Travelling fair: Targeting equitable transit by understanding job location, sectorial concentration, and transit-use among low-wage workers.

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Abstract

Low-wage workers have a pressing need for adequate and affordable transportation services. 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 disadvantaged populations should be a concern for transit planners and elected officials. The purpose of this research is to determine where low-wage employment zones are, where different types of low-wage jobs concentrate, and determine if job type and location have an effect on transit ridership for low-wage workers. We use a previously proposed method to identify low-wage employment zones in the Greater Toronto Hamilton Area, Canada and measure job type concentration using a gravity approach. We then test to see if job type concentration and employment centres relate to ridership, while controlling for other factors that influence mode share. Our results indicate significant differences in transit-use for different occupations exist. These results can help guide more transit investment and research by tackling specific occupation's travel needs.

1. Introduction

There is a growing need to consider social equity in transport planning and policy (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. For this reason, social equity concerns are particularly important for proponents of public transit. Arguments for investment in 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. A growing concern is that public transit agencies are directing new service to choice commuters rather than to transit captives, who are often poor and reside in areas of social exclusion (Garrett & Taylor, 1999). In response, equity is often mentioned as a goal in transportation plans. However, clear objectives and benchmarks are often lacking, which produces plans that contain a veneer of fairness without any means to enforce it (Manaugh et al., 2015).

For this reason, many researchers have attempted to develop methods to assess the equitable distribution of transportation services in a region (Currie, 2010; Delbosc & Currie, 2011; Hay, 1993; Ramjerdi, 2006). There is no clear consensus on what a fair or equitable distribution of transportation goods actually looks like, and ideas about equity vary between people and places (Martens et al., 2012). Nevertheless, recent work has used regional transit accessibility measures to compare transit provisions in areas of social disadvantage to advantaged areas (El-Geneidy et al., 2015; Foth, Manaugh, & El-Geneidy, 2013; Grengs, 2010, 2015; Manaugh & El-Geneidy, 2012). The idea behind this approach is that areas of poverty should have equal or greater transit accessibility to employment opportunities when compared to other areas. Surprisingly, some of these studies indicate 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 accessibility is higher there. Yet, this finding is by no means universal. For instance, a study in Melbourne, Australia, found that areas of social need are actually located in the periphery of the city where there is little to no transit service (Currie, 2010).

Nevertheless, the idea in previous research is to compare levels of transit service (often measured using accessibility) to areas of social disadvantage. If these measures line up then transit is equitable, if they do not line up then transit is inequitable. However, the connection between high transit access and high transit use in disadvantaged areas is not always strong. 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 (Legrain, El-Geneidy, & Buliung, 2015). Across the day, 23% higher-wage workers use transit, compared to only 11% of low-wage workers in the GTHA. This study also demonstrated that transit accessibility to employment is not related to ridership for low-wage workers in the region. These findings may indicate that transit even if it is readily available may not help low-wage workers get to where they need to go. Simple equity assessments that compare accessibility between poor and other areas may suggest that transit is being provided equitably. Yet, the fact that low-wage workers use transit less than higher-earners calls into question the clarity of this assessment.

In this research we want to shift research focus on how job location and job type relate to transit use for low-wage workers. If transit accessibility to work is high for low-wage workers but they are still not using transit then other factors must be in play. The hope is that understanding factors at the place of employment can help uncover these factors and lead to more equitable transit service. Most literature looking at the variables impacting mode share focus on the home and factors surrounding that location. Instead, this paper focuses 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.

This paper is organized as follows. First, we discuss the research context, arguing that a focus on the place of employment is beneficial for equitable transit planning. Second, we present our methodology, which aims to discover how job location and job type concentration relate to transit mode use. Third and fourth, we discuss our study area and data used. We then present our results, discuss their implications, and present one possible way to target transit investment using our findings. We finally end the manuscript with a conclusion.

2. Research Context

What influences transit use? In what follows we argue that there is a persistent lack of focus on the place of employment in transit studies, and that just such a focus would be beneficial for planning more equitable transit service. Many studies demonstrate the importance of availability, reliability, and frequency to transit mode share (Ewing & Cervero, 2010; Foth, Manaugh, & El-Geneidy, 2014; Mercado, Paez, Farber, Roorda, & Morency, 2012). Proximity to rapid transit stations has also been linked to higher transit use (Crowley, Shalaby, & Zarei, 2009). Availability or proximity to other transportation infrastructure, such as controlled access highways, has also been related to less transit use (Foth et al., 2014; Kawabata, 2009).

However, 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, not employment locations. Yet, this is not to say that there have been no studies on employment factors' influence on transit use. A study looking at factors influencing light rail ridership found that employment density had a positive influence (Currie, Ahern, & Delbosc, 2011). Occupation has also been linked to commuting distance and behavior. In a study on Montreal, workers in high-tech manufacturing, transport, or higher order services had the longest commute distances in the region (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 growing dominance of polycentric urban form makes studying a job location's influence on commuting behaviour an even more compelling research direction for transportation scholars and professionals. If people are travelling to increasingly dispersed employment centres, then different factors at these centres may have a crucial influence on mode choice. Studies have shown that an employment centre's location in a region and the socio-demographic makeup of workers travelling to them influence commuting choices. Sultana (2000) demonstrates that a more dispersed employment pattern (a polycentric metropolis) leads to shorter mean commute times. In addition, she reports 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 greater 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 suburbanization of employment has been linked to important equity concerns. Spatial mismatch theory contends that the increasing importance of suburban job centres 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 occurs (Houston, 2005). The primary problem, Houston (2005) contends, is one of spatial, not racial, inequality.

