# JOB ACCESSIBILITY AND LABOUR MARKET OUTCOMES AMONG IMMIGRANTS IN MONTREAL AND TORONTO

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## Abstract

Addressing the economic wellbeing of immigrants is a key component of the integration process and a growing policy concern in Canada. While recent research captures a broad range of social factors that affect immigrant labour market outcomes, relatively few studies examine how these factors interact with geographic barriers to employment. This study uses the 2016 Census of Canada to explore how spatial accessibility to jobs impacts the likelihood of employment among immigrants and non-immigrants in Montreal and Toronto. Job accessibility (defined as the cumulative number of jobs accessible within 45 minutes of travel by public transit from residential locations) is evaluated against demographic, human capital, and other contextual determinants of employment. This study finds that cumulative job accessibility is negatively associated with employment in Montreal and positively associated with employment in Toronto, though increasing levels of accessibility lower the odds of employment overall. Demographic characteristics explain much of the variance in likelihood of employment for working populations in both CMAs. While recent immigrants and visible minorities account for a considerable portion of the employment differential between immigrants and non-immigrants, completing post-secondary studies in Canada invariably increases the odds of employment for both populations. Age and cohort of migration, along with source region, are more important for understanding labour market dynamics within the immigrant population. Contrary to previous research and immigration policy, human capital characteristics and neighborhood-level factors bear relatively little influence on labour market outcomes among immigrants and non-immigrants in Montreal and Toronto.

**Résumé**

Le bien-être économique des immigrants est un élément clé du processus d'intégration et une importante préoccupation politique au Canada. Bien que les recherches récentes portent sur un ensemble de facteurs sociaux qui affectent les résultats des immigrants sur le marché du travail, relativement peu d'études examinent comment ces facteurs interagissent avec les obstacles géographiques à l'emploi. Cette étude utilise le Recensement du Canada de 2016 pour explorer comment l'accessibilité spatiale aux emplois influe la probabilité d'emploi des immigrants et des non-immigrants à Montréal et à Toronto. L'accessibilité à l'emploi (le nombre cumulatif d'emplois accessibles dans les 45 minutes suivant un déplacement en transport en commun à partir de lieux résidentiels) est évaluée en fonction des facteurs démographiques, du capital humain et d'autres déterminants contextuels de l'emploi. Cette étude révèle que l'accessibilité cumulative à l'emploi est associée négativement à l'emploi à Montréal et positivement à l'emploi à Toronto, bien que l'augmentation des niveaux d'accessibilité diminue les chances d'emploi en général. Les caractéristiques démographiques expliquent en grande partie la variance de la probabilité d'emploi pour la population active dans les deux RMR. Bien que les immigrants récents et les minorités visibles représentent une part considérable de l'écart d'emploi entre les immigrants et les non-immigrants, la poursuite d'études postsecondaires au Canada augmente invariablement les chances d'emploi des deux populations. L'âge et la cohorte de migration, ainsi que la région d'origine, sont plus importants pour comprendre la dynamique du marché du travail au sein de la population immigrante. Contrairement aux politiques d'immigration et aux études récentes, les caractéristiques du capital humain et les facteurs à l'échelle du quartier ont relativement peu d'influence sur les résultats des immigrants et des non-immigrants sur le marché du travail à Montréal et à Toronto.

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## Dedication

Many of the sociospatial processes discussed in this thesis are fundamental to my very being - if it were not for chain migration, immigrant neighborhoods, and occupational segmentation, my parents would have never met, and I would have never been born. So, I would like to dedicate this work primarily to the O.G. immigrants in my life: my mom and tatuś (dad). I thank them for abhorring the 'ordinary' and for raising me in a context that was always a little different from those of my friends - a rich cultural mélange of languages, cuisines, customs, and stories of home. Thanks for migrating to (and meeting in) Chicago, thanks for making me learn French and Polish, thanks for showing me how to work hard and how to do hard work, and thanks for encouraging me to continue our family's migratory tradition. Most of all, thanks (Tatuś) for imbuing me with curiosity and skepticism, and thanks (Mom) for encouraging me to find my own answers to my questions.

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# 1. Introduction

## 1.1 Background

Addressing the economic wellbeing of immigrants is a key component of the integration process and a growing policy concern in Canada (Piché et al. 2002; Picot and Sweetman 2005; Picot 2008). Faced with declining labour market outcomes and the increasing concentration of low income among Canada's immigrant groups, much recent research addresses the causes of unemployment within this population subset (Fong and Hou 2013; Green and Worswick 2010; Hou and Picot 2003; Hou and Picot 2014; Picot and Sweetman 2005; Warman 2007). While this work captures a broad range of social factors that affect the economic wellbeing of immigrants, relatively few studies examine how these factors interact with geographic barriers to employment. Research on the transportation needs of socially disadvantaged populations draws attention to the uneven distribution of employment opportunities across the urban landscape (Foth, Manaugh, and El-Geneidy 2013; Manaugh and El- Geneidy 2012). As studies in the U.S. have shown, residential settlement patterns can affect employment prospects based on transportation availability among transit-reliant populations (Blumenberg 2008a; Joassart-Marcelli 2009; Cathy Yang Liu 2009; C. Y. Liu and Painter 2012; Sanchez 1999; Shen 2007; Thompson 2001; Tyndall 2015).

Population and landuse dynamics complicate planning for an equitable provision of public transit. As planners anticipate geographic areas of population growth, they must also take into account the increasing diversity of urban population composition and how this might impact the provision of public transit (Lo, Shalaby, and Alshalalfah 2011). Both the suburbanization of population growth and the share of population growth attributable to migratory increase are becoming increasingly important in the Canadian context (Heisz and LaRochelle-Cote 2005;

Statistics Canada 2015). These population dynamics operate in tandem to changes in the urban economic landscape, with job growth occurring in different urban and suburban areas across Canadian cities (Shearmur and Coffey 2002). Kain's (1968) spatial mismatch hypothesis states that the suburbanization of job growth, particularly low-skilled occupations, can pose a problem for employment accessibility among disadvantaged, transit-reliant, residentially segregated populations. From this perspective, the spatial mismatch between areas of supply and demand for labour can lead to negative employment outcomes due to the increasing geographic separation between locations of residence and locations of work.

Immigrant geographies of unemployment are intriguing due to the spatial characteristics of the settlement process. According to the spatial assimilation model of immigrant integration, patterns of ethnic residential and occupational segregation are facilitated by information sharing through social networks (Massey 1985). Although research shows that previous immigrant cohorts have tended to disperse over time (both residentially and occupationally), more recent immigrant communities in Canada are displaying greater residential coherence (Bauder and Sharpe 2002; Fong 1996; Hou 2006; Myles and Hou 2004; Mendez 2009). Co-ethnic concentration in locations of work and residence can have a moderating effect on labour market outcomes by virtue of the resources provided within co-ethnic social networks (Fong and Hou 2013). The distinctive commuting patterns and increasing transit-reliance of immigrants in North America offer further incentive to investigate how social networks and spatial accessibility interact in shaping economic wellbeing (Lo, Shalaby, and Alshalalfah 2011; C. Y. Liu and Painter 2012).

Limited research on the relationship between transportation accessibility and employment among immigrants is cause for concern due to the role of immigration in driving Canadian population growth, the changing residential settlement patterns of recent immigrant cohorts, and the suburbanization of job growth in Canadian metropolitan areas. Immigrants greatly contribute to public transit ridership in Canadian cities, and their economic integration hinges on the spatial accessibility of employment opportunities. Recent downward trends in labor market outcomes among immigrants warrant further attention with regards to how this population subgroup navigates geographical barriers to employment. Although evidence from the U.S. can contribute to our knowledge of the travel needs of immigrants in Canada, differences in composition, immigration policies, occupational segmentation, and regional settlement patterns suggest that more research is needed to inform equitable transportation planning in Canadian cities.

### 1.2 Objectives and Research Questions

The purpose of this study is to investigate how spatial barriers to employment influence labour market outcomes among residents of Canada's largest cities. More precisely, this study aims to explore the role of job accessibility in finding employment among immigrants in Montreal and Toronto and to further understand how immigrant neighborhoods and social networks interact in shaping the commute patterns of this population subset.

Two questions guide this inquiry:

- To what extent does spatial accessibility to jobs impact the likelihood of employment among immigrants in Montreal and Toronto relative to the non-immigrant population?
- How is the relationship between spatial accessibility and employment among immigrants further influenced by immigrant residential segregation, source region, and length of residence in Canada?

The first research question addresses how spatial accessibility to locations of work influences the probability of employment within the Canadian labour force. This question further seeks to determine whether immigrant status alters the relationship between accessibility and employment across different urban landscapes. Taking into account Montreal and Toronto's varying urban development trajectories, we might expect to find different employment patterns based on metropolitan-specific spatial configurations of home and work locations. Furthermore, given differences in immigrant composition between these cities and the distinctive experiences of immigrants in urban labour markets, we might expect that accessibility to jobs influences the likelihood of employment differently for immigrants relative to the Canadian-born.

The second research question adds complexity to the relationship between accessibility and employment by evaluating the role of specific factors that affect the economic wellbeing of immigrants over time and at different levels of analysis. On an individual level, time and timing might affect an immigrant's incorporation into the labour market. The immigrant settlement process unfolds over time but is also situated within the economic conditions at the time of arrival: both the period of immigration and length of residence can affect the likelihood of finding employment. Labour market incorporation is also conditioned by certain group- and neighborhood-level factors. Residence in a neighborhood that is concentrated with co-ethnics can offer immigrants resources for finding employment. At the same time, ethnic overrepresentation in different economic sectors or occupational segments could impact the type of work that immigrants pursue as well as their prospects for getting hired.

### 1.3 Outline

The remainder of this report is structured in four sections. First, a literature review introduces relevant theoretical frameworks and empirical findings, highlighting gaps in the research on immigrant commuting behavior and geographical barriers to employment across Canadian cities. The third section describes the methodological approach for addressing the research questions outlined above, including data sources and analytic strategy. Results of the study are presented in section four and are discussed in the context of the literature in section five.

## 2. Literature Review

### 2.1 Equity and Accessibility

Much of the contemporary literature on sustainable transportation planning frames the goals of public transit in terms of providing accessibility, especially for segments of the population that have limited transportation options (Litman 2015b; Manaugh and El- Geneidy 2012; Morency et al. 2011; Welch 2013). Accessibility can be defined in several ways, ranging from Hansen's (1959, 73) formulation of accessibility as the "potential of opportunities for interaction" to Guers and van Wee's (2004, 128) passenger transport-specific definition of accessibility as the "extent to which land-use and transport systems enable (groups of) individuals to reach activities or destination by means of a (combination of) transport mode(s)." Accessibility can be more generally defined as "the ease of reaching goods, services, activities and destinations, which together are called opportunities" (Litman 2015b, 5). The adoption of accessibility as an evaluative metric in transportation planning reflects a paradigmatic shift away from mobility-based planning (Litman 2013; Litman 2015b; Manaugh and El-Geneidy 2012). Whereas the conventional focus on mobility emphasizes the physical aspects transportation and favors improvements in automobile travel, accessibility-based analysis takes into consideration a wider range of impacts and favors incentivizing and improving multimodal travel, such as public transit and active transportation (Litman 2013; Litman 2015b).

Concurrently, the notion of equity has recently gained traction within planning fields. Here, equity refers to the "distribution of impacts (benefits and costs) and whether that distribution is considered fair and appropriate" (Litman 2015a, 3). Equitable transportation policies can be further categorized between those favoring an egalitarian distribution of impacts (horizontal equity), or those that seek so compensate for social inequities by explicitly favoring disadvantaged groups (vertical equity) (Litman 2015a). Consequently, evaluating the equity of transportation systems requires categorizing individuals according to socioeconomic or behavioral characteristics, with the aim of identifying those that might be socially or spatially disadvantaged. In the spirit of social justice, much recent work has been devoted to addressing the mobility needs of disadvantaged groups by assessing the accessibility and equity of transportation systems from the perspective of these population segments (Blumenberg 2008a; Foth, Manaugh, and El-Geneidy 2013; Manaugh and El- Geneidy 2012; Manaugh, Badami, and El-Geneidy 2015; Mercado et al. 2012; Morency et al. 2011; Preston, McLafferty, and Liu 1998; Valenzuela 2000).

### 2.1.1 Urban Population Dynamics and Economic Development

Residential land-use patterns and urban economic development shape the distribution and intensity of accessibility over time and across urban areas. Two interrelated types of population dynamics are becoming increasingly important in the Canadian context, namely: the suburbanization of population growth and the share of population growth attributable to migratory increase (Heisz and LaRochelle-Cote 2005; Statistics Canada 2015). According to the 2016 Census of Canada, approximately 21.9% of Canada's population was foreign-born, 16.1% of which immigrated between 2006 and 2011 (Government of Canada 2017). Moreover, 61.4% of these recent immigrants settled in Canada's three largest Census Metropolitan Areas (CMAs): Toronto, Montreal, and Vancouver. While migratory increase currently accounts for approximately 67% of population growth across Canada, it is projected to account for 80% of population growth by 2031 (Statistics Canada 2015).

Changes in the composition of population growth highlight some of the demographic pressures on equitable public transit provision, but these changes do not occur uniformly across urban landscapes. Identifying locations of population growth allows for a better understanding of the geographic context of Canada's evolving residential areas. As with the increasing diversity of metropolitan populations, changing patterns of residential preference have important implications for public transit accessibility. Urban sprawl, or the expansion of primarily residential areas away from inner cities, has been identified as a major policy concern for urban development across North America (Turcotte and Vezina 2010). Suburban areas are often characterized by the presence of detached single family homes, lower levels of population density, single-use zoning, and heavy reliance on automobile travel (Turcotte 2008). Between 2001 and 2011, the majority of Canadian metropolitan population growth occurred in suburban areas (Statistics Canada 2015). Immigration accounts for an important share of suburban population growth in Toronto and Vancouver, and to a lesser extent in Montreal (Statistics Canada 2008), suggesting that Canadian suburbs are becoming more heterogeneous over time (Turcotte and Vezina 2010).

Research on suburbanization in Canada highlights some of the diverging development trajectories between metropolitan areas. Filion et al. (2010) investigate trends of intensification and sprawl between 1971 and 2006, finding differences in residential density patterns across cities. Whereas Montreal shows signs of decentralization, Toronto appears to be recentralizing and Vancouver is experiencing intensification. Bunting et al. (2000) come to similar conclusions regarding patterns of residential centrality. Millward (2008) offers a different approach by exploring the spatial clustering of population densities for the same period, finding that some suburban areas are showing signs of increased density. Moos and Mendez (2015) and Moos et al. (2015) find further support for the increasing heterogeneity of Canadian suburban areas, as well as the appearance of 'suburban ways of living' (characterized by homeownership, automobile commuting, and single-family housing) within central cities.

The suburbanization of employment growth introduces another dimension of urban development. Bourne (1989) examines the possibility of polynucleation across Canadian cities between 1971 and 1981, finding limited evidence of polynucleation but definitive signs of employment dispersal away from city centers. Shearmur and Coffey (2002) analyze changes in the intrametropolitan distribution of employment center growth within Montreal, Toronto, Vancouver, and Ottawa from 1981 to 1996. Overall, they find that employment remains concentrated in the CBDs of each city, but also that suburban areas experience employment growth at a faster pace than the CBD. Shearmur and Coffey further note important differences between each metropolitan area: whereas Montreal and Ottawa's CBDs are not matched by other local job centers, Toronto, and to a lesser extent Vancouver, show signs of polynucleation. Furthermore, employment growth is found to vary by industry, with manufacturing experiencing the greatest degree of CBD job decline in for all four metropolitan areas.

### 2.1.2 Spatial Mismatch

The suburbanization of economic activity, particularly low-skilled occupations, has implications for the supply of labour by virtue of the spatial constraints it imposes on employment accessibility (Fernandez and Su 2004). Scholars have explored spatial barriers to employment in terms of the spatial mismatch between areas of residence and locations of suitable jobs (Houston 2005b). Originally articulated by Kain (1968), the spatial mismatch hypothesis relates lower employment rates in disadvantaged inner-city populations to economic restructuring and the associated relocation of low-skilled or semi-skilled occupations to suburban areas. Disadvantaged and transit-reliant populations, including minority communities in urban areas, might experience difficulty in reaching areas of job growth due to the geographic distance between residence and employment, resulting in a greater risk of unemployment, lower wages, and longer commutes (Gobillon, Selod, and Zenou 2007; Heisz and LaRochelle-Cote 2005; Houston 2005b). Workers residing in suburban areas can also experience spatial mismatch due to difficulties of reverse or inter-suburban commuting, especially affecting those who rely on public transit for their journey to work (Heisz and LaRochelle-Cote 2005).

Alternative explanations of unemployment are often placed in opposition to the spatial mismatch hypothesis. The most prevalent account views failure to secure employment in terms of 'skills mismatch,' proposing that unemployment arises due to the mismatch of between the skills of the unemployed and those demanded by employers (Houston 2005). Some urban residents cannot access urban labour markets because they cannot compete with the higher-skilled labour supplied by those who reside further away from the urban core. As Houston (2005) points out, the skills mismatch perspective assumes that local labour markets have a great amount of occupational and spatial mobility, neglecting the importance of economic restructuring on the demand side of labour as well as spatial friction of metropolitan labour market accessibility. Others have argued that issues resulting from changing residential and occupational locations, such as longer commute durations and patterns of unemployment, can be viewed in terms of 'automobile mismatch' or 'modal mismatch' (Apparicio et al. 2014; Grengs 2010; Taylor and Ong 1995). This approach posits that spatial mismatch is primarily about the appropriateness of a given mode of travel, arguing that automobile accessibility and the efficiency of public transit systems contribute to job accessibility (Apparicio et al. 2014).

In light of these varying perspectives on the causes of unemployment, Preston and McLafferty (1999) opt for a broader definition of spatial mismatch as "the geographical barriers to employment for inner city residents that arise from changing social and economic relations and the impacts of those barriers on labor market achievement" (1999, 388). This view is intended to accommodate the role of social networks, skills mismatch, transportation availability, and occupational segmentation within a wider framework of understanding how these factors interact with geographical distance in affecting labour market outcomes.

Research addressing spatial barriers to employment has been predominantly focused on the U.S., with mixed empirical evidence supporting the spatial mismatch hypothesis (Houston 2005b; Ihlanfeldt and Sjoquist 1998; Kain 1992; Preston and McLafferty 1999). Research on spatial mismatch in Canada is more limited. In one of the earliest accounts, Bourne (1989) investigates changes in commuting distances between the 1971 and 1981 Censuses. Bourne finds that distances separating locations of residence and locations of work increased, although commuting distances for some suburban residents decreased, suggesting a certain extent of labour market adjustment among suburban residents. Others have further examined patterns in commuting distances and commute durations, addressing accessibility from locations of residence and locations of work along different social dimensions (Axisa, Scott, and Newbold 2012; Heisz and LaRochelle-Cote 2005; Manaugh and El- Geneidy 2012; Foth, Manaugh, and El-Geneidy 2013; Shearmur 2006). Heisz and LaRochelle-Cote (2005) comprehensively examine changes in commuting distances across Canada's eight largest CMAs between 1996 and 2001. They find that commute patterns have shifted, both in terms of commuting distances and mode share, and that this is related the proportion of job growth in suburban areas.

Within the Canadian literature, few studies have specifically examined the relationship between employment and spatial accessibility to jobs. Aubin-Beaulieu et al. (2013) examine low-skilled employment accessibility among disadvantaged populations in Montreal, Laval, and Longueil in 2006, finding minimal evidence of spatial mismatch within a 25-minute commute by public transit. Building on these findings, Apparicio et al. (2015) explore the relationship between employment and job accessibility across the Montreal Metropolitan Employment Zone in 2011. They focus on employment patterns among women, visible minorities, and recent immigrants, and further distinguish job accessibility based on sets of distances from residential areas. Apparicio et al. (2015) find some evidence for spatial mismatch: although the effect of distance is minimal for women and visible minorities, spatial mismatch is found to affect recent immigrants within a 5km distance from residential areas.

### 2.1.3 Measuring Employment Accessibility

Several methods have been used as a means to test the spatial mismatch hypothesis, including: analyzing how residential segregation affects labour market outcomes; comparing commuting distances or commuting durations for different population subsets; comparing workers' earnings or wages in relation to residential locations; measuring job accessibility from residential locations; and making use of exogenous shocks to work locations, residential locations, or transportation systems as a form of spatial experimentation (Houston 2005b; Ihlanfeldt and Sjoquist 1998; Kain 1992). Of these methods, comparisons of commute durations and measures of job accessibility have become increasingly popular (Houston 2005b). Although the logic behind using commute durations as a test for spatial mismatch is fairly straightforward, comparing commute durations is methodologically flawed. Echoing earlier criticisms (Derango 2001; Ihlanfeldt and Sjoquist 1998), Houston (2005b) notes that comparing commute durations is a limited method of testing for spatial mismatch because it does not fully account for constrained opportunity or group-level variations in commuting propensity, while also relying on biased sample selection. To elaborate on these three points: 1) longer commuting durations can be interpreted as evidence of both spatial mismatch and high mobility, while shorter commutes may reflect spatially constrained labour markets; 2) commute durations can further reflect group-level differences in propensities for commuting, and these are often conditioned by mode of travel; and 3) commute durations capture the travel behavior of those who are employed, and these are used to explain the likelihood of unemployment, often without accounting for characteristics of the unemployed population.

Measures of job accessibility offer a more robust avenue for testing spatial mismatch by directly assessing the level of mismatch between work locations and residential locations of the unemployed (Houston 2005b). Location-based measures of accessibility express the degree of accessibility between a location and sets of spatially-distributed activities (Geurs and van Wee 2004). The spatial extent of activities can be determined using either a distance-based threshold (the distance between a location and a set of opportunities or the cumulative opportunities accessible within a certain distance) or a gravity function (the potential accessibility of opportunities, where an opportunity's influence decays with distance). Compared to distance measures, potential accessibility measures are more theoretically sound, since they evaluate the interactions between landuse and transportation while also incorporating perceptions of opportunities through the distance decay function. Furthermore, potential accessibility measures can be adapted to account for labour market competition effects as well as different travel modes (Geurs and van Wee 2004; Houston 2005b; Kawabata and Shen 2006; Shen 1998). For instance, Shen (1998) and Kawabata and Shen (2006) propose a potential accessibility measure that incorporates the spatial distribution of labour supply and demand by mode of transportation. Another approach to incorporating competition effects into location-based measures of accessibility relies on the inverse balancing factors of Wilson's (1971) doubly constrained spatial interaction model. This measure iteratively assesses the equilibrium between the supply and demand for labour in each area given commuting patterns between areas.

### 2.1.4 Characterizing Urban Environments

The suburbanization of population and employment growth is an important theme within the literature on spatial mismatch. The evolution of urban environments is linked to residential and occupational segregation by virtue of landuse patterns and the spatial concentration of residential and employment opportunities (Massey and Denton 1988). Suburbanization is further tied to employment accessibility, given the centralizing structure of urban transportation systems as well as the costs associated with penetrating suburban housing and employment markets (Ihlanfeldt 2006).

In order to analyze the effects of different urban environments on patterns of employment across cities, it is necessary to systematically categorize neighborhoods as being predominantly urban or suburban. Several methods have been developed as a means to characterize urban environments. The literature on factorial ecology and economic geography focuses on how the internal structure of cities is defined by the location of the central business district (CBD) (Turcotte 2008). Within the frameworks of concentric zone theory and axial development theory, patterns of residential, industrial, and commercial land uses are viewed as emanating outward from the CBD, with spatial differentiation developing either as a function of distance from the center or within sectors along transportation routes (Harris and Ullman 1945). This perspective is echoed in Massey and Denton’s (1988) dimension of centralization in residential segregation, or the extent to which a group is located in proximity to the center of the city.

Bunting et al (2004) propose to classify neighborhoods according to age of housing. They divide metropolitan areas into the inner city, inner suburbs, and outer suburbs, given the stock of housing built before 1946, between 1946 and 1971, and after 1971, respectively. Bunting et al. (2004) further categorize neighborhoods based on contiguity to similar neighborhoods. Patterson et al. (2014) add shares of non-single detached dwellings and shares of transit or active commuting to the share of pre-1946 housing as a means to identify the urban core. The Urban Core Index can be modified to distinguish the rest of the urban landscape between inner and outer suburban areas. In particular, the inclusion of transit mode share is useful for capturing the extent of job accessibility by public transit.

### 2.2 Immigrant Settlement and Incorporation

The literature on international migration offers a rich foundation for investigating the patterns and processes of immigrant incorporation into receiving societies. Much of this work explores the social changes associated with the integration of minority immigrant groups into larger populations (Massey 1999). Several sets of theoretical frameworks have been developed in order to account for observed patterns of residential and occupational segregation. These approaches offer different interpretations of the factors shaping immigrant labour market outcomes.

#### 2.2.1 Residential Segregation and Spatial Assimilation

Previous research into ethnic residential segregation adopts the conceptual framework of Urban Ecology, founded on the notion that spatial relations mirror social relations (Massey 1985). Within the ecological framework, societal differentiation evolves as a function of economic development, producing social heterogeneity in terms of class, family structure, and ethnic makeup. These markers of social differentiation are, in turn, reflected spatially by the residential and economic structure of neighborhood configurations. From this perspective, the process of industrialization produces an economic specialization of urban space, and implicitly the concentration of employment locations. While the development of public transit in North America historically allowed members of the middle and upper classes to separate their locations of employment and residence, recent immigrants could not afford to access public transit and were, therefore, inclined to settle near their place of work (Massey 1985).

Two mechanisms reinforce the tendency of spatial concentration for immigrant groups, including the network structure of migration and the institutionalization of ethnic neighborhoods. Migration through networks, or "chain migration," reinforces ethnic concentration by providing new immigrants with social capital and directing them towards places of employment, eventually fostering a "cultural division of labor" (Massey 1985, 318). As immigrant communities begin to concentrate spatially, they often become institutionalized in the form of ethnic stores, services, religious organizations, clubs, and newspapers. Urban economic conditions further shape the extent and pace of neighborhood concentration and succession for immigrant groups. Factors such as urban expansion, economic stagnation, industrial centralization/decentralization, and access to public transit can affect the likelihood than an ethnic enclave will persist over time (Massey 1985).

Spatial forces of dispersion, namely structural and cultural assimilation, offset the process of concentration and neighborhood succession for immigrant groups (Massey 1985). As immigrants relocate in order to gain better access to opportunities and resources that are unevenly distributed across the urban landscape, they participate in spatial assimilation to the receiving population. Acculturation and socioeconomic mobility enable immigrants to disperse into 'native' residential areas, often over the course of several generations. The context of urban economic development, along with the pace of immigration, affects the balance between succession and assimilation, with higher levels of ethnic residential segregation observed during times of rapid immigration.

Although earlier research on North American residential segregation supports the propositions of the spatial assimilation model (Lieberson 1961; Massey 1985), this framework does not fully account for persistent patterns of immigrant residential segregation, nor does it capture the experiences of all immigrant groups. As such, the place stratification model has been proposed to account for persistent racial segregation (Arvantidis and Skouras 2008), while the residential preference model accounts for resilient ethnic residential clustering (Brown and Chung 2006). According to the latter view, segregation is a matter of individual preference to reside in spatial proximity to co-ethnics due to the benefits of accessing social capital and maintaining ethnic identity. Thus, immigrant groups may become economically integrated within receiving societies without necessarily experiencing spatial assimilation.

Recent work on immigrant integration in Canada has challenged the standard spatial assimilation model. Based on Census data from 1986 to 1996, Bauder and Sharpe (2005) find that the residential distribution of visible minorities in Montreal, Toronto, and Vancouver has become more even over time, and that visible minority communities are becoming more coherent. Bauder and Sharpe argue that differences between cities are largely due to differences in housing markets, the distribution of housing stock, and minority groups' preferences for housing characteristics. On the other hand, Hou (2006) finds that the residential distribution of visible minorities is becoming less even and more isolated over time, based on 1981-2001 Census data for Montreal, Toronto, and Vancouver. Noting important differences between immigrant arrival cohorts, Hou argues that high levels of immigration, coupled with the socioeconomic characteristics of immigrant groups, have generated different patterns of own-group and other visible minority neighborhood compositions. Myles and Hou (2004) and Mendez (2009) find further support for a bifurcated model of residential attainment for immigrant groups: immigrant social mobility is no longer necessarily tied to spatial dispersion; the resilience of ethnic communities is, in part, conditioned by own-group preference and residential attainment (homeownership).

