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Factors Affecting MARTA Ridership: TOD, Non-Pedestrian Access, or Something Else?

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FACTORS AFFECTING MARTA RIDERSHIP:
TOD, NON-PEDESTRIAN ACCESS,
OR SOMETHING ELSE?

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master of City and Regional Planning

by
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Accepted by:
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ABSTRACT

Public transit has emerged as a socially acceptable sustainable transportation solution to the urban ills of 21st century cities. Understanding the factors that affect public transit ridership is of great need to transit agencies, planners, and policy makers. The literature suggests two main avenues for improving transit ridership in the US context. One option is to create Transit Oriented Developments (TOD) that mimic historically strong transit land-uses and built environments, including high densities of populations, jobs, and pedestrian friendliness. The other suggests that in the modern American sunbelt cities, populations, jobs, and activity centers are scattered throughout the metro area and therefore transit ridership should seek to increase the access and catchment areas of rail stations by improving non-pedestrian modes like local bus connectivity and parking facilities.

This study focuses on the MARTA system in Atlanta, GA in the Sunbelt region of the US. Using demographic, land-use, service characteristics, and origin-destination rail transit ridership data, a multilevel (mixed-effects) linear regression direct demand ridership model was created to statistically test the significance and influence of these factors on average daily ridership. The study sought to understand whether TOD factors or non-pedestrian factors showed greater significance, however a different outcome was found. In the case of MARTA, jobs and bus connectivity were the most significant positive predictors of ridership. Requiring a rail transfer, the overall MARTA travel time, median household income, and WalkScore® were found to be significant and have a negative effect on ridership. This result was not the either-or finding that was expected

and proposed, but did allow for the conclusion that in the Atlanta context the most important factor is connecting people to jobs in a dispersed and polycentric metro area. Hence, some TOD aspects (mainly job density at stations) and non-pedestrian accessibility (mainly bus connectivity) are critical determinants of ridership on MARTA.

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CHAPTER ONE

INTRODUCTION

Improving sustainable transportation through cities and regions is a 21st century necessity. The convergence of accelerating global warming (IPCC, 2018), the negative effects of climate change, mass urbanization, congestion, and influx of populations to cities warrants effective and efficient mass transit systems that minimize environmental impacts and maximize socio-economic gains. Improving public transit and encouraging the development of supportive land-use and built-environment attributes around and near stations has moved to the forefront to help combat these urban ills in the United States (Ewing & Cervero, 2010). Weak social and political support for policies aimed at transferring the social costs of externalities from automobile usage onto drivers has made this combined land-use/transit policy a second-best option (Giuliano & Hanson, 2017).

The share of trips taken by public transit in the U.S has increased to 2.5% of all trips from 1.9% in 2009 according to the 2017 National Household Travel Survey. Yet, it remains vastly overshadowed by the 82.6% of trips taken by the far less sustainable private automobile (McGuckin & Fucci, 2018). The share of trips taken by public transit remained roughly stagnant throughout the 1990's and into the 2000's, but between 2010 and 2014, following the Great Recession, there were several years of record setting public transit ridership. However, overall transit patronage has begun to fall again and thus cause concern among transit agencies and urban sustainability advocates (NTD, 2017; Schmitt, 2018). Understanding the factors that are affecting the rises and falls in

public transit ridership, and more specifically what factors are responsible for ridership on U.S rapid-transit systems, is therefore of great necessity to transit agencies and policy makers.

