a suburban employment zone or in the urban core) are accounted for. It should be remembered that all possible interactions were tested, but only those significant are included in our final models. Of more interest is the direction and strength of the relationship between each sector and transit mode share, which will allow researchers and practitioners to target research and investment (respectively) to areas based on sectorial make-up.

We find that being in a suburban employment zone is positively related to transit mode share during both peak and off-peak hours. Suburban employment zones increase mode share by 7% and 5% during the peak and off-peak periods respectively, while keeping all other variables at their mean values. This indicates that suburban areas of significant low-wage employment (regardless of sector) experience high transit use throughout the day. Also, being in the urban core has a positive impact on transit mode use, but this is only significant during off-peak hours. Being in the urban core increases the mode share by 8% during the off—peak period.

First, it should be noted that higher-order services did not demonstrate any significant location interactions, either within suburban employment zones or the urban core. Thus, the relationship between this sector's concentration and transit mode share is not location specific: A 1,000 unit increase in higher-order service potential leads to a 0.31% increase in transit mode share during the peak and a 0.27% increase during off-peak periods. It also has the highest beta coefficient ($\beta = 0.48$) in both models, indicating that it has the most strength among the variables included. Education and government services also have a positive relationship with transit mode share, but only when located in the urban core of the region during peak travel periods. An increase of 1,000 in education and government services' potential leads to a 7.5% increase in transit mode share in the urban core.

Turning to those sectors with a negative relationship, it is immediately apparent that health sector concentrations, at both peak and off-peak periods, have a negative impact on transit mode share. More worrisome is the absence of significant interaction terms for this variable, indicating that this negative pull is significant for the entire study area. An increase of 1,000 in this sector's potential leads to a 6.6%-7.2% decrease in transit mode share throughout the day.

Trades, transport, and manufacturing concentrations have a negative pull on ridership outside of suburban employment zones during the morning peak. An increase of 1,000 in this sector's potential leads to an 11% decrease in transit mode share outside of suburban employment zones when all other variables are kept at their mean. However, this sector has a strong positive pull on ridership when located in suburban employment zones during both peak and off-peak periods. An increase of 1,000 in this sector's potential in a suburban employment zone during the peak leads to a 21% increase in transit mode share, and during the off-peak a 14% increase. This finding is heartening for transit providers in the region. Low-wage employees in trades, transport, and manufacturing, whether they are working during peak or off-peak periods, seem to find transit service efficient enough to reach suburban employment zones. This is made more reassuring by remembering that this sector tends to concentrate in suburban employment zones (see Table 5 and Figure 6).

Primary occupations have no significant positive or negative pull on transit mode during off-peak periods. One would think that this sector, which is more diffuse throughout the area and has many high concentrations found outside of suburban employment zones (see Table 5 and Figure 6), would be impervious to location interaction effects. However, primary sector concentrations have a very large negative relationship with transit ridership when located in suburban employment zones during the morning peak travel period. An area is predicted to experience around a 30% decrease in transit use for a 1,000 increase in this sector's potential. It should be noted however, that mean primary potential is around 50 in suburban employment zones for this sector (Table 5), and its confidence interval indicates a wide range of interpretation for this relationship (Table 7). Nevertheless, an increase of just 50 in this sector's potential is related to a 2% decrease in transit share. In light of this finding, transit planners could focus investment (not just infrastructure, but marketing) at suburban employment zones with high levels of primary employment. By doing so, areas of generally significant low-wage employment that have concentrations of low-wage workers that are finding transit difficult to use (primary sector workers) could be focused on. This would allow for low-wage workers' needs to be addressed in a more efficient and equitable fashion.

Control variables

Although not the focus of this study, directions and significance of control variables confirm that our models have similar findings to a related study (Legrain et al., 2015), and offer interesting insights into low-wage worker travel behaviour. Most interesting is when a variable is significant in only one of our two models, indicating a change in influence between peak and off-peak travel. For instance, proximity to the closest highway on-ramp has a negative relationship during off-peak hours (a one kilometre decrease in distance is related to a 0.13 % decrease in transit mode share), and, conversely, proximity to a GO (commuter rail) station has a positive effect during peak hours (a one kilometre decrease in distance to a GO station is related to an increase of 0.19% in transit mode share). This may indicate changing levels of efficiency. Commuter rail is efficient at getting low-wage workers to work during peak hours, and highway travel is more efficient outside of peak hours. Related to these changes is the effect of average distance travelled, which has a negative relationship during both the peak (b=-0.4) and off-peak (b=-0.27). The strength of mean distance effect during the peak (β=-0.11) is about half of the off-peak effect (β=-0.22). Similarly, accessibility, which has a positive relationship with transit mode share throughout the day (0.11% in the peak, 0.32% in the off-peak), has about half of the coefficient strength during the peak (β=0.12) compared to its off-peak access effect (β=0.23). This indicates that the negative pull of distance or the positive pull of access has more influence outside of peak hours, showing that modes besides transit are more attractive outside of the peak.