Scholars have also challenged the spatial assimilation model's assumptions regarding occupational segregation and initial residential centralization. Using Census data for Canadian metropolitan areas in 1981 and 1991, Balakrishnan and Hou (1999) find that, although immigrant groups continue to display high levels of residential segregation varying by ethnicity, occupational segregation is declining over time. Focusing on Toronto, Murdie and Ghosh (2010) come to similar conclusions, and additionally find that more recent immigrants are bypassing traditional urban residential spaces and settling directly in suburban areas. Suburban settlement is, in turn, patterned by income, with wealthier immigrants settling in outer suburbs and less wealthy immigrants settling in inner suburbs. Similar studies equally find support for the residential preference model, suggesting that co-ethnic social capital, coupled with the institutionalization of ethnic identity in urban space, are arguably valuable components of the integration process for recent immigrant cohorts (Hou 2006; Joassart-Marcelli 2014).

### 2.3.2 Occupational Segregation and Labour Market Incorporation

The model of ethnic residential segregation and spatial assimilation suggests that immigrants' entry into the labor market is initially facilitated by co-ethnic residential concentration (Massey 1985). The model further implies that occupational segregation decreases over time as a function of socioeconomic and residential mobility. Theories of immigrant labour market incorporation elaborate on the process of finding employment, addressing occupational segregation as a function of residential location, human and social capital, and employers' discriminatory hiring practices (Samers and Snider 2015). These frameworks generally borrow from Becker's (1964) Human Capital Theory (HCT), which posits that labour market outcomes are conditioned by individual characteristics and decision-making. Research on immigrant employment often combines human capital variables (such as levels of education and skill) with other individual characteristics (religious affiliation, ethnicity, age, and gender) and group-level variables (global representation and neighborhood concentration) (Samers and Snider 2015).

Other models of immigrant labour market incorporation complement the HCT approach by framing the process of finding employment in terms of the supply and demand for labour in urban economies. From the demand side, proponents of labour market segmentation theory argue that immigrant employment outcomes are shaped by employers' discriminatory practices, including the segmentation of workers into different job categories (Samers and Snider 2015). To a certain extent, an employer's expectations regarding immigrants' cultural capital influences the hiring process within labour market segments (Bauder 2005). On the supply side, the social network approach emphasizes the role of social capital in the process of finding employment. Social networks of co-nationals or co-ethnics can connect new arrivals with employment opportunities, reinforcing the concentration of ethnic groups within certain industrial sectors or "niche" occupations (Logan, Alba, and Stults 2006). Some have taken the HCT approach one step further by investigating immigrant employment patterns with reference to geographies of both home and work. For instance, Ellis, Wright, and Parks (2009) examine intra-urban variations in occupational niching among immigrant groups in Los Angeles, finding that an immigrant group's propensity to niche is positively related to residential proximity to work, and is diminished by residential proximity to competing immigrant groups. Together, these theories offer varying perspectives on the limitations of estimating immigrant labour market outcomes using only human capital variables.

Issues surrounding the economic wellbeing of immigrants have been gaining attention in Canada. Faced with declining labour market outcomes and increasing concentration of low income among immigrant groups, researchers have sought to determine the causes of immigrant earnings penalties and unemployment relative to the Canadian-born population. The majority of this work focuses on the individual-level factors that might affect immigrants' reception into the labour market. In particular, several studies relate gaps in wages, entry earnings, and earnings growth to changes in immigrant source countries and declining returns on foreign education and foreign work experience (Boudarbat and Lemieux 2014; Frenette and Morissette 2003; Green and Worswick 2010; Piché et al. 2002; Picot and Sweetman 2005). Contextual factors might also influence immigrant employment outcomes. Based on longitudinal data for immigrants entering Canada between 1982 and 2010, Hou and Picot (2014) find that decreases in immigrant earnings are related to the size of entry cohorts, net of macroeconomic conditions.

Some recent research explores the role of ethnic communities on immigrant economic wellbeing. Using the 2002 Ethnic Diversity Survey, Frank et al. (2006) decompose the wage gap between immigrants and the Canadian-born according to attitudinal and behavioral expressions of ethnic identity. Although they find that the wage gap is largely explained by immigrants' sociodemographic characteristics, behavioral expressions of ethnic identity (including: language spoken at home, political participation, religious affiliation, and proportion of ethnic friends) also explain a portion of the difference between immigrant and non-immigrant earnings.

The few Canadian studies that investigate immigrant employment with reference to ethnic residential and occupational segregation reveal interesting patterns. Hou and Picot (2003) and Warman (2007) find that residence in an ethnic enclave is related to negative labour market outcomes among immigrants in Canadian cities between 1981 and 2001. Fong and Hou (2013) expand on this by examining the influence of ethnic residential, workplace, and industrial segregation on immigrant earnings in Canada's eight largest cities for the 2006 Census period. Overall, Fong and Hou (2013) similarly find that earnings are negatively related to ethnic enclosure in residential neighborhoods and workplaces, although this trend is inconsistent for industrial segregation. Interestingly, they find that ethnic enclosure in two places has a positive effect on immigrant earnings, with the strongest association observed for segregation in both residence and industry. Fong and Hou conclude that although ethnic enclosure in either home or work or industry can negatively impact immigrant's earnings, enclosure in more than one context plays a moderating role on earnings, reflecting the positive effect of ethnic social capital. Consequently, immigrants who are "extensively embedded" within their respective ethnic communities might fare better due to their ability to take advantage of social networks in both home and work locations (Fong and Hou 2013, 1071).

**2.3.3 Measuring Residential and Occupational Segregation**

An important area of debate within the study of ethnic residential segregation concerns the methodological approach towards conceptualizing and measuring degrees of segregation between groups across urban landscapes (Brown and Chung 2006; Massey and Denton 1988; Reardon and O'Sullivan 2004). Criticisms arising over the nature and measurement of spatial segregation generally call into question the dimensions of segregation measured by standard indices. According to Massey and Denton (1988), residential segregation, or the "degree to which two groups live separately from one another, in different parts of the urban environment," can be measured with reference to five dimensions: evenness, exposure, concentration, centralization, and clustering (1988, 282). The most commonly used measures of segregation – the Dissimilarity Index $D$ and the Isolation Index $P*$ – respectively measure the dimensions of evenness and exposure between two groups at the global scale. The Dissimilarity Index is calculated as:

$$D = \sum_{i=1}^{n} [t_i|p_i - P|2TP(1-P)]$$

where $t_i$ is the total population and $p_i$ is the minority population of areal unit $i$. $T$ and $P$ are the total and minority populations of the entire urban area, respectively, and $n$ is the number of areal units within the urban area. The Isolation Index is calculated as:

$$_xP_x^* = \sum_{i=1}^{n} [x_i/X][x_i/t_i]$$

where $x_i$ is the total minority population and $t_i$ is the total population of areal unit $i$. $X$ is the total minority population of the urban area, and $n$ is the total number of areal units within the urban area. Both indices return values ranging from 0 to 1.

An underlying problem in measures of segregation is the implicit reliance on aspatial indices calculated with reference to arbitrarily aggregated social units (Reardon and O'Sullivan 2004). In essence, standard (global) measures of segregation are not sensitive to the spatial patterning of aggregated social units. Thus, while global segregation indices emphasize the demographic composition of spatial units, they ignore the spatial proximity of those units – otherwise known as the "checkerboard problem." Furthermore, reliance on data collected at the level of census tracts accentuates the modifiable areal unit problem (MAUP). Given that census tracts are not necessarily based on meaningful spatial units, segregation indices that rely on aggregated data are not sensitive to the principle that individuals residing in closer proximity across units are (potentially) more similar than individuals living within the same unit. Finally, since census boundaries are based on population counts and change with time, issues of scale arise when global indices of segregation are used to compare levels of segregation between urban settings at different points in time (Gilliland and Olson 2010). Consequently, global measures of segregation might be useful as a comparative metric for evaluating inter-metropolitan levels of segregation, but they reveal little about the spatial patterning of group segregation within metropolitan areas.

More recent analyses of residential segregation have sought to adopt methods that are explicitly sensitive to spatial relationships (Logan 2012). Multilevel modeling offers an avenue for distinguishing individual-level processes from group-level or city-level contextual effects within the patterning of residential areas (Logan and Zhang 2012). Another methodological advancement involves the use of local indices of segregation. Reardon and O'Sullivan (2004) argue that the dimensions of residential segregation can be conceptually collapsed into two dimensions: evenness/clustering and isolation/exposure, which together define four patterns of residential location. They arrive at measures of spatial evenness and spatial exposure by decomposing, respectively, the spatial information theory index ($\tilde{H}$) and the spatial isolation/exposure index ($\tilde{P}*$). Brown and Chung (2006) take a different approach by conceptualizing dimensions of segregation in terms of concentration/evenness and clustering/exposure. In an effort to heighten spatial sensitivity, Brown and Chung propose using the Location Quotient (*LQ*) for local measures of concentration and using local indicators of spatial autocorrelation (LISA or Local Moran's *I*) to identify areas of residential clustering. Within the literature, several studies have relied on LISA indicators (e.g. Logan, Zhang, and Alba 2002) or location quotients (e.g. C. Y. Liu and Painter 2012; Wright, Ellis, and Parks 2010) to identify ethnically-concentrated residential areas.

Similar issues arise in the identification of occupational segregation. Researchers have generally relied on odds ratios, representation indices, or location quotients to identify ethnically concentrated workplaces, industries, or occupations (Wang and Pandit 2007). Each of these measures estimates group concentration with reference to different economic populations. In particular, location quotients are more sensitive to the distribution of ethnic groups across employment sectors. However, as Wang and Pandit (2007) point out, all three indices generate similar results if the concentration of an ethnic group is under 50%. At the same time, researchers have used different threshold values to determine at which point concentration is considered to be an ethnic niche, with values generally ranging from 1.2 to 2 for all three measures. There is also some debate over the minimum level of workplace aggregation: small but concentrated workplaces would display high values despite the fact that they do not reflect a large portion of the immigrant labour force. Wang and Pandit (2007) suggest using relative restrictions, such as percentages of the labour force, instead of raw values. Liu and Painter (2012) and Wright, Ellis, and Parks (2010) follow this method, and measure ethnic residential, workplace, and industrial concentration using location quotients, with threshold values at 1.5 to identify significant clusters. Global segregation measures are sometimes used to examine group distributions across industries or occupations. Balakrishnan and Hou (1999) measure ethnic residential and occupational segregation using the Dissimilarity Index *D*, which allows them compare the distribution of various groups across categories. Although measures with single index scores obscure patterns of concentration within ethnic groups, they are effective for capturing the evenness of group distributions across units and simplify comparisons between various sociodemographic groups.

### 2.3.4 Travel Behavior and Commute Patterns

The literature on immigrant integration into receiving societies stresses the importance of ethnic residential and occupational segregation, and reveals the varying causes, extents, and effects of these phenomena over time, across cities and between immigrant groups. Commuting is what ties together home and work locations, and research into immigrant travel behavior shows that immigrants rely on public transit for commuting to a greater extent than the Canadian-born population (Heisz and Schellenberg 2004). Given that immigrants' propensity to rely on public transit is partly influenced by residential and workplace locations, it is important to consider how commuting patterns are related to ethnic clustering (Liu and Painter 2012). Demographic commonalities between individuals help to justify grouping them according to similar behavioral patterns (Blumenberg et al. 2007). To the extent that demographic characteristics are associated with common choices and attitudes, we might expect that individuals with similar demographic profiles exhibit similar behavior. Furthermore, an individual's membership in a community might influence behavior due to common cultural norms and information sharing within the community.

Much of the literature on the travel behavior of immigrants has revealed two types of "immigrant effect" in commuting. The first type of immigrant effect relates to the individual characteristic of being an immigrant and how this might affect behavior. Several studies have found that immigrant status is an independent predictor of travel behavior, even after controlling for other socioeconomic and demographic characteristics (Chatman 2014; Heisz and Schellenberg 2004; Mercado et al. 2012). The second type of immigrant effect captures the process of acculturation and how this changes behavior over time. Virtually all studies that categorize immigrants according to their length of residence in receiving societies find that immigrants tend to assimilate their travel behavior to that of the 'native' population (Chatman and Klein 2009; Chatman 2014; Heisz and Schellenberg 2004; Lo, Shalaby, and Alshalalfah 2011; Smart 2015). The immigrant effect is strongest during the first five years of residence, and diminishes over length of stay.

Studies of immigrants in the U.S. have yielded insight into the distinct travel patterns of this population subset. While the majority of these studies focus on the effect of immigrant status and ethnic neighborhoods on mode choice (Blumenberg et al. 2007; Blumenberg 2008b; Blumenberg and Smart 2009; Blumenberg and Smart 2010; Blumenberg and Smart 2014;

Chatman and Klein 2009; Chatman 2014; Smart 2010; Smart 2015; Tal and Handy 2010; Valenzuela 2000), some further address the role of transportation accessibility to employment opportunities (Blumenberg 2008a; C. Y. Liu and Painter 2012; Shen 2007). Overall, this research shows that immigrants, compared to the U.S.-born, are more likely to rely on public transit, carpooling, cycling, and walking for their commute. Studies of carpooling show that co-ethnic social networks are essential for this type of travel, and this is often related to ethnically segregated occupations (Blumenberg and Smart 2010; Blumenberg and Smart 2014). Lack of automobile access is sometimes revealed to be a barrier to employment, and helps to explain wage disparities between immigrants and other low-income groups (Blumenberg 2008a). These patterns often vary by ethnicity and length of residence.

Notably, there has been far less research on immigrant commuting patterns in the Canadian context. The few extant studies on this topic echo findings from the U.S. In their study of public transit use among recent immigrants to Toronto, Montreal, and Vancouver, Heisz and Schellenberg (2004) find that not only are immigrants disproportionately more likely to rely on public transit for commuting than the Canadian-born population, but also that recent immigrants exhibit higher rates of public transit use than previous immigrant cohorts. Mercado et al. (2012) similarly find that public transit commuting is patterned by immigrant status among low-income populations in Quebec and Ontario. Variations in immigrant commute mode are related to settlement patterns in Toronto, depending on residential location in inner- or outer-suburbs (Lo, Shalaby, and Alshalalfah 2011). Furthermore, studies have shown that commute time and distance are associated with immigrant status and duration of residence in Canada (Axisa, Scott, and Newbold 2012; Morency et al. 2011; Axisa, Scott, and Newbold 2012).

Thus far, research on spatial mismatch in Canada has largely overlooked how social networks interact with employment accessibility. Fong and Hou (2013) propose that the moderating effects of co-ethnic concentration in both locations of work and residence on employment outcomes are evidence of institutional completeness. From this perspective, immigrants who are extensively embedded in ethnic social networks are in a structurally advantageous position, given their capacity to access greater social capital. However, it is unclear how ethnic social networks accommodate spatial barriers to employment in Canadian metropolitan areas. As Fernandez and Su propose, "understanding how space and networks interact in producing labour market outcomes should be a high priority for future research" (2004, 564).

## 3. Research Design and Methodology

### 3.1 Data Sources

#### 3.1.1 Population-level data

This study relies on population-level data from the 2016 Canadian Census of Population long-form, which contains questions relating to employment and residential location, mode of transportation to work, and a host of demographic, socioeconomic, and labour market characteristics. Confidential microdata files were accessed between November 2018 and July 2019 through the McGill-Concordia Laboratory of the Quebec Inter-University Centre for Social Statistics (QICSS), part of Statistics Canada's network of Research Data Centres (RDCs). Confidential files were preferred over Public-Use Microdata files given the interest in exploring interactions between different levels of geography, particularly how neighborhood contexts influence employment outcomes. Neighborhood-level population data from the 2016 Census, accessed through the Computing in the Humanities and Social Sciences (CHASS) Data Centre at the University of Toronto, were used to generate maps shown in sections 3.1.2 and 4.2.1. Population-level data from the 2006 Canadian Census of Population was accessed at the McGill RDC, and is used to provide context for the descriptive statistics described in section 4.1.

#### 3.1.2 Study area & population

This study focuses on members of the labour force aged 15-65 residing within the Montreal and Toronto Census Metropolitan Areas (CMAs). Labour force participants were excluded if they were employed in the Armed Forces, or if their place of birth generated methodological difficulties. Individuals whose place of birth was coded as "Other," non-immigrants who were born outside Canada, and immigrants born in Canada were excluded from the analysis.[1] Montreal and Toronto

[1] Sample sizes not reported to maintain Census respondent confidentiality for subpopulations.

were chosen as study areas due to the proportions of their immigrant populations: in 2016, roughly 23% of Montreal's population and 46% of Toronto's population was foreign-born (Statistics Canada, 2017). Montreal and Toronto also attract the largest numbers of recent immigrants to Canada: in 2016, roughly 29% of all recent immigrants settled in Toronto, and roughly 15% settled in Montreal. Although the figures for Toronto dwarf those for Montreal, these actually represent an increase in the share of immigrants settling in Montreal and a decrease of those settling in Toronto (Banikowska, Hou, Picot, 2015). Recent changes in Canadian immigration programs and shifting immigrant source regions partly account for this trend. Linguistic differences also offer another point of comparison between Montreal and Toronto - French is the official language of the Province of Quebec, and French proficiency plays an important role in the immigration process in Montreal. Together, the commonalities and differences between these two CMAs suggest that analyses of Montreal and Toronto might offer insight into labour market outcomes among immigrants in Canada. Figures 1 and 2 show the geographical extents and Census Consolidated Subdivisions (CSDs) of the Montreal and Toronto CMAs, respectively.

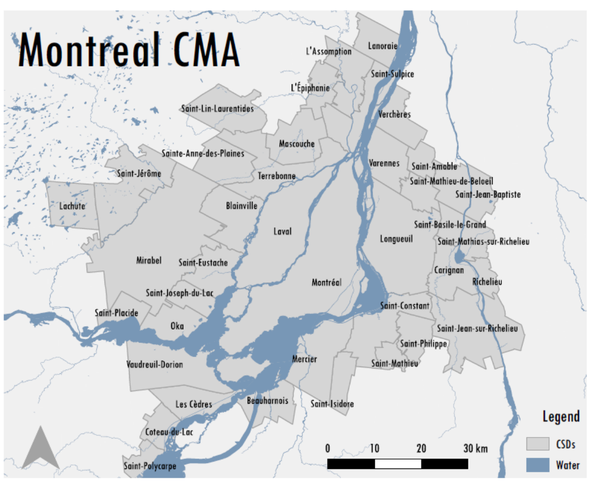


Figure 1 Map of Montreal CMA

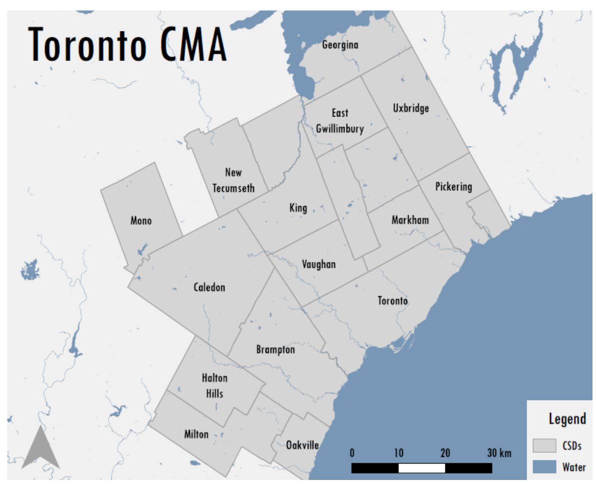


**Figure 2** Map of Toronto CMA

### 3.1.2 Geospatial data

Several types of geospatial data were used for mapping, exploratory spatial data analysis (ESDA), and generating spatial variables in the final analysis. Maps of census tract boundaries for the Montreal and Toronto CMAs were extracted from the 2016 Census Tract Boundary shapefile distributed by Statistics Canada using ArcGIS v10. Combined with population data, these census tract boundary maps were used to identify and to visually represent concentrations of immigrants in residential areas, as well as spatial concentrations of (un)employment within the immigrant and Canadian-born populations. Census tract shapefiles were also used to evaluate the extent of global and local spatial autocorrelation of neighborhood-level employment rates, as well as identifying tracts that meet the criteria for Patterson et al.'s (2014) Urban Core Index.

The job and worker accessibility datasets (described below) included in this analysis were created using Statistics Canada's road network shapefiles combined with General Transit Feed Specification (GTFS) data defining the spatial and temporal attributes of public transit services. Statistics Canada's CMA boundary shapefiles and water body shapefiles were used for cartographic purposes.

### 3.1.3 Job Accessibility and Worker Accessibility data sets

The Job Accessibility and Worker Accessibility data sets were graciously provided by the Transportation Research at McGill (TRAM) research group.[2] Job and worker accessibility measures were computed using public transit schedules available in the General Transit Feed Specification (GTFS) format for each public transit agency operating in Montreal and Toronto.[3]

[2] Access Across Canada. This research was funded by SSHRC project number 435-2017-0328. Investigators: Ahmed El-Geneidy, Kevin Manaugh, and Ron Buliung. Research assistants: Catherine Cui, Robbin Deboosere and Genevieve Boisjoly.

[3] For Montreal, this includes feeds from the Société de transport de Montréal (STM), Réseau de transport de transport de Longueuil (RTL), Société de transport de Laval (STL), and the Agence métropolitaine de transport (AMT) now known as the Réseau de transport métropolitain (RTM, or the 'Exo' brand). For Toronto, this includes feeds

These schedules were joined to road networks using the *Add GTFS to a road network dataset* add-on for ArcGIS. The joint network was then used to calculate the fastest route (either by walking along the road network or by taking public transit, or both) between pairs of census tract centroids within Montreal and Toronto. Fastest routes were calculated during morning peak travel time (8 AM) on Tuesday March 14th, 2017 for Toronto, and on Tuesday May 16th, 2017 for Montreal. Jobs and workers data were acquired from Statistics Canada's commute tables, representing the number of commuters working in each census tract, classified by personal total income and mode of transport. Job accessibility was measured as the cumulative number of job opportunities reachable within sets of travel time thresholds:

$$A_j = \sum_i O_i f(t_{ij}) \ and \ f(t_{ij}) = \begin{cases} 1 \ if \ t_{ij} \leq t_{threshold} \\ 0 \ if \ t_{ij} > t_{threshold} \end{cases}$$

where $A_j$ is job accessibility at census tract $j$, $O$ is the total number of jobs in census tract $i$, and $t_{ij}$ is the travel time between census tracts $i$ and $j$. Similarly, worker accessibility was measured as the cumulative number of people who can reach job opportunities within sets of travel time thresholds:

$$D_j = \sum_i P_i f(t_{ij}) \ and \ f(t_{ij}) = \begin{cases} 1 \ if \ t_{ij} \leq t_{threshold} \\ 0 \ if \ t_{ij} > t_{threshold} \end{cases}$$

where $Dj$ is accessibility to workers at census tract $j$, $P$ is the total number of workers in census tract $i$, and $t_{ij}$ is the travel time between census tracts $i$ and $j$. Whereas job accessibility $Aj$ represents the number of potentially unfilled positions in census tract $j$, worker accessibility $Dj$ represents the potential demand for workers residing in census tract $j$.

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from York Region Transit (YRT), Toronto Transit Commission (TTC), Oakville Transit, MiWay, Milton Transit, GO Transit, Durham Region Transit, Burlington Transit, and Brampton Transit.

### 3.2 Variables

The dependent variable in this analysis is whether or not an individual was employed at the time of the 2016 Census, coded as a binary indicator. The independent variables are categorized according to their respective levels of analysis. See Appendix A for list of corresponding Census variables and details about variable coding.

#### 3.2.1 Individual-level variables

***Demographic Characteristics***

The analysis includes several individual-level demographic characteristics that are known to affect travel behavior (Blumenberg et al., 2007), these include respondents' sex, age, marital status, and number of children aged 0 to 5 years. The analysis also includes a squared term for respondents' age, as well as an interaction term for female respondents with young children.

***Individual-level Factors***

Immigrant status is the main individual-level variable of interest for addressing the first research question. Several other individual-level variables are included in order to evaluate different aspects of the immigrant experience in receiving societies. Attending school or having recently immigrated might limit an individual's ability to participate in the labour market. Individuals who are members of a visible minority or whose parents were not born in Canada potentially face barriers in the labour market due to the dynamics of racialization and economic integration. Part one includes immigrant status, school attendance, recent immigrant status, second generation status, and visible minority status as individual-level employment factors.

The second research question focuses exclusively on the immigrant population. Several individual-level variables are added to the model to explore how the context of arrival influences future labour market outcomes. Individual immigration cohort, age at immigration, and region of birth are included to capture the potential for acculturation and integration in the context of urban macroeconomic structure, (co-ethnic) social capital, and labour market segmentation (both in terms of discriminatory hiring practices and self-selection into occupations/industries shaped by group-level labour market information sharing). The period of entry into the Canadian labour market affects both an individual's amount of labour market experience and their ability to navigate labour market information. Research shows a generally positive cohort effect for immigrant labour market outcomes (Hou and Picot 2014; Tal and Handy 2010), where earlier cohorts have better outcomes compared to more recent cohorts. On the other hand, there is mixed evidence for the role of age at immigration, possibly capturing positive effects of acculturation (Schaafsma and Sweetman 2001) or negative effects of labour market saturation by age-group (Crossman 2012). Finally, place of birth might influence individual human capital characteristics such as educational quality or language ability (Sweetman 2004). An individual's place of birth can be indicative of their social capital and potential for tapping into labour market information - for instance, through the presence and size of a landed immigrant community in Canada, or the extent to which group members are occupationally segmented (van Tubergen, Maas, and Flap 2004). Furthermore, place of birth is sometimes associated with immigrant travel behavior (Tal and Handy 2010). In this analysis, place of birth is divided into the following major source regions: United States, Europe/Oceania, Latin America, Sub-Saharan Africa, Middle-East/North Africa, East Asia, South Asia, and Southeast Asia. Appendix B lists the birth places included in each region, along with corresponding 2016 Census codes.

***Human Capital Factors***

Human capital characteristics play an important role in Canada's immigrant selection process and are often examined as indicators of labour market outcomes (Picot, Hou, and Qiu 2016). The 'skills mismatch' counterpoint to the spatial mismatch hypothesis is also based on the human capital framework, wherein individual unemployment is tied to a lack of quantifiable skills (Houston 2005a). Research shows that the positive association between human capital characteristics and labour market outcomes among immigrants in Canada is declining over time - for instance, through decreased returns on higher education for more recent immigrant cohorts (Picot, Hou, and Qiu 2016).

The first part of the analysis includes variables measuring official language knowledge, highest level of education completed, whether a respondent completed post-secondary studies in Canada, and whether a respondent was admitted to Canada as a principal applicant in the economic migration stream. Montreal and Toronto differ in terms of their enforcement of official language use in places of work. Montreal is subject to Quebec's provincial adoption of French as the sole official language, with limited language rights awarded to Anglophones. On the other hand, Ontario has adopted a mixed language policy, whereby some regions have English as their sole official language and other regions (including Toronto) have both English and French as official languages. In this analysis, language ability is categorized according to knowledge of: only English, only French, both English and French, and neither English nor French.

Educational attainment is another important component of individual human capital. A respondent's highest level of education is categorized as having completed: a high school diploma or less, a diploma or certification between the high school diploma and a Bachelor's Degree, or a Bachelor's Degree and higher. Educational attainment is categorized in this manner to avoid collinearity between higher levels of education and the dependent variable, and because of the overall distribution of educational attainment within the working population of both CMAs. (See Table 1 for details about the distribution of educational attainment in Montreal and Toronto.) For those who are university-educated, the location of post-secondary studies is associated with education quality, and might influence how potential employers judge the value of education attained. Research shows that individuals (both immigrants and non-immigrants) who have completed post-secondary studies in Canada fare better in the Canadian labour market (Hango et al. 2015). More importantly, studies have found that immigrants who have earned their highest degree in Canada have better labour market outcomes compared to immigrants who did not earn their highest degree in Canada, and that they exhibit credential transferability that is comparable to their Canadian-born counterparts (Hango et al. 2015; Rollin 2011). Finally, individuals in the economic migration stream (principal applicants) are admitted to Canada based largely on their human capital characteristics, and principal applicant economic migrants typically have better labour market outcomes compared to secondary applicants and immigrants in other migration streams (Xue 2008). The analysis includes a variable specifying whether respondents are principal applicant economic migrants, partly as an indication that their human capital characteristics have been vetted (and deemed adequate) for the Canadian labour market, and partly as a point of comparison with immigrants who were admitted to Canada through other migration streams.

