A Direct Ridership Model for Rail Rapid Transit in Canada

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Abstract

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Rail rapid transit forms the backbone of many public transportation systems in cities globally moving people at both high speed and at high capacity. As cities seek to alleviate problems of congestion and environmental pollution many are constructing or expanding urban and suburban rail networks including in Canada where in 2015 numerous projects were underway or recently completed. Traditionally travel choices have been considered to be products of time and monetary cost academics and researchers have resented strong evidence also linking travel behaviour to factors including the built environment, station amenities, and street networks.

This thesis links local station level factors, including built form, street network, station amenities and service, and socioeconomic characteristics, and rail rapid transit ridership in Canada. A direct ridership model (DRM) approach is used with OLS, robust, and two-stage least squares regression and bootstrapping is used to enhance the models. Data was collected for from 342 station locations in Canada's five largest metropolitan areas with an average weekday ridership of over 3 million. Average weekday station boardings were used as the dependent variable and 53 socioeconomic, built environment, and system attributes were chosen as potential explanatory variables that were chosen after a review of the DRM and travel demand literature. The study yielded three sets of models with an adjusted r-squared values ranging between 0.650 and 0.864. Canadian rail rapid transit stations were tested together and separately as urban and suburban service types. The most important factor identified in the models was the supply of transit service, followed by inter-modal connections (bus stops for urban stations and primarily parking for suburban stations), and residential population density. Socioeconomic factors of the population in the area surrounding stations were not found to be significant. The absence of socioeconomic variables in the final model indicates that planners and policy makers have significant scope to exert influence over transit use through land use planning, design, and service features.

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1. Introduction

1.1. Background

Rail rapid transit forms the backbone of many public transportation systems in cities globally; it moves people at both high speed and high capacity. Rail rapid transit in this context refers to fixed guideway public transit system operating in exclusive or shared rights of way, and includes subways, light rail transit (LRT), heavy suburban rail, and elevated rail. Rail rapid transit, and public transit in general, has many benefits when compared with private motorized transportation. Mobility (the potential for movement) and accessibility (the potential for interaction) can be provided with less traffic and better public health as a result of more walking and less pollution. Transit can also be cost effective in providing mobility and accessibility as it does not require the vast amounts of roads, highways, parking, and energy that automobiles do. Shifting the share of travel from automobiles to transit is one way of reducing air pollution and greenhouse gas emissions. Indirectly, transit can also encourage economic growth and urban growth leading to agglomeration economies caused by clustering and densification (Chatman & Noland, 2014). Finally, in terms of social justice, public transit can also ensure a more equitable distribution of transportation resources and access (Deka, 2004).

Despite the negative effects of automobile use and the potential benefits of transit in Canada, roughly only 20% of people living in urban areas use transit to commute to work in 2011 (Statistics Canada, 2013). Toronto and Montréal had the highest transit mode shares (23.3% and 22.2% respectively), followed by Ottawa-Gatineau (20.1%), Vancouver (19.7%), Calgary (15.9%), Winnipeg (13.4%), Halifax (12.5%), and Edmonton (11.3%) (Statistics Canada, 2013).

Reasons for the relatively low transit commute shares in Canada's largest cities compared to that of private automobiles include low residential densities and low levels of transit provision outside of city cores, attitudes towards transit use, and long transit commute times (Turcotte, 2011). The fact that transit commute times in Canadian cities are significantly longer than those for automobiles (44 minutes vs. 27 minutes on average in Canada's largest cities) indicates that transit service does not, in most cases, compete in terms of travel times (Turcotte, 2011). This is likely a major contributing factor that has made large numbers of people reliant on automobiles, often used at low capacity, generating considerable congestion at peak hours. Automobile dependence has also grown globally with countries such as Sweden, France, Germany, and the United Kingdom, reaching levels of automobile ownership and use approaching those found in the United States (Handy, 2002). This trend, however, may be on the decline, with some researchers suggesting that automobile use in industrialized countries has slowed or halted in terms of growth (Jones, 2014; Millard-Ball & Schipper, 2011).

While transit usage is generally higher in Canada compared with the United States, Canada's transit share is small compared with most other high income countries (Stantec Consulting Ltd. & Victoria Transport Policy Institute, 2011). Despite higher transit use, average commute times in Canada's largest cities are comparable to those south of the border (Statistics Canada, 2013). In 2011, Toronto had the longest average automobile commute times in Canada at 29.3 minutes, while the longest in 2011 in the United States was found in the New York-Northern New Jersey-Long Island metropolitan area at 29.02 minutes (Statistics Canada, 2013; U.S. Census Bureau, 2014a, 2014b). Transport Canada (2006) estimates the direct costs of congestion in terms of delay, emissions, and wasted fuel at $2.3 billion to $3.7 billion for Canada's nine largest urban regions. The C.D. Howe Institute (Dachis, 2013) estimates a $1.5 billion to $5 billion in congestion costs for the Toronto region alone due to economic externalities such as foregone income and clustering, and agglomeration benefits. The effects of congestion are also not spread evenly, with 80% of the total costs coming from Canada's largest cities, 42.5% for Toronto, 20.6% for Montréal, and 16.6% for Vancouver (COMT, 2012). Population growth in the largest metro areas and increasing private automobile ownership rates are likely to continue the trend of increased congestion and associated costs (Transport Canada, 2006). Increasingly, governments at the provincial, regional, and municipal levels are seeking strategies to remediate automobile congestion and transportation issues have become important debates in political campaigns. As awareness of transportation issues on the part of the public increases and the need to replace aging transport infrastructure in many Canadian cities grows, a major opportunity exists to plan and build in more sustainable ways.

Evidence suggests that increasing road infrastructure is an ineffective means to reducing traffic congestion as it reduces the cost of automobile travel and induces new demand, resulting in traffic congestion returning to similar levels (Duranton & Turner, 2011). Therefore new strategies including new transit infrastructure and improved transit service that aim to reduce congestion, increase accessibility, and limit the harmful effects of automobile emissions are required. McIntosh et al. (2014) have suggested in a global analysis of travel behaviour that the provision of rail-based transit has a strong relationship with decreased automobile travel. Baum-Snow & Kahn (2000) have also shown that increasing proximity to transit service can also increase transit commuting. Kohn (2000) observed that service cuts made by transit agencies in some Canadian cities in the 1990s contributed to a decrease in riders. Given this evidence, the recent trend of increased transit funding for operations and capital investments in Canada are encouraging. There are currently eight rail rapid transit projects under construction or recently completed in Canada: Vancouver's Evergreen Line, Edmonton's Metro Line, the Waterloo Region's Ion LRT, Toronto's York-Spadina Subway Extension, Eglington Crosstown LRT, Toronto's Union-Pearson Airport train, Ottawa's Confederation Line LRT, and Montréal's Train de l'Est, which will add a total of 109.7 km of new track and 78 new stations. The Canadian Urban Transit Agency (CUTA) in 2012 estimated that the estimated cost of transit infrastructure plans in Canada for 2012 to 2016 were $53.3 billion, while existing funding sources only amounted to $40 billion (Felio, 2012). The New Building Canada Plan announced by the federal government in 2013 will provide $53 billion in infrastructure investments over 10 years, although investments are not limited to transit projects (CUTA, 2014). Despite these new infrastructure investments funding for transit, and equally important integrated land use policies, still fall short of the level necessary to effectuate large scale changes in travel behaviour.

The history of rail rapid transit began in Canada in 1954 when Toronto opened its first subway line. Canadian cities began to transition from bus- and streetcar-based systems to urban rail rapid transit soon after. Montréal inaugurated its Metro in 1966, followed by Edmonton's (1977) and Calgary's (1982) light rail, and Vancouver's elevated SkyTrain (1986). Overall transit ridership over this period grew steadily from less than 1.1 billion passengers annually in 1970 to 1.53 billion in 1990, when it began to decline (Kohn, 2000). Suburbanization, the falling cost of automobile travel, and cuts to funding and service are likely to have played a role in this decline by eroding any advantage transit may have had in terms of convenience and travel time competitiveness (Kohn, 2000). More recent data suggests that transit use had rebounded in Canada and reached over 2 billion passengers in 2012 (CUTA, 2012). After several years of decline, transit ridership began to rebound in Toronto in 1999, Vancouver in 2000, and Montréal in 2003 (Agence Métropolitaine de Transport, 2008; Toronto Transit Commission, 2003;

TransLink, 2013). This was matched by a 9.5% increase in its supply (measured as total vehicle kilometres) between 2008 and 2012 and the initiation of several new rail transit infrastructure services or expansions (CUTA, 2012). In North America in general, the 1990s marked a turning point in the direction of transit ridership. Allen & Levinson (2014) present evidence that indicates that since then, ridership on commuter rail service, in terms of commuter rail distance travelled, has outpaced the growth of highway vehicle distance travelled. They attribute this success in part to the adoption of higher capacity trains, faster service, off-peak scheduling, and the growth of park-and-ride lots. All of these are elements that help to increase the accessibility and convenience of transit for growing suburban populations.

Table 1 – List of Canadian Rail Rapid Transit Systems

System	Name & Type	Daily Passengers (2012)	Length	Stations (Stations/km)	Average Passengers per station
Calgary C-Train	Surface and elevated LRT	210,495	49 km	36 (0.73)	5,847
Edmonton LRT	Surface and underground LRT	72,422	21 km	15 (0.71)	4,828
Montreal Metro	Underground	845,718	69 km	68 (0.99)	12,437
Toronto Subway	Underground and surface heavy & elevated LRT	881,160	76 km	75 (0.99)	11,749
Vancouver SkyTrain	Elevated and underground LRT	327,625	69 km	47 (0.68)	6,971
Montreal AMT	Heavy railway	68,887	204 km	51 (0.25)	1,351
Toronto GO Train	Heavy railway	191,376	450 km	63 (0.14)	3,037
Vancouver West Coast Express	Heavy railway	11,309	69 km	8 (0.12)	1,414

The purpose of this study is to determine station-level and network factors that influence transit ridership in Canadian cities and to quantify their effects. Factors at the station level, particularly those related to the built environment and station amenities, have the potential to influence demand for transit and a better understanding of the magnitude of their effects will help to better plan new transit projects and improve existing ones. One means of assessing the influence of these factors is through the use of Direct Ridership Models (DRMs) which typically use a set of variables found within a given distance of a station to estimate ridership at the stop, line, or system level.

The scope of this study are the areas immediately surrounding rail rapid transit stations in Canada's five largest metropolitan regions: Toronto, Montréal, Vancouver, Calgary, and Edmonton. Each city has at least one form of rail rapid transit; a summary of system characteristics can be found in Table 1 and maps of each city in Figure 1-5.

Rail rapid transit in Canada encompasses a number of technologies from diesel or electric locomotive driven suburban services to subways, light rail on reserved right of way and mixed with traffic, and elevated trains. They also vary significantly in terms network length, stop density, service frequency, and average boardings per station. As a result, two major functional classifications are used for this study: suburban rail and urban rail, which generally serve two distinct purposes. Suburban rail is oriented towards commuter service, often exclusively, and serves to connect outlying areas directly to the downtown with the bulk of service at peak hours. Urban service, on the other hand, serves a more diverse purpose with higher frequencies, all-day service, more interconnections, and denser stop spacing. Montréal's AMT, Toronto's GO and Vancouver's West Coast Express train services fall into the suburban rail category, while the Calgary C-Train, Edmonton LRT, Vancouver SkyTrain, Montréal Metro, and Toronto Subway are considered urban. Both forms are examined together and in separate models in an effort to highlight any effects specific to either type of service. Temporally, station boarding data was collected for 2012 and all other data was collected for dates as close as possible. Socioeconomic data comes from the 2011 Canadian Census and National Household Survey and jobs figures are from the 2006 Canadian Census.

Figure 1 – Map of Toronto

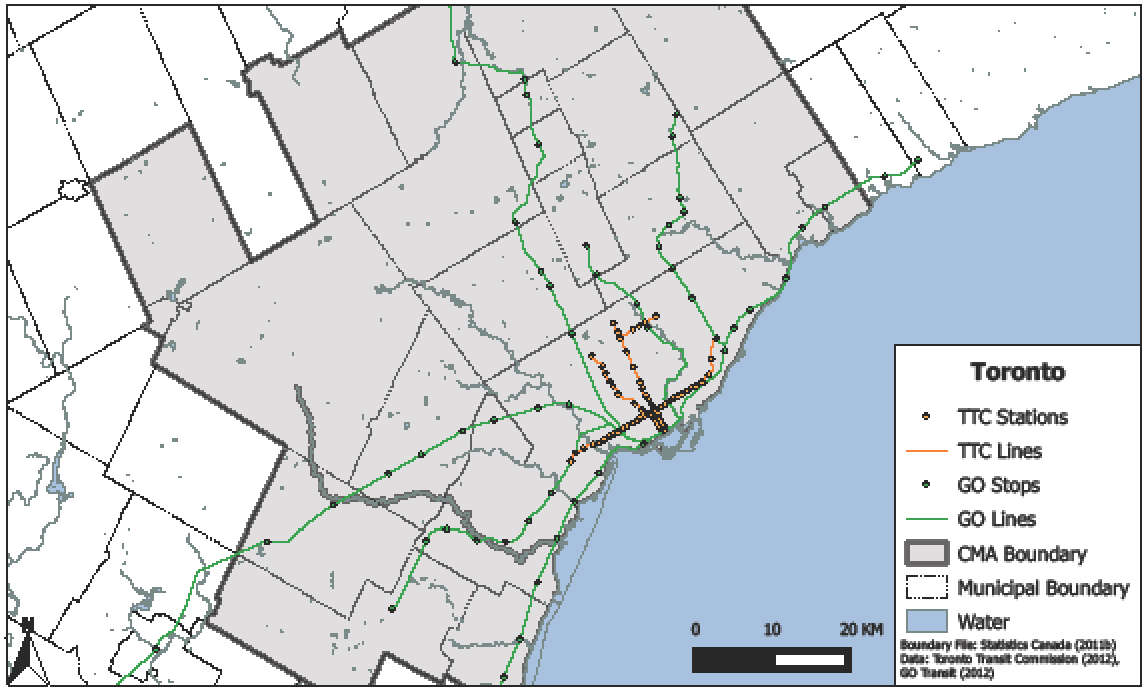


Figure 2 – Map of Montréal

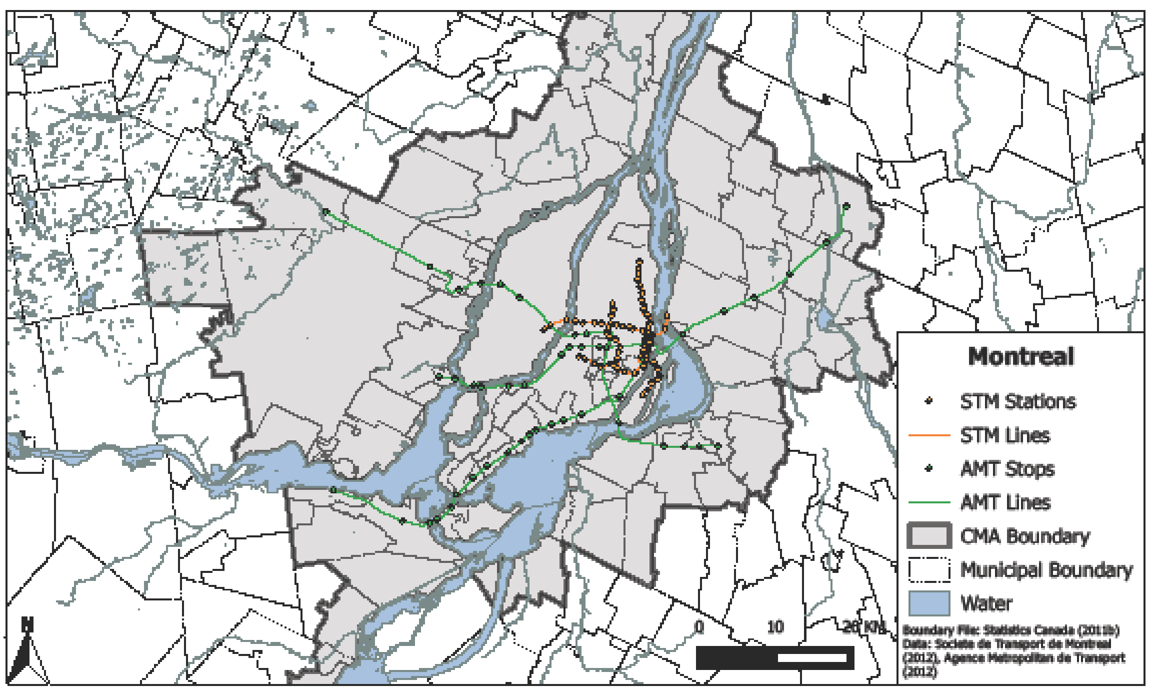


Figure 3 – Map of Vancouver

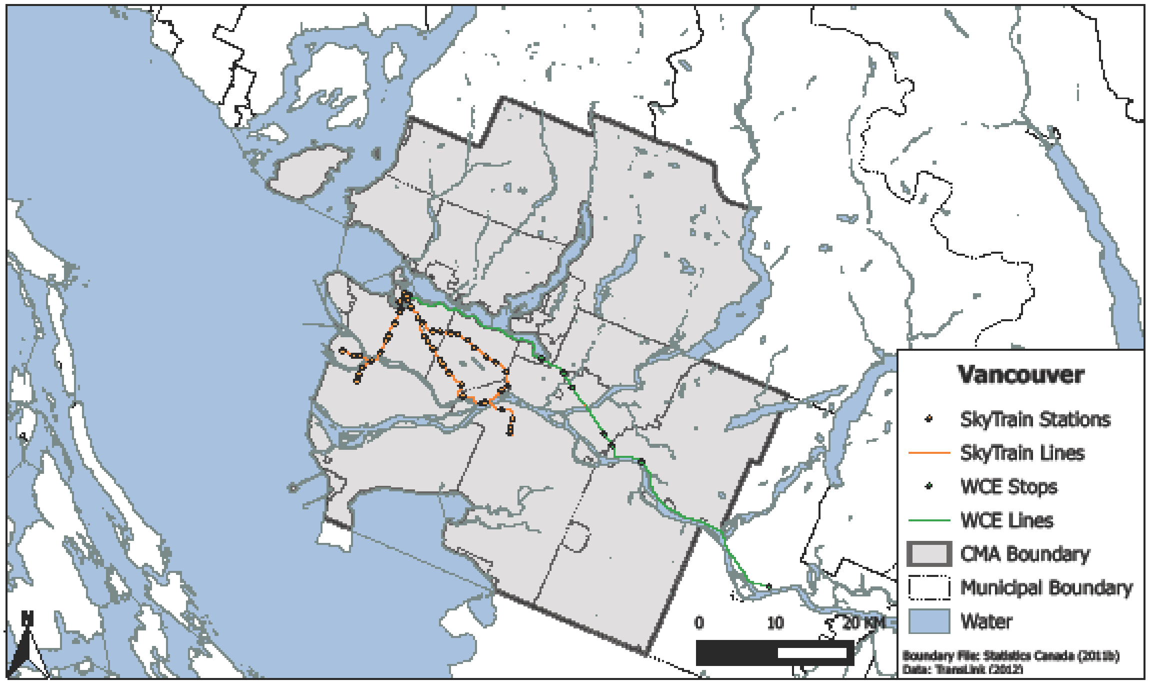


Figure 4 – Map of Calgary

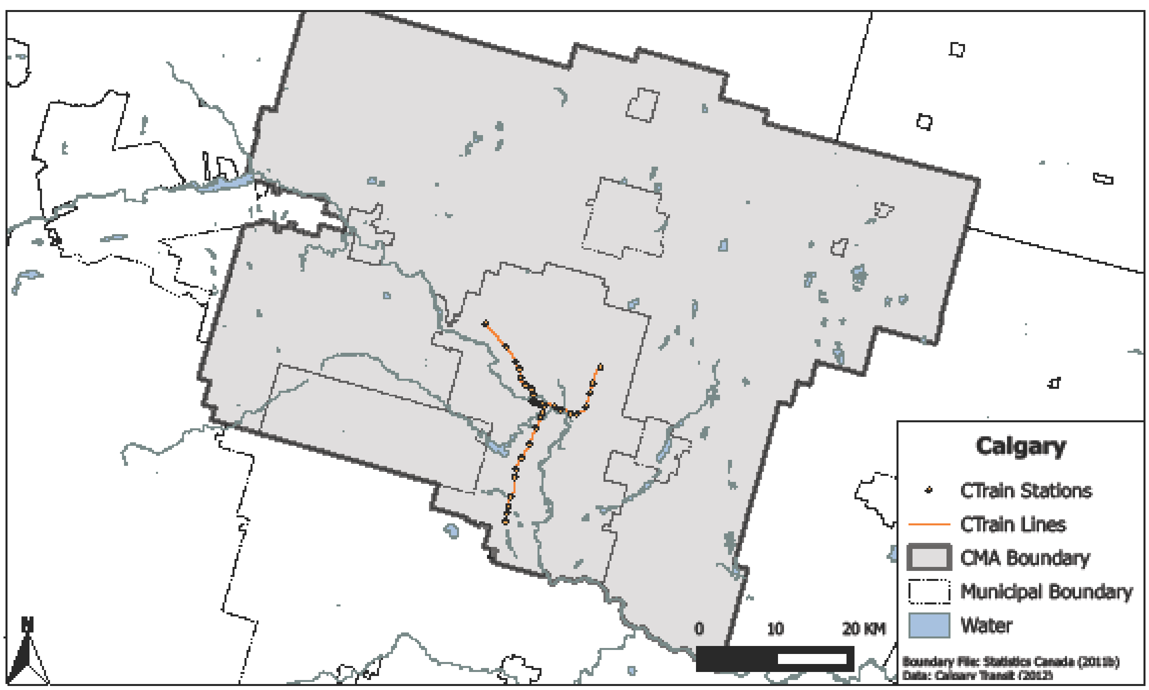
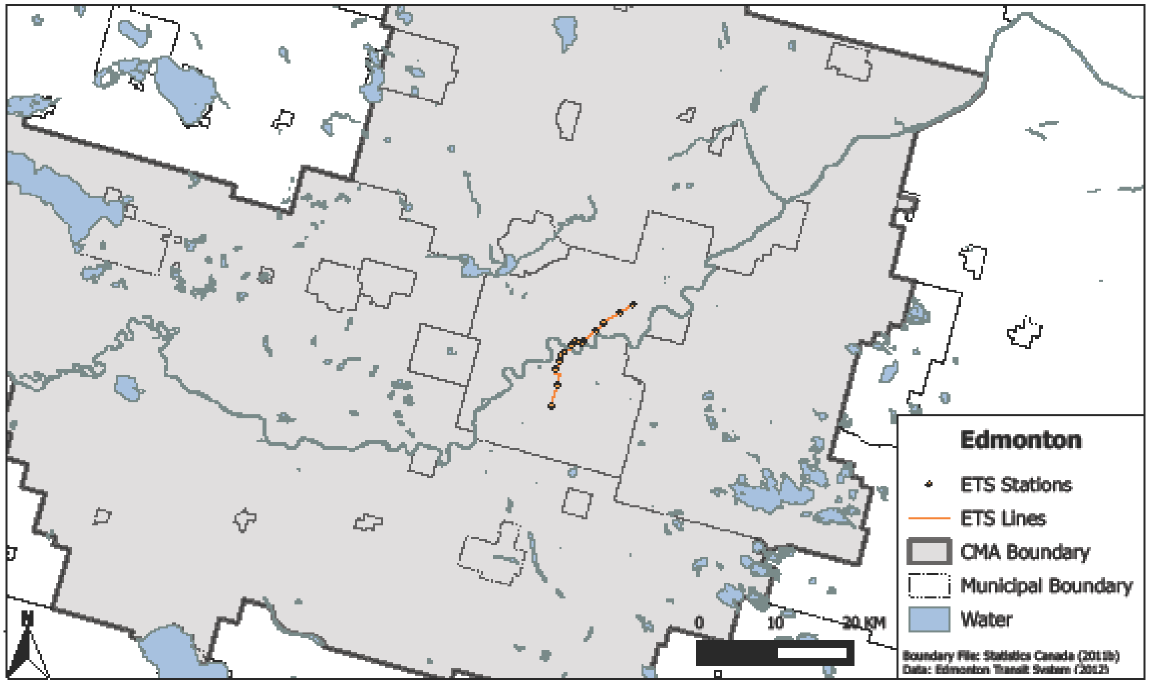


Figure 5 – Map of Edmonton



The shift towards more transit use in Canadian cities can be attributed to factors related to the increasing cost of automobile travel (e.g. increasing fuel costs), transit service improvements, and greater acceptance of transit particularly among younger segments of the population (Turcotte, 2011). Land use planning and policy can also affect behaviour to favour collective and active modes thought changes to neighbourhood and street designs. As a result, a number of planning movements and theories such as Transit Oriented Development (TOD), Smart Growth, and New Urbanism have emerged as approaches to designing cities with an aim to reduce automobile dependence and increase active and transit mode share.

TOD refers to planning around transit for existing and future stations, aiming to generate ridership and capitalize on development encouraged by proximity to a transit station (Calthorpe, 1990, 1993). It can also be used to describe the actual physical environment of station areas. TODs generally aim to create mixed-use, high density, and accessible neighbourhoods around stations to facilitate transit use and walking, and to discourage automobile travel (Cervero, Ferrell, & Murphy, 2002). New Urbanism and Smart Growth refer to broader urban design movements that emphasize walkable communities with a mixture of land uses developed in reaction to automobile induced urban sprawl (Calthorpe, 1990, 1993; Duany & Plater-Zyberk, 1994; Duany & Talen, 2002).

The application of TOD principles is not new to Canada; the developments surrounding stations of the Yonge Subway line in Toronto in the 1950s and 60s can be seen as early examples of the creation of transit-supportive neighbourhoods (CUTA, 2004). Official plans for transit-supportive, pedestrian friendly, dense, and diverse neighbourhoods also appear in planning documents prepared by the City of Ottawa (RMOC Planning Department, 1973) and the Greater Vancouver Regional District (GVRD, 1975) as early as the 1970s. TOD principles have since become common in Canadian urban planning practice and elements have been adopted to varying degrees in many station area developments. The Canada Mortgage and Housing Corporation (CMHC) examined 10 TOD applications in Canadian cities, finding a wide range of development sizes (0.45ha to 73ha), housing types (single-family homes to high-rise towers), pedestrian connectivity features, and land use mix (CMHC, 2009). What remained constant, however, was the fact that residents owned fewer automobiles, drove less, and used transit more in these developments (CMHC, 2009). Another common theme among the case studies was the lack of involvement on the part of the local transit agency itself in the planning of these projects, perhaps indicating a greater need for the involvement of transit agencies not only in the provision of service, but also in land use and development planning.

Planning for transit and, specifically, in immediate station areas has thus been a major focus in transit infrastructure decisions, but their application and their success vary depending on location (CMHC, 2009). Filion & Kramer (2012) have argued that the support for urban intensification and a reduction in automobile dependence in planning policies of the six largest metropolitan regions in Canada is an indication of the adoption of Smart Growth and New Urbanist principles. Further, they argue that most of the six regions have adopted "nodal" development typical of TOD. Generally it has been found that TOD and neighbourhoods that emphasize transit-supportive density, diversity, and design can achieve higher rates of transit use and active mode share, while reducing automobile travel (Evans et al., 2003).

As transit is seeing a resurgence in popularity among users and increasing government support understanding what may influence transit ridership at the station level can be useful for planners. As a result, transit agencies and planners seek to optimize the resources allocated to them. One means to achieving this goal is to use available data and technology to better understand which local factors influence transit use to better plan new infrastructure investments. Traditional four-stage travel demand models estimate travel flows between traffic analysis zones (TAZs) by first estimating the number of trips originating in each TAZ, distributing the trips between TAZs, estimating mode choice of travellers, then assigning traffic to the travel networks (Cervero, 2006). Four-stage demand models can accurately predict commuting flows at a regional scale and are an essential element of long term transit planning but are not capable of assessing the role of small scale design and land use factors (Cervero, 2006; Usvyat, Meckel, DiCarlantonio, & Lane, 2009). They are also data-intensive and require specialized knowledge to derive accurate results. A Transit Cooperative Research Program (TCRP) survey found that out of 36 transit agencies across North America that responded, only 51% used four-stage models (Boyle, 2006). Data quality, accuracy, and availability were among major concerns of respondents and it is reported that several agencies at the time were in the process of developing new tools to better assess local scale factors influencing transit use (Boyle, 2006). Four-stage models are still seen as an effective means to plan in the long term at a regional scale but impractical for smaller scale changes where professional judgement, rules of thumb, and service elasticities are widely employed (Boyle, 2006; Chatman et al., 2014).

One alternative to four-stage modelling is station level modelling, also known as direct ridership modelling (DRM), which uses ridership as a measure of transit demand, DRMs have been developed to better guide the transit planning process at the local scale and to define the factors that have the greatest potential to influence ridership. Transit planners in the United States interviewed by Chatman et al. (2014) as part of the development of project level and regional scale ridership models indicate that these types of models will be beneficial in future planning. To this date most ridership models have been conducted in the United States. Thus there is an academic base of knowledge on what influences transit ridership in the United States. It is likely, given the different historical development processes, roles of government, and social structure that some of the factors that influence travel behaviour vary between Canada and the United States. For example, race or ethnicity appears to play an important role in transit use in many US studies (e.g. Chu, 2004; Dill et al., 2013; Ryan & Frank, 2009; Chow et al., 2003) where racial segregation is stronger than in Canada (Walks & Bourne, 2006)

The goal of this study is to develop a direct ridership model in order to predict station-level boardings with a variety of socioeconomic, built environment, station, and network characteristics mostly within walking catchment areas around stations. A secondary goal is to develop separate models for urban rail rapid transit and suburban commuter rail to see if different station-level factors are influential. Finally, this project also aims to make recommendations that could be used to produce greater ridership, better situate planned transit stations, and improve existing ones.

1.2. Summary

Chapter 2 provides a review of the travel demand literature and a summary of the DRMs surveyed for this project. This is followed by a summary of important factors associated with ridership: socioeconomics, internal factors, built form, and station access. Finally, statistical methods used for this analysis are discussed.

Chapter 3 presents the methodology used in this study describing how catchment areas were determined, which variables were used and how they were collected, the statistical methods employed in the analysis, and the steps of the modelling process.

Chapter 4 presents the models that were developed and provides a discussion of the findings.

Chapter 5 discusses the implications of the findings presented in Chapter 4 and policy recommendations, as well as outlines the limitations of the research and proposals for future improvements.

2. Literature Review

This section reviews the literature analysing links between factors associated with transit usage including the built environment, socioeconomics, and service supply. It also provides a summary of the DRM approach and a survey of published DRMs. Section 2.1 - A Brief History of Urban Transport provides a general overview of the ways in which travel and built form are linked through a history of urban development and its relation to transportation technology and contemporary research on the topic. Section 2.2 - Direct Ridership Models describes the DRM approach and the links it with the broader travel and built environment research. A fundamental component of DRMs is the delineation of station catchment areas, typically a walking distance from a station, which is addressed in Section 2.3. Finally, sections 2.4 to 2.6 review in detail studies of factors influencing transit use, divided into three categories: socioeconomics, internal factors, and urban form. Section 2.4 - Socioeconomics describes the various socioeconomic factors found in the literature to be associated with travel behaviour. Section 2.5 - Internal Factors reviews the literature examining the influence of transit service directly influenced by transit providers such as pricing, service, and station amenities. Finally, Section 2.6 - Urban Form summarizes research analyzing the elements of the built environment including land uses and street networks that are thought to influence travel behaviour.

2.1. A Brief History of Urban Transport

One of the most influential forces shaping the spatial patterns of urban growth throughout history has been the diffusion of new transportation technology. Newman and Kenworthy (1999) identified three distinct city forms shaped by the dominant transportation technology of the time:

1. The walking city
2. The transit city
3. The automobile city

Early cities were limited in size to areas accessible by foot, generally no larger than an individual could walk more than 45 minutes from the center. As a result, population densities in major centers reached levels similar to those found in the densest modern cities (Muller, 2004; Pushkarev & Zupan, 1977). It was not until the implementation of the first public transit systems that cities began to grow to cover larger areas of land and people at lower densities (Kain, 1999). The first American mass transit system, a horse-drawn streetcar, was established in New York in

1852 (Muller, 2004). This resulted in the expansion of the city beyond its walking city size, enabling the affluent and middle-class to escape the crowded core while maintaining the same level of access to employment and services (Kain, 1999; Muller, 2004). From 1852 to 1888, cities across the United States and Canada implemented horse-drawn street car systems and slowly expanded outward (Muller, 2004).

In 1888, the electric street car was used for the first time in North America and spread almost immediately to most major cities (Kain, 1999). Cities began to expand much more rapidly along new streetcar lines, affording a larger segment of the population a chance to escape the still crowded urban centers (Muller, 2004). City development in this era occurred in radial corridors along the streetcar lines further than ever before from the core (Newman & Kenworthy, 1999; Porter, 1997). Streetcars served as backbones of neighbourhoods, with residential streets fanning out for several blocks along the lines (Muller, 2004). The electric streetcar dramatically increased the speed of travel, opening up large areas of new land for residential and commercial use and permitting the construction of even lower density neighbourhoods (Newman & Kenworthy, 1999). Harrison & Kain (1974) estimated that each new mile of streetcar track built in cities in the United States between 1890 and 1910 resulted in a 3.2% increase in single-family homes in an urban region. The first transit systems clearly exerted a decentralizing effect on cities but at the same time, facilitated the clustering of functions, particularly employment, in areas with the greatest access (Porter, 1997). The electric streetcar also increased the economic and ethnic segregation initiated by their horse-drawn predecessor, with homes growing larger and neighbourhoods more affluent further from downtown (Muller, 2004).

Although the automobile was introduced in the 1890s, it was not until Henry Ford's process of mass production 20 years later that car ownership rates began to increase and transit use decreased dramatically (Kain, 1999; Muller, 2004). By the 1920s, suburban growth exceeded that of the center cities for the first time and the spaces between the streetcar suburbs and beyond began to undergo intensive development (Muller, 2004).

The period between World War I and II was characterized by steady suburban growth and increasing ethnic homogenization in neighbourhoods, as well as the suburbanization and segregation of industry and commerce (Muller, 2004). After World War II, the construction of freeway networks, improved automobile technology, and still increasing automobile ownership rates facilitated a massive outward expansion (Muller, 2004). Baum-Snow (2007) has estimated that the construction of highways through central cities in the United States, facilitating mobility and decreasing the cost of automobile travel, contributed directly to a decline in central area populations. Increasing income levels and preferences for lower density living also contributed to the decline of transit in North America (Kain, 1999). Wealthier families were able to afford to live in increasingly lower density neighbourhoods where transit provision is difficult (Kain, 1999). Nearly ubiquitous automobile ownership and readily accessible high speed road infrastructure effectively rendered most areas of a city easily accessible, drastically reducing the need for clustering or concentration of activities. This, combined with zoning codes that tended towards separating land uses, helped to entrench the automobile as the preferred, and often only viable, means of transport in North American cities. Mobility was no longer dependent on fixed infrastructure and the cost of moving almost anywhere within an urban region was much more equal. This also served to decrease the importance of the center both in terms of population and employment. This is notable as centralized employment is a particularly important element in the success of the fixed guideway transit systems constructed in the early- to mid-19th century, which were oriented towards delivering commuters to downtowns from outlying areas (Kain, 1999).

By the 1950s and 1960s, academics, planners, and consultants began to recognize the links between widespread automobile ownership and the rapid rate of suburbanization. In the 1970s, researchers turned to understanding the interaction between built environment and public transit amidst concerns about rapidly declining transit use, particularly in the United States (see Adams, 1970; Newman & Kenworthy, 1989b; Pushkarev & Zupan, 1977; Smith, 1984). It became clear that transportation technologies and infrastructure played a major role in shaping cities in terms of their size and how land uses were distributed, and that automobile use and infrastructure were drastically changing the urban environment. Once the implications of automobile-centered development on the environment and social structure of the city were understood attention turned to how design and planning could mitigate its negative effects. In Canada this manifested itself in planning policies at the municipal and regional level in cities such as Toronto and Vancouver, which favoured intensification of already built-up areas (Taylor & Burchfield, 2010). Later, planning movements such as New Urbanism and Smart Growth emerged as responses to the unchecked growth of suburbia and the negative consequences of this type of development.

These movements emphasized the creation of relatively dense, mixed use communities that supported active transport and the use of transit. Through the provision of high quality street environments, greater residential densities, and a mix of land use functions, it is believed that walking and transit trips could be encouraged and automobile trips reduced significantly (Handy, 2002).

The relationship between the built environment and travel behaviour continues to be a major motivation for research on transport. Researchers have examined links between travel behaviour and the built environment through measurements of vehicle kilometres travelled (VKT), station boardings, mode choice, and frequency of walking trips among others at scales varying from the metropolitan level to individual travellers (Ewing & Cervero, 2010). Ewing & Cervero (2010) provided a comprehensive meta-analysis of the built environment-travel literature comprising 62 studies covering a range of methods, data types, statistical controls, and locations. They examined the built environment's effects, specifically land use intensity, land use mix, and design on VKT, the rate of walking trips, and transit use. They found that individually built environment variables had relatively small effects on the three types of travel behaviour but that in combination, the effects may be larger. With respect to walking, they found that intersection density, the ratio of jobs to housing, and distance to commercial services exhibited the strongest relationships. For transit use, it was found that access to transit was the most important factor in the mode share and likelihood of transit use followed by intersection density and land use mix. These findings indicate that the policies encouraging densification and mixed use development around bus stops and rail rapid transit stations have the potential to influence travel behaviour. Cervero & Kockelman (1997) in an examination of the 3 "D"s (density, diversity, and design) of the built environment, found that built form variables had statistically significant, although moderate, effects on single occupant vehicle trip making and VMT. Density, diversity, and design later expanded to include distance to transit and destination accessibility, representing five major ways that the built environment influences travel behaviour including transit share (Cervero & Murakami, 2008).

Density is typically measured in terms of population and sometimes job concentration, and it is broadly accepted that high densities are if not a prerequisite, at least a strong contributing factor to the success of transit (Cervero, 1998; Cervero et al., 2002; Ewing, Pendall, & Chen, 2003).

Some of the first studies to assess the viability of transit projects conducted by Pushkarev & Zupan (1977) and Pushkarev, Zupan & Cumella (1982) established minimum density thresholds for various transit types. Higher densities can increase the potential opportunities for individuals to interact and increase the total number of services that can be supported (Banister, 2005; ECOTEC, 1993). Density shortens the distances between work, home, and commercial activities, which reduces average travel distances (Banister, 2005; ECOTEC, 1993; Holtzclaw, Clear, Dittmar, Goldstein, & Haas, 2002; Steiner, 1994). If the distance required to travel is shortened, the time advantage of driving is reduced. This coupled with parking restrictions typically found in denser settings has the potential to make automobile use much less convenient than walking, cycling, or transit (Kuzmyak et al., 2003). The links between densities and travel behaviour have received much attention in the past with higher density generally being associated with a range of travel-related phenomena at varying scales. Higher population densities have been linked to lower levels of energy consumption for transportation (Naess, 1993; Newman & Kenworthy, 1989a, 1989b), higher work and shopping trip transit mode share (Frank & Pivo, 1994; Kitamura, Mokhtarian, & Laidet, 1997), a reduction in total distance travelled (Holtzclaw, 1990; Holtzclaw et al., 2002), as well as lower levels of automobile ownership (Dunphy & Fisher, 1996) and automobile trip making (Steiner, 1994).

On a metropolitan scale, there appears to be a correlation between density, road supply, and transit usage with less dense and more automobile-oriented North American cities demonstrating considerably less transit usage (Cervero, 1998; Kuzmyak et al., 2003). Both population and job density in station areas have also been shown to be associated with passenger distance travelled on transit systems at a metropolitan scale in the United States (Chatman et al., 2014). On a smaller scale, Lee et al. (2011) used a cluster analysis to identify a number of neighbourhood types, finding that, overall, neighbourhoods with higher densities and better transit access tended to produce more transit trips. Population and employment density at the station catchment level is associated with increased ridership for new transit projects (Chatman et al., 2014). Individuals living in compact neighbourhoods (defined as areas with mixed housing, nearby commercial services, and transit access) have also been associated with more walking, cycling, and transit trips (Dunphy & Fisher, 1996; Karash et al., 2008).

Despite a significant body of evidence that connects density to travel behaviour measures used in travel behaviour assessments represent density as well as a number of related factors (Kuzmyak et al., 2003). The effects of density then also incorporate the higher levels of accessibility, greater congestion, and restrictions on parking that are usually associated with higher density environments (Kuzmyak et al., 2003). Density on its own likely does contribute in a small way to travel behaviour, though “second order” effects of density may be more influential (Kuzmyak et al., 2003) .

Diversity, often measured as a jobs-to-housing ratio (Johnson, 2003; Kuzmyak et al., 2003), the proportions of various land use types (Dill, Schlossberg, Ma, & Meyer, 2013; Johnson, 2003; Sohn & Shim, 2010), or a composite land use mix index (Dill et al., 2013; Estupinan & Rodriguez, 2008; Ryan & Frank, 2009), exerts a similar effect as density. By providing a diversity of opportunities to work and shop close to residences, trip lengths can be shortened reducing the need to use automobiles and making active transport and public transit more feasible alternatives (Banister, 2005). Diverse neighbourhoods, particularly in suburban centers, tend to produce more transit, walking, and cycling trips (Porter, 1997). Having retail services situated between a transit stop and one’s residence has also been shown to increase work transit trip rates (Cervero, 1996). While jobs-to-housing ratios have not generally shown strong associations with travel behaviour, other measures such as land use entropy indices and distance to nearest commercial location often do (Ewing & Cervero, 2010; Kuzmyak et al., 2003; Vance & Hedel, 2007).