There is disagreement in the literature as to whether external factors (e.g. land use, the built environment, socioeconomics, and demographics) or internal transit service quality factors (e.g. frequency, speed, network alignment, service coverage, and fare) have a greater effect on transit ridership, and which would be a more feasible avenue for policy intervention (Taylor, Miller, Iseki, & Fink, 2009; Thompson, Brown, & Bhattacharya, 2012). Those who find external factors to be the primary drivers of ridership suggest transit should attempt to mimic the characteristics and metropolitan structure of historically strong transit cities – compact, high density, and serving a strong central business district or a well-connected set of sub-centers. The modern solution in transit planning is the creation of Transit Oriented Developments (TODs) which seek to create these conditions in localized areas surrounding rapid transit stations. However, many thriving modern American metro areas came of age with the automobile and therefore have a metropolitan structure that is sprawling, low density, and poly-centric, especially in the American Sunbelt region (Brown & Thompson, 2008a). In these systems, the internal transit service quality factors appear to drive transit ridership. They appear most strongly related to travel time and connection to decentralized employment and destinations (Brown, Thompson, Bhattacharya, & Jaroszynski, 2014; Thompson et al., 2012).

Historically, public transit patronage was estimated simply as a modal split component of the region travel demand ‘four-step’ model. However, the four-step model has multiple problems including a dependence on existing trends, computation and data intensity, and coarse levels of detail (Miller, 2017). Within the last few decades, a new methodology for predicting transit ridership has emerged which uses multiple regression in direct-demand models of ridership.

Direct demand models allow for simultaneous evaluation of many independent variables that can assess impacts on ridership at a fine grain spatial level. Direct-demand models typically use station-level passenger counts as the dependent variable and the station as the unit of analysis. In all but the largest transit systems, the total number of stations is too low to include enough independent variables to produce a model with strong predictive power. To bypass this issue, either multiple transit systems are examined cross-sectionally or more sophisticated statistical techniques must be employed.

Instead of using station level passenger counts, this study will use station origin-destination (O-D) passenger flow counts. This data is more difficult to obtain due to the necessity of specific automatic fare collection technology being used by the transit agency, but when it is available it allows for the delineation between attributes that produce trips, those that attract trips, and the transit service quality in-between. Additionally, the number of unique observations in a system is nearly the station count squared, which provides adequate observations for a thorough investigation of ridership

factors for an individual system (Duncan, 2010). Only four studies from the literature have employed O-D direct demand models to investigate ridership factors: two in Asia, one on the Bay Area Rapid Transit system in the San Francisco Bay area, and one on Metrorail in the greater Washington DC metro area.

The transit agency that will serve as the case study for this research is the Metropolitan Atlanta Rapid Transit Authority (MARTA). MARTA is the primary transit operator in the greater Atlanta, Georgia metropolitan area and the system consists of heavy-rail transit and extensive local bus service. Atlanta is a typical sunbelt metropolis and ranks as the second most sprawling metro area according to the Smart Growth America Measuring Sprawl Report (2014). MARTA is one of the few U.S agencies that uses automatic fare collection technology and therefore collects both origin and destination information for every trip. As such, it is an ideal case to study the relevance of external and internal factors in a large, dispersed metro area.

In seeking to improve our understanding of transit ridership factors in U.S. rapid systems this study aims to answer three research questions:

- *RQ1: Using an origin-destination direct demand model, what factors significantly influence MARTA rapid transit ridership?*
- *RQ2. Do non-pedestrian access factors to MARTA stations (e.g. Park & Ride, Bus Connectivity) show a stronger effect on ridership than TOD factors (e.g. Pedestrian friendliness, Densities)?*

- *RQ3. What significance does the downtown Central Business District (CBD) play in predicting ridership in Atlanta?*

The next section presents a review of the literature surrounding general public transit ridership factors, specifically along the three major categories related to: 1- land use/built environment; 2- socioeconomics and demographics; 3- and transit service quality factors. A review of transit planning theories and research-oriented modeling follows, discussing the four-step model and direct-demand models of ridership, both at the station level and for O-D flows. Then, findings from the four studies on O-D modeling will be discussed in detail. A discussion on metropolitan structure, service orientation and access, and travel behavior concludes the literature review.