Part two includes the human capital variables listed above and expands the set of immigration categories to differentiate members of major migration streams. Immigrants are categorized as: economic migrants (principal applicants), economic migrants (secondary applicants), family migrants, or refugees/other migrants. Immigration categories are associated with labour market outcomes in Canada (Xue 2008). For instance, while principal applicant economic migrants (and, indirectly, their spouses - often secondary applicants) might have an advantage in the labour market due to their human capital characteristics, family migrants potentially have access to wider social networks that can transmit labour market information and provide job contacts (Aydemir 2011). Family migrants are fundamentally reliant on social capital, increasing the likelihood of residential self-selection into certain neighborhoods and, consequently, vulnerability to local spatial dynamics. Although they are usually ranked lowest among immigration categories in terms of short-run labour market outcomes, refugees tend to exhibit large gains in rates of labour market participation and employment over time spent in Canada (Xue 2008). Research shows that the economic integration of refugees is influenced by job accessibility (Åslund, Östh, and Zenou 2010), neighborhood co-ethnic residential concentration (Edin, Fredriksson, and Åslund 2003), skills acquired since landing (Xue 2008), and local labour market conditions (Åslund and Rooth 2007).

### 3.2.3 Neighborhood-level variables

This analysis delineates neighborhoods using Census Tracts (CTs) from the 2016 Census of Canada. Census tracts are used to subdivide Census Metropolitan Areas or Census Agglomerations into small geographical areas with less than 10,000 inhabitants. Although CT boundaries might seem arbitrary, they are defined according to physical features of the urban environment and homogenous socioeconomic characteristics (Government of Canada 2016).

***Job and worker accessibility***

Measures of accessibility to jobs and accessibility to workers are applied at the neighborhood (CT) level using the datasets described in section 3.1.3. This analysis defines job accessibility as the total number of jobs accessible within 45 minutes of travel by public transit during the peak morning period (8 AM). This specific travel time threshold was chosen because it is a commonly used indicator in representations and analyses of job accessibility (Boisjoly and El- Geneidy 2017). The job accessibility variable is scaled down to 1:100,000 jobs, with values ranging from 0 to 9.

Since job accessibility is one of the main variables of interest, it is introduced with immigrant status before all other variables in each model.

Worker accessibility is defined as the total number of labour market participants who can reach a specific census tract within 45 minutes of travel by public transit. The worker accessibility variable is scaled down to 1:100,000 workers, with values ranging from 0 to 6. Measures of job accessibility that account for labour market competition exhibit higher levels of association with labour market outcomes compared to accessibility measures that ignore competition for jobs (Merlin and Hu 2017). Although this variable is not applied as part of a competitive job accessibility measure, worker accessibility is included in the analysis as a proxy for general labour market competition around areas of residence.

***UCI***

Census tracts are categorized as within or outside the urban core using Patterson et al.'s (2014) Urban Core Index. The UCI takes into account the age and structure of dwellings along with residents' transportation mode shares. Tracts are defined as 'urban' if the combined variable *z*-scores are equal to or above 1. This analysis applies the UCI according to an individual's census tract of residence in order to explore the influence of residential urban form and local travel behavior on employment.

***Residential Segregation***

Residential segregation is measured at the census tract level, using Location Quotients (LQs) as local indices of spatial concentration. The Location Quotient for census tract *i* is calculated as:

$$LQ_i = (e_i/t_i)/(E/T)$$

where $e_i$ and $t_i$ are the ethnic and total populations in census tract *i*, and *E* and *T* are the ethnic and total populations in the study area. In this case, ethnic populations are designated as individuals from the same place of birth region residing within either CMA. LQs were calculated separately for members each place of birth region over all neighborhoods in Montreal and Toronto. Next, neighborhood LQs were classified as high (LQ>1.2), medium (0.8≦LQ≦1.2), or low (LQ<0.8) levels of concentration by place of birth region. These neighborhood LQ categories are applied at the individual-level according to respective place of birth regions.

### 3.2.3 Data Analysis

***Mapping & Exploratory Spatial Data Analysis***

Mapping serves the dual purposes of communicating and analyzing social heterogeneity (Logan 2012). Mapping is used to visually explore subgroup patterns of residential and workplace clustering, as well as spatial patterns of employment. The process of mapping clustered data, or identifying non-random spatial variation, entails an exploratory spatial data analysis (ESDA) approach (Anselin 1999; Logan 2012). Anselin (1999) defines ESDA as a "collection of techniques to describe and visualize spatial distributions, identify atypical locations (spatial outliers), discover patterns of spatial association (spatial clusters), and suggest different spatial regimes and other forms of spatial instability or spatial non-stationarity" (258). Consequently, ESDA enables the visualization of spatial distributions and spatial autocorrelation. Thematic mapping is also useful for conveying complex relationships between units of observation. Producing maps allows for the visual communication of variation as well as the spatial pattern of variation (Logan 2012).

***Regression Modeling and Postestimation***

Logistic regressions are used to assess whether, and to what extent, the variables outlined above influence the likelihood of employment among immigrants and non-immigrants residing in the Montreal and Toronto CMAs. The logit link function is appropriate given the binary nature of the dependent variable (employment status). The analysis is divided into two parts, each addressing one of the research questions stated in section 1.2, with separate models by CMA. The main variables of interest - immigrant status and neighborhood-level job accessibility - are introduced before other variables in each set of models. This fitting method tracks how the association between immigrant status, job accessibility, and employment varies when accounting for separate and cumulative demographic, socioeconomic, and spatial factors.

The logistic regression model results are further examined through different postestimation methods. For models in part one, variable coefficients are interpreted in terms of their marginal effects on the likelihood of employment. Since marginal effects are measured on the probability scale, results are estimated as differences in probabilities of the outcome given the marginal change of the predictor variables, facilitating interpretation of model results (Leeper 2017). Predicted probabilities are used to interpret each variable's magnitude of effect on employment over successive models and for separate populations. Average marginal effects and marginal effects at representative values are computed using Stata's `margins` command, as well as the `mchange` module (Long and Freese 2014). For categorical variables, marginal effects are expressed as changes in outcome probability given discrete changes between independent variable categories. For continuous variables, marginal effects are expressed as discrete changes in probability at representative values (+1 unit centered and +1 standard deviation centered) as well as the marginal change (the instantaneous rate of change in the continuous variable underlying the discrete change in the outcome variable). Graphs are used to visualize the marginal effects of continuous variables on the likelihood of employment, as well as the effects of categorical variables at different values of continuous variables.

Overall model fit is assessed using several goodness-of-fit measures for models in parts one and two. Unlike ordinary least squares (OLS) regressions, logistic regressions do not generate $R^2$ values expressing model fit. First, McKelvey and Zavoina's pseudo-$R^2$ is used to assess explained variability in the dependent variable, as well as the strength of correlation between predicted and actual values. McKelvey & Zavoina's pseudo-$R^2$ is calculated as:

$$R^2 = \frac{\hat{V}ar(\hat{y}^*)}{\hat{V}ar(\hat{y}^*) + Var(\varepsilon)}$$

where model fit is computed by decomposing the variance of the estimated logits (McKelvey and Zavoina 1975). Several other fit statistics are reported for each regression model, including: model log-likelihood, intercept-only model log-likelihood, deviance, Wald test, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). All model fit statistics are calculated using the `fitstat` Stata module (Long and Freese 2001).

## 4. Results

### 4.1 Descriptive Statistics

Descriptive statistics are presented in Table 1. Certain differences between the two CMAs stand out in the data. Immigrants account for approximately one quarter of the working-age population in Montreal, whereas they account for just over half of the working-age population in Toronto. The employment rate is nearly 4% lower for immigrants in Montreal compared to the Canadian-born population. In Toronto, the employment rate is roughly equal for immigrants and the Canadian-born, with a slight (0.35%) edge among immigrants. The percentage of females in either sub-population is nearly equal in Toronto, while it is about 2% higher for the Canadian-born in Montreal. In both CMAs, the mean age of immigrants is higher than that of the Canadian-born, with a larger difference in Toronto (6.06 years) compared to Montreal (2.62 years). The proportion of individuals who are married is much higher among immigrants in both CMAs, with a larger difference in Montreal (32.26%) compared to Toronto (25.68%). On the other hand, in both CMAs there is a less than 5% difference between immigrants and the Canadian-born in terms of the proportion of individuals with young children.

Differences between Montreal and Toronto sharpen with the next set of socio-demographic characteristics. In both CMAs, the proportion of individuals with visible minority status is over 50% higher among immigrants compared to the Canadian-born. However, there is a larger Canadian-born visible minority population in Toronto (21.94%) versus Montreal (6.7%). Similarly, second generation Canadians make up around 52% of the working-age population in Toronto, but only 18% in Montreal. Rates of school attendance among Canadian-born individuals are fairly similar in both CMAs. Whereas the rate of school attendance among immigrants in

Montreal is close to that of the Canadian-born (<1% difference), the rate among immigrants in Toronto is lower compared to their Canadian-born counterparts (>7% difference).

There are greater similarities between cities and subpopulations in terms of human capital characteristics. The distribution of official language knowledge is the main understandable difference between Montreal and Toronto: a larger share of Montreal's total working-age population knows only French or both French and English, whereas the vast majority of those in Toronto know only in English. Focusing on subpopulations, knowledge of both languages is lower and knowledge of neither French nor English is higher among immigrants in both CMAs. Although the proportions of French-only individuals are similar between subpopulations in Montreal, a comparatively larger share of immigrants report knowing only English.

In terms of educational achievement, a larger share of non-immigrants in Toronto and immigrants in both CMAs have obtained a Bachelor's Degree or higher. On the other hand, a larger share of non-immigrants in Montreal have obtained a diploma or certificate below the level of a Bachelor's. Still, the distribution of educational achievement is overall similar for all subpopulations. Compared to immigrants, a larger proportion of the Canadian-born have completed post-secondary degrees in Canada (roughly 29% difference in both CMAs), though these figures are higher for both subpopulations in Montreal.

Immigrant populations in Montreal and Toronto are fairly similar in terms of their distribution across admission categories and immigration cohorts. A smaller share of immigrants in Toronto were admitted to Canada as economic migrants (principal applicants), while a larger share were admitted as family migrants or refugees. Even so, there is a similar proportion of individuals belonging to each admission category; the difference in the percentage of immigrants in each category varies from about 1% to 8% across CMAs.

**Table 1** Descriptive Statistics

| | | Montreal | | Toronto | |
|---|---|---|---|---|---|
| | | **Canadian-born** | **Immigrants** | **Canadian-born** | **Immigrants** |
| **N** | | 1538005 | 536005 | 1484935 | 1555995 |
| **Employed** | | 93.74% | 89.88% | 92.12% | 92.47% |
| **Sex (% Female)** | | 49.28% | 47.37% | 48.85% | 48.73% |
| **Age (mean, years)** | | 39.92 | 42.54 | 37.64 | 43.7 |
| **Married** | | 25.93% | 58.19% | 38.79% | 64.47% |
| **Kids aged 0-5** | | 34.70% | 39.34% | 30.54% | 28.49% |
| **Visible Minority Status** | | 6.70% | 64.37% | 21.94% | 76.65% |
| **Attending School** | | 18.59% | 17.84% | 20.00% | 12.46% |
| **Second Generation Canadian** | | 18.19% | N/A | 52.59% | N/A |
| **Recent Immigrant** | | N/A | 17.89% | N/A | 11.97% |
| **Official Language Knowledge** | English only | 2.06% | 14.38% | 88.43% | 91.85% |
| | French only | 26.85% | 24.90% | 0.01% | 0.06% |
| | Both | 71.08% | 59.29% | 11.54% | 4.88% |
| | Neither | 0.01% | 1.43% | 0.02% | 3.21% |
| **Education** | High School Degree or less | 30.34% | 26.93% | 34.26% | 30.97% |
| | Dip/Cert <Bachelor's Degree | 42.62% | 33.90% | 28.14% | 26.64% |
| | Bachelor's Degree or more | 27.05% | 39.18% | 37.60% | 42.39% |
| **Completed Post-secondary Degree in Canada** | | 68.97% | 39.91% | 63.24% | 34.54% |
| **Immigration Category** | Economic migrants (PA) | N/A | 29.29% | N/A | 21.55% |
| | Economic migrants (SA) | N/A | 15.02% | N/A | 14.15% |
| | Family migrants | N/A | 21.70% | N/A | 25.23% |
| | Refugees & Other migrants | N/A | 23.90% | N/A | 27.56% |
| **Age at immigration (mean, years)** | | N/A | 25 | N/A | 24.1 |
| **Immigration Cohort** | Before 1981 | N/A | 11.50% | N/A | 12.86% |
| | 1981-1990 | N/A | 13.85% | N/A | 15.96% |
| | 1991-2000 | N/A | 22.19% | N/A | 29.04% |
| | 2001-2010 | N/A | 34.57% | N/A | 30.18% |
| | 2011-2016 | N/A | 17.89% | N/A | 11.97% |

**Table 1** Descriptive Statistics *cont.*

| | | Montreal | | Toronto | |
|---|---|---|---|---|---|
| | | **Canadian-born** | **Immigrants** | **Canadian-born** | **Immigrants** |
| **Place of Birth Region** | Canada | 100.00% | | 100.00% | |
| | US | N/A | 1.65% | N/A | 1.42% |
| | Latin America | N/A | 22.85% | N/A | 14.55% |
| | Europe & Oceania | N/A | 23.45% | N/A | 19.12% |
| | Sub-Saharan Africa | N/A | 7.85% | N/A | 4.82% |
| | Middle-East / North Africa | N/A | 26.19% | N/A | 9.55% |
| | East Asia | N/A | 5.81% | N/A | 15.93% |
| | Southeast Asia | N/A | 7.37% | N/A | 12.29% |
| | South Asia | N/A | 4.84% | N/A | 22.33% |
| **Mode of Transportation to Work** | Active Transport | 6.68% | 5.69% | 7.79% | 4.12% |
| | Motorized | 67.24% | 52.55% | 60.72% | 61.42% |
| | Public Transit | 17.15% | 29.48% | 20.82% | 23.30% |
| | Other | 0.56% | 0.67% | 0.76% | 0.81% |
| | Work at home | 6.12% | 6.23% | 7.04% | 6.34% |
| | N/A | 2.26% | 5.38% | 9.91% | 10.34% |
| **Commute distance (mean, km)** | | 11.96 | 10.22 | 13.49 | 13.09 |
| **Commute duration (mean, min)** | | 29.1 | 33.35 | 32.44 | 35.91 |

Likewise, the distribution of individuals by immigration cohort is reciprocal between the two cities: Toronto has slightly higher shares of immigrants who arrived before 1981 and between 1981 and 1990, while Montreal has a slightly higher share of immigrants who arrived between 2001 and 2010. The largest differences appear in the 1991-2000 cohort (about 7% higher share in Toronto) and in the 2011-2016, or recent immigrant, cohort (about 6% higher share in Montreal). The mean age at migration is nearly equal, with a <1 year difference between CMAs. On the other hand, Montreal and Toronto's immigrant populations are fairly different in terms of their composition by region of birth. The largest share of immigrants in Montreal originate from the Middle-east/North Africa, followed by Europe/Oceania and Latin America, accounting for 72.49% of immigrants. The distribution of immigrants across birth regions is more even in Toronto, with the largest share originating from South Asia, followed by Europe/Oceania and East Asia; accounting for 57.37% of immigrants.

Characteristics of the journey to work reveal interesting transportation dynamics in both Montreal and Toronto. There is a similar distribution of individuals according to main modes of commuting among the Canadian-born and, separately, among immigrants across CMAs. The majority of working-aged people in Montreal and Toronto commute to work by car, truck, or van (as drivers or passengers), with Canadian-born Montrealers reporting the highest mode share (67.24%), followed by almost equal proportions of immigrants and the Canadian-born in Toronto (61.42% and 60.72%, respectively). Overall, subpopulation shares by mode of transportation are very similar in Toronto: the largest gap is the higher rate of active transportation (3.66% difference) and lower rate of public transit use (2.49% difference) for the Canadian-born relative to immigrants. In contrast, differences in transportation mode share between subpopulations in Montreal are larger. Most importantly, the rate of commuting by car, truck, or van (as drivers or passengers) is nearly 15% lower for immigrants in Montreal compared to the Canadian-born. At the same time, immigrants in Montreal are more dependent on public transit than any other subpopulation, respectively reporting about 12% and 8% higher shares of public transit commuting compared to the Canadian-born population in Montreal and either subpopulation in Toronto. Mean commute distances and durations are overall higher for the combined working-age population in Toronto. Still, immigrants report shorter travel distances and longer travel durations in both CMAs. Although mean commute distance is longer for Canadian-born Montrealers versus immigrants

(1.74km difference), this gap is far narrower between subpopulations in Toronto (0.4km difference). Similarly, the mean commute duration is longer for immigrants in Montreal and, to a lesser extent, in Toronto, versus the Canadian-born (4.25min and 3.47min difference, respectively). Rates of commuting by other modes (including individuals who mainly commute by passenger ferry or 'Other method') as well as proportions of individuals who work at home are very similar between subpopulations and CMAs.

***Immigrant Birthplaces: 2006 - 2016***

Tables 2 and 3 show 2006 unemployment rates (total population, percent unemployed, percent recent immigrant, percent unemployed recent immigrant) and 2006-2016 population growth for immigrants in Montreal and Toronto, respectively, according to region of birth.[4] These tables clarify the trajectory of immigrant labour market outcomes from 2006 to 2016, contextualizing the birthplace distribution outlined in Table 1 in terms of the changing composition and growth of immigrant subpopulations.

Unemployment rates among immigrants in Montreal are generally consistent with the proportion of recent immigrants by place of birth region. In 2006, 16% of immigrants born in Sub-Saharan Africa were unemployed, 37% were recent immigrants, and 8% were unemployed recent immigrants – the largest proportions in each employment category. This pattern holds fairly well for other groups with relatively large shares of recent immigrants in 2006: 15% of immigrants born in the Middle-East / North Africa were unemployed, 27% immigrated after 2000, and 7% were unemployed recent immigrants, representing the second or third highest value in each category. These two groups also experienced the largest increases in population between 2006 and 2016: the number of immigrants born in Sub-Saharan Africa or in the Middle-East / North Africa grew by

[4] Immigrants born in Oceania are coded as Southeast Asia in 2006 and are coded as Europe in 2016.

109% and 54%, respectively. Immigrants born in East Asia are an exception to this pattern, displaying low unemployment rates relative to the proportion of recent immigrants in 2006 and population growth between 2006 and 2016.

**Table 2** Immigrant unemployment rates and population growth by birthplace in Montreal (2006-2016) reported as percentages

| | | 2006 | | | | Population Growth 2006-2016 (total population) |
|---|---|---|---|---|---|---|
| | | Total Population | Unemployed | Recent Immigrant | Unemployed Recent Immigrant | |
| Place of Birth Region | US | 9,245 | 6% | 12% | 1% | -5% |
| | Latin America | 90,800 | 12% | 18% | 3% | 35% |
| | Europe & Oceania | 122,940 | 8% | 18% | 3% | 2% |
| | Sub-Saharan Africa | 20,130 | 16% | 37% | 8% | 109% |
| | MENA | 91,160 | 15% | 27% | 7% | 54% |
| | East Asia | 23,245 | 10% | 32% | 5% | 34% |
| | Southeast Asia | 35,335 | 8% | 10% | 1% | 12% |
| | South Asia | 22,985 | 16% | 24% | 5% | 13% |

**Table 3** Immigrant unemployment rates and population growth by birthplace in Toronto (2006-2016) reported as percentages

| | | 2006 | | | | Population Growth 2006-2016 (total population) |
|---|---|---|---|---|---|---|
| | | Total Population | Unemployed | Recent Immigrant | Unemployed Recent Immigrant | |
| Place of Birth Region | US | 23,015 | 5% | 11% | 1% | -4% |
| | Latin America | 227,045 | 7% | 11% | 1% | 0% |
| | Europe & Oceania | 365,145 | 5% | 10% | 1% | -19% |
| | Sub-Saharan Africa | 63,695 | 9% | 19% | 3% | 18% |
| | MENA | 97,200 | 10% | 24% | 4% | 53% |
| | East Asia | 204,485 | 8% | 21% | 3% | 21% |
| | Southeast Asia | 154,220 | 6% | 16% | 1% | 24% |
| | South Asia | 251,990 | 9% | 30% | 4% | 38% |

Unemployment rates and proportions of recent immigrants by place of birth region are far lower in Toronto compared to Montreal. Still, immigrant unemployment rates in 2006 coincide more or less with the relative size of recent immigrant populations. In Toronto, immigrants born in the South Asia and the Middle-East / North Africa rank similarly across employment categories: 9% of those born in South Asia were unemployed, 30% immigrated after 2000, and 4% were unemployed recent immigrants; 10% of those born in and the Middle-East / North Africa were unemployed, 24% were recent immigrants, and 4% were unemployed recent immigrants. However, the population of immigrants born in the Middle-East / North Africa increased by 53% between 2006 and 2016, compared to a 38% increase for those born in South Asia.

Several birthplace groups had smaller proportions of recent immigrants and lower employment rates in both CMAs in 2006. Compared to all other groups, immigrants born in the U.S. or in Europe had the lowest unemployment rates overall, smallest proportions of recent immigrants, and lowest unemployment rates among recent immigrants in Montreal and Toronto. These two groups also rank lowest in terms of population growth in both CMAs. At the same time, immigrants born in the Middle-East / North Africa ranked nearly highest in all unemployment characteristics and in population growth in Montreal and Toronto.

## 4.2 Exploratory Spatial Data Analysis

### 4.2.1 Visualizing Urban Geographies

A visual examination of accessibility, employment, and immigrant residential locations in Montreal and Toronto reveals interesting geographic congruities and outliers. Figures 3 and 4 show the number of jobs accessible (scaled to 1:100,000 jobs accessible within 45 minutes of commuting via public transit) by census tract in the Montreal and Toronto CMAs, respectively. In Montreal, areas of higher job accessibility (>800,000 jobs) are generally situated along metro lines, and accessibility diminishes with distance from the metro. Census tracts with mid-range accessibility (300,000 to 600,000 jobs) appear only within a few kilometers from metro lines. Most areas off the Island of Montreal are dominated by low-accessibility census tracts (<100,000 jobs), with the exception of areas in Laval and Longueil that are serviced by metro lines.

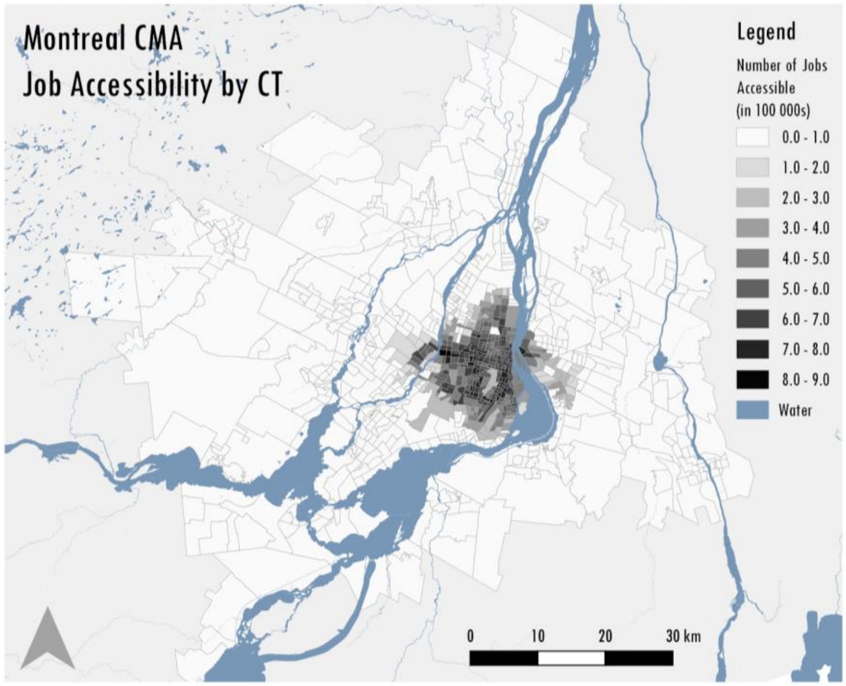


**Figure 3** Montreal CMA Job Accessibility by CT

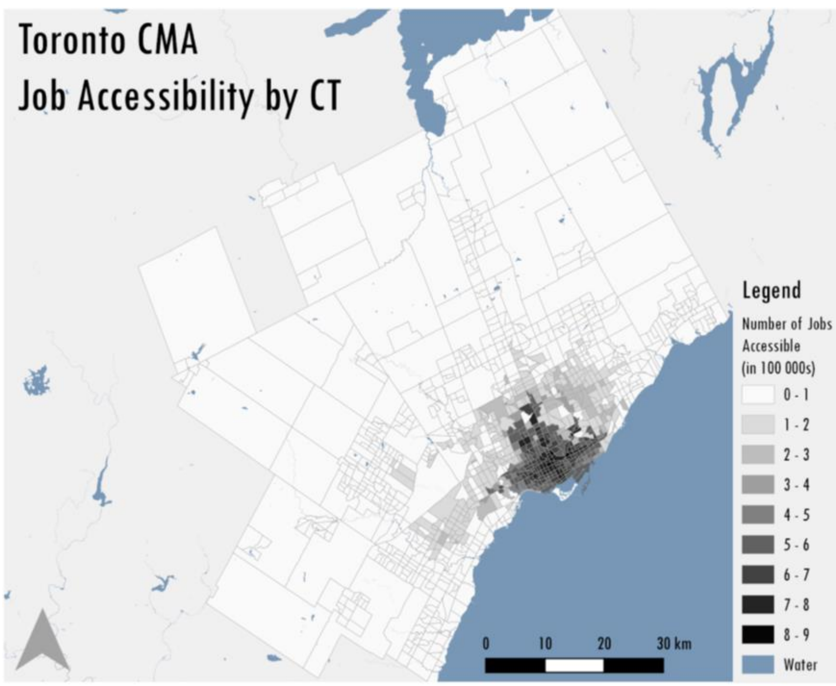


**Figure 4** Toronto CMA Job Accessibility by CT

Accessibility is also influenced by subway infrastructure in Toronto, although to a lesser extent than in Montreal. While high accessibility census tracts fall along subway lines, tracts with accessibility to 100,000 to 300,000 jobs extend to upwards of 10km away from subway lines in certain parts of the CMA. This suggests that alternate forms of public transit (such as commuter rail lines or bus services) have a greater influence on patterns of job accessibility in Toronto than they do in Montreal, and that job locations are less centralized in Toronto. Still, nearly all census tracts outside of the City of Toronto have low job accessibility, with clusters of lower mid-range (100,000 to 300,000 jobs) accessibility tracts in neighboring census subdivisions.

Figures 5 and 6 show the number of workers accessible (scaled to 1:100,000 workers accessible within 45 minutes of commuting via public transit) by census tract in the Montreal and Toronto CMAs, respectively. In Montreal and Toronto, worker accessibility is closely aligned with job accessibility: areas that have high accessibility to jobs also have high accessibility to workers and vice-versa. However, in both CMAs, the maximum level of worker accessibility is far lower than the maximum level of job accessibility (~600,000 workers versus ~900,000 jobs), suggesting that many job-holders commute from areas that are inaccessible within 45 minutes of public transit, either commuting by public transit for longer durations or commuting by other modes.