Design refers to street network patterns and amenities (e.g. lighting, sidewalks, and shading) that have the potential to influence travel behaviour by providing safe environments and convenient routes. Street network patterns can be measured in a number of ways including intersection density, street density, average block length, and intersection to street link ratio. Intersection density is a common measure of neighbourhood permeability that is frequently associated with lower VKT and higher rates of walking, cycling, and transit use (Boer, Zheng, Overton, Ridgeway, & Cohen, 2007; Ewing & Cervero, 2010). Street density is a simple measure of the length of the street network in a given area divided by the size of the area. Higher street densities would then indicate that road space comprises a large proportion of a given area. Average block length is determined by dividing the total number of street links (sections of road between intersections) by the total length of streets. This yields another measure of network permeability with longer average block lengths indicating more distance between intersections and therefore fewer options for alternative routes. Similarly, intersection to street link ratio measures the total number of intersections divided by the links between them and provides a measure of permeability with higher ratios indicating a wider range of route options. Cervero & Kockelman (1997) found that walking quality, particularly intersection density, block length, sidewalk provision, and limited street parking were associated with lower levels of single-occupant vehicle travel. Pedestrian friendliness, often measured as a composite index of amenities, route directness, and quality, also shows some correlations with higher rates of transit, walking, and cycling trips (Ewing & Cervero, 2010; Porter, 1997). For example, Estupinan & Rodriguez (2008) found that a composite factor of ‘walking supports’ including pedestrian and bike friendliness, sidewalk quality, and perceptions of safety and cleanliness was strongly associated with transit use for Bogota’s BRT stations. Pedestrian environment factors have also been associated with reduced VKT, higher transit and active transport mode shares, and higher active transport station access mode share (Kuzmyak et al., 2003).

Distance to transit refers to the local accessibility of transit services, which may be a determining factor in whether or not an individual chooses transit for any trip type (Lee et al., 2011). Krizek (2003) analyzed the effects of residential relocation on mode choice in the Seattle area, finding that households that move to areas providing greater options for transit and active transport modes tend to drive less. Baum-Snow & Kahn (2000), using data from five U.S. cities from 1980 to 1990, found that decreasing distance to rail transit stations from an average of 5.79 km to 4.79 km increases transit commute shares at the census tract level by 1.4%. El-Geneidy et al. (2014) have presented evidence for Montréal that shows that walking distance to transit can vary by transit, trip, and household type, but that the majority of walking access to transit occurs between 873 m and 1259 m for rail based transit. Cervero & Gorham (1995) found that neighbourhood type (automobile vs. transit oriented) in San Francisco and Los Angeles also influenced commuting behaviour noting, however, that this effect may be dependent on a metropolitan area’s orientation towards one form of transit or the other. This relates to the final “D”: destination accessibility, which refers to how well a transit station, for example, connects a neighbourhood to the rest of the region (Cervero & Murakami, 2008). Metropolitan regions that favour transit connectivity with higher overall transit accessibility are likely to produce higher transit usage simply by connecting more useful locations (Cervero & Gorham, 1995).

The nature and strength of the relationship between urban form and travel is still subject to debate and is potentially confounded by factors such as residential self-selection (the propensity for people who prefer one mode of transportation moving to areas where it is easier to use that mode). When accounted for, researchers generally find that built environment variables are still associated with travel behaviour although the effect is mitigated, in part, by residential self-selection (Cao, Mokhtarian, & Handy, 2009; Ewing & Cervero, 2010; Mokhtarian & Cao, 2008). The results, however, vary with Ewing & Cervero (2010) finding that in some cases, self-selection actually enhanced the built environment's effect on travel behaviour, while Cao et al. (2009) found that the effect is attenuated by it. Chatman (2009) has also argued that residential self-selection may actually underestimate the built environment's effect on travel choices, particularly for transit-preferring households as these households may be opting to use transit regardless of their neighbourhood type.

2.2. Direct Ridership Models

Predicting potential ridership of proposal is important in the transport planning process. One means of assessing the potential drivers of transit ridership is the use of a direct ridership model (DRM). A DRM is a methodological tool that has grown in popularity owing to ease of implementation and interpretation of results. Fundamentally, DRMs estimate ridership, typically measured at the station, line, or system level, and are frequently used in the assessment of transit infrastructure proposals and in investigations of built form, station amenity, and service supply effects on transit use. In contrast with the traditional four-stage transit demand modelling, DRMs allow for the analysis of small-scale local factors often not included in large-scale regional model. DRMs represent a cost-effective alternative as many transit agencies simply do not have the resources available to conduct four-stage demand models (Boyle, 2006; Usvyat et al., 2009). Advances in GIS technology and increasingly large amounts of data available are enabling transit agencies to better understand what drives transit ridership and consequently plan for better service. Still, a large proportion of transit agencies rely on rules of thumb, professional judgement, comparisons with existing routes, or published elasticities for many planning decisions (Boyle, 2006; Chatman et al., 2014).

Nineteen DRMs were surveyed for this study: 11 from the United States, two from Spain, and one each from Canada, Colombia, Mexico, South Korea, and Taiwan, Some studies examine only one form of transit (Cardozo, Garcia-Palomares, & Gutierrez, 2012; Cervero, 2006; Cervero, Murakami, & Miller, 2010; Chan & Miranda-Moreno, 2013; Chow, Zhao, Liu, Li, & Ubaka, 2003; Duduta, 2013; Estupinan & Rodriguez, 2008; Gutierrez, Cardozo, & Garca-Palomares, 2011; Johnson, 2003; Kuby, Barranda, & Upchurch, 2003; Ryan & Frank, 2009; Sohn & Shim, 2010) while others combine several (Chu, 2004; Dill et al., 2013; Kohn, 2000; Lane, DiCarlantonio, & Usvyat, 2006; Taylor, Miller, Iseki, & Fink, 2008) covering bus, BRT, trolley, light rail, heavy rail, and subway systems. The majority employ standard OLS regression, while others use two-stage least squares (2SLS), geographically weighted regression (GWR), and structural equation modelling (SEM). A notable absence in the DRM literature is the role of service supply and its interactions with ridership. Taylor et al., (2008) and Estupinan & Rodriguez, (2008) use 2SLS with an instrumental variable finding that service provision is strongly associated with demand. Sohn & Shim (2010) go further using SEM to evaluate two-way relationships between a range of potentially interacting variables finding a number of significant links. Another element lacking in most DRM studies, including all 19 cited here, is the potential for a spatial relationship among variables. In other words these analyses do not account for the fact that ridership at certain stations or in certain areas may be clustered. Statistical techniques exist to account for these relationships and may help to explain some of the observed variation in ridership that is not captured by traditional regression modelling.

Five of the 19 studies mentioned here combine multiple cities for their analysis using from 265 (Taylor, et al., 2008) to 8 different locations (Kohn, 2008). While aggregating data for multiple regions may mask location-specific influences on transit use it has the added benefit of increasing the sample size and generating better estimates. Most cases are limited to one form of transit though some combine light rail and commuter services (Lane et al., 2006), multiple transit types (Taylor et al., 2008), bus and light rail (Dill et al., 2013), and bus, trolley, and LRT (Chu, 2004). One benefit of combining urban and suburban rail services is again to obtain a large sample of stations from which to derive estimates as well as to account for the fact that suburban train stations in some cases exist in relatively dense environments more typical of urban rail station settings while the opposite is true for many urban rail stations. The majority of the DRM literature surveyed relied on average daily boarding data as opposed to AM/PM or peak/off-peak periods while Chan & Miranda-Moreno (2013) estimated separate models for trip production and trip attraction at the AM peak.

The diversity of locations, methods used, types of transit, and variables considered in the models have resulted in a range of potentially significant factors. In order to simplify the large number of variables used in other studies and considered in this one, four categories are used: socioeconomics, station, neighbourhood and street network, and service attributes. Table 2 contains a summary of the key attributes and findings of the DRMs surveyed for this study. The variables tested in these models guided the choice of variables to be used in this study.

Table 2 - DRM Literature Review Summary

Authors	Chu, 2004	Cervero et al., 2010	Chan & Miranda-Moreno, 2013
Location	Jacksonville, Florida	Los Angeles, California	Montréal, Québec
Transit Type	Bus, trolley, light rail	Bus Rapid Transit (BRT)	Subway
Method	Poisson regression	OLS Regression	OLS Regression
Socioeconomic	• Population • Age • % female pop. • Ethnicity • Household income • No-vehicle households	• Population	• Population • Income
Station and Network	• Bus stops within walking distance • Other bus stops in area • Trolley stop dummy	• Bus line dummy • Rail line dummy • Distance to next closest stop • Interaction term between dedicated BRT lane, bus lines, rail lines, population, and parking availability	• Bus stops within walking distance • Bus routes within walking distance • Distance to downtown terminus • Terminal station dummy • Transfer station dummy
Neighbourhood and Street Network	• Jobs		• Commercial land use area • Government/institutional land use area
Service		• Daily bus supply	• High frequency service dummy
Other			

Authors	Dill et al., 2013	Kuby et al., 2003	Lane et al., 2006
Location	Portland, Oregon	9 US Cities	17 US Cities
Transit Type	Bus, light rail	Light Rail	Light and Commuter Rail
Method	OLS Regression	OLS Regression	OLS Regression
Socioeconomic	• % white population • % pop. under 17/over 65 • Pop. with higher education • Households with a vehicle • Households > poverty line • Population	• Population • % renters • % no-vehicle households	• Average household size • Total households • Population
Station and Network	• Distance to downtown • Stop location • Transfer station dummy • Rail or BRT station • Park and ride spaces • Transit center dummy • Total stations in area	• Parking availability dummy • Terminal station dummy • Transfer station dummy • Total bus connections • Relative accessibility	• Parking availability dummy • Total bus connections • Transit center dummy • Fare • Total stations on network • Distance to nearest station
Neighbourhood and Street Network	• % single floor residential • % multi-floor residential • % commercial land use • Total park area • Land use mix index • Employment • Pedestrian destinations • Street connectivity • Multi-use/bike paths (km)	• Employment	• Employment
Service	• Average headway • Maximum coverage time		• Time and speed to center • Midday headway
Other	• Job accessibility		• CBD/metro employment • CBD pop. density • Metro area pop.

Authors	Usvyat et al., 2009	Lin & Shin, 2008	Cervero, 2006
Location	10 US Cities	Taipei, Taiwan	Charlotte, North Carolina
Transit Type	Heavy Rail	Subway	Light Rail
Method	OLS Regression	OLS Regression	OLS Regression
Socioeconomic	• Population	• Household income • Car ownership • Motorcycle ownership	• Population
Station and Network	• Parking spaces • Terminal station dummy • Distance to downtown • Rail connections	• Transfer station dummy • Intermediate station dummy • Transfer bus availability	• CBD station dummy • Parking availability • Total bus connections • Terminal station dummy • Distance to nearest station
Neighbourhood and Street Network	• Employment • Bus routes within walking distance	• 4-way intersections • Sidewalk length • Retail/service floor/area ratio	• Interaction between CBD employment and density
Service	• Midday headway		• Level of service
Other			

Authors	Ryan & Frank, 2009	Duduta, 2013	Sohn & Shim, 2010
Location	San Diego, California	Mexico City, Mexico	Seoul, South Korea
Transit Type	Bus	Bus Rapid Transit (BRT)	Subway
Method	OLS Regression	OLS Regression	OLS Regression/SEM
Socioeconomic	• Income • No vehicle households • % female pop. • % Hispanic pop. • % White pop. • % youth	• Population density	• Population density
Station and Network		• Microbus connections • Microbus terminal dummy • Total bus/BRT connections • Number of connecting subway lines • Long distance bus connection dummy • Direct distance to CBD	• Number of transfers to center • Feeder bus connections • Transfer station dummy
Neighbourhood and Street Network	• Walkability index		• Employment • University dummy • Commercial land use area
Service	• Level of service		
Other			

Authors	Estupinan & Rodriguez, 2008	Taylor et al., 2008	Gutierrez et al., 2011
Location	Bogota, Colombia	265 US metro regions	Madrid, Spain
Transit Type	Bus Rapid Transit	Various	Subway
Method	2SLS	2SLS	Distance decay regression
Socioeconomic	• Education • Unemployment rate • Socioeconomic stratum	• Population • Unemployment rate • % college students • Recent immigrants • Ethnicity • No-vehicle households	• Foreign population
Station and Network	• Total amenities		• Urban bus connections • Suburban bus connections • Parking availability • Station accessibility on network • Number of lines at station
Neighbourhood and Street Network	• Cleanliness and safety • Accidents • Thefts and deaths • Traffic calming • Sidewalk length • Bike path length • Land use mix • Intersection count • Road density	• Freeway lane length	• Employment • Employment in commercial sector • Employment in education sector • Land use mix
Service		• Vehicle revenue hours • Fares • Headways	
Other		• Gas prices	

Authors	Chow et al., 2003	Cardozo et al., 2012	Kohn, 2000
Location	Broward County, Florida	Madrid, Spain	8 Canadian Cities
Transit Type	Bus	Subway	Various
Method	Distance decay regression	Distance decay regression	OLS Regression
Socioeconomic	• Ethnicity • No-vehicle households • Vehicle ownership rate for households with no children		
Station and Network		• Suburban bus connections • Number of lines at station	
Neighbourhood and Street Network	• Employment	• Employment	
Service	• Vehicle service hours • Fares		• Fares • Vehicle revenue hours
Other			

Authors	Johnson, 2003
Location	Minneapolis, Minnesota
Transit Type	Bus
Method	OLS Regression
Socioeconomic	• % household with access to a car • % of pop. 0-16 • Population density
Station and Network	
Neighbourhood and Street Network	• Multi-family housing (1/8 mile and 1/8 to 1/4 mile from stops) • Mixed use land • Retail land use • Housing/jobs balance • Housing/shopping balance
Service	
Other	

2.3. Station Access and Catchment Areas

How far individuals are willing to walk to access transit is a key consideration for planners and is something that can vary dependent on location, time of day, trip purpose, and type of transit used (El-Geneidy et al., 2014). The accessibility of transit is also a key factor in travel decision-making as Baum-Snow & Kahn (2000) have demonstrated, decreasing the distance to transit has a positive effect on transit use in the United States. Station access modes can be split into three categories: automobile, other transit, and active transport. In Canada, access mode share for rail rapid transit varies within a wide range by station, system and by transit type (see Table 3).

Table 3 - Station Access Mode Share by Transit Operator

Operator	Transit Type	Automobile	Transit	Active
AMT	Suburban	62%	12%	26%
STM	Urban	8%	46%	46%
GO	Suburban	80%	10%	10%

(Agence Métropolitaine de Transport, 2012)
(Salsberg, 2013)

Urban stations are typically accessed by active transport and other modes of transit while suburban station access is mostly dominated by automobile and other transit (Agence Métropolitaine de Transport, 2012; Crowley, Shalaby, & Zarei, 2009). Quantifying these access variables using measures of physical infrastructure rather than surveys of other travel behaviour data is relatively easy for automobile (e.g. the number of parking spaces at a station) and other transit (e.g. the number of connection bus lines at a station) and are consistently found to be associated with ridership in station level models (Cardozo et al., 2012; Cervero, 2006; Cervero et al., 2010; Chan & Miranda-Moreno, 2013; Chu, 2004; Dill et al., 2013; Duduta, 2013; Gutierrez et al., 2011; Kuby et al., 2003; Lane et al., 2006; Lin & Shin, 2008; Sohn & Shim, 2010; Usvyat et al., 2009).

Active transport access, on the other hand, is less clearly quantified and in most cases requires the delineation of a station catchment area from where it is assumed that the majority of local riders originate or the use of a distance decay function, which weights the effect of access by distance.

Variables measuring the permeability of street networks and the diversity of land uses in station areas are often positively correlated with transit ridership in stop-level analyses, which aim to capture a station area's potential to facilitate pedestrian trips (Chu, 2004; Estupinan & Rodriguez, 2008; Johnson, 2003; Lin & Shin, 2008; Ryan & Frank, 2009). Permeability simply refers to the degree to which a street network facilitates travel by providing a diversity of routes. Gridded street networks with relatively short blocks, for example, have a high degree of permeability, which can be contrasted with suburban neighbourhoods comprising curvilinear streets and cul-de-sacs that limit through traffic. Estupinan & Rodriguez (2008) found that station areas that provided supports to walking, such as sidewalk quality, continuity, and width had significant positive effects on BRT station-level ridership in Bogota. Similarly, Ryan & Frank (2009) found that the inclusion of a composite walkability variable capturing land use mix, density, and street network form helped to explain station level bus ridership in San Diego. Intersection density and sidewalk length (Lin & Shin, 2008), and pedestrian destinations and street connectivity measured as the number of intersections divided by the number of links between them (Dill et al., 2013) were positively associated with ridership at the stop level as well. Other measures of pedestrian access, such as land use mix or proportions of residentially or commercially zoned land, were associated with increased transit use (Chan & Miranda-Moreno, 2013; Dill et al., 2013; Gutierrez et al., 2011; Johnson, 2003; Lin & Shin, 2008; Sohn & Shim, 2010). In the travel demand literature, intersection density, population and employment density, and jobs-housing balance were generally found to be positively associated with an increased frequency of walking trips and that more integrated, or mixed, land uses can encourage transit trip frequency (Ewing & Cervero, 2010; Kuzmyak et al., 2003). Regardless of the measure employed, all aim to capture how well an area can provide access to non-motorized travellers through providing a diversity of opportunities or routes.

Methods of measuring station catchment areas include fixed boundaries, either network based or circular, or without fixed boundaries through the use of geographically, or distance-decay, weighted regression that discount the effects of variables as distance from the station increases (see: Cardozo et al., 2012; Chow et al., 2003; Gutierrez et al., 2011). It is generally accepted that 800 m (≈ ½ mile) is the distance within which most walking trips to rail rapid transit occur, and an adequate representation of a person's willingness to walk to access transit, and there is some evidence to suggest that boundary size and shape (network-based vs. circular) have little influence on station level predictions of transit ridership (Guerra, Cervero, & Tischler, 2012). However, El-Geneidy et al. (2014) suggest, using origin destination survey data for Montréal, that the distances passenger was to stations depends on numerous factors including the type of transit being accessed. They found that travel on foot to access transit varies based on location, personal characteristics, and service type. They found that mean walking distances to Montréal's Metro stations is 565 m (0.35 miles) and 873 m (0.54 miles) at the 85th percentile. For suburban train stations, the mean walking distance was 818 m (0.5 miles) and 1,259 m (0.78 miles) at the 85th percentile, suggesting that larger service areas for suburban train stations more accurately capture its catchment area.

2.4. Socioeconomics

The majority of reviewed DRMs found associations between socioeconomic variables and transit usage. The wide range of variables tested in the models and likely high collinearity among them makes it difficult to isolate one or even several factors. Significant predictors included in DRMs were income, economic status (e.g. population below poverty line), employment rates, housing tenure, and car ownership. Several studies in the United States found significant relationships between variables representing ethnicity (or race) and transit use (Chu, 2004; Dill et al., 2013; Ryan & Frank, 2009; Taylor et al., 2008), while those conducted elsewhere did not find these factors to be significant. Several studies found negative associations between income and transit ridership (Chan & Miranda-Moreno, 2013; Chu, 2004; Dill et al., 2013; Lin & Shin, 2008; Ryan & Frank, 2009), while the inverse was true for unemployment rates (Estupinan & Rodriguez, 2008; Taylor et al., 2008).

Car ownership influenced transit ridership in both DRMs (Chow et al., 2003; Dill et al., 2013; Johnson, 2003; Kuby et al., 2003; Lin & Shin, 2008; Ryan & Frank, 2009; Taylor et al., 2008) and in the travel demand literature (Bento, Cropper, Mobarak, & Vinha, 2005; Paulley et al., 2006; Taylor & Fink, 2003). This is likely as a result of the faster speeds and greater convenience offered by private automobiles relative to public transit in most places. Finally, age groups in a station area were found to influence boardings with higher proportions of youth and seniors positively related to transit ridership (Chu, 2004; Dill et al., 2013; Johnson, 2003; Ryan & Frank, 2009). Dill (2013) and Johnson (2003) found a positive association between the proportion of youth in the population and transit use, while Ryan & Frank (2009) observed the opposite relationship. Differences in the direction of the relationship from one model to the next may be explained by local factors. In the case of Portland, where Dill (2013) conducted a study, students were provided free transit passes, which was not the case in San Diego, the location of the Ryan & Frank (2009) study. Possible explanations for the effect age has on transit usage include the fact that youth and seniors may not be able to drive or afford an automobile. Again, it is likely that these variables exhibit a high degree of collinearity. Collinearity among socioeconomic variables and the potential complications of residential self-selection discussed previously make interpreting the role of socioeconomic variables in ridership models difficult. Socioeconomic variables included in ridership models in most cases reflect income or class. Housing tenure, unemployment, car ownership, and even age groups can be seen as proxy variables for income.

It is clear from the literature that income affects travel behaviour by reducing the cost of automobile travel. These effects may, however, vary depending on location owing to transit service levels and attitudes towards transit use (Buehler & Pucher, 2012). Regions with more integrated and convenient transit service do not have the same relationships between mode share and income normally found in North America. Buehler & Pucher (2012) found that it is the "integrated package of complementary policies that explains…" (pg. 563) how German public transport succeeds in attracting riders away from automobile use across all income groups. This is achieved through providing transit service that approaches the convenience and speed of private automobile use. This relates to Cervero & Gorham's (1995) statement that some of the variation in the effects of neighbourhood type on travel behaviour observed in San Francisco and Los Angeles may be explained by metropolitan scale orientations towards one form of transport auto neighbourhoods vs. transit neighbourhoods. It should therefore be expected that regions with more comprehensive transit planning and better transit service will not exhibit the same relationships between socioeconomic, and potentially other variables, and transit ridership as areas with weaker transit policies.

2.5. Internal Factors

Internal factors, as termed by Taylor & Fink (2003), refer to the elements of a transit system under the direct control of a transit agency and include elements such as fares, station amenities (e.g. shelters or schedule information), and service supply. Taylor & Fink (2003) in a survey of factors influencing transit ridership concluded that internal factors are related to ridership, but their effect is less than that of external factors such as urban form. In Canada, Syed & Khan (2000) found that scheduling information provided at stations was positively associated with bus ridership in Ottawa. In the United States, scheduling information was also associated with increased transit ridership (Evans et al., 2004). Station amenities are, however, typically not included in many ridership assessments owing to time consuming data collection that usually involve site audits. Ridership estimations and DRMs typically include fares when comparing between different transit agencies and the supply of service at a station.

Researchers have examined the relative effect of increasing transit capacity (number of passenger spaces) or supply (number of trains or busses) and have found that supply is positively associated with ridership (Currie & Delbosc, 2011; Peng, Dueker, Strathman, & Hopper, 1997; Taylor et al., 2008). In Canada, Kohn (2000) demonstrated that revenue vehicle hours, a measure of transit supply, were positively associated with transit ridership at the system level in the period from 1992 to 1998, using data from 85 transit agencies. In a single equation approach to estimating demand, service supply is potentially endogenous as the supply of transit is likely to be at least partially related to its demand. It is reasonable to assume that a transit agency will increase service in a particular location in response to increased ridership, while it is also likely that more frequent service will then attract more ridership. As a result, this violates the exogeneity assumption of OLS regression. A violation of this assumption is likely to bias the estimates of the model. Chu (2004) proposes three alternatives when evaluating the potential for endogeneity in ridership models:

a) estimate a reduced form model without the endogenous variable,
b) account for the endogenous problem within the model, or
c) include the endogenous variable and ignore the problem.

Among the DRM studies surveyed some, such as Estupinan & Rodriguez (2008) and Taylor et al.(2008), explicitly account for the nature of this relationship through the use of 2SLS where supply and demand are estimated in a system of equations, others use supply (Cervero et al., 2010) or average headways (Dill et al., 2013; Usvyat et al., 2009) directly in a single regression equation, while others forgo the use of supply variables altogether. Whether supply variables are estimated directly or in a separate equation it is generally found to increase ridership. This is likely as a result of making service more convenient and accessible by providing more departure times and reducing waiting time and the time spent travelling on linked transit trips. The effects of service increases may, however, not be equal with infrequent services being more sensitive to service increases (Evans et al., 2004). Evans et al. (2004), in a survey of transit scheduling and service frequency literature, found that suburban commuter train service was more likely to see a larger increase in riders as result of increased frequency than high frequency services such as subways.

In the United States, both Lane et al (2006) and Taylor et al. (2008) found that fares are significantly negatively associated with transit ridership at the stop level. Kohn (2000) also found that fares were negatively associated with ridership in Canada at the system level. Overall, however, this effect was small and he concluded that demand for transit in Canada was relatively inelastic to changes in price. Similar results were found in the United States where in most cases ridership was more strongly affected by service frequency changes than by changes in fares (Evans et al., 2004). The use of fares in ridership models may be useful when comparing between different transit agencies but may be strongly correlated with distance from the city if there is a variable fare structure as is the case for many suburban rail services.

In the context of DRMs both Estupinan & Rodriguez (2008) and Taylor et al. (2008) used the 2SLS method to account for the supply of transit service. Estupinan & Rodriguez (2008) conducted their analysis at the station level for BRT in Bogota. First they employed factor analysis to narrow down the range of potential explanatory variables, then they estimated a two equation simultaneous model. They found that the supply of transit is a strong predictor of transit usage in Bogota, along with supports for walking, barriers to car use, and perceptions of safety and security. Talyor et al. (2008) employed a slightly different approach estimating transit ridership at the metropolitan level over a sample of 265 US urbanized areas. First they predicted vehicle revenue hours, then estimated total and per capita transit ridership. They found that internal factors (fares and service supply) explained 26% of the observed variance in per capita transit usage. These findings indicated that factors directly under the control of transit agencies do play a role in influencing transit ridership but that external factors contribute equally or more.

2.6. Urban Form

As urban form is likely to have at least some effect on travel behaviour and transit ridership at the station level, a number of metrics have been developed. The most basic urban form measurement, and one popularly cited in the travel and transit literature, is population density. Population density is often cited as one of the most important drivers of transit use leading to the popular belief that transit requires a certain level of density to be feasible. Planning strategies to reduce car dependence specifically emphasize density and mixed land uses as a means to encourage the use of alternative transport. Many DRMs also find that population density within station areas is positively associated with ridership (Cervero, 2006; Cervero et al., 2010; Chan & Miranda-Moreno, 2013; Chu, 2004; Dill et al., 2013; Duduta, 2013; Johnson, 2003; Kuby et al., 2003; Lane et al., 2006; Sohn & Shim, 2010; Taylor et al., 2008; Usvyat et al., 2009). Other measures, related to population density, that have also been tested include household density and population and household intensity (density in residentially zoned land). It is assumed that increasing the number of people in station areas will encourage transit ridership by making transit closer to more people and therefore more accessible.

Job density is another factor often associated with higher transit use. In fact, some research has argued that workplace or trip end attributes such as job density are more important than trip origin attributes when assessing travel behaviour (Chatman, 2003; Lee et al., 2011). In DRMs a number of studies have demonstrated links between employment in station areas and transit ridership (Cardozo et al., 2012; Chow et al., 2003; Chu, 2004; Dill et al., 2013; Estupinan & Rodriguez, 2008; Gutierrez et al., 2011; Kuby et al., 2003; Lane et al., 2006; Sohn & Shim, 2010; Usvyat et al., 2009).

Land use variables are also commonly used measures of urban form and often measure either their total area or proportion. Composite metrics have also been developed including land use entropy, land use mix, and walkability indices. The first, taken from Cervero (2010) is a mixed-use entropy index where p_i = proportion of land in use i of total of all land, k = the six categories of land use (water is excluded).

Equation 1 – Entropy Index

$$\text{Entropy} = -1 \times \left(\frac{\sum_{i=1}^{k} p_i \times \ln(p_i)}{\ln(k)} \right)$$

The second is a land use mix variable adapted from Chan & Miranda-Moreno (2013):

Equation 2 – Land Use Mix Index

$$\text{Mix} = \frac{\text{Household Density} \times \text{Job Density} \times \text{Commercial Density}}{\text{Household Density} + \text{Job Density} + \text{Commercial Density}}$$

And finally, a walkability index adapted from Ryan & Frank (2009):

Equation 3 – Walkability Index

$$\text{Walkability} = 2\times \begin{bmatrix} \text{Z[Land Use Mix]}\times\text{Z[Household Density]}\times \\ \text{Z[Commercial Sites]}\times\text{Z[Intersection Density]} \end{bmatrix}$$

Where Land Use Mix refers to the entropy measure in Equation 1, household density is the total number of households in a station area, and Z refers to the Z-scores of the inputs. The level of mix is assumed to be positively associated with transit ridership. This is partially supported by transport and land use literature that indicates that elements such as job-housing balance and mixed uses can reduce car travel and increase walking and transit trips (Cervero & Kockelman, 1997; Ewing & Cervero, 2010; Johnson, 2003).

Finally, street network characteristics are a means of assessing the built environment in station areas. Numerous methods have been suggested to capture how permeable, pedestrian friendly, and complete a street network is (see Tresidder (2005) for a summary). Intersection density, road density, link to node ratio, and average block length have all been examined in either the travel demand literature or in DRMs. More complete or permeable street networks with more pedestrian friendly designs are thought to be positively associated with transit by making stations more easily accessible. Estupinan & Rodriguez (2008) found that street environments that support walking had a strong effect on BRT boardings in Bogota while Ryan & Frank (2009) found that walkability (see Equation 3) was positively related to bus boardings in San Diego. Lin & Shin (2008) also found that four-way intersection density and sidewalk length in station areas were positively associated with subway boardings.

3. Methods

The purpose of this study was to apply the method of direct ridership modelling of station boardings to a series of variables measuring factors mainly within walking catchment areas of all urban and suburban rapid transit stations in Canada. The study began with the selection of variables based on a review of the literature. It then proceeded to the data collection phase. This chapter presents the methods adopted for this study including the selection, collection, and treatment of candidate variables, the geographic context of the analysis, and the statistical methods used to analyze the data.

3.1. Catchment Areas

As discussed in section 2.3 there are several methods of establishing the catchment area of transit stations, including fixed distance boundaries with network-based or circular buffers or through the use of spatial regression which discounts the effect of a given variable based on distance. For this analysis, fixed distance network-based boundaries are employed to capture the maximum distance to which users would be willing to regularly access transit by foot. 800 m buffers were used for urban rail and 1000 m were used for suburban rail. Network-based buffers represent the potential for pedestrian access to stations and were used for this analysis. The benefit of this type of buffer is highlighted particularly in suburban train station settings, where road networks are not as regular and result in small effective walking areas.

In order to properly capture station accessibility, RouteLogistics road shapefiles for Canada created by DMTI Spatial were used and then manually edited to include footpaths and pedestrian access not already included (DMTI Spatial, 2013a). The manual addition of road links and footpaths was accomplished through the use of Google Maps satellite imagery and the Google Maps base layer accessed through ArcGIS version 10.2. This manual editing process resulted in the expansion of some catchment areas that the initial road network did not accurately capture. This was particularly evident for many suburban rail stations where road access was fairly limited but footpaths provided additional accessibility. As the goal of establishing the catchment areas was to capture walking, access highways, and other roadways where pedestrians are not permitted were excluded from the network. Finally, a non-overlapping buffer, or exclusive catchment area was chosen for this analysis to prevent overlapping catchment areas and double counting. If non-overlapping buffers were used, certain areas fall within the catchment areas of several stations. If boundaries were to overlap certain features, such as land uses, amenities, and road network, features may be double counted. Boundaries were determined automatically using the service area tool in ArcGIS. When exclusive service areas are chosen and buffers overlap, ArcGIS automatically determines the midpoint between the stations and draws the boundary. Figure 6 and Figure 7 depict the areas reachable on foot from the Cedar Park suburban train station in Montréal and demonstrate how a station catchment area can change in size and shape after the manual addition of missing footpath and road links.

As the station catchment areas did not align with census tract boundaries, the number of persons, for example, was assigned proportionally depending on both how much residentially zoned land of a given tract fell within the catchment area. In other words, it was assumed that population and employment were dispersed evenly in the appropriately zoned land (i.e. residential, commercial, resource/industrial) derived from the RouteLogistics shapefiles and were then assigned proportionally to each catchment area. While this introduced some error into the measurement, it was the best method given the scale of the census data available and the fact that it accounted for the varying land uses found within the tracts, rather than assuming population and employment are spread evenly throughout the whole tract.

Figure 6 - 1000m Service Area before Addition of Footpaths

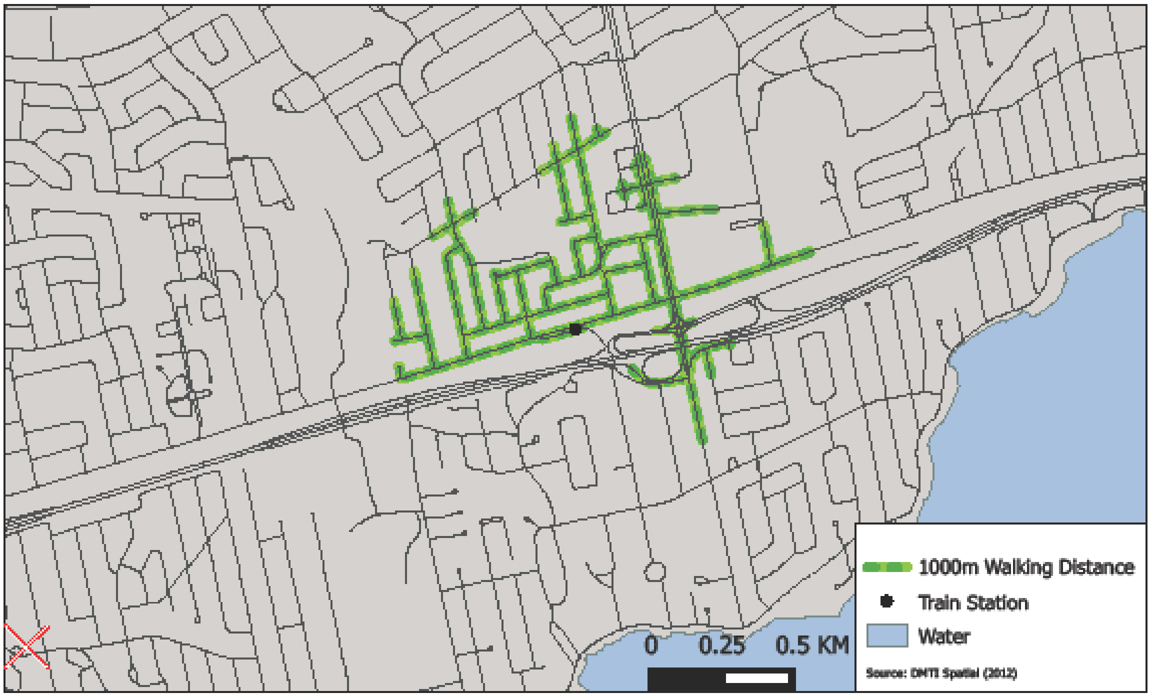
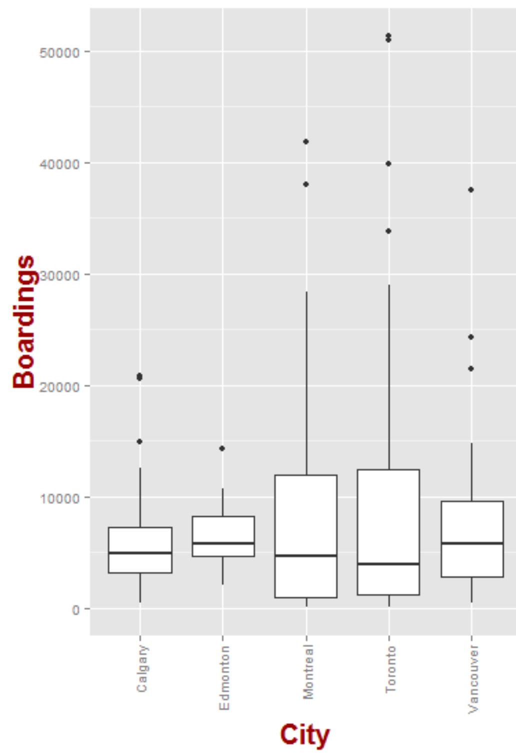


Figure 7 - 1000m Service Area after Addition of Footpaths

3.2. Dependent Variable

The dependent variable, average daily weekday boardings at 353 stations in 2012, were chosen as the highest demand for transit service is experienced on weekdays. Also, suburban train services on some lines only offer service on weekdays. Each boarding represents one leg of a trip. Boarding data was obtained directly from transit operators either through their websites or through access to information requests. Figure 8 presents the raw boardings data by city, demonstrating the large range of the data particularly for Montréal and Toronto that occurs as a result of combining suburban and urban train services. Eight transfer stations in Toronto (Spadina, St. George, Bloor-Yonge, Sheppard-Yonge, and Kennedy) and Vancouver (Columbia, Commercial-Broadway, and Bridgeport) were removed from the analysis. In these cases, data was collected at the platform level as opposed to at the station entrance, and passengers transferring from one platform to another were included in the data resulting in very high boarding counts for these stations. This method of data collection was not used in some of the cities in the analysis and would be problematic in the assessment of local area effects on boardings. Data for all agencies except Montréal's STM were collected from cordon counts at the platform level and represent the best available depiction of average daily ridership at the stop level. Data for Montréal's STM was collected at the turnstiles. Counts were conducted over a period of one to several weeks, mostly in the fall, and were averaged to obtain the figures used. While it is likely that motivations for transit use vary dependent on trip purpose and time of day data was not available from all transit operators for AM/PM or peak/off-peak periods. As a result the data does not differentiate between work or school trips which make up the bulk of transit trips in Canada (e.g. El-Geneidy et al., 2013; TransLink, 2013a) and trips for other purposes such as leisure or shopping. As mentioned in Section 2.2 all but one DRM (Chan & Miranda-Moreno, 2013) surveyed used average daily or monthly boardings as a dependent variable likely as a result of data availability as in this case.

Figure 8 - Average Weekday Boardings by City



3.3. Independent Variables

Through the review of the literature and examination of 19 DRM studies, a total of 53 independent variables that may influence transit ridership at the station level were identified. These variables were separated into four categories: socioeconomic, station and network, neighbourhood and street network, and service attributes.

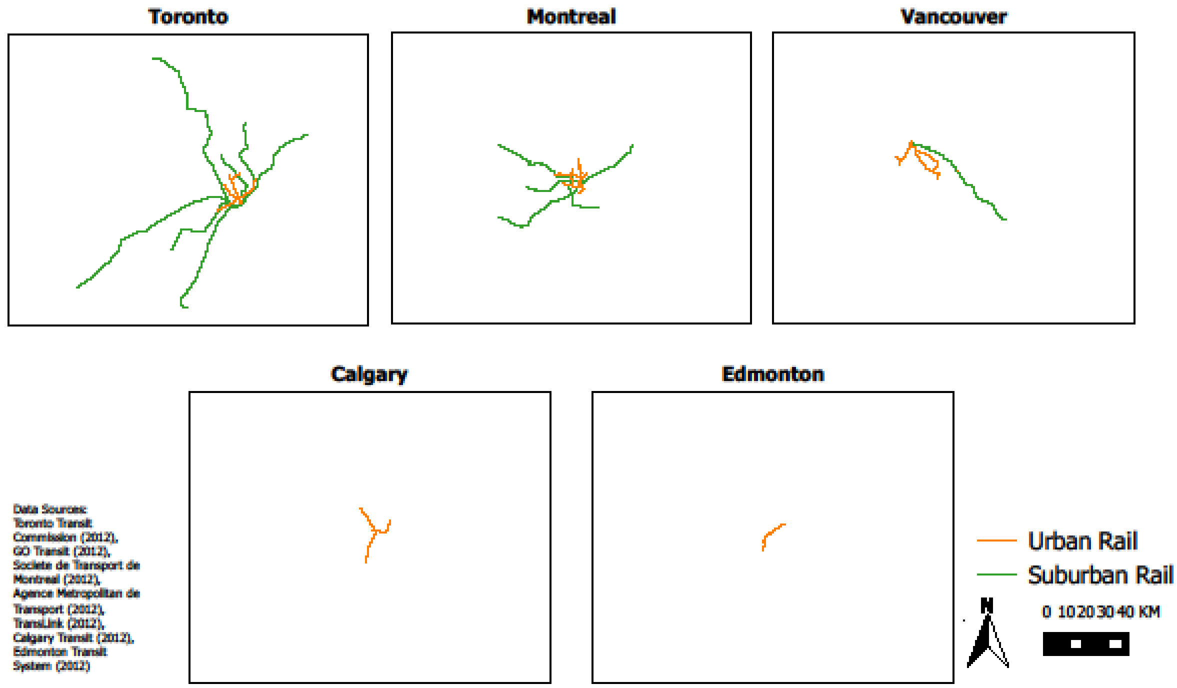
3.3.1. Socioeconomics

In order to understand the effect the presence of different age groups in a station catchment area may have on ridership the proportion of ages 20 to 30, 30 to 40, 40 to 50, 50 to 60, and 60 to 70 were tested in the modelling process. It was assumed that certain age groups were more likely to take transit, therefore, a larger presence of these groups was likely to influence station demand. Young people, for example, may not have as high incomes as other age groups and may be more reliant on transit. Other socioeconomic variables that were considered include the share of renters, the median household income, and the unemployment rate within a station area. These variables aim to control for the effects of income on transit use. Data for these variables were collected from Statistics Canada using the 2011 census are were processed as described in Section 3.1.

