SYNERGISTIC EFFECTS OF TRANSIT AND NONMOTORIZED TRANSPORTATION INFRASTRUCTURE ON COMMUTING BEHAVIOR IN SEVEN CITIES IN THE UNITED STATES

A Thesis

by

KYUHYUN LEE

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF URBAN PLANNING

Chair of Committee,	Wei Li
Committee Members,	Jun-Hyun Kim
	Kunhee Choi
Head of Department,	Shannon Van Zandt

December 2017

Major Subject: Urban and Regional Planning

ABSTRACT

Although investment in nonmotorized transportation (walking and bicycling) infrastructure has been increasingly common in recent years, very little is known about the synergistic impact of jointly developed transit and nonmotorized infrastructure systems. This study fills this gap by investigating how transit commuting is affected by the coincidence of transit, pedestrian, and bicycle facilities. Seven representative cities were chosen for this study. Zero-inflated negative binomial and negative binomial regression models were adopted to quantify the synergistic effects between transit stops and three nonmotorized facilities (sidewalks, bike lanes, and bike racks) on commuters. One notable finding is that the presence of transit stops in close proximity to commuters' origins has a significant impact on choosing public transit as their commuting mode. However, sidewalks and bike lanes are not contributing factors for commuters' travel mode choice. Bike racks do not directly influence a transit system's commuting mode share, but when combined with transit networks, they hold the potential to increase transit ridership. The findings of this study can accordingly support transportation authorities and planners in devising forward-thinking, sustainable transportation infrastructure environments, and should be of value to those who plot proactive multimodal transportation plans.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a thesis committee consisting of Dr. Wei Li and Dr. Jun-Hyun Kim of the Department of Landscape Architecture and Urban Planning, and Dr. Kunhee Choi of the Department of Construction Science.

All work conducted for the thesis was completed by the student independently.

Funding Sources

I am grateful for the funding support from the National Science Foundation (Award#: 1461766).

TABLE OF CONTENTS

LIST OF FIGURES

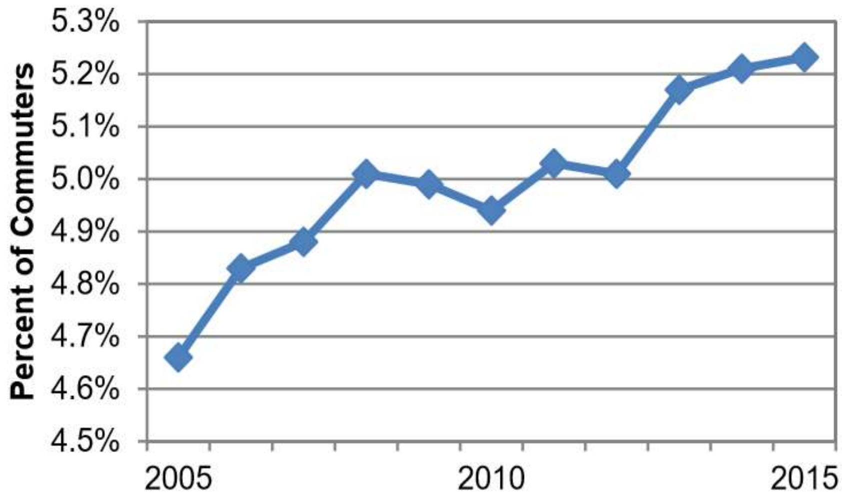
Page

LIST OF TABLES

Page

1. INTRODUCTION

Concerns about car-related problems (e.g., vehicle congestion, time spent in traffic, energy consumption, exhaust fumes, and their social costs) have led to increasing investments in public transit and nonmotorized transportation (i.e., pedestrian and bicycle) systems in the United States over the past decades. According to the National Transit Database from the Federal Transit Administration, government spending on transit systems has increased by 60.5 percent, from $40.9 billion to $65.7 billion between 2005 and 2015 (Federal Transit Administration, 2016). In addition, pedestrian and bicycle funding of the Federal Highway Administration has increased from $400.0 million to $833.7 million during the same period (American Public Transportation Association, 2017). Some federal funds have been allocated to a "multimodal access to transit" strategy to support walking and bicycling to public transit (U.S. Department of Transportation, n.d.). However, these investments are not proportionally translated into transit market share in terms of commuting. The U.S. Census American Community Survey (ACS) reported that the proportion of employees who chiefly commute by public transit has only slightly increased from 4.6 percent to 5.2 percent in the last 10 years (Figure 1) (American Public Transportation Association, 2017).



(Source: American Public Transportation Association, 2017)

Figure 1. Percent of Workers Commuting by Transit

Given that nonmotorized transportation infrastructure is necessary for comfortable and easy access to public transit services, synergistic effects with public transit systems could potentially bring the benefits of increased transit ridership; however, relevant empirical evidence is limited. This study aims to fill the gap by analyzing the influence of public transit and nonmotorized transportation facilities on commuting behavior (home-based work trips) in seven U.S. cities. The key motivation of the study is to estimate the synergistic effects of transit stops and nonmotorized transportation facilities using three interaction terms. The presence of a significant interaction indicates that the effects of transit stops on commuting by transit differ depending on the levels of the nonmotorized facility provisions (sidewalks, bike lanes, and bike racks). This nationwide analysis provides empirical evidences for devising proactive multimodal transportation plans and sustainable transportation infrastructure.

2. LITERATURE REVIEW

With enhanced private vehicle mobility, the mounting number of automotive vehicles on the roadways have caused diverse urban concerns: traffic congestion, car accidents, atmospheric contamination, and reduced physical activities. For the purpose of alleviating these issues, public policies have continuously invested multi-billions of dollars in encouraging alternative modes of transport use. In accordance with the efforts at the government level, there have been a considerable number of studies of the relationship between the public transportation system and travel behavior. This section summarizes past work on such associations, primarily focusing on employees' journey-to-work trips in North America. Afterward is a review of what previous studies have revealed about how nonmotorized transportation infrastructure affects commuting by transit to date.

2.1. Impacts of Public Transit Accessibility on Commuting by Transit

In the late 20th century, with the advent of New Urbanism, proponents of this new theory approached car-related problems from the aspects of a holistic urban form. They proposed that urban settings should be reshaped into anti-sprawl, high-density, multi-use, and pedestrian-friendly neighborhoods (Boarnet & Crane, 2001). With this planning intervention, transit-oriented development (TOD) emerged as a promising planning strategy, and its popularity is ongoing in U.S. cities that struggle with high traffic density (Carlton, 2009). Over recent decades, TOD has been frequently discussed within initiatives to decrease auto-dependency by improving access to transit (Dill, 2008; Lund et al., 2004). In an earlier study at the neighborhood level in California, Cervero and Gorham (1995) made a comparison of commuting patterns between transit-oriented communities and auto-oriented communities in the San Francisco Bay area and Los Angeles County. They found that transit-oriented neighborhoods in the San Francisco Bay area and Los Angeles County had 5.1 and 1.4 percent more transit commuting, respectively, than did auto-oriented neighborhoods in both the San Francisco Bay area and southern California, controlling for residential densities and incomes (Cervero & Gorham, 1995). In 2003, a TOD survey of residents' travel characteristics was carried out on a large scale based on nine major urban rail projects including 26 residential developments in the same state (Lund et al., 2004). The results indicated that workers living near transit stations were approximately five times more likely to travel to work using transit (26.5 percent) compared to average commuters (5.4 percent) in the surrounding cities (Lund et al., 2004). More recent travel surveys conducted in the Portland region revealed that the transit market share of modern transit-oriented neighborhoods was higher than that measured across the city (Dill, 2008). On average, 25 percent of respondents living near four light-rail stations chose transit as their primary commute mode, while only 10 percent of survey respondents to the 2000 Census used transit for a majority of their commuting trips.

While extensive literature has emphasized the importance of walking access in transit usage, few studies have tried to quantify how transit ridership responds to improved transit access when adding more transit stops in neighborhoods (Hess, 2009; Hsiao et al., 1997; Zhao et al., 2002). One study estimated the impacts of establishing transit stops at the census tract level: 10 more transit stops per square mile near homes and work were related to 10 and 5 percent higher odds of transit commuting, respectively (Chakrabarti, 2017). When transit agencies and authorities must decide about the inclusion of new transit facilities, a question might arise: how many more people will commute by transit if one more transit stop is added in a community? However, despite great concerns about transit accessibility, quantified effects of transit stops are underexplored.

2.2. Sidewalks and Commuting by Transit

Commuting by transit involves access/egress trips due to the rigid nature of fixed-route systems. As reported by previous studies, walking is the primary means of getting to public transit systems. In the study of walk-and-ride transit usage in the San Francisco Bay area, the dominant access mode to transit stations for journeys to work was walking up to 5/8 of a mile (1 km) (Cervero, 2001). Another study examining pedestrian access to transit in the same region, but based on home-base-all-trips, pointed out that walking was the most frequent mode of egress trips at 76 percent, whereas walking was used in 24 percent of access trips (Loutzenheiser, 1997). The Southeast Florida Travel Characteristic Study conducted in 2000 reported that almost 80 percent of travelers surveyed walked to transit stops (Zhao et al., 2002).

Considering that walking is largely involved in transit trips, a walkable environment could be attractive to transit riders. As the benefits of walking receive growing attention, previous studies have tried to discover how the built environment affects the frequency of walking trips. Many studies have found that pedestrian facilities and walking quality can facilitate more frequent walking trips (Cervero & Kockelman, 1997; Moudon et al., 1997). Street and sidewalk connectivity has also revealed a positive relationship with walking frequency (Ewing & Cervero, 2001). When considered within transit-based chain trips, pedestrian-friendly environments may influence access mode choice as well. With a focus on sidewalks, the supply of sidewalks considerably promoted commuters' choices to walk to transit, and sidewalk availability was positively related to transit market share (Cervero, 2001; Lund et al., 2004; Rodríguez & Joo, 2004). Prior literature has confirmed that the supply of sidewalks considerably affected whether or not commuters walked to transit stations rather than used other feeder modes (Cervero, 2001). In a study estimating the relationship between nonmotorized trips and local physical attributes at the University of North Carolina, Chapel Hill, sidewalk availability was appreciably related to transit market share (Rodríguez & Joo, 2004). Lund, Cervero, and Wilson (2004) predicted the probability that residents near stations use mass transport services in California. In the study, they found a positive correlation between the presence of sidewalks on the way to transit stations and transit usage (Lund et al., 2004).

While sidewalks have been commonly included in travel behavior studies as the primary street facility for pedestrian safety and comfort, less attention has been paid to the quantified effects of sidewalks on transit ridership. Moreover, there is a dearth of knowledge about whether supplying sidewalks in neighborhoods generates greater market performance than providing transit stops alone.

2.3. Integration of Bike Facilities with Transit Networks

The most common means of getting to public transit is walking, but this is limited by distance. The widely accepted comfortable walking distance is a quarter mile and sometimes stretches to a half mile or 5/8 mile, depending on trip purpose, personal propensity, and other circumstances (Cervero, 2001; Crowley et al., 2009; Untermann, 1984). Beyond the distance, those willing to take transit must find a faster submode to cover longer distances than walking. One possible scenario is park-and-ride, assuming that parking spaces are provided near transit stops. Driving is less limited by distance, but this requires parking spaces and lessens surface traffic efficiency around transit nodes (Cervero, 2001; Loutzenheiser, 1997; Pucher & Buehler, 2009). Bus-and-ride is another option; transit riders switch transport mode at an intermediate destination for the remainder of their journey. However, increased time for waiting and transfer can be a barrier to transit mode choice (Chakrabarti, 2017; Fan & Machemehl, 2011). Lastly, bicycling is emerging as a viable solution to the first- and last-mile problem. Bicycling may extend the catchment areas of rigid transit networks, allowing transit riders improved transit access (Pucher & Buehler, 2009). This potential has spurred a growing number of studies on the integration of transit and bicycle. Current trends in transit-bike coordination programs are categorized into bike racks on buses, bikes on board, and bike parking at transit stops (Pucher & Buehler, 2009). Among them, bikes on board is preferred by bicyclists, rather than parking bikes near transit stops. An online survey performed in Montreal, Canada, in 2010 reported that current cycle-transit riders preferred to bring their bikes on transit vehicles (Bachand-Marleau et al., 2011). A study that surveyed stated-preference bike and transit integration options showed a consistent result: the most preferred option was bikes on transit in seven communities in Colorado, Illinois, New York, Oregon, and California (Krizek & Stonebraker, 2011). However, when the vehicle capacity of carrying bicycles is reached (normally two to four bicycles on a transit vehicle), cyclists must wait for the next bus or rail. Paradoxically, the more the bike carrying succeeds, the more problematic carrying capacity becomes. As a solution to onboard capacity challenges, bike parking or bike share programs are suggested (Krizek & Stonebraker, 2011).

A handful of studies explored the potential of jointly developed bike sharing and public transport systems in facilitating transit trips. Martin and Shaheen (2014) mapped the locations of survey participants in Washington, D.C., and Minneapolis, Minnesota. The findings of the study represented different outcomes depending on the urban environment. Transit riders in less dense areas were more likely to use bike share to access transit, while people in an urban core with a higher population density used bike sharing to get to transit faster or replaced transit with shared bikes (Martin & Shaheen, 2014). Literature on bike share systems and related plans in Austin, Texas, and Chicago, Illinois, evaluated the opportunity of the shared use of a bicycle fleet and suggested directions for improving intermodal planning (Griffin & Sener, 2016).

While transit-bicycle integration is receiving great attention, there is a lack of empirical evidence about increased ridership for commuting when transit and bike facilities are jointly developed. Several studies have revealed that bike-sharing programs facilitate transit usage, but the studies are limited to shared bicycle facilities (Ma et al., 2015; Shaheen et al., 2013). Furthermore, bike lanes are less addressed in the transit-bicycle integration studies, despite the necessity to secure cyclists' safety (Dill & Carr 2003; Muhs & Clifton, 2016; Nelson & Allen, 1997).

2.4 Summary

To summarize, existing literature justifies the need for nonmotorized infrastructure, as well as transit facilities, to promote transit commuting, but quantified direct and synergistic effects of the transport infrastructure remain to be seen. In the context of efficiency of entire transportation networks, quantitative estimates of the effects are necessary before deciding on new infrastructure provisions and while operating current systems.

3. METHODOLOGY

3.1. Study Area

To explore the impacts of transportation infrastructure on the number of transit commuters, seven major cities in the United States were selected: Austin, Texas; Dallas, Texas; Denver, Colorado; Fort Worth, Texas; Portland, Oregon; San Antonio, Texas; and Seattle, Washington. To decide the study areas, the largest 30 cities were enumerated by population size, according to the 2011–2015 ACS. From the 30 cities, seven cities were chosen because they had a wide range of population (0.5 to 1.5 millions) and distinct levels of transit ridership for commuting. Easy access to the latest data on diverse transport infrastructures was another critical reason for the choice of the seven cities. Table 1 illustrates basic information from the 2011–2015 ACS about the study areas: population size, land area, residential density, and commuting mode share by transportation type.