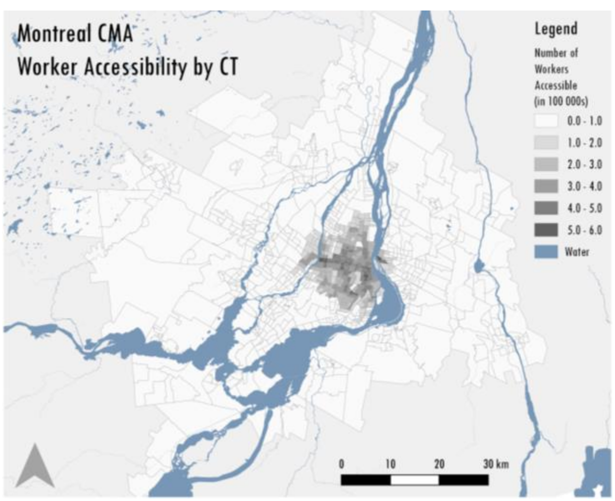


**Figure 5** Montreal CMA Worker Accessibility by CT

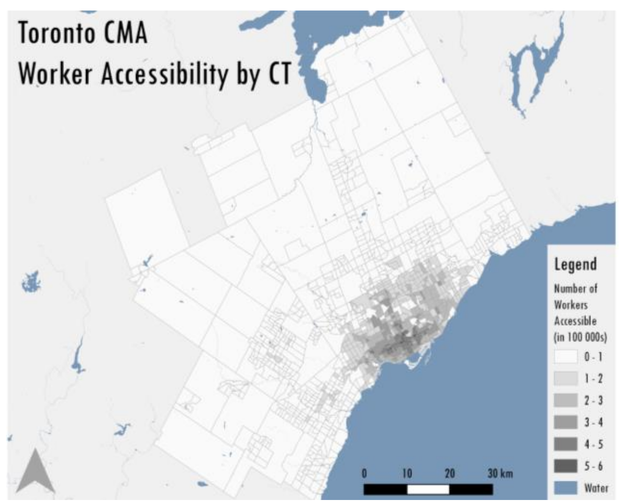


**Figure 6** Toronto CMA Worker Accessibility by CT

Visualizing transit-based job and worker accessibility is useful for understanding the relationships between transit infrastructures, job locations, and commuting potential. Geographies of employment and immigrant residential locations complicate these dynamics by highlighting incongruences and outliers. Figures 7 and 8 show unemployment rates by census tract in the Montreal and Toronto CMAs. Unemployment is patchy in Montreal: some clusters of tracts with high (>13%) unemployment rates are surrounded by a gradient of tracts with decreasing unemployment, while some high-unemployment tracts are contiguous to low-unemployment (<2.4%) tracts. Although there is a visible overlap of high accessibility and low unemployment in certain areas, many census tracts with above-average (>7.5%) unemployment rates are also census tracts with relatively high job accessibility. Several of these high-access and high-unemployment clusters are located within Montreal's urban core; the remainder are located along the boundaries of high-accessibility areas outside the urban core. In Toronto, most areas with high unemployment rates are outside of the urban core and appear to extend outwards relatively aligned with the gradient of accessibility. While Toronto's urban core has some census tracts with above-average unemployment (>7.7%) and relatively high job accessibility, there are large clusters of high unemployment rates in lower-accessibility areas outside the urban core.

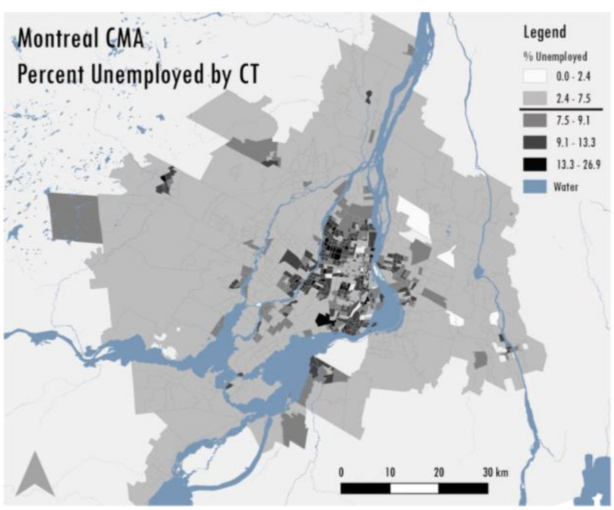


Figure 7 Montreal CMA Percent Unemployed by CT

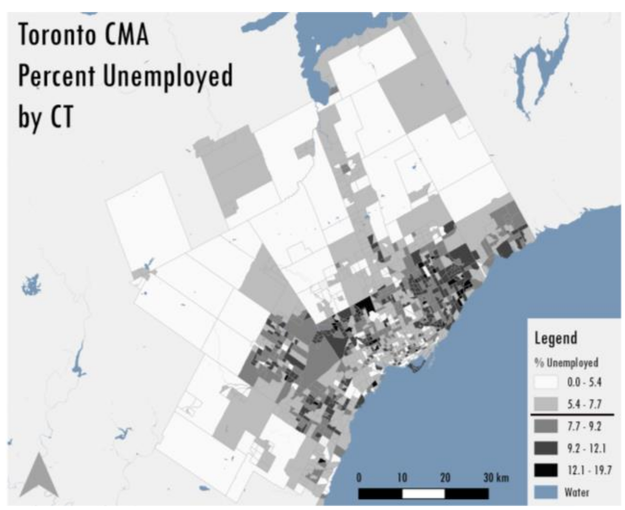


Figure 8 Toronto CMA Percent Unemployed by CT

Figures 9 and 10 show the percentage of census tract residents with immigrant status in the Montreal and Toronto CMAs. Census tracts with high proportions of immigrant residents are fairly clustered on the Island of Montreal, with two clusters extending into the South-shore and Laval areas. Overall, there is a gradient in the distribution of immigrant residential locations, covering almost all of the Island of Montreal and spreading outwards throughout the nearest subdivisions. There are several clusters of census tracts that show an overlap of high job accessibility, high unemployment rates, and higher proportions of immigrant residents. Toronto displays an overall similar immigrant residential distribution: although there are some clusters of census tracts with larger proportions of immigrants within the urban core, there are far larger clusters outside Toronto's urban core, and these extend outward as a gradient of immigrant residents throughout the entire CMA. There are relatively few census tracts that show an overlap of high job accessibility, high unemployment rates, and a large proportion of immigrant residents. Importantly, this is a somewhat uneven comparison between the two CMAs: whereas the proportion of immigrant residents per census tract varies from 0% to 67% in Montreal, the maximum proportion of immigrant residents per tract in Toronto is 77%.

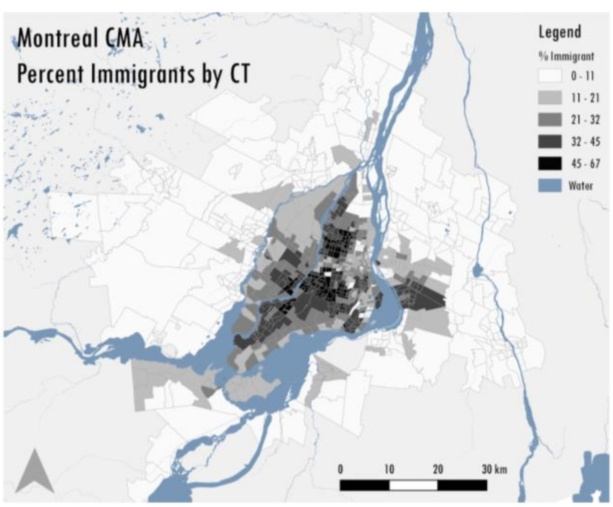


Figure 9 Montreal CMA Percent Immigrants by CT

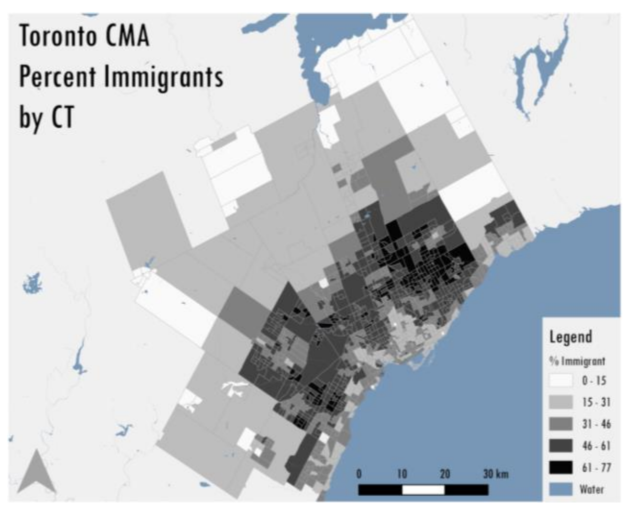


Figure 10 Toronto CMA Percent Immigrants by CT

### 4.2.2 Measuring and Accounting for Spatial Autocorrelation

Global indices of spatial autocorrelation are used to test for neighborhood spatial dependence in the dependent variable. Global indices were calculated using the Moran's *I* statistic, expressed as:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}\, z_i z_j}{\sum_{i=1}^{n} z_i^2}$$

where $z_i$ is the deviation in the proportion of employed residents in census tract $i$ from the mean level of employed residents $w_{i,j}$ $(xi - \bar{X})$, $w_{i,j}$ is the spatial weight between census tracts $i$ and $j$, and $n$ is the total number of census tracts in the study area. $S_0$ is the aggregate of all spatial weights, expressed as:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}$$

Global indices were computed using the *Spatial Autocorrelation (Global Moran's I)* tool available in ArcGIS v10, with spatial relationships conceptualized as inverse distances. The tool outputs the Moran's *I* value, which is then compared with an estimated *I* value. The tool calculates a z-score and p-value estimating the significance of the Moran's *I* value based on the difference between the actual and estimated *I*.

Moran's *I* values vary between -1 and +1 and must be interpreted in the context of the null hypothesis. In this case, the null hypothesis states that employment is randomly distributed across census tracts in the study areas. The results for the Moran's *I* test are reported in Table 4. Since the p-values are significant ($p<0.001$) and the z-scores are positive, we may reject the null hypothesis for both CMAs. The spatial distribution of census tracts with high- and low- proportions of employed residents is more clustered than what would be expected if employed residents were randomly distributed over census tracts.

**Table 4** Moran's I results for Montreal and Toronto CMAs

| | Montreal | Toronto |
|---|---|---|
| Moran's *I* | 0.193222 | 0.159477 |
| E[*I*] | -0.001048 | -0.000872 |
| Variance | 0.000014 | 0.000014 |
| z-score | 51.690008 | 43.399541 |
| p-value | 0.000 | 0.000 |

A spatial lag of the dependent variable was created in order to account for potential spatial spillover effects in neighborhood-level employment rates. Stata's `sp` commands were used to convert CT shapefiles into Stata-format datasets, merge census data with the Stata-formatted shapefiles using unique CT identifiers, create spatial weighting matrices from the CT datasets, and finally generate variables containing spatial lags of neighborhood-level employment. Spatial lag variables are included in all final regression models, accounting for potential effects that employment rates in one census tract have on employment rates in nearby census tracts.

### 4.3 Regression Modeling

#### 4.3.1 Part One: Accessibility and Employment

The first set of models focus on job accessibility and the likelihood of employment among immigrants and non-immigrants in Montreal and Toronto. Logistic regression models in part one take the form:

$$P_i(E) = f(IM_i, A_i, D_i, IF_i, HC_i, N_i, \lambda W_E)$$

where $P_i(E)$ is the probability of employment for individual $i$, $IM_i$ is an indicator of immigrant status, $A_i$ is the measure of spatial accessibility to jobs from individual $i$'s census tract of residence, $D_i$ is a vector of demographic characteristics, $IF_i$ is a vector of individual-level factors, $HC_i$ is a vector of human capital characteristics, $N_i$ is a vector of neighborhood characteristics from individual $i$'s census tract of residence, and $\lambda W_E$ is the spatial lag of the dependent variable.

*Logistic Regressions*

Table 5 shows the logistic regression outputs for Montreal Models 1-5,[5] reported as odds ratios. Immigrant status and job accessibility are significant ($p<0.001$) and negative throughout all models. In Model 5, the odds of being employed for immigrants is 0.732 times that of Canadian-born labour force members. Each additional level of job accessibility (+100,000 jobs) is associated with a 3% lower odds of being employed in the final model.

The odds associated with all individual-level demographic characteristics - sex, age, age$^2$, marital status, having young children, and the interaction between female sex and having young children - are fairly consistent throughout Models 1-5, and are all significant ($p<0.001$) in the final model. Sex, age, and marital status are positively associated with employment in Montreal. In Model 5, women have a 19.4% higher chance of being employed than men, and individuals who are married have a 31% higher chance of being employed than those who are not married. Although each additional year of age is associated with an 11.9% higher chance of being employed, the negative and significant ($p<0.001$) effect of age$^2$ suggests that as individuals get older, the effect of age is lessened. Having children aged 0-5 is associated with a 13.9% lower odds of being employed than not having young children. Interestingly, the effect of the interaction term (female sex*young children) is negative and significant ($p<0.001$) in Model 5, while it is not significant and minimally significant ($p<0.05$) in Models 2 and 3, respectively. Women with young children have an 8% lower chance of being employed than women without young children and men with or without young children.

[5] See Appendix C Table C1 for Model 5 full regression output.

| **Table 5** Logistic regression results for odds of being employed in Montreal - Part 1 Models 1-5 (odds ratios) | | **M1** | | **M2** | | **M3** | | **M4** | | **M5** | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| IMMIGRANT STATUS | | 0.632 | *** | 0.496 | *** | 0.682 | *** | 0.705 | *** | 0.732 | *** |
| JOB ACCESSIBILITY | | 0.954 | *** | 0.965 | *** | 0.975 | *** | 0.962 | *** | 0.97 | *** |
| SEX (FEMALE) | | | | 1.181 | *** | 1.205 | *** | 1.194 | *** | 1.194 | *** |
| AGE | | | | 1.191 | *** | 1.164 | *** | 1.119 | *** | 1.119 | *** |
| AGE^2 | | | | 0.998 | *** | 0.998 | *** | 0.999 | *** | 0.999 | *** |
| MARRIED | | | | 1.24 | *** | 1.298 | *** | 1.307 | *** | 1.31 | *** |
| KIDS AGED 0 to 5 | | | | 0.854 | *** | 0.86 | *** | 0.86 | *** | 0.861 | *** |
| SEX*KIDS 0 to 5 | | | | 0.956 | | 0.943 | * | 0.921 | *** | 0.92 | *** |
| RECENT IMMIGRANT | | | | | | 0.548 | *** | 0.592 | *** | 0.595 | *** |
| VISIBLE MINORITY | | | | | | 0.697 | *** | 0.745 | *** | 0.751 | *** |
| ATTENDING SCHOOL | | | | | | 0.729 | *** | 0.68 | *** | 0.682 | *** |
| SECOND GEN. CANADIAN | | | | | | 0.836 | *** | 0.79 | *** | 0.814 | *** |
| OFFICIAL LANGUAGE KNOWLEDGE (BASE BOTH) | ENGLISH ONLY | | | | | | | 0.769 | *** | 0.752 | *** |
| | FRENCH ONLY | | | | | | | 0.814 | *** | 0.813 | *** |
| | NEITHER | | | | | | | 0.728 | *** | 0.73 | *** |
| EDUCATION (BASE HIGH SCHOOL DEGREE OR LESS) | DIP/CERT <BACH | | | | | | | 0.967 | | 0.96 | |
| | BACH DEGREE OR | | | | | | | 1.238 | *** | 1.228 | *** |
| ECON MIGRANT PRINCIPAL APPLICANT | | | | | | | | 1.209 | *** | 1.201 | *** |
| POST-SECONDARY STUDIES IN CANADA | | | | | | | | 1.513 | *** | 1.523 | *** |
| WORKER ACCESSIBILITY | | | | | | | | | | 1.012 | |
| URBAN CORE INDEX (BASE SUBURBAN) | | | | | | | | | | 0.808 | *** |
| SPATIAL LAG | | | | | | | | | | 0.644 | *** |
| INTERCEPT | | 16.564 | *** | 0.474 | *** | 0.959 | | 1.639 | *** | 2.439 | *** |
| **MODEL FIT** | | | | | | | | | | | |
| PSEUDO-R2 (McKelvey & Zavoina) | | 0.021 | | 0.075 | | 0.083 | | 0.102 | | 0.104 | |
| LOG LIKELIHOOD MODEL | | -534400.604 | | -519729.11 | | -515420.997 | | -510465.217 | | -510124.277 | |
| LOG LIKELIHOOD INTERCEPT-ONLY | | -539776.117 | | -539776.117 | | -539776.117 | | -539776.117 | | -539776.117 | |
| DEVIANCE | | 1068801.207 | | 1039458.22 | | 1030841.995 | | 1020930.434 | | 1020248.555 | |
| WALD | | 2595.087 | | 9691.439 | | 12250.641 | | 14727.974 | | 14816.583 | |
| AIC | | 1068807.207 | | 1039476.22 | | 1030867.995 | | 1020970.434 | | 1020294.555 | |
| BIC | | 1068840.604 | | 1039576.411 | | 1031012.716 | | 1021193.082 | | 1020550.599 | |

*** = p<0.001, ** = p<0.01, * = p<0.05

The effects of individual-level factors - recent immigrant status, visible minority status, school attendance, and having parents born outside Canada - are stable, negative, and significant ($p<0.001$) throughout Models 3-5. In the final model, recent immigrants have a 40.5% lower chance of being employed than long-term immigrants and non-immigrants in the labour force. Recent immigrant status has the strongest negative effect of all variables in Model 5. Visible minorities have a 24.9% lower chance of being employed than those who are not visible minorities. Individuals who are currently attending school have a 31.8% lower chance of being employed than those who are not attending school. Finally, individuals with parents born outside Canada have an 18.6% lower chance of employment compared to immigrants and individuals whose parents were born in Canada.

Human capital characteristics - official language knowledge, level of education, admittance through the economic migration stream, and completion of postsecondary studies in Canada - have positive and negative effects on the likelihood of employment in Montreal. These effects are consistent and nearly all are significant ($p<0.001$) throughout Models 4-5. Compared to those who speak both English and French, individuals who speak only English, only French, or neither French nor English have a 24.8%, 18.7%, and 27% lower chance of being employed, respectively. Individuals who have completed a Bachelor's Degree or higher levels of education have a 22.8% higher chance of being employed than those who have completed a High School Diploma or less. The effect of completing a Diploma or Certificate between High School and a Bachelor's Degree is negative (4% lower chance than those with a High School education or less) and not significant ($p>0.05$). Immigrants who were admitted to Canada as economic migrants (principle applicants) have a 20.1% higher chance of being employed than other immigrants and non-immigrants. Completing post-secondary studies in Canada is associated with a 52.3% higher chance of being employed compared to not completing post-secondary studies and completing post-secondary studies outside Canada. This factor has the highest odds ratio of all variables in Model 5.

Neighborhood-level variables - worker accessibility, the urban core index, and the spatial lag of employment - are introduced in the final model. Although there is a positive association between worker accessibility and employment status in Montreal, the effect is minor and not significant ($p>0.05$). Individuals living outside the urban core have a 19.2% lower chance of being employed compared to those who reside within the urban core. The effect of the neighborhood-level spatial lag of employment is negative and significant ($p<0.001$).

Table 6 shows the logistic regression outputs for Toronto Models 1-5,[6] reported as odds ratios. Unlike in Montreal, the effects of immigrant status and job accessibility are inconsistent and vary in significance across Models 1-5. Although immigrant status has a positive and significant ($p<0.001$) effect on the likelihood of employment in Model 1, this changes to a negative effect in Models 2-4, and is no longer significant in Models 4 and 5 ($p>0.05$). On the other hand, job accessibility is not a significant predictor of employment status in Models 1-3, but becomes significant ($p<0.001$) in Model 4 and ultimately has a positive and significant effect in Model 5. In the final model, a one-unit increase in job accessibility (+100,000 jobs) is associated with a 3.9% greater chance of employment.

The effects of individual-level demographic characteristics are fairly consistent throughout Models 1-5, and nearly all are significant ($p<0.001$) in the final model. Sex, age, marital status, and having young children are positively associated with employment in Toronto. Women have a 2.1% greater chance of being employed relative to men, though this effect is not significant ($p>0.05$). Individuals who are married have a 41% greater chance of being employed compared to

[6] See Appendix C Table C2 for Model 5 full regression output.

those who are not married, and individuals with young children have a 14.7% greater chance of being employed compared to those without young children. Although each additional year of age is associated with a 10.4% higher chance of being employed, the negative and significant ($p<0.001$) effect of age$^2$ suggests that as individuals get older, the effect of age is lessened. The interaction term combining the effects of female sex and having young children is consistent throughout models, decreasing the chance of employment by 27.3% ($p<0.001$).

The effects of individual-level factors are stable across Models 1-5. Recent immigrant status, visible minority status, and school attendance are negatively and significantly ($p<0.001$) associated with employment in Toronto. Recent immigrants have a 36.9% lower chance of being employed compared to long-term immigrants and non-immigrants. Individuals who are members of a visible minority have a 26.2% lower chance of being employed than those who are not members of visible minorities. Individuals who are attending school have a 42.6% lower chance of being employed compared to those who are not attending school. School attendance is the strongest negative effect in Model 5. Having parents who were born outside Canada has a positive, though not significant ($p>0.05$), association with employment in Toronto.

While the values for human capital characteristics are generally stable across models, many variables are not significantly associated with employment status in Model 5. In terms of official language knowledge, individuals who only know English have a slight advantage over those who know both French and English, though this effect is not significant ($p>0.05$). Individuals who speak only French or speak neither English nor French have a 37.1% and 28.6% lower chance of being employed compared to those who speak both languages, respectively. Still, these effects are only minimally significant ($p<0.05$).

| **Table 6** Logistic regression results for odds of being employed in Toronto - Part 1 Models 1-5 (odds ratios) | | **M1** | **M2** | **M3** | **M4** | **M5** |
|---|---|---|---|---|---|---|
| IMMIGRANT STATUS | | 1.051 *** | 0.717 *** | 0.958 ** | 0.999 | 1.032 |
| JOB ACCESSIBILITY | | 1.001 | 1.002 | 1.001 | 0.992 *** | 1.039 *** |
| SEX (FEMALE) | | | 1.001 | 1.029 ** | 1.021 | 1.021 |
| AGE | | | 1.191 *** | 1.137 *** | 1.104 *** | 1.104 *** |
| AGE^2 | | | 0.998 *** | 0.999 *** | 0.999 *** | 0.999 *** |
| MARRIED | | | 1.375 *** | 1.409 *** | 1.428 *** | 1.410 *** |
| KIDS AGED 0 to 5 | | | 1.133 *** | 1.141 *** | 1.148 *** | 1.147 *** |
| SEX*KIDS 0 to 5 | | | 0.761 *** | 0.749 *** | 0.727 *** | 0.727 *** |
| RECENT IMMIGRANT | | | | 0.592 *** | 0.626 *** | 0.631 *** |
| VISIBLE MINORITY | | | | 0.724 *** | 0.726 *** | 0.738 *** |
| ATTENDING SCHOOL | | | | 0.574 *** | 0.573 *** | 0.574 *** |
| SECOND GEN. CANADIAN | | | | 1.010 | 1.004 | 1.025 |
| OFFICIAL LANGUAGE KNOWLEDGE (BASE BOTH) | ENGLISH ONLY | | | | 1.029 | 1.031 |
| | FRENCH ONLY | | | | 0.622 * | 0.629 * |
| | NEITHER | | | | 0.701 *** | 0.714 * |
| EDUCATION (BASE HIGH SCHOOL DEGREE OR LESS) | DIP/CERT <BACH DEGREE | | | | 0.978 | 0.977 |
| | BACH DEGREE OR MORE | | | | 1.088 *** | 1.085 *** |
| ECON MIGRANT PA | | | | | 1.280 *** | 1.282 *** |
| STUDIES IN CAN. | | | | | 1.469 *** | 1.467 *** |
| WORKER ACCESSIBILITY | | | | | | 0.937 *** |
| URBAN CORE INDEX (BASE SUBURBAN) | | | | | | 0.882 *** |
| SPATIAL LAG | | | | | | 0.726 *** |
| INTERCEPT | | 11.658 *** | 0.305 *** | 1.068 | 1.446 *** | 2.001 *** |
| **MODEL FIT** | | | | | | |
| PSEUDO-R2 (McKelvey & Zavoina) | | 0.000 | 0.082 | 0.095 | 0.105 | 0.106 |
| LOG LIKELIHOOD MODEL | | -825046.780 | -786176.923 | -777864.609 | -773377.504 | -772819.313 |
| LOG LIKELIHOOD INTERCEPT-ONLY | | -825114.575 | -825114.575 | -825114.575 | -825114.575 | -825114.575 |
| DEVIANCE | | 1650093.561 | 1572353.846 | 1555729.218 | 1546755.009 | 1545638.625 |
| WALD | | 31.063 | 18942.494 | 23628.418 | 25985.115 | 26147.050 |
| AIC | | 1650099.561 | 1572371.846 | 1555755.218 | 1546795.009 | 1545684.625 |
| BIC | | 1650134.093 | 1572475.443 | 1555904.859 | 1547025.225 | 1545949.374 |

*** = p<0.001, ** = p<0.01, * = p<0.05

The effect of completing a diploma or certificate between high school and a Bachelor's Degree is negative (2.3% lower chance than those with a high school education or less) and not significant ($p>0.05$). Individuals who have completed a Bachelor's Degree have an 8.5% greater chance ($p<0.001$) of being employed, compared to those with a high school diploma or less. Immigrants who were admitted to Canada as economic migrants (principal applicants) have a 28.2% higher chance of being employed than non-immigrants and immigrants who were admitted through other streams. As in Montreal, completing post-secondary studies in Canada has the highest odds ratio of all variables in Model 5. In Toronto, individuals who completed post-secondary studies in Canada have a 46.7% higher chance of being employed compared to those who completed post-secondary studies outside Canada and those who have not completed post-secondary studies.

All neighborhood-level variables are negatively related to the likelihood of employment ($p<0.001$) in the final model. A one-unit increase in worker accessibility lowers the odds of employment by 6.3% in Toronto. Residing outside the urban core is associated with an 11.8% lower chance of employment compared to residing within the urban core. The spatial lag of neighborhood-level employment rates is negatively associated with the likelihood of employment.

***Model Fit***

There is a consistent increase in goodness-of-fit over Montreal Models 1-5. As reported in the bottom portion of Table 3, each additional set of variables improves on the model fit of previous models. Model 2 understandably offers the greatest improvement over Model 1. Models 3 (versus Model 2) and 4 (versus Model 3) show a similar magnitude of improvement in terms of changes in log-likelihood, Wald tests, AIC, and BIC, although Model 4 accounts for a comparatively greater change in pseudo-$R^2$. The addition of neighborhood-level variables in Model 5 improves model fit to a lesser degree than previous models.

Similarly, demographic variables added in Model 2 improve model fit for Toronto more than any other set of variables. Models 3 (versus Model 2) and 4 (versus Model 3) show decreasing magnitudes of improvement for all tests. Focusing on changes in pseudo-$R^2$, we observe only minor improvements with Models 2-4. Montreal and Toronto show similar magnitudes of improvement in model fit with the inclusion of neighborhood variables.

***Marginal Effects***

Marginal effects are first examined as the average marginal effects of all variables on the probability of employment in each model. Table 7 presents the average marginal effects for Montreal Models 1-5. Although most of the marginal effects are significant ($p<0.001$), several discrete changes within the human capital variables and all changes reported for the worker accessibility variable are not significant ($p>0.05$). Table 8 shows the separate marginal effect of each variable added between Montreal Models 2 and 3 (recent immigrant, visible minority, attending school, second generation Canadian). All marginal effects reported in Table 8 are significant ($p<0.001$).

The marginal effect of immigrant status decreases after individual-level factors are incorporated in Model 3. Considering the separate effect of each variable added to Model 3, it is evident that the marginal effect of immigrant status decreases when recent immigrant status and, to a greater extent, visible minority status are included in Models 3.1 and 3.2, respectively. The effect of immigrant status is lowest after the introduction of neighborhood-level variables. Similarly, the marginal negative effect of job accessibility decreases slightly for every model that accounts for combined individual-level factors.