3.3.2. Station and Network

A number of variables related to the transit network and the station's placement within it were also considered. Dummy variables for terminal and transfer stations were tested, as these types of stations were observed to attract more ridership. Terminal stations averaged 11,649 daily riders while non-terminal stations averaged 6,982. Similarly, the average daily ridership at transfer stations was 15,719 compared to 7,026 at non-transfer stations. A transfer station refers to a station that either serves more than one line on the same system (except for those that were excluded as a result of the data collection method) or connects to other rapid transit systems. Distance to the downtown terminus was included as was a measure of centrality similar to the one proposed by Kuby et al. (2003). The total distance of each station to the downtown terminus was divided by the longest distance on the network to permit comparisons between systems. This method accounts for the differing sizes of the rail networks under study as demonstrated Figure 9, which shows the rail rapid transit networks at the same scale. Distance in this case refers to network distance as opposed to straight line distance. Station spacing is included as a measurement of the next closest station to account for a station's catchment outside of the buffer and the fact that some catchment areas are relatively small owing to their proximity to other stations. It was expected that stations that were closer together may draw less ridership owing to competition between them.

Figure 9- System Maps



Station accessibility variables measured the level of other transport infrastructure located at stations as well as the location of each station relative to the nearest terminus and to the nearest station. First, the total number of bus routes serving each station was counted from transit agency websites and second, the total number of parking spaces provided by the transit agency (park and ride) was counted. Only official park-and-ride lots mentioned on a transit agency's website were included and not private parking lots. And finally, a bike parking dummy and total number of car share reserved space variables were included. These variables were collected through transit agency websites and Google Street View, if the information was not available.

3.3.3. Neighbourhood and Street Network

Two measures of residential population density (total residents/total land area of station catchment and total dwellings/total land area of station catchment) were used to represent the intensity of residential use of land within each station area. Similarly, two measures of employment density (total jobs/total land of station catchment area and total jobs/total commercial, resource or industrial, or government and institutional land in station catchment) were used which are termed job density and job intensity. Jobs data was acquired from the 2006 census data on place of work by census tract of work and population and dwelling data were collected from the 2011 census and processed in the same manner as described in Section 3.1 (Statistics Canada, 2006, 2011).

Total nodes (or three- and four-way intersections), link to node ratio (total links/total nodes), total number of links (or blocks), street density (total street length/catchment area size), average block length, and intersection density were included as measures of the local street network. As network-based catchment areas were used, the total in square metres was also included as a measure of the street network. Larger catchment areas indicate a more complete or connected road network, while smaller ones indicate lower levels of connectivity. Land use data obtained from DMTI Spatial's RouteLogistics package includes seven types of land use: open area, parkland, water, industrial and resource, government and institutional, residential, and commercial (DMTI Spatial, 2013a). These designations were tested as proportions of the total station catchment area and also in the composite land use mix or entropy measures described in section 2.6.

The total number of commercial locations was chosen as a variable was collected from the DMTI Enhanced Points of Interest shapefile, which contains the locations of over one million commercial and recreational points of interest. Included for each point in the file is a precision code ranging from one to eight, with one being the most accurate (point aligned to the building using satellite imagery) and eight being the municipality's centroid. Only points with a precision code up to six (postal code area centroid) were used. The total number of locations was further narrowed down to retail trade, services, and public administration categories by Standard Industrial Classification (SIC) code divisions included in the data (DMTI Spatial, 2013b). This variable represents the total commercial and business opportunities present in a station's catchment area and was tested as a total number and as commercial site density.

As mentioned in section 2.6, three composite land use and street network variables, land use entropy, land use mix, and walkability, were found in the literature. These three metrics were included as potential explanatory variables in addition to the Walk Score obtained from the website walkscore.com. The Walk Score is a number from 0 to 100 that aims to measure how walkable a given neighbourhood is based on proximity to basic amenities weighted according to their distance from the point of interest (WalkScore, 2014). The Walk Score has been demonstrated to perform as well as other walkability indices (Carr, Dunsiger, & Marcus, 2011) and was obtained for each station in the study.

A central business district (CBD) dummy variable was tested in the models to account for the fact that downtown stations may attract more ridership by virtue of their location and the surrounding attractions and services. No clear definition of CBDs exists, so the procedure developed by Lane et al. (2006) was used. The procedure involves computing the job density of census tracts, logarithmically transforming the figure, and delimiting the CBD as contiguous tracts with job densities at least two standard deviations above the mean for the city. Where census tracts greater than 2 SD above the mean were separated by a tract with a job density at least 1.5 SD greater than the mean, both were included as well. Stations falling within these tracts are considered to be CBD stations and are coded 1 while all outside are coded 0. Figure 10 and Figure 11 demonstrate the outcome of the procedure for Montréal and Toronto. The CBD stations designated using this method saw an average daily ridership of 16,557 compared with 5,779 for non-CBD stations.

Since built neighbourhood and street network variables have the potential to be correlated with one another, factor analysis was tested as a means to reduce the number of variables and to test if any combination was better at explaining transit ridership. Using a limited range of variables associated with density produced two useable factors that satisfied basic criteria for factor analysis (i.e. Bartlett's test, Kaiser-Meyer-Olkin index, Cronbach's Alpha). One factor showed heavy loadings on population density, dwelling density, and the walkability index, while the other loaded heavily on commercial site density, jobs density, and the walkability index. These factors, however, added little additional explanatory value compared with using the variables themselves when tested in the models and owing to difficulty inherent in the interpretation of composite factors the original variables were used instead.

Figure 10 - Montréal CBD Map

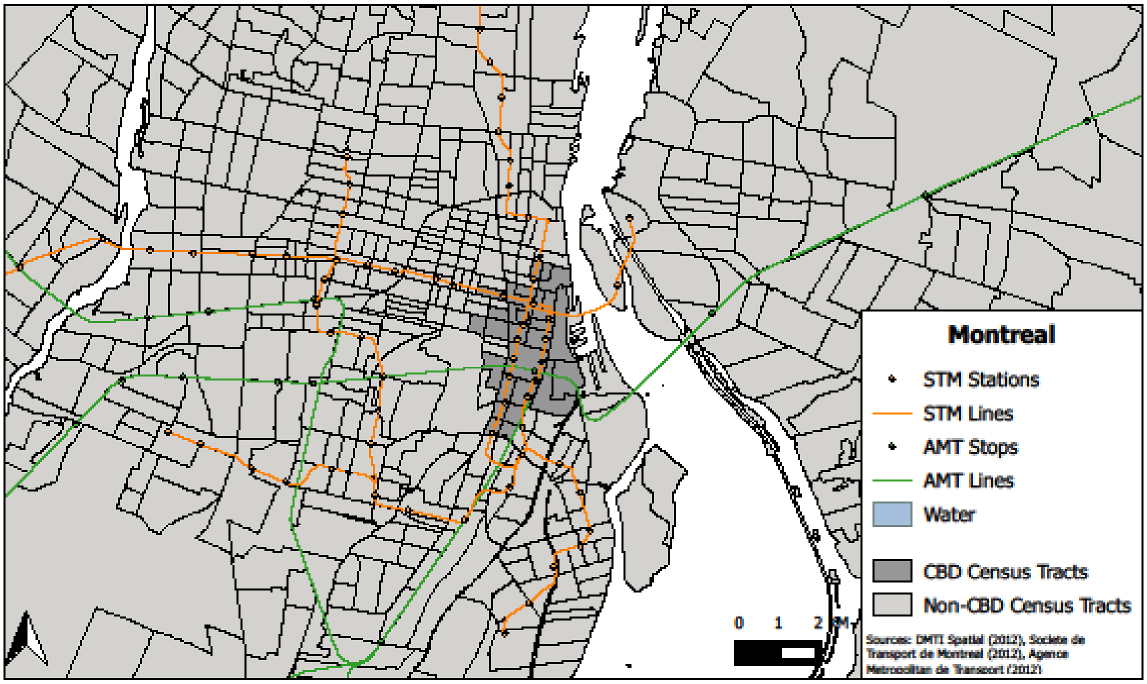
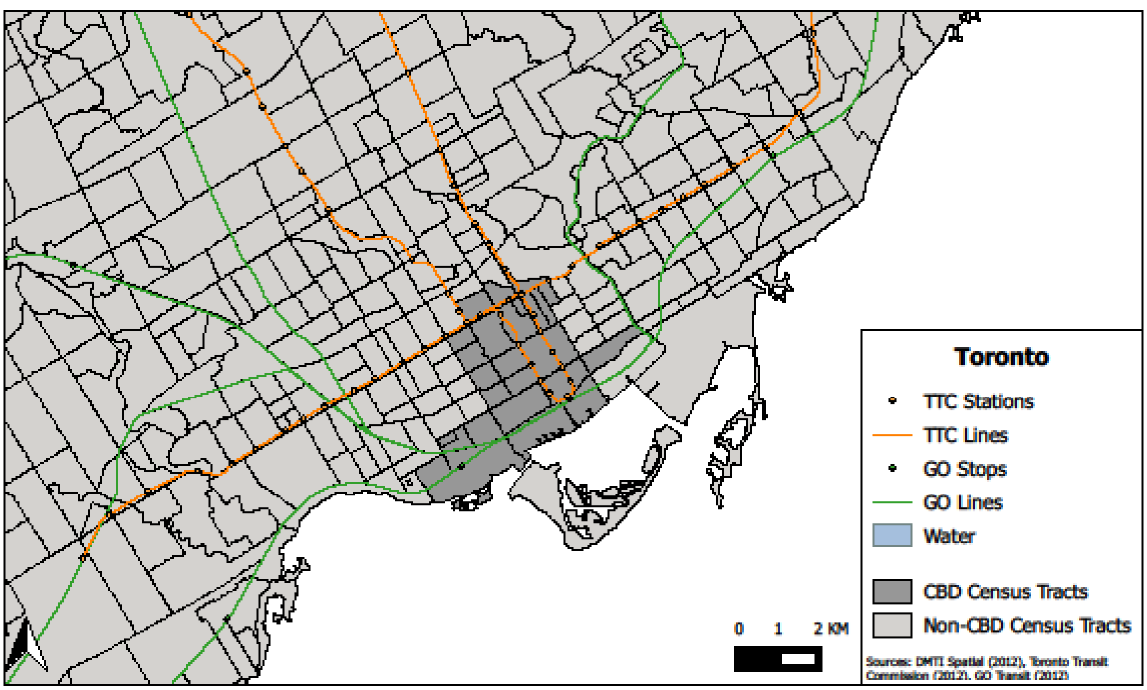


Figure 11 - Toronto CBD Map



3.3.4. Service

The effect service supply has on ridership is difficult to assess as service supply is likely to be decided in conjunction with ridership. Estupinan & Rodriguez (2008) and Taylor et al. (2008) both attempt to control for this effect through the use of two-stage simultaneous models with instrumental variables for supply, both finding that supply does indeed influence ridership even when their reciprocal relationship is considered; ignoring this fact has the potential to bias regression estimates. Five service level variables, a peak service only dummy variable, a count of the total number of trains stopping at a station daily, average headway, average headway at peak hours, and average headway at off-peak hours were included. The peak-only variable is used to differentiate the small number of low ridership stations that only have service during peak periods. While the service count is used to assess the total level of service a station sees on a daily basis. Average headways are simply the average amount of time between trains stopping at a station over the whole day, peak period, and off-peak period. Two fare variables are also included in the models, monthly pass cost and cost of a single fare to the downtown, in order to assess the direct user cost effects of transit on its use.

Table 4 - Variable Descriptions

	All Stations		Suburban Stations		Urban Stations	
Variable	Mean	SD	Mean	SD	Mean	SD
Dependent						
Boardings	7,437.39	8,273.04	1,401.64	1,365.02	10,674.75	8,612.10
Socioeconomics						
% unemployed	7.8%	2.7%	7.5%	2.6%	8.0%	2.4%
Median household income ($)	58,545	21,128	66,070	23,335	54,467	18,868
Median personal income ($)	30,108	9,073	30,697	8,454	29,793	9,392
% renter households	46.2%	22.6%	30.9%	20.4%	54.4%	19.2%
% aged 20 to 30	17.3%	7.6%	12.5%	4.9%	19.8%	7.5%
% aged 30 to 40	15.7%	5.1%	12.9%	4.9%	17.3%	4.5%
% aged 40 to 50	14.4%	3.1$	14.8%	3.8%	14.1%	2.7%
% aged 50 to 60	13.2%	3.1%	13.9%	3.9%	12.9%	2.5%
% aged 60 to 70	9.0%	2.5%	9.6%	3.0%	8.7%	2.1%
% aged 70 to 80	5.5%	1.9%	5.8%	2.3%	5.4%	1.8%
Station attributes						
Bus connections	6.88	9.13	6.07	4.95	6.87	9.19
Park-and-ride spaces	344.95	599.98	667.65	709.19	171.33	445.52
Terminal station (1=yes)	9.76% of stations		11.86% of stations		8.63% of stations	
Transfer station (1=yes)	4.73% of stations		3.38% of stations		5.45% of stations	
Distance to terminus	16,006	16,095	30,022	17,751	8,225	5,717
Relative distance to terminus	0.39	0.24	0.37	0.21	0.40	0.26
Spacing	2,211	3109	4,609	4,284	895	537.25
Bike parking dummy (1= yes)	76.33% of stations		93.22% of stations		67.27% of stations	
Car Share Dummy (1=yes)	20.71% of stations		52.54% of stations		3.64% of stations	
Neighbourhood, street network, and land use						
Population density (/km^2)	5,279.43	4,392.16	2,705.43	2,257.16	6,660.18	4,634.48
Jobs + population density (/km^2)	21,687.62	39,780.73	7,811.60	13,101.75	29,130.22	46,734.19
Nodes	74.36	37.47	74.42	46.12	74.34	31.99
Link/Node Ratio	1.31	0.36	1.34	0.32	1.30	0.38
Total Links	96.56	54.14	100.26	67.51	92.95	40.66

Total Road Length (m)	11,542	5,208	12,906.09	6,731.46	10,700.58	3,767.45
Street Density (/km^2)	3,815.70	5,368.27	10,704.83	3,075.98	120.61	53.90
Average Block Length	138.38	71.57	164.84	107.76	124.18	32.78
Intersection Density (/km^2)	82.88	36.59	60.53	26.60	94.87	35.62
% Open Area	9.0%	14.2%	15.7%	20.5%	5.4%	7.3%
% Park Area	8.0%	9.9%	6.3%	7.3%	8.9%	11.0%
% Residential Area	51.3%	21.2%	51.8%	23.0%	55.3%	20.0%
Resource/industrial Area	18.5%	18.6%	19.2%	20.5%	17.8%	17.2%
%Government/institutional Area	6.0%	11.4%	4.1%	5.4%	8.9%	13.1%
% Commercial Area	3.0%	6.1%	2.5%	5.2%	3.2%	6.4%
Residential/non-residential	6.91	67.60	11.62	113.81	4.38	9.68
Job density (/km^2)	16,408.10	38,681.35	5,106.17	12,361.08	22,470.04	45,989.92
Employment intensity (/km^2)	50,087.79	94,894.95	21,184.11	33,600.32	65,590.67	112,081.9
Dwelling density (/km^2)	2,820.91	2,770.87	1,219.79	1,187.35	3,679.69	2,989.85
University Dummy	7.3% of stations		1.6% of stations		10.45% of stations	
CBD Dummy	15.8% of stations		2.5% of stations		22.27% of stations	
Land use Mix	19,597.73	52,446.77	4,427.56	20,144.66	27,730.00	61,850.75
Land use entropy	0.64	0.16	0.64	0.17	0.64	0.15
Walkability index	-0.07	2.24	-0.54	2.42	0.17	2.12
Walk Score	73.58	23.18	56.79	23.87	82.59	16.99
Commercial Sites	383.17	455.19	290.05	459.66	433.12	445.85
Commercial Site Density (/km^2)	524.09	825.67	239.61	449.49	676.68	934.94
Service attributes						
Peak only	13.5% of stations		38.1% of stations		0% of stations	
Pass cost ($)	128.02	63.22	182.60	77.11	98.75	22.52
Regular fare ($)	4.20	2.18	6.55	2.12	2.94	0.61
Supply	305.30	239.88	27.18	23.29	454.47	155.64
Average headway (Peak)	13.96	40.43	33.00	64.38	5.09	1.34
Average headway	37.05	68.24	96.84	88.93	3.75	1.04
Average headway (off peak)	97.89	173.14	268.76	202.73	6.24	1.73

3.4. Regression Analysis

3.4.1. OLS

OLS regression is the most commonly employed statistical tool used for DRM studies and was employed by 14 of the 19 studies mentioned in Table 2 at some stage of their analyses and is the used as the first stage in this analysis. Regression analysis is a statistical method that can analyse the relationship between two or more variables. Some basic assumptions must be met when employing OLS:

1. Constant error variance (homoscedasticity)
2. Independence of errors
3. Linear relationship between response and predictor variables

Errors, in this case, refer to the differences between the model's prediction for a given value and the actual value itself. OLS assumes that the errors follow a normal distribution, that they are constant and display no systematic pattern, and that they are independent or uncorrelated with one another. Under these conditions, OLS provides the best linear unbiased estimate (BLUE) of the model's parameters. If the data fails to meet these basic assumptions estimates from the model may be biased and unreliable.

Several tests can be performed to satisfy these criteria. Normal error distribution can be tested using the Shapiro-Wilk test for normality and visual inspection of error plots (Fox, 1997). The null hypothesis of the Shapiro-Wilk test is that the samples come from a normal distribution, when applied to model residuals a significant score on the test indicates a non-normal error distribution. Error variance can also be examined using residual plots as well as a score test for heteroscedasticity proposed by Fox & Weisberg (2011a). The null hypothesis of this test is that the samples are homoscedastic meaning that a significant test score for model errors would indicate an unequal error distribution (Fox & Weisberg, 2011a). The independence of errors is tested using the Durbin-Watson test for autocorrelation and the Moran's I test for spatial autocorrelation. If the errors are truly independent most of the autocorrelation among residuals should fall within a limited range which is dependent on the sample size and number of regressors in the model for the Durbin-Watson test (Kleiber & Zeileis, 2008). The Moran's I test was implemented using a neighbours matrix generated with GeoDA and tested in R using the spdep package (Bivand & Piras, 2015). The k-nearest neighbours method was chosen for determining the weights matrix with the five geographically closest stations being counted. Moran's I values fall between -1 and 1 with -1 indicating dispersion, 1 meaning perfect clustering, and 0 no pattern. If strong spatial autocorrelation is observed it is possible to create a spatial lag or a spatial error model to compensate for this effect. A spatial lag model involves the creation of a lagged independent variable while the spatial error model corrects the error term of the model. Finally, the functional form of the model can be tested using Ramsey's RESET (regression specification error test) which takes the powers of the fitted values and checks if they influence the model when added (Kleiber & Zeileis, 2008). The RESET test's null hypothesis is that the model is properly specified so when tested, a significant result would reject this assumption and indicate a misspecification in the model. Additionally, the gvlma function in R provides an assessment of the four main model criteria as well as a global test of model suitability (Pena & Slate, 2006, 2014).

If any models do not meet these criteria, remedial measures can be taken to account for certain violations. In the case of non-constant error variance (heteroscedasticity), the statistical significance of variables may not be correct with some variables appearing to be significant when they should not. In this case, it is possible to use a heteroscedasticity-corrected covariance matrix to correct for the violation of the assumption and to obtain appropriate p- and t-values (Fox, 1997). In the case of non-normal errors, it is possible to transform variables (e.g. using the Box-Cox method) to obtain more normally distributed results or to bootstrap the model for reliable confidence interval estimates, as discussed later in this section.

A final diagnostic for the OLS models is an examination of unusual data points that may cause undue influence on the model's estimates. Three types of unusual data points can be identified: outliers, high-leverage points, and influential observations. Outliers are simply values with large residuals or, in other words, values that the model does not predict well. High leverage points are observations that have a high potential to shift the regression plane, and influential points are observations that are both outliers and high leverage points. A number of tests have been developed to detect these types of unusual observations that will be employed for this analysis. Outliers can be detected visually by examining residuals plots, as well as through the use of the outlierTest function in the car package for the R statistical analysis software program (Fox & Weisberg, 2011a). This test takes the observations with the largest absolute residual value and computes a Bonferonni-corrected t-test to assess whether or not the magnitude of the residual value should be expected given the total number of observations (Fox & Weisberg, 2011a). In large sample sizes, it should be expected that some large residual values appear and this test allows for an empirical assessment of whether or not these points are abnormally large. If the test returns a significant result for a residual, it suggests that the value is abnormally high and should be further examined (Fox & Weisberg, 2011a). High leverage points can be detected again using the car package by examining the hat-values (a measure of the relationship between observations and fitted values). No absolute cut-off for hat-values exists, but it is suggested that hat-values three times that of the average may have a significant effect on the model and should be examined closely (Fox, 1997; Kleiber & Zeileis, 2008). Finally, influential observations can be identified by computing Cook's distances, which is a measure of a given data point's influence on the model. Cook's distances are calculated for each observation and simply compares the model's prediction with the observation to its prediction with the observation removed (Fox, 1997). It has been suggested that values greater than 1 indicate highly influential observations, but that this should not be considered an absolute rule (Fox, 1997). Rather than relying on a fixed maximum value for Cook's distances, values greater than those calculated by Equation 4 (Fox, 1991).

Equation 4 – Cut-Off Value for Cook's Distances

$$\frac{4}{n-k-1}$$

Where n is the number of observations and k is the number of predictor variables used.

If influential points are observed, robust regression methods can be used to account for the unusual data. Robust in this case refers to the robustness of results in the face of violations of the OLS assumptions regarding outlying residuals and can produce results similar to those of OLS in cases when outliers are present (Fox, 1997). Robust regression handles influential points by reweighting them, effectively decreasing the effect they have on the model's results. A number of robust regression methods have been developed to deal with data with heavy-tailed distributions including so-called M-estimators, MM-estimators, S-estimators, and bounded-influence regression methods such as least-trimmed squares (Fox, 1997; Fox & Weisberg, 2011b). Each method attempts to select "bad" data points based on a breakdown point, or critical value, and reweights them to reduce their influence (Fox, 1997). This, in effect, down-weights influential observations, reducing the effect that these points have on the model's estimates.

3.4.2. 2SLS

Two-stage least squares regression with instrumental variables is a method of performing a linear regression when one or more independent variables are correlated with the error term, such as in the case of measuring the effect of service supply on station ridership. Endogenous variables are variables that are, or could be, correlated with the error term and, in this case, arise from the simultaneity between the supply of transit service and demand for it. It is possible that the parking and bus services variables are also endogenous in the case of transit demand as transit agencies may adapt parking or bus service strategies to meet increasing numbers of users. Instruments refer to one or more variables that can be used in substitution for an endogenous regressor to correct for the violation of the independence assumption. This method involves replacing the endogenous variable with one (or more) that is not correlated with the error term of the model. There are two main conditions for the use of instrumental variables:

1. that the instrument must be at least partially correlated with the endogenous variable
2. that no correlation exists with the independent variable other than through the endogenous.

The first condition is easily tested, however, the second is less apparent, making the choice of appropriate instruments sometimes difficult.

Three tests can be performed to assess the validity of instruments: a simple correlation between the instrument and endogenous variable, a test of the strength of the instrument, and the Hausmann test for endogeneity. The first step in selecting an instrument is to find a variable that is partially correlated with the endogenous variable. Once a potential instrument is identified, it can be tested in the 2SLS model for validity using the F-statistic of a joint test of whether or not the instrument is significant. The general rule of thumb for this test is if the F-test is greater than 10, the instrument is valid with one endogenous variable. Stock & Yogo (2005) expand on this general rule and provide a table of critical values for the F-statistic which will be used for this study. If an instrument is determined to be valid, the Hausmann test can then be used to assess whether or not the variable in question is actually endogenous in the model. This involves comparing the coefficients of the OLS model with the endogenous regressor to those of the 2SLS model and seeing if they are significantly different from one another. A statistically significant score on the Hausmann would indicate that the models do differ significantly and that the variable in question is endogenous. The Hausmann test only performs properly under homoscedastic conditions; in the case where this is not met it is possible to run an additional regression using the residuals of the first stage with a heteroscedasticity-corrected covariance matrix as outlined in Wooldridge (2002).

3.4.3. Bootstrapping

Observation bootstrapping is a non-parametric approach to regression that involves the random resampling of cases with replacement and does not require any distributional assumptions (Fox, 1997; Weisberg, 2005). Two forms of bootstrapping regression models exist: case resampling and residual resampling. Case resampling is considered to be the more robust method to non-normal error distribution and the type of bootstrapping considered for this study (Chernick, 2008). In other words, the bootstrapping method treats the sample as a population and samples randomly from within it a large number of times to simulate large sample sizes (Fox & Weisberg, 2011a). In cases where OLS model error distributions are skewed, it is possible to bootstrap the model to obtain more accurate coefficient estimates by simulating larger sample size and to obtain reliable confidence intervals.

3.5. Model Development Process

The first step in the modelling process involved the selection of candidate explanatory variables from those presented in Table 4. Variable selection for the models proceeded generally in a backwards stepwise process while some variables were re-added to the models when necessary, aiming to maximize the fit of the model while minimizing information loss. Akaike's Information Criterion (AIC) was used to assess the various iterations of all models and those that scored the best (i.e. lowest AIC score) were chosen. The AIC is a tool for model comparison that measures the trade-off between model complexity (the number of parameters in the model) and the overall fit of the model to the data.

Attention was paid to the basic assumptions of OLS regression: linearity, independence, no multi-collinearity, and constant error variance. This was accomplished by conducting a series of tests (discussed in section 3.4.1) in order to ensure that the model and data satisfied these criteria and corrective measures were undertaken (i.e. logarithmic/power transformations and corrected covariance matrices) if they did not as discussed in section 3.4.1. Diagnostics plots including QQ-Plots, fitted vs. residual plots, and residual histograms are presented in Appendix B. Two of the three initial OLS regression models presented a potential endogeneity problem (a service supply variable) and were further assessed using the 2SLS method and all were bootstrapped to obtain confidence intervals for coefficient estimates.

In the process of analysing the data it became apparent that several stations were extreme outliers and in total eight stations were omitted from the analysis. These stations included two downtown terminal stations of the heavy rail systems (Toronto's Union Station, and Montréal's Central Station), which exhibited very high ridership in comparison with others, suburban rail terminal stations with very low ridership and low levels of service (Montréal's Hudson, and Toronto's Allandale Waterfront), and stations serving solely specific destinations (Vancouver's Airport SkyTrain station and the Metro station serving Montréal's Parc Jean Drapeau). In total, with the eight stations removed for data collection reasons outlined in Section 3.2, 15 stations were removed from the initial dataset of 353 leaving 338 observations for the analysis.

Figure 12- Histogram of Boardings for All Stations

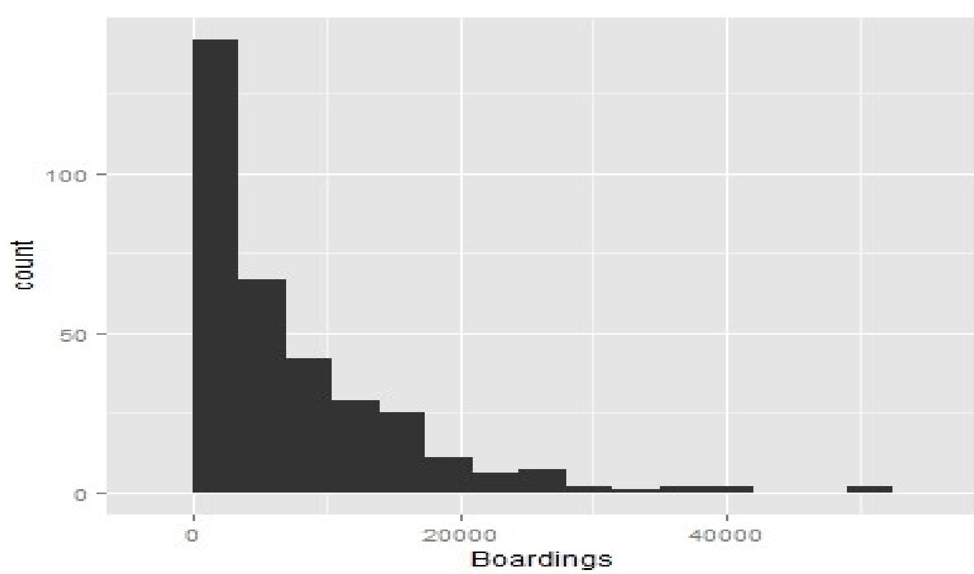
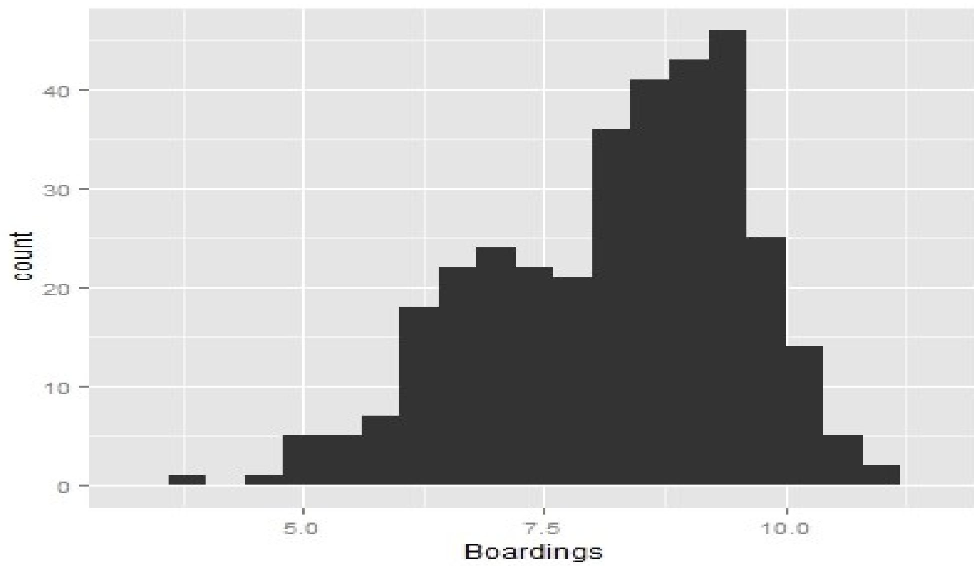


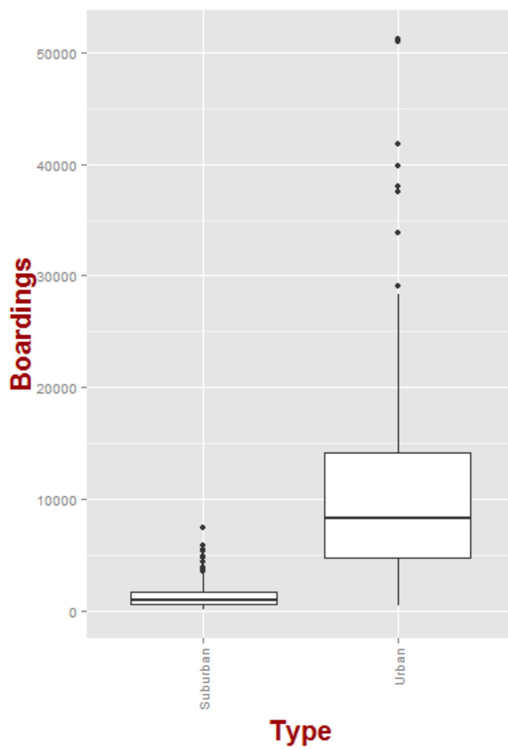
Figure 13 - Histogram of Boardings after Transformation for All Stations



4. Model Results

Linear models were developed for urban stations, suburban stations, and for both types combined. Urban and suburban stations were modelled separately because of the large difference in average boardings between the two. Figure 14 demonstrates how large the difference in the raw boardings data is between suburban and urban service types. Raw boardings data for each station can be found in Appendix A. The following section describes the model formulation process and presents the findings.

Figure 14- Boardings by Transit Type



4.1. All Stations Models

Table 6 presents the results of the first OLS model for all 338 rail rapid transit stations. The dependent variable (station boardings) was log-transformed for all the models to correct for the heavy left-skew of the data. Figure 12 shows the boardings variable for all stations and Figure 13 shows the boardings data after the log transformation. Some independent variables were also transformed where necessary. The initial OLS model for all stations produced an adjusted R^2 score of 0.83, indicating that the model explains a large portion of the variation within the data.

This result is at the higher end of model fit in comparison to other DRMs using OLS methods with R^2, which range from 0.51 (Duduta, 2013) to 0.95 (Cervero et al., 2010) with an average of 0.65. The associations between population density, the number of bus connections, the CBD dummy variable, the number of park and ride spaces, and average headways were all found to be highly significant (p-value < 0.001).

A relatively high degree of positive correlation was observed between many of the variables leading to a concern about the potential for small changes in the model to result in large changes in coefficient estimates. The variance inflation factor (VIF) scores shown in Table 5, measure of the degree of multicollinearity present between variables, with values representing how much larger the variance of each coefficient as a result of collinearity (O'Brien, 2007). In other words, the variance of the service park and ride variable is 1.487 times larger than it would be if it were linearly independent of all other variables in the model. A commonly cited indication of serious multicollinearity is a VIF score of 10, although values as low as four have also been suggested (O'Brien, 2007). As Table 5 shows, however, VIFs for the all stations model's predictors were close to their minimum value of one indicating that multicollinearity among them was not a serious problem. Another method for quantifying multicollinearity is through the use of a condition index, which is the square root of the ratio of the largest to smallest eigenvalue of the model's matrix (Fox, 1997). Condition indexes were calculated in this case using the colldiag function in the perturb package for R (Hendrickx, 2012). A commonly cited cut-off value for the condition index that indicates serious multicollinearity is 30 (Belsley, Kuh, & Welsch, 1980). None of the three models exceeded this cut-off (unweighted: 18.48; weighted: 24.34; 2SLS: 16.97) and, in conjunction with the low VIF scores, indicate that multicollinearity is not strongly present.

Table 5 - All Stations OLS and Weighted OLS Models VIF Scores

Coefficients	VIF Unweighted	VIF Weighted	VIF 2SLS
log(Population Density)	1.261	1.251	1.851
log(Bus Connections)	1.266	1.268	1.276
CBD Dummy	1.160	1.164	1.375
Park and Ride Spaces	1.485	1.472	1.838
log(Average Headway)	1.226	1.274	2.957

The Durbin-Watson test for autocorrelation (DW = 1.4998) showed that some autocorrelation was present. For a sample size of 338 with five regressors (the constant is excluded), the test score should fall within the range of 1.787 to 1.845 (Cummins, 2012). A Durbin-Watson test score of 1.5 does then mean that the model's residuals are not entirely independent of one another. This should not be surprising given the fact that the data comes from five different cities and two distinct rail rapid transit technologies, and that stations close to one another may experience similar levels of ridership owing to their proximity. The only added variable that caused this test statistic to fall within the acceptable range was the categorical variable for the line the station serves. Some of the variation in station boardings was likely to ridership on the line as a whole, despite this finding the degree of autocorrelation is relatively low. The Moran's I test for the residuals of the OLS model 0.16 ($p = <0.000$) and 0.15 ($p = <0.000$) again indicated some positive spatial autocorrelation, as a result a spatial lag and spatial error model were also tested and presented in Table 7 and Table 10. A comparison of the spatial lag and error models for the initial OLS model reveals that the error model performed better demonstrating better fit (log-likelihood of -273 vs. -284) and a lower AIC score (564.89 vs. 581.03). Comparing the spatial models to the original OLS model shows that the model's fit improved from an AIC score of 584.71. The score test for heteroscedasticity suggested by Fox & Weisberg (2011a) indicated that the distribution of errors in the OLS model was heteroscedastic ($p = 0.006$) and in the spatial lag ($p = 0.002$) and spatial error ($p = 0.001$) models. As a result, a heteroscedasticity-corrected covariance matrix found in the Sandwich package for R (Zeileis, 2004) is used for the OLS, robust, and 2SLS models and the spreg function in the sphet package for the spatial lag and error models (Piras, 2010). The Shapiro-Wilk test for normality ($p = 0.103$) showed that the errors were normally distributed and fall outside the critical value of 0.05. Finally, the RESET test for model specification results in a p-value of 0.74, which is not low enough to reject the assumption of a properly specified model. Further diagnostic plots (QQ-plots and residuals vs. fitted plots are presented in Appendix B).

Table 6 - All Stations Unweighted OLS Model with Bootstrapped Estimates

	Dependent variable:			
	log(Boardings)			
	Unweighted			
	OLS			
			Conf. Intervals	
	Estimate (SD)	Boot Estimate (SD)	2.5%	97.5%
log(Population Density)	0.150*** (0.022)	0.153 (0.307)	0.056	0.218
log(Bus Connections)	0.416*** (0.044)	0.418 (0.044)	0.332	0.505
CBD Dummy	0.655*** (0.090)	0.652 (0.110)	0.442	0.875
Park and Ride Spaces	0.0004*** (0.0001)	0.0003 (0.0001)	0.0002	0.0005
log(Average Headway)	-0.735*** (0.024)	-0.735 (0.031)	-0.795	-0.673
Constant	7.951*** (0.211)	7.928 (0.307)	7.293	8.501
Observations	338			
R^2	0.830			
Adjusted R^2	0.827			
Resid. Std. Err. (df = 213)	0.557			
F Statistic (df = 5; 332)	323.16*** (p = 0.00)			
Note:	p < 0 ‘***’ p < 0.001 ‘**’ p < 0.01 ‘*’ p < 0.05 ‘x’ p < 0.1			

Table 7 - All Stations Unweighted Spatial Lag and Spatial Error Models

	Dependent variable: log(Boardings) *Unweighted Spatial Models*	
	Lag Estimate (SD)	Error Estimate (SD)
log(Population Density)	0.150*** (0.022)	0.127*** (0.023)
log(Bus Connections)	0.422*** (0.044)	0.420*** (0.042)
CBD Dummy	0.649*** (0.095)	0.707*** (0.113)
Park and Ride Spaces	0.0004*** (0.0001)	0.0004*** (0.0001)
log(Average Headway)	-0.722*** (0.031)	-0.750*** (0.028)
Constant	7.700*** (0.467)	8.164*** (0.220)
ρ/λ	0.024	0.368***
Observations	338	338
Log-likelihood	-282.52	-274.45
Wald statistic	6.008 (p = 0.014)	27.404 (p = < 0.000)
Note:	p < 0 '***' p < 0.001 '**' p < 0.01 '*' p < 0.05 'x' p < 0.1	

The initial examination of outliers in R indicated that two residual values were abnormally large (i.e. Bonferonni p value <0.05). When hat values, a measure of discrepancy between observed and predicted values, were examined to assess whether or not a high leverage points were present, 12 potentially problematic points were observed using a cut-off value of 0.062 (three times the average hat value as suggested by Keliber & Zeileis (2008). Further inspection using Cook's distances, which combines residual discrepancy and leverage, with a cut-off value of four divided by the number of observations minus number of regressors minus one as suggested by Fox (1997), in this case 0.012, revealed 22 observations that may be influential (see Appendix C for plots of Hat Values and Cook's Distances for all models).

Since numerous outliers were present, a robust regression was run to better fit the data. As discussed in section 2.7.1, several types of robust regression estimators can be used, each with different breakdown points resulting in different weights and therefore slightly different results. The rlm function found in the MASS package for R was used for the robust regression, which iteratively reweights observations, in this case using an MM-estimator (Venables & Ripley, 2002). This method was chosen as it achieved the best results as measured by reduction in the outlying data compared to other estimator type combinations and R functions. The results of the robust regression are presented in Table 8, which can be compared to the original OLS model estimates in Table 6.

The robust, or weighted, model shows some changes in the magnitude of the estimated coefficients, most notably an increase in the strength of the bus connections variable and a decrease for the CBD dummy. The model's fit improves from an adjusted R^2 of 0.827 to 0.864. Cook's distance values dropped significantly in the robust model with only 11 values exceeding the upper limit, down from 25, while the largest value dropped from 0.164 to 0.062. Plots of Cook's Distances and Hat Values are presented in Appendix C. Deletion of observations with the largest Cook's distance values did not result in significant changes to the model's coefficient estimates, significance, or model fit and were therefore left in the final model. In addition to improvements in the model's fit, the heteroscedasticity score test ($p = 0.14$) indicated that error variance is constant. On the other hand, the test for normality of residuals ($p = 0.04$) suggested that the errors of the weighted model were not entirely normally distributed. A visual inspection of residuals also revealed some departures from normality. The RESET test ($p = 0.74$) again suggested a properly specified model and the Durbin-Watson test (DW = 1.4998) indicated the same degree of autocorrelation was present. VIF scores also remained relatively low for the weighted model (see Table 5).

Table 8 - All Stations Weighted OLS Model with Bootstrapped Estimates

	Dependent variable: log(Boardings) *Weighted OLS*			
			Conf. Intervals	
	Estimate (SD)	Boot Estimate (SD)	2.5%	97.5%
log(Population Density)	0.180*** (0.021)	0.181 (0.219)	0.139	0.226
log(Bus Connections)	0.442*** (0.038)	0.444 (0.036)	0.374	0.516
CBD Dummy	0.570*** (0.080)	0.568 (0.084)	0.405	0.733
Park and Ride Spaces	0.0003*** (0.0001)	0.0003 (0.0001)	0.0002	0.0004
log(Average Headway)	-0.726*** (0.022)	-0.726 (0.022)	-0.770	-0.682
Constant	7.682*** (0.196)	7.792 (0.226)	7.237	8.128
Observations	338			
R^2	0.866			
Adjusted R^2	0.864			
Resid. Std. Err. (df = 213)	0.457			
F Statistic (df = 5; 332)	430.29*** (p = 0.00)			
Note:	p < 0 ‘***’ p < 0.001 ‘**’ p < 0.01 ‘*’ p < 0.05 ‘x’ p < 0.1			

The results of the bootstrapped model showed relatively minor changes in the coefficient estimates. The 95% confidence intervals reported also demonstrate that the bootstrapped coefficient estimates for all variables were statistically significant at the 0.05 level. From these new coefficient estimates, it is possible to calculate elasticities to evaluate the effects of each explanatory variable. Elasticity conversion formulae used are as shown in equations 5 through 7 (Fox, 2011). Histograms of the bootstrap procedure results for each variable are also presented in Appendix D showing the bootstrapped estimate and confidence intervals.