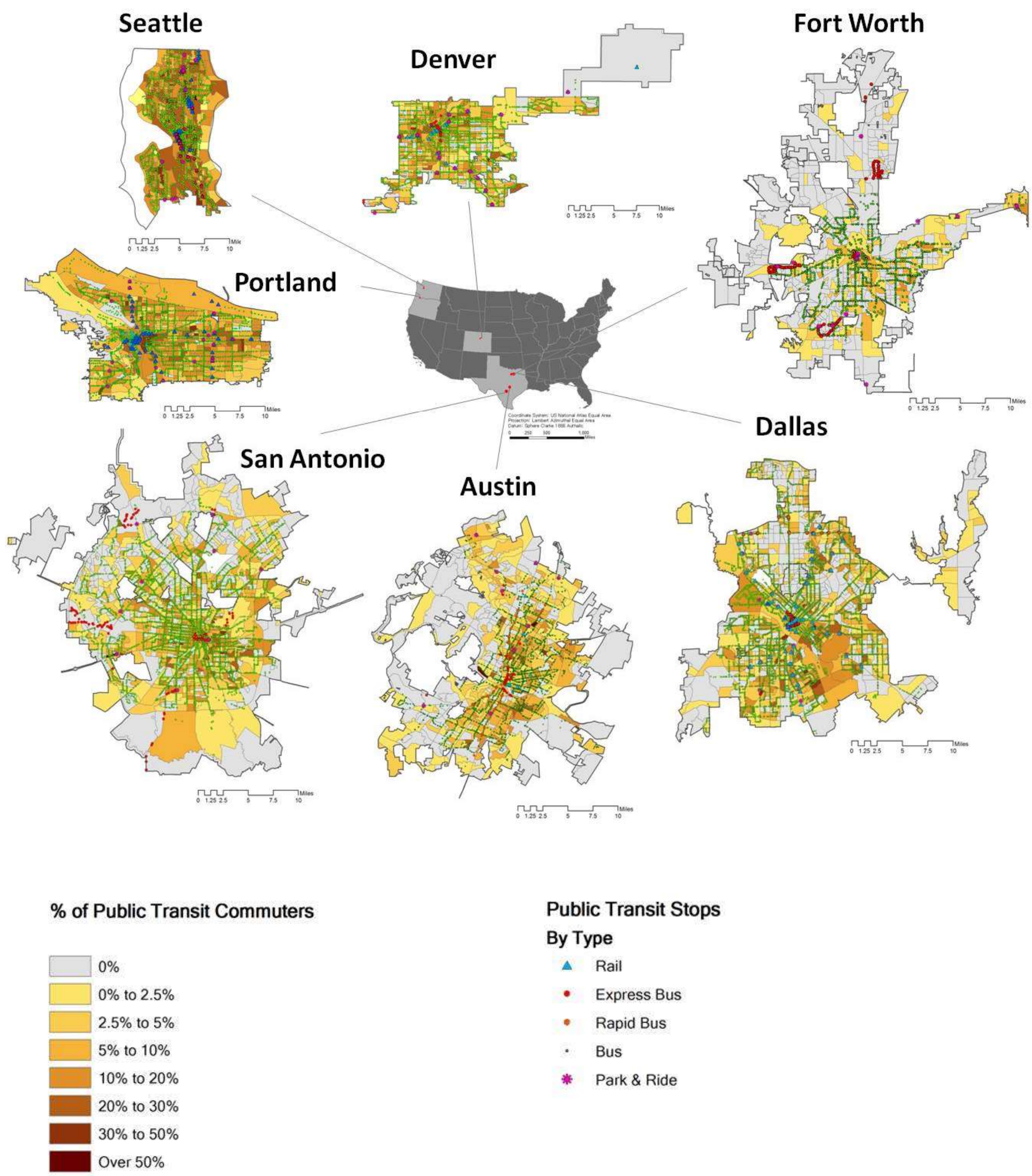
Table 1. Basic Information about Study Areas

	Austin	Dallas	Denver	Fort Worth	Portland	San Antonio	Seattle
Population (1,000)	887	1,261	649	797	612	1,414	653
Land Area (Sq. Mile)	298	341	153	339	133	461	84
Population Density (per Sq. Mile)	2,978	3,702	4,264	2,344	4,588	3,067	7,779
Commuting Mode Share (Percent)							
Cars	83.5%	87.7%	78.9%	93.0%	67.0%	90.3%	58.4%
Transit	4.3%	4.4%	7.0%	1.0%	12.2%	3.4%	20.2%
Bicycle	1.5%	0.2%	2.3%	0.2%	6.4%	0.3%	3.8%
Walking	2.5%	1.9%	4.5%	1.3%	5.9%	1.8%	9.6%

Notes: 1) The commuting mode share indicates the percentage of means of transportation to work for workers 16 years of age and over.
2) The sum of the transit mode share is less than 100% because work at home and other modes are not included.

Dallas and San Antonio have the largest populations at over 1 million, and the remaining cities have relatively similar populations between 600,000 and 900,000. Looking at the population density, it is apparent that Texas cities sprawl much more than do Denver, Portland, and Seattle cities due to a larger area. In particular, Seattle has twice the density as the cities in Texas. Portland and Denver have 1.5 times the density as cities in Texas.

When comparing means of transportation to work, the differences between Texas and non-Texas cities are noticeable. The market share of public transit is over 20 percent in Seattle, 12 percent in Portland, and 7 percent in Denver, while the Texas cities have less than 5 percent. Despite the consistently low proportion of mass transit patrons across Texas, the degree of market share differs within Texas: Austin and Dallas have over 4 percent ridership but not by much, followed by San Antonio with 3.4 percent. Employees in Fort Worth rarely ride transit to get to work (only 1 percent). Figure 2 represents the locations of the study areas and spatial patterns of commuting behaviors on the map (larger size maps are provided in Appendix A through Appendix G).



(Sources: U.S. Census Bureau, city and transit agency, the General Transit Feed Specification, and Google Maps)

Figure 2. Spatial Patterns of Transit Commuting in the Study Areas

Table 2 provides information about public transportation systems in the seven metropolitan areas where study areas are located. In terms of rail systems, six areas have at least one surface rail system; San Antonio does not. The Denver region runs two heavy rail systems and seven light rail systems, and Portland, Dallas, and Seattle operate from four to six urban rail systems to provide rapid transportation services largely for commuters. The Seattle and Denver regions operate a substantial number of bus routes because they serve extensive areas. Compared to the other cities in Texas, Dallas has a relatively larger number of bus lines.

Table 2. Public Transportation Systems in the Study Regions

	Austin	Dallas	Denver	Fort Worth	Portland	San Antonio	Seattle
Operator	Capital Metro (www.capmetro.org)	Dallas Area Rapid Transit (DART) (www.dart.org)	Regional Transportation District (www.rtd-denver.com)	Fort Worth Transportation Authority (www.the-t.com)	TriMet (www.trimet.org)	VIA Metropolitan Transit (www.viainfo.net)	Sound Transit (www.soundtransit.org)
Service Area (City Area)	535 sq. miles (298 sq. miles)	700 sq. miles (341 sq. miles)	2,342 sq. miles (153 sq. miles)	350 sq. miles (339 sq. miles)	533 sq. miles (133 sq. miles)	527 sq. miles (461 sq. miles)	2,134 sq. miles (84 sq. miles)
Heavy Rails	Not operated	1 route	2 routes	1 route	1 route	Not operated	2 routes
		Trinity Railway Express		-Trinity Railway Express	-Westside Express Service		-Sounder Train
Light Rails	1 route	4 routes	7 routes	Not operated	5 routes	Not operated	2 routes
	Capital metrorail	-A–F -H			-Red -Blue -Green -Orange -Yellow		-Link light rail -Tacoma link light rail
Bus	86 Routes	150 routes	150 routes	42 routes	81 routes	85 routes	233 routes
	-Local (16) -Flyer (9) -Feeder (10) -Crosstown (11) -Special service, and shuttle (28) - Night owl, high-frequency, and E-bus (12)	-Local (132) -Regional Express (25) -Flatiron Flyer (7) -Airport (6)		-Express (6) -Local (36)	-Frequent (13) -Express (1) -Night (1) -Other (66)	-Express (8) -Local (74) -Sightseer (3)	-Express (34) -Rapid (6) -Local (175) -DART (15) -Night owl (3)
Street Car	Not operated	2 routes	Not operated	1 route	3 routes	1 route	2 routes
Park and Ride (Parking Available)	12 centers	53 centers	83 centers	12 centers	18 centers	6 centers	63 centers

Note: Data sources are each city and transit agency, the General Transit Feed Specification, and Google Maps

3.2. Data and Variables

3.2.1 Data

This study selected the U.S. Census block group (BG) as a unit of analysis to examine current commuting behaviors using identical data sources. For an aggregate analysis of transit commuting at each BG, the number of commutes by transit was derived from the 2011–2015 ACS. Starting with 2005, the U.S. Census Bureau has been reporting the means of transportation to work for employees 16 years of age and over in the ACS (American Public Transportation Association, 2017). The home-based work trip survey asks respondents in the workforce to determine a single mode for their journey to work; the specific question asked is "How did you usually get to work last week?" Survey participants indicate the main mode required for the longest distance. The ACS travel survey asks about only work trips, whereas the National Household Travel Survey (NHTS) collects the how, when, why, and by what means people travel in their daily lives. However, there is a limit to the use of the NHTS data for this study. The most recently published NHTS was conducted in 2009, so there is a substantial time lag in measuring current commuting trends as well as the impacts of transport infrastructure established since 2009. In addition, since the NHTS covers less than 3 percent of the ACS sample size, it is better to use the ACS data to examine overall commuting behaviors across the nation (Pucher & Buehler, 2009).

Socioeconomic characteristics for each BG and geographical boundaries were downloaded from the U.S. Census Bureau. Data on urban infrastructure such as streets, sidewalks, bike lanes, bike racks, and park-and-ride centers were gathered from cities and transit agencies, and digitized using Google Maps service. Bike rack data were excluded for Austin, Dallas, Fort Worth, and San Antonio because they were not available at the city scale. To identify transit service types or routes, the General Transit Feed Specification (GTFS) was used. The GTFS is a worldwide data format that provides comprehensive transit service information (e.g., transit stop locations, routes, and schedules). Since its creation in 2005, this new system has become popular, and more and more agencies have shared their GTFS data openly with the public, so the GTFS data were readily acquired (from the website transitfeeds.com) (Antrim & Barbeau, 2013). Table 3 summarizes the data sources for the seven cities.

Table 3. Data Sources

Data	Austin	Dallas	Denver	Fort Worth	Portland	San Antonio	Seattle
Socioeconomic Factors							
Population density	American Community Survey (2011–2015) by the U.S. Census Bureau (www.socialexplorer.com)						
Employment density	Origin-destination employment statistics (2014) from the Longitudinal Employer-Household Dynamics program by the U.S. Census Bureau (lehd.ces.census.gov/data)						
Median household income	American Community Survey (2011–2015) by the U.S. Census Bureau (www.socialexplorer.com)						
Percent of African-American	American Community Survey (2011–2015) by the U.S. Census Bureau (www.socialexplorer.com)						
Percent of non-White Hispanic	American Community Survey (2011–2015) by the U.S. Census Bureau (www.socialexplorer.com)						
Percent of nonfamily household	American Community Survey (2011–2015) by the U.S. Census Bureau (www.socialexplorer.com)						
Percent of one-unit housings	American Community Survey (2011–2015) by the U.S. Census Bureau (www.socialexplorer.com)						
Median year of housing built	American Community Survey (2011–2015) by the U.S. Census Bureau (www.socialexplorer.com)						
Means of transportation to work	American Community Survey (2011–2015) by the U.S. Census Bureau (www.socialexplorer.com)						
Block group boundary	The TIGER shapefiles (2015) by the U.S. Census Bureau (www.census.gov/geo/maps-data)						
Public Infrastructure							
Transit stops	Open data and GTFS	Open data and GTFS	Open data and GTFS	Open data and GTFS	Open data and GTFS	Open data and GTFS	Open data and GTFS
Street	Open data	Open data	Open data	Open data	Open data	Open data	Open data
Sidewalk	Open data	Open data	Open data	Open data	Open data	Open data	Open data
Bike lane	Open data	Open data	Open data	Open data	Open data	Open data	Open data
Bike racks	N/A	N/A	N/A	N/A	Open data	Open data	Open data
Park and ride	Google Maps	Google Maps	Open data	Google Maps	Open data	Google Maps	Open data

Note: N/A denotes that data are not available at the city scale because bike racks are concentrated in downtown areas or sample size is limited.

3.2.2 Variables

The variable definition, measurements, and statistics are tabulated in Table 4. Collected data were converted to quantifiable indicators at the BG level using geographic information systems (GIS). As for sample size, Dallas and San Antonio have about 900 BGs, while the other five cities have similar population sizes at approximately 500. The average number of transit commuters per BG (the dependent variable) significantly varies between cities (from 7 to 159), although there was no remarkable variation in the number of workers (from 665 to 950). In Seattle, on average 159 commuters used the public transit systems as their main modes of transport to commute. The second highest figure was reported from Portland (88 transit commuters), followed by Denver and Austin. Commuting with public transit appeared not to be attractive to workers in Fort Worth; on average, only 7 persons commuted by transit in a BG.

Four socioeconomic features were tested: median household income, African-Americans, non-White Hispanics, nonfamily households, and single-family units. Median household income was measured in 1,000 units to avoid lengthy numbers. Workers in the study areas tended to make a median household income between $47,000 and $77,000. For race and ethnicity, Dallas and Fort Worth have similar population compositions, with similar percentages of African-Americans and non-White Hispanics. In terms of family type across the cities, about 40 percent of the households were made up of unrelated persons or a single person living alone.