A method for targeting equitable transit investment

The final thrust of this study is to use the above results to discover areas where transit investment would be most beneficial for low-wage workers. We do this by focusing on employment zones where actual mode share is lower than predicted mode share. Up to this point, we have determined areas of significant low-wage employment (employment zones), measured where sectors of low-wage employment concentrate in the region (sector potential scores), and modeled transit mode share using sectorial potential scores and location as explanatory variables. These models explain between 44% (in the off-peak) to 55% (in the peak) of the variation in transit mode share in the region, and confirm that job location and occupational sector have a significant impact on transit mode share for low-wage workers. We argue that areas where actual ridership is lower than predicted ridership are areas that have all the right ingredients for high transit use, but transit service is not adequately addressing the needs of the workers there. Thus, these are areas where transit investments would most likely succeed

To find these areas we first restrict our attention to low-wage employment zones (determined using the above method). It should be remembered that these areas contain the majority of low-wage jobs in the region (59%) but only represent 10% of all CTs (131 out of 1328). Employment zones are significant low-wage worker poles, attracting workers from outside their boundaries and hosting at least 1,000 low-wage jobs. For these reasons, policies and transit investment directed to employment zones would benefit a large proportion of low-wage workers. Second, we use the above models to predict transit mode share for these employment zones. We then restrict our sample to zones where actual mode share is lower than predicted mode share. Finally, we focus on only those areas that have at least two neighbours. Figure 7 shows these areas, and indicates whether more service is needed during the peak, off-peak, or during both periods.

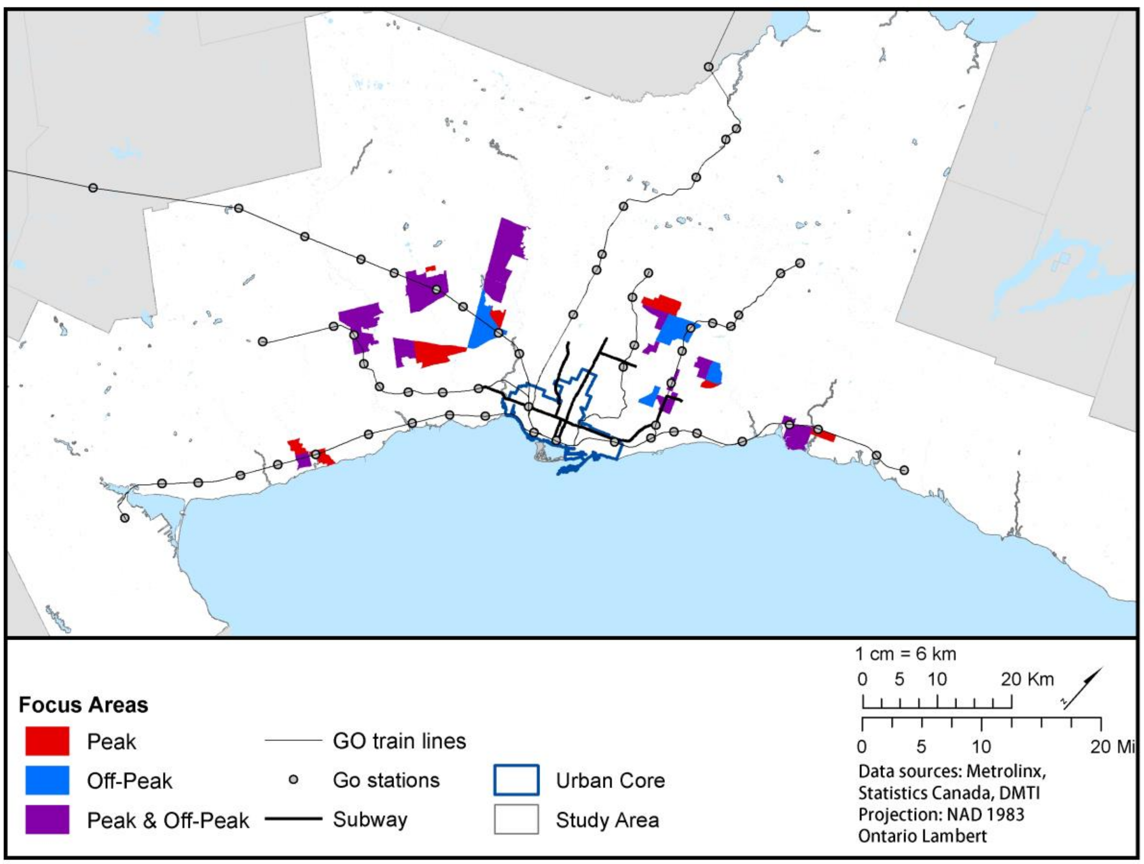

Figure 7: Focus areas

These focus areas host a total of 88,880 low-wage jobs (14% of all low-wage jobs in the region, and 24% of low-wage jobs in employment zones), and have, on average, actual transit mode share of 9% during the peak and 12% during the off-peak, compared to 22% during the peak and 24% during the off-peak for all employment zones. Their predicted mode shares are, on average, 6% greater at both time periods. Thus these areas should have fairly high transit mode share but do not. This disconnect between predicted mode share and actual mode share indicates that these areas have all the right attributes for high transit mode share. We argue that investments directed towards these areas have a good chance of increasing transit use. Furthermore increasing transit service in these areas will help a significant proportion of low-wage workers use transit to get to their place of work, making transit provisioning in the GTHA more equitably distributed.