Equation 5 – Elasticity Calculation for Log-Transformed Response Variables

$$\beta \times 10$$

Equation 6 – Elasticity Calculation for Non-Transformed Response Variables

$$(\beta \times \bar{x}) \times 10$$

Equation 7 – Elasticity Calculation for Discrete Response Variables

$$\left(\frac{\exp(\beta)-1}{\exp(\beta)}\right) \times 100$$

Where β is the coefficient estimate and $\bar{x}$ is the mean of the variable in question.

For logged response variables the log-log formula was used, which is simply the coefficient itself, for linear response variables the log-linear formula was used, and for dummy variables the discrete was used. The variable that exerted the strongest effect on the model was the average headway variable, which refers to the average time between trains with an elasticity of -7.26%. This means that the model predicts that a 10% increase in headways would result in a 7.3% decrease in boardings. This was followed by the bus connections variable (4.44%), population density (1.81%), and finally the number of park and ride spaces (1.06%). As the CBD dummy is a binary variable (1 = station in CBD; 0 = station not in CBD), the elasticity is calculated as a change from one to zero, which in this case indicated that CBD stations in this model are predicted to have 43.3% more boardings than non-CBD stations.

Since service supply, as measured by average headways, represents a potential endogeneity problem, the model for all Canadian rail rapid transit stations was reassessed using the two-stage least squares method with an instrumental variable as described in section 3.4.2. Unfortunately no suitable instruments for the park and ride and bus connections variables, which may also exhibit the endogeneity problem, were found. As the instrumental variable regression works in a similar way as an OLS regression the weights from the robust regression were extracted and used to weight the observations on the 2SLS model. Station age was used as an instrument for service supply as it is assumed that station age does not directly influence station ridership. It is possible that stations in the period immediately after construction may not reach full ridership but that is not a major concern in this case as the large majority of stations are over 10 years old, with a mean age of 29.12 years. Station age also correlates fairly well with service supply with a Pearson correlation coefficient of 0.44. While the correlation is not very strong, it merited further testing for validity as an instrument for supply. Since spatial autocorrelation is potentially present a spatial lag and spatial error model using the instrumental variable approach were also tested and presented in Table 10.

The initial 2SLS model yields an F-test score of 43.304 (p = <0.0005), well above the traditional rule of thumb of 10 and Stock & Yogo's (2005) critical value for one endogenous regressor and one instrument of 16.38. It is therefore safe to conclude that station age is a strong enough instrument. The Hausmann test yielded a significant result with a p-value of 0.0196, which indicated that the model containing the instrument was significantly different from the model containing the supply variable. Results of the 2SLS model are presented in Table 9 alongside bootstrapped coefficient estimates and confidence intervals.

Table 9 - All Stations Instrumental Model with Bootstrapped Coefficient Estimates

	Dependent variable: log(Boardings) *Instrumental variable*			
			Conf. Intervals	
	Estimate (SD)	Boot Estimate (SD)	2.5%	97.5%
log(Population Density)	0.137^{***} (0.029)	0.114 (0.031)	0.039	0.186
log(Bus Connections)	0.427^{***} (0.042)	0.407 (0.048)	0.315	0.503
CBD Dummy	0.477^{***} (0.095)	0.560 (0.106)	0.318	0.810
Park and Ride Spaces	0.0004^{***} (0.0001)	0.0004 (0.0001)	0.0003	0.0006
log(Average Headway)	-0.887^{***} (0.072)	-0.895 (0.079)	-1.062	-0.744
Constant	8.451^{***} (0.386)	8.656 (0.410)	7.780	9.629
Observations	338			
R^2	0.844			
Adjusted R^2	0.841			
Resid. Std. Err.(df = 332)	0.494			
Wald Test (df = 5; 332)	206.5^{***} (p = 0.0)			
Note:	p < 0 '***' p < 0.001 '**' p < 0.01 '*' p < 0.05 'x' p < 0.1			

Table 10 - All Stations Instrumental Spatial Lag and Spatial Error Models

	Dependent variable: log(Boardings) *Instrumental Spatial Models*	
	Lag Estimate (SD)	Error Estimate (SD)
log(Population Density)	0.141^{***} (0.024)	0.123^{***} (0.023)
log(Bus Connections)	0.432^{***} (0.045)	0.418^{***} (0.042)
CBD Dummy	0.545^{***} (0.104)	0.702^{***} (0.113)
Park and Ride Spaces	0.0004^{***} (0.0001)	0.0004^{***} (0.0001)
log(Average Headway)	-0.679^{***} (0.060)	-0.766^{***} (0.028)
Constant	6.379^{***} (0.799)	8.176^{***} (0.220)
ρ/λ	0.178^{*}	0.387^{***}
Observations	338	338
Note:	p < 0 ‘***’ p < 0.001 ‘**’ p < 0.01 ‘*’ p < 0.05 ‘x’ p < 0.1	

Table 11 - Elasticity Estimates for All Stations Models

	OLS	Spatial Error	Weighted	2SLS	2SLS Error
Population Density	1.50%	1.27%	1.82%	1.14%	1.23%
Bus Connections	4.16%	4.20%	4.43%	4.07%	4.18%
CBD Dummy	48.06%	50.72%	43.30%	42.90%	50.43%
Park and Ride Spaces	1.24%	1.24%	1.06%	1.49%	1.25%
Average Headway	-7.35%	-7.50%	-7.25%	-8.95%	-7.66%

Table 11 presents a comparison of the elasticity estimates of the bootstrapped unweighted, weighted, and 2SLS models and spatial error corrections for the OLS and 2SLS models. Service supply underwent the largest change ranging in elasticity from -7.05% to -8.95%. The parking supply variable also demonstrated a large range of values from 1.06% to 2.41%. Population density decreased in explanatory power from the original OLS models to the 2SLS models. The

CBD dummy variable appeared to be strongly affected by the spatial error correction with an elasticity estimate above 50% for both the OLS and 2SLS. It is obvious from the results of the 2SLS model that service supply is an importantfactor in explaining the variation in ridership between stations for Canadian rail rapid transit. This coupled with the two access variables, bus connections with a relatively high elasticity and parking supply, indicates that internal factors, those under the control of transit agencies, can strongly influence transit ridership. The sole built environment variable, population density, is markedly weaker in its effect although it does appear to increase in strength when the spatial component is included in the 2SLS model.

The strong effect exerted by the average headways and the CBD dummy variables reflect the disparity in both boardings and headways for urban and suburban rail transit types. Suburban stations in Canada averaged 1,402 boardings on an average weekday, while urban stations saw 10,675 riders. Similarly, the average headway for suburban stations was 96.6 minutes with three stations in the CBDs and only 5.1 minutes for urban stations with 49 being in the CBDs. Large disparities also existed for parking spaces (suburban average = 669; urban average = 171) and population density (suburban average = 2,705 persons/km^2; urban average = 6,660 persons/km^2). The bus connections variable, on the other hand, was much more similar between the two types (suburban average = 6.07; urban average = 6.87).

The relatively small number of explanatory variables found for the all stations model reflects the large differences in boardings found among the stations examined (see Figure 14). Generally this model demonstrates that the success of transit in Canada depends first on the frequency of service. This is supported by findings in other research on the topic of determinants of transit ridership. For example, Messenger & Ewing (1996) found that the frequency of bus service had a positive increase in ridership in Florida at the TAZ level, while Taylor et al. (2008) found that 26% of the variance in transit ridership among urban areas in the United States could be explained by the effects of service frequency. In Canada, Habib, Kattan & Islam (2011) demonstrated that users' perception of convenience of transit service, which includes transit frequency, may influence transit usage in Calgary. Similarly, El-Geneidy et al. (2014) demonstrate that service frequency may influence users' inclination to walk longer distances to access transit in Montréal. Supply variables were also found to be significant in several DRM studies (Cervero, 2006; Cervero et al., 2010; Chan & Miranda-Moreno, 2013; Chow et al., 2003;

Dill et al., 2013; Kohn, 2000; Lane et al., 2006; Ryan & Frank, 2009; Usvyat et al., 2009). Dill et al. (2013). In an examination of three bus and light rail services in Portland, Oregon, Dill et al. (2013) show that service variables including headways explain between 25% and 46% of variation in transit ridership and that elasticities for average daily headway are between -9% and -11.5% for a 10% increase in headway. For heavy rail systems only, Lane et al. (2006) report that a 10% increase in average midday headway would result in a -7.5% decrease in ridership in their model. These results correspond with the findings in this model in which service supply accounted for between 43.11% for the 2SLS model and 47.45% for the unweighted model of the variation in total station ridership, and average headway elasticity between -7.25% and -8.95% for a 10% increase in average headway.

Of the DRMs surveyed in Table 2, only Cervero (2006) found a link between a CBD dummy variable and station boardings with CBD stations in Charlotte having 36.7% higher ridership than non-CBD stations. In the all stations, model CBD stations show 42.9% to 50.72% more boardings than non-CBD stations.

While the headway and CBD variables explain the differences between the two transit types, the significance of the bus connections and parking spaces variables offer valuable insight into the role transit agencies may have in generating demand for service. As discussed in section 2.3, automobile and other transit service comprise two of the most important modes of station access and are frequently found to be significant contributors to transit ridership in other models (e.g. Dill et al., 2013; Sohn & Shim, 2010). The findings of this model would indicate that the role of bus connections is stronger than that of parking provision, although it is important to note that the bus connections variable counts the total number of bus lines connecting at a station, while the parking variable counts the total number of spaces. The other station access mode, by foot or bicycle, is captured through the population density variable as it is assumed that higher population densities are associated with higher levels of pedestrian and cyclist access.

Several DRMs for rail surveyed for this project found significant positive relationships between bus connection variables at the station level and ridership (Cardozo et al., 2012; Cervero, 2006; Cervero et al., 2010; Duduta, 2013; Gutierrez et al., 2011; Lane et al., 2006; Lin & Shin, 2008; Sohn & Shim, 2010; Usvyat et al., 2009). As rail services generally operate as trunk lines with bus services feeding the stations, it is not surprising that bus connection variables are associated with ridership in a large number of studies. Park and ride lots serve a similar purpose and provide a means for individuals with cars who may lack convenient transit service to access stations. While parking provisions may be useful means to increasing station ridership, particularly in outlying areas where bus service may be infrequent, they require large amounts of paved land and occupy areas close to stations that may be better suited to development. This would indicate a potential conflict in goals between providing access to stations by automobile and creating denser environments to support transit around stations. As mentioned by Parsons, Brinckerhoff, Quade & Douglas, Inc. (1996) and indicated by the large difference in parking spaces available at suburban (669) versus urban (171) stations total parking spaces are likely to have a larger effect in suburban and outlying locations where connecting bus service is likely less extensive and land around stations less likely to be developed. The difference in effect between urban and suburban rail stations are tested in the individual models presented in sections 4.1 and 4.2.

The final variable in this model, population density, is the only one that reflects an aspect of the built environment. Between the models, elasticity estimates indicate that a 10% increase in population density would correspond with a 1.14% to 1.82% increase in station ridership. Population density or total population count within a station service area is consistently found to be significantly associated with transit use in DRMs. As mentioned in section Direct Ridership Models, high density has often been seen as necessary to the success of transit but that it may also represent aspects of the built environment that are commonly associated with dense urban environments (Kuzmyak et al., 2003). It is impossible to tell whether or not the effect population density has according to this model is as a result of either the density itself, related aspects of built form, or a combination of both. Throughout the model building process, however, few of the built form variables including measures of street network characteristics, land use, and composite indices appeared to have any strong associations with station level ridership particularly when compared to the effect of population density.

In contrast to many DRMs, no other socioeconomic variable was found to have to be associated with transit use in Canada. Income (Chan & Miranda-Moreno, 2013; Dill et al., 2013; Lin & Shin, 2008; Ryan & Frank, 2009), age (Chu, 2004; Dill et al., 2013; Johnson, 2003; Ryan & Frank, 2009), unemployment (Estupinan & Rodriguez, 2008), ethnicity (Chow et al., 2003; Chu, 2004; Dill et al., 2013; Gutierrez et al., 2011; Ryan & Frank, 2009; Taylor et al., 2008), and housing status (Kuby et al., 2003) have all been tied to transit use, reflecting the fact that in many places transit is most often used by low income groups that are unable to afford a car. One conclusion that can be drawn from this model is that transit in Canada may be more equally shared among income or socioeconomic groups.

4.1.1. Suburban Station Models

Table 12 presents the results of a regression model run with only the suburban rail stations. Variables found in the global model are also found to be significant for the suburban stations, along with the addition of a dummy variable representing stations that serve an intermodal or transfer function and the relative distance to the downtown terminus from the station. Like the combined model, several influential points were observed and, as a result, a robust regression was used to better fit the data (see Appendix C for a comparison between the unweighted and weighted models). Cook's distances greater than the cut-off value calculated from Equation 4 were reduced from 11 to six with a reduction in their maximum value from 0.24 in the unweighted model to 0.10 in the weighted model.

The heteroscedasticity score test (unweighted $p = 0.016$, weighted $p = 0.10$) indicated that non-normal error variance may be present in the unweighted model, therefore, the corrected p-values are presented. For both models, autocorrelation was not observed in the residuals according to the Durbin-Watson test score of 1.656 (unweighted) and 1.733 (weighted) which were within the acceptable range of 1.576 to 1.827 (Cummins, 2012). Moran's I results for the suburban model indicate some positive spatial autocorrelation with a score of 0.131 ($p = 0.001$) for the OLS model but -0.16 ($p = 0.5$) for the robust model. As a result of the spatial autocorrelation observed in the OLS model a spatial lag and spatial error models were run and presented in Table 12. The Shapiro-Wilk test indicated that the residuals were normally distributed in the unweighted model ($p = 0.077$) but not in the weighted version ($p = 0.002$). Further inspection of a quantile plot of residuals revealed some deviations from a theoretical normal distribution, but not significantly enough to discount the validity of the model. The RESET test for model specification yielded a p-value of 0.000004, which may indicate an important omitted variable. It was, however, not possible to construct a stable model by adding new variables to the existing model and was left as is. VIF scores (Table 14) for both models fall close to their minimum value and the condition is below 30 (unweighted: 29.45; weighted: 12.28) multicollinearity was not considered to be a problem.

Table 12 - Unweighted Suburban OLS Model

	Dependent variable: log(Boardings) *Unweighted OLS*			
			Conf. Intervals	
	Estimate (SD)	Boot Estimate (SD)	2.5%	97.5%
log(Population Density)	0.085^{**} (0.029)	0.086 (0.034)	0.017	0.151
log(Bus Connections)	0.294^{***} (0.078)	0.299 (0.092)	0.119	0.478
CBD Dummy	0.840^{*} (0.354)	0.901 (0.435)	0.260	2.179
Park and Ride Spaces	0.001^{***} (0.0001)	0.0001 (0.0001)	0.001	0.001
log(Average Headway)	-0.224^{*} (0.090)	-0.232 (0.104)	-0.440	-0.032
Transfer Dummy	1.181^{***} (0.312)	1.156 (0.308)	0.585	1.838
Rel. Distance to Terminal	-0.569^{*} (0.270)	-0.546 (0.282)	-1.109	-0.005
Constant	6.270^{***} (0.456)	6.291 (0.549)	5.203	7.407
Observations	118			
R^2	0.746			
Adjusted R^2	0.729			
Resid. Std. Err. (df = 110)	0.491			
F Statistic (df = 7; 110)	46.065^{***}			
Note:	p < 0 '***' p < 0.001 '**' p < 0.01 '*' p < 0.05 'x' p < 0.1			

Table 13 – Suburban Unweighted Spatial Lag and Spatial Error Models

	Dependent variable: log(Boardings) *Unweighted Spatial Models*	
	Lag Estimate (SD)	Error Estimate (SD)
log(Population Density)	0.082^{**} (0.028)	0.085^{**} (0.028)
log(Bus Connections)	0.295^{***} (0.075)	0.296^{***} (0.075)
CBD Dummy	0.866^{*} (0.345)	0.834 (0.834)
Park and Ride Spaces	0.001^{***} (0.0001)	0.001^{***} (0.0001)
log(Average Headway)	-0.212^{*} (0.088)	-0.219^{*} (0.087)
Transfer Dummy	1.190^{*} (0.301)	1.150^{***} (0.300)
Rel. Distance to Terminal	-0.602^{***} (0.262)	-0.592^{*} (0.259)
Constant	6.780^{***} (0.794)	6.253^{***} (0.438)
ρ/λ	-0.077	-0.099
Observations	118	118
Log-likelihood	-79.13	-79.23
Wald statistic	0.603 (p = 0.460)	0.361 (p = 0.548)
Note:	p < 0 '***' p < 0.001 '**' p < 0.01 '*' p < 0.05 'x' p < 0.1	

Table 14 – Suburban Stations OLS and Weighted OLS Models VIF Scores

Coefficients	VIF Unweighted	VIF Weighted
log(Population Density)	1.133	1.105
log(Bus Connections)	1.339	1.362
CBD Dummy	1.521	1.539
Park and Ride Spaces	1.858	1.474
log(Average Headway)	1.677	-
Transfer Dummy	1.560	1.582
Relative Distance to Terminal	1.501	1.820

Neither the spatial lag nor spatial error models performed well, showing only slight improvements in AIC for the spatial error model and Wald test statistics for the significance of the spatial terms too high to consider them good models.

The most notable difference between the OLS models and the robust (shown in Table 15) is the removal of the average headways variable, which, after weighting was found to be not statistically significant. As a result, it was left out of the model and the 2SLS procedure is not required. As with the previous model, bootstrapped coefficient estimates and confidence intervals for the weighted model were generated which are presented in Table 15.

Table 15 - Weighted Suburban Stations OLS Models with Bootstrapped Estimates

	Dependent variable: log(Boardings) *Weighted OLS*			
			Conf. Intervals	
	Estimate (SD)	Boot Estimate (SD)	2.5%	97.5%
log(Population Density)	0.098^{***} (0.025)	0.099 (0.030)	0.037	0.158
log(Bus Connections)	0.276^{***} (0.068)	0.284 (0.063)	0.163	0.410
CBD Dummy	0.800^{***} (0.285)	0.859 (0.318)	0.525	2.038
Park and Ride Spaces	0.001^{***} (0.0001)	0.001 (0.00001)	0.001	0.001
log(Average Headway)	-	-	-	-
Transfer Dummy	1.205^{***} (0.253)	1.190 (0.196)	0.789	1.513
Rel. Distance to Terminal	-0.678^{**} (0.210)	-0.690 (0.213)	-1.118	-0.289
Constant	5.288^{***} (0.228)	5.276 (0.274)	4.737	5.831
Observations	118			
R^2	0.777			
Adjusted R^2	0.765			
Resid. Std. Err. (df = 110)	0.391			
F Statistic (df = 7; 110)	64.66^{***}			
Note:	p < 0 '***' p < 0.001 '**' p < 0.01 '*' p < 0.05 'x' p < 0.1			

A comparison of the elasticity estimates of the two models presented in Table 16 reveals mostly minor changes in the magnitude of effects of the coefficients. The largest increase in explanatory power, that of relative distance to the terminus, was likely as a result of the removal of the average headways variable. Stations that lie further from the terminus generally have less service and greater headways between trains. Other coefficient estimates remained relatively stable between the models with the transfer dummy, park and ride spaces, and CBD dummy variables exerting the strongest effect. The inclusion of the spatial effect reduced the estimated effect of the population density variable, bus connections, and the transfer dummy while the park and ride spaces stayed roughly the same and the effect of service supply increased.

Table 16 - Comparison of Bootstrapped Elasticity Estimates for Suburban Stations Models

	OLS	Weighted
Population Density	0.86%	0.99%
Bus Connections	2.98%	2.84%
CBD Dummy	59.38%	57.64%
Park and Ride Spaces	5.47%	5.76%
Average Headway	-2.32%	-
Transfer Dummy	68.52%	69.58%
Relative Distance to Terminal	-1.99%	-2.55%

In comparison to the all stations model, the same variables show sizeable changes in the magnitude of their effects. First, the elasticity for population density in the weighted suburban stations model is 0.99%, a decrease from the 1.13% seen in the all stations 2SLS model. A potential explanation for this is that densities around suburban train stations do not draw a large number of their riders from the immediate surrounding area and instead rely on other transit service and cars for station access. This is supported by the evidence presented in Table 3, which shows that for Canada's two largest suburban train operators, station access by active modes is 26% and 10%, compared with 46% walking access share for Montréal's urban system operator, the STM. This is corroborated by Parsons, Brinckerhoff, Quade & Douglas (1996) who, through their analysis and a number of case studies argue that residential density in station areas is less likely to influence ridership than the provision of parking spaces. In a survey of station access mode share in the United States, Coffel et al. (2012) also found that there are about 0.75 parking spaces per boarding for commuter rail stations. This is supported again by the models, where in the all stations 2SLS model a 10% increase in the number of parking spaces at a station would correspond with a 1.49% increase in ridership compared with the weighted suburban model elasticity estimate of 5.47%.

The elasticity of the CBD dummy variable (59.38%) in the weighted suburban model was slightly higher than the one estimated by the all stations models (42-50%). This likely reflects the orientation of suburban rail networks, which primarily transport riders from outlying areas to downtown locations. In this case, it is also important to remember that the downtown terminal stations located in the CBDs for all three suburban rail networks are not included in this model as boarding figures for these stations were significantly larger (Montréal: 15,405; Toronto: 90, 671; Vancouver 5,380) than the average (1,402) and were very large outliers. This means that the CBD dummy variable refers only to the non-terminal CBD stations.

The most notable difference between the previous set of models and the suburban models is the effect of the service variable. The unweighted suburban model estimated that a 10% increase in headways would correspond with a 2.32% decrease in ridership, compared with over 8% in the 2SLS all stations model. Additionally, when the weights were applied to reduce the effect of outliers, the significance of the headway variable changed dramatically ($p = 0.04$ to $p = 0.11$) and the model's fit was worse as measured by the AIC (142.96 when average headways were included in the weighted model and 139.13 without). One possible explanation for this is that since suburban rail serves mostly commuters and acts as a scheduled service, the changes in the amount of time between trains is less likely to influence rider behaviour from a convenience standpoint.

In addition to the variables found in the all stations models, a transfer dummy variable was included, which in the weighted model predicts that stations with at least one transfer to a transit mode other than buses experience 68% to 70% more boardings than those without. This is unsurprising as intermodal connections help to deliver riders to these rail stations and frequently serve as connection points to the urban rail networks. The final additional variable is the relative distance to the downtown terminal, which ranks stations on the rail network according to their distance on the same scale. The results of the weighted model indicate that increasing distance from the terminus has a negative effect on boardings. Other DRMs have shown similar results for urban rail systems (Chan & Miranda-Moreno, 2013; Sohn & Shim, 2010), heavy rail (Usvyat et al., 2009), and BRT (Duduta, 2013) and likely reflects the negative effect that longer commute times, particularly relative to competing modes, can have on transit ridership.

4.2. Urban Stations Models

The final set of models presented uses only the urban stations and was initially tested with the coefficients determined to be significant in the first set of models. As shown in Table 18, the population density and bus connections, and a service supply variable were also found to be associated with boardings at urban rail stations, while the parking spaces and CBD dummy were not. In addition, the road link to node ratio, the walkability index, and a university dummy variable were also found to be significant. Model diagnostic tests indicated that the model's residuals were homoscedastic (score test p = 0.07), normally distributed (Shaprio-Wilk p = 0.12), uncorrelated (Durbin Watson test score = 1.717, within the acceptable range of 1.714 to 1.845 and a Moran's I value of 0.08, p = 0.006), and that the model was properly specified (RESET test p = 0.04). Similar to the other models the presence of outliers was observed and a robust regression was also run, which achieved a reduction in the number of high leverage and influential points, and a reduction in their magnitude from a maximum Cook's Distance of 0.85 to 0.14 and hat value of 0.91 to 0.27 (see tables in Appendix C for more detail). The outlierTest function in R also indicated that no residual was abnormally large. Diagnostic tests for the weighted model achieved similar results to the unweighted version (score test p = 0.23; Shaprio-Wilk p = 0.06; Durbin Watson test score = 1.717; Moran's I = 0.08 p = 0.006; RESET test p = 0.04). Coefficient estimates between the two models were also similar with minor changes including a decrease in the estimated effect of the bus connections, walkability, and supply variables, and increase in the estimated effect of population density.

Table 17 - Urban Stations OLS and Weighted OLS Models VIF Scores

Coefficients	VIF Unweighted	VIF Weighted	VIF 2SLS
log(Population Density)	1.514	1.546	2.077
Link to Node Ratio	1.064	1.069	1.423
log(Bus Connections)	1.112	1.117	1.223
University Dummy	1.024	1.031	1.076
Walkability	1.577	1.638	1.973
Service Supply	1.174	1.166	2.995

VIF scores, presented in Table 17, were slightly higher than for both the unweighted and weighted urban stations models than for the previous ones. The highest values were found for population density and service supply, which may occur as a result of the fact that stations in more densely populated closer to the center have a higher level of service than outlying ones. The VIF score for the walkability index is also fairly high, which is likely related to the fact that more walkable urban environments have higher density population densities. The higher multicollinearity among variables found in the urban models is also reflected in the higher condition index of 25.59 for the unweighted model, 19.79 for the weighted model, and 21.26 for the 2SLS model. Despite a higher degree of multicollinearity found in the urban stations models, diagnostic score tests still fall within an acceptable range. Ridge regressions were also run to assess the degree of multicollinearity. Coefficient estimates were plotted to examine the effect the introduction of an increasing amount of bias had which showed that they remained relatively stable.

Table 18 - Unweighted Urban Stations OLS Model with Bootstrapped Estimates

		Dependent variable: log(Boardings) *Unweighted OLS*		
			Conf. Intervals	
	Estimate (SD)	Boot Estimate (SD)	2.5%	97.5%
log(Population Density)	0.142*** (0.031)	0.155 (0.049)	0.078	0.277
Link to Node Ratio	0.278** (0.089)	0.269 (0.093)	0.086	0.452
log(Bus Connections)	0.463*** (0.041)	0.470 (0.047)	0.381	0.563
University Dummy	0.465*** (0.107)	0.470 (0.138)	0.198	0.741
Walkability	0.108*** (0.019)	0.105 (0.021)	0.062	0.145
Service Supply	0.001*** (0.0002)	0.001 (0.0001)	0.001	0.002
Constant	6.029*** (0.291)	5.920 (0.431)	4.908	6.636
Observations	220			
R^2	0.672			
Adjusted R^2	0.663			
Resid. Std. Err. (df = 213)	0.482			
F Statistic (df = 6; 213)	72.85*** (p = 0.000)			
Note:	p < 0 '***' p < 0.001 '**' p < 0.01 '*' p < 0.05 'x' p < 0.1			

As with the all stations model, a two-stage least squares regression was also run to account for the simultaneity between the supply of transit, in this case the total daily supply of service, and demand. Additionally, the models were bootstrapped to obtain confidence intervals for the coefficient estimates presented in Table 18, Table 20, and Table 21.

Table 19 - Urban Stations Spatial Lag and Spatial Error Models

	Dependent variable: log(Boardings) *Unweighted* *Spatial Models*	
	Lag Estimate (SD)	Error Estimate (SD)
log(Population Density)	0.134*** (0.032)	0.116*** (0.033)
Link to Node Ratio	0.262** (0.091)	0.262** (0.096)
log(Bus Connections)	0.471*** (0.042)	0.473*** (0.042)
University Dummy	0.460*** (0.109)	0.517*** (0.110)
Walkability	0.102*** (0.0003)	0.125*** (0.022)
Service Supply	0.001*** (0.0002)	0.001*** (0.0002)
Constant	5.178*** (0.646)	6.312*** (0.310)
ρ/λ	0.108	0.258*
Observations	220	220
Log-likelihood	-154.02	-152.54
Wald statistic	2.369 (p = 0.124)	7.384 (p = < 0.007)
Note:	p < 0 ‘***’ p < 0.001 ‘**’ p < 0.01 ‘*’ p < 0.05 ‘x’ p < 0.1	

Results of the spatial lag and spatial error models for urban stations are presented in Table 19. The spatial lag model did not show much improvement on the initial model (AIC 326.03 vs. 325.99) and a Wald test p-value of 0.124. The spatial error model was a slight improvement in terms of AIC (323.08) with a satisfactory Wald test result (p = 0.007). As the Moran’s I test showed relatively weak positive spatial autocorrelation the spatial error model’s estimates are not much different from those of the original OLS model.

Table 20 - Weighted Urban Stations OLS Models with Bootstrapped Estimates

	Dependent variable:			
	log(Boardings)			
	Weighted OLS			
			Conf. Intervals	
	Estimate (SD)	Boot Estimate (SD)	2.5%	97.5%
log(Population Density)	0.161*** (0.029)	0.168 (0.037)	0.109	0.259
Link to Node Ratio	0.244** (0.079)	0.240 (0.076)	0.088	0.388
log(Bus Connections)	0.449*** (0.037)	0.454 (0.038)	0.382	0.531
University Dummy	0.489*** (0.097)	0.491 (0.112)	0.270	0.711
Walkability	0.099*** (0.017)	0.098 (0.018)	0.063	0.132
Service Supply	0.001*** (0.0001)	0.001 (0.0001)	0.001	0.001
Constant	5.956*** (0.268)	5.890 (0.328)	5.113	6.434
Observations	220			
R^2	0.717			
Adjusted R^2	0.709			
Resid. Std. Err. (df = 213)	0.406			
F Statistic (df = 6; 213)	90.09*** (p = 0.000)			
Note:	p < 0 '***' p < 0.001 '**' p < 0.01 '*' p < 0.05 'x' p < 0.1			

Table 21 - Weighted Instrumental Variable Model for Urban Stations with Bootstrapped Estimates

	Dependent variable: log(Boardings) *Instrumental variable*			
			Conf. Intervals	
	Estimate (SD)	Boot Estimate (SD)	2.5%	97.5%
log(Population Density)	0.127^{***} (0.037)	0.109 (0.046)	0.003	0.235
Link to Node Ratio	0.154 (0.100)	0.159 (0.122)	-0.101	0.396
log(Bus Connections)	0.471^{***} (0.043)	0.497 (0.051)	0.401	0.601
University Dummy	0.529^{***} (0.109)	0.522 (0.132)	0.213	0.839
Walkability	0.084^{***} (0.021)	0.086 (0.025)	0.034	0.135
Service Supply	0.002^{**} (0.001)	0.003 (0.001)	0.001	0.005
Constant	5.722^{***} (0.321)	5.660 (0.381)	4.690	6.428
Observations	220			
R^2	0.660			
Adjusted R^2	0.650			
Resid. Std. Err. (df = 213)	0.446			
Wald Test (df = 6; 213)	71.87^{***} (p = 0.000)			
Note:	p < 0 '***' p < 0.001 '**' p < 0.01 '*' p < 0.05 'x' p < 0.1			

Table 23 presents elasticity estimates for the bootstrapped instrumental variable and weighted regression models. The most obvious change is in elasticity estimate is the of the supply variable. In the instrumental variable model, it is estimated that a 10% increase in the supply of service would correspond with a 13.6% increase in transit ridership, compared with to 5.3% for the weighed and unweighted OLS models. Station age was again used as an instrument for supply, with a Pearson correlation coefficient of 0.41, which, like in the all stations model is not very high but high enough to investigate further. The next largest effect is that of bus connections, followed by population density and the walkability index. The university dummy variable also exerts a stronger effect in the instrumental variable model with stations with a university within the catchment area experiencing almost 41% higher ridership than those without.

Table 22 - Urban Stations Instrumental Spatial Error Model

	Dependent variable:
	log(Boardings)
	Instrumental Spatial Model
	Error Estimate (SD)
log(Population Density)	0.093^{*} (0.038)
Link to Node Ratio	0.167 (0.110)
log(Bus Connections)	0.488^{***} (0.047)
University Dummy	0.516^{***} (0.120)
Walkability	0.104^{***} (0.024)
Service Supply	0.003^{***} (0.001)
Constant	5.877^{***} (0.355)
ρ	0.178^{x}
Observations	220
Note:	p < 0 '***' p < 0.001 '**' p < 0.01 '*' p < 0.05 'x' p < 0.1

Table 23 - Comparison of Elasticity Estimates for Bootstrapped Unweighted OLS and Weighted OLS and Instrumental Variable Urban Stations Models

	OLS	Spatial Error	Weighted	2SLS	2SLS Error
log(Population Density)	1.55%	1.16%	1.68%	1.09%	0.93%
Link to Node Ratio	3.50%	3.41%	3.15%	2.07%	2.17%
log(Bus Connections)	4.70%	4.73%	4.54%	4.97%	4.88%
University Dummy	37.50%	40.35%	38.80%	40.67%	40.29%
Walkability	0.18%	0.20%	0.17%	0.15%	0.17%
Service Supply	5.32%	4.61%	5.28%	13.63%	11.97%

It is clear again from the elasticity estimates that the supply of transit service has the greatest potential to influence transit ridership. Although not directly comparable, the estimated change in ridership in response to a 10% change in the supply variable is larger for urban stations than in the all stations model. The elasticity of the effect of the supply of busses remains consistent with the previous models (between 2 and 5%) and other studies and reinforces the point that intermodal connections play a significant role in generating rapid transit ridership. The estimated elasticity of population density is also similar between all models (between 1 and 2%) reflecting partially the aspects of urban form can play.

Link to node ratio, which is the ratio of street links between two intersections to the total number of intersections within a catchment area, is estimated to result in a 2 to 3.5% increase in ridership for a 10% increase in the ratio of links to nodes indicating that more permeable street networks have the potential to increase transit ridership. Using the same measure, Dill et al. (2013) found that the link to node ratio exerts a small but significant effect on transit use in the Portland, Oregon area. Similarly, Lin & Shin (2008) found that the percentage of four-way intersections, another measure of street network connectivity, was positively associated with rapid transit usage in Taipei, Taiwan. Walkability, a composite measure that includes land use mix, commercial sites, residential density, and number of intersections is also positively associated with boardings, although the magnitude of the effect is much smaller. The urban models estimate that a 10% increase in the walkability score of a station would correspond with a 0.15 to 0.18% increase in station ridership. Ryan & Frank (2009) also used the same walkability index and similarly found that it explained only a small portion of the variation (0.5%) in bus transit ridership in the San Diego area. The significance of the three urban form related variables supports the notion that urban rapid transit stations draw a significant portion of their ridership base from the immediate surrounding area and that urban form that supports pedestrian access can have a strong positive influence on transit ridership at the station level.

The final variable in the urban stations model is a dummy variable for the presence of a university within a station's catchment area. These models predict that stations that serve university campuses experience between 37.5 to 41% more ridership than stations that do not. This finding occurs likely as a result of the large number of students and faculty that access university campuses and the fact that students, with lower incomes and consequently lower automobile ownership rates, are more likely to be dependent on transit. Another related reason for why university stations experience more ridership is that campuses counted by this variable are often in higher density central locations, where the provision of parking is limited and cost is high. Sohn & Shim (2010), one of the DRMs included in the literature review, found that the presence of a university in a station's catchment area had a strong positive association with metro ridership in Seoul, South Korea. In Canada, Chan & Miranda-Moreno (2013) found that a similar variable, the area occupied by government and institutional land uses (which included universities), had a strong relationship to metro ridership in Montréal, where it was estimated that a 10% increase in area would correspond with a 6.7% increase in transit ridership.

5. Conclusions and Recommendations

The goal of this thesis was to develop a station-level direct ridership model of rail rapid transit in Canada to assess which local level factors were associated with rapid transit ridership and to compare models for different transit types. Data for 53 variables were used to develop three models of boardings at different types of transit stations: urban, suburban, and both urban and suburban together. This final chapter summarizes the results of the models, answers the research questions, makes recommendations for policy-makers and planners, and proposes refinements to the models and data collection methods.

5.1. Summary of Results and Recommendations

The models fit the ridership data well with adjusted R^2 values of 0.841 for the all stations 2SLS, 0.765 for the suburban robust, and 0.650 for the urban 2SLS models offering a relatively high degree of explanatory value. Several variables also appear to be consistently significantly associated with ridership between the models. The population density and bus connections variables appear in all three, while the CBD dummy, parking spaces, and average headways variables appear in two of the models. Table 24 presents the range of elasticity estimates derived (representing the change in boardings expected if the variable in question were to increase by 10%) from the models generated.

The elasticity estimate for population density remained consistent between the models and ranged between 0.86% and 1.82% (see Table 24). This finding supports policies designed to raise population densities in order to increase transit usage. Unfortunately the population density variable on its own does not provide any means to differentiate between the actual effects of population density and its accompanying “second-order” effects mentioned by Kuzmyak et al. (2003). For example, higher density areas tend to coexist with gridded street patterns, greater street network permeability, and mixed land uses. The significance of the link to node ratio and walkability variables, in conjunction with the lower elasticity estimate of population density, compared to those of the all stations model may be an indication that these effect have been partially captured. This is further supported by the fact that when the urban model was run omitting the two built environment variables, link to node ratio and walkability, the estimated elasticity of population more than doubled to 2.32%

Table 24 – Range of Elasticity Estimates for all Models

	Elasticity All Stations	Elasticity Suburban	Elasticity Urban
Population Density	1.14% - 1.82%	0.86% - 0.99%	0.93% - 1.68%
Bus Connections	4.07% - 4.43%	2.84% - 2.98%	4.54% - 4.97%
CBD Dummy	42.90% - 50.72%	57.64% - 59.38%	-
Park and Ride Spaces	1.06% - 1.49%	5.47% - 5.76%	-
Average Headway	-8.95% - -7.35%	-2.32%	-
Transfer Dummy	-	65.52% - 69.58%	-
Relative Distance to Terminal	-	-2.55% - -1.99%	-
Link to Node Ratio	-	-	2.07% - 3.50%
University Dummy	-	-	37.50% - 40.67%
Walkability	-	-	0.15% - .020%
Service Supply	-	-	4.61% - 13.63%

The elasticity for the bus connections variable is strongest in the urban stations model. This makes sense as there are likely to be people beyond walking distance but who are unwilling or unable to access stations by car. Its estimated effect on suburban stations also indicates that providing bus service to commuter rail stations increases transit use. The effect of bus service in the suburban model is outweighed by that of park and ride spaces where the model estimates that a 10% increase in parking spaces would correspond with a 5.42% to 5.76% increase in ridership at that station. This finding, in conjunction with the data presented in Table 3, supports the observation that many Canadian commuter rail riders either depend on or prefer to use their cars to access transit. This can be considered evidence to support the policies already adopted by Metrolinx for Toronto's GO rail transit stations, where the number of spaces available at stations between 2000 and 2013 has doubled; Metrolinx plans to continue to add parking spaces at new and existing stations (Metrolinx, 2013). Similar plans exist to expand the park and ride service offered among other transit providers owing to increasing levels of demand for spaces in these lots, which in many cases operate near or at maximum capacity (Agence Metropolitaine de Transport, 2014; Metrolinx, 2013; The City of Edmonton, 2015). The ridership effects of parking spaces should also consider the potentially negative effects increased parking and consequently increased driving may have. Evidence in has been presented by Parkhurst (1995, 2000) that argues that park-and-ride provision may increase road traffic in station areas. Wiseman et al. (2012) also show that newly constructed park-and-ride lots can, in fact, divert commuters away from other forms of transit and into their cars for station access trips.

The supply of transit (as measured by total number of trains or by average headways) was a significant factor in two of the final models with relatively high elasticity estimates. In the all stations model, it was estimated that 10% increase in the time between trains at a stations would correspond with an almost 7% to 9% reduction in the use of that station. In the urban model, a different supply variable was shown to exert an even stronger effect where the model estimated that a 10% increase in the supply of service (measured as the total number of trains arriving at a station on an average weekday) would correspond with as much as a 13.6% increase in station ridership. The significance of these variables and their strong estimated effect reflect findings in the literature (e.g. Peng et al., 1997; Taylor & Fink, 2003; Taylor et al., 2008) that indicate that as transit service provision increases demand for service does as well.

Inherent in the use of transit supply as a predictor of transit use is the problem of endogeneity or the cyclical relationship between supply for transit and its demand as discussed previously. This makes it difficult to separate the effect supply or the availability can have on its demand as transit agencies can respond to increases in demand for service with greater supply. It is hoped that the use of the 2SLS model with an instrumental variable adequately compensates for this effect and provides a more accurate depiction of the role service supply plays in influencing transit usage. Model elasticity estimates for both supply variables were observed to change significantly between the standard OLS and robust models and the 2SLS models. For the all stations models, the original OLS model estimated a -7.35% elasticity, the robust estimated it at -7.26%, while the 2SLS result was nearly -9%. Similarly for the urban OLS model, the estimated elasticity of service supply was 5.32% and 5.27% for the robust compared to 13.63% in the 2SLS model. When a spatial component was added as in the urban and all stations 2SLS models the effect of supply was shown to decrease slightly but still remained higher than in the weighted and unweighted OLS. These results indicate that increases in the supply of transit should be met with increases in the use of transit. This cannot be the case forever and as supply increases, demand would likely level off and increases in transit provision would be met with decreasing gains in use. It is possible to argue that transit agencies already provide transit service meeting existing demand and that further increases in service would not translate into greater use. This, however, is unlikely given the fact that transit use in Canada's major cities has continued to rise since the early 2000s (Statistics Canada, 2015) in conjunction with increases in transit funding (CUTA, 2012). Recent evidence from Montréal's STM 2014 annual report also shows that ridership on the transit network as a whole (including buses and the Metro) only grew by 0.2% from 2013, a period where transit service was cut by almost 5% (STM, 2015). The case of Montréal does not provide adequate evidence to conclusively link the decrease in funding to much smaller gains in ridership than in previous years (1% between 2012-2013 and 1.9% between 2011-2012) but, combined with evidence presented here and in other studies suggests that ridership is still sensitive to supply of service (STM, 2013, 2014)

Results of the all stations model demonstrate the strongest fit as measured by R^2 also has the most limited range of significant explanatory variables. Among them, the bus connections, parking spaces, and average headways variables could be of use in the transit planning process. While no new variables previously tested in other DRMs are found to be significant, the estimated effects of each provide some insight into the effectiveness of certain strategies transit providers can easily adopt.