CHAPTER TWO

LITERATURE REVIEW

Public Transportation

Public transit stands apart from other modes of city travel primarily due to its collective nature. Though there is some flexibility in the term, the definition that Walker (2011) presents provides a clear set of guidelines for what is typically considered public transit. Public transit is transportation that is publicly open to all paying customers (common-carrier), it utilizes a vehicle on a set scheduled route, and it carries multiple passengers who have varying origins or destinations. This eliminates some modes that may at times be confused with public transit like walking or cycling, carpools, and taxis. These modes all violate at least one of the criteria and are primarily individual forms of transportation. Additionally, this study will not discuss paratransit. Though a necessary and regular part of American transit, it is not designed, planned, or analyzed in a manner congruous with traditional fixed-route scheduled service.

The literature classifies public transit with respect to stop spacing and service into categories including local, express, and rapid transit (*Transit Capacity and Quality of Service Manual*, 2013). Local service, usually provided by city buses, stops at the greatest number of locations (Grava, 2003). Express service operates on the other end of the spectrum, stopping farther apart at areas such as park-and-rides and central business districts (CBD). Express service can also use city buses or high-floor intercity charter

buses. Rapid-transit serves the greatest capacity of riders and operates on a fixed route with regularly spaced stops, larger catchment areas, and greater fixed infrastructure to delineate the ‘station’.

The mode designated as rapid-transit for the purpose of this study is Heavy-rail transit (HRT), though Light-rail Transit (LRT) and Bus-rapid transit (BRT) are also typical forms of rapid-transit. HRT (also known as metro) uses rail car sets with steel wheels on steel rails and is powered by an electrified ‘third’ rail for quick acceleration and braking (Vuchic, 2005). HRT has level-boarding height platforms with multiple wide doors and operates on exclusive grade-separated guideways (Grava, 2003).

General Ridership Factors

The vast majority of transit agencies in the US experienced a fall in transit ridership in the past year (NTD, 2017). As transit agencies and policy makers try to maintain patronage and plan for urban growth, understanding the factors that affect public transit ridership becomes a necessary first step to reversing this downward trend. As such, the literature is full of studies attempting to determine the most relevant and significant attributes to maintaining and encouraging new transit ridership. The following sections discuss the general categorizations of public rapid-transit ridership factors as found in the relevant literature.

Internal and External Factors

The literature typically places factors that influence transit ridership into two categories: external factors and internal factors (Taylor, Brian & Fink, 2002; Taylor et al.,

2009). The external/internal categorization describes the level of control the transit system and its managers have over the factor. External factors encompass all of those factors which fall outside of the traditional role of the transit agency and transit planners. External factors can be broken down into two categories: socioeconomic factors and land-use / built-environment factors. Internal factors, those which are directly influenced by the transit service provider, include the details and quality of service provision, and are easier to ascertain directly for study from the agencies. Common internal factors are fare policy, train frequency, network design, service windows, and alignment. Each of these major ridership factor categories are defined and discussed in the following sections.

Land-Use and the Built Environment

When considering the role that land-use and the built environment plays in travel behavior (not limited to just transit ridership), the most common set of factors cited are known as the 5D's, originally laid out by Cervero and Kockelman (1997) and updated by Ewing (2010). The three original factors were Density, Diversity, and Design. Destination accessibility and Distance to transit were later added.

Density can refer to several specific categories such as population, job, dwelling units, or floor area measures, but the key operational component is that it is measured as variable of interest over unit of area. Diversity measures the entropy of land-uses in the specified area, also described as the level of land-use mix. Design attempts to quantify the effect that urban form has on travel or ridership at a station or stop. This factor is

often operationalized and measured as any number of physical factors that would produce a more pedestrian oriented environment (as opposed to an auto-oriented environment). These measures can include intersections per unit area, average block size, sidewalk continuity and coverage, and other aspects like trees or pedestrian crossings.

Additionally, other multi-dimensional indices have been created with the intent to capture ‘pedestrian friendliness’ such as WalkScore®. Destination accessibility typically uses a gravity model to measure the relative ease of access to trip attractors such as job opportunities within the system. For traditional transit cities focused on serving productive CBDs, this means that destination accessibility is highest closer to the center, and lower in the more distant stations. Distance to transit is a literal measure from work or residential addresses to the station in question, either in straight-line or street-network distance.