Conclusion

This study explores what relates to low-wage transit mode share at the place of employment and develops a method to equitably target transit investment. Instead of focusing on the residence and the factors around the residence that influence mode choice, we demonstrate that job location and occupational sector have a relationship with transit use for low-wage workers. We model transit mode share and use these models to determine areas where investment should be focused. We suggest that areas with significant low-wage employment (employment zones) that have low actual transit mode share rates but have higher predicted rates would be the most efficient place for investment if planners wish to increase equitable transit service in the region.

Previous research has shown that low-wage workers use is, on average, less transit than higher-wage earners in the GTHA (Legrain et al., 2015). Legrain et al. also revealed that low-wage worker transit mode share is not related to transit accessibility at any time period. Paradoxically, other research has shown that disadvantaged residents in the GTHA live in areas with above average access to both low-wage jobs and higher-wage jobs (El-Geneidy et al., 2015). This is a perplexing series of findings. Poorer residents have high access. However poorer workers use transit less than higher-wage workers, and poorer workers' transit mode share does not respond to increases in transit accessibility. For us, this indicates that structural problems in the transit system are preventing their transit use. To overcome these problems, this paper has determines how location and occupational sector influence low-wage ridership. Using these findings, we find areas where policies and investment would be beneficial for this vulnerable population.

This study should be of interest to economic geographers and urban and transportation planners. Methodologically, it demonstrates that studying the destination of commuting, the place of work, is worthwhile. Although this finding may seem self-evident, the great majority of studies on the factors influencing travel behavior have focused on the origin of the trip. In addition, future research should look at why certain job sectors have a negative relationship with transit mode use. The specific needs, residential locations, or work habits of these occupational sectors may be related to transit use, and policies that take these discoveries into consideration would be most effective at providing adequate transit service to this population.

More importantly, this study's methodology can be used to target equitable transit investment; a pressing concern for the GTHA if we consider that transit ridership for low-wage workers is lower than ridership for higher-wage workers. Using the findings from this study, policies, infrastructure, and marketing can be focused on low-wage occupational sectors that demonstrate a problematic relationship with transit mode use. In addition, significant areas of low-wage employment (employment zones) that have low levels of transit use can be focused on, and interventions can be tailored to these areas' specific sectorial make-up, built environment, and present transit infrastructure. This method can be applied to many jurisdictions, and this study can be used as an argument for research into why different sectors of employment relate to mode choices. Crucial to the success of transit investment is discovering what factors lead to these sectorial differences. For instance, what are the travel-needs of primary workers? What are the travel-needs of health workers, and how do they differ? Discovering these needs and then planning interventions and policies with these in mind will help low-wage workers get to where they need to go.

Afterword

Getting from point A to point B is important. We travel everyday: we travel to get to work, to school, to visit friends, to visit family. Travelling is fundamental to people's happiness and success. In Canada, where eight out of every ten people reside in cities, access to reliable and usable transportation is a pressing concern. Part of access means being able to reach jobs affordably.

Transit services, when properly planned, allow people of a variety of incomes and abilities to travel to their jobs in Canada's largest cities. However, more and more activities, including employment opportunities, are located in suburban areas, where transit access is often lacking. Transportation, as one of our basic necessities, should be equitably provided. Although not everyone can enjoy the same level of transit accessibility, those who have fewer travel choices, including the poor, should, at most, be receiving adequate transit services, and at minimum, not be loosing access to employment as cities grow and change.

This project has looked at how workers earning under the living wage in the Greater Toronto and Hamilton Area travel to work. The thrust of this research was to discover how low-wage worker travelling habits differ from the rest of the population. Discover these differences help highlight areas and times periods where more service is needed, and where policies could be developed to help this vulnerable population.

Major findings

Our most important findings can hopefully guide future research and practice:

1. Low-wage workers use transit less than their higher-wage counterparts. This demonstrates that for many workers, transit is not a viable or effective mode of transportation to their place of work.
2. Low-wage workers use transit at different times than those who earn more. Investment in peak transit service increases may help higher earning workers, but is not specifically targeting the needs of low-wage workers.
3. An increase in distance between home and work for higher-wage earners leads to more transit use among this population during the morning peak. For low-wage workers, it leads to a decrease in transit use. This indicates that peak express services (the GO

system, for instance) makes transit an attractive service for higher-earning workers, but does little for low-wage earners.

4. Different sectors of low wage employment relate differently to transit use. Findings from Chapter 2 can help pinpoint transit policies and investment to areas with a concentration of vulnerable sectorial employment. In particular, areas of primary and health concentrations should be focused on.
5. Areas of significant low-wage employment are related to increased transit usage, indicating that transit providers in the region are, in general, adequately serving these areas.

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