The suburban model suffers from a similar problem, although with the addition of the transfer dummy variables it is clear that stations serving an alternative mode are important points on a suburban rail network. The relative distance to the terminus indicates that greater travel times are more likely to discourage transit use. Again, the estimated magnitude of each effect may be of more interest than the variables themselves. Generally the suburban model demonstrates that commuter rail use in Canada is largely dependent on ease of access particularly by car but also by transit, as well as access to other rapid transit networks. The comparatively similar elasticity estimate of population density to that of the urban model highlights the potential for development in station areas even in suburban settings.

Finally, the urban model offers more insight into the role urban form and the street network can play in influencing transit use. The findings indicate that stations in denser, more permeable, and more walkable settings can encourage ridership. In addition to the urban form variables, the university dummy variable is significant with the presence of a university in a station area corresponding with a roughly 40% increase in ridership at that station. This may indicate the role large destinations and centers of employment can have in generating significant transit usage. The prominence of universities is owed likely to the fact that they are visited most often by younger people, who are less likely to own cars and increasingly more likely to live in urban and transit-accessible environments.

5.2. Study Limitations and Future Research

One major limitation of the research is the temporal scale of the ridership data. For several cities, only data for 2012 were available. Historical ridership data may have enabled a better estimation of the effect of supply by using the previous year's ridership data as a predictor of the next year's transit supply. Where historical data was readily available (for Edmonton's LRT and Toronto's Subway), this approach was attempted and achieved similar results to the 2SLS model. Another area in which the analysis may be improved is through the use of one or more better instrumental variables for transit supply. Similarly, the use of alternative modelling techniques, such as structural equations modelling (as used by Sohn & Shim, 2010), may help to better account for the interrelationships between supply and demand, as well as the relations between other variables tested. Measures of service quality may also have improved the models as it has been argued that aspects of service quality such as timeliness and comfort can influence a commuter's decision to take transit (Taylor & Fink, 2003). Separating boardings by AM and PM peak periods may also help to further refine the models. Additionally estimating models using alighting data may help to better define factors associated with trip attraction which has been shown to be an important element in transit use decision making (Barnes, 2005; Chatman, 2003)

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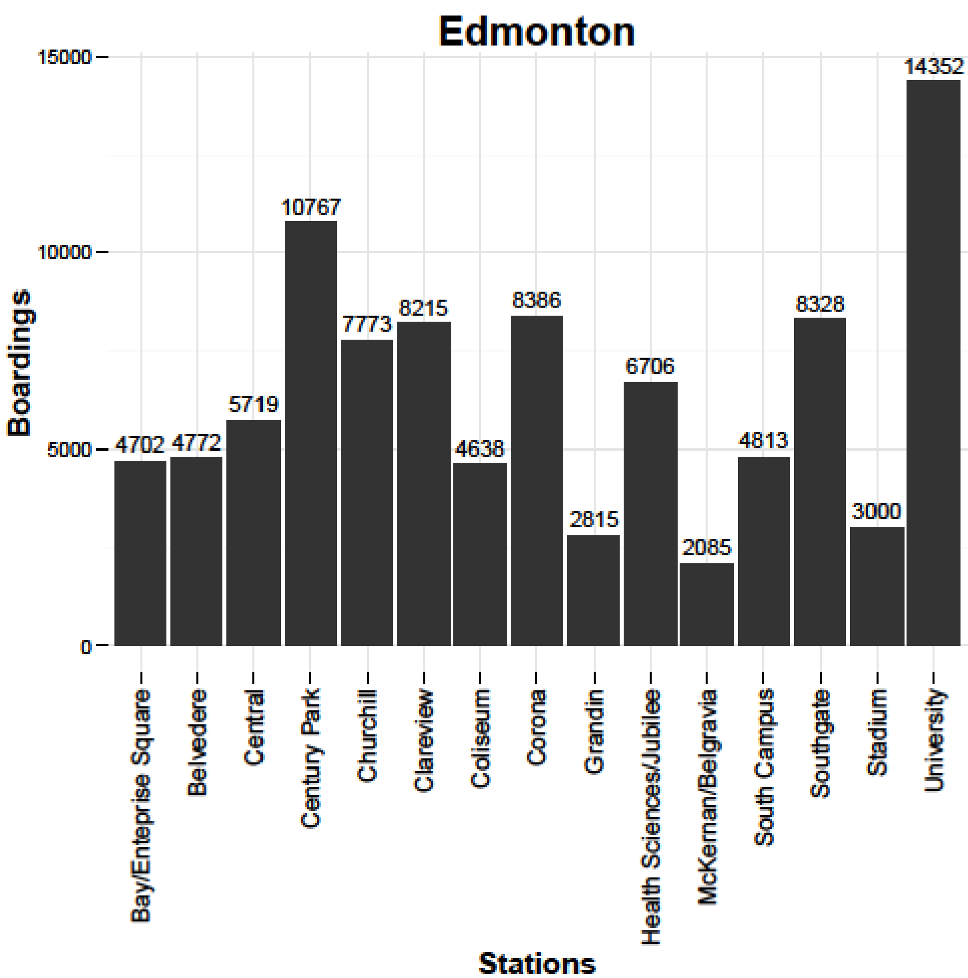
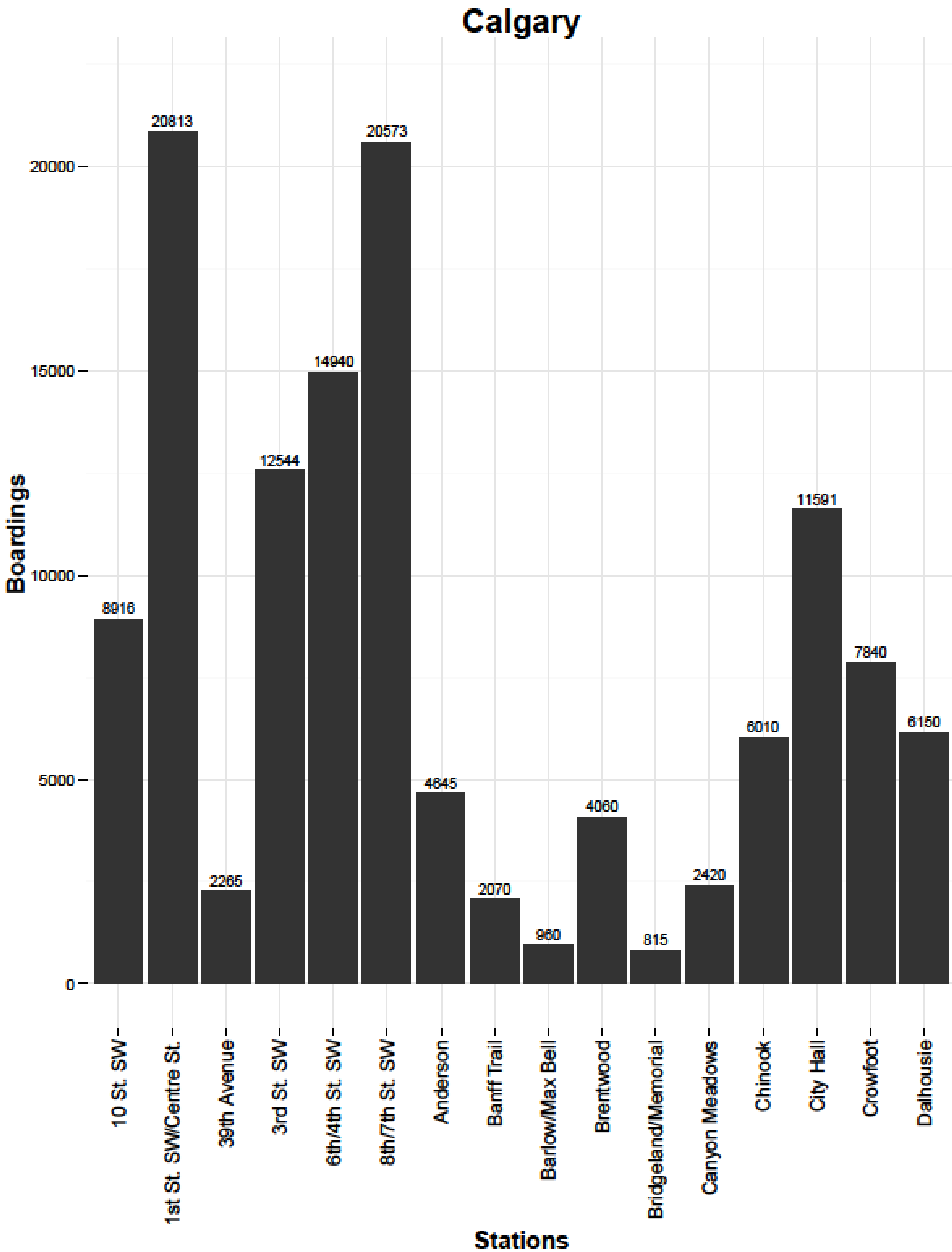
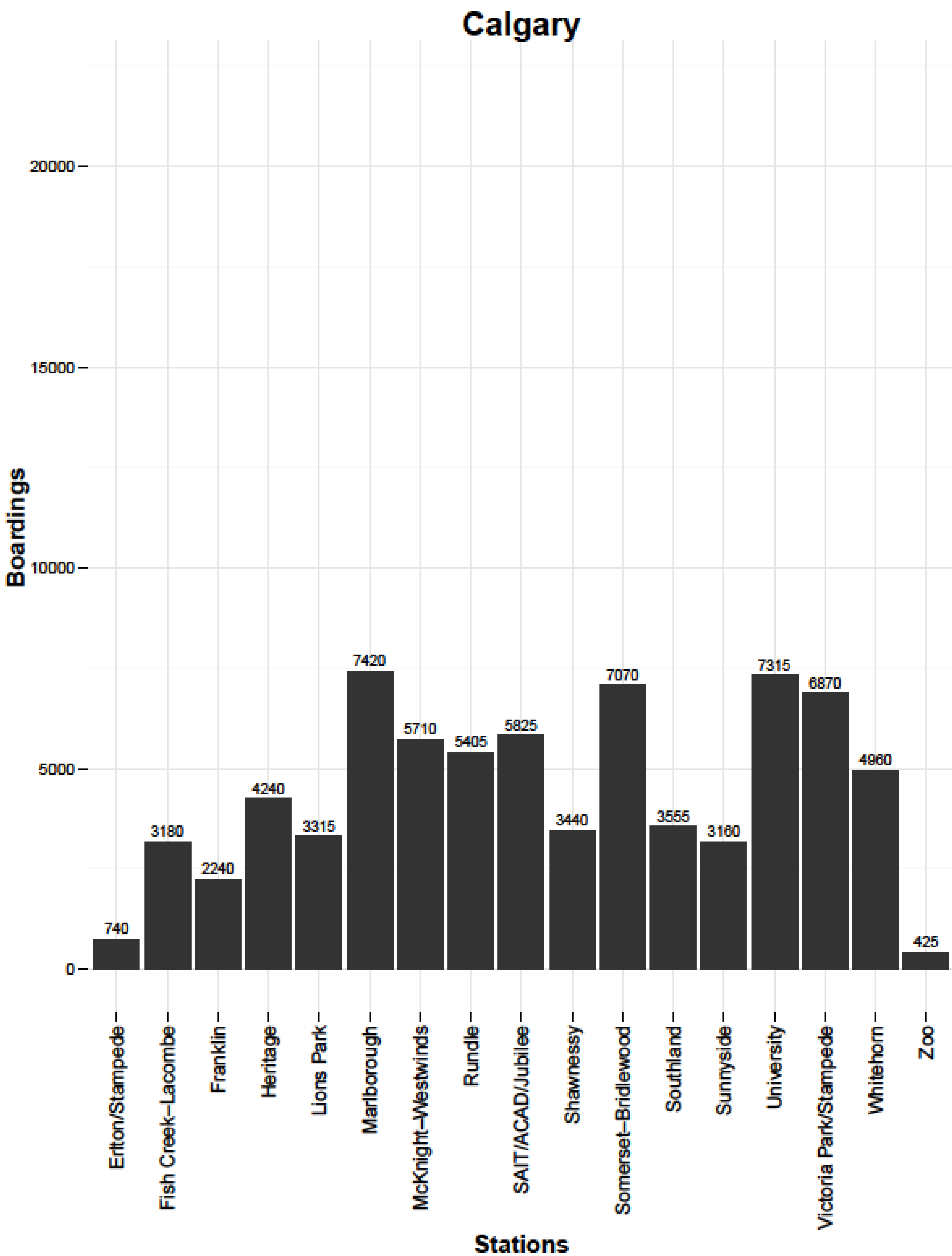
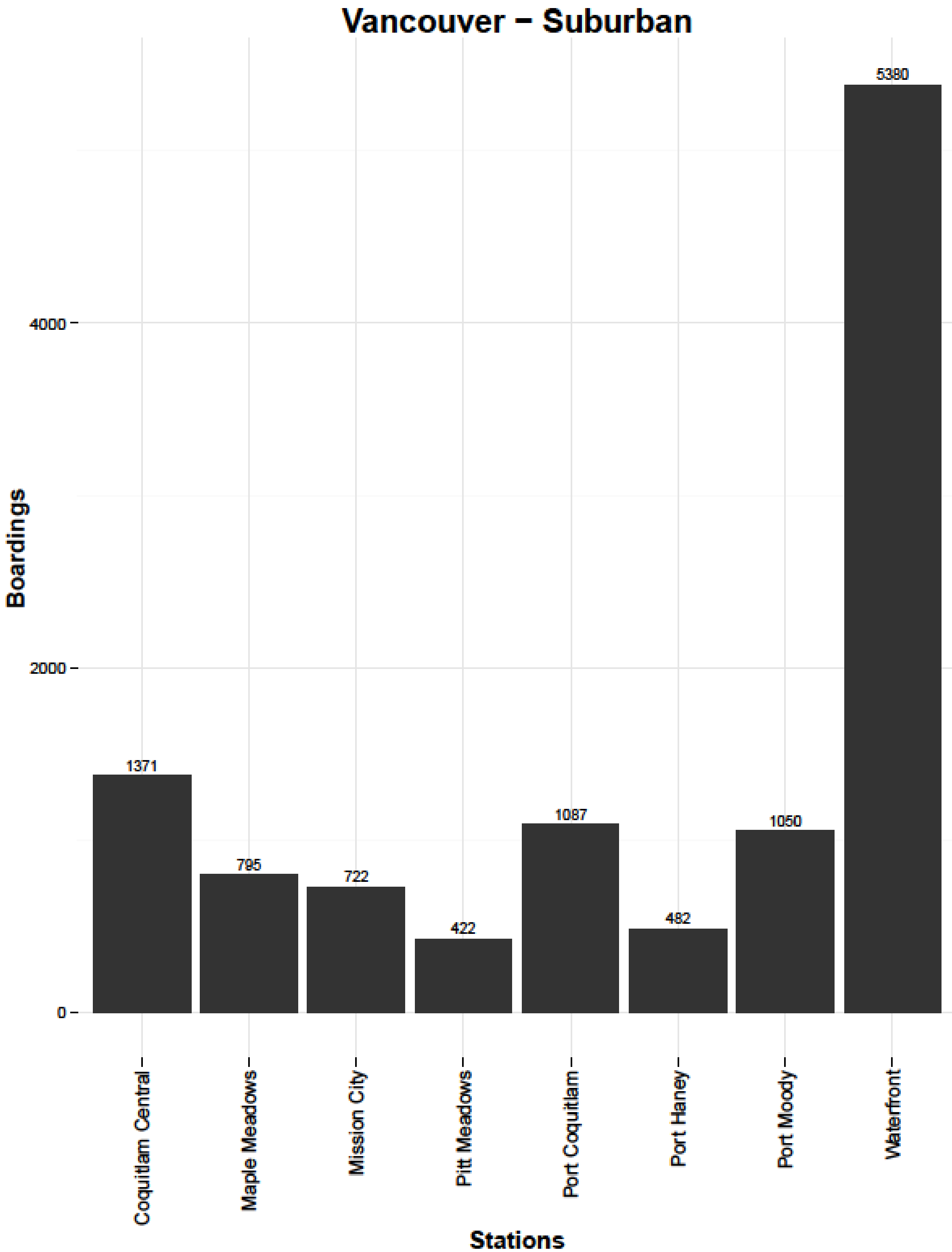
Appendix A


Edmonton
Boardings
Stations
15000
10000
5000
0
4702
4772
5719
10767
7773
8215
4638
8386
2815
6706
2085
4813
8328
3000
14352
Bay/Enteprise Square
Belvedere
Central
Century Park
Churchill
Clareview
Coliseum
Corona
Grandin
Health Sciences/Jubilee
McKernan/Belgravia
South Campus
Southgate
Stadium
University

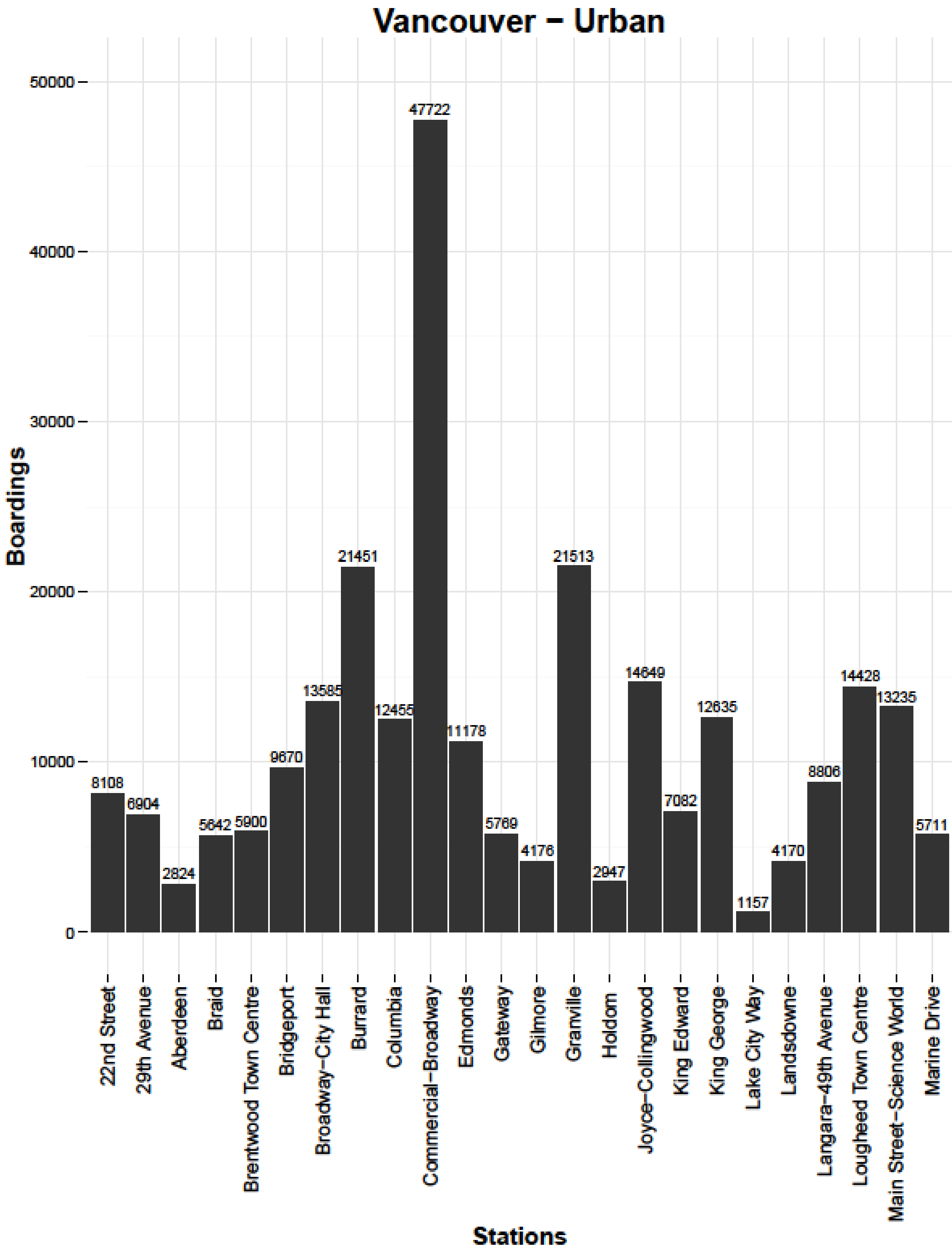


Calgary
Boardings
Stations
0
5000
10000
15000
20000
8916
20813
2265
12544
14940
20573
4645
2070
960
4060
815
2420
6010
11591
7840
6150
10 St. SW
1st St. SW/Centre St.
39th Avenue
3rd St. SW
6th/4th St. SW
8th/7th St. SW
Anderson
Banff Trail
Barlow/Max Bell
Brentwood
Bridgeland/Memorial
Canyon Meadows
Chinook
City Hall
Crowfoot
Dalhousie

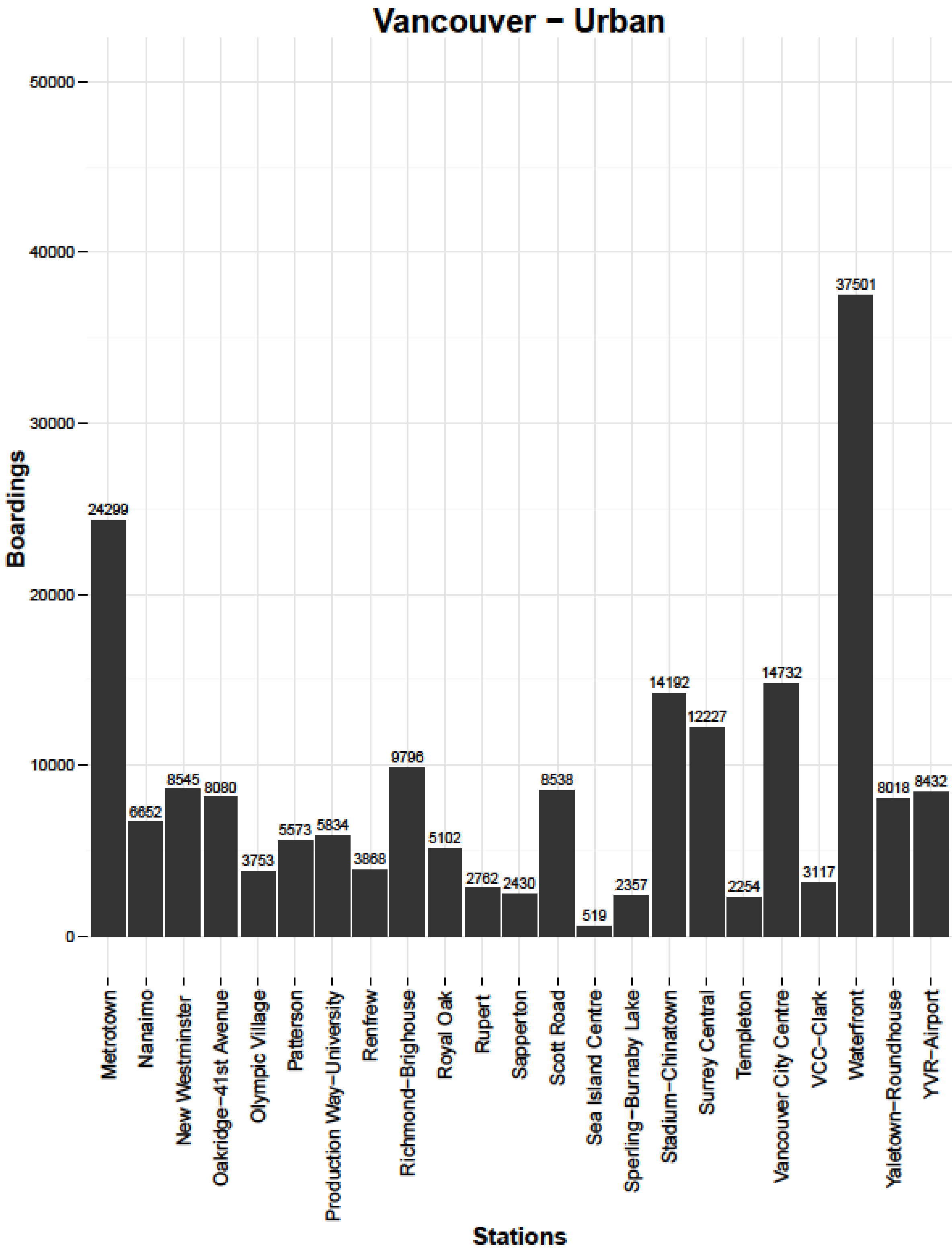

Calgary
Boardings
Stations
20000
15000
10000
5000
0
740
3180
2240
4240
3315
7420
5710
5405
5825
3440
7070
3555
3160
7315
6870
4960
425
Erlton/Stampede
Fish Creek–Lacombe
Franklin
Heritage
Lions Park
Marlborough
McKnight–Westwinds
Rundle
SAIT/ACAD/Jubilee
Shawnessy
Somerset–Bridlewood
Southland
Sunnyside
University
Victoria Park/Stampede
Whitehorn
Zoo

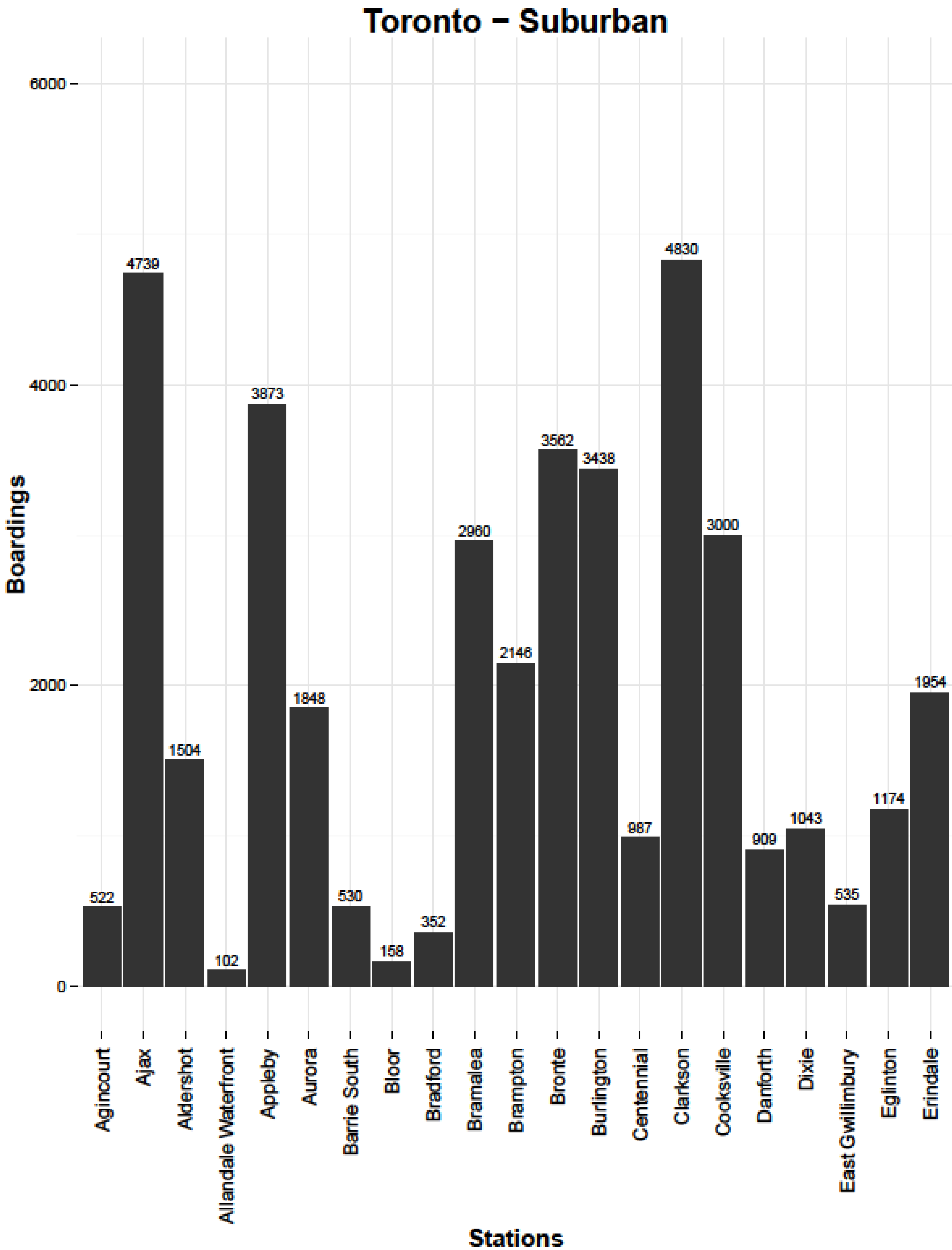


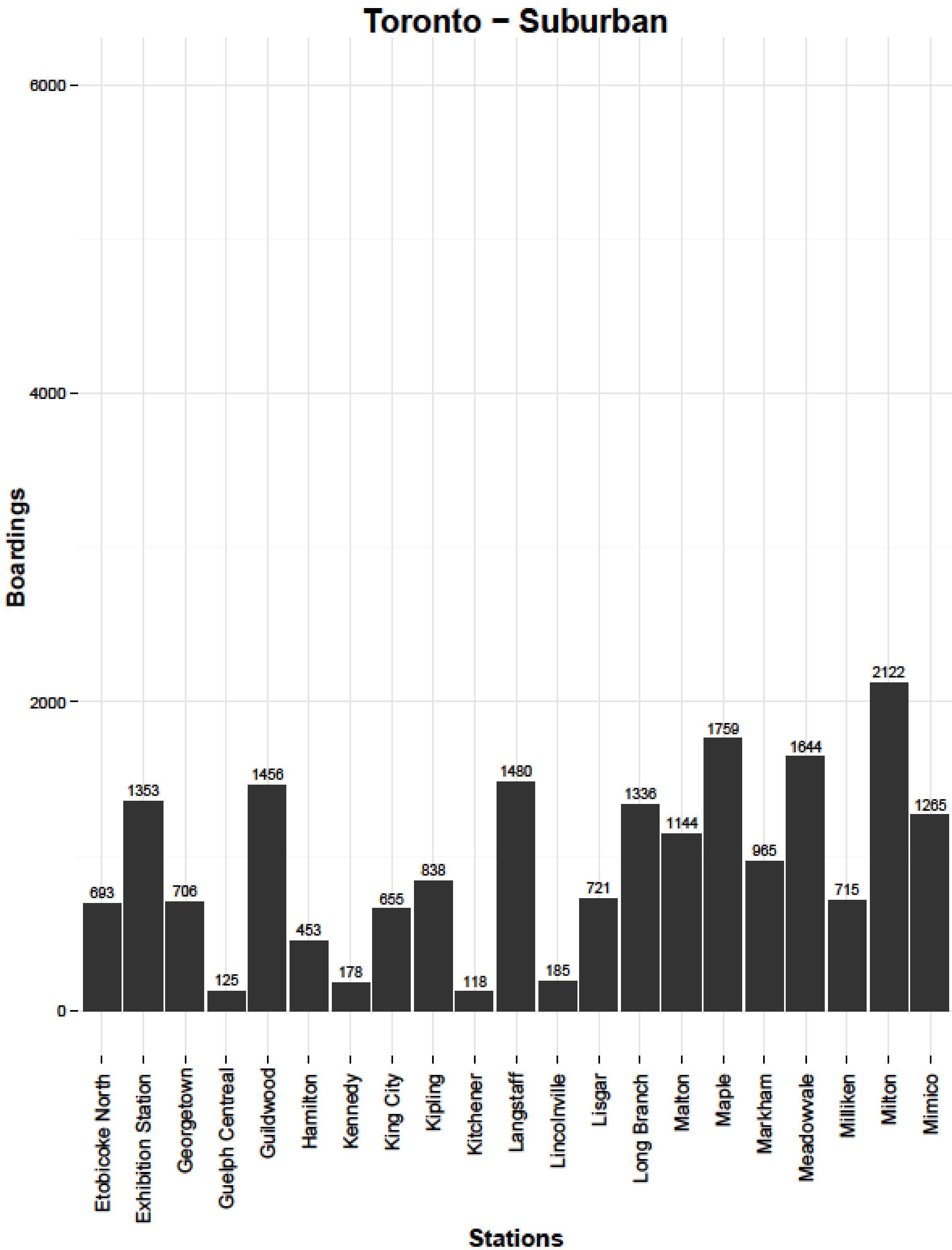
Vancouver − Suburban
Boardings
4000
2000
0
1371
795
722
422
1087
482
1050
5380
Coquitlam Central
Maple Meadows
Mission City
Pitt Meadows
Port Coquitlam
Port Haney
Port Moody
Waterfront
Stations

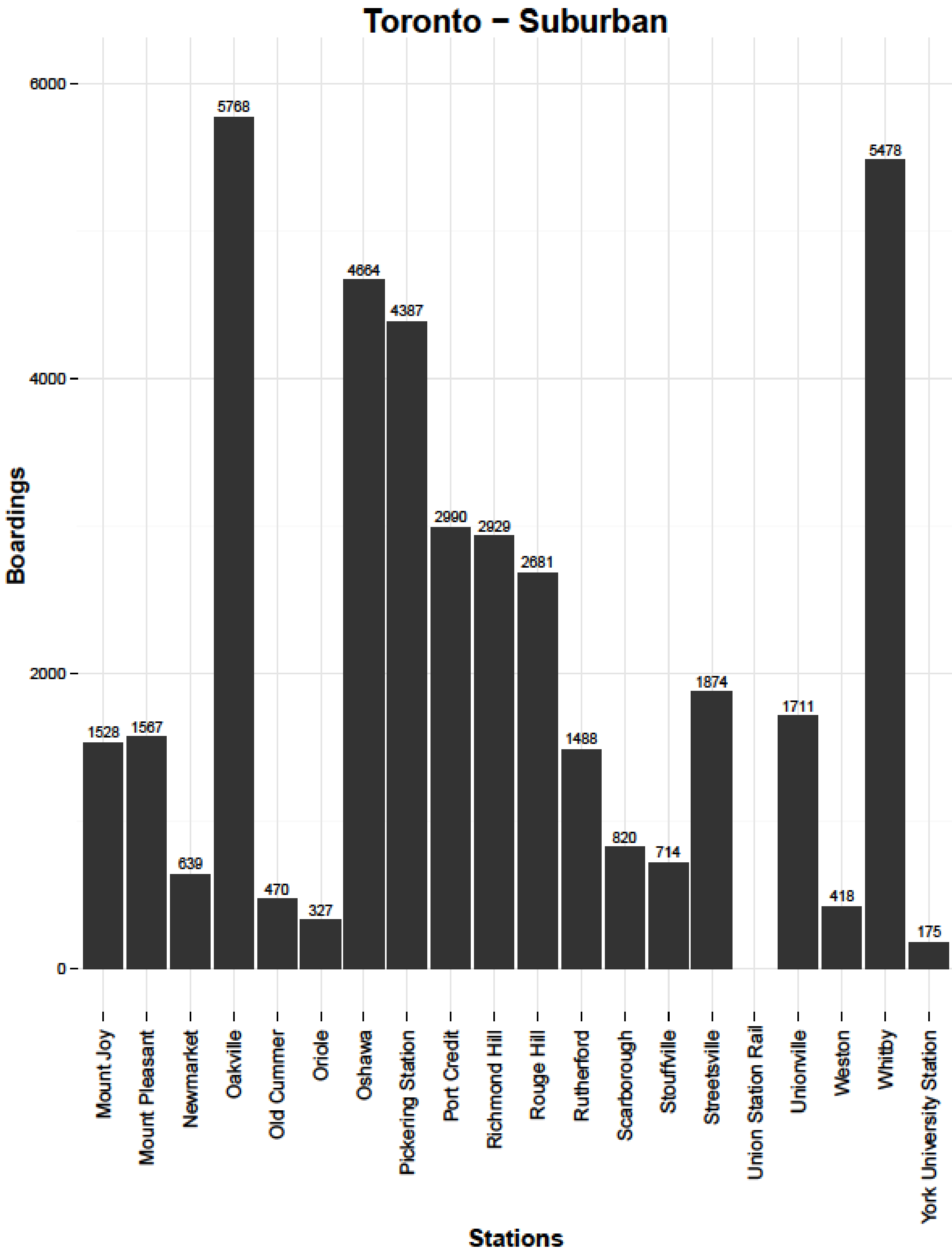


Vancouver − Urban
Boardings
Stations
0
10000
20000
30000
40000
50000
8108
6904
2824
5642
5900
9670
13585
21451
12455
47722
11178
5769
4176
21513
2947
14649
7082
12635
1157
4170
8806
14428
13235
5711
22nd Street
29th Avenue
Aberdeen
Braid
Brentwood Town Centre
Bridgeport
Broadway−City Hall
Burrard
Columbia
Commercial−Broadway
Edmonds
Gateway
Gilmore
Granville
Holdom
Joyce−Collingwood
King Edward
King George
Lake City Way
Landsdowne
Langara−49th Avenue
Lougheed Town Centre
Main Street−Science World
Marine Drive

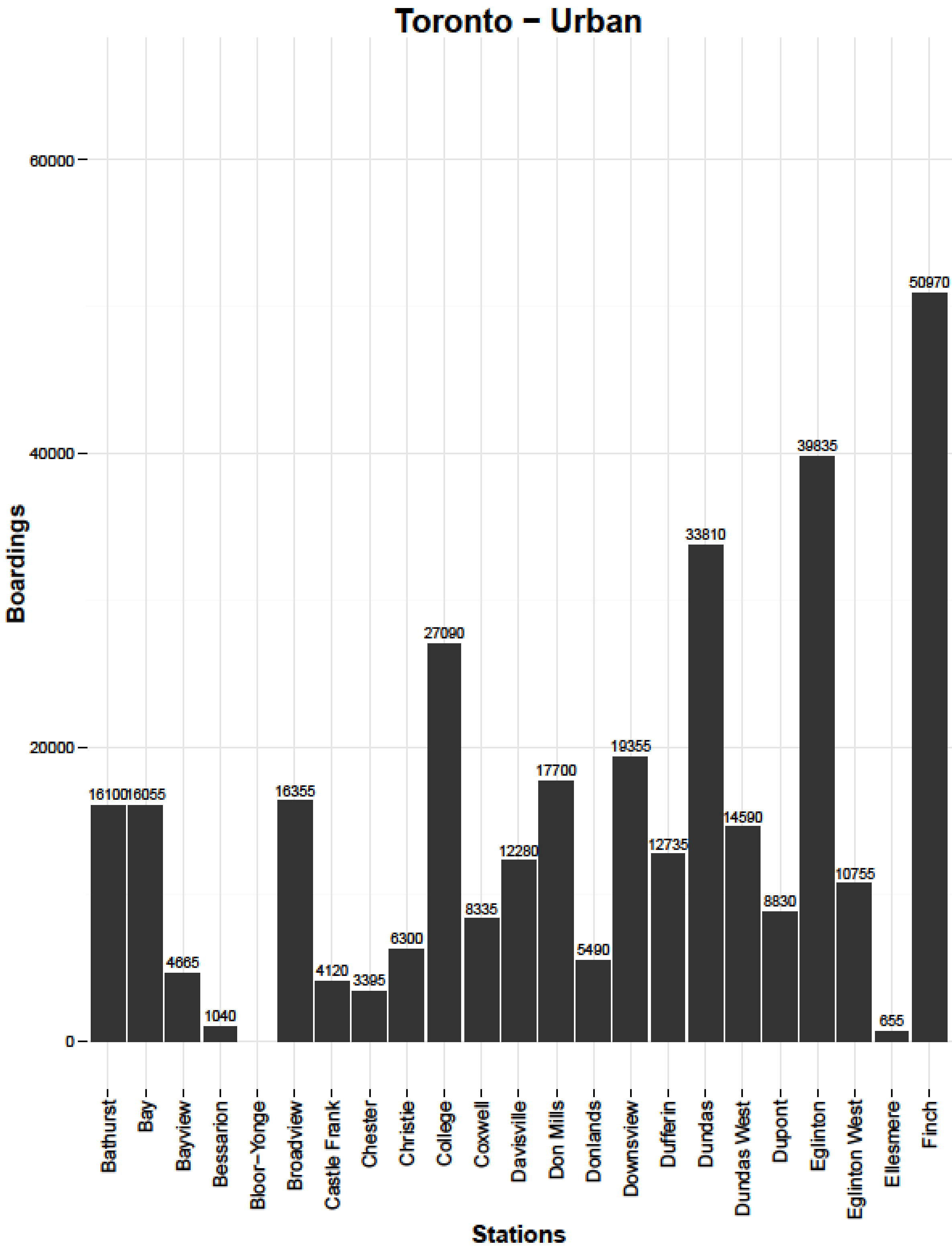

Vancouver − Urban
Boardings
Stations
50000
40000
30000
20000
10000
0
24299
6652
8545
8080
3753
5573
5834
3868
9796
5102
2762
2430
8538
519
2357
14192
12227
2254
14732
3117
37501
8018
8432
Metrotown
Nanaimo
New Westminster
Oakridge−41st Avenue
Olympic Village
Patterson
Production Way−University
Renfrew
Richmond−Brighouse
Royal Oak
Rupert
Sapperton
Scott Road
Sea Island Centre
Sperling−Burnaby Lake
Stadium−Chinatown
Surrey Central
Templeton
Vancouver City Centre
VCC−Clark
Waterfront
Yaletown−Roundhouse
YVR−Airport