Even if disadvantaged residents have wonderful access to transit, this service may not actually get them to where they need to go. Furthermore, this 'mismatch' between transit service and travel needs may be increasing because of suburban job growth. It is inequitable when those with little means to move to job rich areas are cut-off from new employment zones because of a lack of transportation choices. Simply saying that these disadvantaged residents enjoy some of the best transit service in the region is misleading if this service does not address their actual travel needs. Indeed, one study demonstrated that access to transit had virtually no impact on welfare recipients' search for employment in a number of U.S. cities (Sanchez, Shen, & Peng, 2004).

To conclude, suburbanization of jobs is hard on low-income workers. Although public transportation is often an affordable option, low-income workers may need to use private automobiles to reach jobs that are increasingly located in areas not adequately served by transit. It follows that for new transit planning to be equitable we need to understand how a low-wage worker's job location and place of work impact their ability to use transit.

3. Study Area

Our area of study is the Greater Toronto and Hamilton Area (GTHA), Canada, excluding two rural western census subdivisions (see FIGURE 1). 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). A subway system and streetcar network in the City of Toronto offers frequent service throughout the day. Outside of Toronto, eight local transit agencies provide bus services with a wide variety of frequencies. In addition, GO Transit offers commuter train and bus service throughout the region with most lines running during peak periods. In rural areas almost no transit service exists. Because of the multiplicity of transit providers, fares vary widely by scheme and cost, with most single ride fares around $3.00 CAD, whereas on GO Transit fares are based on distance travelled.

This study uses census tract (CT) level data. Census tracts are small geographic areas used for Canada's Census and National Household Survey, which are conducted every five years. CT boundaries are relatively stable and are designed to maintain CT populations between 2,500 – 8,000 persons. In the area of study, there are 1,328 CTs with an average area of 5.53 km^2 and an average population of 4,925 persons.

FIGURE 1 Study Area

4. Methodology

This study focuses on how transit mode share of low-wage workers is impacted not by where they live but by where they work and the type of jobs around their place of work. As discussed in the literature review, many studies focus on the social, economic, and built environment factors in residential neighbourhoods and how they relate to commuting behaviour. We argue that the destination of a commuting trip, one's place of work, should also receive focus. To determine how place of employment relates to transit use for low-wage workers, this study poses three questions:

1. Where are significant areas of low-wage employment, or 'low-wage employment zones'?
2. Where do different sectors of low-wage employment spatially concentrate? Do certain types of job locate together in specific areas of the study area?
3. Does being or not being a low-wage employment zone (determined when answering question 1) relate to the share of low-wage workers using transit to travel to that area? Does the type of low-wage job concentrating in an area

(determined when answering question 2) relate to the share of low-wage workers using transit to travel to that area?

4.1 Answering question 1: Locating employment zones

Although low-wage jobs can be found in almost all CTs, most employment, including low-wage employment, tends to be located in a few areas. These areas are often called employment zones. The classic example of an employment zone is a city's downtown core. The downtown has few residents but a majority of jobs, meaning many people travel to it for work. However, as discussed in the literature review, employment zones may increasingly be found in suburban locations. We test low-wage employment zone's relation with transit mode share by seeing if a CT's low-wage transit mode share is influenced by that CT being a low-wage employment zone or not.

Debate around how to locate and define employment zones has generated a substantial literature. Typical methods involve classifying geographic areas (CTs for instance) 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, could be 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. To overcome this problem, Shearmur and Coffey (2002a) offer a simple way to determine which CTs are employment zones. First, employment zones should be CTs that attract workers. Second, the number of CTs classed as employment zones should be minimized while the share of employment in them should be maximized. We follow these rules by doing the following:

First, we calculate a ratio of low-wage employment to low-wage workers who reside in the CT in question (E/R). An E/R greater than one indicates that a CT has more low-wage jobs than low-wage employed residents. It follows that these CTs are commuting destinations for low-wage workers in the region (Forstall & Greene, 1997; Shearmur & Coffey, 2002b). However, a CT with an E/R greater than one could have few low-wage jobs. For example, a CT with ten low-wage jobs and only one low-wage resident would have an E/R equal to ten but certainly should not be considered an employment zone in the region. Instead, we should only consider CTs that have a large amount of low-wage jobs, i.e. meet a minimum threshold of low-wage employment, as employment zones. This threshold must keep the majority of low-wage jobs in the region in employment zones while also holding the number of CTs defined as employment zones to a minimum. A variety of thresholds were tested. A threshold of 1,000 is used because it keeps the majority of low-wage jobs in low-wage employment zones and limits the number of low-wage employment zones. Put simply, most low-wage jobs in the region are found in CTs with low-wage job counts greater than 1,000.