Table 4. Variable Mean and Other Statistics (in Parenthesis) Measured at the BG Level

Variable Definition and Unit	Austin	Dallas	Denver	Fort Worth	Portland	SA	Seattle
Number of block groups, sample size	494	915	479	507	440	881	478
Number of transit commuters, dependent variable	41.263	28.631	49.706	6.913	88.000	24.220	158.960
(Standard deviation)	*(73.138)*	*(38.666)*	*(51.193)*	*(15.830)*	*(70.254)*	*(34.761)*	*(104.097)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(1,142)*	*(331)*	*(319)*	*(131)*	*(380)*	*(260)*	*(735)*
Number of workers, exposure	949.603	664.827	715.505	705.145	727.557	722.257	786.023
(Standard deviation)	*(607.120)*	*(373.621)*	*(464.198)*	*(483.411)*	*(325.612)*	*(491.584)*	*(297.037)*
(Min.)	*(38)*	*(38)*	*(88)*	*(113)*	*(90)*	*(7)*	*(93)*
(Max.)	*(4,939)*	*(2,688)*	*(4,744)*	*(3,227)*	*(2,304)*	*(4,000)*	*(3,064)*
Socioeconomic Factors							
Median household income, $1,000	62.848	56.193	61.584	53.217	62.352	46.754	77.202
(Standard deviation)	*(34.455)*	*(44.079)*	*(33.579)*	*(30.598)*	*(30.241)*	*(26.297)*	*(38.038)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(202.614)*	*(250.001)*	*(237.785)*	*(177.798)*	*(205.278)*	*(210.893)*	*(238.021)*
Percent of African-American, 0-1	0.068	0.231	0.082	0.184	0.053	0.061	0.067
(Standard deviation)	*(0.093)*	*(0.269)*	*(0.120)*	*(0.209)*	*(0.073)*	*(0.099)*	*(0.104)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(0.663)*	*(1)*	*(0.743)*	*(0.871)*	*(0.465)*	*(0.765)*	*(0.638)*
Percent of non-White Hispanic, 0-1	0.075	0.099	0.077	0.099	0.033	0.118	0.028
(Standard deviation)	*(0.101)*	*(0.125)*	*(0.089)*	*(0.105)*	*(0.049)*	*(0.101)*	*(0.042)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(0.716)*	*(0.894)*	*(0.499)*	*(0.573)*	*(0.320)*	*(0.549)*	*(0.306)*
Percent of nonfamily household, 0-1	0.471	0.383	0.473	0.320	0.468	0.328	0.509
(Standard deviation)	*(0.205)*	*(0.205)*	*(0.209)*	*(0.172)*	*(0.182)*	*(0.168)*	*(0.200)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(1)*	*(0.937)*	*(0.961)*	*(0.958)*	*(1)*	*(0.886)*	*(1)*

Table 4. Variable Mean and Other Statistics (in Parenthesis) Measured at the BG Level, continued

Variable Definition and Unit	Austin	Dallas	Denver	Fort Worth	Portland	SA	Seattle
Built Environment							
Population density, 1,000 per sq. mile	5.936	8.091	8.667	5.002	8.396	5.563	12.767
(Standard deviation)	*(5.396)*	*(8.291)*	*(5.820)*	*(3.723)*	*(5.839)*	*(3.109)*	*(12.278)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0.067)*	*(0)*	*(0)*	*(0.487)*
(Max.)	*(50.837)*	*(59.126)*	*(40.294)*	*(27.943)*	*(59.357)*	*(25.053)*	*(141.622)*
Employment density, 1,000 per sq. mile	2.834	2.894	5.606	1.187	4.976	1.761	9.815
(Standard deviation)	*(6.128)*	*(10.375)*	*(21.805)*	*(3.149)*	*(15.106)*	*(4.294)*	*(40.584)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0.017)*	*(0)*	*(0.056)*
(Max.)	*(74.811)*	*(175.407)*	*(314.364)*	*(44.227)*	*(173.457)*	*(47.031)*	*(722.006)*
Percent of one-unit housing, 0-1	0.564	0.588	0.636	0.747	0.668	0.727	0.567
(Standard deviation)	*(0.326)*	*(0.386)*	*(0.339)*	*(0.297)*	*(0.285)*	*(0.295)*	*(0.322)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(1)*	*(1)*	*(1)*	*(1)*	*(1)*	*(1)*	*(1)*
Median year housing built, year	1956	1962	1948	1919	1956	1956	1948
(Standard deviation)	*(217.576)*	*(130.987)*	*(155.951)*	*(324.269)*	*(16.571)*	*(176.105)*	*(156.054)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(1939)*	*(0)*	*(0)*
(Max.)	*(2007)*	*(2008)*	*(2007)*	*(2008)*	*(2004)*	*(2006)*	*(2005)*
Direct distance to CBD, mile	6.101	7.300	4.373	6.471	4.219	7.139	4.317
(Standard deviation)	*(3.511)*	*(3.807)*	*(2.683)*	*(3.394)*	*(2.099)*	*(3.742)*	*(2.122)*
(Min.)	*(0.158)*	*(0.252)*	*(0.168)*	*(0.468)*	*(0.192)*	*(0.192)*	*(0.125)*
(Max.)	*(16.568)*	*(21.344)*	*(17.997)*	*(20.332)*	*(9.713)*	*(19.046)*	*(8.799)*
4-way intersection density, count per sq. mile	35.566	67.091	119.622	56.886	154.393	54.878	175.779
(Standard deviation)	*(39.977)*	*(49.575)*	*(78.105)*	*(49.760)*	*(114.685)*	*(56.319)*	*(106.199)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(1.255)*	*(0)*	*(10.171)*
(Max.)	*(237.610)*	*(278.129)*	*(379.458)*	*(284.940)*	*(816.055)*	*(372.712)*	*(829.814)*

Note: SA stands for San Antonio.

Table 4. Variable Mean and Other Statistics (in Parenthesis) Measured at the BG Level, continued

Variable Definition and Unit	Austin	Dallas	Denver	Fort Worth	Portland	SA	Seattle
Active Commuter							
Number of walking commuters, count	24.401	11.912	32.251	9.041	42.336	13.010	75.368
(Standard deviation)	*(55.648)*	*(32.821)*	*(77.511)*	*(25.003)*	*(73.149)*	*(55.272)*	*(129.505)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(756)*	*(441)*	*(742)*	*(251)*	*(691)*	*(1,376)*	*(1,167)*
Number of bike commuters, count	*14.399*	*1.478*	*16.672*	*1.247*	*46.005*	*1.846*	*29.674*
(Standard deviation)	*(27.375)*	*(6.617)*	*(27.918)*	*(5.721)*	*(49.435)*	*(7.332)*	*(38.363)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(299)*	*(90)*	*(207)*	*(51)*	*(443)*	*(66)*	*(378)*
Transport Infrastructure							
Transit stop density, count per sq. mile	26.906	81.642	76.048	23.581	91.492	56.993	100.372
(Standard deviation)	*(25.973)*	*(66.725)*	*(53.743)*	*(25.904)*	*(58.763)*	*(44.865)*	*(79.360)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(145.482)*	*(488.878)*	*(444.707)*	*(175.394)*	*(516.197)*	*(261.506)*	*(525.284)*
Sidewalk density, length per sq. mile	16.339	19.890	37.385	13.775	44.890	19.904	46.587
(Standard deviation)	*(9.411)*	*(11.726)*	*(10.255)*	*(11.446)*	*(28.253)*	*(11.948)*	*(13.371)*
(Min.)	*(0)*	*(0)*	*(0.257)*	*(0)*	*(0)*	*(0)*	*(4.961)*
(Max.)	*(55.230)*	*(45.738)*	*(59.369)*	*(51.352)*	*(117.769)*	*(55.719)*	*(112.129)*
Bike lane density, length per sq. mile	11.026	1.230	5.426	1.639	33.791	3.349	38.212
(Standard deviation)	*(5.340)*	*(3.124)*	*(4.942)*	*(3.414)*	*(10.611)*	*(4.345)*	*(12.533)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(4.160)*	*(0)*	*(10.731)*
(Max.)	*(42.212)*	*(24.443)*	*(34.937)*	*(32.320)*	*(67.715)*	*(25.249)*	*(100.911)*
Bike rack density, count per sq. mile	N/A	N/A	18.656	N/A	63.554	N/A	108.677
(Standard deviation)			*(106.404)*		*(168.738)*		*(226.822)*
(Min.)			*(0)*		*(0)*		*(0)*
(Max.)			*(1236.240)*		*(1442.380)*		*(1695.150)*

Note: SA stands for San Antonio.

Table 4. Variable Mean and Other Statistics (in parenthesis) Measured at the BG Level, continued

Variable Definition and Unit	Austin	Dallas	Denver	Fort Worth	Portland	SA	Seattle
BG within 0.5 miles from rapid transit: 1	0.233	0.114	0.173	0.120	0.248	0.038	0.251
(Standard deviation)	*(0.423)*	*(0.318)*	*(0.379)*	*(0.326)*	*(0.432)*	*(0.190)*	*(0.434)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(1)*	*(1)*	*(1)*	*(1)*	*(1)*	*(1)*	*(1)*
BG within 1.5 miles from park and ride: 1	0.132	0.273	0.309	0.112	0.298	0.075	0.220
(Standard deviation)	*(0.338)*	*(0.446)*	*(0.463)*	*(0.316)*	*(0.458)*	*(0.263)*	*(0.415)*
(Min.)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
(Max.)	*(1)*	*(1)*	*(1)*	*(1)*	*(1)*	*(1)*	*(1)*

Notes: 1) N/A denotes not available due to a lack of adequate data.
2) SA stands for San Antonio.

Six variables served as indicators of built environment characteristics: population density, employment density, percent of one-unit housing, median year housing built, direct distance to the Central Business District (CBD), and four-way intersection density. Seattle has the greatest population and employment density, followed by Denver and Portland. Texas cities had lower densities (in both population and employment) compared to the non-Texas cities. The proportion of one-unit housing types did not considerably vary between cities. As for year of housing built, the median year ranged from 1919 to 1962 across the cities. The direct distance from each BG to the CBD was measured using weighted mean centers. Because the CBD serves as a significant part of the commercial and business functions in a city, the districts hold the highest levels of job and activity generation. For these reasons, the urban core areas have solid transportation systems and act as a transit hub where people start or end their trips and often transfer to get to their final destinations. The beelines in Texas were 1.5 times longer than those outside of Texas, ranging from 4 to 7 miles across the seven cities. As for intersection density, the GIS network analyst function was employed to extract four-way intersections among all cross streets. The level of street connectivity was calculated by dividing the number of four-way intersections by the area (square mile). Denver, Portland, and Seattle tended to have two to five times better street connectivity than cities in Texas.

Since nonmotorized travel modes (walking, bicycling, and public transit) are likely to compete, mode shares of walking and bicycling were controlled. The preference for walking to work was highest in Seattle (75 workers), followed by Portland and

Denver. Among the four cities in Texas, Austin had a relatively greater number of walking commuters than other cities. Cycling to work was most popular in Portland among the study areas. In San Antonio, Dallas, and Fort Worth, very low figures were reported in the bicycle population for work trips; only one person rode a bicycle to work in a BG.

As for transport infrastructure, the densities of transit stop, sidewalk, bike lane, and bike rack were measured for each BG. The influences of proximity to rapid transit services (trains, rails, and express buses) and park-and ride centers were considered. To measure transit stop density (this study covers all modes of public transit services), expanded BGs needed to be applied. The U.S. Census geographies normally overlap with arterial roadways, and most transit stops exist along arterial thoroughfares and local roads. Thus, if transit stops were located slightly outside the borders of the BGs, they were not counted as accessible transit, despite the easily accessible distance to neighborhoods. To deal with this issue, the boundaries had to be enlarged by 200 ft to contain the readily reachable transit stops, even those outside boundaries. The 200-ft buffers were determined based on previous literature; Dumbaugh et al. (2011) indicated that 200 ft is “roughly the row width of a fully designed principal arterial.” However, these buffers were not applied to the other three transport facilities (sidewalks, bike lanes, and bike racks) because multicollinearity problems arose. The total length of sidewalks (regardless of width) and bike lanes (all kinds of bike ways regardless of width), and the total number of bike racks (locations of a stationary fixture regardless of the number of bicycles parked there) were directly divided by the areas of the normal

BGs. Overall, Seattle and Portland showed higher infrastructure densities than the other cities. Portland had the second highest figures. Texas showed lower levels of transportation infrastructure density than the other states overall. To assess the influences of rapid transit services (trains, rails, and express buses) and park-and-ride centers on preference for transit commuting, 0.5- and 1.5-mile buffers were created from the transportation facilities, respectively.

3.3. Analytical Methods

3.3.1 Best-Fitting Model Choice

Since the dependent variable contained excessive zeros (there were no transit commuters in the BG) and overdispersed distribution, zero-inflated negative binomial (ZINB) and negative binomial (NB) regression models were chosen (ZINB for six cities and NB for Seattle).

The proportion of BGs with no public transit commuter (zero BGs) ranged from 30.8 to 68.6 percent throughout the four cities in Texas. The same patterns were in part found in Denver and Portland, but not as prominently as in Texas. About 14 percent of BGs in Denver failed to report any number (not zero) in terms of transit commuters. Portland had an absence of transit commuters in approximately 4 percent of the communities. Conversely, Seattle reported that almost all BGs had at least one transit commuter (Table 5). Another determinant factor for model choice was detected from the distribution patterns of the dependent variable. All the cities showed intense overdispersions of the count data; the variance in the number of transit commuters was much greater than the mean value (Table 6).

Table 5. Percentage of the Block Groups with No Transit Commuter

City	Total Number of BGs	Number of BGs with Zero Transit Commuter
Austin	496	153 (30.8%)
Dallas	919	308 (33.5%)
Denver	480	69 (14.4%)
Fort Worth	507	348 (68.6%)
Portland	441	16 (3.61%)
San Antonio	882	333 (37.7%)
Seattle	478	4 (0.8%)

Table 6. Overdispersion Patterns of the Dependent Variable

City	Average Number of Transit Commuters	Variance in the Number of Transit Commuters
Austin	41.1	5,334.4
Dallas	28.5	1,492.1
Denver	49.6	2,620.4
Fort Worth	6.9	250.6
Portland	87.8	4,942.0
San Antonio	24.2	1,207.6
Seattle	159.0	10,836.1

The ZINB and NB models are extension versions of the Poisson regression model. When the dependent variable is a non-negative integer and the count is not normally distributed, the Poisson regression model is more appropriate for statistical modeling than the ordinary least squares model. When the dependent variable meets these conditions and the distribution of the count is heavily skewed at the same time—the variance is considerably greater than the mean—the NB regression model is preferred. In addition to the evidence for the NB model, if the count variable has a preponderance of zeros as well, the ZINB model is more suitable than the NB model (Long & Freese, 2006). Formal evidence was obtained using the Vuong and Alpha tests (Table 7).

Table 7. Vuong and Alpha Test Results

City	Vuong Test		Alpha Test		Best Suited Model
	Statistics	P-value	Statistics	P-value	
Austin	11.90	0.0000	0.5039	0.000	ZINB
Dallas	16.40	0.0000	−2.2036	0.000	ZINB
Denver	4.05	0.0000	0.2309	0.000	ZINB
Fort Worth	7.32	0.0000	0.3915	0.000	ZINB
Portland	8.39	0.0000	0.4158	0.000	ZINB
San Antonio	16.33	0.0000	0.5275	0.000	ZINB
Seattle	N/A	N/A	0.2205	0.000	NB

Notes: N/A denotes that the Vuong test is not applicable for Seattle.