Toronto − Suburban
6000
4000
2000
0
Boardings
522
4739
1504
102
3873
1848
530
158
352
2960
2146
3562
3438
987
4830
3000
909
1043
535
1174
1954
Agincourt
Ajax
Aldershot
Allandale Waterfront
Appleby
Aurora
Barrie South
Bloor
Bradford
Bramalea
Brampton
Bronte
Burlington
Centennial
Clarkson
Cooksville
Danforth
Dixie
East Gwillimbury
Eglinton
Erindale
Stations

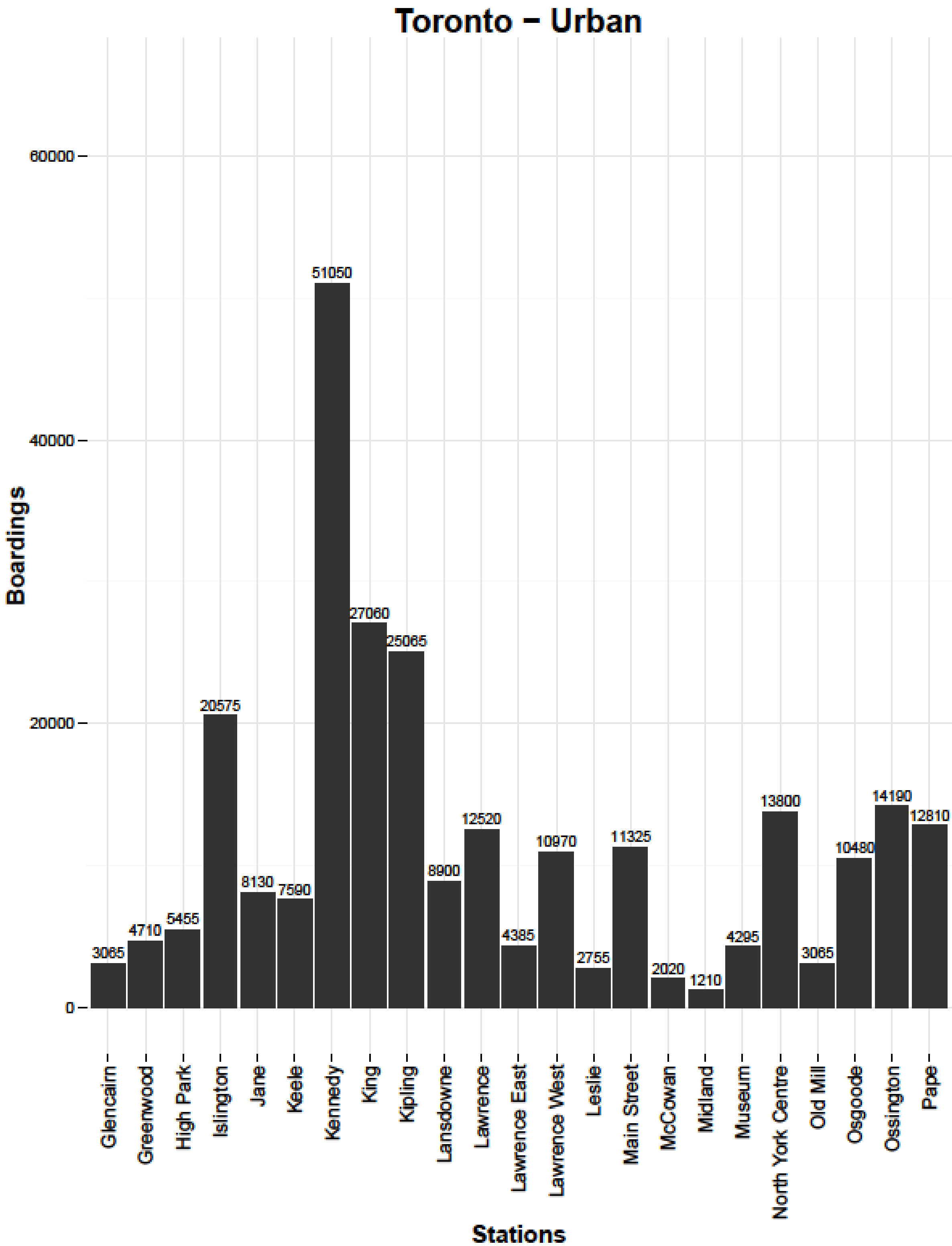

Toronto − Suburban
Boardings
6000
4000
2000
0
693
1353
706
125
1456
453
178
655
838
118
1480
185
721
1336
1144
1759
965
1644
715
2122
1265
Etobicoke North
Exhibition Station
Georgetown
Guelph Centreal
Guildwood
Hamilton
Kennedy
King City
Kipling
Kitchener
Langstaff
Lincolnville
Lisgar
Long Branch
Malton
Maple
Markham
Meadowvale
Milliken
Milton
Mimico
Stations



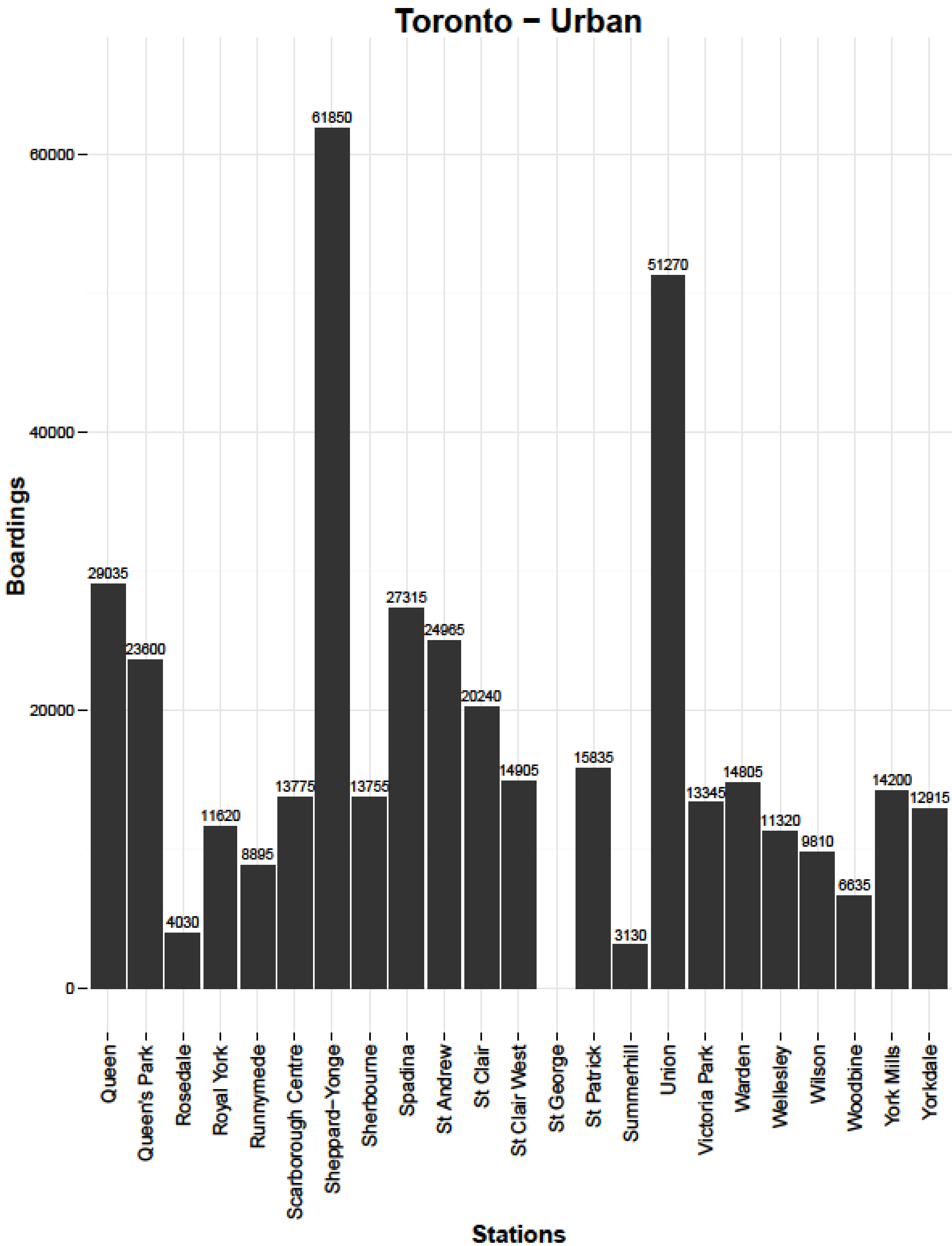
Note: Union Station (90,671 boardings) is omitted.



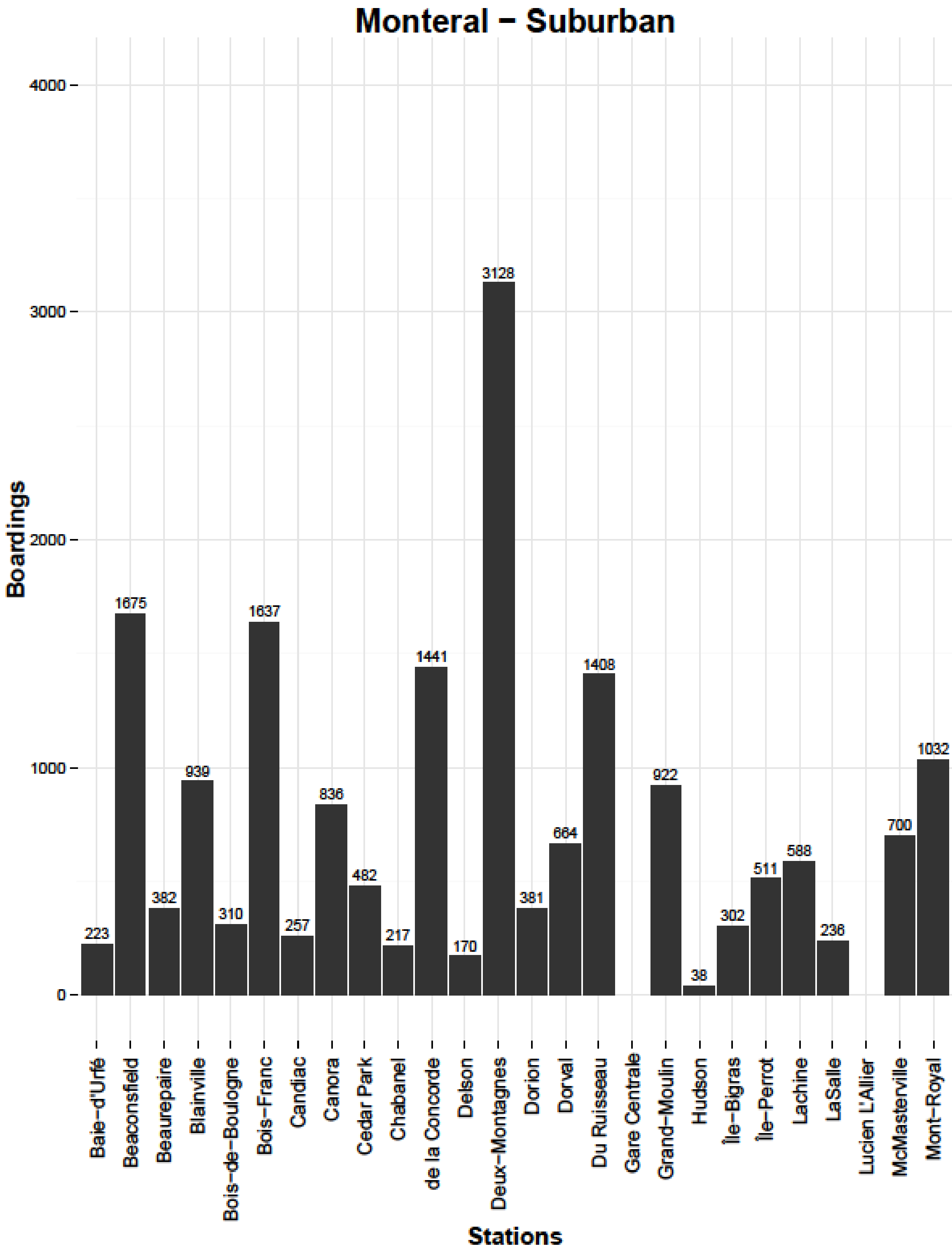
Note: Bloor-Yonge Station (208,085 boardings) is omitted.



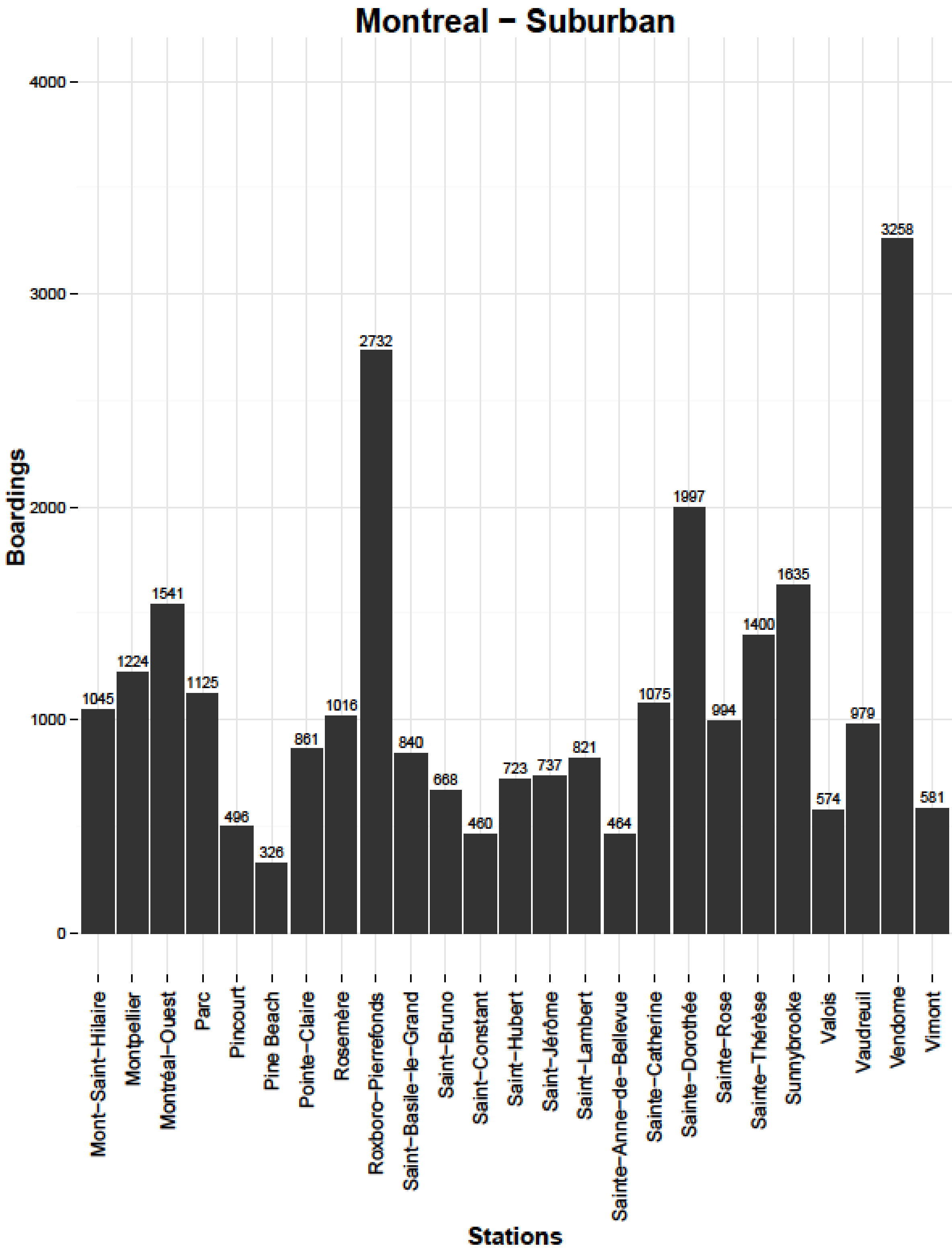
Toronto − Urban
Boardings
60000
40000
20000
0
3065
4710
5455
20575
8130
7590
51050
27060
25065
8900
12520
4385
10970
2755
11325
2020
1210
4295
13800
3065
10480
14190
12810
Glencairn
Greenwood
High Park
Islington
Jane
Keele
Kennedy
King
Kipling
Lansdowne
Lawrence
Lawrence East
Lawrence West
Leslie
Main Street
McCowan
Midland
Museum
North York Centre
Old Mill
Osgoode
Ossington
Pape
Stations

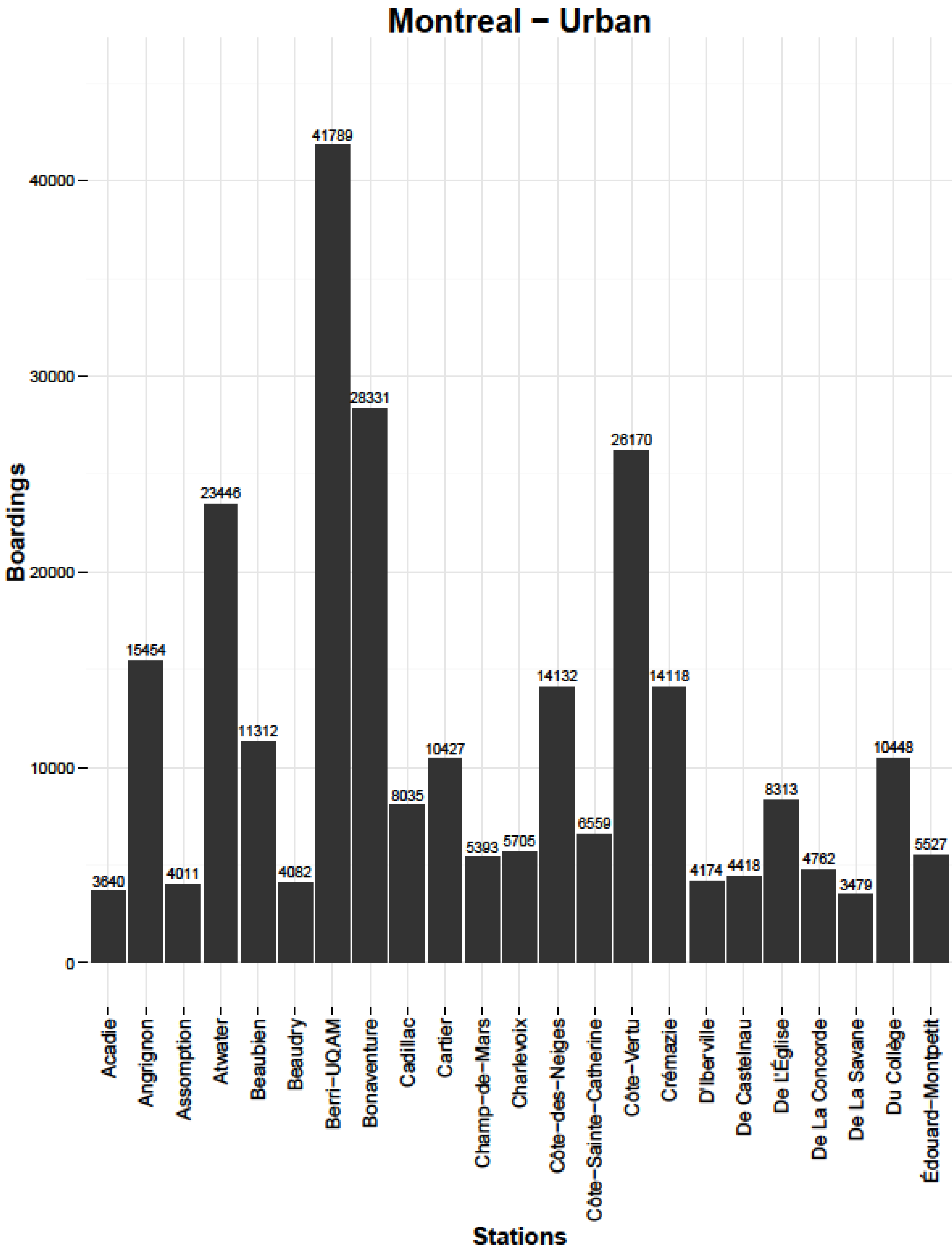


Note: St. George Station (133,385 boardings) is omitted.

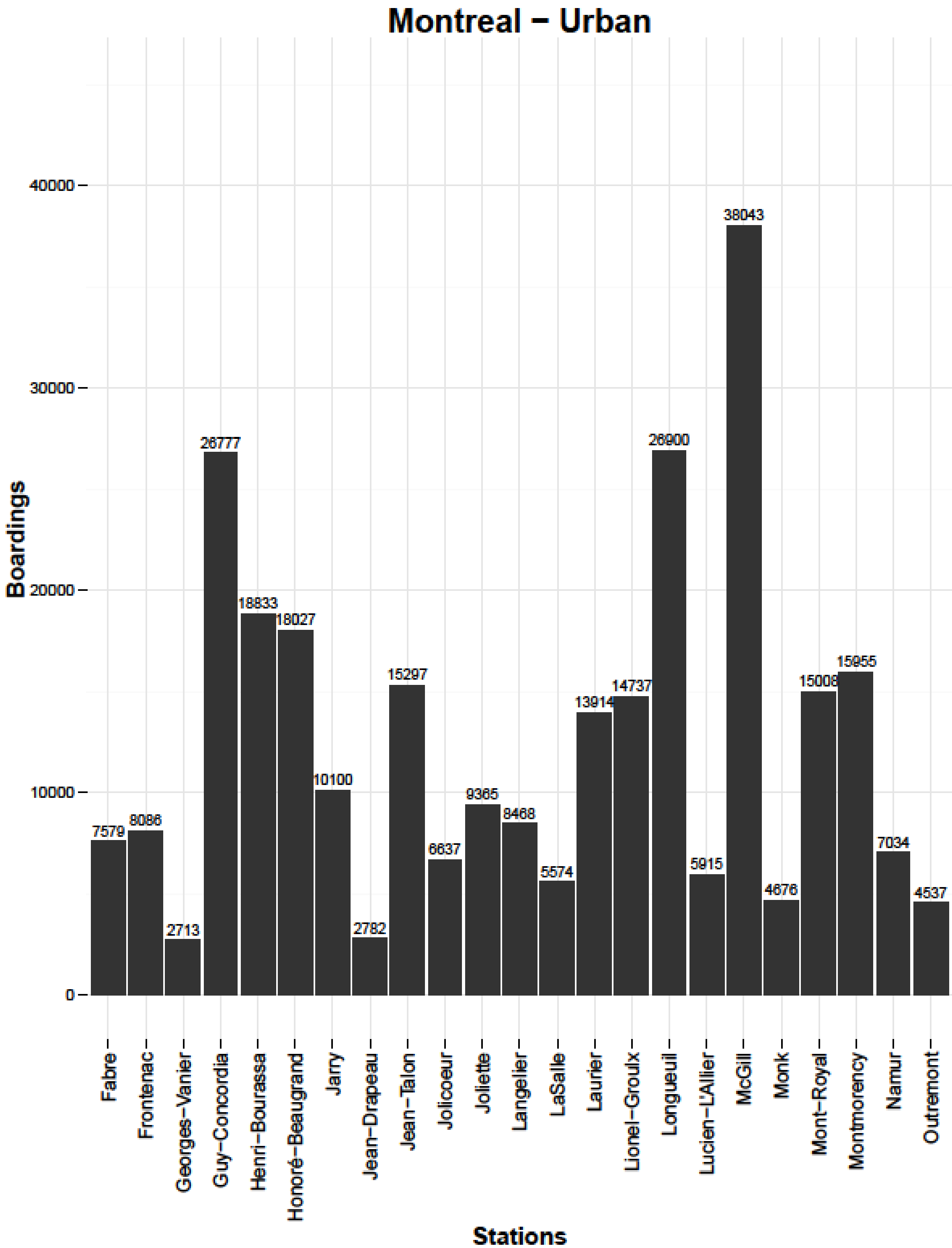


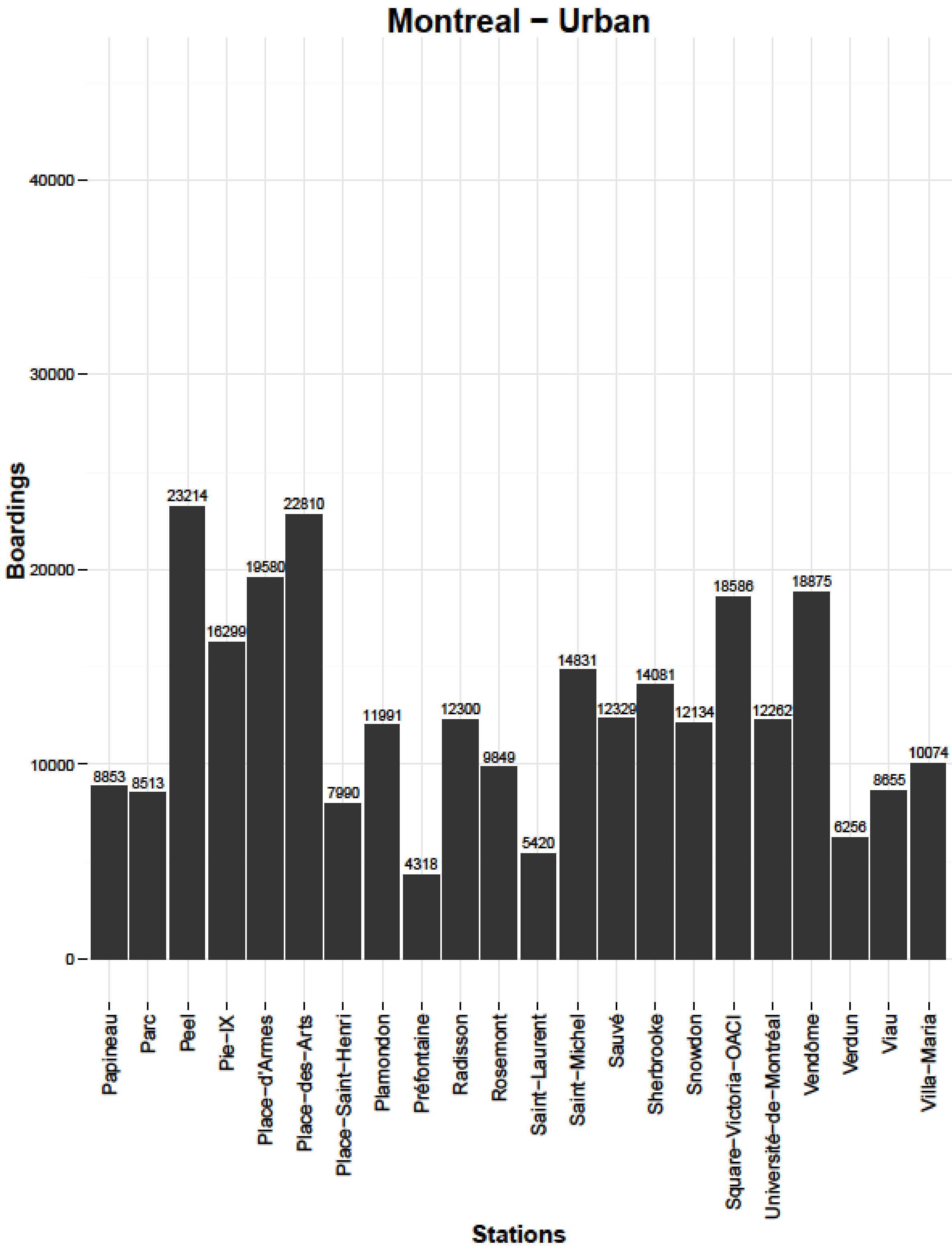
Note: Gare Centrale (15,405 boardings) and Lucien-L’Allier Station (7431 boardings) are omitted.


Montreal − Suburban
Boardings
4000
3000
2000
1000
0
1045
1224
1541
1125
496
326
861
1016
2732
840
668
460
723
737
821
464
1075
1997
994
1400
1635
574
979
3258
581
Mont−Saint−Hilaire
Montpellier
Montréal−Ouest
Parc
Pincourt
Pine Beach
Pointe−Claire
Rosemère
Roxboro−Pierrefonds
Saint−Basile−le−Grand
Saint−Bruno
Saint−Constant
Saint−Hubert
Saint−Jérôme
Saint−Lambert
Sainte−Anne−de−Bellevue
Sainte−Catherine
Sainte−Dorothée
Sainte−Rose
Sainte−Thérèse
Sunnybrooke
Valois
Vaudreuil
Vendome
Vimont
Stations

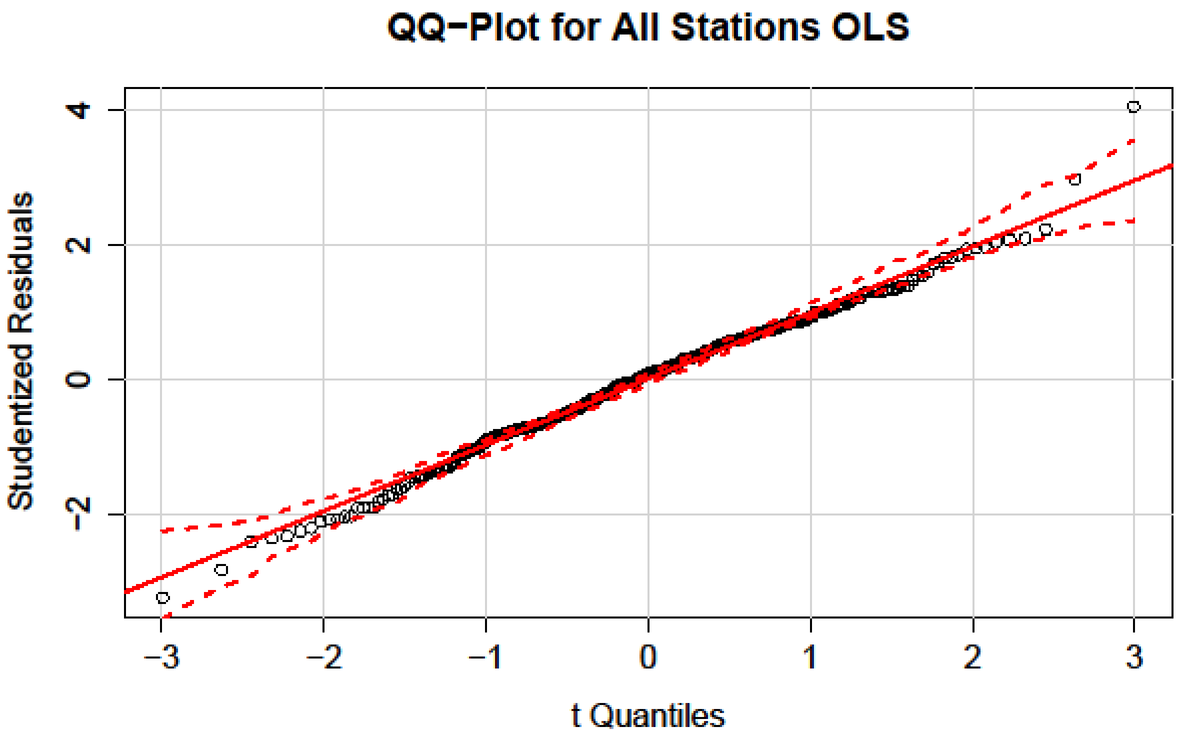


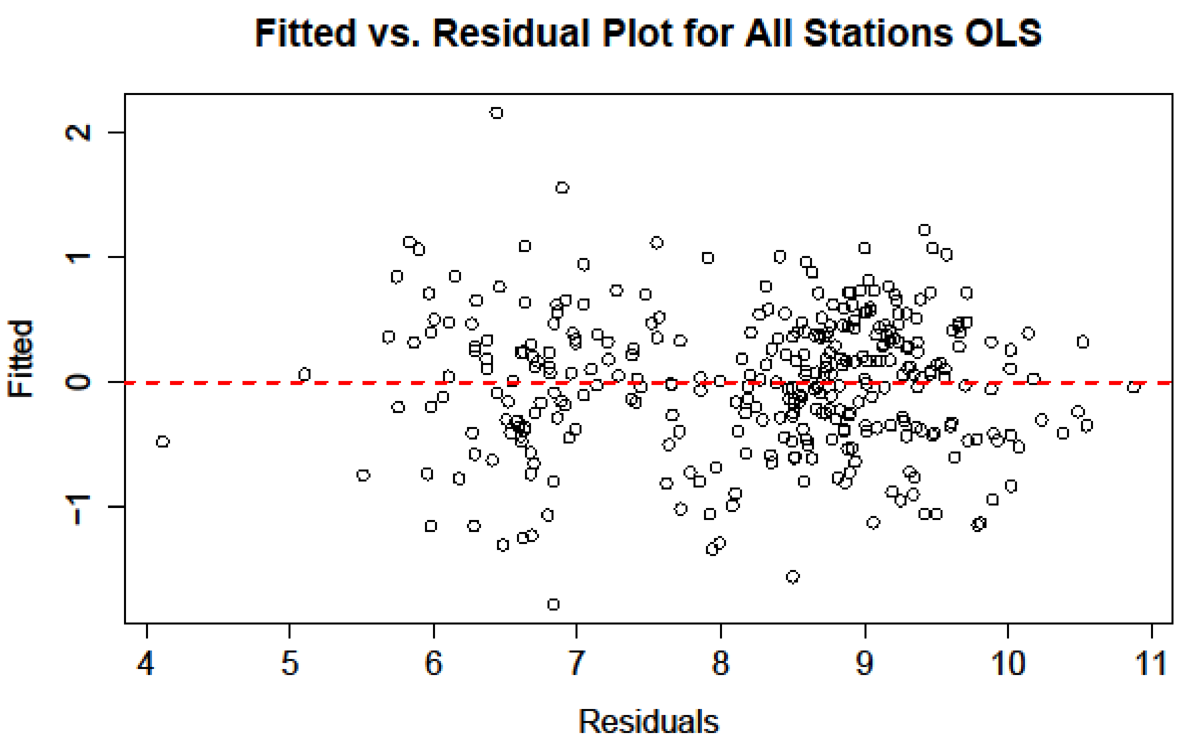
Montreal − Urban
Boardings
40000
30000
20000
10000
0
41789
28331
26170
23446
15454
14132
14118
11312
10427
10448
8035
8313
6559
5705
5393
5527
4762
4418
4174
4082
4011
3640
3479
Acadie
Angrignon
Assomption
Atwater
Beaubien
Beaudry
Berri−UQAM
Bonaventure
Cadillac
Cartier
Champ−de−Mars
Charlevoix
Côte−des−Neiges
Côte−Sainte−Catherine
Côte−Vertu
Crémazie
D'Iberville
De Castelnau
De L'Église
De La Concorde
De La Savane
Du Collège
Édouard−Montpetit
Stations

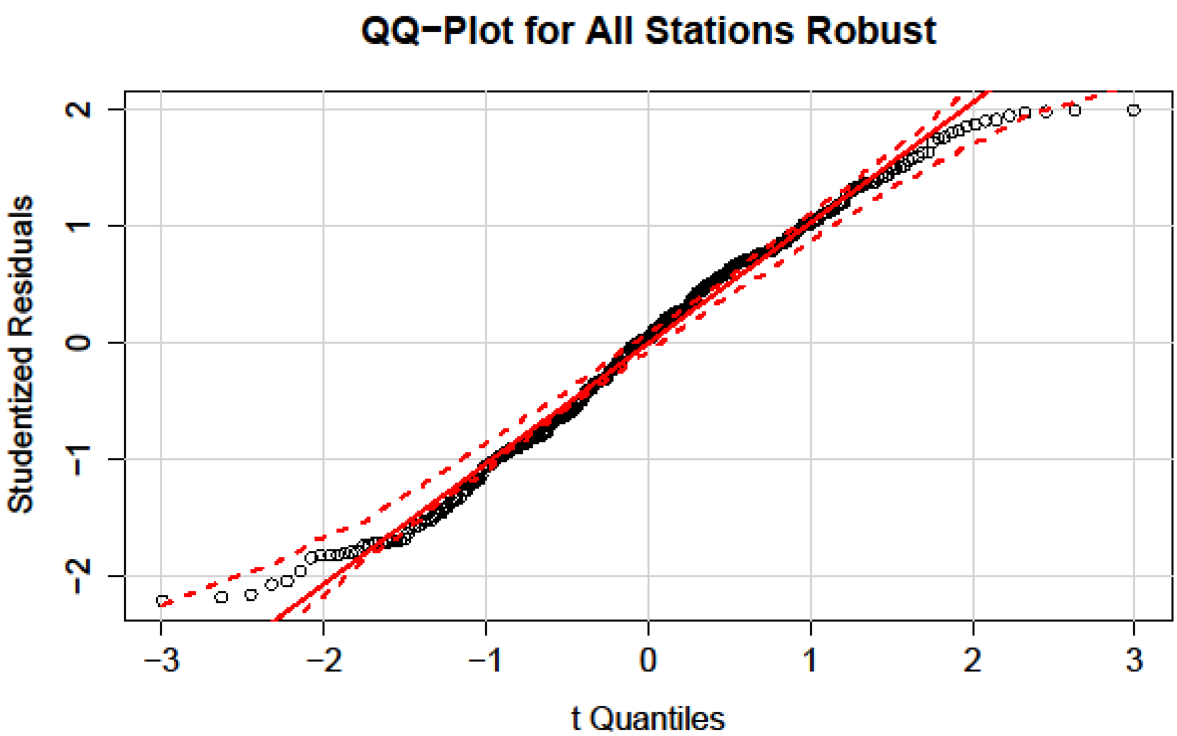

Montreal − Urban
Boardings
40000
30000
20000
10000
0
7579
8086
2713
26777
18833
18027
10100
2782
15297
6637
9365
8468
5574
13914
14737
26900
5915
38043
4676
15008
15955
7034
4537
Fabre
Frontenac
Georges−Vanier
Guy−Concordia
Henri−Bourassa
Honoré−Beaugrand
Jarry
Jean−Drapeau
Jean−Talon
Jolicoeur
Joliette
Langelier
LaSalle
Laurier
Lionel−Groulx
Longueuil
Lucien−L'Allier
McGill
Monk
Mont−Royal
Montmorency
Namur
Outremont
Stations

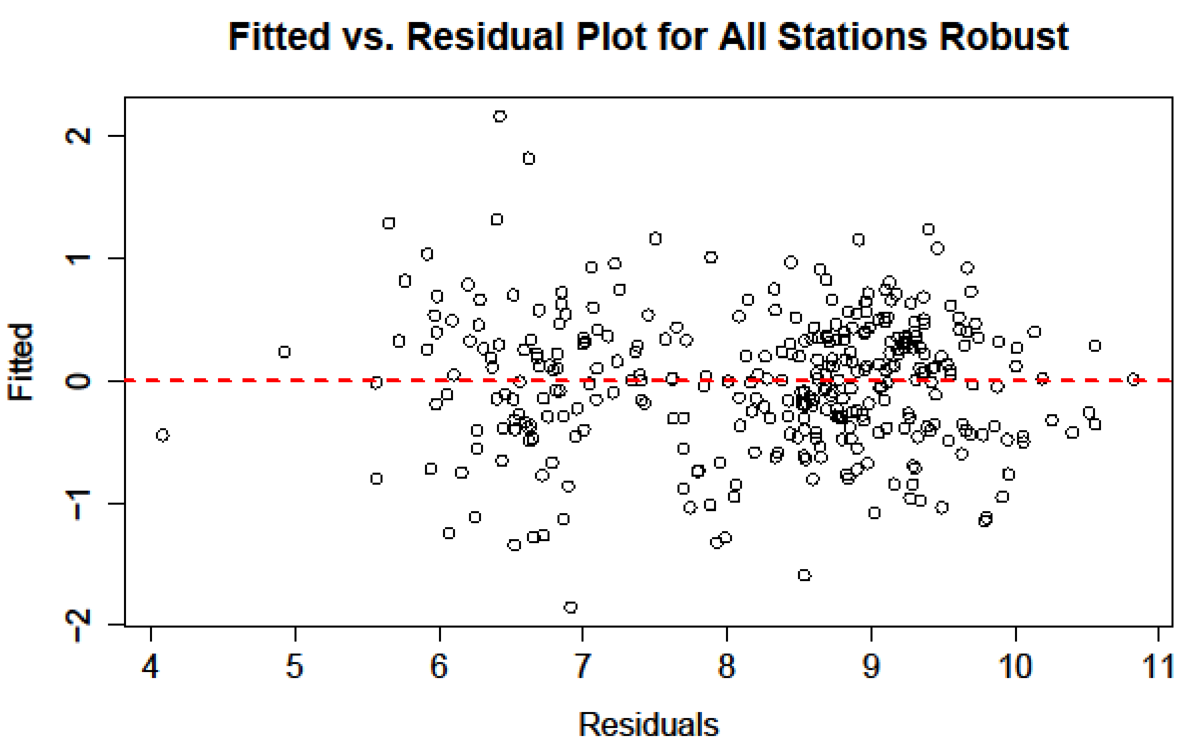

Montreal − Urban
Boardings
40000
30000
20000
10000
0
8853
8513
23214
16299
19580
22810
7990
11991
4318
12300
9849
5420
14831
12329
14081
12134
18586
12262
18875
6256
8655
10074
Papineau
Parc
Peel
Pie−IX
Place−d'Armes
Place−des−Arts
Place−Saint−Henri
Plamondon
Préfontaine
Radisson
Rosemont
Saint−Laurent
Saint−Michel
Sauvé
Sherbrooke
Snowdon
Square−Victoria−OACI
Université−de−Montréal
Vendôme
Verdun
Viau
Villa−Maria
Stations