**Table 7** Marginal effects on probability of being employed in Montreal – Part 1 Models 1-5

| Variable | Margin | M1 | | M2 | | M3 | | M4 | | M5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | dy/dx | | | | | | | | | |
| IMMIGRANT STATUS | 1 vs 0 | -0.033 | *** | -0.053 | *** | -0.027 | *** | -0.024 | *** | -0.021 | *** |
| JOB ACCESSIBILITY | +1 centered | -0.003 | *** | -0.002 | *** | -0.002 | *** | -0.003 | *** | -0.002 | *** |
| | +SD centered | -0.009 | *** | -0.007 | *** | -0.005 | *** | -0.007 | *** | -0.006 | *** |
| | Marginal | -0.003 | *** | -0.002 | *** | -0.002 | *** | -0.003 | *** | -0.002 | *** |
| SEX | 1 vs 0 | | | 0.01 | *** | 0.011 | *** | 0.009 | *** | 0.009 | *** |
| AGE | +1 centered | | | 0.012 | *** | 0.01 | *** | 0.007 | *** | 0.007 | *** |
| | +SD centered | | | 0.163 | *** | 0.137 | *** | 0.098 | *** | 0.097 | *** |
| | Marginal | | | 0.012 | *** | 0.01 | *** | 0.007 | *** | 0.007 | *** |
| AGE^2 | +1 centered | | | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** |
| | +SD centered | | | -0.145 | *** | -0.129 | *** | -0.091 | *** | -0.09 | *** |
| | Marginal | | | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** |
| MARRIED | 1 vs 0 | | | 0.014 | *** | 0.016 | *** | 0.017 | *** | 0.017 | *** |
| KIDS | 1 vs 0 | | | -0.012 | *** | -0.012 | *** | -0.013 | *** | -0.012 | *** |
| RECENT IMMIGRANT | 1 vs 0 | | | | | -0.049 | *** | -0.041 | *** | -0.041 | *** |
| VISIBLE MINORITY | 1 vs 0 | | | | | -0.025 | *** | -0.02 | *** | -0.02 | *** |
| ATTENDING SCHOOL | 1 vs 0 | | | | | -0.022 | *** | -0.027 | *** | -0.027 | *** |
| SECOND GENERATION | 1 vs 0 | | | | | -0.012 | *** | -0.016 | *** | -0.014 | *** |
| OFFICIAL LANGUAGE KNOWLEDGE | 2 vs 1 | | | | | | | 0.004 | *** | 0.006 | ** |
| | 3 vs 1 | | | | | | | 0.018 | *** | 0.02 | *** |
| | 4 vs 1 | | | | | | | -0.004 | N.S. | -0.002 | N.S. |
| | 3 vs 2 | | | | | | | 0.014 | *** | 0.014 | *** |
| | 4 vs 2 | | | | | | | -0.008 | N.S. | -0.008 | N.S. |
| | 4 vs 3 | | | | | | | -0.022 | *** | -0.022 | *** |
| EDUCATION | 1 vs 0 | | | | | | | -0.002 | N.S. | -0.003 | N.S. |
| | 2 vs 0 | | | | | | | 0.013 | *** | 0.013 | *** |
| | 2 vs 1 | | | | | | | 0.015 | *** | 0.016 | *** |
| ECON MIGRANT PA | 1 vs 0 | | | | | | | 0.012 | *** | 0.011 | *** |
| PS STUDIES IN CANADA | 1 vs 0 | | | | | | | 0.027 | *** | 0.028 | *** |
| WORKER ACCESSIBILITY | +1 centered | | | | | | | | | 0.001 | N.S. |
| | +SD centered | | | | | | | | | 0.001 | N.S. |
| | Marginal | | | | | | | | | 0.001 | N.S. |
| UCI | 1 vs 0 | | | | | | | | | 0.013 | *** |
| SPATIAL LAG | +1 centered | | | | | | | | | -0.029 | *** |
| | +SD centered | | | | | | | | | -0.009 | *** |
| | Marginal | | | | | | | | | -0.029 | *** |

*** = p<0.001, ** = p<0.01, * = p<0.05, N.S. = p>0.05

**Table 8** Marginal effects of individual-level factors on probability of being employed in Montreal - Part 1 Model 3

| Variable | Margin | M2 | | M3.1 | | M3.2 | | M3.3 | | M3.4 | | M3 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | dy/dx | | | | | | | | | | | |
| IMMIGRANT STATUS | 1 vs 0 | -0.053 | *** | -0.042 | *** | -0.032 | *** | -0.051 | *** | -0.059 | *** | -0.027 | *** |
| JOB ACCESSIBILITY | +1 centered | -0.002 | *** | -0.002 | *** | -0.002 | *** | -0.002 | *** | -0.002 | *** | -0.002 | *** |
| | +SD centered | -0.007 | *** | -0.006 | *** | -0.006 | *** | -0.006 | *** | -0.006 | *** | -0.005 | *** |
| | Marginal | -0.002 | *** | -0.002 | *** | -0.002 | *** | -0.002 | *** | -0.002 | *** | -0.002 | *** |
| SEX | 1 vs 0 | 0.01 | *** | 0.01 | *** | 0.01 | *** | 0.011 | *** | 0.01 | *** | 0.011 | *** |
| AGE | +1 centered | 0.012 | *** | 0.012 | *** | 0.011 | *** | 0.01 | *** | 0.011 | *** | 0.01 | *** |
| | +SD centered | 0.163 | *** | 0.165 | *** | 0.16 | *** | 0.135 | *** | 0.162 | *** | 0.137 | *** |
| | Marginal | 0.012 | *** | 0.012 | *** | 0.011 | *** | 0.01 | *** | 0.011 | *** | 0.01 | *** |
| AGE^2 | +1 centered | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** |
| | +SD centered | -0.145 | *** | -0.149 | *** | -0.145 | *** | -0.123 | *** | -0.146 | *** | -0.129 | *** |
| | Marginal | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** |
| MARRIED | 1 vs 0 | 0.014 | *** | 0.016 | *** | 0.014 | *** | 0.013 | *** | 0.015 | *** | 0.016 | *** |
| KIDS | 1 vs 0 | -0.012 | *** | -0.01 | *** | -0.012 | *** | -0.013 | *** | -0.013 | *** | -0.012 | *** |
| RECENT IMMIGRANT | 1 vs 0 | | | -0.05 | *** | | | | | | | -0.049 | *** |
| VISIBLE MINORITY | 1 vs 0 | | | | | -0.031 | *** | | | | | -0.025 | *** |
| ATTENDING SCHOOL | 1 vs 0 | | | | | | | -0.025 | *** | | | -0.022 | *** |
| SECOND GENERATION | 1 vs 0 | | | | | | | | | -0.022 | *** | -0.012 | *** |

Age and age$^2$ (+1 standard deviation, centered) respectively have the largest positive and negative marginal effects on the likelihood of employment throughout Models 1-5. The effect of both variables decreases substantially with the combination of education-related individual-level factors and human capital characteristics in Model 4. Since the marginal effect of the discrete change between education levels 1 and 0 is not significant ($p>0.05$), the marginal effect of educational attainment is driven by the discrete change between the highest level of education and both lower levels ($p<0.001$ in both cases). After age and age$^2$, recent immigrant status has the next largest (negative) marginal effect on employment, though the magnitude of this effect decreases with the addition of human capital variables in Model 4.

In terms of official language knowledge, the effects of discrete changes from knowing neither English nor French (oln=4) to knowing only English (oln=1) or only French (oln=2) are not significant, while the effect of a discrete change from not knowing either language to knowing both languages (oln=3) is significant (p<0.001). On the other hand, there is a positive marginal effect of knowing both English and French over all other language categories.

The marginal effects for Toronto Models 1-5 are presented in Table 9, and the marginal effects of separate individual-level factors are reported in Table 10. There is a greater number of non-significant (p>0.05) marginal effects throughout the Toronto models compared to the Montreal models. While most effects are significant (p<0.001) in the final Toronto model, immigrant status, second generation status, and several human capital categories do not have significant (p>0.05) marginal effects on employment probability.

Montreal and Toronto are especially different in terms of the marginal effects of immigrant status and job accessibility on the probability of employment. The effect of immigrant status fluctuates considerably across models, starting with a significant (p<0.001) yet minor effect in Model 1, then shifting to a significant (p<0.001) negative effect in Models 2 and 3, finally returning to a non-significant (p>0.05) positive effect in Models 4 and 5. As in Montreal, recent immigrant and visible minority status separately and jointly reduce the marginal effect of immigrant status on employment in Toronto.

The effects of job accessibility similarly reverse significance in Model 4 and shift in direction in Model 5. Discrete and marginal changes in job accessibility have no effect (p>0.05) on employment probability in Models 1-3. This becomes a significant (p<0.001) and very minor negative marginal effect once human capital variables are accounted for in Model 4, turning to a significant (p<0.001) and slightly greater positive effect with the inclusion of neighborhood variables in Model 5. The marginal effect of job accessibility exhibits the greatest positive change when models account for worker accessibility and the spatial lag of neighborhood employment.

**Table 9** Marginal effects on probability of being employed in Toronto – Part 1 Models 1-5

| | | M1 | | M2 | | M3 | | M4 | | M5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Margin** | | | | | **dy/dx** | | | | | |
| IMMIGRANT STATUS | 1 vs 0 | 0.004 | *** | -0.023 | *** | -0.003 | ** | 0.000 | N.S. | 0.002 | N.S. |
| JOB ACCESSIBILITY | +1 centered | 0.000 | N.S. | 0.000 | N.S. | 0.000 | N.S. | -0.001 | *** | 0.003 | *** |
| | +SD centered | 0.000 | N.S. | 0.000 | N.S. | 0.000 | N.S. | -0.001 | *** | 0.007 | *** |
| | Marginal | 0.000 | N.S. | 0.000 | N.S. | 0.000 | N.S. | -0.001 | *** | 0.003 | *** |
| SEX | 1 vs 0 | | | -0.005 | *** | -0.004 | *** | -0.005 | *** | -0.005 | *** |
| AGE | +1 centered | | | 0.012 | *** | 0.009 | *** | 0.007 | *** | 0.007 | *** |
| | +SD centered | | | 0.17 | *** | 0.119 | *** | 0.089 | *** | 0.09 | *** |
| | Marginal | | | 0.012 | *** | 0.009 | *** | 0.007 | *** | 0.007 | *** |
| AGE^2 | +1 centered | | | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** |
| | +SD centered | | | -0.141 | *** | -0.104 | *** | -0.076 | *** | -0.076 | *** |
| | Marginal | | | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** |
| MARRIED | 1 vs 0 | | | 0.022 | *** | 0.023 | *** | 0.024 | *** | 0.023 | *** |
| KIDS | 1 vs 0 | | | -0.001 | N.S. | -0.001 | N.S. | -0.002 | * | -0.002 | ** |
| RECENT IMMIGRANT | 1 vs 0 | | | | | -0.043 | *** | -0.037 | *** | -0.036 | *** |
| VISIBLE MINORITY | 1 vs 0 | | | | | -0.022 | *** | -0.022 | *** | -0.021 | *** |
| ATTENDING SCHOOL | 1 vs 0 | | | | | -0.043 | *** | -0.043 | *** | -0.043 | *** |
| SECOND GENERATION | 1 vs 0 | | | | | 0.001 | N.S. | 0.000 | N.S. | 0.002 | N.S. |
| OFFICIAL LANGUAGE KNOWLEDGE | 2 vs 1 | | | | | | | -0.041 | * | -0.04 | * |
| | 3 vs 1 | | | | | | | -0.002 | N.S. | -0.002 | N.S. |
| | 4 vs 1 | | | | | | | -0.03 | *** | -0.029 | *** |
| | 3 vs 2 | | | | | | | 0.039 | * | 0.038 | * |
| | 4 vs 2 | | | | | | | 0.011 | N.S. | 0.012 | N.S. |
| | 4 vs 3 | | | | | | | -0.028 | *** | -0.027 | *** |
| EDUCATION | 1 vs 0 | | | | | | | -0.002 | N.S. | -0.002 | N.S. |
| | 2 vs 0 | | | | | | | 0.006 | *** | 0.005 | *** |
| | 2 vs 1 | | | | | | | 0.007 | *** | 0.007 | *** |
| ECON MIGRANT PA | 1 vs 0 | | | | | | | 0.016 | *** | 0.016 | *** |
| PS STUDIES IN CANADA | 1 vs 0 | | | | | | | 0.026 | *** | 0.026 | *** |
| WORKER ACCESSIBILITY | +1 centered | | | | | | | | | -0.004 | *** |
| | +SD centered | | | | | | | | | -0.006 | *** |
| | Marginal | | | | | | | | | -0.004 | *** |
| UCI | 1 vs 0 | | | | | | | | | 0.008 | *** |
| SPATIAL LAG | +1 centered | | | | | | | | | -0.022 | *** |
| | +SD centered | | | | | | | | | -0.006 | *** |
| | Marginal | | | | | | | | | -0.022 | *** |

*** = p<0.001, ** = p<0.01, * = p<0.05, N.S. = p>0.05

**Table 10** Marginal effects of individual-level factors on probability of being employed in Toronto - Part 1 Model 3

| Variable | Margin | M2 | | M3.1 | | M3.2 | | M3.3 | | M3.4 | | M3 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | dy/dx | | | | | | | | | | | |
| IMMIGRANT STATUS | 1 vs 0 | -0.023 | *** | -0.017 | *** | -0.01 | *** | -0.022 | *** | -0.028 | *** | -0.003 | ** |
| JOB ACCESSIBILITY | +1 centered | 0.000 | N.S. | 0.000 | ** | 0.000 | N.S. | 0.000 | N.S. | 0.000 | N.S. | 0.000 | N.S. |
| | +SD centered | 0.000 | N.S. | 0.001 | ** | 0.000 | N.S. | 0.000 | N.S. | 0.000 | N.S. | 0.000 | N.S. |
| | Marginal | 0.000 | N.S. | 0.000 | ** | 0.000 | N.S. | 0.000 | N.S. | 0.000 | N.S. | 0.000 | N.S. |
| SEX | 1 vs 0 | -0.005 | *** | -0.005 | *** | -0.005 | *** | -0.004 | *** | -0.005 | *** | -0.004 | *** |
| AGE | +1 centered | 0.012 | *** | 0.012 | *** | 0.012 | *** | 0.009 | *** | 0.012 | *** | 0.009 | *** |
| | +SD centered | 0.17 | *** | 0.169 | *** | 0.169 | *** | 0.12 | *** | 0.171 | *** | 0.119 | *** |
| | Marginal | 0.012 | *** | 0.012 | *** | 0.012 | *** | 0.009 | *** | 0.012 | *** | 0.009 | *** |
| AGE^2 | +1 centered | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** |
| | +SD centered | -0.141 | *** | -0.143 | *** | -0.142 | *** | -0.101 | *** | -0.142 | *** | -0.104 | *** |
| | Marginal | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** | 0.000 | *** |
| MARRIED | 1 vs 0 | 0.022 | *** | 0.024 | *** | 0.021 | *** | 0.021 | *** | 0.022 | *** | 0.023 | *** |
| KIDS | 1 vs 0 | -0.001 | N.S. | 0.001 | N.S. | -0.001 | N.S. | -0.003 | *** | -0.001 | N.S. | -0.001 | N.S. |
| RECENT IMMIGRANT | 1 vs 0 | | | -0.044 | *** | | | | | | | -0.043 | *** |
| VISIBLE MINORITY | 1 vs 0 | | | | | -0.023 | *** | | | | | -0.022 | *** |
| ATTENDING SCHOOL | 1 vs 0 | | | | | | | -0.044 | *** | | | -0.043 | *** |
| SECOND GENERATION | 1 vs 0 | | | | | | | | | -0.009 | *** | 0.001 | N.S. |

The marginal effects of age and age$^2$ in Toronto are similar to those found in Montreal in terms of direction, magnitude, and patterns of fluctuation. Age and age$^2$ have the largest positive and negative marginal effects on the likelihood of employment in Toronto, and the magnitude of these effects is fairly similar across corresponding models of Montreal. The marginal effects of age and age$^2$ fluctuate with the inclusion of school attendance, educational attainment, and completing post-secondary studies in Canada, and these effects decrease most when all three education-related variables are included (Models 4 and 5).

In order to further explore the relationship between immigrant status, job accessibility, and likelihood of employment, marginal effects of independent variables are estimated separately by subpopulation (immigrants versus non-immigrants) and level of job accessibility (units of 100,000 jobs). Table 11 shows the marginal effect of (most) Model 5 categorical variables on the probability of employment for immigrants and non-immigrants in Montreal and Toronto.

**Table 11** Marginal effects on probability of being employed by immigrant status (Model 5)

| | | Montreal | | Toronto | |
|---|---|---|---|---|---|
| | | dy/dx | | dy/dx | |
| | SEX | 0.008 | *** | -0.004 | *** |
| | | ***0.012*** | *** | ***-0.005*** | *** |
| | MARRIED | 0.014 | *** | 0.022 | *** |
| | | ***0.024*** | *** | ***0.024*** | *** |
| | KIDS | -0.011 | *** | -0.002 | * |
| | | ***-0.017*** | *** | ***-0.002*** | ** |
| | VISIBLE MINORITY | -0.018 | *** | -0.022 | *** |
| | | ***-0.024*** | *** | ***-0.019*** | *** |
| | ATTENDING SCHOOL | -0.024 | *** | -0.042 | *** |
| | | ***-0.036*** | *** | ***-0.044*** | *** |
| OFFICIAL LANGUAGE KNOWLEDGE | ENGLISH ONLY | -0.017 | *** | 0.002 | N.S. |
| | | ***-0.026*** | *** | ***0.002*** | N.S. |
| | FRENCH ONLY | -0.012 | *** | -0.039 | N.S. |
| | | ***-0.018*** | *** | ***-0.038*** | N.S. |
| | NEITHER ENGLISH NOR FRENCH | -0.019 | *** | -0.027 | *** |
| | | ***-0.029*** | *** | ***-0.026*** | *** |
| EDUCATION | DIP/CERT <BACH. | -0.002 | N.S. | -0.002 | N.S. |
| | | ***-0.004*** | N.S. | ***-0.002*** | N.S. |
| | BACH. AND HIGHER | 0.011 | *** | 0.006 | *** |
| | | ***0.017*** | *** | ***0.005*** | *** |
| | POST-SECONDARY STUDIES IN CANADA | 0.025 | *** | 0.027 | *** |
| | | ***0.035*** | *** | ***0.025*** | *** |
| | UCI (OUTSIDE URBAN CORE) | -0.012 | *** | -0.008 | *** |
| | | ***-0.018*** | *** | ***-0.008*** | *** |
| | SPATIAL LAG | -0.025 | *** | -0.022 | *** |
| | | ***-0.039*** | *** | ***-0.022*** | *** |

*** = p<0.001, ** = p<0.01, * = p<0.05, N.S. = p>0.05

Subpopulations denoted as ***Immigrants*** vs Non-immigrants

All marginal effects estimated for Montreal are significant ($p<0.001$), except for the effects of one educational attainment category (diploma or certification below the Bachelor's level). Although the direction of covariate marginal effects is the same for immigrants and non-immigrants for all categorical variables, the magnitude of (positive and negative) marginal effects on employment is greater for the immigrant subpopulation in Montreal compared to the non-immigrant subpopulation, ranging from a 0.1% to a 1.3% difference in effect on employment probability. However, categorical variables exert parallel effect magnitudes by subpopulation: completing post-secondary studies in Canada has the largest positive marginal effect on the likelihood of employment for both immigrants and non-immigrants (3.5% and 2.5% increase in employment probability, respectively) in Montreal, while the spatial lag variable and visible minority status have similarly large negative marginal effects on employment (the spatial lag is associated with a 3.9% and 2.5% decrease in employment probability for immigrants and non-immigrants, respectively; visible minority status is associated with a 3.6% and 2.4% decrease in employment probability for immigrants and non-immigrants, respectively).

The marginal effects of several human capital variables are not significantly associated ($p>0.05$) with employment probability in Toronto. Non-significant marginal effects include language knowledge (French-only and English-only) and, as in Montreal, one educational attainment category (diploma or certification below the Bachelor's level). Although the direction of effects is the same for immigrants and non-immigrants in Toronto, two variables have contrary directions of effect when comparing the two CMAs. First, sex (female) has a small positive effect on employment probability in Montreal, and a smaller negative effect on employment in Toronto. Second, knowledge of only English has a strong negative effect on employment in Montreal, and a minor positive (though not significant at $p>0.05$) effect in Toronto. Differences in the magnitude of marginal effects between subpopulations are far smaller in Toronto compared to Montreal, ranging from a 0.002% to a 0.2% difference in marginal effect magnitude across categorical predictors. Unlike Montreal, many categorical variables have a smaller marginal effect on employment probability for immigrants versus non-immigrants in Toronto.

Similar to what was observed in Montreal, categorical variables exert parallel effect magnitudes relative to one another for either subpopulation. Completing post-secondary studies in Canada has the largest positive marginal effect on the likelihood of employment for both immigrants and non-immigrants (2.5% and 2.7% increase in employment probability, respectively) in Toronto, while attending school has the largest negative marginal effect on employment (4.4% and 4.2% decrease in employment probability for immigrants and non-immigrants, respectively).

Figures 11 and 12 show the marginal effects of age and worker accessibility on the probability of employment among immigrants and non-immigrants in Montreal and Toronto, respectively. The top portions of each figure support earlier observations: age has a similar marginal effect on the probability of employment across CMAs, and the marginal positive effect of age decreases as age increases. Age has a slightly higher effect on employment for immigrants and non-immigrants in Montreal compared to Toronto, but this distinction is nearly eliminated for workers aged 55 and older. In both CMAs, age has a larger positive effect on employment among immigrants compared to non-immigrants. While increasing levels of worker accessibility have virtually no marginal effect on employment for both immigrants and non-immigrants in Montreal, worker accessibility levels have very minor, but increasingly larger negative effects on employment probability in Toronto, with nearly overlapping effects by subpopulation.

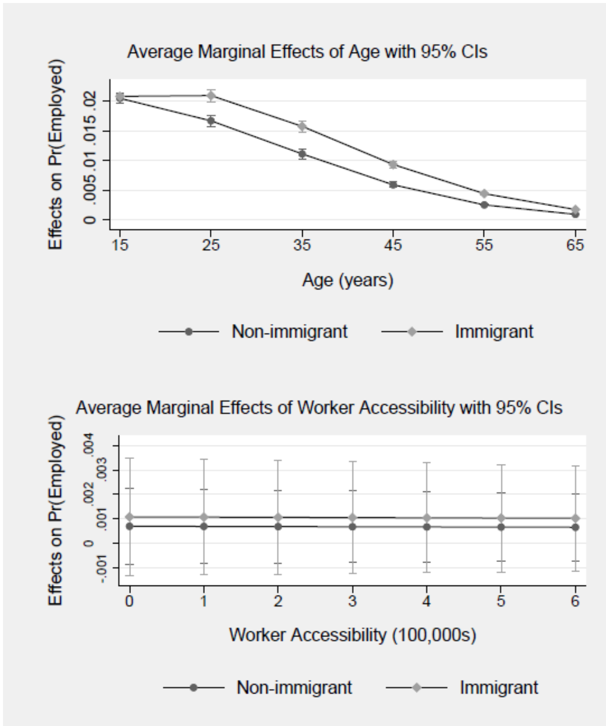


**Figure 11** Average marginal effects of age and worker accessibility on employment by subpopulation in Montreal M5

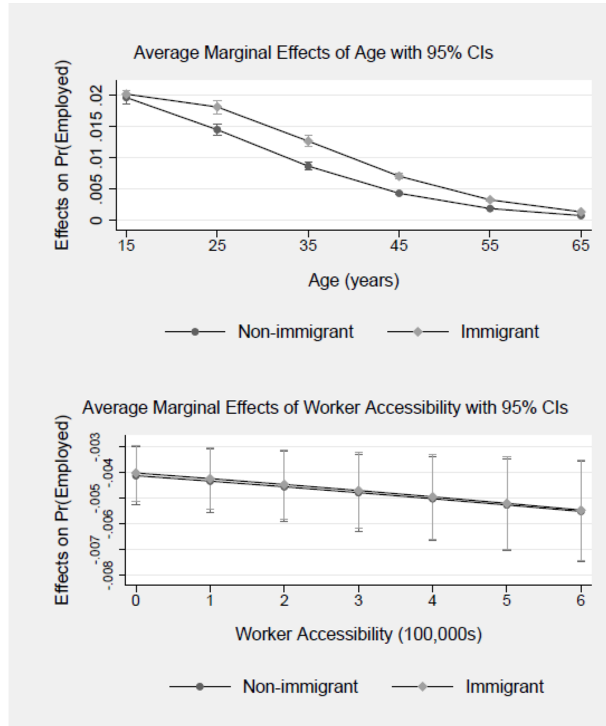


**Figure 12** Average marginal effects of age and worker accessibility on employment by subpopulation in Toronto M5

Figures 13 and 14 show the marginal effects of increasing levels of accessibility on the probability of employment for each subpopulation in Montreal Models 1-5 and Toronto Models 1-5, respectively. These figures facilitate tracking changes in the relationship between accessibility and employment when different sets of covariates are added to the CMA models.

There is a clear downward slope in the negative marginal effect of accessibility in Montreal Model 1, with a visible gap between marginal effects by subpopulation and a steeper slope for immigrants. The subpopulation gap, slope, and magnitude of the marginal effect change noticeably once demographic characteristics and individual factors are accounted for in Models 2 and 3. Accounting for human capital variables in Model 4 increases the negative effect and slope of accessibility, as well as the difference in effect by subpopulation. Model 5 decreases the effect of accessibility and dramatically extends the confidence intervals for both subpopulations.