3.3.2 Details of ZINB and NB Model

The probability equations of the ZINB model consist of two functions: (1) for the two kinds of zeros (false zeros and true zeros), and (2) for positive counts that are negative-binomially distributed. The second function calculates the predicted probability for a positive count that is negative-binomially distributed.

$$f(y_i = 0) = \pi_i + (1-\pi_i) \times \left(\frac{k}{\mu_i + k}\right)^k \quad (1)$$

$$f(y_i \mid y_i > 0) = (1-\pi_i) \times f_{NB}(y) \quad (2)$$

where

- f stands for the probability function,
- y_i is the possible outcome for the i^{th} observation,
- k=1/α, α is a parameter of dispersion,
- π_i is the probability of falling into the false zeros, and
- $1-\pi_i$ is the probability of falling into the true zeros and counts for the i^{th} observation. The equation for the π_i is as follows:

$$\pi_i = \frac{e^{\mu_i}}{1+e^{\mu_i}} \quad (3)$$

The probability function for the NB model, $f_{NB}(y)$, is written as:

$$f_{NB}(y) = f(y_i \mid y_i > 0) = \frac{\Gamma(y_i + k)}{y!\Gamma(k)} \times \left(\frac{k}{\mu_i + k}\right)^{k} \left(\frac{k}{\mu_i + k}\right)^{y_i} \quad (4)$$

where Γ is the gamma function regarding over-dispersion.

The expected count, μ, for a BG in a city, follows the equation:

$$\mu = \exp\left[\, \alpha + \ln(E) + \boldsymbol{\beta}_{\mathbf{N}}\mathbf{N} + \boldsymbol{\beta}_{\mathbf{T}}\tilde{\mathbf{T}} + (\beta_S + \boldsymbol{\beta}_{\mathbf{X}}\tilde{\mathbf{T}})\tilde{S} + \boldsymbol{\beta}_{\mathbf{B}}\mathbf{B} + \varepsilon \,\right] \quad (5)$$

where

- α is a constant;
- $\ln(E)$, the exposure variable, is the logarithm of total number of workers in a BG;
- **N** is a (11 × 1) vector of explanatory variables;
- $\tilde{\mathbf{T}}$ is a (3 × 1) vector of variables for the density of pedestrian and bicycle facilities;
- $\tilde{\mathbf{S}}$ is transit stop density;
- **B** is a (2 × 1) vector of binary variables for existence of rapid transit and park-and-ride facilities;
- $\boldsymbol{\beta}_{\mathbf{N}}$, $\boldsymbol{\beta}_{\mathbf{T}}$, and $\boldsymbol{\beta}_{\mathbf{B}}$ are vectors of coefficients, $\boldsymbol{\beta}_{\mathbf{S}}$ is the coefficient of transit stop density, and $\boldsymbol{\beta}_{\mathbf{X}}$ is the coefficient of interaction terms; and

- ε is the error term.

To facilitate the interpretation of results, four variables (transit stop density, sidewalk density, bike lane density, and bike rack density) were normalized following previous research (Anderson & West, 2006; Li et al., 2015; Saphores & Li, 2012).

$$\tilde{\mathbf{m}} = \frac{\mathbf{m} - \bar{\mathbf{m}}}{\bar{\mathbf{m}}} \quad (6)$$

where

- m is the original value of variable m,
- $\bar{m}$ is the sample mean of the variable m, and
- $\tilde{m}$ is the normalized value of variable m.

Multicollinearity between independent variables was tested using the variance inflation factor 10 (VIF). The VIF of bike rack density and its interaction term with transit stop density exceeded 10 in Denver (15.2 and 15.0). After removing the bike rack density in Denver, the value of the interaction term decreased to 2.27, and coefficients on other variables are not considerably affected.

4. REGRESSION RESULTS

Table 8 shows the ZINB/NB regression results. The ZINB model estimates two regression equations concurrently for the data with excessive numbers of zeros and non-zeros (positive integers); one is for the non-zero observations (Table 8), and the other is for the zero observations (Appendix H). For ease of interpretation, the model coefficients (non-zero observations) were transformed into percent changes in the expected number of transit commuters per unit in explanatory variables (Table 9). Regression results are reported using the transformed percent changes.

Table 8. ZINB and NB Regression Models Estimating Transit Commuter (Non-zero Observation)

Variable Name	Austin	Dallas	Denver	Fort Worth	Portland	San Antonio	Seattle
Socioeconomic Factors							
Median household income, $1,000	**−0.0126*****	**−0.0032****	**−0.0070*****	−0.0047	**−0.0069*****	**−0.0090*****	**−0.0024*****
	(0.0022)	*(0.0013)*	*0(.0014)*	*(0.0038)*	*(0.0015)*	*(0.0022)*	*(0.0009)*
Percent of African-American, 0-1	0.3355	**1.0289*****	**1.1271*****	**1.0266*****	0.1643	0.4069	0.1192
	(0.4530)	*(0.1378)*	*(0.3200)*	*(0.3071)*	*(0.3634)*	*(0.2960)*	*(0.2541)*
Percent of non-White Hispanic, 0-1	−0.3252	**0.5577****	0.1565	0.4146	0.2950	0.2859	0.1005
	(0.5130)	*(0.2700)*	*(0.4430)*	*(0.7676)*	*(0.5493)*	*(0.3648)*	*(0.5570)*
Percent of nonfamily household, 0-1	0.2069	**−0.3919***	−0.2286	−0.0510	**0.7516*****	**−0.4797***	**0.3646***
	(0.3441)	*(0.2004)*	*(0.2773)*	*(0.4208)*	*(0.2565)*	*(0.2648)*	*(0.2062)*
Built Environment							
Population density, 1,000 per sq. mile	0.0039	**−0.0101****	−0.0023	−0.0261	0.0095	**−0.0529*****	−0.0053
	(0.0108)	*(0.0043)*	*(0.0085)*	*(0.0223)*	*(0.0072)*	*(0.0134)*	*(0.0032)*
Employment density, 1,000 per sq. mile	**0.0142****	−0.0011	**−0.0055***	0.0136	0.0003	**−0.0136***	**−0.0014****
	(0.0072)	*(0.0036)*	*(0.0030)*	*(0.0160)*	*(0.0029)*	*(0.0079)*	*(0.0006)*
Percent of one-unit housing, 0-1	−0.2981	**−0.4674*****	**−0.5445*****	**−0.6749****	−0.1910	**−0.9561*****	**−0.2510***
	(0.2218)	*(0.1310)*	*(0.2014)*	*(0.2769)*	*(0.1700)*	*(0.1829)*	*(0.1482)*
Median year housing built, year	−0.0004	0.0001	−0.0000	−0.0001	0.0020	−0.0000	0.0001
	(0.0004)	*(0.0003)*	*(0.0002)*	*(0.0004)*	*(0.0024)*	*(0.0003)*	*(0.0001)*
Direct distance to CBD, mile	**−0.0543*****	**−0.0589*****	**−0.0722*****	−0.0096	−0.0341	**−0.0483*****	−0.0154
	(0.0185)	*(0.0104)*	*(0.0186)*	*(0.0219)*	*(0.0242)*	*(0.0149)*	*(0.0161)*
4-way intersection density, count per sq. mile	−0.0000	−0.0001	−0.0004	0.0004	0.0005	**0.0029*****	0.0007
	(0.0015)	*(0.0009)*	*(0.0008)*	*(0.0021)*	*(0.0006)*	*(0.0009)*	*(0.0005)*
Active Commuter							
Walking commuters, count	**−0.0042*****	−0.0017	−0.0005	−0.0030	**−0.0012****	**−0.0014*****	**−0.0005****
	(0.0009)	*(0.0011)*	*(0.0006)*	*(0.0032)*	*(0.0005)*	*(0.0005)*	*(0.0002)*
Bike commuters, count	−0.0022	0.0011	−0.0018	0.0022	0.0005	0.0005	0.0004
	(0.0016)	*(0.0038)*	*(0.0014)*	*(0.0086)*	*(0.0006)*	*(0.0039)*	*(0.0006)*

Notes: 1) ***P-value < 0.01, **P-value < 0.05, *P-value < 0.1.
2) Standard errors are in parentheses.

Table 8. ZINB and NB Regression Models Estimating Transit Commuter (Non-zero Observation), continued

Variable Name	Austin	Dallas	Denver	Fort Worth	Portland	San Antonio	Seattle
Transport Infrastructure							
Normalized transit stop density, count per sq. mile	**0.2017***** *(0.0655)*	**0.2076***** *(0.0498)*	−0.0121 *(0.0704)*	**0.1381*** *(0.0774)*	0.0769 *(0.0641)*	**0.1909***** *(0.0633)*	**0.0927*** *(0.0509)*
Normalized sidewalk density, length per sq. mile	0.0208 *(0.0999)*	**−0.1643**** *(0.0743)*	0.1150 *(0.1918)*	0.1287 *(0.1031)*	−0.0927 *(0.0930)*	0.0801 *(0.0866)*	0.0051 *(0.1511)*
Normalized bike lane density, length per sq. mile	−0.0188 *(0.1083)*	0.0089 *(0.0144)*	0.0308 *(0.0400)*	0.0351 *(0.0411)*	0.0776 *(0.1429)*	0.0416 *(0.0312)*	−0.0716 *(0.1477)*
Normalized bike rack density, count per sq. mile	N/A	N/A	N/A	N/A	−0.0110 *(0.0235)*	N/A	0.0090 *(0.0252)*
Normalized transit stop density × normalized sidewalk density	**−0.1652*** *(0.0855)*	**−0.1470**** *(0.0662)*	−0.3429 *(0.2373)*	−0.0941 *(0.0855)*	**−0.3099***** *(0.1174)*	**−0.1818**** *(0.0762)*	**−0.2401*** *(0.1283)*
Normalized transit stop density × normalized bike lane density	−0.1018 *(0.1021)*	0.0032 *(0.0130)*	0.0097 *(0.0528)*	−0.0254 *(0.0297)*	−0.0539 *(0.1851)*	**−0.0564**** *(0.0280)*	0.0484 *(0.1063)*
Normalized transit stop density × normalized bike rack density	N/A	N/A	0.0047 *(0.0031)*	N/A	**0.0191*** *(0.0109)*	N/A	0.0016 *(0.0145)*
BG within 0.5 miles from rapid transit: 1	**−0.2438**** *(0.1040)*	−0.0605 *(0.0983)*	0.0769 *(0.1057)*	**−0.4712**** *(0.2384)*	0.0517 *(0.0610)*	0.2547 *(0.1844)*	**0.1663***** *(0.0626)*
BG within 1.5 miles from park and ride: 1	0.1768 *(0.1253)*	0.0888 *(0.0704)*	0.0622 *(0.0830)*	0.1178 *(0.2385)*	0.0885 *(0.0598)*	0.0484 *(0.1189)*	0.0862 *(0.0608)*
Constant	−0.9636 *(0.8554)*	−2.2036*** *(0.6200)*	−1.3847*** *(0.5037)*	−2.8025*** *(0.8555)*	−5.8769 *(4.7733)*	−1.1509* *(0.6036)*	−1.7762*** *(0.3282)*
Number of observations (non-zero/zero)	341/153	607/308	410/69	159/348	424/16	548/333	474/4
LR chi2	180.8	255.0	111.5	63.6	184.1	222.8	128.521
Prob > chi2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Log likelihood	−1863.5	−3222.8	−2110.0	−886.0	−2150.3	−2957.0	−2150.3

Notes: 1) ***P-value < 0.01, **P-value < 0.05, *P-value < 0.1.
2) Standard errors are in parentheses.
3) N/A denotes not available.

Table 9. Expected Number of Transit Commuters in Percent Changes

Variable Name	Austin	Dallas	Denver	Fort Worth	Portland	San Antonio	Seattle
Socioeconomic factors							
Median household income, $1,000	**−1.3*****	**−0.3****	**−0.7*****	−0.5	**−0.7*****	**−0.9*****	**−0.2*****
Percent of African-American, 0-1	0.4	**1.8*****	**2.1*****	**1.8*****	0.2	0.5	0.1
Percent of non-White Hispanic, 0-1	−0.3	**0.7****	0.2	0.5	0.3	0.3	0.1
Percent of nonfamily household, 0-1	0.2	**−0.3***	−0.2	−0.1	**1.1*****	**−0.4***	**0.4***
Built Environment							
Population density, 1,000 per sq. mile	0.4	**−1.0****	−0.2	−2.6	1.0	**−5.1*****	−0.5
Employment density, 1,000 per sq. mile	**1.4****	−0.1	**−0.6***	1.4	0.0	**−1.4***	**−0.1****
Percent of one-unit housing, 0-1	−0.3	**−0.4*****	**−0.4*****	**−0.5****	−0.2	**−0.6*****	**−0.2***
Median year housing built, year	−0.0	0.0	−0.0	−0.0	0.2	−0.0	0.0
Direct distance to CBD, mile	**−5.3*****	**−5.7*****	**−7.0*****	−1.0	−3.4	**−4.7*****	−1.5
4-way intersection density, count per sq. mile	−0.0	−0.0	−0.0	0.0	0.0	**0.3*****	0.1
Active Commuter							
Number of walking commuters, count	**−0.4*****	−0.2	−0.0	−0.3	**−0.1****	**−0.1*****	**−0.1****
Number of bike commuter, count	−0.2	0.1	−0.2	0.2	0.1	−0.0	0.0
Transport Infrastructure							
Nor. transit stop density, count per sq. mile	**22.3*****	**23.1*****	−1.2	**14.8***	5.1	**21.0*****	**9.7***
Nor. sidewalk density, length per sq. mile	2.1	**−15.2****	12.2	13.7	−8.9	8.3	0.5
Nor. bike lane density, length per sq. mile	−1.9	0.9	3.1	3.6	8.1	4.3	−6.9
Nor. bike rack density, count per sq. mile	N/A	N/A	N/A	N/A	−2.9	N/A	1.9
Nor. transit stop density × nor. sidewalk density	**−15.2***	**−13.7****	−29.0	−9.0	**−26.6*****	**−16.6****	**−21.3***
Nor. transit stop density × nor. bike lane density	−9.7	0.3	1.0	−2.5	−5.2	**−5.5****	5.0
Nor. transit stop density × nor. bike rack density	N/A	N/A	0.5	N/A	**1.9***	N/A	0.2
BG within 0.5 miles from rapid transit: 1	**−21.6****	−5.9	8.0	**−37.6****	5.3	29.0	**18.1*****
BG within 1.5 miles from park and ride: 1	19.3	9.3	6.4	12.5	9.3	5.0	9.0

Notes: 1) ***P-value < 0.01, **P-value < 0.05, *P-value < 0.1.
2) N/A denotes not available.
3) Nor. Stands for normalized.