4.2 Answering question 2: locating job type concentrations

Our next step is to determine how different types of jobs concentrate in the region. We include these measures of concentration in our models to test for the influence of job type on transit mode share. Inspired by Shearmur and Coffey (2002b), we use a gravity model to measure the potential of each job type present at each CT. To define our job types we use Canada's National Occupation Classification (NOC) scheme, which classifies jobs into ten major groups: Management, business and finance, cultural production, sales and service, trades and transport, primary, health, education and government, manufacturing, and natural and applied sciences occupations. However, natural and applied sciences were excluded from this study since no low-wage workers are employed in this group in our study area. We calculate potential scores for the nine remaining groups, resulting in nine measures of concentration for each CT. This potential is measured in the following manner:

$$P_{zi} = \sum_{i=1 \text{to} n} \left(\frac{E_{zj}}{D_{ji}^2} \right)$$

Where P_{zi} = potential of sector z in tract i; E_{zj} = employment in sector z in tract j; D_{ji} = Euclidian distance between tract j and i, if j = i, $D_{ii} = 1/2\sqrt{(a_i/\pi)}$; a_i = area of tract i; n = number of census tracts.

This formula allows for the number of jobs in a certain group at a CT to be taken into account while factoring in the number of jobs in the same group 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. The use of this formula is beneficial for a number of reasons. First, the formula blurs CT boundaries. This fuzziness is advantageous since CT boundaries are based on population rules and pay little attention to economic activity. Second, the formula gives all CTs a share of what surrounds them, meaning areas surrounded by significant employment in one group will also have a high potential score for that group.

Potential scores for each occupational group were calculated for every CT in the area. To simplify the data we use a principal component analysis (PCA) to determine if any of these group potentials tend to collocate. If collocation occurs we can collapse together the collocating groups. PCA is a method to collapse variables together when their variation across cases is similar. In the first step of PCA, all nine group potential scores are included. Each score is grouped into 'components.' These components are made up of potential scores that tend to be similar in each CT. If too little variation is accounted for, the suspect potential scores are excluded, and another PCA is calculated. This continues until all variation is acceptably accounted for.

4.3 Answering question 3: relating employment zone and job type concentration to transit mode share

Ordinary least-square regressions are used to test if employment zone and job type relate to transit mode share. CTs are used as our geographic unit of analysis: they are used to represent different areas of employment. Transit mode share, the dependent variable in our models is the percentage of low-wage workers travelling to a CT by transit for their commute. First and foremost, it is crucial that the relationships between employment zone, job type concentration and transit mode share be understood over and above other factors that influence transit mode share. For this reason, we control for time of departure, the built environment, transit service, and distance travelled.

Many may question the absence of socio-demographic variables from this list of controls. Our models do not explicitly account for variation in these variables for two reasons: First, our study is already focused on a specific socio-demographic group. We are looking at the travel patterns of those working in a job that, on average, earns less than the living wage ($16 an hour) in the region, or 'low-wage workers.' Findings relating income to transit use within this group would be difficult to interpret and would have little basis, to our knowledge, in the literature. Second, the data used does not gather socio-demographic information at the place of work but at place of residence. We argue that residential socio-demographic variables in the area surrounding one's place of employment should have little influence on the choice to use transit to reach that area.

In the next sections we present the control variables included in our models.

4.1.1 *Controlling for time of departure*

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 both models is transit mode share during the time period in question.

4.1.2 *Controlling for 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 1998, see FIGURE 1). This area is densely inhabited and is a typical urban built environment. 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 1998. Although less dense than the City of Toronto, these areas were also praised for their transportation planning before amalgamation (Keil, 2000).

4.1.3 *Controlling for highway access*

In addition, distance from each CT's centroid to the nearest controlled access highway on-ramp, using network distance, is included to account for the impact of auto-infrastructure on transit mode share, this method can be found in Foth et al (2014) and Kawabata (2009).

4.1.4 *Controlling for transit service*

Variables accounting for proximity of transit and accessibility using transit have been linked to transit mode share (Ewing & Cervero, 2010; Foth et al., 2014; Mercado et al., 2012), and are controlled for in our two models. Distances from a CT's centroid to the closest subway station and closet GO station (commuter rail) are included.

Also, measures of accessibility to low-wage 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 the CT in question and the distance to the low-wage worker's residence, 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 (Foth et al., 2014). OpenTripPlanner uses GTFS data to calculate a shortest route between each point using transit, accounting for transfer time and scheduling. It is similar to using Google Maps to generate transit directions and travel time estimates. For C_{ij}, average travel times for the period in question (peak or off-peak) were used.

4.1.5 *Controlling for 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 (Apparicio, Shearmur, Brochu, & Dussault, 2003; Levinson & El-Geneidy, 2009) 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 for simplicity reasons.