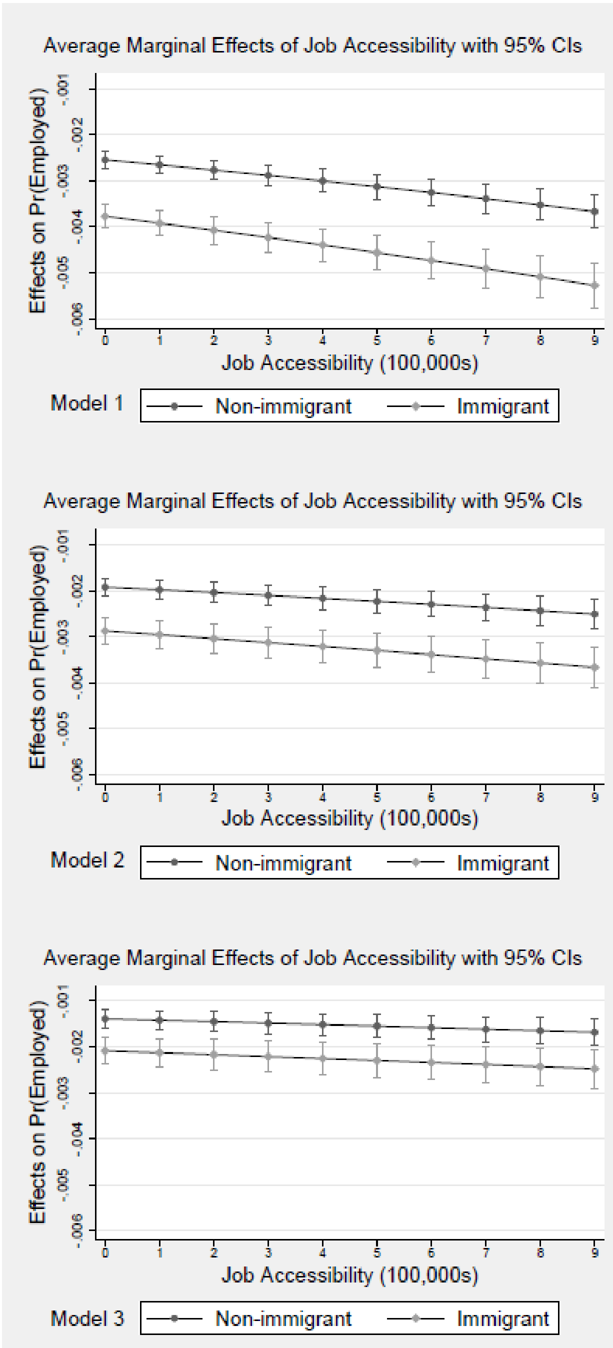


**Figure 13** Average marginal effects of job accessibility on employment by subpopulation in Montreal M1-5

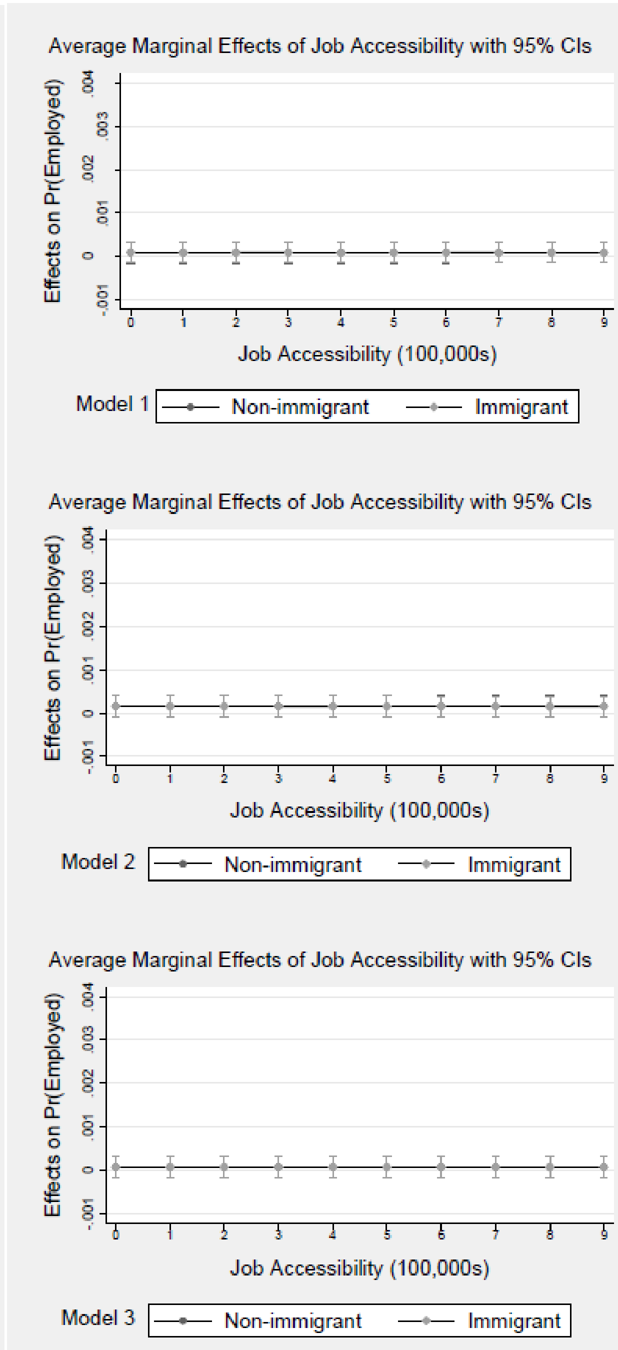


**Figure 14** Average marginal effects of job accessibility on employment by subpopulation in Toronto M1-5

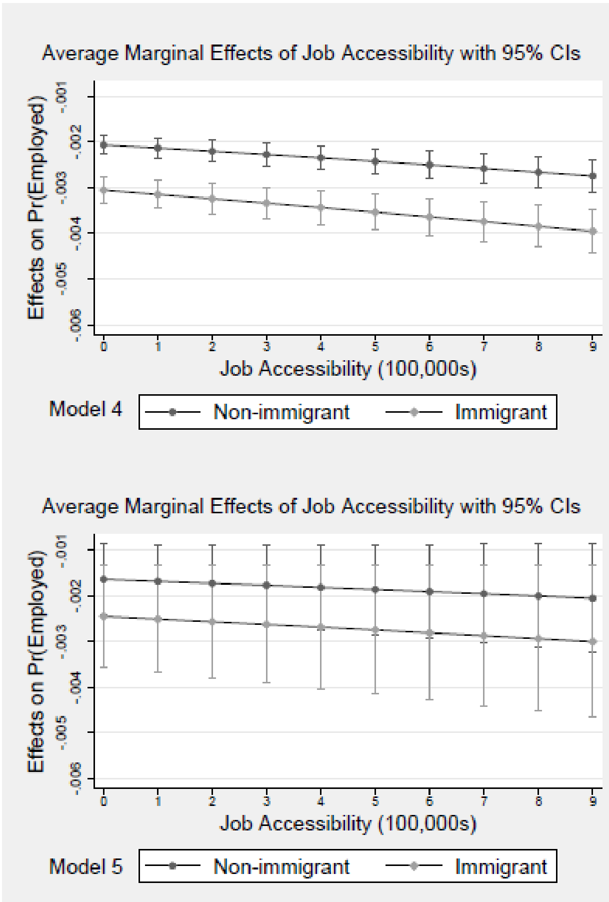


**Figure 13** *Continued*

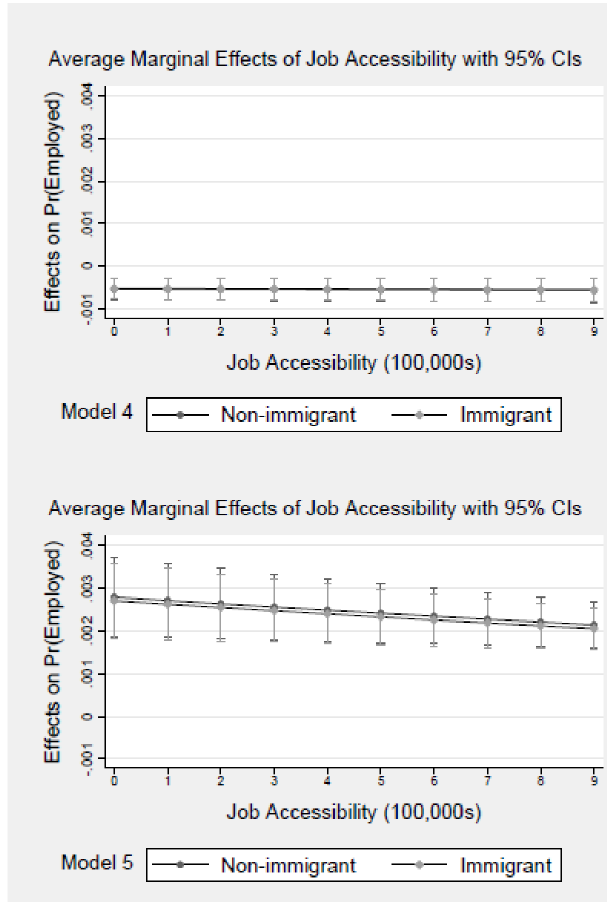


**Figure 14** *Continued*

Compared to Montreal, there is a minimal difference in the marginal effect of job accessibility between subpopulations in Toronto. In Models 1-3, accessibility has the same effect on employment at all values of accessibility (with slopes very close to 0). Once human capital variables are accounted for in Model 4, we observe an extremely small (but significant at $p<0.001$) upward gradient in the negative effect of accessibility on employment probability. There is a noticeable change in the direction and slope of marginal accessibility effects when neighborhood variables are incorporated in Model 5. The positive effect of accessibility on employment decreases over increasing levels of job accessibility.

In both CMAs, we observe a downward slope in the marginal effect of job accessibility, even after accounting for worker accessibility (a rough measure of labour market competition) and spatial autocorrelation of employment rates. Furthermore, both sets of subpopulations consistently display roughly parallel slopes across models.

### 4.3.2 Part Two: Immigrant Labour Market Dynamics

The second set of models explore how socio-spatial contexts and individual characteristics affect the likelihood of employment among immigrants in Montreal and Toronto. Logistic regression models in part two take the form:

$$P_i(E) = f(A_i, D_i, IF_i, HC_i, IC_i, N_i, \lambda W_E)$$

where $P_i(E)$ is the probability of employment for individual $i$, $A_i$ is the measure of spatial accessibility to jobs from individual $i$'s census tract of residence, $D_i$ is a vector of demographic characteristics, $IF_i$ is a vector of individual-level factors, $HC_i$ is a vector of human capital characteristics, $IC_i$ is a vector of contextual characteristics at migration, $N_i$ is a vector of neighborhood characteristics from individual $i$'s census tract of residence, and $\lambda W_E$ is the spatial lag of the dependent variable.

***Logistic Regressions***

Table 12 shows the logistic regression outputs for Montreal Models 1-6, reported as odds ratios.[7] The odds ratio for job accessibility is significant ($p<0.001$ in Models 1-5; $p<0.05$ in Model 6), negative, and increases slightly throughout Models 1-6. Each additional level of job accessibility is associated with a 2.6% decrease in the odds of being employed in the final model.

The odds associated with all individual-level demographic characteristics are mostly consistent throughout Models 1-6, and are all significant ($p<0.001$) in the final model. Female sex, age$^2$, having young children, and the interaction between female sex and having young children are negatively associated with the likelihood of employment among immigrants in Montreal. Unlike what was observed in part one, women have 9.6% lower odds of being employed compared

[7] See Appendix C Table C3 for Model 6 full regression output.

to men. Although these odds increase slightly with individual-level and human capital factors introduced in Models 3 and 4, they decrease again once age at migration, cohort, and place of birth region are taken into account. In the final model, immigrants with young children and female immigrants with young children have a 9.9% and 15.9% lower chance of being employed, respectively. Age and marital status are positively associated with employment in Model 6. While the odds of employment increase by 8.7% with additional years of age, the negative odds reported for $age^2$ suggests that the positive effect of age decreases over time. Although being married is associated with marginally lower odds of employment ($p>0.05$) in Models 2 and 3, this variable is positively linked with employment ($p<0.05$) as of Model 4. The odds of employment for married individuals increase by 14.4% with the inclusion of immigration context, and increase by another 7% with the addition of spatial factors. In the final model, immigrants who are married have a 19.8% higher chance of being employed compared to those who are not married.

Individual-level factors are negatively ($p<0.001$) associated with employment outcomes throughout Models 3-6. In the final model, visible minorities have a 12.8% lower chance of being employed, an increase of 13.5% from Model 3, especially once human capital and immigration context variables are added to the model. Immigrants who are attending school have a 40.1% lower chance of being employed, with very consistent odds reported across models.

The odds and significance of human capital characteristics fluctuate between Models 4 and 6. All language categories are negatively ($p<0.001$) associated with the likelihood of employment in the final model. Compared to those who know both English and French, immigrants who know only English, only French, or neither English nor French have 19.1%, 15.7%, and 31% lower odds of being employed, respectively. Of these, the values reported for French-only increase by 4.1% once immigration context variables are added to the model.

**Table 12** Logistic regression results for odds of being employed in Montreal - Part 2 Models 1-6 (odds ratios)

| | | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|---|
| JOB ACCESSIBILIY | | 0.943 *** | 0.954 *** | 0.953 *** | 0.954 *** | 0.960 *** | 0.974 * |
| SEX | | | 0.909 *** | 0.934 ** | 0.937 * | 0.905 *** | 0.904 *** |
| AGE | | | 1.122 *** | 1.088 *** | 1.076 *** | 1.088 *** | 1.087 *** |
| AGE^2 | | | 0.999 *** | 0.999 *** | 0.999 *** | 0.999 *** | 0.999 *** |
| MARRIED | | | 0.994 | 0.988 | 1.047 * | 1.191 *** | 1.198 *** |
| KIDS AGED 0 to 5 | | | 0.813 *** | 0.824 *** | 0.829 *** | 0.900 *** | 0.901 *** |
| SEX*KIDS 0 to 5 | | | 0.891 ** | 0.869 *** | 0.863 *** | 0.842 *** | 0.841 *** |
| VISIBLE MINORITY | | | | 0.737 *** | 0.803 *** | 0.870 *** | 0.872 *** |
| ATTENDING SCHOOL | | | | 0.585 *** | 0.558 *** | 0.598 *** | 0.599 *** |
| OFFICIAL LANGUAGE KNOWLEDGE (BASE BOTH ENGLISH AND FRENCH) | ENGLISH ONLY | | | | 0.844 *** | 0.812 *** | 0.809 *** |
| | FRENCH ONLY | | | | 0.760 *** | 0.831 *** | 0.843 *** |
| | NEITHER | | | | 0.631 *** | 0.674 *** | 0.688 *** |
| EUCATION (BASE HIGH SCHOOL OR LESS) | DIP/CERT <BACH DEGREE | | | | 1.047 | 1.175 *** | 1.166 *** |
| | BACH DEGREE OR MORE | | | | 1.112 *** | 1.281 *** | 1.265 *** |
| POST-SECONDARY STUDIES IN CAN | | | | | 1.390 *** | 1.197 *** | 1.201 *** |
| IMMIGRATION CAT | ECON S.A. | | | | 0.902 * | 1.117 | 1.117 |
| | FAMILY | | | | 0.857 *** | 0.976 | 0.980 |
| | REFUGEE | | | | 0.806 *** | 0.930 | 0.939 |
| AGE AT IMMIGRATION | | | | | | 0.983 *** | 0.984 *** |
| IMMIGRATION COHORT | 1981-1990 | | | | | 1.159 | 1.157 |
| | 1991-2000 | | | | | 1.264 * | 1.258 * |
| | 2001-2010 | | | | | 1.373 * | 1.365 * |
| | 2011-2016 | | | | | 0.971 | 0.974 |
| PLACE OF BIRTH REGION | US | | | | | 0.781 ** | 0.781 ** |
| | LATIN | | | | | 0.702 *** | 0.714 *** |
| | EUROPE | | | | | 0.792 *** | 0.800 *** |
| | SUB-SAHARAN AFRICA | | | | | 0.607 *** | 0.613 *** |
| | MENA | | | | | 0.463 *** | 0.475 *** |
| | EAST ASIA | | | | | 0.686 *** | 0.686 *** |
| | SOUTH ASIA | | | | | 0.604 *** | 0.611 *** |
| WORKER ACCESSIBILITY | | | | | | | 1.002 |
| URBAN CORE INDEX | | | | | | | 0.828 *** |
| LQ CATEGORY BY POB REGION | POB NEIGH LQ <0.8 | | | | | | 1.093 * |
| | POB NEIGH LQ >1.2 | | | | | | 0.970 |
| SPATIAL LAG | | | | | | | 0.654 *** |
| INTERCEPT | | 10.913 *** | 0.945 | 2.858 *** | 3.340 *** | 3.131 *** | 4.695 *** |

**Table 12** *continued*

| MODEL FIT | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| PSEUDO-R2 (McKelvey & Zavoina) | 0.009 | 0.032 | 0.048 | 0.065 | 0.088 | 0.090 |
| LOG LIKELIHOOD MODEL | -174903.000 | -172630.000 | -171067.000 | -169619.000 | -167458.000 | -167280.000 |
| LOG LIKELIHOOD INTERCEPT-ONLY | -175611.000 | -175611.000 | -175611.000 | -175611.000 | -175611.000 | -175611.000 |
| DEVIANCE | 349805.900 | 345260.800 | 342133.800 | 339237.300 | 334916.500 | 334560.900 |
| WALD | 353.675 | 1498.056 | 2283.948 | 2920.699 | 3846.880 | 3902.807 |
| AIC | 349809.900 | 345276.800 | 342153.800 | 339275.300 | 334978.500 | 334632.900 |
| BIC | 349829.500 | 345355.100 | 342251.700 | 339461.200 | 335281.900 | 334985.100 |

*** = p<0.001, ** = p<0.01, * = p<0.05

Within the immigrant population, obtaining a diploma or certification above the high school level increases the odds of employment by 16.6% (p<0.001), and attaining the bachelors level and higher increase those odds by 26.5% (p<0.001) versus high school diplomas or lower. Odds ratios for both education categories increase by over 10% between Models 4 and 6. Immigrants who have completed post-secondary studies in Canada have a 20.1% (p<0.001) higher chance of being employed compared to those who have not completed post-secondary studies in Canada, though his effect decreases by roughly 20% between Models 4 and 5. The immigration category variables are significant (in order: p<0.05, p<0.001, and p<0.001) and negative in Model 4, though all three effects decrease considerably and are no longer significant in Model 5.

Some immigration context variables are strongly associated with the likelihood of employment. Age at migration and all birth regions are negatively (p<0.001, with the exception of the US birth region, p<0.01) associated with immigrant employment outcomes in Models 5 and 6. A one-year increase in age at migration is associated with 1.6% lower chance of employment among immigrants in Montreal. Odd ratios reported for different regions should be interpreted with caution. In order to avoid collinearity, immigrants from Southeast Asia were coded as the base category within the birth region variable. In terms of relative odds of employment, immigrants born in Europe/Oceania and the U.S. rank closest to the base category, while immigrants born in the Middle-East/North Africa rank lowest. Surprisingly, immigration cohort effects are not strongly related with employment outcomes. Recent immigrants (arrived between 2011 and 2016) have lower chances of employment compared to immigrants who arrived before 1981. There is somewhat of a reverse cohort effect for the other three categories, where immigrants in the 2001-2010, 1991-2000, and 1981-1990 cohorts exhibit decreasing positive odds of employment (36.5% ($p<0.05$), 25.8% ($p<0.05$), and 15.7% ($p>0.05$), respectively) compared to immigrants who landed in Canada before 1981.

Neighborhood variables are introduced in Model 6. The odds reported for the urban core index and for the spatial lag of employment are both significant ($p<0.001$) and negatively associated with employment. Living outside the urban core lowers the odds of employment by 17.2% among immigrants in Montreal. Worker accessibility is weakly associated with the likelihood of employment, though the effect is not significant ($p>0.05$). Residing in low-LQ neighborhoods ($LQ<0.8$) increases the odds of employment by 9.3% ($p<0.05$) compared to residing in a neighborhood where concentration by place of birth is similar to the average concentration in the CMA ($0.8 \leqq LQ \leqq 1.2$). Residing in a high-LQ neighborhood ($LQ>1.2$) decreases the odds of employment by 3%, but this association is not significant ($p>0.05$).

Table 13 shows the logistic regression outputs for Toronto Models 1-6, reported as odds ratios.[8] Although job accessibility is associated with lower odds of employment in Models 1-5 ($p<0.001$), this shifts to higher odds of employment in Model 6. A one-unit increase in accessibility to jobs increases the chances of employment by 2.8% ($p<0.001$) in the final model.

[8] See Appendix C Table C4 for Model 6 full regression output.

All individual-level demographic characteristics are significant ($p<0.001$) in the final model. Female sex, $age^2$, and the interaction of female sex and having young children are negatively associated with the likelihood of employment among immigrants in Toronto. Immigrant women have a 19.06% lower chance of being employed relative to immigrant men, a far larger gap in odds of employment compared to Montreal. Within the immigrant population, women with young children have 25.5% lower odds of being employed than women without children and men with or without children. Age, marital status, and having young children are positively associated with the likelihood of employment. Odds ratios for age decrease slightly across Models 1-6. In the final model, an additional year of age increases the odds of employment by 13.2%. However, the negative odds ratio for $age^2$ suggests that the positive effect of age decreases as age increases. Married individuals and those with young children have a 13.2% and 12.7% higher chance of being employed, respectively. Both values increase significantly once immigration context is accounted for in Model 5.

Visible minority status and attending school are negatively and significantly ($p<0.001$) associated with the likelihood of employment among immigrants in Toronto. Immigrants who are visible minorities have 23.6% lower odds of being employed compared to those who are not visible minorities, and immigrants who are attending school have 37.5% lower odds of being employed compared to those who are not attending school. These odds are fairly stable across Models 3-6. Visible minority status has a stronger impact on employment in Toronto compared to Montreal, but the odds observed for school attendance are roughly equal for both CMAs.

**Table 13** Logistic regression results for odds of being employed in Toronto  - Part 2 Models 1-6 (odds ratios)

| | | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|---|
| JOB ACCESSIBILIY | | 0.968 *** | 0.982 *** | 0.977 *** | 0.976 *** | 0.976 *** | 1.028 *** |
| SEX | | | 0.824 *** | 0.838 *** | 0.827 *** | 0.809 *** | 0.809 *** |
| AGE | | | 1.171 *** | 1.136 *** | 1.125 *** | 1.133 *** | 1.132 *** |
| AGE^2 | | | 0.998 *** | 0.999 *** | 0.999 *** | 0.999 *** | 0.999 *** |
| MARRIED | | | 1.109 *** | 1.090 *** | 1.143 *** | 1.248 *** | 1.235 *** |
| KIDS AGED 0 to 5 | | | 1.056 * | 1.037 | 1.053 * | 1.126 *** | 1.127 *** |
| SEX*KIDS 0 to 5 | | | 0.791 *** | 0.787 *** | 0.773 *** | 0.748 *** | 0.746 *** |
| VISIBLE MINORITY | | | | 0.738 *** | 0.759 *** | 0.765 *** | 0.764 *** |
| ATTENDING SCHOOL | | | | 0.609 *** | 0.605 *** | 0.625 *** | 0.625 *** |
| OFFICIAL LANGUAGE KNOWLEDGE (BASE BOTH ENGLISH AND FRENCH) | ENGLISH ONLY | | | | 1.148 *** | 1.086 ** | 1.090 ** |
| | FRENCH ONLY | | | | 0.583 ** | 0.717 | 0.729 |
| | NEITHER ENGLISH NOR FRENCH | | | | 0.708 *** | 0.721 *** | 0.729 *** |
| EUCATION (BASE HIGH SCHOOL DEGREE OR LESS) | DIP/CERT <BACH | | | | 0.983 | 1.116 *** | 1.112 *** |
| | BACH DEGREE OR MORE | | | | 1.013 | 1.193 *** | 1.185 *** |
| POST-SECONDARY STUDIES IN CAN | | | | | 1.412 *** | 1.178 *** | 1.179 *** |
| IMMIGRATION CAT | ECON S.A. | | | | 0.910 *** | 1.103 | 1.098 |
| | FAMILY | | | | 0.900 *** | 1.102 | 1.098 |
| | REFUGEE | | | | 0.814 *** | 1.086 | 1.090 |
| AGE AT IMMIGRATION | | | | | | 0.982 *** | 0.982 *** |
| IMMIGRATION COHORT | 1981-1990 | | | | | 1.115 | 1.117 |
| | 1991-2000 | | | | | 1.199 * | 1.199 * |
| | 2001-2010 | | | | | 1.211 * | 1.209 * |
| | 2011-2016 | | | | | 0.959 | 0.959 |
| PLACE OF BIRTH REGION | US | | | | | 0.596 *** | 0.575 *** |
| | LATIN AMERICA | | | | | 0.578 *** | 0.570 *** |
| | EUROPE | | | | | 0.604 *** | 0.588 *** |
| | SUB-SAHARAN AFRICA | | | | | 0.479 *** | 0.472 *** |
| | MENA | | | | | 0.434 *** | 0.428 *** |
| | EAST ASIA | | | | | 0.641 *** | 0.642 *** |
| | SOUTH ASIA | | | | | 0.526 *** | 0.515 *** |
| WORKER ACCESSIBILITY | | | | | | | 0.929 *** |
| URBAN CORE INDEX | | | | | | | 0.904 *** |
| LQ CATEGORY BY POB REGION | POB NEIGH LQ <0.8 | | | | | | 0.959 |
| | POB NEIGH LQ >1.2 | | | | | | 0.961 * |
| SPATIAL LAG | | | | | | | 0.712 *** |
| INTERCEPT | | 13.123 *** | 0.382 *** | 1.126 | 1.111 | 1.459 ** | 2.251 *** |

**Table 13** *continued*

| **MODEL FIT** | **M1** | **M2** | **M3** | **M4** | **M5** | **M6** |
|---|---|---|---|---|---|---|
| PSEUDO-R2 (McKelvey & Zavoina) | 0.002 | 0.050 | 0.058 | 0.068 | 0.088 | 0.090 |
| LOG LIKELIHOOD MODEL | -415184.000 | -403202.000 | -400795.000 | -398592.000 | -394667.000 | -394365.000 |
| LOG LIKELIHOOD INTERCEPT-ONLY | -415495.000 | -415495.000 | -415495.000 | -415495.000 | -415495.000 | -415495.000 |
| DEVIANCE | 830367.500 | 806403.500 | 801589.300 | 797184.600 | 789334.100 | 788730.300 |
| WALD | 156.996 | 6254.739 | 7640.529 | 8748.386 | 10254.000 | 10365.220 |
| AIC | 830371.500 | 806419.500 | 801609.300 | 797222.600 | 789396.100 | 788802.300 |
| BIC | 830393.200 | 806506.300 | 801717.700 | 797428.700 | 789732.400 | 789192.800 |

*** = p<0.001, ** = p<0.01, * = p<0.05

As in Montreal, the odds ratios for human capital characteristics fluctuate in direction and significance across Models 4-6. In terms of official language knowledge, immigrants who know only English have 9% (p<0.01) higher odds of being employed compared to those who know both English and French. Knowing only French or knowing neither language each decrease the odds of employment by 27.1% (p<0.001), though the results are not significant for French-only. All three odds ratios fluctuate across models 4-6, with the largest changes occurring after the inclusion of immigration context variables in Model 5. Notably, the positive odds for English-only decrease across models, but the negative odds for French-only increase (by a similar amount) and are no longer significant after Model 5.

On the other hand, both education categories have little effect on employment and are not significant in Model 4 (p>0.05). The odds ratios reported for education levels become highly significant (p<0.001) and increase dramatically in Model 5. In the final model, earning a diploma or certificate after high school or a bachelor's degree and higher have similar positive effects on the likelihood of employment, increasing the odds by roughly 18% each (p<0.001). Very similar to what was observed in the Montreal models, completing post-secondary studies in Canada is associated with 17.9% higher odds of employment, decreasing from 41.2% higher odds between

Models 4 and 5. This effect is significant across models ($p<0.001$). The odds ratios for all three immigration categories are negatively associated ($p<0.001$) with employment outcomes in Model 4. However, all three categories are positively, though not significantly ($p>0.05$), associated with employment in Model 5, each displaying a roughly 20% increase in the odds of employment.

Immigration context variables follow a similar pattern in Toronto and Montreal. Age at migration is significantly associated with employment among immigrants in Toronto, where every year increase in age at migration decreases the odds of employment by 1.8% ($p<0.001$). Even though the range of odds ratios is narrower in Toronto, immigration cohorts show the same 'reverse cohort effect' as was observed in Montreal. Compared to immigrants who arrived before 1981, recent immigrants have a 4.1% ($p>0.05$) lower chance of being employed. Immigrants who are in the 2001-2010, 1991-2000, and 1981-1990 cohorts have a 20.9% ($p<0.05$), 19.9% ($p<0.05$), and 11.7% ($p>0.05$) higher chance of being employed relative to those who arrived before 1981. All of the place of birth variables are significant ($p<0.001$) and negatively associated with employment in the final model. The range of odds ratios reported for place of birth categories is far narrower in Toronto compared to Montreal. Immigrants who were born in East Asia rank highest relative to the base group. As in Montreal, immigrants who were born in the Middle-East/North Africa region have the lowest likelihood of employment relative to the base group.

All neighborhood-level variables are negatively associated with employment in Toronto. Unlike in Montreal, worker accessibility is significantly ($p<0.001$) associated with employment, where a one-unit increase in worker accessibility decreases the odds of employment by 7.1%. Living outside the urban core reduces the chance of employment by 9.6% ($p<0.001$) among immigrants in Toronto. Also unlike Montreal, both LQ categories are negatively related to employment, though the odds ratio reported for the low LQ category are not significant ($p>0.05$).

Residing in a neighborhood with a high LQ value by place of birth region decreases the odds of employment by 3.9% ($p<0.05$). The spatial lag variable is negatively ($p<0.001$) associated with employment outcomes among immigrants in Toronto.

***Model Fit***

There is a consistent increase in goodness-of-fit over Montreal Models 1-6. As reported in the bottom portion of Table 12, each additional set of variables improves on the fit of previous models. Similar to the models in part one, accounting for demographic characteristics in Model 2 produces the greatest improvement over Model 1. Interestingly, Models 3 (versus Model 2) and 4 (versus Model 3) show a similar magnitude of improvement in terms of reducing log-likelihood, deviance, AIC, and BIC, though Model 3 increases the pseudo-$r^2$ to a greater degree than Model 4. However, Model 5 reduces the log-likelihood, deviance, AIC, and BIC very similarly to Model 2, improving the pseudo-$r^2$ to an even greater extent than Model 3. Conversely, Model 6 improves model fit to a lesser extent than any other model.