4.1. Influential Factors on Transit Commuting

4.1.1 Socioeconomic Factors

The impacts of the socioeconomic characteristics of the neighborhoods where workers reside are first reported as percent changes in the expected number of transit commuters per unit in independent variables. For most cities, household income was a strong predictor and was negatively associated with transit ridership for work journeys, as acknowledged in previous literature. For every $1,000 increase in median household income, the expected number of workers who commute by public transit in a BG decreased by 0.2 percent to 1.3 percent across the cities, holding other factors equal.

Looking at the influences of a certain type of race and ethnicity, the concentration of African-American communities affected transit ridership in Dallas, Fort Worth, and Denver, whereas non-White Hispanics were statistically associated with transit use solely in Dallas. For the first three cities, for an additional 1 percent increase in African-American communities, it is expected that there will be about 2 percent more workers who mainly use public transportation services to get to work. In Dallas, 1 percent more non-White Hispanics resulted in 0.7 percent more work trips made by public transit.

Transit commuting was in part explained by family type, but results were somewhat confounding. While a higher nonfamily household rate (an additional 1 percent) was negatively correlated with transit commuting in Dallas (−0.3 percent) and

San Antonio (−0.4 percent), it was a positive predictor in Portland (1.1 percent) and Seattle (0.4 percent).

4.1.2 Built Environmental Factors

Built environment characteristics varied by city. Population density represented counterintuitive results. Population density was inversely related to transit mode share in Dallas and San Antonio (1,000 more people per square mile were significantly correlated with 1.0 percent and 5.1 percent lower transit ridership, respectively) but did not affect transit commuting in the other cities. The other remaining cities did not show any significant relationship with transit commuting.

Employment density showed similar patterns. In Denver, San Antonio, and Seattle, higher job density was negatively linked to the greater number of transit commuters, indicating a 0.1 percent, 0.6 percent, and 1.4 percent reduction, respectively, with 1,000 more employees per square mile ($p < 0.05$, $p < 0.1$, and $p < 0.1$, respectively). By contrast, for Austin, a one-unit increase in employment density had a positive correlation, with a 1.4 percent more transit market share at the 5 percent confidence level.

Employees living in a single-family housing community were less likely to use mass transit services to get to work in five cities. Controlling other variables, with a 1 percent increase in single-unit houses, the number of workers willing to take public transit was reduced by 0.2 percent to 0.6 percent in Dallas, Denver, Fort Worth, San Antonio, and Seattle.

The year housing was built was not a determinant factor in any city. As for proximity to the CBD, a greater distance from the CBD was correlated with fewer workers using transit in four cities. On average, an additional 1-mile longer distance was associated with a decrease in the number of transit commuters by 5.0 percent to 7 percent (Austin, Dallas, Denver, and San Antonio).

Better street connectivity measured by four-way intersection density had a positive influence on transit usage only in San Antonio. When there is one or more intersection per square mile in the community, it was expected that the number of public transit patrons would climb by 0.3 percent, which was significant at a 1 percent level.

4.1.3 Active Commuters

Walking indicated trade-off associations with transit commuters in Austin, Portland, San Antonio, and Seattle. With each additional commuter walking to work, the number of transit commuters decreased by 0.1 to 0.4 percent. While public transit was in a competitive correlation with walking, cycling neither invaded nor complemented the spheres of transit services throughout the study areas.

4.2. Effects of Transport Infrastructure

Increasing transit stop density in a neighborhood would encourage some commuters to switch from automobiles to transit in five cities. In Austin, when transit stop density increased by its mean value (26.9 stops/mile^2), the expected number of public transit commuters grew by 22.3 percent, holding all other variables at their means. For ease of interpretation, this can be expressed again as follows: if 27 bus stops are added in a neighborhood where 10 bus stops exist already—that is, if the number of bus stops increases from 10 to 37 per square mile—the number of transit users for work trips will rise by 22.3 percent, fixing all the other factors at their average level. Applying the same approach to Dallas, if transit agencies establish on average 82 bus stops per square mile in the existing mass transportation networks, about 23.1 percent more people will get to work using public transport services, keeping Condition α ($p < 0.001$). In Fort Worth, when the density increases by its average value (about 24 stops/mile^2) with Condition α, this city will be able to expect 14.8 percent more transit passengers during rush hour ($p < 0.1$). For San Antonio, having a transit stop density higher than the sample mean (nearly 57 bus stops/square mile) than now under Condition α, the ratio of employees who commute on public transit will increase by 21.0 percent, all else being equal at their mean ($p < 0.01$). Seattle seems to need greater investments in transit systems to increase ridership; the coefficient indicated that 100 more transit stops per square mile would enhance transit commuting rates by an average of 9.7 percent ($p < 0.1$). However, residents in Denver and Portland would not change their commuting mode even if additional transit facilities were provided in their neighborhoods.

Sidewalks showed a statistical significance only in Dallas in an inverse way. Specifically, when there were approximately 20 more miles of sidewalks per square mile and other variables remained at their means, on average 15.2 percent of workers were more likely to drive to work than take transit at a 5 percent confidence level.

As for bike facilities, bike lanes, and bicycle racks, it appears that they did not matter in mode choice for transit work trips in general. The bike lane density at the BG level did not have significant associations with the levels of transit usage in all of the study areas. Bike rack density, which was assessed for Portland and Seattle due to data availability (Texas cities) and a high multicollinearity problem (Denver), was not directly statistically related with transit ridership.

When it comes to the impacts of rapid transit services, two Texas cities, Austin and Fort Worth, presented unexpected outcomes. If the BG is inside a 0.5-mile radius from the transit stops or stations that serve commuters with higher speed and fewer stops, the estimated number of people who commute by public transit in the neighborhood dropped by 21.6 percent and 37.6 percent in Austin and Fort Worth, respectively ($p < 0.05$). This result is confounding because it contradicts the positive impact of increased transit stops. In contrast, the proximity to the rapid commuting services was effective in increasing transit patronage in Seattle by 18.1 percent, which is significant at a 5 percent confidence level. For another binary variable to estimate the relationship between park-and-ride centers and the transit market share, it seems that these facilities were unfruitful in encouraging commuters to use transit by allowing them to park their cars near transit hubs and transfer to public transit in all the cities, at least in this analysis.

4.3. Synergistic Effects of Public Transport Infrastructure

The quantifying process is described using percent changes in Table 10, assuming sidewalk, bike lane, and bike rack density increases by the amount of its mean value for a city.

Table 10. Synergistic Effects of Transit Stops and Nonmotorized Infrastructure by Percent Change

Variable	Classification	β_S ①	β_X ②	$\beta_S + \beta_X$ ① + ② = ③	③ - ①
Sidewalk	Austin				
	coefficient	*0.2017******	*−0.1652**	*0.0365*	
	% change	**22.3%**	**−15.2%**	**3.7%**	18.6% (↓)
	Dallas				
	coefficient	*0.2076******	*−0.1470****	*0.0606*	
	% change	**23.1%**	**−13.7%**	**6.3%**	16.8% (↓)
	Portland				
	coefficient	*0.0769*	*−0.3099******	N/A	N/A
	% change	5.1%	**−26.6%**		
	San Antonio				
	coefficient	*0.1909******	*−0.1818****	*0.0091*	
	% change	**21.0%**	**−16.6%**	**0.9%**	20.1% (↓)
	Seattle				
	coefficient	*0.0927**	*−0.2401**	*−0.1474*	
	% change	**9.7%**	**−21.3%**	**−13.7%**	23.4% (↓)
Bike lane	San Antonio				
	coefficient	*0.1909******	*−0.0564****	*0.1346*	
	% change	**21.0%**	**−5.5%**	**14.4%**	6.6% (↓)
Bike rack	Portland				
	coefficient	*0.0769*	*0.0191**	N/A	N/A
	% change	5.1%	**1.9%**		

Notes: 1) ***P-value < 0.01, **P-value < 0.05, *P-value < 0.1.
2) N/A denotes that the calculation is not available because the main effect is insignificant.

Contrary to expectations, there was no impressive synergistic impact of integrated public transit systems and nonmotorized transportation supportive facilities.

The coefficients of sidewalk density were consistently negative and significant in five cities, indicating that the impact of increased transit stop density on transit usage would decrease due to additional sidewalk provision. For Austin, when sidewalk density doubled from its sample mean (16.3 miles per square mile), transit stop density increased by its mean value (26.9 stops per square mile), and other variables were controlled at their means; the number of workers commuting by transit increased by 3.7 percent. The percent change was 22.3 percent when the transit stop density increased alone. In other words, well-connected sidewalks were more likely to decrease the effect size of transit stops on the number of workers commuting by transit rather than support public transportation systems. In Dallas, applying the same process, the expected transit ridership would increase by 6.3 percent (this figure is 16.8 percent lower than the stand-alone effects of transit at 23.1 percent). In Portland, although the direct effects of transit stop density were insignificant, the interaction term was statistically significant. Only focusing on interaction terms, the estimation resulted in a considerable decrease in the number of transit commuters by 26.6 percent. This means that transit stops in residential areas did not affect workers' commutes by transit, but when there were more sidewalks, the percent of transit commuters even decreased. Under the same scenario of transit and sidewalk doubling, transit commuting increased by 0.9 percent (dropped from 21.0 percent) for San Antonio. In Seattle, the percent change declined from 9.7 to −13.7 percent.

The synergistic effects of bicycle facilities on transit commuting is nonsignificant for all cities but San Antonio. When bike lane density doubled from its sample mean (3.4 miles per square mile) and transit stop density increased by 57.0 stops per square mile, the percent change in transit ridership for commuting was 14.4 percent. This percent change is lower than the 21.0 percent change when transit stop density increased by the sample mean alone, with all other variables unchanged at their means. Among the three cities where bike rack data were available, only Portland represented a statistical significance. When bike rack density and transit stop density increased at their sample means, there would be 1.9 percent more public transit commuters in neighborhoods.

5. DISCUSSION AND CONCLUSIONS

5.1. Discussion and Conclusions

This study explores how transportation infrastructure affects transit usage, focusing on commuting. Transit accessibility, as represented by transit stop density, was positively related to the use of public transit. Overall, availability of transit stops was an important factor in deciding to take transit to get to work, which is consistent with claims in a previous study that used the same density measurement (Chakrabarti, 2017). Commuters from the Texas cities seemed to be more sensitive to transit accessibility improvement than commuters from the other cities; this might be associated with lower population density and existing transit stop density. When transit stop density increased by each city's average value (other factors remaining at their means), on average transit commuters would grow by 20 percent in the four Texas cities, implying a high demand for transit stops. Based on the quantified effects of transit stops, sprawled areas are expected to reap greater benefits from providing transit stops than would high-density cities.

Some previous studies found that sidewalk continuity had positive correlations with transit mode choice (Cervero, 2001; Hess, 2009; Loutzenheiser, 1997). However, this study shows that sidewalks did not generate direct effects on transit commuting. Further, this study found that more sidewalks might compromise the effect of transit stop density on transit commuting. Neighborhoods built recently tend to have better sidewalk networks, and thus average housing age was controlled in the statistical analysis. Such an unexpected finding might be due to two reasons. First, built environments and infrastructure conditions around workplaces were not considered in the final model. For workers, the choice of commuting mode may be affected by employment-based conditions (e.g., free parking opportunities at work). Second, good neighborhood transportation infrastructure might positively affect residence selection, but self-selection would not directly translate into transit mode choice. People might prefer to live in communities with good transportation infrastructure but do not use them for work trips. In addition to sidewalks, bike networks were ineffective in helping urban transportation systems attract more commuter passengers. Even in San Antonio, the effect was negative. Enhanced bike lane networks are not yet a significant matter in terms of transit performance. These results raise concerns about the beliefs and strategies around integrating transit systems with sidewalk and bicycle networks.

Bike parking facilities were found to have the potential for bike and ride. In Portland, a high density of bike parking facilities was positively associated with the impact of transit stops on more transit commuting. Although provision of transit stops was insignificant alone, it worked with bike racks. The findings in Portland are in line with the city's efforts over recent decades and what it has accomplished to date; their bike commuting rate is over 6.4 percent, the highest of any of the 50 largest cities in the United States, according to the U.S. Census Bureau (2016). Given that Portland is recognized as one of the most bike-friendly cities in the United States, is frequently benchmarked for its progressive policies, has made great provision of bike infrastructure, and contains a considerably large bike-riding population, this result suggests policy implications for other cities. The growing bicycle share programs are expected to play a role in facilitating bike-and-ride or ride-and-bike trips. For agencies considering integrating cycling and transit networks, transit-rich communities would be preferred as a priority target area for establishing bike parking facilities. From a transport equity perspective, it is essential to consider neighborhoods with low transit accessibility. Low-income minority neighborhoods could benefit from integration of transit and bike parking services.

As for socioeconomic factors, household income was a critical predictor in estimating transit use for home-based work trips in six study areas. While non-White Hispanics have been recognized as major transit patrons in previous studies, this community only mattered in Dallas when controlling other factors (Chu, 2004; Pucher & Renne, 2003). The composition of households also affected transit usage in four cities in a counterintuitive way: negative in two cities (Dallas and San Antonio) and positive in two other cities (Portland and Seattle). This may be related to the percentage of college students, who are more likely to live in nonfamily households and use public transportation systems because of limited access to personal vehicles. When the ratios were compared (see Appendix I), Dallas and San Antonio had about 6 and 7 percent college students, respectively, while Portland and Seattle had about 10 and 12 percent, respectively. Members of the nonfamily households in Dallas and San Antonio could be more likely to be car owners, whereas transit-dependent students are more likely be in this type of household in Portland and Seattle.

In terms of built environment factors, a few outcomes turned out to be contrary to expectations. First, either high population density or employment density had consistently negative or no significant relationship with transit ridership in all the cities except for Austin. This counterintuitive result can be partially supported by a previous study. Rodriguez and Joo (2004) tested the relationship between population density and mode choice and had the same outcomes. Contrary to their initial expectations, the residential density of BGs negatively affected people's preference to use transit. In addition to this study, other scholars' suggestions are helpful to explain the results. High population density at trip origins can be a catalytic factor that stimulates transit use rather than a direct determinant due to the intensively linked transit networks, short trip distances to destinations, and better access to transit in the highly dense area (Cervero, 2001; Ewing & Cervero, 2001). Accordingly, density might not be directly associated with greater transit market share in comparing neighborhoods across a city.