5. DATA

We use data from the 2011 National Household Survey, aggregated to the census tract level. The National Household Survey is designed to provide detailed demographic, social, and economic information, including information on commuting patterns, and be accurate for small geographic areas. It was a voluntary survey sent to Canadian households, with an overall response rate of 69% (Statistics Canada, 2011). Data derived from this survey include home and work locations, commute departure times and mode used for low-wage workers in the study area. Low-wage workers were 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. 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 region's living-wage (Mackenzie & Stanford, 2008). More information on this method can be found in two related studies (El-Geneidy et al., 2015; Legrain et al., 2015). We also know how many low-wage workers are in each NOC group by CT, which was also derived from the 2011 National Household Survey. Nine (out of a possible ten) NOC major groups are included (see TABLE 1). The missing category (natural and applied sciences and related occupations) has no low-wage workers in the region.

TABLE 1: Low-wage employment by NOC group

Short Name	Long Name	# of Low-Wage Jobs in Region	% of Total
Management	Management Occupations	7,695	1.26%
Administration	Business, Finance, and Admin.	145,440	23.84%
Cultural Prod.	Occupations in Art, Culture, Rec. and Sport	8,950	1.47%
Sales & Service	Sales and Service	332,785	54.55%
Trades & Trans.	Trades, Transport, and Equipment Operations	8,090	1.33%
Primary	Agriculture, Landscaping, Natural Resources	7,100	1.16%
Health	Health Occupations	1,425	0.23%
Edu. & Gov't	Occupations in Education and Gov't Services	12,830	2.10%
Mfg.	Manufacturing and Utilities	85,710	14.05%
	Total Low-Wage Jobs	**610,025**	**100.00%**

In addition to 2011 National Household Survey data, GTFS data is used to calculate our accessibility measures. General Transit Feed Specification (GTFS) formatted data was pulled from eight transit agencies' websites. GTFS data is a common format used by transit agencies to describe their schedules and routes, and is used by Google and others to provide interactive transit directions. When combined, the GTFS data from the eight agencies provided comprehensive information on schedules, frequencies, routes, and stops for all scheduled transit service in the study area, and were up-to-date at the time of research (July, 2014). Finally, CT boundary shapefiles, provided by Statistics Canada, were used, as well as shapefiles sourced from DMTI and Open Street Map.

It should be noted that for our models only those CTs where low-wage employment is greater than zero (1,069 out of a possible 1,328 in the area) are included. This restriction insures that transit share numbers are meaningful. Furthermore, areas with a transit mode share greater than 70% are excluded from each model 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 unique places in the region.

6. Process and Findings

6.1 Where are low-wage employment zones?

We discover low-wage employment zones by 1) only considering CTs with an E/R greater than one and 2) excluding CTs with low-wage employment counts less than 1,000. Doing so produces employment zones that meets Shearmur and Coffey (2002a) requirements: First, the number of CT's defined as employment zones is low. Just 131 CTs (representing 10% of all CTs in the region) are employment zones. Furthermore, these CTs contain a majority (59%) of low-wage jobs in the region. These results are quite similar to the findings of Shearmur and Coffey (2002a) for the Toronto CMA. Their employment zones contained 53% of employment in the area, while representing 12% of all CTs. FIGURE 2 shows low-wage employment zones defined using our method.