The D’s have been tested across many studies and in a variety of different ways and with varied results. However, the majority of these studies have found positive statistical significance but relatively small magnitude of individual effects of land-use and the built environment affecting ridership when assessing both large meta-analyses and wide breadth case studies (Ewing & Cervero, 2010; Taylor et al., 2009)

Demographic and Socioeconomic Factors

Demographic and socioeconomic factors have been extensively investigated in the transit ridership literature, so much so that ‘Demographics’ has sometimes been considered the 6th ‘D’. In a review of the 2001 National Household Transportation

Survey, it was found that racial minorities, and those with lower incomes and lower vehicle ownership relied on public transportation at far greater rates than others (Pucher & Renne, 2003). However, when considering more recent data on rapid-transit systems in Atlanta, Los Angeles, and New York, those making above \$75,000 a year made up a significant portion of rail transit riders, likely due to the concentration of wealth surrounding central rapid-transit stations. (Schweitzer, 2017). However, those who rode the bus for some part of their journey did not show this same trend.

Also, employment variables and the economic vitality of a metro area are often strongly correlated with overall ridership, with some studies showing total job counts in an area with a stronger effect than the total number of residents in an area. (Duncan, 2010; Taylor, Miller, Iseki, & Fink, 2003). Vehicle ownership or availability is also key factor and is consistently identified as having a strong and negative influence on ridership, particularly in the US (Ramos-Santiago & Brown, 2016). These external socioeconomic factors are certainly outside of the control of transit agencies (though not necessarily policy makers), but are often found significant and predictive, which leads them to be used as controls in statistical regression analyses of transit ridership.

Transit Service Quality

Though some of the literature finds the strength of external factors to be greater for predicting rapid transit ridership, several studies—both case studies and meta-analyses—have found that internal factors can also have a significant effect (Boisjoly et al., 2018; Kain & Liu, 1999; Taylor et al., 2009). These studies investigated the roles that

transit service quantity, quality, and cost have on ridership. Quantity was measured in the forms of headway, operating hours, and vehicle revenue miles traveled. Service quality was determined by measures such as ridership survey results, on-time performance, as well as general levels of transit system connectivity. Fares were also examined as both full cost and cost per mile.

The findings corresponded to common thoughts on how ridership would respond. Specifically, better frequency and timeliness and lower fares, especially per mile, are associated with higher transit patronage following from a microeconomic rational utilitarian model where riders seek to minimize costs and maximize benefits (Ramos-Santiago, 2018; Taylor, Miller, Iseki, & Fink, 2009; Walker, 2011). In a pair of cases in Houston and San Diego, transit service improvements and fare reductions were cited to have protected agencies from national trends of large losses in passengers and actually showed an uptick in patronage (Kain & Liu, 1999). Also, Thompson et al. (2012) cite the transit success in Broward County, Florida that demonstrates none of the typical land use characteristics that are associated with strong ridership, but remains a successful (bus) transit system by serving decentralized populations and employment centers.

The literature does not offer a single vector of explanatory variables as the complete determinant factor of transit ridership (Boisjoly et al., 2018), and some studies even consider individual interacting terms in the analysis (Duncan, 2010). Taylor et al. (2009) found that transit ridership variation is primarily affected by factors outside of the transit agency's control, not with any one determining factor, but a combination of

regional geography, metropolitan economy, population characteristics, and auto infrastructure characteristics. However, they note that fare levels and service frequency make an impact on ridership.

These findings, and those of Ewing & Cervero (2010) suggest that increasing densities of employment and population and diverse land uses, which are associated with TOD, increased transit patronage – but they note that it is because of the ease of transit access. The findings of Brown & Thompson (2008b) suggest that transit productivity is related to an agency’s ability to serve a multi-destinational region by better matching the transit network design to the metropolitan poly-centric structure. Though the factors that Ewing & Cervero and Brown & Thompson cite for increasing ridership are different, the core issue – access *to*, and access *from* provided by the transit system – is still the same.