Transit and walking appear to compete with each other in mode share. The higher the proportion of walking commuters, the lower the ratio of commuters using transit, as was reported in four cities. These results are inconsistent with the study that longitudinally explored the potential long-term complementary relationship of the two modes (Singleton & Clifton, 2015). In that study, increased bike commuting was positively related with transit ridership in large U.S. urbanized areas from 2000 to 2010. However, the findings of this current cross-sectional study based on seven cities demonstrated that cycling neither invaded nor complemented the spheres of transit services.

5.2. Limitations

This study has several limitations. First, the findings might not be applicable to every city because determinant factors on commuting mode choice were not all controlled (e.g., personal propensity, workplace conditions, and vehicle availability). Second, the density measurement did not categorize facility types based on different levels of user comfort (e.g., protected bike lanes are preferred by bicyclists). As previous literature has pointed out, adequate bike facility data were limited (Schneider, 2005).

Despite these limitations, future studies could develop a robust framework based on the research findings to measure transit performance combined with nonmotorized infrastructure. Transit agencies and transportation authorities could then have a better understanding of how to coordinate investments in transit infrastructure to improve the efficiency of the entire transportation network. The results provide quantified direct and synergistic effects of transport infrastructure on transit commuting through empirical evidence across the cities studied. At the same time, the results suggest that infrastructure alone may not be sufficient to encourage commuting by transit.

REFERENCES

American Public Transportation Association. (2017). *2016 Public Transportation Fact Book*. American Public Transportation Association, Washington, DC.

Anderson, S. T., & West, S. E. (2006). Open Space, Residential Property Values, and Spatial Context. *Regional Science and Urban Economics*, *36*(6), 773-789.

Antrim, A., & Barbeau, S. J. (2013). *The Many Uses of GTFS Data–Opening the Door to Transit and Multimodal Applications.* Location-Aware Information Systems Laboratory at the University of South Florida. Retrieved from http://www.locationaware.usf.edu/wp-content/uploads/2010/02/The-Many-Uses-of-GTFS-Data-%E2%80%93-ITS-America-submission-abbreviated.pdf.

Bachand-Marleau, J., Larsen, J., & El-Geneidy, A. (2011). Much-Anticipated Marriage of Cycling and Transit: How Will It Work? *Transportation Research Record: Journal of the Transportation Research Board*, (2247), 109-117.

Boarnet, M. G., & Crane, R. (2001). *Travel by Design: The Influence of Urban Form on Travel*. Oxford University Press on Demand.

Carlton, I. (2009). *Histories of Transit-Oriented Development: Perspectives on the Development of the TOD Concept*. Working Paper. Institute of Urban and Regional Development, University of California, Berkeley.

Cervero, R., & Gorham, R. (1995). Commuting in Transit versus Automobile Neighborhoods. *Journal of the American Planning Association*, *61*(2), 210-225.

Cervero, R., & Kockelman, K. (1997). Travel Demand and the 3Ds: Density, Diversity, and Design. *Transportation Research Part D: Transport and Environment*, *2*(3), 199-219.

Cervero, R. (2001). Walk-and-Ride: Factors Influencing Pedestrian Access to Transit. *Journal of Public Transportation*, *7*(3). 1-23.

Chakrabarti, S. (2017). How Can Public Transit Get People out of Their Cars? An Analysis of Transit Mode Choice for Commute Trips in Los Angeles. *Transport Policy*, *54*, 80-89.

Chu, X. (2004). *Ridership Models at the Stop Level*. Final Report NCTR-473-04, BC 137-31. National Center for Transit Research, University of South Florida

Crowley, D., Shalaby, A., & Zarei, H. (2009). Access Walking Distance, Transit Use, and Transit-Oriented Development in North York City Center, Toronto, Canada. *Transportation Research Record: Journal of the Transportation Research Board*, (2110), 96-105.

Dill, J. (2008). Transit Use at Transit-Oriented Developments in Portland, Oregon, Area. *Transportation Research Record: Journal of the Transportation Research Board*, (2063), 159-167.

Dill, J., & Carr, T. (2003). Bicycle Commuting and Facilities in Major US Cities: If You Build Them, Commuters Will Use Them. *Transportation Research Record: Journal of the Transportation Research Board*, (1828), 116-123.

Dumbaugh, E., Rae, R., & Wunneberger, D. (2011). Using GIS to Develop a Performance-Based Framework for Evaluating Urban Design and Crash Incidence. *Urban Design International*, *16*(1), 63-71.

Ewing, R., & Cervero, R. (2001). Travel and the Built Environment: A Synthesis. *Transportation Research Record: Journal of the Transportation Research Board*, (1780), 87-114.

Fan, W., & Machemehl, R. (2011). Bi-level Optimization Model for Public Transportation Network Redesign Problem: Accounting for Equity Issues. *Transportation Research Record: Journal of the Transportation Research Board*, (2263), 151-162.

Federal Transit Administration (2016). *Total Funding Time-Series*. Retrieved from https://www.transit.dot.gov/ntd/data-product/ts11-total-funding-time-series-0.

Griffin, G. P., & Sener, I. N. (2016). Planning for Bike Share Connectivity to Rail Transit. *Journal of public transportation*, *19*(2), 1-22.

Hess, D. B. (2009). Access to Public Transit and Its Influence on Ridership for Older Adults in Two U.S. Cities. *Journal of Transport and Land Use*, 2(1), 3–27.

Hsiao, S., Lu, J., Sterling, J., & Weatherford, M. (1997). Use of Geographic Information System for Analysis of Transit Pedestrian Access. *Transportation Research Record: Journal of the Transportation Research Board*, (1604), 50-59.

Krizek, K., & Stonebraker, E. (2011). Assessing Options to Enhance Bicycle and Transit Integration. *Transportation Research Record: Journal of the Transportation Research Board*, (2217), 162-167.

Li, W., Joh, K., Lee, C., Kim, J. H., Park, H., & Woo, A. (2015). Assessing Benefits of Neighborhood Walkability to Single-Family Property Values: A Spatial Hedonic Study in Austin, Texas. *Journal of Planning Education and Research*, *35*(4), 471-488.

Long, J. S., & Freese, J. (2006). *Regression Models for Categorical Dependent Variables Using Stata*. Stata Press.

Loutzenheiser, D. (1997). Pedestrian Access to Transit: Model of Walk Trips and Their Design and Urban Form Determinants around Bay Area Rapid Transit Stations. *Transportation Research Record: Journal of the Transportation Research Board*, (1604), 40-49.

Lund, H. M., Cervero, R., & Wilson, R. W. (2004). *Travel Characteristics of Transit-Oriented Development in California*. Bay Area Rapid Transit District and California Department of Transportation.

Ma, T., Liu, C., & Erdoğan, S. (2015). Bicycle Sharing and Public Transit: Does Capital Bikeshare Affect Metrorail Ridership in Washington, DC? *Transportation Research Record: Journal of the Transportation Research Board*, (2534), 1-9.

Martin, E. W., & Shaheen, S. A. (2014). Evaluating Public Transit Modal Shift Dynamics in Response to Bikesharing: A Tale of Two US cities. *Journal of Transport Geography*, *41*, 315-324.

Moudon, A., Hess, P., Snyder, M., & Stanilov, K. (1997). Effects of Site Design on Pedestrian Travel In Mixed-Use, Medium-Density Environments. *Transportation Research Record: Journal of the Transportation Research Board*, (1578), 48-55.

Muhs, C. D., & Clifton, K. J. (2016). Do Characteristics of Walkable Environments Support Bicycling? Toward a Definition of Bicycle-Supported Development. *Journal of Transport and Land Use*, *9*(2). 147-188.

Nelson, A., & Allen, D. (1997). If You Build Them, Commuters Will Use Them: Association between Bicycle Facilities and Bicycle Commuting. *Transportation Research Record: Journal of the Transportation Research Board*, (1578), 79-83.

Pucher, J., & Buehler, R. (2009). Integrating Bicycling and Public Transport in North America. *Journal of Public Transportation*, *12*(3), 79-104.

Pucher, J., & Renne, J. L. (2003). Socioeconomics of Urban Travel: Evidence from the 2001 NHTS. *Transportation Quarterly*, 57(3), 49-77.

Rodríguez, D. A., & Joo, J. (2004). The Relationship between Non-motorized Mode Choice and the Local Physical Environment. *Transportation Research Part D: Transport and Environment*, *9*(2), 151-173.

Saphores, J. D., & Li, W. (2012). Estimating the Value of Urban Green Areas: A Hedonic Pricing Analysis of the Single Family Housing Market in Los Angeles, CA. *Landscape and Urban Planning*, *104*(3), 373-387.

Schneider, R. (2005). *Integration of Bicycles and Transit, TCRP Synthesis of Transit Practice.* Transit Cooperative Research Program (TCRP) Synthesis 62, Transportation Research Board, Washington, DC.

Shaheen, S. A., Martin, E. W., & Cohen, A. P. (2013). *Public Bikesharing and Modal Shift Behavior: A Comparative Study of Early Bikesharing Systems in North America.* Transportation Sustainability Research Center, University of California, Berkeley.

Singleton, P., & Clifton, K. (2015) Exploring Synergy in Bicycle and Transit Use. *Transportation Research Record: Journal of the Transportation Research Board* (2417), 92-102

Untermann, R. K. (1984). *Accommodating the Pedestrian: Adapting Towns and Neighbourhoods for Walking and Bicycling*. Van Nostrand Reinhold, New York.

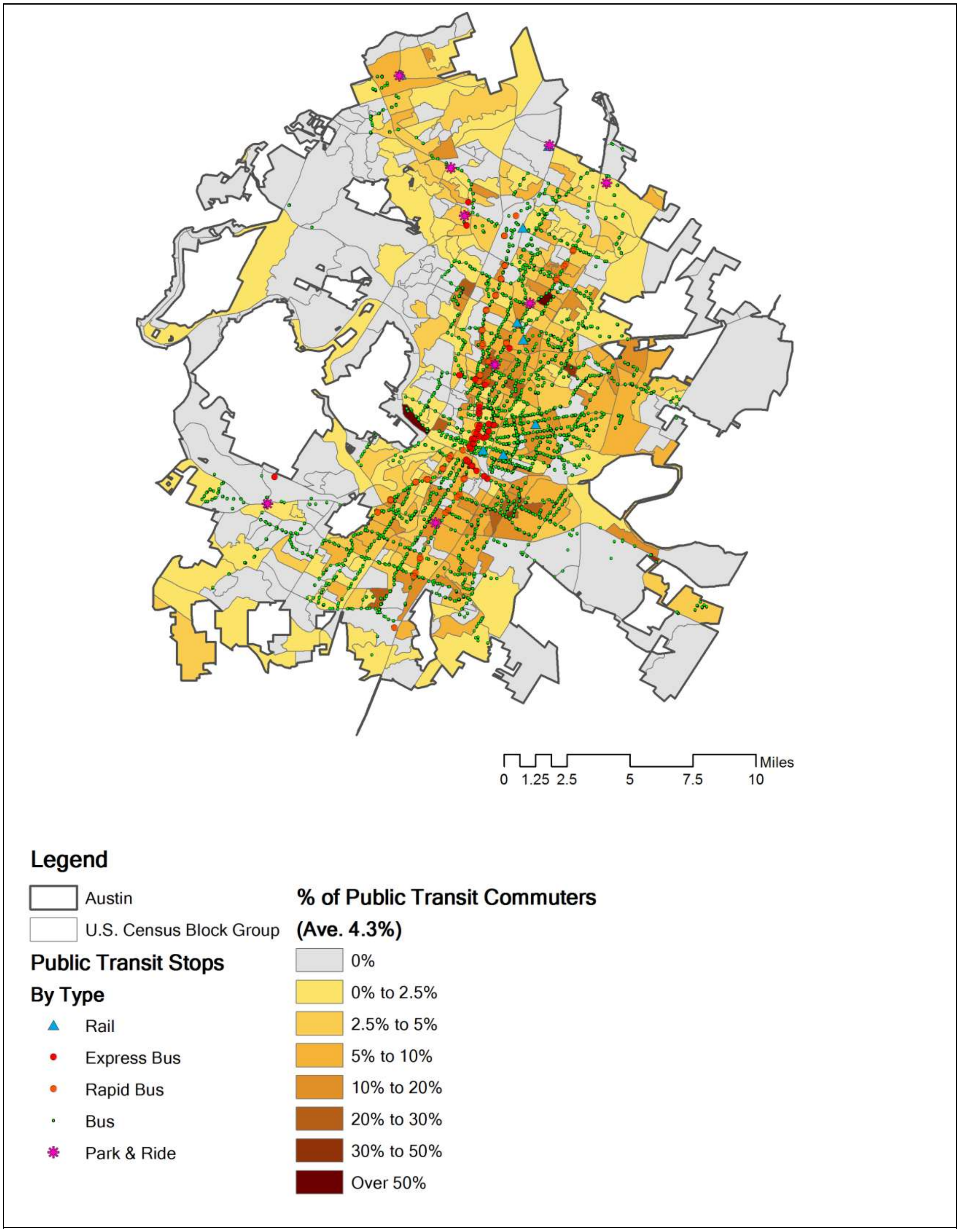
U.S. Census Bureau (2016). American Community Survey 5-Year Estimates (2011-2015). Retrieved from https://www.census.gov/programs-surveys/acs/

U.S. Department of Transportation (n.d.). *Use of Federal Funds for Bicycle and Pedestrian Efforts*. Retrieved from https://www.transportation.gov/mission/health/use-federal-funds-bicycle-pedestrian-efforts.

Zhao, F., Li, M. T., Chow, L. F., & Shen, L. D. (2002). *FSUTMS Mode Choice Modeling: Factors Affecting Transit Use and Access.* National Center for Transit Research, University of South Florida, Tampa, Florida.