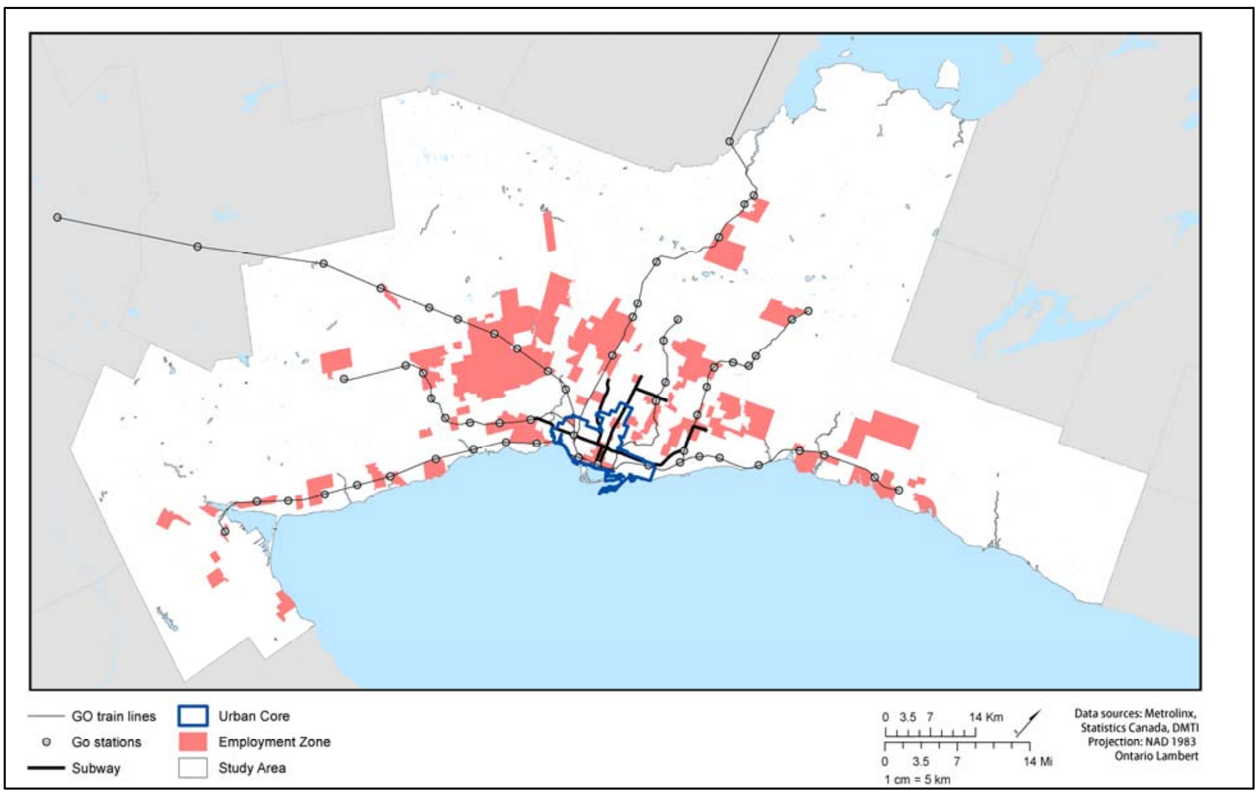

FIGURE 2: Low-wage employment zones

It should come as no surprise that a concentration of employment zones occurs in the urban core of the region. These CTs represent 17% (25 out of 145 CTs) of the urban core. Outside of the urban core, low-wage employment zones represent 8% of all CTs. 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).

6.2 Where do different jobs locate in the region?

Our NOC group potential score is a measure of how different job types spatially concentrate in the region. A CT with a high potential score in the health group, for instance, is a place where low-wage health jobs are heavily concentrated. We carry out a PCA analysis to simplify our nine groups by finding if any groups tend to collocate. Our first round of PCA 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, meaning less than 50% of their variation are accounted for, which is unacceptable. They are excluded from our final PCA, shown in .

TABLE 2.

This final PCA has two components, both with eigenvalues greater than one. Together, these components account for 87% of the included potential scores' variation. These groupings are corroborated by previous studies (Shearmur, 2007; Shearmur & Coffey, 2002b) on job type collocation in Canadian cities, which found that trades, manufacturing, and warehousing jobs often collocate, similar to our "trades, transport, and manufacturing" component, and find that higher order services and sales tend to collocate, similar to our "higher-order services" component.

TABLE 2: PCA of 9 major low-wage employment categiroes, final results

		Component Loadings		
Component Name	**NOC Group**	**Higher-Order Services**	**Trades, Trans. & Mfg.**	**Communalities**
Higher-Order Services	Management	0.95	0.117	0.917
	Administration	0.955	0.094	0.92
	Cultural Prod.	0.895	0.119	0.815
	Sales & Service	0.963	0.079	0.934
Trades, Trans. & Mfg.	Trades & Trans.	0.062	0.912	0.835
	Mfg.	0.136	0.899	0.826
Excluded	Health		Excluded	

Edu.& Gov't		Excluded	
Primary		Excluded	
Eigenvalue	3.72	1.53	
Cum. % of Variance			87%

Since the variation, loadings, and communalities are so high our final group scores were calculated by summing for each component the sector potential scores that are part of it. In FIGURE 3 we map our final five group scores to show how each job type spatially concentrates in the region. These maps (FIGURE 3) demonstrate that different occupations concentrate in different areas of the GTHA. Higher order services, health occupations, and education and government services are, for the most part, centrally located. Health-care jobs also show clear concentrations outside of the urban core, especially in Hamilton (south-west of the center of the region). 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.

The findings from FIGURE 3 are substantiated in TABLE 3, which shows summary statistics for each job type in the entire region, in suburban employment zones, and in the urban core. An inspection of each job type's mean at each location shows clear divisions in where occupations locate (the highest mean per job type is bold). Trades, transport, and manufacturing occupations are more heavily located in suburban employment zones than elsewhere in the region. 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 be concentrated in the center of the region.