Toronto Models 1-6 perform very similarly to the Montreal models. Fit measures presented in the bottom portion of Table 13 show the same pattern of improvement over successive models: Model 2 decreases variance more than other models; Models 3 and 4 improve on previous models to nearly equal degrees; Model 5 improves fit to a greater extent than Models 3 and 4, and Model 6 improves fit overall, but not by much. Notably, the immigration context variables included in Model 5 do not reduce variance to the same degree as demographic variables do in Model 2. Compared to CMA models in part one, models in part two show greater agreement between Montreal and Toronto in terms of model fit.

## 5. Discussion

Sustainable transportation planning emphasizes the importance of curbing automobile reliance through the provision of public transit services and the promotion of alternate modes of transportation in urban areas (Litman 2015b). Accessibility (the ease of reaching opportunities) and equity (the fair distribution of transportation benefits) are useful metrics for evaluating public transit service delivery and for identifying inadequacies in public transit systems. Commuting between locations of residence and work influences mode choice for members of the labour force. The suburbanization of population and employment growth across Canada complicates equitable public transit planning (Heisz and LaRochelle-Cote 2005; Statistics Canada 2015). At the same time, an increasing share of Canadian population growth is driven by immigration. Recent immigrant cohorts are distinct in terms of their composition by source region, residential location patterns, and (greater) reliance on public transit (Heisz and Schellenberg 2004). Research suggests that spatial barriers to employment could partly explain declining labour market outcomes among immigrants in Canada (Houston 2005a).

The purpose of this study is to investigate how different socio-spatial factors influence labour market outcomes among immigrants in Canada's largest cities. Specifically, this study explores the effect of spatial accessibility to jobs on the likelihood of employment for immigrants and non-immigrants in Montreal and Toronto. The analysis adopts a cumulative measure of neighborhood-level accessibility, where job accessibility is defined as the number of jobs accessible within 45 minutes of travel by public transit from census tracts of residence. The impact of job accessibility is evaluated against other determinants of immigrant labour market outcomes identified in the literature, namely: demographic and socioeconomic characteristics (Blumenberg et al. 2007), human capital characteristics (Samers and Snider 2015), contextual aspects of migration (Hou and Picot 2014), and residential environment (Hou and Picot 2003). Logistic regressions and marginal effects estimations are used to analyze how different sets of factors impact the likelihood of employment within the urban workforce. The analysis is divided into two parts, each focusing on different perspectives and dimensions of the economic integration of immigrants in Canadian urban areas.

**5.1 Accessibility and Employment**

Part one addresses the research question: to what extent does spatial accessibility to jobs impact the likelihood of employment among immigrants in Montreal and Toronto, relative to the non-immigrant population? This research question seeks to evaluate the influence of job accessibility on the likelihood of employment, and whether immigrant status alters this relationship. Furthermore, this question implicitly aims to gain insight into the determinants of immigrant labour market outcomes by comparing findings from two distinct urban areas.

Surprisingly, cumulative job accessibility has a weak effect on the odds of employment in Montreal and Toronto, and increasing levels of accessibility are associated with decreasing employment probabilities. In both CMAs, we observe a downward slope in the marginal effect of job accessibility, even after accounting for worker accessibility (a rough measure of labour market competition) and spatial autocorrelation of employment rates. The downward slope of marginal effects is present in all five Montreal models, suggesting that there is either a generally inverse relationship between transit-based job accessibility and employment outcomes in this urban area, or that there are unobserved factors influencing employment probability at different levels of accessibility. In Toronto, this means that the positive effect of accessibility on employment found in Model 5 is slightly misleading - even though accessibility is associated with positive odds of employment in the final model, the marginal effect of accessibility is contingent on other spatial factors, and increases in job accessibility are associated with lower employment probabilities for immigrants and non-immigrants. Furthermore, both sets of subpopulations consistently display roughly parallel slopes across models. For Montreal, this means that immigrants and non-immigrants show similar changes in employment probability over different levels of job accessibility, notwithstanding the gap in employment probability between subpopulations. For Toronto, this means that job accessibility levels have almost equal effects on the likelihood of employment among immigrants and non-immigrants.

We observe other similarities between the two CMAs. First, demographic characteristics explain a greater portion of the overall variance in likelihood of employment than individual-level factors, human capital characteristics, or neighborhood context. However, visible minority status, recent immigrant status, and completing postsecondary studies in Canada reduce the negative marginal effect of immigrant status more than other variables. In general, the odds of employment are lowest for those who are currently attending school and are highest for those who have completed post-secondary studies in Canada. This implies (unsurprisingly) that even though time invested in developing human capital can have negative effects on concurrent employment, investing time in education – especially if this includes post-secondary studies in Canada – can increase the odds of labour market success in the long-term.

Another similarity between the two CMAs is the negative effect of the spatial lag on the dependent variable at the neighborhood-level. This is surprising given the positive spatial lag value reported in the Global Moran's *I* tests for both CMAs, which suggests that neighborhoods are expected to have high employment rates if neighboring areas have high employment rates (Ward and Gleditsch 2008). On the other hand, a negative spatial lag parameter would suggest that neighborhoods with high employment rates are near neighborhoods with low employment rates –

or, competition between neighborhoods outweighs cooperation (Kao and Bera 2013). This finding is difficult to interpret and could imply an improper specification of the spatial lag variable (in terms of the conceptualization of spatial relationships, for instance) or an omitted estimation of spatial error in neighborhood employment rates. One possible interpretation is that, after adjusting for all other covariates, there is an unexplained spatial patterning of neighborhood employment that features highly localized employment rates. Otherwise, it is possible that the worker accessibility variable does not capture neighborhood-level labour market competition, or that this measure is not adequately calibrated to local labour market conditions (e.g. where individuals participate in mutually-exclusive labour markets).

The results show important distinctions between Montreal and Toronto in terms of the relationships between immigrant status, job accessibility, and likelihood of employment. Immigrants in Montreal have a lower likelihood of employment compared to the Canadian-born population, after accounting for all sets of covariates. Recent immigrants and visible minorities account for a significant portion of the negative marginal effect of immigrant status. Completing post-secondary studies in Canada, living outside the urban core, and the spatial lag of neighborhood employment rates reduce the negative effect of immigrant status, although to a lesser extent than recent immigrant or visible minority status.

In the final model, job accessibility is negatively associated with the odds of employment, meaning that greater accessibility to all jobs lowers the chances of being employed in Montreal, even after accounting for worker accessibility. This can be interpreted as: a negative effect of labour market competition or population density that is not captured by the worker accessibility measure, a generally counterintuitive effect of job accessibility, or a pattern of residential location preference towards low-accessibility areas among employed individuals (that is not accounted for by the urban core index). The gap in employment probability between immigrants and non-immigrants persists at all levels of accessibility, suggesting that the cumulative measure of job accessibility does not explain the difference in probability of employment between subpopulations. At the same time, the relationship between accessibility and employment shifts once different covariates are introduced into the model. It appears that demographic characteristics and individual-level factors explain some of the negative effects of accessibility and the effect differential by subpopulation, especially for higher accessibility levels (500,000+ jobs). Once we discount the positive effects of obtaining a (≧ Bachelor's) post-secondary degree and completing any postsecondary studies in Canada, we observe greater negative effects of accessibility on employment probability, especially for immigrants. Neighborhood-level variables decrease the effect of accessibility and extend the confidence intervals for both subpopulations. Accordingly, other spatial factors (residence outside the urban core or an uneven distribution of neighborhood employment) explain some of the negative marginal effect of accessibility, as well as the strength of a differential effect by subpopulation.

Contrary to Montreal, immigrant status alone does not predict the likelihood of employment in Toronto, after adjusting for all sets of covariates. The initially observed negative marginal effect of immigrant status decreases in magnitude and approaches zero in all models that account for visible minority and recent immigrant status. This suggests that visible minority and recent immigrant status condition the negative marginal effects of immigrant status on employment probability in Toronto. However, these variables explain less of the variance in odds of employment compared to Montreal.

Unlike Montreal, job accessibility is positively associated with employment in Toronto, after accounting for all sets of covariates. These inconsistent results are possibly influenced by differences in the spatial distributions of residential areas and job locations between the two CMAs. Compared to Montreal, greater portions of Toronto's immigrant and recent immigrant populations reside outside the urban core. Even though the Urban Core Index is factored into the final models, it is conceivable that individuals residing in different suburban areas might be more sensitive to overall job accessibility. At the same time, varying spatial distributions of job locations (centralized in Montreal vs. polynucleated in Toronto) redefine the importance of other spatial factors (for instance, by delimiting the spatial extent of labour market competition), potentially altering the relationship between job accessibility and employment. Changes in the effect of job accessibility across models support this assertion: the marginal effect of job accessibility exhibits the greatest positive change in magnitude when models account for worker accessibility and the spatial lag of neighborhood employment. Overall, these patterns imply that the (positive) marginal effect of job accessibility is complicated by other (negative) spatial effects - worker accessibility (or, arguably, labour market competition) and the spatial distribution of employed individuals explain a portion of this larger spatial process.

## 5.2 Immigrant Labour Market Dynamics

Part two addresses the research question: how is the relationship between spatial accessibility and employment among immigrants further influenced by immigrant residential segregation, source region, and length of residence in Canada? This research question focuses on the immigrant population and examines how the individual context of migration and neighborhood residential segregation alter the relationship between accessibility and employment outcomes in Montreal and Toronto.

We observe several important similarities between CMAs in part two. Demographic characteristics and immigration context variables explain much of the variance in labour market outcomes within the immigrant populations of Montreal and Toronto. The associations between many covariates and the likelihood of employment shift dramatically once immigration context variables are introduced in the models. Individual-level factors and human capital characteristics explain a relatively lesser degree of immigrant labour market dynamics. Finally, and similar to the models in part one, once all individual-level variables are taken into account, neighborhood variables do not add much to our understanding of what drives differences in the likelihood of employment among immigrants in either CMA.

Several other similarities stand out in the results. Excepting place of birth regions, we observe that attending school lowers the odds of employment among immigrants to a greater extent than any other variable. In terms of human capital variables, both education categories positively affect immigrant labour market outcomes, contrary to what was observed in the models including both immigrants and non-immigrants. Similar to what was observed in part one, completing post-secondary studies in Canada increases the odds of employment to an impressive extent, supporting other research in this field (Hango et al. 2015; Rollin 2011). Surprisingly, immigration category variables are no longer significantly associated with the likelihood of employment once immigration context variables are introduced in the models. This suggests that the associations between immigration categories and labour market outcomes are conditioned on age at immigration, cohort, and place of birth region. Furthermore, these variables reverse nearly all of the negative effects reported for each immigration category.

Montreal and Toronto display fairly parallel results in terms of immigration context and neighborhood-level variables. First, increasing age at migration negatively affects immigrant employment outcomes, supporting the view that acculturation is important for immigrant economic integration (Schaafsma and Sweetman 2001). Next, we observe an unexpected reverse cohort-effect in both CMAs, contrary to some of the findings within the literature on immigrant economic integration (Heisz and Schellenberg 2004). In the final models, odds of employment are highest for those who immigrated 5-15 years prior and decrease with length of stay. However, we do find a limited cohort effect - recent immigrant status (or the 2011-2016 cohort) is negatively, though not significantly, associated with employment. Echoing previous research on immigrant employment and residential segregation in Canada (Fong and Hou 2013; Hou and Picot 2003; Warman 2007), this study finds that neighborhood overrepresentation (LQ>1.2) by birth region negatively impacts the likelihood of employment among immigrants. This implies that immigrants who reside in segregated neighborhoods might be hindered by local labour market competition and saturation. As in part one, residing outside the urban core and the spatial lag of neighborhood employment rates negatively affect immigrant employment outcomes in both CMAs.

Immigrant populations in Montreal and Toronto display similar rankings by place of birth region – this finding adds explanatory power to the models, but is somewhat difficult to interpret. Certain patterns are evident across CMAs: all place of birth regions have lower odds of employment compared to the base region (Southeast Asia); Europe, East Asia, and the United States usually have the highest relative rank; and South Asia, Sub-Saharan Africa, and the Middle-East/North Africa usually have the lowest relative rank in likelihood of employment. One possible interpretation relates the size of entry cohorts by birth region to labour market outcomes (Hou and Picot 2014). We might expect that immigrants who rely on nativity-based social capital for labour market information could be more affected by own-group performance and saturation in the labour market. In other words, the presence of a large, economically integrated own-group immigrant community in Canada might facilitate the job search process for new immigrants. Considering the 2006-2016 trends in immigrant sub-population growth reported in Tables 2 and 3, it is evident that the lower ranking birth region groups in Montreal and Toronto had larger relative shares of unemployed, recent, and unemployed recent immigrants in 2006. Furthermore, these same groups experienced some of the highest rates of subpopulation growth between 2006 and 2016. Although the pattern is not definitive (for instance, immigrants born in East Asia do not conform), these findings suggest that current immigrant labour market outcomes are sensitive to the pace of immigration by birth region, as well as the extent of labour market success of previous immigrant cohorts. Newer immigrants who rely on nativity-based social capital might access fewer employment opportunities when they participate in saturated labour markets, and when their more established peers have limited labour market information due to tenuous employment trajectories. This interpretation is complimented by theories of labour market segmentation and cultural capital: employers' racialization and judgments of cultural capital within the immigrant work force could partly account for the employment barriers experienced by immigrants born in the Middle-East/North Africa, Sub-Saharan Africa, and South Asia (Samers and Snider 2015).

Interestingly, Montreal and Toronto's immigrant populations differ in terms of how neighborhood-level variables alter the odds of employment by place of birth region. Once worker accessibility, the urban core index, residential segregation, and the spatial lag of employment are taken into account, the odds of employment increase slightly for many birth regions in Montreal, but these odds decrease slightly in Toronto. This suggests that spatial factors (especially residing outside the urban core and the spatial patterning of neighborhood-level employment rates) partly account for the lower odds of employment by subgroup in Montreal. On the other hand, the same spatial factors (especially worker accessibility, suburban residence, and the spatial lag of employment) have the opposite effect in Toronto, potentially accounting for either a labour market advantage for certain subgroups or a disadvantage for the reference group (immigrants born in Southeast Asia).

Similar to part one, Montreal and Toronto differ with regards to how job accessibility and other neighborhood variables affect the likelihood of employment among immigrants. In Montreal, job accessibility negatively affects employment, albeit to a lesser extent once demographic characteristics and immigration context are taken into account. As in part one, worker accessibility is not related to immigrant labour market outcomes. In terms of residential segregation, underrepresentation ($LQ<0.8$) by place of birth region has a positive effect on the odds of employment for immigrants in Montreal, though the direction of causation is unclear.[9]

In Toronto, job accessibility positively affects immigrant employment only once other spatial factors are incorporated into the model. Worker accessibility, residing outside the urban core, residential segregation, and the spatial lag of employment account for the negative effects of job accessibility. Given the similarities between the two CMAs in terms of neighborhood effects, it is possible that worker accessibility influences labour market outcomes to a greater extent in Toronto than in Montreal. This suggests that the worker accessibility measure approximates labour market competition, and is potentially indicative of a less segmented labour market in Toronto. Unlike Montreal, immigrant underrepresentation reduces the odds of employment in Toronto, indicating that immigrants are disadvantaged in either under- or overrepresented neighborhoods according to birth region.

**5.3 Limitations**

This study is primarily limited by the operationalization of neighborhood- and group-level variables and the choice of statistical modeling techniques. The study's approach to job

[9] See section 5.3 for a discussion on residential self-selection.

accessibility, source region classification, and residential segregation are problematic, while measures of occupational segregation and group-level population growth are omitted from the models. At the same time, the use of single-level regression models, the specification of the spatial lag parameter, and the cross-sectional approach limit the inferences drawn from model outputs.

The cumulative measure of job accessibility used in this analysis is flawed in terms of the specification of: accessible jobs, the spatial extent of activities, and labour market competition (Houston 2005b; Geurs and van Wee 2004; Kawabata and Shen 2006; Shen 1998). First, accessibility is measured as the number of jobs accessible within 45 minutes of travel by public transit, regardless of individual skill, job vacancies, and access to automobiles. In other words, this measure captures the total number of jobs reachable within a certain time threshold without considering: the required skills to perform different jobs, whether those jobs are available, and jobs accessible through other modes of transportation.[10] A 45-minute travel time threshold was chosen for this analysis because it is a commonly used indicator in representations and analyses of job accessibility (Boisjoly and El-Geneidy 2017). However, this cumulative measure of job accessibility imposes a (somewhat arbitrary) travel time limit on the definition of reachable opportunities, ignoring sub-population differences in travel behavior and potentially accessible opportunities past the designated threshold. Finally, this job accessibility measure does not explicitly account for the effects of labour market competition. Although the worker accessibility measure is used as a separate, imperfect proxy for competition effects, these should be incorporated into measures of job accessibility (Stoll and Melendez 2002; Merlin and Hu 2017) in a way that is relevant for the population of interest (Parks 2004). Potential accessibility measures can be adapted

[10] The job accessibility data set used in this analysis distinguishes between all jobs and low-income jobs (defined as jobs filled by individuals earning less than $30,000 per year CAD). This study uses measures of accessibility to all jobs due to the imperfect alignment of skills and income levels across the broader labour market, as well as the varying relationships between skills and wages within immigrant labour markets in Canada.

to address many of these limitations by incorporating competition effects (Geurs and van Wee 2004), several modes of travel (Shen 1998; Kawabata and Shen 2006), job growth over job turnover (Raphael 1998), and specific skill requirements or subpopulations (Parks 2004).

The cumulative approach to job accessibility is also limited by the endogenous effects of automobile accessibility and residential self-selection, hindering the potential for valid inference. Having access to automobiles introduces endogeneity into our understanding of the impact of job accessibility: do individuals use automobiles because they are employed or are individuals employed because they have access to automobiles? Accounting for accessibility to automobiles requires appropriate data on car ownership (not included in the 2016 Census data), as well as appropriate statistical modeling (Ong and Miller 2005). The issue of residential self-selection is related to automobile accessibility. Residential self-selection obscures the direction of causality in studies of job accessibility: are individuals employed because they live in high-accessibility neighborhoods or do employed individuals prefer residing in certain neighborhoods due to non-work amenities, regardless of spatial accessibility to jobs? The simultaneous effect of residential self-selection complicates nearly all analyses of neighborhood effects (Dietz 2002; Cao, Mokhtarian, and Handy 2009). For instance, in part two of this study, it is difficult to determine if employed immigrants prefer to reside in less-segregated neighborhoods or if immigrants are employed because they reside in less-segregated neighborhoods. Studies of job accessibility that control for residential self-selection often do so by restricting population samples according to an individual's assumed (lack of) control over residential location, usually focusing on: youth residing with parents (Ihlanfeldt and Sjoquist 1998), refugees or other individuals participating in housing placement programs (Åslund, Östh, and Zenou 2010), or household residents other than the household head (Zhu, Liu, and Painter 2014).

The neighborhood-level measure of residential segregation is another methodological flaw in this study. Although the analysis incorporates under- and over-representation relative to individual region of birth, the use of census tract-level Location Quotients over the entire immigrant population obscures sub-group differences, ignores the spatial patterning of census tracts, and applies a limited understanding of neighborhood boundaries. Running separate models by immigrant sub-group would allow for a more precise understanding of the associations between levels of residential segregation and labour market outcomes (Parks 2004). In addition, the measurement of residential segregation can be augmented by adopting a broader view of spatial clustering, wherein immigrant neighborhoods or ethnic enclaves are identified as clusters of census tracts through the use of local indices of spatial autocorrelation (Poulsen, Johnston, and Forrest 2011). This method of defining residential clustering would be sensitive to spatial dispersion over contiguous census tracts and would highlight isolated areas of immigrant sub-group concentration. Another solution is to utilize novel methods of identifying neighborhood boundaries, overlooking census tracts in favor of individual-level residential locations (Spielman and Logan 2013).

Immigrant neighborhoods cannot be identified without appropriate definitions of salient subgroups. This study defines subgroups according to aggregated places of birth – a classification that is obviously vague and arbitrary, and one that ignores the complexity of human identity. Still, the generalized place of birth categorization used in this analysis is somewhat valid for predicting labour market outcomes. Although some of these birth regions overlap with nebulous notions of 'ethnicity,'[11] most encompass broad geographical areas and diverse populations. It would be far

[11] In my mind, 'ethnicity' is not much more than the legacy of procreation facilitated by proximity, endowed with meaning by virtue of shared historical experiences, languages, cultures, and ways of life. In this sense, ethnicity is tied to labour market performance to the extent that participants rely on the social capital of those with similar ethnic backgrounds when searching for jobs, as well as the employers' discriminatory hiring practices when recruiting employees or denying employment on the basis of perceived ethnicity.

more appropriate to categorize immigrant source areas according to smaller geographic regions and individual places of birth, or other relevant distinctions (such as language ability).

This study omits variables measuring group-level occupational segregation and population growth. Without a refined sub-group differentiation, any additional group-level variables would induce collinearity in the models presented above. At the same time, accounting for occupational segregation might confuse causality by predicting employment based on the characteristics of those who are employed. It would be more feasible to explore the influence of occupational segregation on labour market outcomes using models separated by birth region or disaggregated measures of occupational segregation. It would also be useful to include a measure of the trajectory of population growth by salient source regions, making it possible to model how cohort sizes affect labour market outcomes (Hou and Pictot 2014).

Single-level logistic regression models limit the analysis of (social or spatial) contextual determinants of individual labour market outcomes. Multilevel, or hierarchical, modeling has been increasingly adopted as a method of statistical analysis within the social sciences (Guo and Zhao 2000), and particularly within the discipline of geography (Duncan and Jones 2010). Part of the appeal of this technique is that it explicitly models population heterogeneity, and allows for the separation of compositional and contextual effects within a hierarchical data structure (Duncan and Jones 2010). Not only does this method tease out the interactions between individuals and places, it also models differences between places and between individuals. Furthermore, multilevel modeling allows for the inclusion of cross-classified structures, such as individuals nested within residential areas and workplaces or social groups. Guo and Zhao (2000) demonstrate that multilevel logit models outperform standard logit models in the context of hierarchical data, as standard models tend to bias parameter estimates and underestimate standard errors. Additionally, within the multilevel framework, estimates of variance and covariance of random effects allow for the decomposition of the total variance to portions attributable to each level of analysis. Multilevel modeling is one of several appropriate methods of accounting for dependence in hierarchical data. This technique would be preferred given that spatial dependence between units of observation can be explored with reference to several levels of geography, allowing for a more nuanced analysis of how spatial interactions influence employment opportunities.

Although multilevel modeling would be useful for exploring the relationships between spatial contexts and individual-level outcomes, this method does not capture the effects of spatial interactions between higher-level units. This analysis attempts to account for potential spillover effects between census tracts using a spatial lag of neighborhood-level employment. However, the results are difficult to interpret and should be tested against other specifications, including a modified conceptualization of spatial relationships and the addition of a spatial error parameter (Kao and Bera 2013).

This study adopts a cross-sectional approach to investigating the effects of job accessibility on the odds of employment. The analysis could be more enlightening with the introduction of temporal factors, such as: neighborhood-level accessibility to areas exhibiting recent job growth, group-level population growth by place of birth region, or CMA-level trajectories of sectoral job growth and decline. Longitudinal modeling would be especially useful for examining how contextual factors (for instance, changes in neighborhood-level job accessibility or own-group residential concentration) affect the odds of employment over time. Although analysis of naturally-occurring spatial experiments (for instance, using individual-level employment data before and after opening or closing a local light rail station) increases validity through the introduction of exogenous factors (Houston 2005), individual record linkage is not possible with the 2016 Census data set used in this study.

**5.4 Conclusions**

This study reveals complex relationships between immigrant status, job accessibility, and likelihood of employment. Overall, the cumulative measure of job accessibility is negatively associated with employment outcomes in Montreal and is positively associated with employment outcomes in Toronto. However, increasing levels of job accessibility lower the probability of employment for immigrants and non-immigrants in both CMAs. Although demographic characteristics explain much of the variance in odds of employment for immigrants and non-immigrants, accounting for recent immigrants and visible minorities reduces the negative effects of immigrant status considerably. Completing post-secondary studies in Canada has one of the strongest positive effects on the likelihood of employment for both immigrants and non-immigrants in Montreal and Toronto. Neighborhood-level factors have different effects on employment in either CMA, but do not explain much of the overall variance in employment.

Focusing on the immigrant population, we observe that the context of migration – age at migration, immigration cohort, and source region – moderates the relationships between employment outcomes and other model covariates. These variables explain a similar degree of variance in employment outcomes among immigrants as do demographic characteristics. However, the effects of immigration context are contingent on other spatial factors and differ by CMA. Residential neighborhood overrepresentation by place of birth region is negatively associated with the odds of employment in Montreal and Toronto.

Future research should aim to utilize more precise measures of job accessibility, residential segregation, and source region classification, as well as more appropriate modeling techniques.

Although cumulative measures of job accessibility are attractive for communicating the volume of opportunities reachable by public transit, these measures are less appropriate for evaluating the efficacy of public transit systems. Measures of job accessibility should be calibrated to reflect accessibility to realistic job opportunities – in terms of skill levels, labour market competition, perceptions of spatial distance, and new job openings (vs the implicit assumption of job turnover). At the same time, investigating spatial determinants of immigrant labour market outcomes requires spatially-sensitive measures of residential segregation and refined classifications of immigrant sub-groups. These measurement issues highlight a greater methodological challenge: analyses of individual and neighborhood effects necessarily violate assumptions of independent observations in statistical models. Several different modeling techniques can be used to account for spatial interactions at different levels of analysis. Furthermore, future research should aim to capitalize on naturally occurring spatial experiments as a means to increase analytic validity. Studies of job accessibility and employment outcomes can mitigate issues of endogeneity and enhance explanatory import by incorporating exogenous individual-level (such as participation in housing placement or automobile accessibility programs) or neighborhood-level factors (such as changes in residential/workplace locations or transportation infrastructure). While this study adds to our understanding of socio-spatial influences on employment, future research should focus on teasing out the relationships between social and spatial context, immigrant status, and labour market outcomes in Canadian urban areas.

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## Appendix A

## Variables derived from Census 2016

Table A1 describes the variables used in this analysis and details the variable coding used in the descriptive statistics and the logistic regressions. Table A1 also includes the original Census 2016 variables from which the analysis variables were derived.