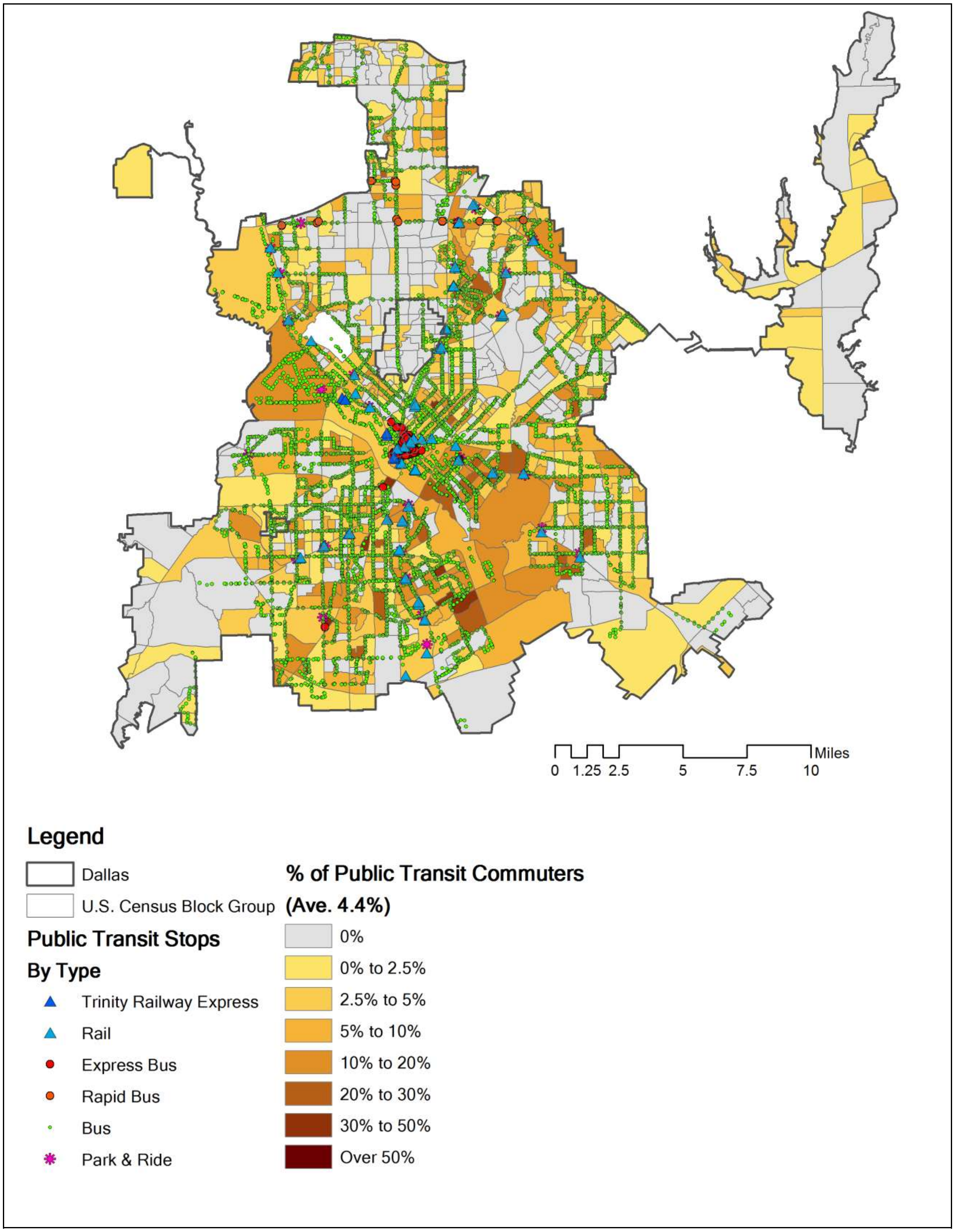
APPENDIX A: SPATIAL PATTERNS OF PUBLIC TRANSPORTATION SYSTEM

IN AUSTIN, TEXAS



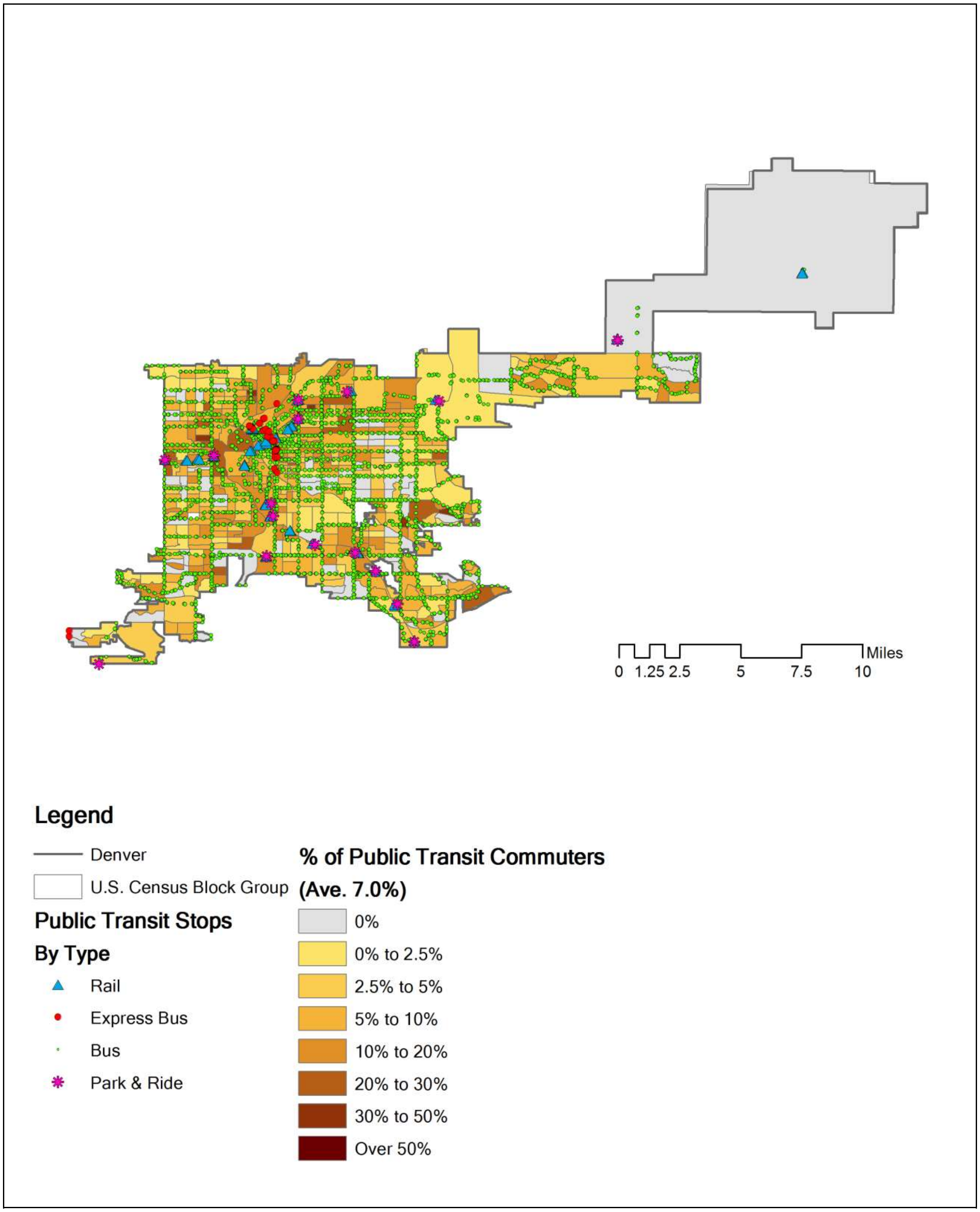
APPENDIX B: SPATIAL PATTERNS OF PUBLIC TRANSPORTATION SYSTEM

IN DALLAS, TEXAS



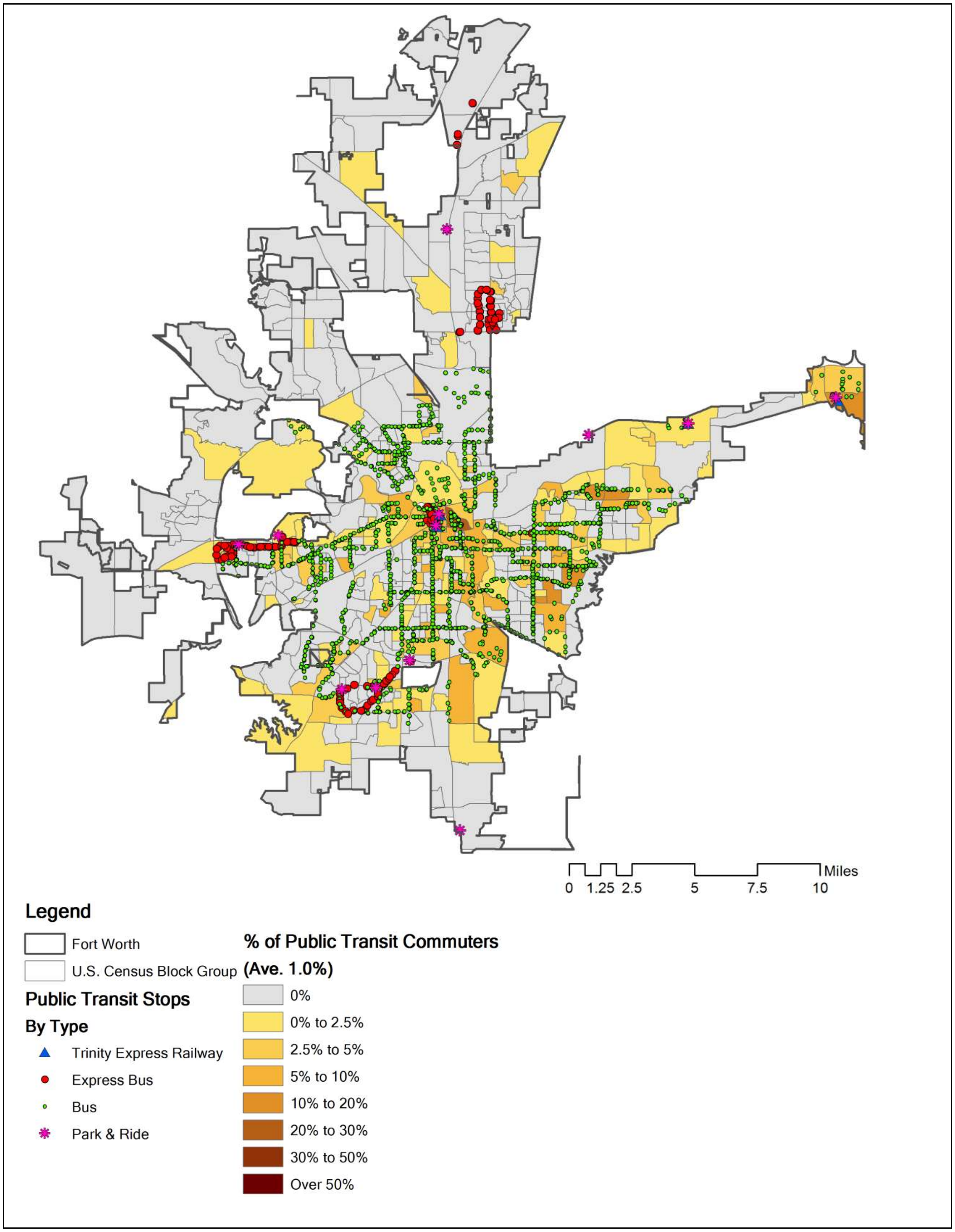
APPENDIX C: SPATIAL PATTERNS OF PUBLIC TRANSPORTATION SYSTEM

IN DENVER, COLORADO



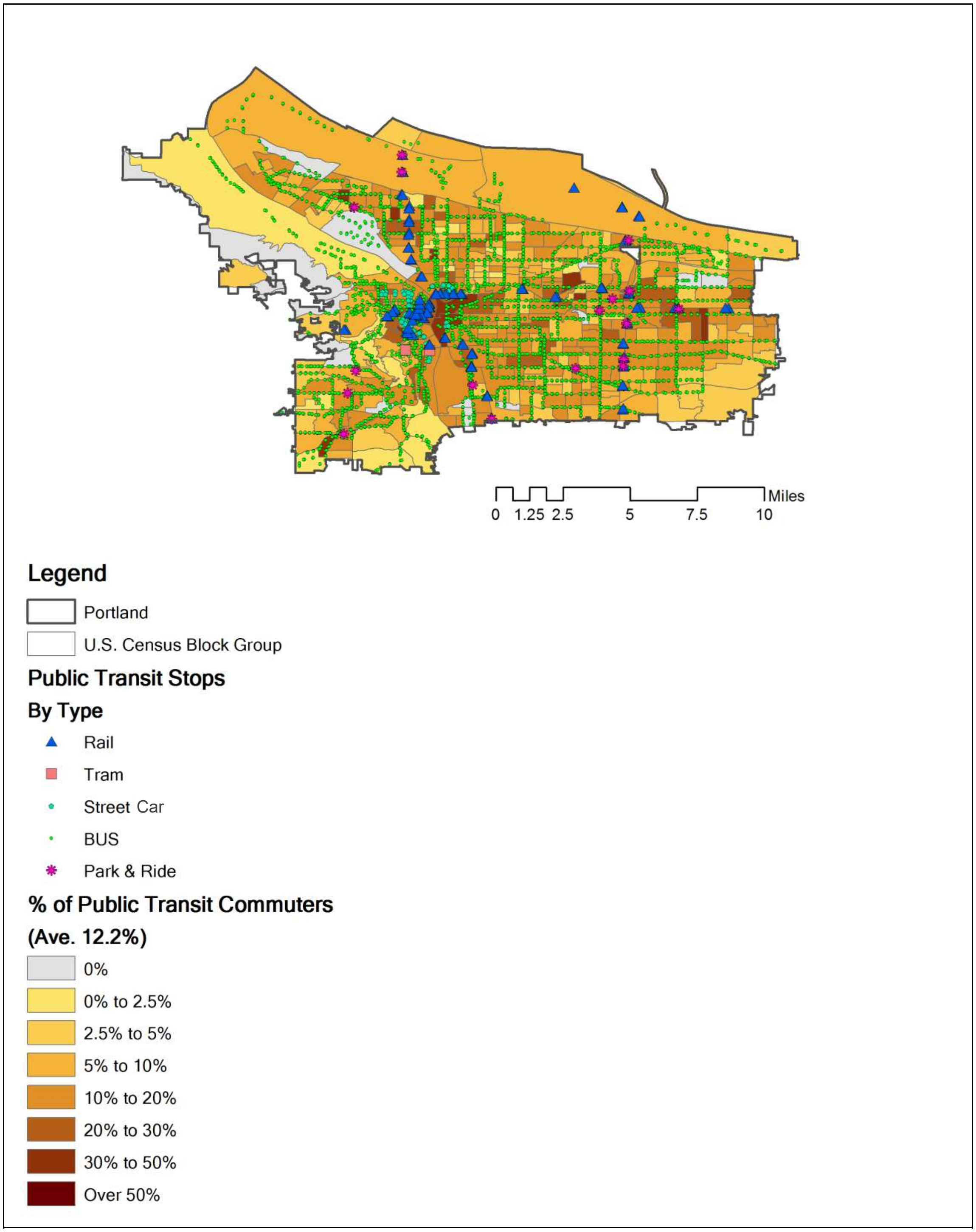
APPENDIX D: SPATIAL PATTERNS OF PUBLIC TRANSPORTATION SYSTEM

IN FORT WORTH, TEXAS



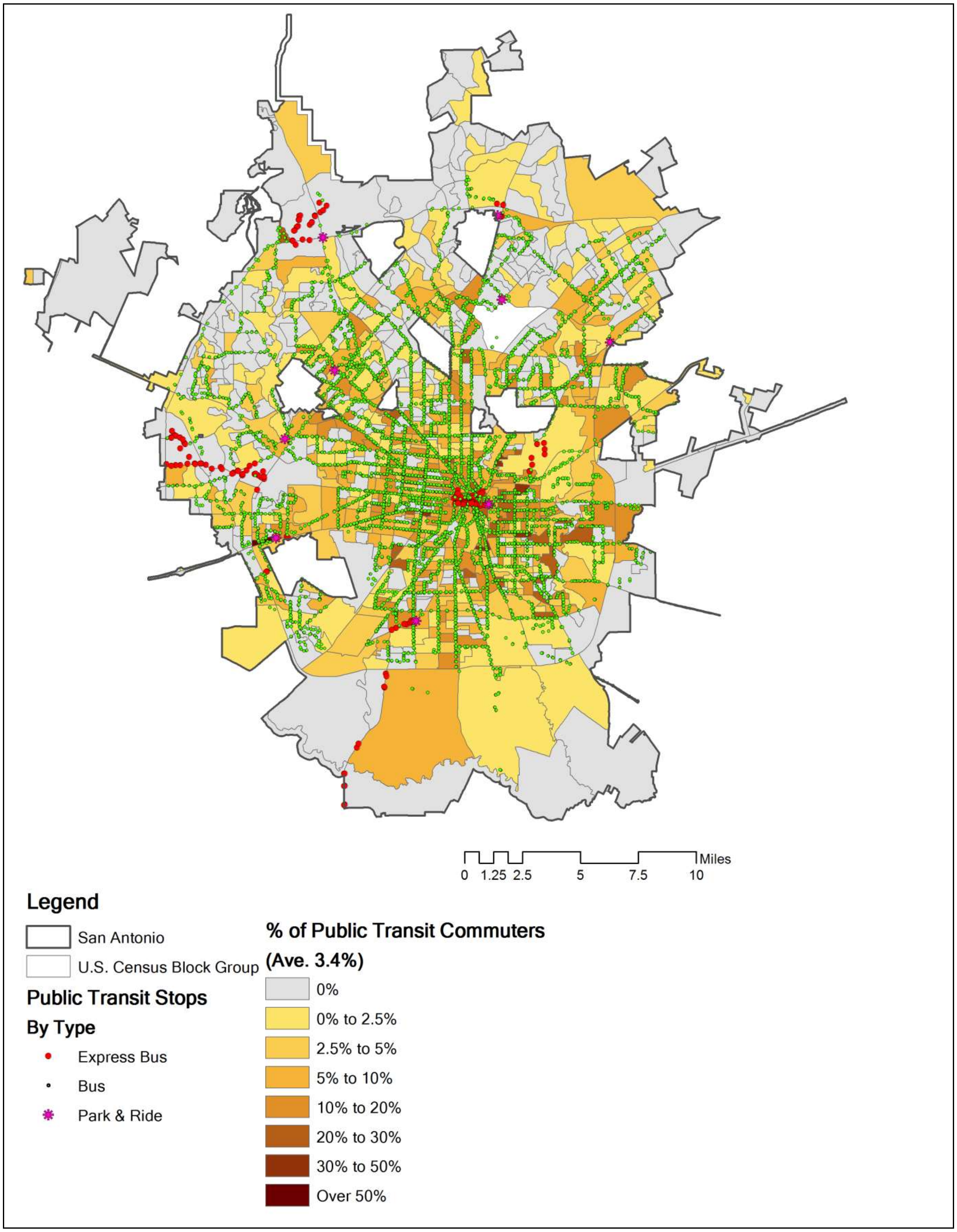
APPENDIX E: SPATIAL PATTERNS OF PUBLIC TRANSPORTATION SYSTEM

IN PORTLAND, OREGON

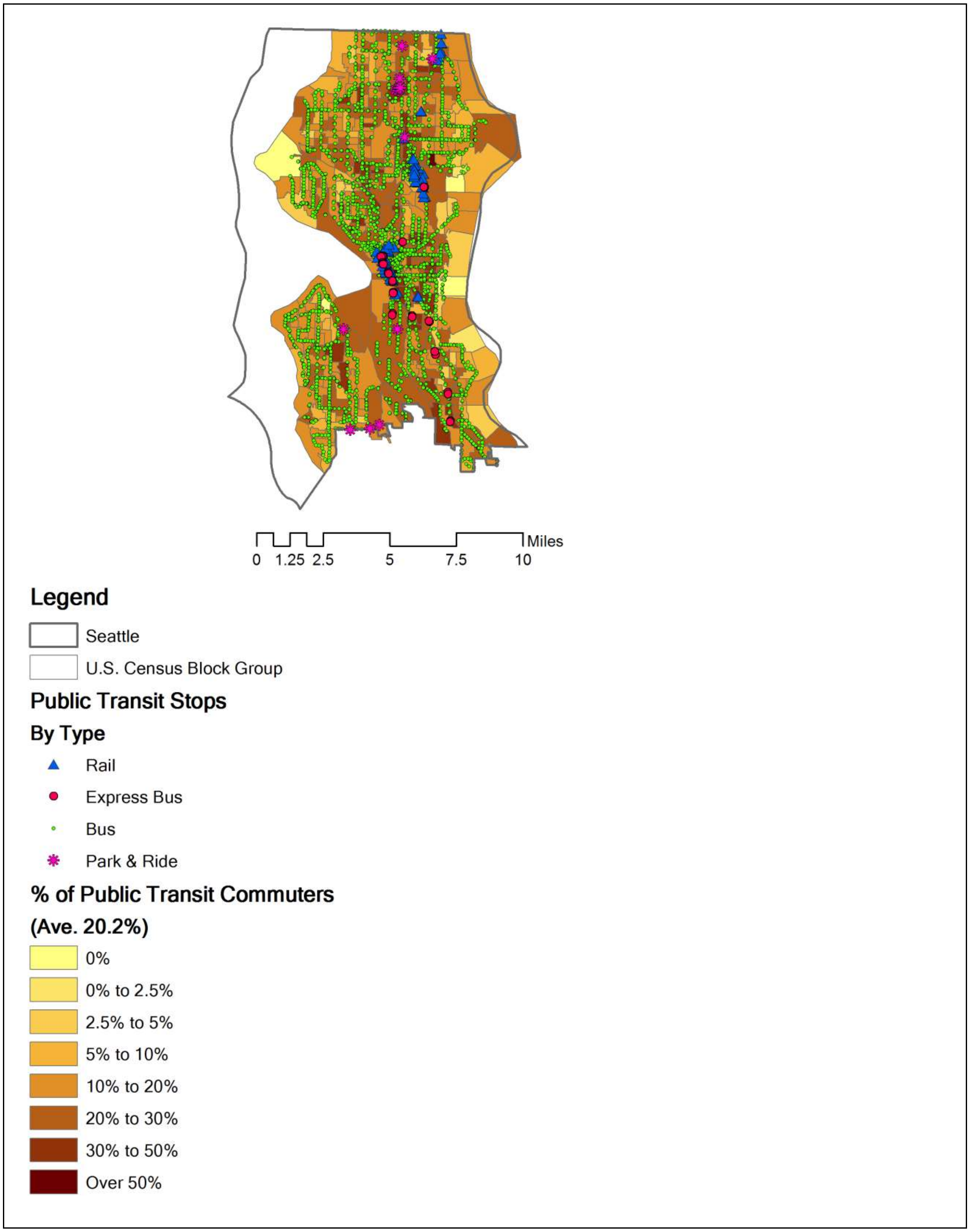


APPENDIX F: SPATIAL PATTERNS OF PUBLIC TRANSPORTATION SYSTEM

IN SAN ANTONIO, TEXAS



APPENDIX G: SPATIAL PATTERNS OF PUBLIC TRANSPORTATION SYSTEM IN SEATTLE, WASHINGTON



APPENDIX H: ZINB AND NB REGRESSION ESTIMATING TRANSIT COMMUTER (ZERO OBSERVATION)

Variable Name	Austin	Dallas	Denver	Fort Worth	Portland	San Antonio	Seattle
Socioeconomic Factors							
Median household income, $1,000	0.0061 (0.00514)	**0.0053**** (0.0053)	0.0067 (0.0051)	−0.0014 (0.0053)	0.0011 (0.0169)	**0.0101**** (0.0045)	N/A
Percent of African-American, 0-1	**−2.840*** (1.6825)	**−1.8032***** (0.4193)	**−3.6894**** (1.7175)	**−1.8835***** (0.5662)	**−35.8854*** (18.4683)	**−2.4087**** (1.0678)	N/A
Percent of non-White Hispanic, 0-1	0.1729 (1.4159)	**−2.2103**** (0.8687)	**−4.6232**** (2.2866)	−0.21724 (1.2181)	**18.0693*** (8.8771)	**18.0693*** (8.8771)	N/A
Percent of nonfamily household, 0-1	−0.8784 (0.9332)	−0.0045 (0.5467)	−1.2551 (1.3523)	−1.0518 (0.8775)	−6.3585 (4.1728)	**1.8433***** (0.6889)	N/A
Built Environment							
Population density, 1,000 per sq. mile	**−0.2023***** (0.0610)	**−0.0718***** (0.0220)	**−0.1929***** (0.0712)	0.0314 (0.0365)	**−0.7374**** (0.2945)	−0.0284 (0.0348)	N/A
Employment density, 1,000 per sq. mile	−0.0250 (0.0336)	−0.0008 (0.0101)	0.0195 (0.0188)	**−0.1009*** (0.0565)	−0.2327 (0.2350)	0.0006 (0.0230)	N/A
Percent of one-unit housing, 0-1	−0.5873 (0.6367)	**0.6640*** (0.3766)	0.3336 (0.9395)	**0.9286*** (0.5406)	4.8101 (3.4271)	**1.1488**** (0.4626)	N/A
Median year housing built, year	**−0.0012*** (0.0006)	−0.0001 (0.0006)	0.0018 (0.0022)	−0.0005 (0.0005)	0.0311 (0.0387)	−0.0005 (0.0006)	N/A
Direct distance to CBD, mile	−0.0107 (0.0477)	**0.0751***** (0.0277)	0.1202 (0.0826)	0.0747 (0.0471)	0.0876 (0.3437)	**0.1776***** (0.0360)	N/A
4-way intersection density, count per sq. mile	**0.0152***** (0.0053)	**0.0120***** (0.0029)	0.0035 (0.0038)	0.0016 (0.0036)	−0.0027 (0.0083)	0.0032 (0.0023)	N/A
Active Commuter							
Walking commuters, count	−0.0034 (0.0047)	−0.0004 (0.0029)	−0.0108 (0.0073)	0.0022 (0.0049)	−0.0023 (0.0104)	−0.0011 (0.0024)	N/A