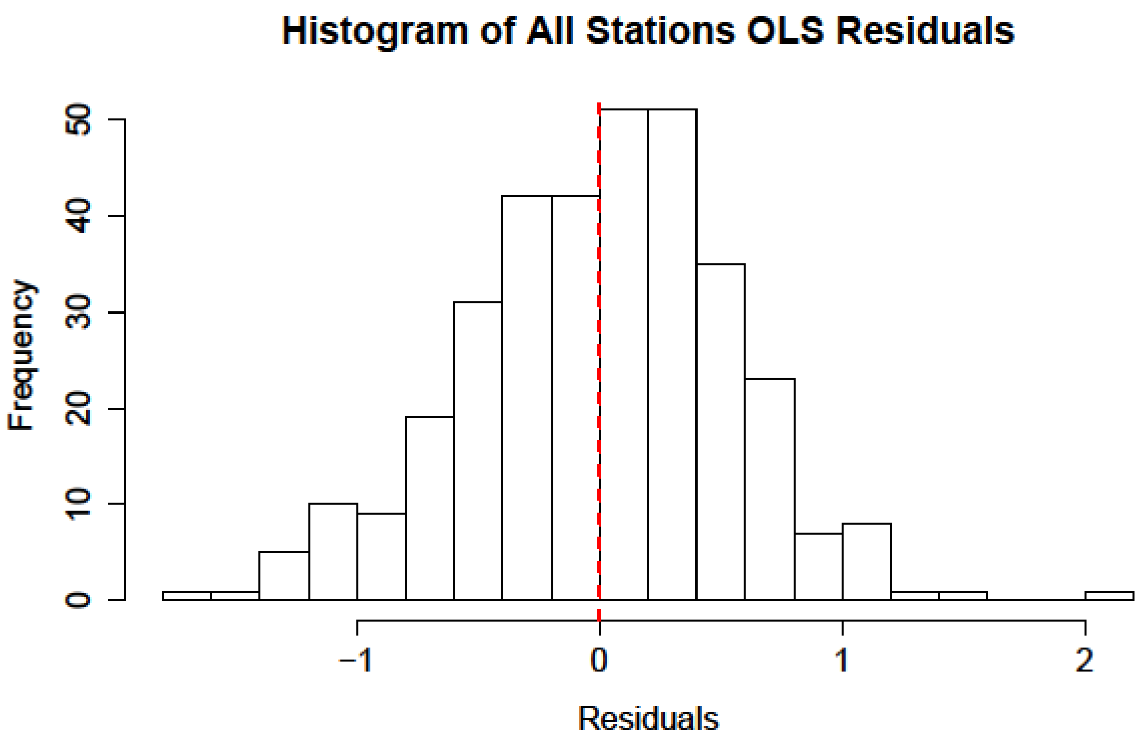
Appendix B

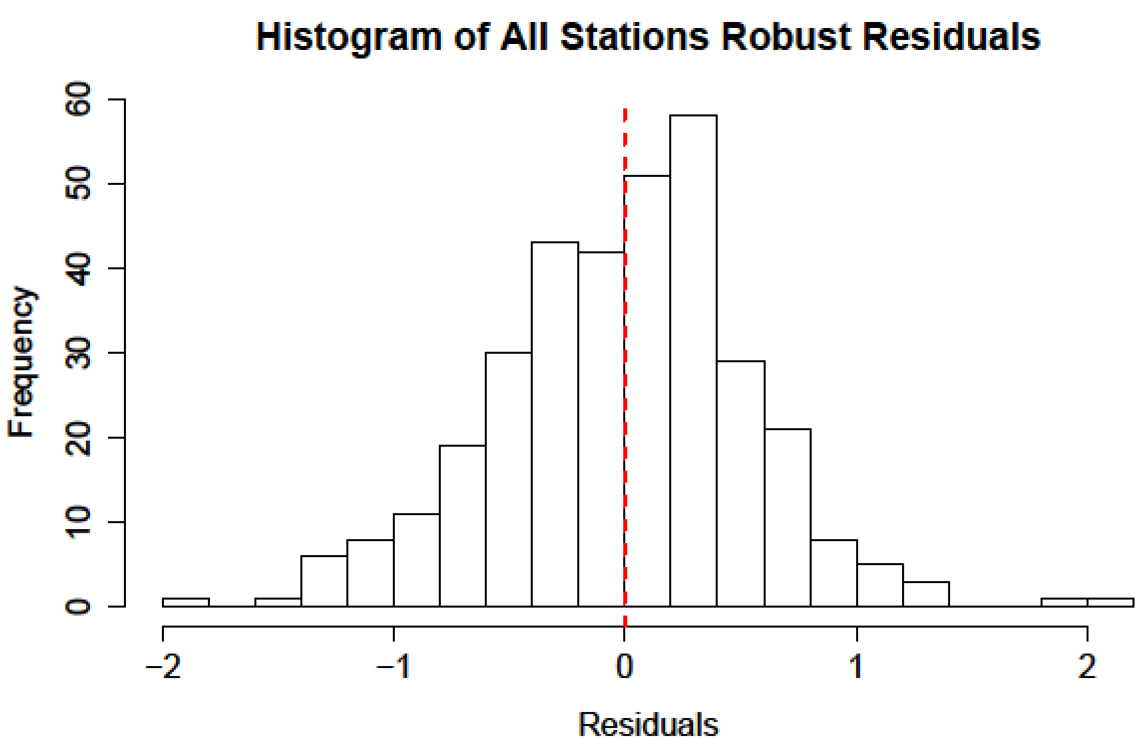

QQ−Plot for All Stations OLS
Studentized Residuals
4
2
0
−2
−3
−2
−1
0
1
2
3
t Quantiles


Fitted vs. Residual Plot for All Stations OLS
Fitted
2
1
0
−1
4
5
6
7
8
9
10
11
Residuals

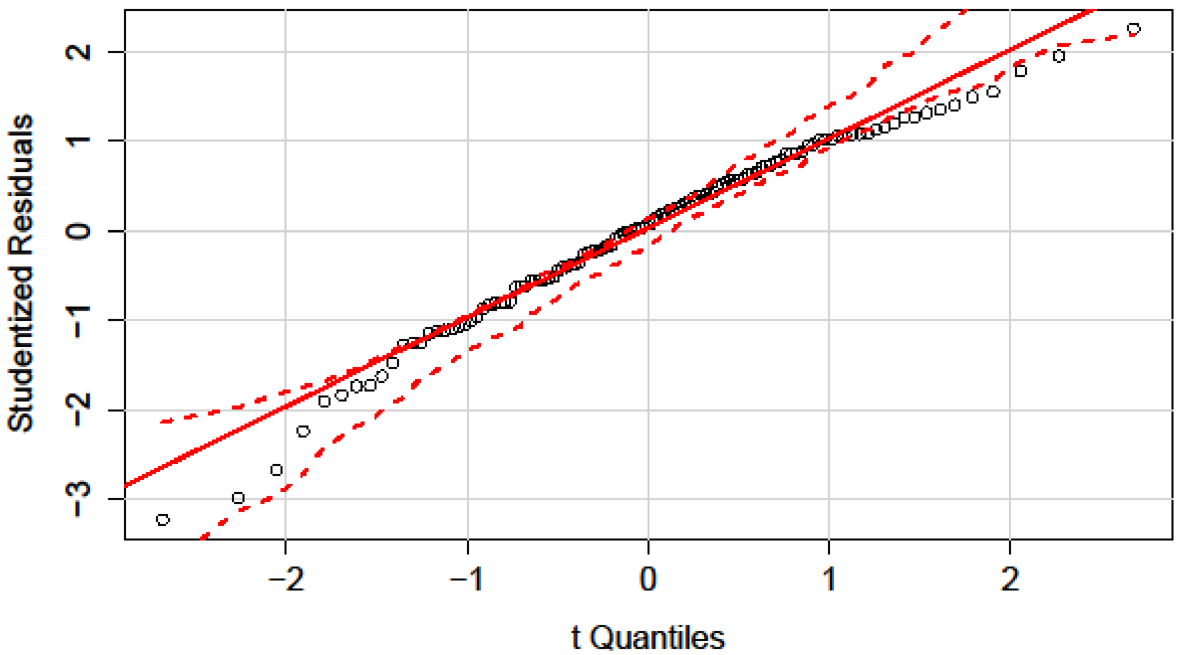

QQ−Plot for All Stations Robust
Studentized Residuals
t Quantiles
−3
−2
−1
0
1
2
3
−2
−1
0
1
2


Fitted vs. Residual Plot for All Stations Robust
Fitted
Residuals
4
5
6
7
8
9
10
11
−2
−1
0
1
2

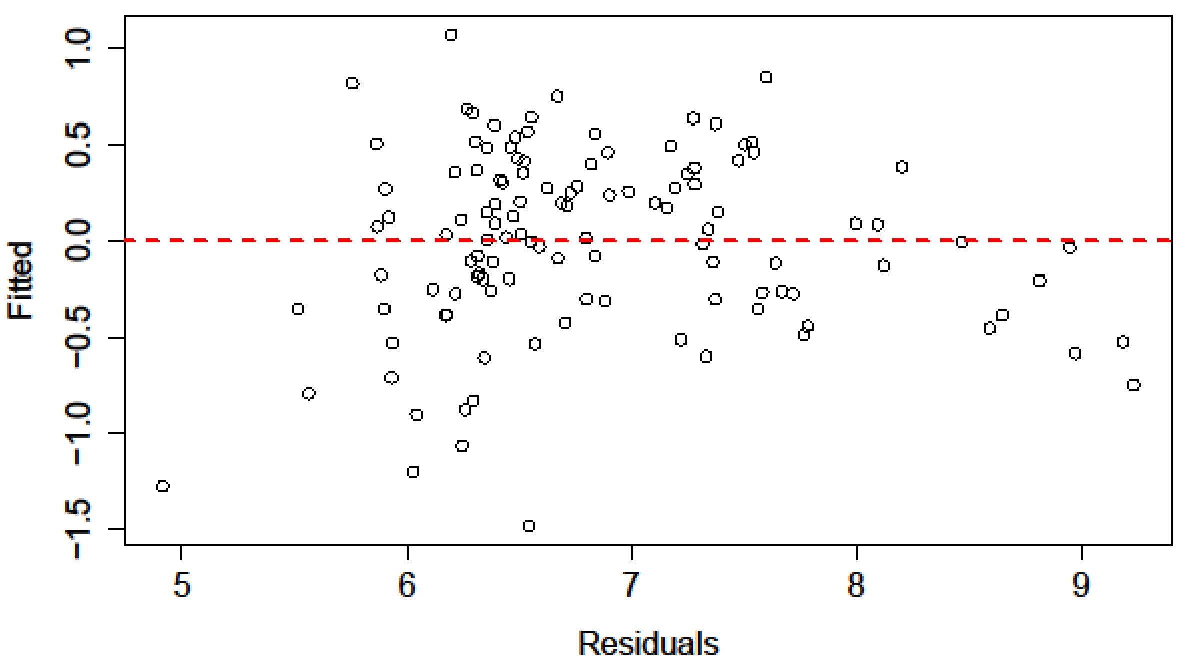

Histogram of All Stations OLS Residuals
Frequency
0
10
20
30
40
50
−1
0
1
2
Residuals


Histogram of All Stations Robust Residuals
Frequency
0
10
20
30
40
50
60
−2
−1
0
1
2
Residuals

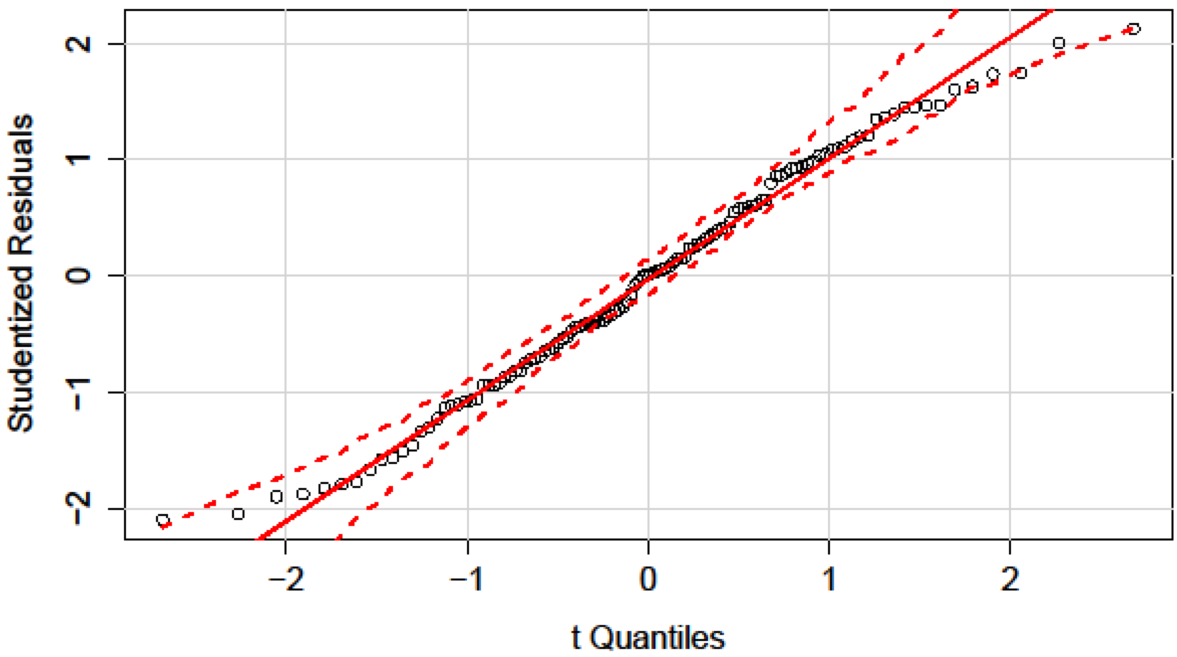
QQ−Plot for Suburban OLS



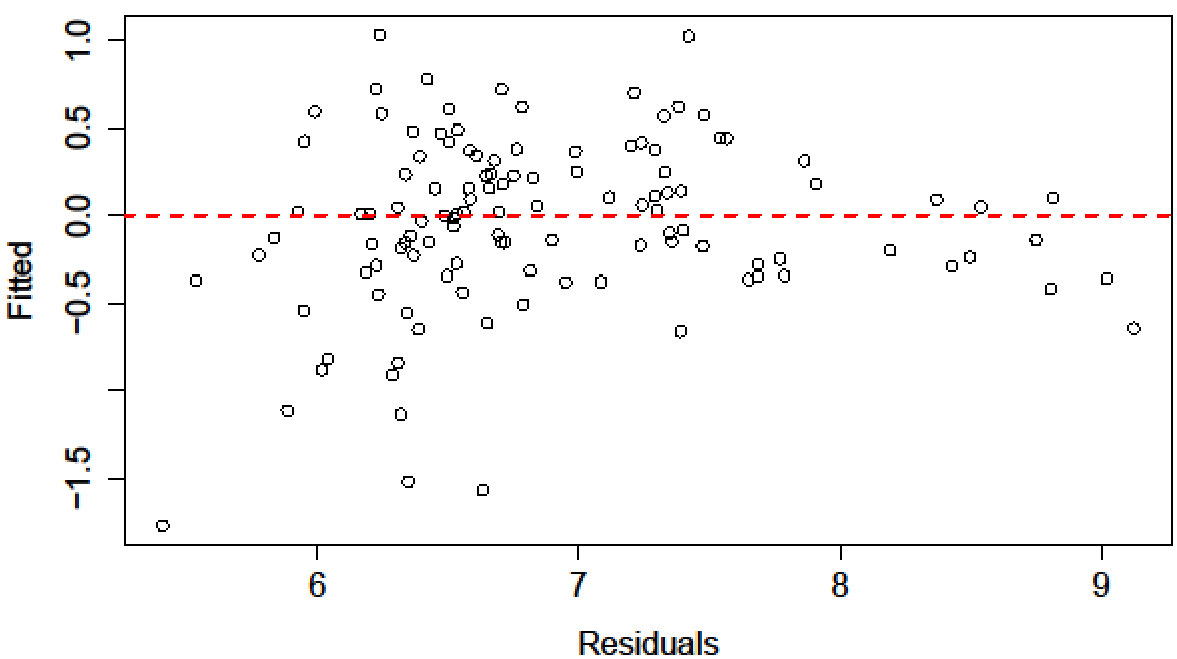
Fitted vs. Residual Plot for Suburban OLS

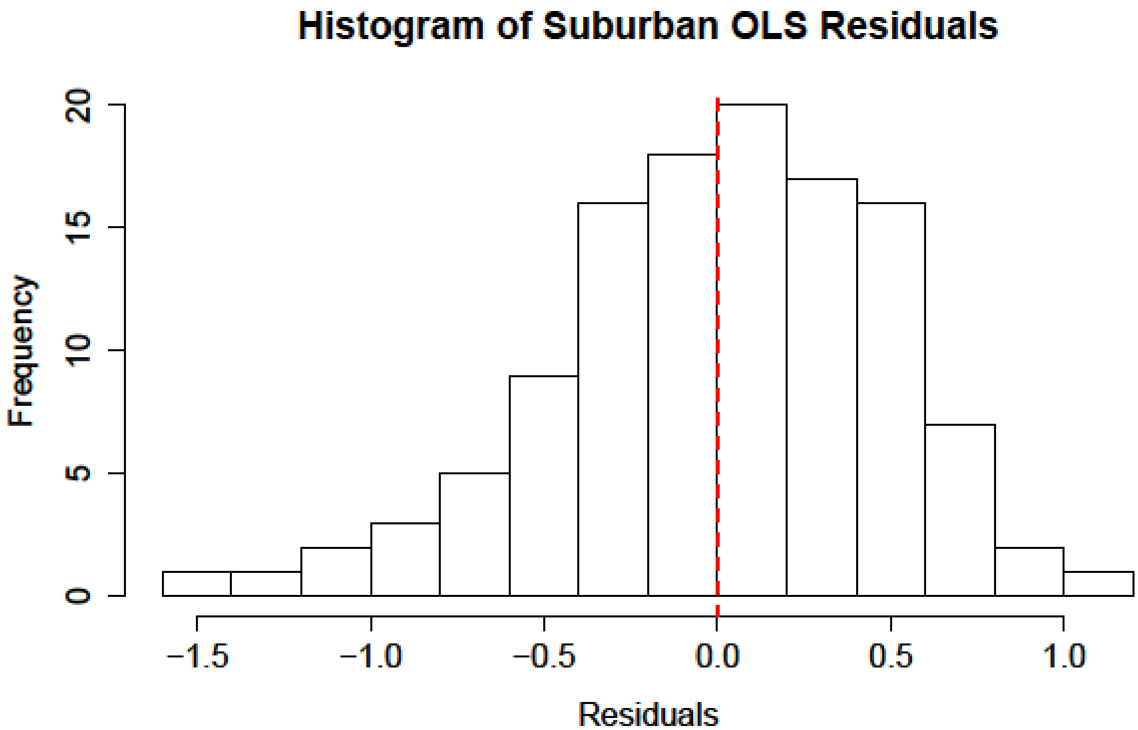


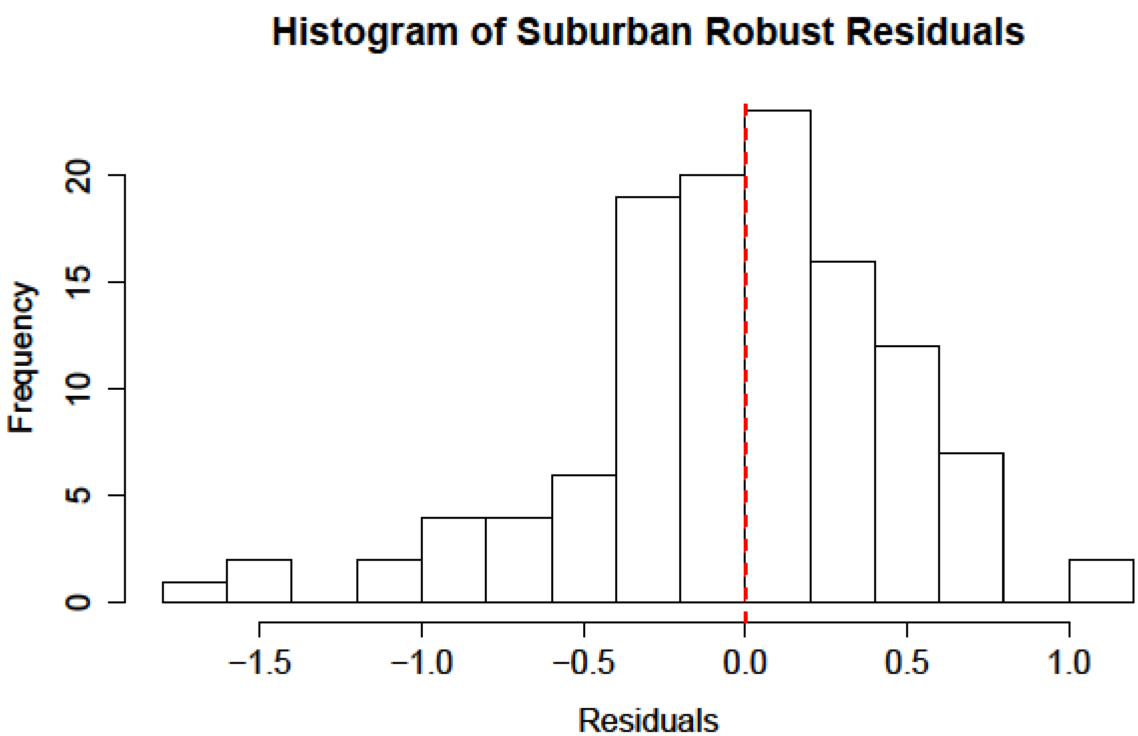
QQ−Plot for Suburban Robust



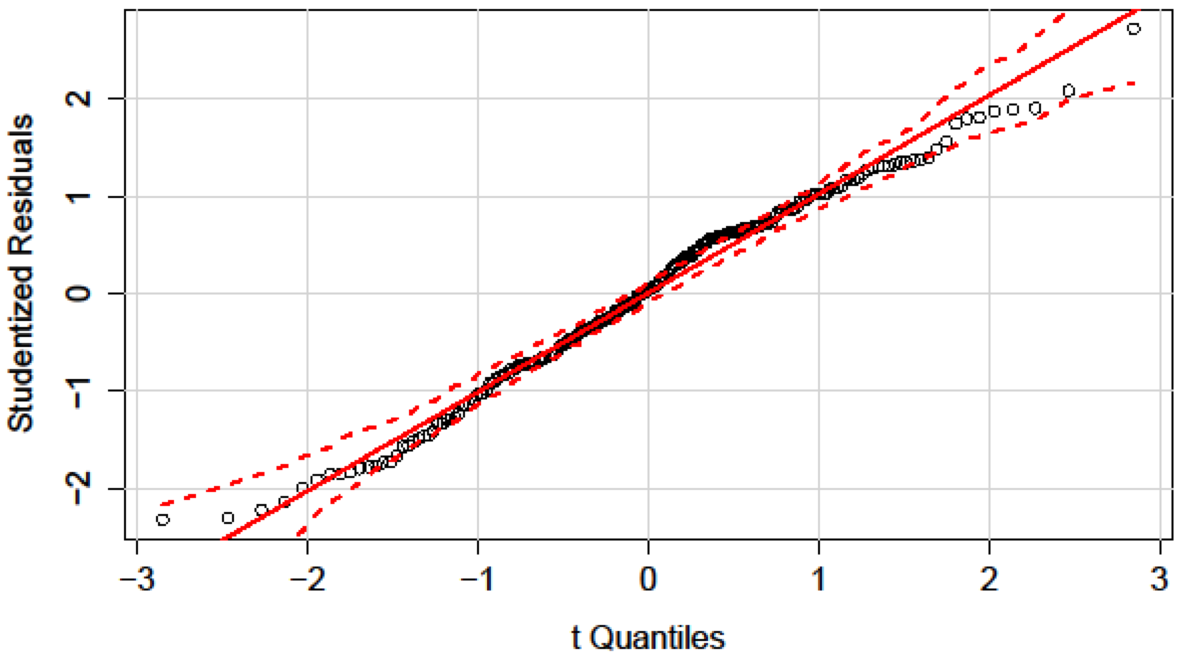
Fitted vs. Residual Plot for Suburban Robust



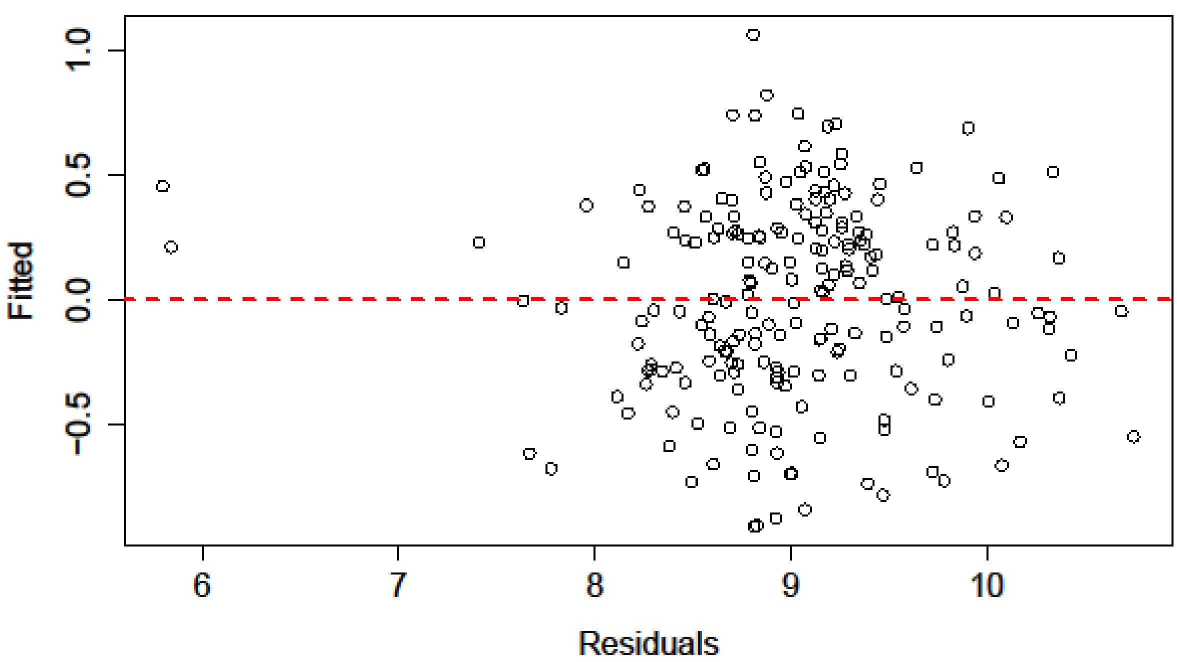

Histogram of Suburban OLS Residuals
Frequency
0
5
10
15
20
−1.5
−1.0
−0.5
0.0
0.5
1.0
Residuals

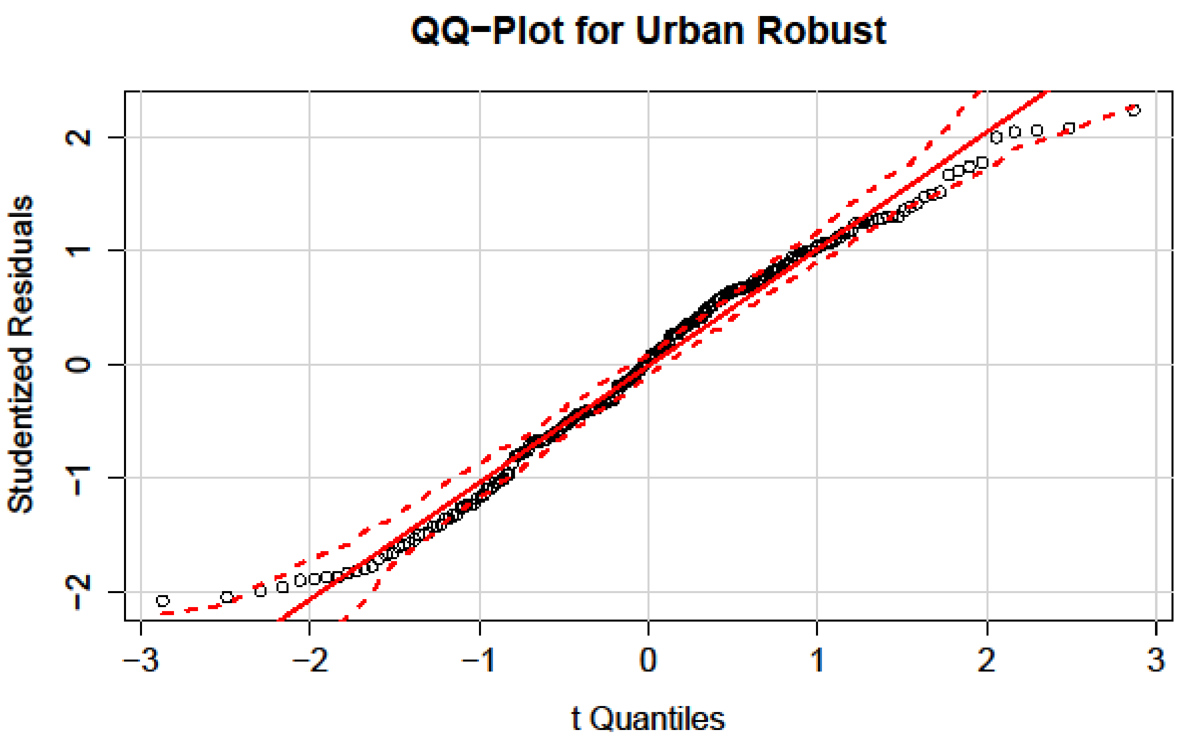

Histogram of Suburban Robust Residuals
Frequency
0
5
10
15
20
−1.5
−1.0
−0.5
0.0
0.5
1.0
Residuals

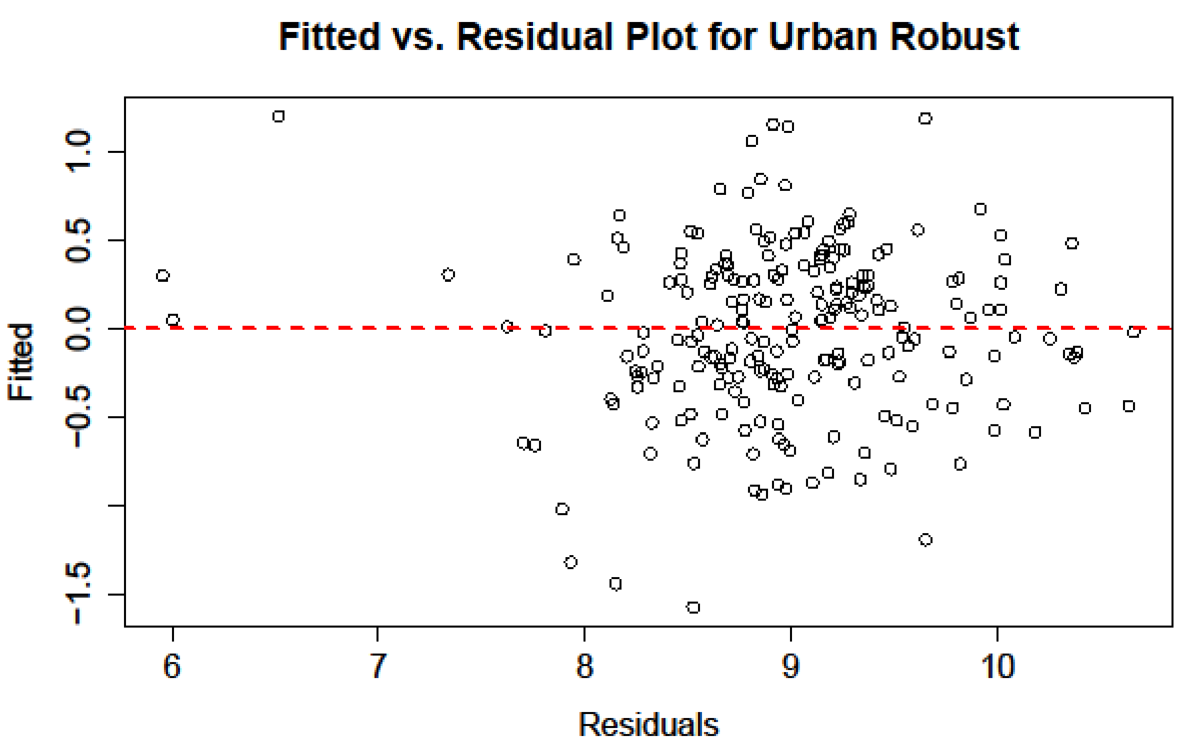
QQ−Plot for Urban OLS

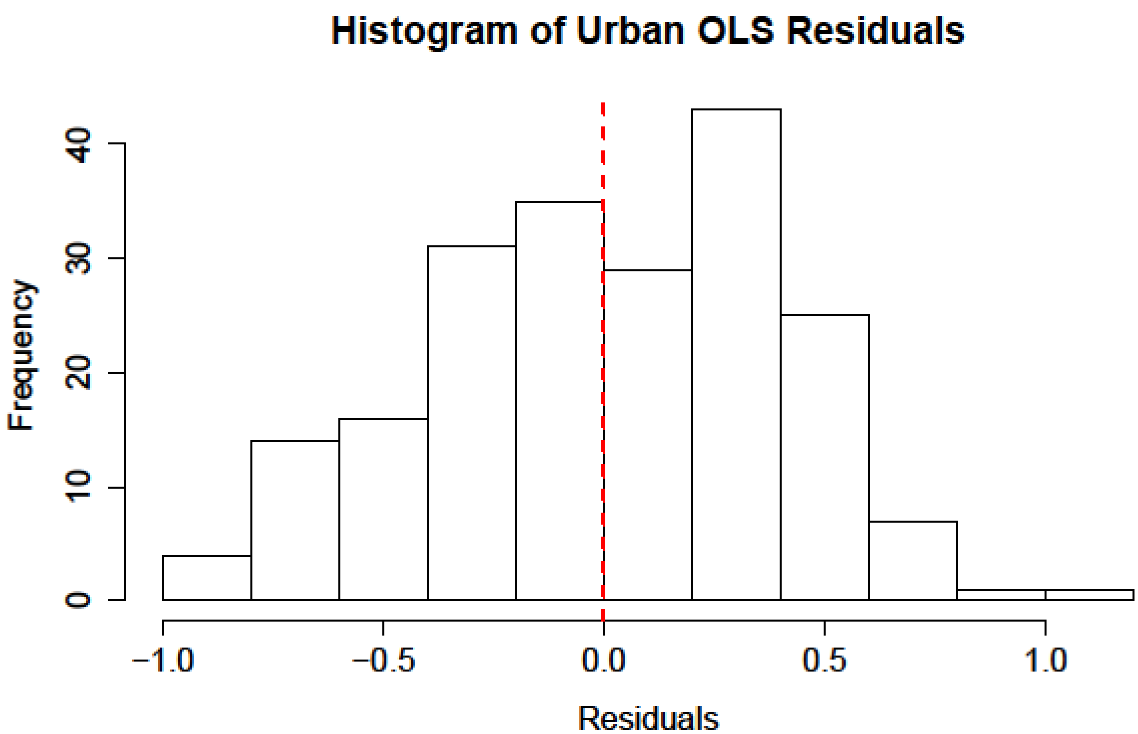


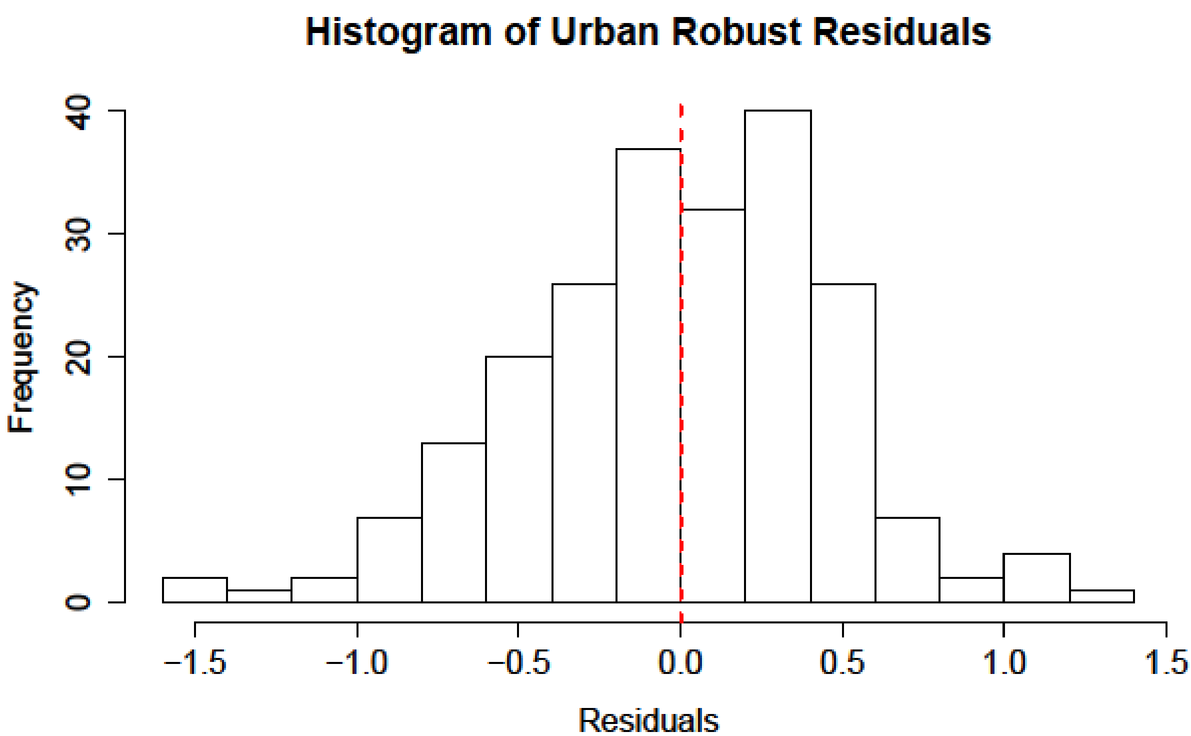
Fitted vs. Residual Plot for Urban OLS



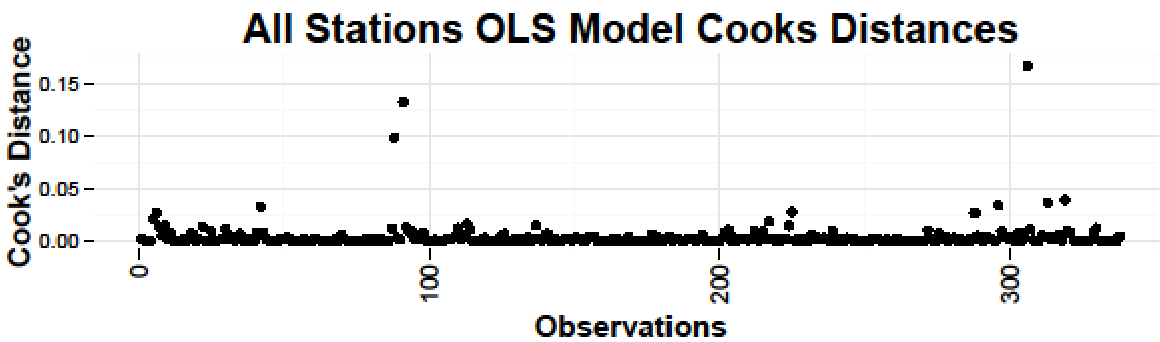

QQ−Plot for Urban Robust
Studentized Residuals
t Quantiles
−3
−2
−1
0
1
2
3

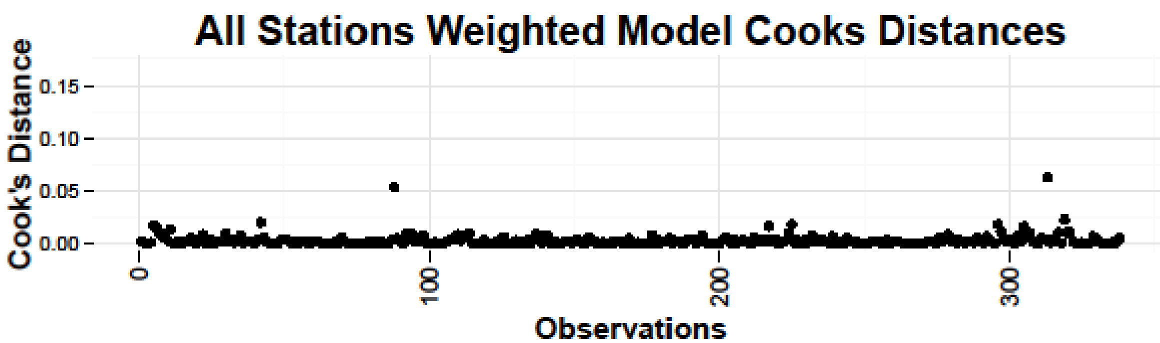

Fitted vs. Residual Plot for Urban Robust
Fitted
Residuals
−1.5
−0.5
0.0
0.5
1.0
6
7
8
9
10

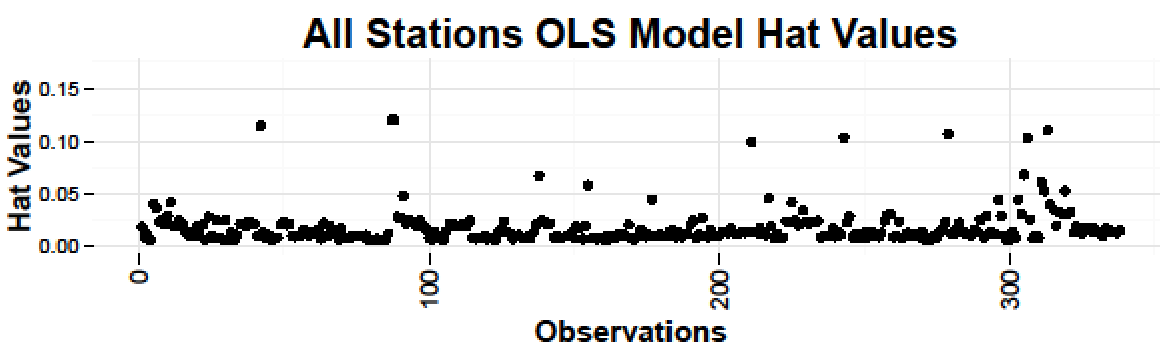

Histogram of Urban OLS Residuals
Frequency
0
10
20
30
40
−1.0
−0.5
0.0
0.5
1.0
Residuals