**Table A1** Variable roles in analysis, coding, and corresponding Census 2016 variables

| Roles in Analysis | Variable codes | | | Description |
|---|---|---|---|---|
| | Code in analysis | Value in Analysis | Derived from | |
| Employment (dependent) | DEPVAR=1 | Employed | lftag | Labor force status |
| | DEPVAR=0 | Unemployed | | |
| Demographics (independent) | age | Continuous age | age | Age |
| | SEX=1 | Female | sex | Sex |
| | SEX=0 | Male | | |
| | MARRIED=1 | Married | marsth | Marital status (de facto) |
| | MARRIED=0 | Not married | | |
| Ethnic origin and visible minority (independent) | VISMIN=1 | Visible minority | dvismin | Visible minority status |
| | VISMIN=0 | Not visible minority | | |
| Language (independent) | oln=1 | English only | oln | Knowledge of official languages |
| | oln=2 | French only | | |
| | oln=3 | English and French | | |
| | oln=4 | Neither English nor French | | |
| Place of birth, immigration citizenship | age_imm | Continuous age | age_imm | Age at immigration |
| | IMMIG=1 | Immigrant | immder | Immigration status |
| | IMMIG=0 | Non-immigrant | | |
| | R_IMMIG=1 | Recent immigrant | perimma | Immigrated between 2011 and 2016 |
| | R_IMMIG=0 | Not recent immigrant | | |
| | SCN_GEN=1 | Second generation | genstpob | Generation status |
| | SCN_GEN=0 | Not second generation | | |

| | | | | |
|---|---|---|---|---|
| | IMMCAT_S=1 | Immigrants who landed before 1980 | immcat5 | Immigration admission category |
| | IMMCAT_S=2 | Economic immigrants (principle and secondary applicants) | | |
| | IMMCAT_S=3 | Immigrants sponsored by family | | |
| | IMMCAT_S=4 | Refugees and other immigrants | | |
| | IMMCAT_S=0 | Non-immigrants | | |
| | IMMCAT_ECON_PA=1 | Economic migrant principal applicant | immcat5 | Economic migrant principal applicant |
| | IMMCAT_ECON_PA=0 | Not economic migrant principal applicant | | |
| | COHORT=1 | Immigrants who landed before 1981 | perimma | Immigrant status and period of immigration (by 5-10 year groups) |
| | COHORT=2 | Immigrants who landed between 1981 and 1990 | | |
| | COHORT=3 | Immigrants who landed between 1991 and 2000 | | |
| | COHORT=4 | Immigrants who landed between 2001 and 2010 | | |
| | COHORT=5 | Immigrants who landed between 2011 and 2016 | | |
| | POB_XREG=1 | Born in United States | pob | Place of birth region (See Appendix B for list of countries in each place of birth region) |
| | POB_XREG=2 | Born in Latin America | | |
| | POB_XREG=3 | Born in Europe / Oceania | | |
| | POB_XREG=4 | Born in Sub-Saharan Africa | | |
| | POB_XREG=5 | Born in Middle-east / North Africa | | |
| | POB_XREG=6 | Born in East Asia | | |
| | POB_XREG=7 | Born in South Asia | | |
| | POB_XREG=8 | Born in Southeast Asia | | |

| | | | | |
|---|---|---|---|---|
| | POB_XREG=0 | Born in Canada | | |
| Education (independent) | attschsum=1 | Attended school | attschsum | School attendance - summary ( Sept. 2015 to May 2016) |
| | attschsum=0 | Did not attend school | | |
| | EDUC_S=1 | No certificate, diploma, or degree. Secondary school diploma. | hcdd_14v | Highest certificate, diploma, or degree |
| | EDUC_S=2 | Certificate or diploma below bachelor level | | |
| | EDUC_S=3 | Bachelor's degree. Doctorate, diploma, degree, or certificate above bachelor level | | |
| | LOC_STUDY_CAN=1 | Highest postsecondary certificate, diploma, or degree obtained in Canada | loc_study | Location of study (highest postsecondary certificate, diploma, or degree) |
| | LOC_STUDY_CAN=0 | No postsecondary certificate, diploma, or obtained outside Canada | | |
| Families and family composition (independent) | KIDS=1 | At least one child in census family aged 0 to 5 | cfkid0t5 | Individual is in census family with at least one child aged 0 to 5 |
| | KIDS=0 | No children aged 0 to 5 | | |
| Geography (independent) | ctpctcode | Census Tract code | ctpctcode | Code for Census Tract of residence |

## Appendix B

## Birthplaces within Place of Birth Regions

Table B1 lists each place of birth classified by region along with the corresponding Census 2016 variable coding.

**Table B1** Birthplaces classified by region, including Census 2016 place codes

| | |
|---|---|
| **LATIN AMERICA** | |
| 12084 | Belize |
| 12188 | Costa Rica |
| 12222 | El Salvador |
| 12320 | Guatemala |
| 12340 | Honduras |
| 12484 | Mexico |
| 12558 | Nicaragua |
| 12591 | Panama |
| 13028 | Antigua and Barbuda |
| 13044 | Bahamas |
| 13052 | Barbados |
| 13060 | Bermuda |
| 13092 | Virgin Islands, British |
| 13136 | Cayman Islands |
| 13192 | Cuba |
| 13212 | Dominica |
| 13214 | Dominican Republic |
| 13308 | Grenada |
| 13312 | Guadeloupe |
| 13332 | Haiti |
| 13388 | Jamaica |
| 13474 | Martinique |
| 13500 | Montserrat |
| 13531 | Curaçao |
| 13533 | Aruba |
| 13534 | Sint Maarten (Dutch part) |
| 13535 | Bonaire, Sint Eustatius and Saba |
| 13630 | Puerto Rico |
| 13652 | Saint Barthélemy |
| 13659 | Saint Kitts and Nevis |
| 13660 | Anguilla |
| 13662 | Saint Lucia |
| 13663 | Saint Martin (French part) |
| 13670 | Saint Vincent and the Grenadines |
| 13780 | Trinidad and Tobago |
| 13796 | Turks and Caicos Islands |
| 13850 | Virgin Islands, United States |
| 14032 | Argentina |
| 14068 | Bolivia |
| 14076 | Brazil |
| 14152 | Chile |
| 14170 | Colombia |
| 14218 | Ecuador |
| 14238 | Falkland Islands (Malvinas) |
| 14239 | South Georgia & South Sandwich Islands |
| 14254 | French Guiana |
| 14328 | Guyana |
| 14600 | Paraguay |
| 14604 | Peru |
| 14740 | Suriname |
| 14858 | Uruguay |
| 14862 | Venezuela |
| **EUROPE** | |
| 21040 | Austria |
| 21056 | Belgium |
| 21250 | France |
| 21276 | Germany |
| 21438 | Liechtenstein |
| 21442 | Luxembourg |
| 21492 | Monaco |
| 21528 | Netherlands |
| 21756 | Switzerland |
| 22100 | Bulgaria |
| 22112 | Belarus |
| 22203 | Czech Republic |
| 22233 | Estonia |
| 22348 | Hungary |
| 22428 | Latvia |
| 22440 | Lithuania |
| 22498 | Moldova |
| 22616 | Poland |
| 22642 | Romania |
| 22643 | Russian Federation |
| 22703 | Slovakia |
| 22804 | Ukraine |

| | |
|---|---|
| 23208 | Denmark |
| 23234 | Faroe Islands |
| 23246 | Finland |
| 23248 | Åland Islands |
| 23352 | Iceland |
| 23372 | Ireland |
| 23578 | Norway |
| 23680 | Sark |
| 23744 | Svalbard and Jan Mayen |
| 23752 | Sweden |
| 23826 | United Kingdom |
| 23831 | Guernsey |
| 23832 | Jersey |
| 23833 | Isle of Man |
| 24008 | Albania |
| 24020 | Andorra |
| 24070 | Bosnia and Herzegovina |
| 24191 | Croatia |
| 24292 | Gibraltar |
| 24300 | Greece |
| 24336 | Holy See (Vatican City State) |
| 24380 | Italy |
| 24470 | Malta |
| 24499 | Montenegro |
| 24620 | Portugal |
| 24674 | San Marino |
| 24688 | Serbia |
| 24705 | Slovenia |
| 24724 | Spain |
| 24807 | Macedonia, Republic of |
| 24983 | Kosovo |
| **SUB-SAHARAN AFRICA** | |
| 31132 | Cabo Verde |
| 31204 | Benin |
| 31270 | Gambia |
| 31288 | Ghana |
| 31324 | Guinea |
| 31384 | Côte d'Ivoire |
| 31430 | Liberia |
| 31466 | Mali |
| 31478 | Mauritania |
| 31562 | Niger |
| 31566 | Nigeria |
| 31624 | Guinea-Bissau |
| 31654 | Saint Helena |
| 31686 | Senegal |
| 31694 | Sierra Leone |
| 31768 | Togo |
| 31854 | Burkina Faso |
| 32108 | Burundi |
| 32174 | Comoros |
| 32175 | Mayotte |
| 32231 | Ethiopia |
| 32232 | Eritrea |
| 32262 | Djibouti |
| 32404 | Kenya |
| 32450 | Madagascar |
| 32454 | Malawi |
| 32480 | Mauritius |
| 32508 | Mozambique |
| 32638 | Réunion |
| 32646 | Rwanda |
| 32690 | Seychelles |
| 32706 | Somalia |
| 32716 | Zimbabwe |
| 32728 | South Sudan |
| 32800 | Uganda |
| 32834 | Tanzania |
| 32894 | Zambia |
| 34024 | Angola |
| 34120 | Cameroon |
| 34140 | Central African Republic |
| 34148 | Chad |
| 34178 | Congo, Republic of the |
| 34180 | Congo, Democratic Republic of the |
| 34226 | Equatorial Guinea |
| 34266 | Gabon |
| 34678 | Sao Tome and Principe |
| 35072 | Botswana |
| 35426 | Lesotho |
| 35516 | Namibia |
| 35710 | South Africa, Republic of |
| 35748 | Swaziland |
| **MIDDLE-EAST/NORTH AFRICA** | |
| 33012 | Algeria |
| 33434 | Libya |
| 33504 | Morocco |
| 33729 | Sudan |
| 33732 | Western Sahara |
| 33788 | Tunisia |
| 33818 | Egypt |
| 41004 | Afghanistan |

| | |
|---|---|
| 41031 | Azerbaijan |
| 41048 | Bahrain |
| 41051 | Armenia |
| 41196 | Cyprus |
| 41268 | Georgia |
| 41275 | West Bank and Gaza Strip (Palestine) |
| 41364 | Iran |
| 41368 | Iraq |
| 41376 | Israel |
| 41398 | Kazakhstan |
| 41400 | Jordan |
| 41414 | Kuwait |
| 41417 | Kyrgyzstan |
| 41422 | Lebanon |
| 41512 | Oman |
| 41634 | Qatar |
| 41682 | Saudi Arabia |
| 41760 | Syria |
| 41762 | Tajikistan |
| 41784 | United Arab Emirates |
| 41792 | Turkey |
| 41795 | Turkmenistan |
| 41860 | Uzbekistan |
| 41887 | Yemen |
| **EAST ASIA** | |
| 42156 | China |
| 42158 | Taiwan |
| 42344 | Hong Kong |
| 42392 | Japan |
| 42408 | Korea, North |
| 42410 | Korea, South |
| 42446 | Macao |
| 42496 | Mongolia |
| **SOUTHEAST ASIA** | |
| 43096 | Brunei Darussalam |
| 43104 | Burma (Myanmar) |
| 43116 | Cambodia |
| 43360 | Indonesia |
| 43418 | Laos |
| 43458 | Malaysia |
| 43608 | Philippines |
| 43626 | Timor-Leste |
| 43702 | Singapore |
| 43704 | Viet Nam |
| 43764 | Thailand |
| **SOUTH ASIA** | |
| 44050 | Bangladesh |
| 44064 | Bhutan |
| 44086 | British Indian Ocean Territory |
| 44144 | Sri Lanka |
| 44356 | India |
| 44462 | Maldives |
| 44524 | Nepal |
| 44586 | Pakistan |
| **OCEANIA** | |
| 51016 | American Samoa |
| 51036 | Australia |
| 51090 | Solomon Islands |
| 51162 | Christmas Island |
| 51166 | Cocos (Keeling) Islands |
| 51184 | Cook Islands |
| 51242 | Fiji |
| 51258 | French Polynesia |
| 51296 | Kiribati |
| 51316 | Guam |
| 51520 | Nauru |
| 51540 | New Caledonia |
| 51548 | Vanuatu |
| 51554 | New Zealand |
| 51570 | Niue |
| 51574 | Norfolk Island |
| 51580 | Northern Mariana Islands |
| 51581 | United States Minor Outlying Islands |
| 51583 | Micronesia, Federated States of |
| 51584 | Marshall Islands |
| 51585 | Palau |
| 51598 | Papua New Guinea |
| 51612 | Pitcairn |
| 51772 | Tokelau |
| 51776 | Tonga |
| 51798 | Tuvalu |
| 51876 | Wallis and Futuna |
| 51882 | Samoa |
| 61010 | Antarctica |
| 61074 | Bouvet Island |
| 61260 | French Southern Territories |
| 61334 | Heard Island and McDonald Islands |

## Appendix C

## Full Final Model Regression Outputs

The following tables contain the full regression outputs for the final models in parts one and two by CMA. The tables are ordered according to the results presented in the main text: Montreal Part 1 Model 5 (Table C1), Toronto Part 1 Model 5 (Table C2), Montreal Part 2 Model 6 (Table C3), Toronto Part 2 Model 6 (Table C4).

| **Table C1** Logistic regression output for Montreal Part 1 Model 5 (odds ratios) | | **Odds Ratio** | **Robust Std. Err.** | **z** | **P>\|z\|** | **[95% Conf. Interval]** | |
|---|---|---|---|---|---|---|---|
| IMMIGRANT STATUS | | 0.732 | 0.015 | -15.210 | 0.000 | 0.703 | 0.762 |
| JOB ACCESSIBILITY | | 0.970 | 0.007 | -3.980 | 0.000 | 0.956 | 0.985 |
| SEX (FEMALE) | | 1.194 | 0.017 | 12.140 | 0.000 | 1.160 | 1.229 |
| AGE | | 1.119 | 0.004 | 34.330 | 0.000 | 1.112 | 1.126 |
| AGE^2 | | 0.999 | 0.000 | -32.640 | 0.000 | 0.999 | 0.999 |
| MARRIED | | 1.310 | 0.019 | 18.420 | 0.000 | 1.273 | 1.349 |
| KIDS AGED 0 to 5 | | 0.861 | 0.014 | -9.030 | 0.000 | 0.834 | 0.890 |
| SEX*KIDS 0 to 5 | | 0.920 | 0.021 | -3.570 | 0.000 | 0.879 | 0.963 |
| RECENT IMMIGRANT | | 0.595 | 0.014 | -22.260 | 0.000 | 0.568 | 0.622 |
| VISIBLE MINORITY | | 0.751 | 0.013 | -16.660 | 0.000 | 0.726 | 0.777 |
| ATTENDING SCHOOL | | 0.682 | 0.011 | -23.890 | 0.000 | 0.661 | 0.704 |
| SECOND GEN. CANADIAN | | 0.814 | 0.015 | -11.000 | 0.000 | 0.785 | 0.845 |
| OFFICIAL LANGUAGE KNOWLEDGE (BASE BOTH) | ENGLISH ONLY | 0.752 | 0.018 | -12.140 | 0.000 | 0.718 | 0.787 |
| | FRENCH ONLY | 0.813 | 0.011 | -15.160 | 0.000 | 0.791 | 0.835 |
| | NEITHER | 0.730 | 0.050 | -4.550 | 0.000 | 0.638 | 0.836 |
| EDUCATION (BASE HIGH SCHOOL DEGREE OR LESS) | DIP/CERT <BACH DEGREE | 0.960 | 0.023 | -1.720 | 0.085 | 0.916 | 1.006 |
| | ≥BACH DEGREE | 1.228 | 0.030 | 8.480 | 0.000 | 1.171 | 1.288 |
| ECON MIGRANT PRINCIPAL APPLICANT | | 1.201 | 0.029 | 7.650 | 0.000 | 1.146 | 1.259 |
| POST-SECONDARY STUDIES IN CANADA | | 1.523 | 0.034 | 18.580 | 0.000 | 1.457 | 1.592 |
| WORKER ACCESSIBILITY | | 1.012 | 0.014 | 0.910 | 0.364 | 0.986 | 1.039 |
| URBAN CORE INDEX (BASE SUBURBAN) | | 0.808 | 0.019 | -9.190 | 0.000 | 0.772 | 0.846 |
| SPATIAL LAG | | 0.644 | 0.029 | -9.630 | 0.000 | 0.589 | 0.704 |
| INTERCEPT | | 2.439 | 0.169 | 12.860 | 0.000 | 2.129 | 2.794 |

| **Table C2** Logistic regression output for Toronto Part 1 Model 5 (odds ratios) | | **Odds Ratio** | **Robust Std. Err.** | **z** | **P>\|z\|** | **[95% Conf. Interval]** | |
|---|---|---|---|---|---|---|---|
| IMMIGRANT STATUS | | 1.032 | 0.017 | 1.920 | 0.055 | 0.999 | 1.065 |
| JOB ACCESSIBILITY | | 1.039 | 0.006 | 6.340 | 0.000 | 1.026 | 1.051 |
| SEX (female) | | 1.021 | 0.011 | 1.900 | 0.057 | 0.999 | 1.043 |
| AGE | | 1.104 | 0.003 | 36.960 | 0.000 | 1.098 | 1.110 |
| AGE^2 | | 0.999 | 0.000 | -31.980 | 0.000 | 0.999 | 0.999 |
| MARRIED | | 1.410 | 0.017 | 28.880 | 0.000 | 1.378 | 1.443 |
| KIDS AGED 0 to 5 | | 1.147 | 0.018 | 8.870 | 0.000 | 1.112 | 1.182 |
| SEX*KIDS 0 to 5 | | 0.727 | 0.015 | -15.550 | 0.000 | 0.698 | 0.757 |
| RECENT IMMIGRANT | | 0.631 | 0.011 | -25.730 | 0.000 | 0.610 | 0.654 |
| VISIBLE MINORITY | | 0.738 | 0.009 | -25.380 | 0.000 | 0.721 | 0.756 |
| ATTENDING SCHOOL | | 0.574 | 0.007 | -44.890 | 0.000 | 0.560 | 0.588 |
| SECOND GEN. CANADIAN | | 1.025 | 0.015 | 1.750 | 0.080 | 0.997 | 1.054 |
| OFFICIAL LANGUAGE KNOWLEDGE (BASE BOTH ENGLISH AND FRENCH) | ENGLISH ONLY | 1.031 | 0.017 | 1.800 | 0.072 | 0.997 | 1.065 |
| | FRENCH ONLY | 0.629 | 0.118 | -2.460 | 0.014 | 0.435 | 0.910 |
| | NEITHER ENGLISH NOR FRENCH | 0.714 | 0.026 | -9.380 | 0.000 | 0.665 | 0.766 |
| EDUCATION (BASE HIGH SCHOOL DEGREE OR LESS) | DIP/CERT <BACH DEGREE | 0.977 | 0.017 | -1.320 | 0.186 | 0.944 | 1.011 |
| | BACH DEGREE OR MORE | 1.085 | 0.017 | 5.110 | 0.000 | 1.052 | 1.120 |
| ECON MIGRANT PA | | 1.282 | 0.024 | 13.350 | 0.000 | 1.236 | 1.330 |
| STUDIES IN CAN. | | 1.467 | 0.023 | 24.900 | 0.000 | 1.423 | 1.512 |
| WORKER ACCESSIBILITY | | 0.937 | 0.009 | -6.640 | 0.000 | 0.919 | 0.955 |
| URBAN CORE INDEX (BASE URBAN) | | 0.882 | 0.019 | -5.750 | 0.000 | 0.845 | 0.920 |
| SPATIAL LAG | | 0.726 | 0.028 | -8.270 | 0.000 | 0.672 | 0.783 |
| INTERCEPT | | 2.001 | 0.117 | 11.850 | 0.000 | 1.784 | 2.245 |

| **Table C3** Logistic regression output for Montreal Part 2 Model 6 (odds ratios) | | **Odds Ratio** | **Robust Std. Err.** | **z** | **P>\|z\|** | **[95% Conf. Interval]** | |
|---|---|---|---|---|---|---|---|
| JOB ACCESSIBILIY | | 0.974 | 0.011 | -2.460 | 0.014 | 0.953 | 0.995 |
| SEX | | 0.904 | 0.024 | -3.850 | 0.000 | 0.859 | 0.952 |
| AGE | | 1.087 | 0.008 | 11.950 | 0.000 | 1.072 | 1.102 |
| AGE^2 | | 0.999 | 0.000 | - | 0.000 | 0.999 | 0.999 |
| MARRIED | | 1.198 | 0.027 | 8.140 | 0.000 | 1.147 | 1.251 |
| KIDS AGED 0 to 5 | | 0.901 | 0.026 | -3.590 | 0.000 | 0.852 | 0.954 |
| SEX*KIDS 0 to 5 | | 0.841 | 0.032 | -4.490 | 0.000 | 0.779 | 0.907 |
| VISIBLE MINORITY | | 0.872 | 0.027 | -4.500 | 0.000 | 0.821 | 0.926 |
| ATTENDING SCHOOL | | 0.599 | 0.015 | - | 0.000 | 0.571 | 0.629 |
| OFFICIAL LANGUAGE KNOWLEDGE (BASE BOTH ENGLISH AND FRENCH) | ENGLISH ONLY | 0.809 | 0.027 | -6.440 | 0.000 | 0.758 | 0.863 |
| | FRENCH ONLY | 0.843 | 0.021 | -6.970 | 0.000 | 0.804 | 0.885 |
| | NEITHER ENGLISH | 0.688 | 0.051 | -5.010 | 0.000 | 0.594 | 0.796 |
| EUCATION (BASE HIGH SCHOOL DEGREE OR LESS) | DIP/CERT <BACH | 1.166 | 0.035 | 5.120 | 0.000 | 1.099 | 1.237 |
| | BACH DEGREE OR | 1.265 | 0.037 | 7.960 | 0.000 | 1.194 | 1.340 |
| POST-SECONDARY STUDIES IN CANADA | | 1.179 | 1.201 | 0.032 | 6.920 | 0.000 | 1.141 |
| IMMIGRATION CAT | ECON S.A. | 1.117 | 0.115 | 1.080 | 0.281 | 0.913 | 1.367 |
| | FAMILY | 0.980 | 0.101 | -0.200 | 0.843 | 0.801 | 1.199 |
| | REFUGEE | 0.939 | 0.098 | -0.600 | 0.548 | 0.766 | 1.152 |
| AGE AT IMMIGRATION | | 0.982 | 0.984 | 0.003 | -4.860 | 0.000 | 0.977 |
| IMMIGRATION COHORT | 1981-1990 | 1.157 | 0.115 | 1.480 | 0.140 | 0.953 | 1.406 |
| | 1991-2000 | 1.258 | 0.136 | 2.130 | 0.033 | 1.018 | 1.555 |
| | 2001-2010 | 1.365 | 0.174 | 2.450 | 0.014 | 1.064 | 1.751 |
| | 2011-2016 | 0.974 | 0.140 | -0.180 | 0.857 | 0.735 | 1.291 |
| PLACE OF BIRTH REGION | US | 0.781 | 0.075 | -2.580 | 0.010 | 0.647 | 0.942 |
| | LATIN AMERICA | 0.714 | 0.035 | -6.920 | 0.000 | 0.649 | 0.786 |
| | EUROPE | 0.800 | 0.046 | -3.900 | 0.000 | 0.715 | 0.895 |
| | SUB-SAHARAN AFRICA | 0.613 | 0.034 | -8.930 | 0.000 | 0.551 | 0.683 |
| | MENA | 0.475 | 0.023 | - | 0.000 | 0.432 | 0.521 |
| | EAST ASIA | 0.686 | 0.040 | -6.550 | 0.000 | 0.613 | 0.768 |
| | SOUTH ASIA | 0.611 | 0.036 | -8.400 | 0.000 | 0.545 | 0.686 |
| WORKER ACCESSIBILITY | | 0.929 | 1.002 | 0.020 | 0.090 | 0.931 | 0.964 |
| URBAN CORE INDEX | | 0.828 | 0.029 | -5.350 | 0.000 | 0.773 | 0.887 |
| LQ CATEGORY BY POB REGION | POB NEIGH LQ <0.8 | 1.093 | 0.039 | 2.510 | 0.012 | 1.020 | 1.172 |
| | POB NEIGH LQ >1.2 | 0.970 | 0.028 | -1.060 | 0.290 | 0.918 | 1.026 |
| SPATIAL LAG | | 0.654 | 0.055 | -5.080 | 0.000 | 0.555 | 0.770 |
| INTERCEPT | | 4.695 | 0.956 | 7.600 | 0.000 | 3.150 | 6.996 |

| **Table C4** Logistic regression output for Toronto Part 2 Model 6 (odds ratios) | | **Odds Ratio** | **Robust Std. Err.** | **z** | **P>\|z\|** | **[95% Conf.** | **Interval]** |
|---|---|---|---|---|---|---|---|
| JOB ACCESSIBILIY | | 1.028 | 0.008 | 3.410 | 0.001 | 1.012 | 1.044 |
| SEX | | 0.809 | 0.013 | - | 0.000 | 0.785 | 0.834 |
| AGE | | 1.132 | 0.005 | 27.460 | 0.000 | 1.122 | 1.142 |
| AGE^2 | | 0.999 | 0.000 | - | 0.000 | 0.999 | 0.999 |
| MARRIED | | 1.235 | 0.020 | 13.240 | 0.000 | 1.197 | 1.274 |
| KIDS AGED 0 to 5 | | 1.127 | 0.024 | 5.510 | 0.000 | 1.080 | 1.176 |
| SEX*KIDS 0 to 5 | | 0.746 | 0.021 | - | 0.000 | 0.706 | 0.789 |
| VISIBLE MINORITY | | 0.764 | 0.023 | -9.040 | 0.000 | 0.721 | 0.810 |
| ATTENDING SCHOOL | | 0.625 | 0.011 | - | 0.000 | 0.604 | 0.647 |
| OFFICIAL LANGUAGE KNOWLEDGE (BASE BOTH ENGLISH AND FRENCH) | ENGLISH ONLY | 1.090 | 0.031 | 3.000 | 0.003 | 1.030 | 1.153 |
| | FRENCH ONLY | 0.729 | 0.144 | -1.610 | 0.108 | 0.495 | 1.072 |
| | NEITHER ENGLISH | 0.729 | 0.033 | -7.020 | 0.000 | 0.667 | 0.796 |
| EUCATION (BASE HIGH SCHOOL DEGREE OR LESS) | DIP/CERT <BACH | 1.112 | 0.024 | 4.900 | 0.000 | 1.066 | 1.161 |
| | BACH DEGREE OR | 1.185 | 0.023 | 8.740 | 0.000 | 1.140 | 1.230 |
| POST-SECONDARY STUDIES IN CANADA | | 1.179 | 0.023 | 8.520 | 0.000 | 1.135 | 1.225 |
| IMMIGRATION CAT | ECON S.A. | 1.098 | 0.082 | 1.250 | 0.211 | 0.949 | 1.270 |
| | FAMILY | 1.098 | 0.082 | 1.260 | 0.207 | 0.949 | 1.271 |
| | REFUGEE | 1.090 | 0.082 | 1.130 | 0.256 | 0.939 | 1.264 |
| AGE AT IMMIGRATION | | 0.982 | 0.002 | -7.910 | 0.000 | 0.978 | 0.987 |
| IMMIGRATION COHORT | 1981-1990 | 1.117 | 0.081 | 1.530 | 0.126 | 0.969 | 1.288 |
| | 1991-2000 | 1.199 | 0.093 | 2.340 | 0.019 | 1.030 | 1.396 |
| | 2001-2010 | 1.209 | 0.107 | 2.150 | 0.032 | 1.017 | 1.437 |
| | 2011-2016 | 0.959 | 0.096 | -0.420 | 0.675 | 0.788 | 1.166 |
| PLACE OF BIRTH REGION | US | 0.575 | 0.037 | -8.690 | 0.000 | 0.508 | 0.651 |
| | LATIN AMERICA | 0.570 | 0.016 | - | 0.000 | 0.539 | 0.603 |
| | EUROPE | 0.588 | 0.023 | - | 0.000 | 0.544 | 0.636 |
| | SUB-SAHARAN AFRICA | 0.472 | 0.017 | -21.220 | 0.000 | 0.440 | 0.505 |
| | MENA | 0.428 | 0.013 | - | 0.000 | 0.404 | 0.454 |
| | EAST ASIA | 0.642 | 0.018 | - | 0.000 | 0.608 | 0.679 |
| | SOUTH ASIA | 0.515 | 0.014 | - | 0.000 | 0.489 | 0.542 |
| WORKER ACCESSIBILITY | | 0.929 | 0.013 | -5.430 | 0.000 | 0.905 | 0.954 |
| URBAN CORE INDEX | | 0.904 | 0.027 | -3.410 | 0.001 | 0.853 | 0.958 |
| LQ CATEGORY BY POB REGION | POB NEIGH LQ <0.8 | 0.959 | 0.021 | -1.880 | 0.060 | 0.919 | 1.002 |
| | POB NEIGH LQ >1.2 | 0.961 | 0.018 | -2.090 | 0.036 | 0.925 | 0.997 |
| SPATIAL LAG | | 0.712 | 0.043 | -5.640 | 0.000 | 0.632 | 0.801 |
| INTERCEPT | | 2.251 | 0.314 | 5.810 | 0.000 | 1.712 | 2.960 |