Bike commuters, count	**−0.0349***** (0.0101)	**−0.0437*** (0.0243)	−0.0179 (0.0118)	−0.0279 (0.0185)	0.0020 (0.0166)	**−0.0446**** (0.0177)	N/A

Notes: 1) ***P-value < 0.01, **P-value < 0.05, *P-value < 0.1.
2) Standard errors are in parentheses.
3) N/A denotes not available.

APPENDIX H: ZINB AND NB REGRESSION ESTIMATING TRANSIT COMMUTER (ZERO OBSERVATION), continued

Variable Name	Austin	Dallas	Denver	Fort Worth	Portland	San Antonio	Seattle
Transport Infrastructure							
Normalized transit stop density, count per sq. mile	**−0.9504***** (0.2662)	−0.2391 (0.1796)	0.1781 (0.3735)	−0.0740 (0.1288)	1.3428 (1.4751)	−0.0106 (0.1650)	N/A
Normalized sidewalk density, length per sq. mile	**0.6293*** (0.3370)	**−0.7864***** (0.2197)	−0.6799 (0.8563)	−0.2520 (0.1840)	1.7386 (1.3208)	−0.0805 (0.1932)	N/A
Normalized bike lane density, length per sq. mile	0.1924 (0.3306)	0.0410 (0.0335)	**0.2884*** (0.1693)	0.0661 (0.0673)	−0.4240 (2.6907)	0.0169 (0.0699)	N/A
Normalized bike rack density, count per sq. mile	N/A	N/A	High VIF	N/A	**1.6868**** (0.8325)	N/A	N/A
Normalized transit stop density × normalized sidewalk density	0.1098 (0.2726)	**−0.4761**** (0.2295)	−0.6139 (1.1746)	0.0653 (0.1447)	−0.0113 (20.2959)	−0.2174 (0.1934)	N/A
Normalized transit stop density × normalized bike lane density	0.3375 (0.3563)	**0.0502*** (0.0301)	0.1289 (0.1633)	−0.0051 (0.0502)	−3.9102 (4.1221)	0.0558 (0.0693)	N/A
Normalized transit stop density × normalized bike rack density	N/A	N/A	0.0062 (0.0134)	N/A	1.3854 (1.3719)	N/A	N/A
BG within 0.5 miles from rapid transit: 1	−0.2438 (0.1040)	−0.2621 (0.3177)	−0.3243 (0.6687)	0.5351 (0.4506)	−97.7128 (4099.854)	0.2793 (0.4393)	N/A
BG within 1.5 miles from park and ride: 1	0.0024 (0.3671)	−0.1251 (0.2066)	**−0.7864*** (0.4314)	−0.5977 (0.4475)	0.7416 (0.0598)	−0.4411 (0.3321)	N/A
Constant	2.7800 1.8760	−1.3660 1.2831	1.2529 4.6070	−2.4302 1.3493	−4.0184 74.9304	−59.5365 1.2554	N/A

Notes: 1) ***P-value < 0.01, **P-value < 0.05, *P-value < 0.1.
2) Standard errors are in parentheses.
3) N/A denotes not available

APPENDIX I: THE PERCENT OF STUDENTS ENROLLED IN COLLEGE

	Austin	Dallas	Denver	Fort Worth	Portland	San Antonio	Seattle
Total population	850,239	1,201,151	621,976	758,163	591,164	1,351,917	632,332
Enrolled in college	100,371	72,603	52,447	55,568	59,034	117,211	73,930
Percent of college student	11.81%	6.10%	8.40%	7.30%	10.00%	8.70%	11.70%

Notes: 1) Total population includes the population over 3 years and over.
2) Enrolled in college means students who enrolled in undergraduate, graduate, and professional schools.
3) Data source is the 2015 American Community Survey (School Enrollment by Detailed Level of School for the Population 3 Years and Over).