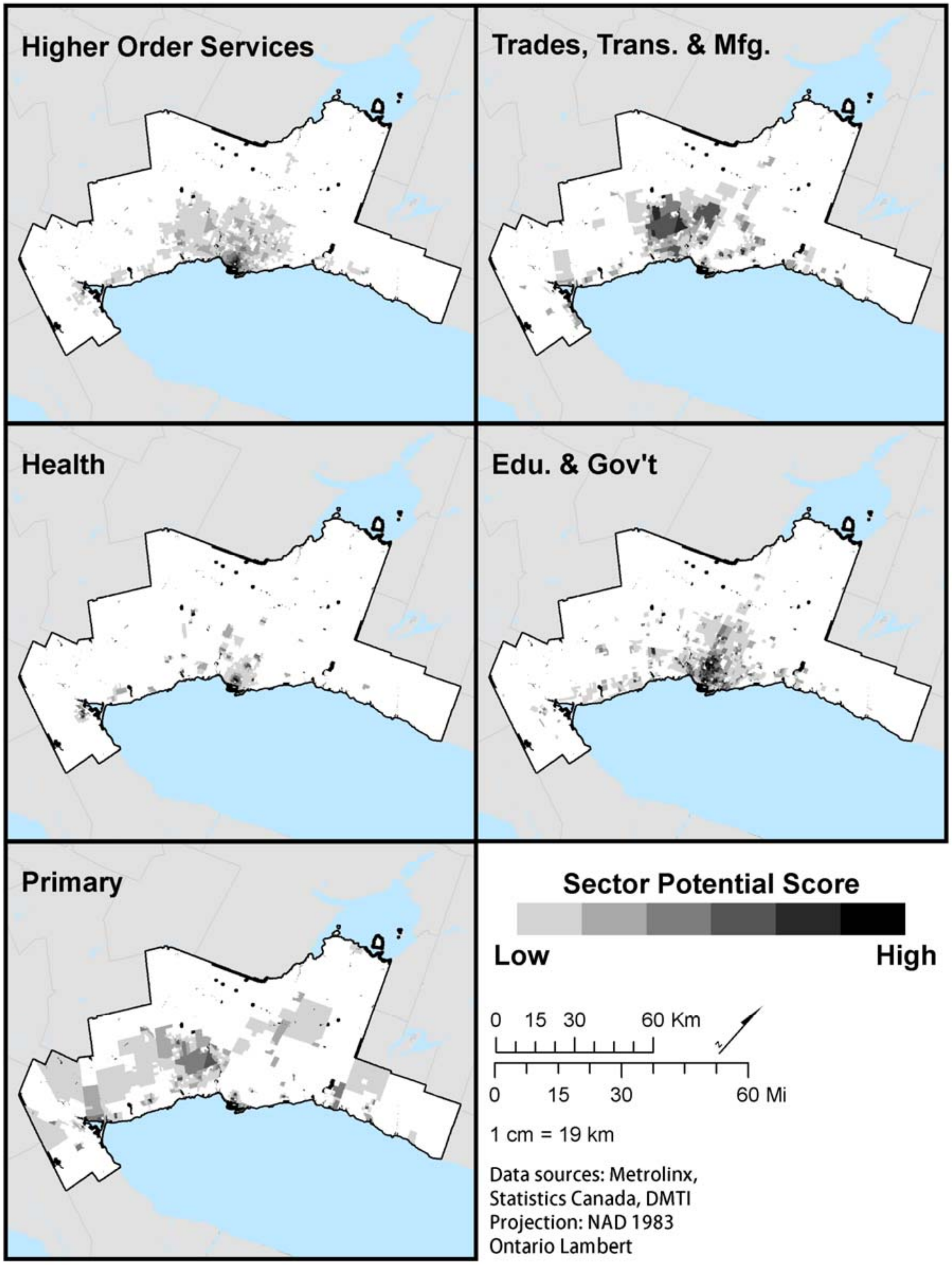

FIGURE 3: How do different jobs locate in the region?

TABLE 3 Job type 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	281.8	33.05
	SD	21,530.02	127.35	200.03	456.91	72.01
	Min	119.97	4.5	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**	91.2	**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

BOLD indicates highest mean value for the category

6.3 How does location and job type relate to transit mode share?

Our five job type scores are included in our models to determine the relationship that occupational concentration has with transit mode share. Also included is a dummy variable indicating if a CT is in a suburban employment zone or not. This allows us to test for the influence suburban employment zones have on transit mode share. We also include interaction terms to test whether occupations relate to transit mode share differently depending on where they are. 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 an occupation'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 an occupation's relationship to transit mode use.

TABLE 4 shows summary statistics and any transformations used for variables included in our models. Job type potentials were mean-centered (the mean was subtracted from each case's score) to minimize multicollinear relationships between potentials and interaction terms. This standardization also leaves coefficients in the same scale as the original 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 4 Summary statistics for regression model input variables

(N=1067)	Transformation	Mean	SD	Min	Max
Same across models					
Sectorial Potential Scores	x /1000, mean-centered		(See Table 3 Above)		
Suburban Employment Zone	None	0.10	0.30	0.00	1.00
Urban Core	None	0.14	0.34	0.00	1.00
Inner Suburbs	None	0.29	0.45	0.00	1.00
Proximity to Highway (km)	None	3.98	4.26	0.02	52.69
Proximity to GO (km)	None	5.28	4.93	0.36	41.83
Mean Distance Travelled (km)	None	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	33086.63	15359.40	234.26	61821.60
Off-Peak Accessibility	x / 1000	19416.31	12093.05	111.31	45293.84

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

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). The Huber-White estimator makes standard errors (and thus significance) more robust while leaving coefficient estimates the same.

6.3.1 *Model findings*

TABLE 5 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 5 Regression results

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

Our models confirm that location and job type relate to transit mode share. It is important to remember that model findings for location and occupation should be understood over and above control variable influence. In other words, by accounting for variations in the built environment, transit service, and commuting distance, we can draw conclusions about location and occupation's relationship with transit mode share independent of these variables.

The results indicate that membership in a suburban employment zone is positively related to transit mode share during both peak and off-peak hours. Suburban employment zones associate with increases in mode share by 7% and 5% during the peak and off-peak periods, respectively. Being in the urban core has a positive association with transit mode use as well, but this is only significant during off-peak hours (an 8% increase).