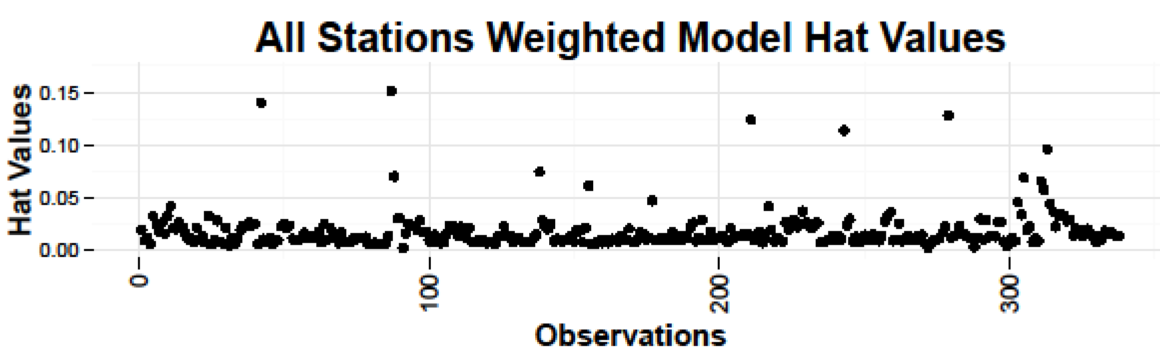

Histogram of Urban Robust Residuals
Frequency
0
10
20
30
40
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
Residuals

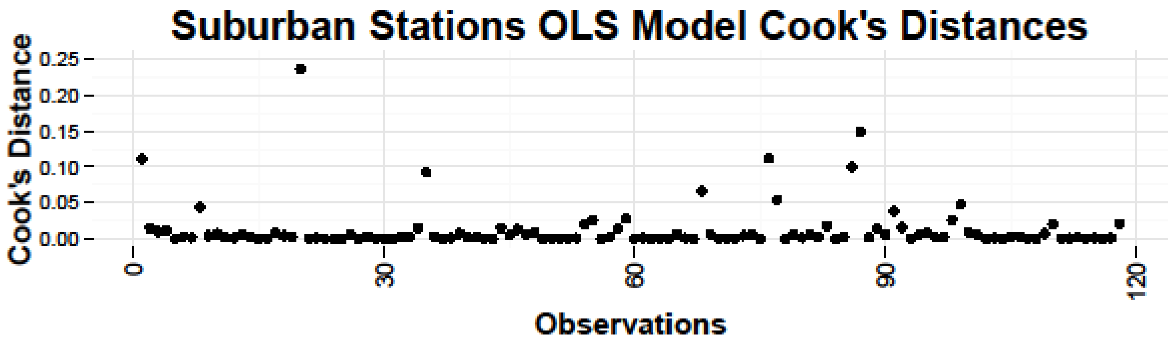
Appendix C

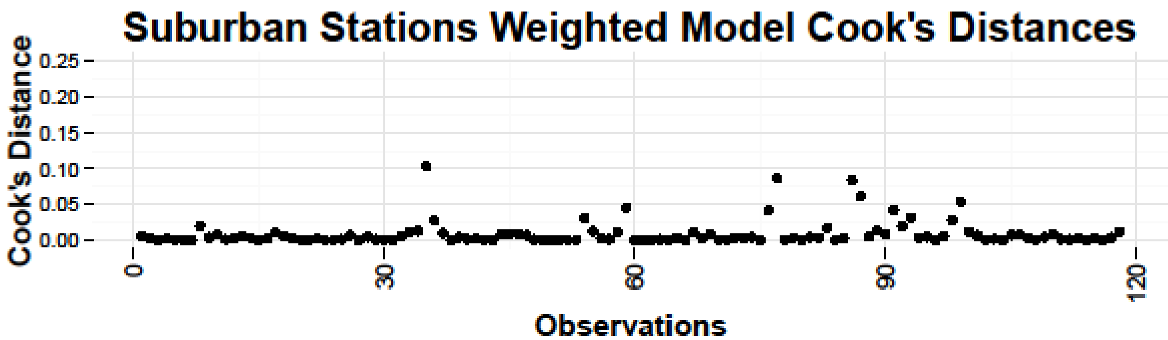

All Stations OLS Model Cooks Distances
Cook's Distance
0.15
0.10
0.05
0.00
0
100
200
300
Observations

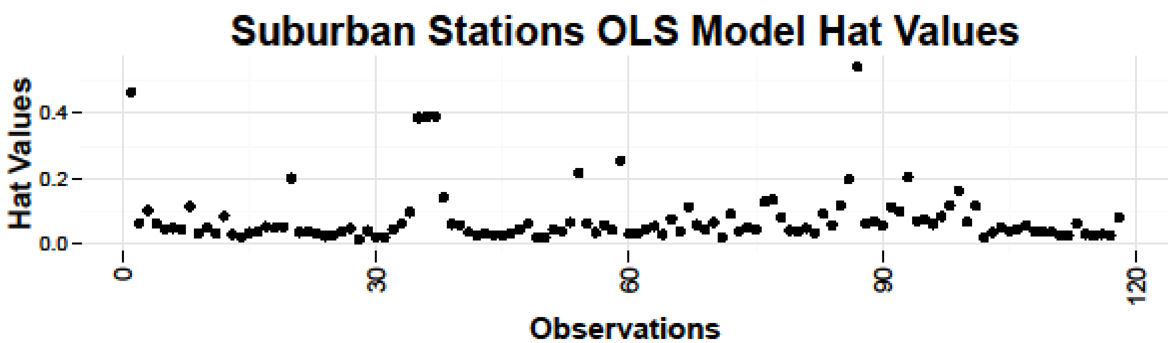

All Stations Weighted Model Cooks Distances
Cook's Distance
0.15
0.10
0.05
0.00
0
100
200
300
Observations

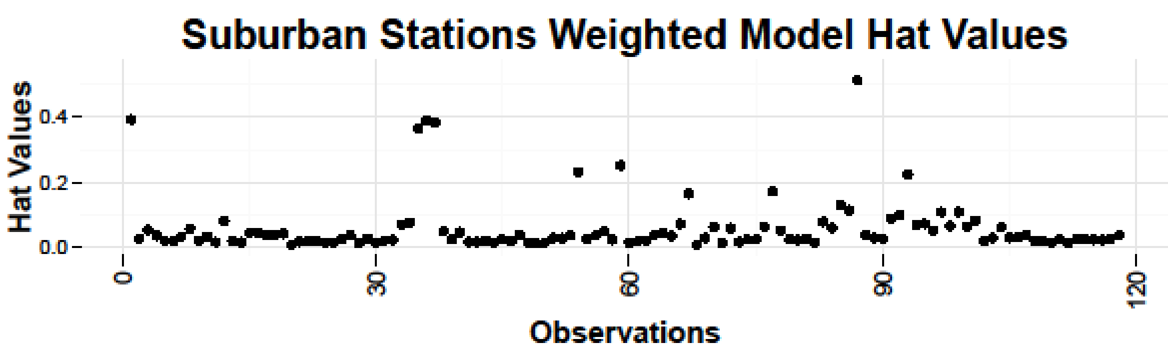

All Stations OLS Model Hat Values
Hat Values
0.15
0.10
0.05
0.00
0
100
200
300
Observations

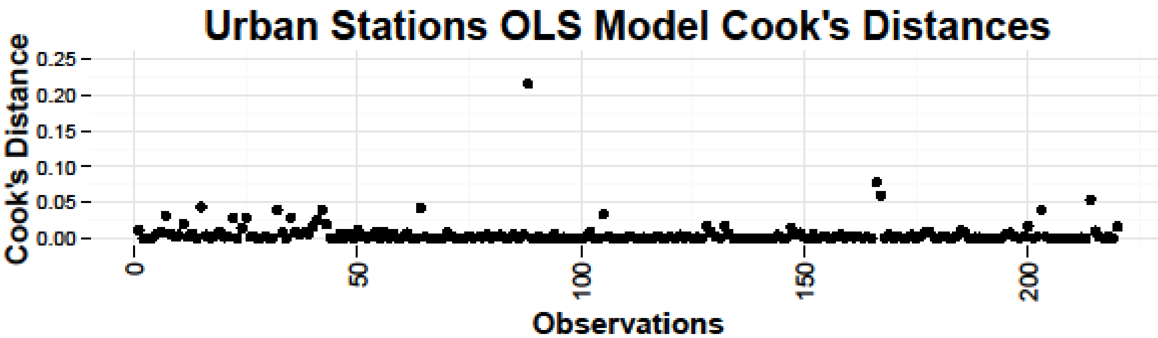

All Stations Weighted Model Hat Values
Hat Values
0.15
0.10
0.05
0.00
0
100
200
300
Observations

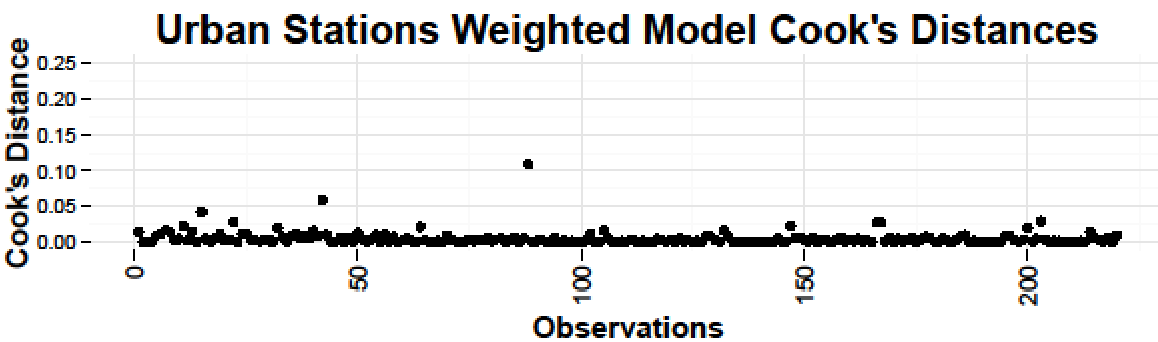

Suburban Stations OLS Model Cook's Distances
Cook's Distance
0.25
0.20
0.15
0.10
0.05
0.00
0
30
60
90
120
Observations

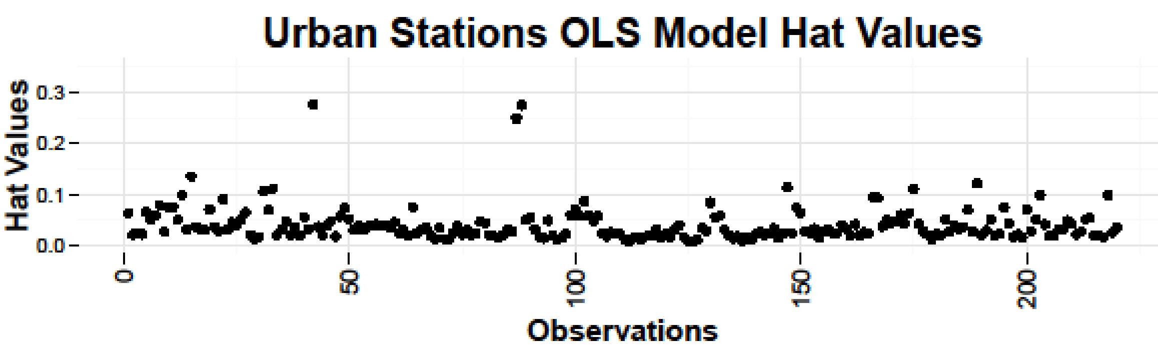

Suburban Stations Weighted Model Cook's Distances
Cook's Distance
0.25
0.20
0.15
0.10
0.05
0.00
0
30
60
90
120
Observations

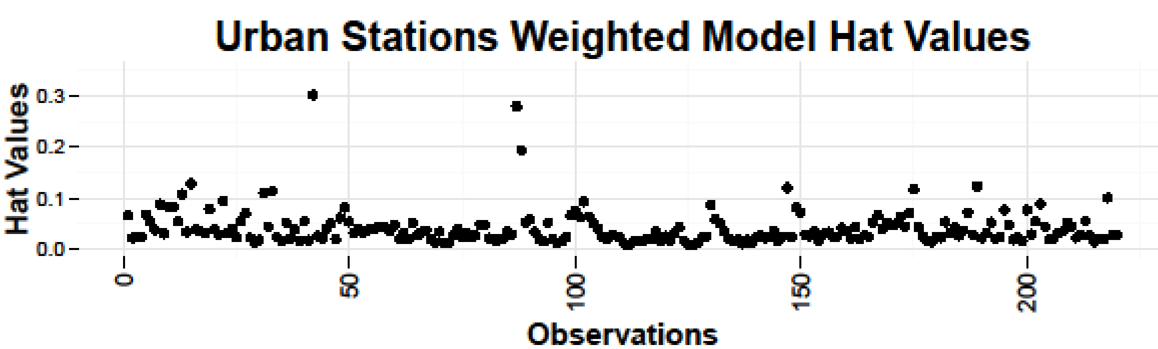

Suburban Stations OLS Model Hat Values
Hat Values
0.4
0.2
0.0
0
30
60
90
120
Observations


Suburban Stations Weighted Model Hat Values
Hat Values
0.4
0.2
0.0
0
30
60
90
120
Observations


Urban Stations OLS Model Cook's Distances
Cook's Distance
0.25
0.20
0.15
0.10
0.05
0.00
0
50
100
150
200
Observations

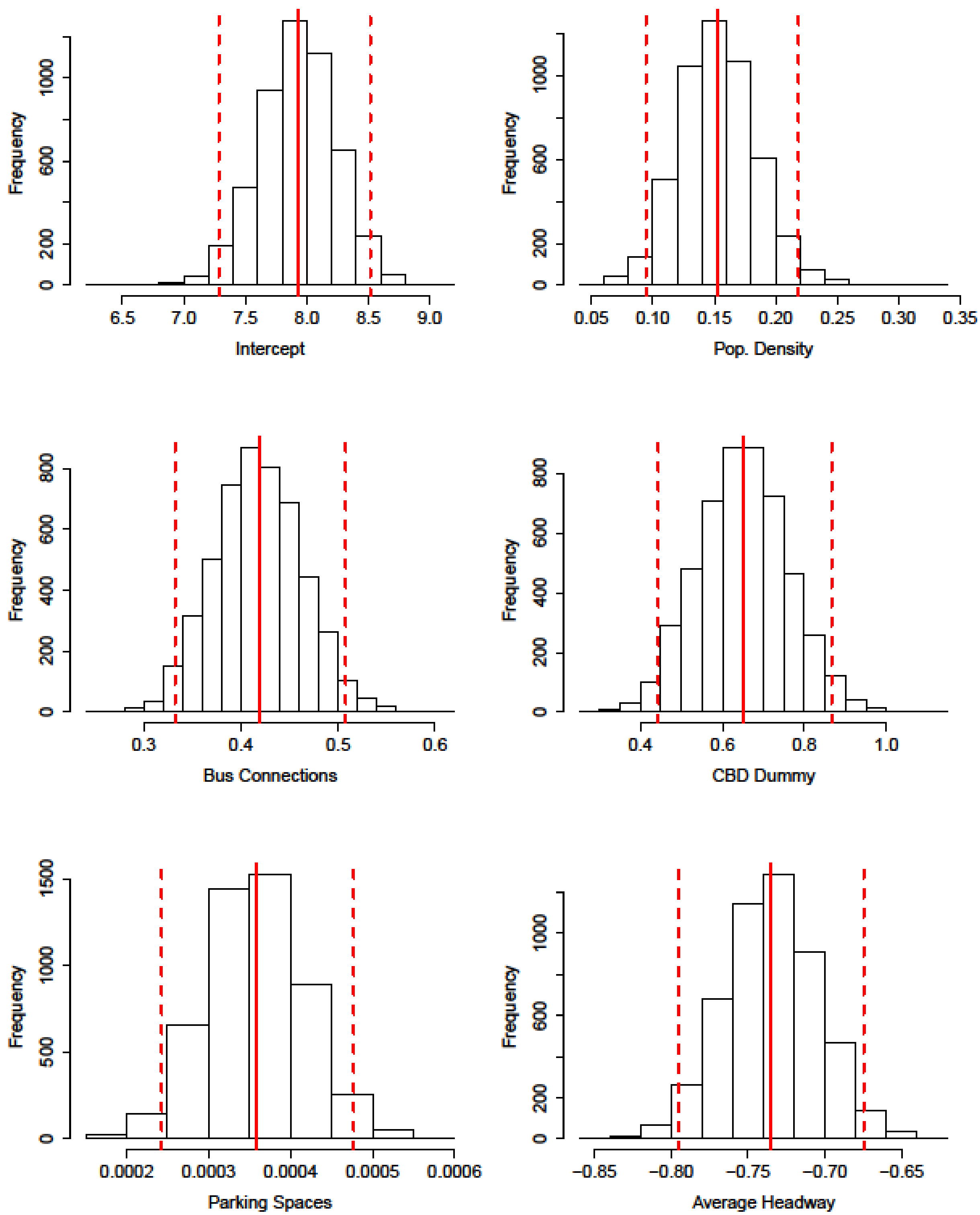

Urban Stations Weighted Model Cook's Distances
Cook's Distance
0.25
0.20
0.15
0.10
0.05
0.00
0
50
100
150
200
Observations


Urban Stations OLS Model Hat Values
Hat Values
0.3
0.2
0.1
0.0
0
50
100
150
200
Observations

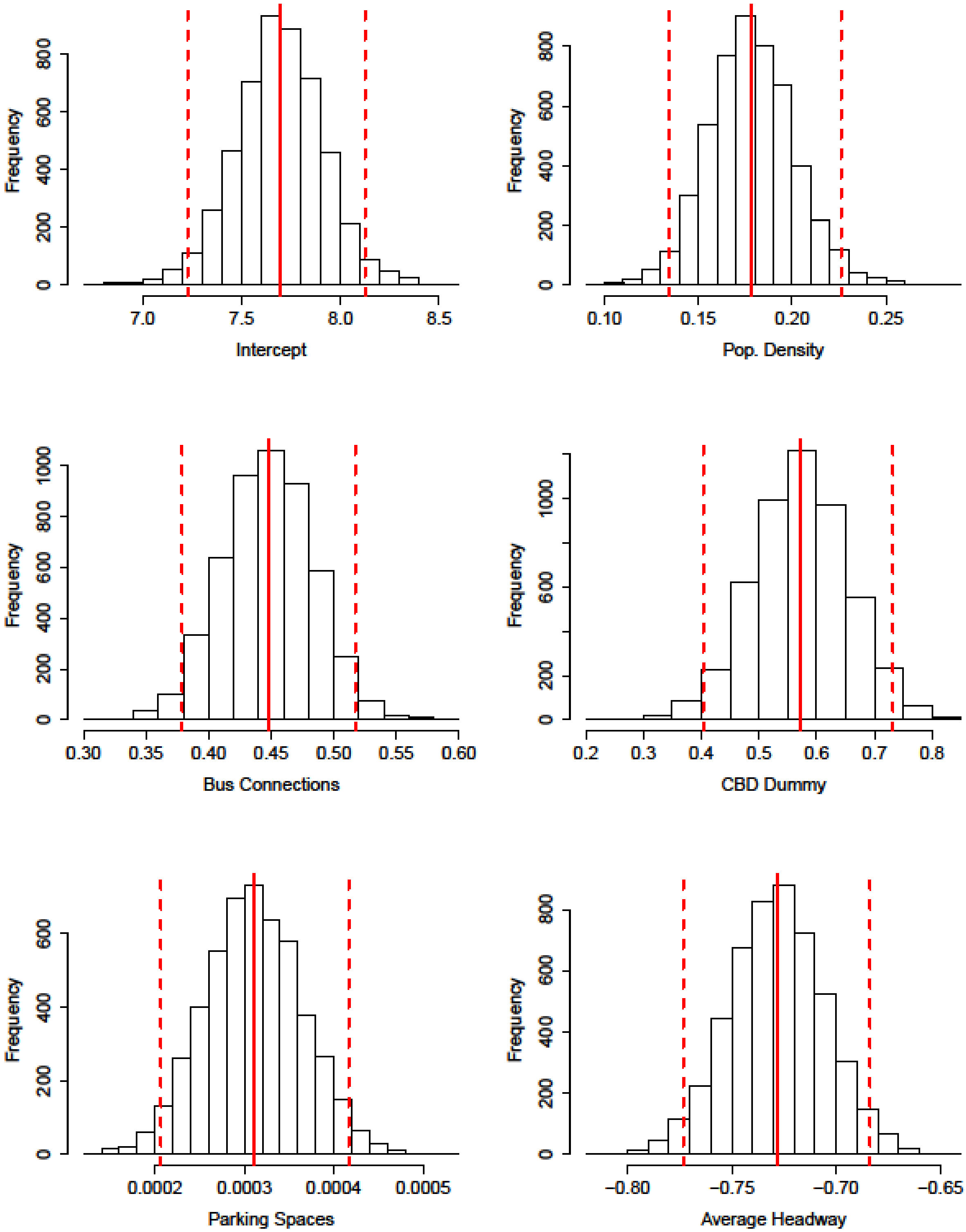

Urban Stations Weighted Model Hat Values
Hat Values
0.3
0.2
0.1
0.0
0
50
100
150
200
Observations

Appendix D

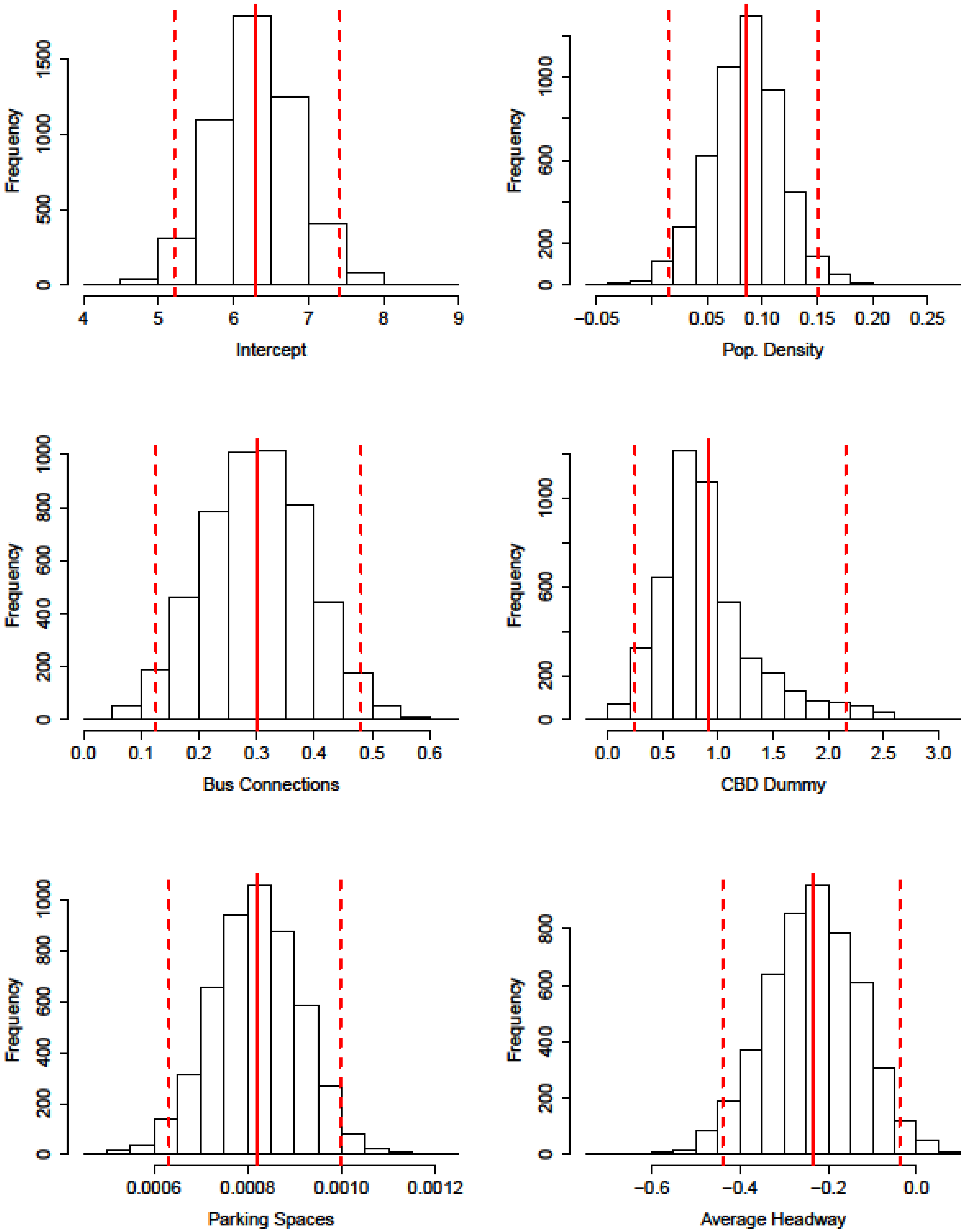
Histograms of Bootstrapped Variable Estimates for All Stations OLS

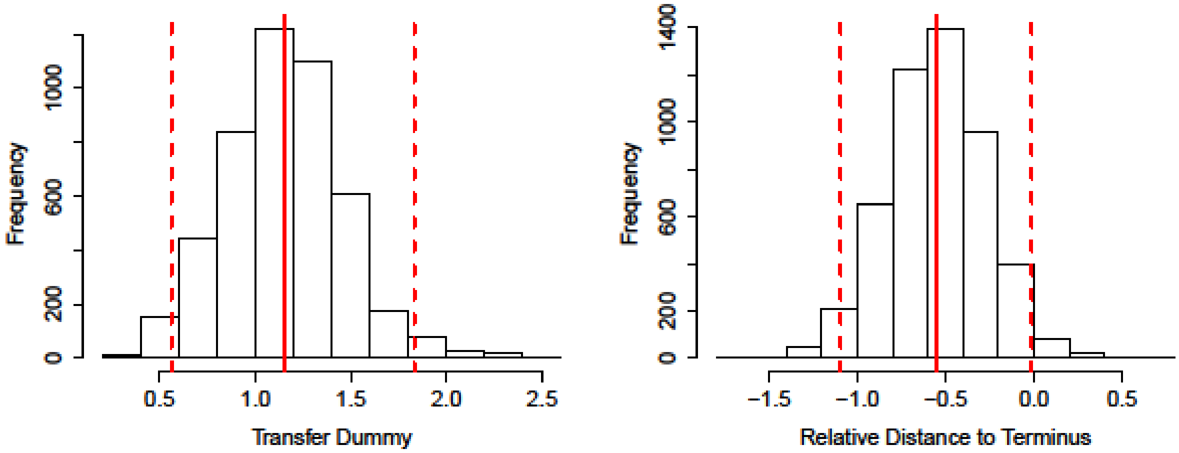


Histograms of Bootstrapped Variable Estimates for All Stations Robust

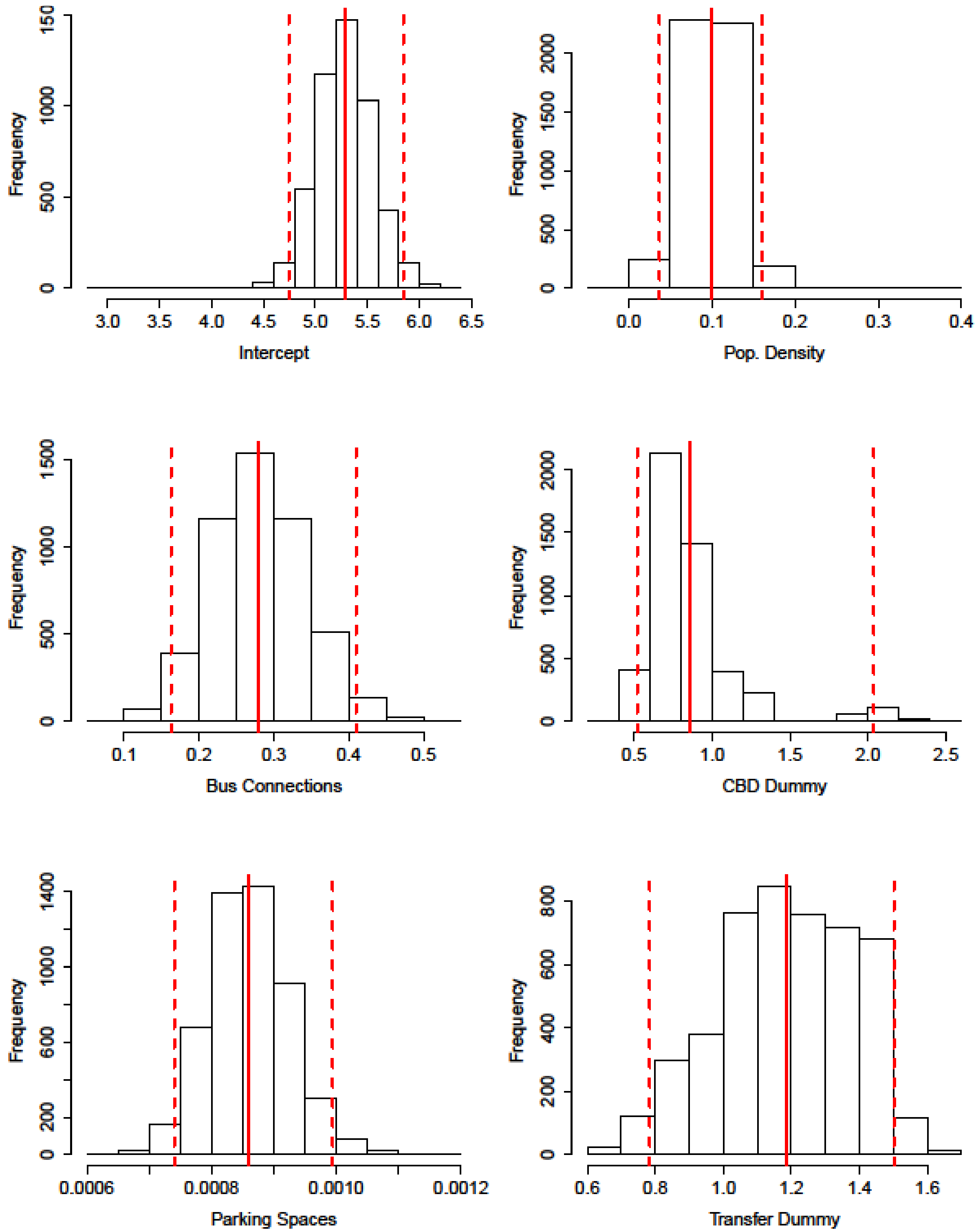


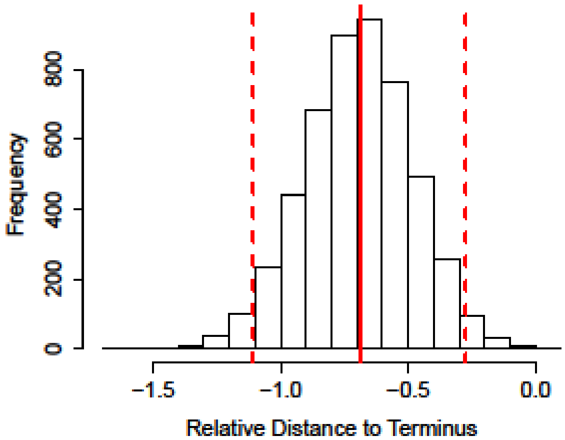
Histograms of Bootstrapped Variable Estimates for Suburban OLS



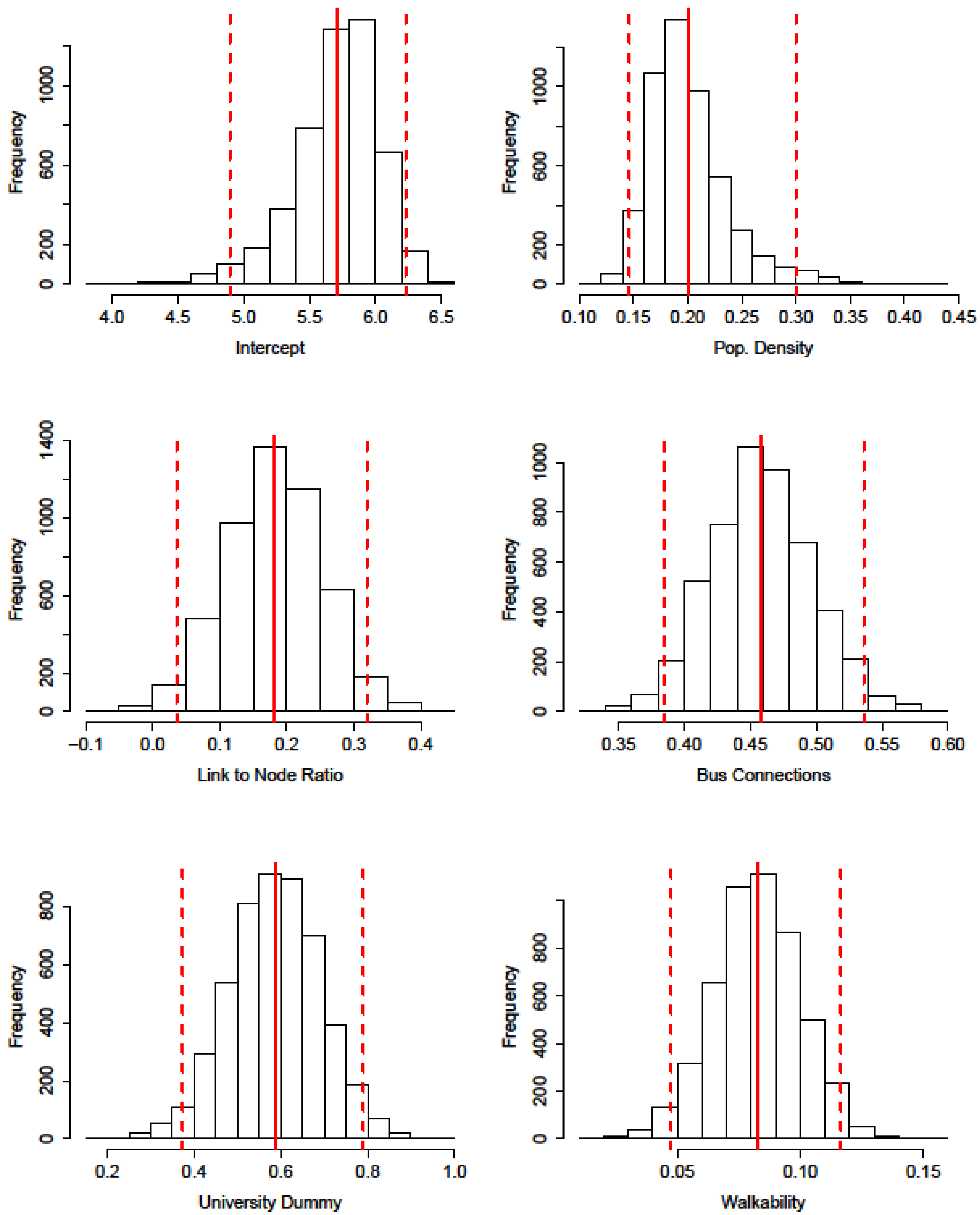

Frequency
0
200
600
1000
0.5
1.0
1.5
2.0
2.5
Transfer Dummy
Frequency
0
200
600
1000
1400
−1.5
−1.0
−0.5
0.0
0.5
Relative Distance to Terminus

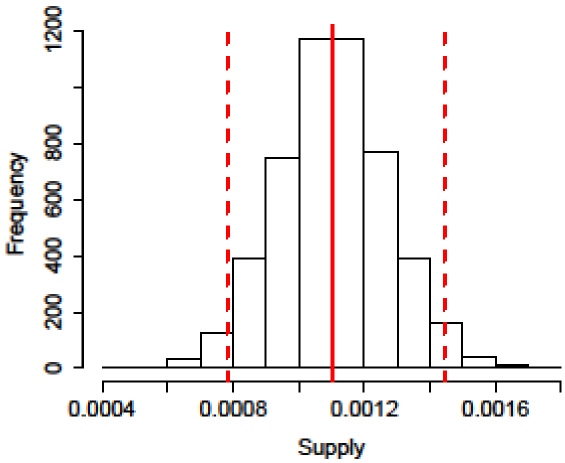
Histograms of Bootstrapped Variable Estimates for Suburban Robust



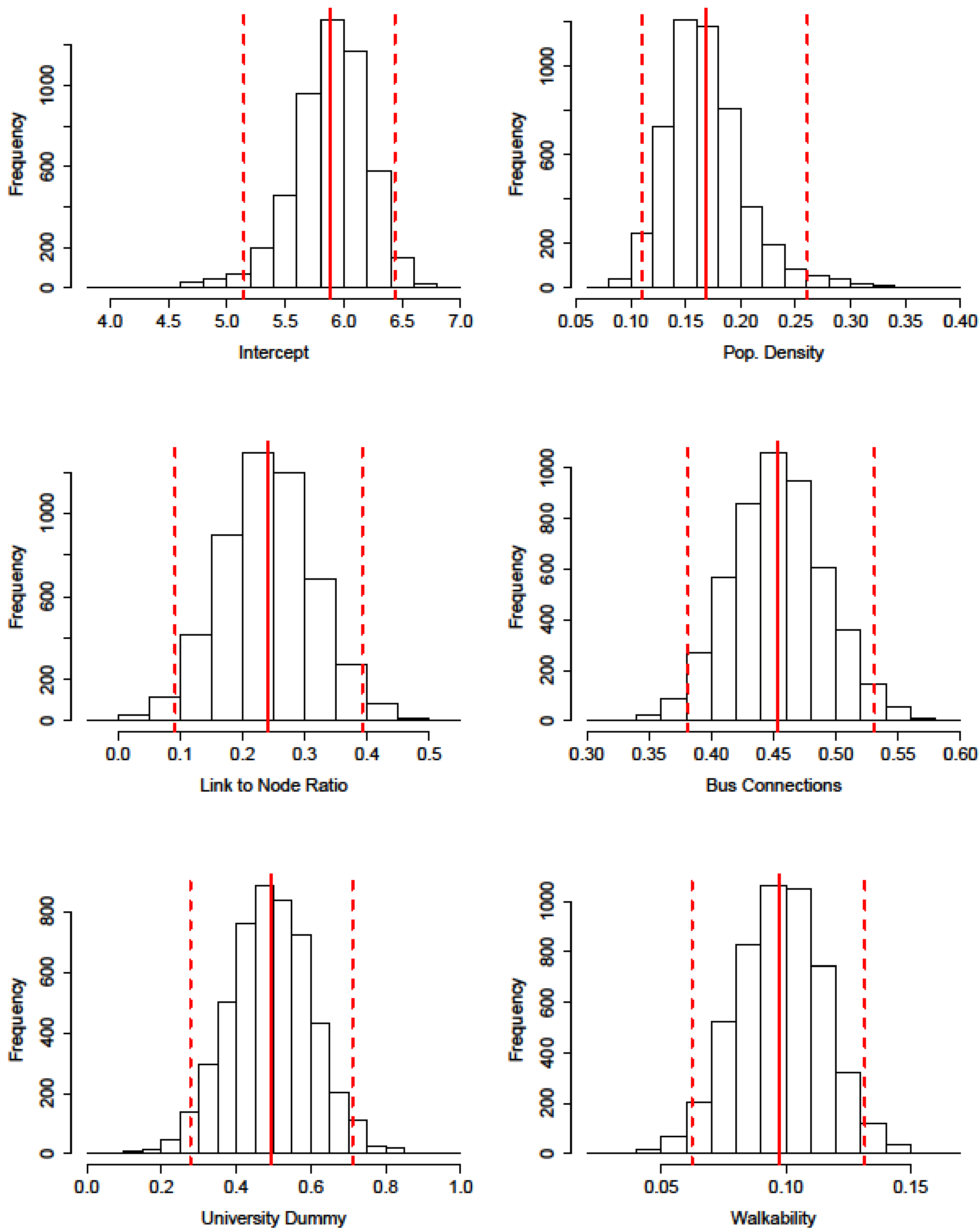

Frequency
0
200
400
600
800
−1.5
−1.0
−0.5
0.0
Relative Distance to Terminus

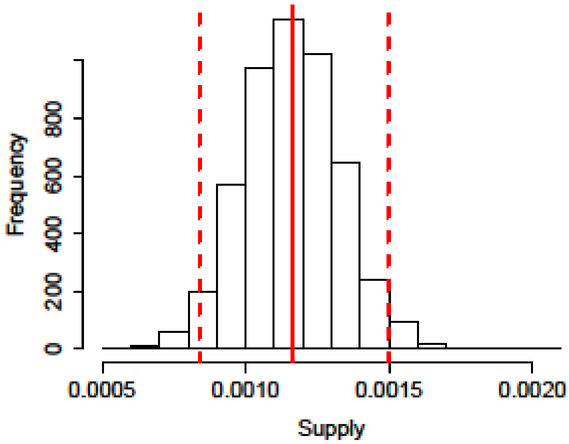
Histograms of Bootstrapped Variable Estimates for Urban OLS




1200
800
600
400
200
0
Frequency
0.0004
0.0008
0.0012
0.0016
Supply

Histograms of Bootstrapped Variable Estimates for Urban Robust




Frequency
0
200
400
600
800
0.0005
0.0010
0.0015
0.0020
Supply