Higher-order services are positively related to transit mode share. A 1,000 unit increase in higher-order service potential is related 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 (β = 0.48) in both models, indicating that it has the most strength among the variables included. Higher-order services did not demonstrate any significant location interactions, either within suburban employment zones or the urban core, suggesting that the relationship between this job type's concentration and transit mode share is not location specific.

Education and government services also have a positive relationship with transit mode share. However, this link is only statistically significant in the urban core during peak travel periods. Other links (in suburban areas or off-peak) were not significant and had low effect size. An increase of 1,000 in education and government services' potential is associated with a 7.5% increase in transit mode share in the urban core.

Health sector concentrations at both peak and off-peak periods have a negative impact on transit mode share. There are no significant interaction terms for this variable, indicating that this negative pull is significant for the entire study area. An increase of 1,000 jobs in this sector's potential relates 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 jobs in this sector's potential associates with an 11% decrease in transit mode share outside of suburban employment zones. 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 jobs in this sector's potential relates to a 14% - 21% increase in transit mode share in suburban employment zones throughout the day.

Primary sector concentrations have a very large negative relationship with transit ridership when located in suburban employment zones for peak travel periods. A suburban employment zone is predicted to experience around a 30% decrease in transit use for a 1,000-unit increase in this occupation's potential score. It should be noted however, that mean primary potential is around 50 in suburban employment zones for this sector (TABLE 3), and its confidence interval indicates a wide range of interpretation for this relationship (TABLE 5). Nevertheless, an increase of just 50 in this sector's potential is related to a 2% decrease in transit share.

6.4 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.

Also of note 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 ($\beta=-0.11$) is about half of the off-peak effect ($\beta=-0.22$). 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 ($\beta=0.12$) compared to its off-peak access effect ($\beta=0.23$). This indicates that the negative pull of distance or the positive pull of access has more influence outside of peak hours.

7. Discussion

Our findings indicate that location and occupation have an effect on transit mode share over and above our controls. These are important findings and can be used as powerful evidence that more research into employment location and occupation's relationship with transit use is warranted.

It is heartening to note that transit mode share is positively related with suburban employment zones in the GTHA. This indicates that there are factors in areas of significant low-wage employment, over and above variation in their built environment, transit service, and the distance travelled to reach them, which help low-wage workers use transit: transit mode share is 5% - 7% greater for suburban employment zones, all other variables being equal. Future research could investigate these factors. It should also be remembered that this relationship has certainly not been proved universal, and future studies could see if this relationship holds in other areas.

Our models also indicate that occupations relate to transit mode share differently, and these relationships vary by location. These findings can be used to pinpoint investment and policies. Occupations that have negative relationships with transit mode share can be focused on and future research can discover why these negative relationships occur. For example, trades, transport, and manufacturing occupations have a negative pull on transit mode share when located outside of suburban employment zones but a positive pull inside suburban employment zones. This finding is promising because it indicates that low-wage trades, transport, and manufacturing jobs can be transit friendly in certain areas. In contrast, primary occupations have a very large negative pull on transit use when located in suburban employment zones. In other words, there is something about primary occupations that partially overcomes the transit friendliness of suburban employment zones. Discovering what these factors are and then tackling them could be an efficient way to target equitable transit investment.

Another way to target transit investment is to use differences between model results and actual transit mode share. We argue that employment zones where actual ridership is lower than predicted ridership are areas that have some of the conditions needed for greater transit use and would warrant more investment. This understanding, of course, is contentious; contentious because our models explain 44% to 55% of the variation in transit mode share in the region, which leaves about half of the variation unexplained.

To find these areas we first restrict our attention to low-wage employment zones. Policies and transit investment directed to employment zones would benefit a large proportion of low-wage workers since these zones are important areas of low-wage employment in the region. 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 that also have actual mode share lower than predicted mode share so that investments are targeting significant clusters of low-wage employment in need of attention. FIGURE 4 shows these areas, and indicates whether attention is needed during the peak, off-peak, or during both periods.

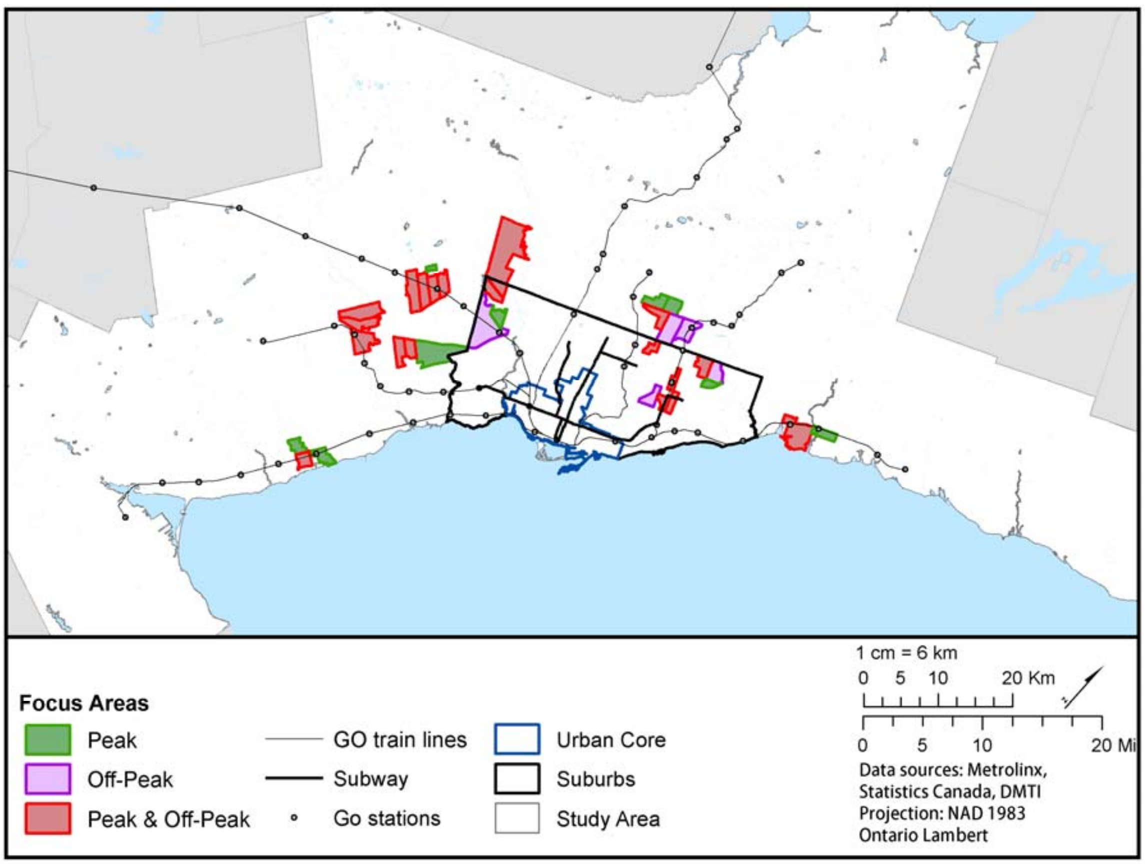

FIGURE 4 Focus areas

These areas host a total of 88,880 low-wage jobs (14% of all low-wage jobs in the region and 24% of all low-wage jobs in employment zones). They 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 than their actual mode shares during both time periods.

It is also interesting that none of these areas are located in the urban core of the region. Instead, these areas cluster close to the boundaries of the inner suburbs. In a sense, they are at the periphery of Toronto's urban extent. This positioning seems to correspond to Young and Keil's notion of the "in-between" city: locations that are too far from the urban core to receive frequent transit service and too close to it to receive adequate suburban-urban shuttle service (Young & Keil, 2010).

Our model findings can also help guide investment towards specific occupations. Interventions in these focus areas should be guided by understanding the needs of the jobs concentrating in them. We conducted independent t-tests (and welch t-tests where variance was not homogenous) to reveal if there are any differences between the types of jobs that concentrate in all employment zones versus the types of jobs that concentrate in these focus areas:

Focus areas have average levels of every potential except for trades, transport and manufacturing. In focus areas, the average potential score of this sector is 270, compared to 201 in all employment zones (see TABLE 6). Thus, these focus areas can be understood as areas of significant trades, transport, and manufacturing employment, indicating that workers in these fields travelling to these locations are having a difficult time using transit. This is interesting because it indicates that although trades, transport and manufacturing concentrations are related to increases in transit use in most suburban employment zones, it may not be the case in these areas. Finding out what the needs of these specific workers are and how their difficulties can be addressed is a crucial step for more effective and equitable transit planning.

TABLE 6 T-tests between employment centres and focus areas

	Mean				
Occupation Potential	**Emp. Centres**	**Focus Areas**	**df**	**t-stat**	
Higher-Order Services	36,543	7,822	97	4.96	†*
Trades, Trans. & Mfg.	201	270	129	-1.40	
Health	181	15	97	2.60	†*
Edu. & Gov't	476	188	129	3.38	†*
Primary	68	51	96	0.96	†

† Welch's t-test used because of heterogeneous variance

* $p < 0.05$

8. Conclusions

Instead of focusing on the residence and factors around the residence that influence mode choice, we demonstrate that job location and job type have a relationship with transit use for low-wage workers. Previous research has shown that low-wage workers use transit less than higher-wage earners in the GTHA (Legrain et al., 2015). This study also revealed that low-wage workers' 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). These are 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 at their place of residence. This may indicate that there are factors at their job that are complicating their use of transit. To investigate these problems this paper determines how location and occupational concentration influence low-wage transit ridership. Using these findings, we find areas where policies and investment would be beneficial for this 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, most studies on the factors influencing travel behavior have focused on the trip origin. In addition, this paper gives much needed evidence supporting future research on why certain occupations relate to transit mode share negatively. Discovering the specific needs or work habits of people employed in these occupations can help explain our findings. Policies that take these discoveries into consideration would be most effective at providing adequate transit service to low-wage workers.

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