In order for patrons to utilize the rapid transit system, and the access it provides generally, the stations must themselves be accessible. This ‘modal access’ to the station can be in the form of walking/biking, which would benefit from TOD characteristics, or it could be via connecting bus feeders or park & ride which would benefit those patrons in decentralized metropolitan areas. In professional planning circles TOD is seen as a strong remedy for strengthening both communities as well as transit patronage (Dittmar & Ohland, 2012). However, park & ride specifically has been shown to draw more ridership than replacing the parking spaces with TOD in the San Francisco Bay area in for some stations (Duncan, 2010), and Ramos-Santiago (2018) showed that local and feeder bus accounted for roughly a third of all rapid-transit passenger’s station access

mode in the Los Angeles area. This suggests that additional consideration should be given to ‘internal’ multi-modal transit service quality factors – specifically with regards to park and rider and bus connectivity factors - when examining transit systems in decentralized metro areas.

Transit Planning and Research-Oriented Ridership Models

The following section discusses transit ridership forecasting models and associated inferential analysis methods identified in the literature review. First the traditional four-step model is presented. Then direct-demand models and variants related to station-level boarding counts and Origin-Destination (O-D) trip flows are discussed.

Traditional Four Step Modeling

The traditional four step model has been the primary method by which Metropolitan Planning Organizations (MPO) planned for and predicted regional travel behavior since federal legislation required that transportation planning be “continuous, comprehensive, and cooperative” (McNally, 2000). Much like MPOs, the four-step model is designed to be regional in scope, and to depend on Transit Activity Zones (TAZ) as its unit of analysis to predict flows and modal splits of urban transportation. Additionally, its process typically favors large capital-intensive projects since it focuses on extrapolating future travel demand needs from current trip count data and is most effective in planning for highway expansions and auto improvements. (Cervero, 2006).

The four-step model is a trip-based approach that uses the sequential steps of trip generation, trip distribution, modal split, and network assignment to model urban travel

demand (Miller, 2017). The trip generation step estimates the total number of trips being generated from and attracted to each TAZ in a specified unit of time. This is often done by estimating the number of working age residents living in a TAZ to serve as originators, and counting the number of jobs and other activity centers which act as destinations. The second step, trip distribution, allocates the generated trips via a spatial ‘Newtonian gravity’ model. The gravity model is similar in form to Newton’s universal law of gravitation. It is a distance decay function that models trips between TAZs as inversely proportional to the square (or other estimated decay factors) of the distance (or time) between them, but proportionally attractive to the total number of generated and attracted trips between the two TAZs (Vuchic, 2005).

Once the trips flows are allocated between TAZs, the modal split step occurs. Modal split divides the flows among the possible modes, typically between auto and transit, but can include biking and walking shares as well. Modal split uses probabilities modeled on the basis of ‘discrete choice’ models where each trip’s mode is decided based on micro-economic theory of ‘utility-maximizing’ behavior (Miller, 2017). The final step, network or trip assignment, determines the routes that each of modal splits between zones will take. This should be an iterative process that seeks a ‘user-optimal’ equilibrium, to account for congestion along the network. Once the stable routes are allocated and determined, planners have network segment flows and corresponding volumes that can be used for predictive planning purposes.

Though the four-step model has legitimate theoretical underpinnings, for predicting travel behavior in modes other than automobiles, it is especially poor. Due to the sizes of TAZs, which can range from the census block group level to the tract level, analysis occurs at a coarse grain of perspective. This requires an aggregation of flows, and assigns them to major thoroughfare routes, which in turn typically suggests expansions of highways, and neglects neighborhood or stop characteristics and especially TAZ internal movements. Additionally, the four-step modeling process is very data intensive, requiring substantial travel survey data for probabilistic modal splits, historical traffic counts for route assignments, and continuous calibrations and computational power which means that it is typically only undertaken when substantial resources are available (Cervero, 2006; McNally, 2000). These issues have pushed transit agencies and scholars to seek other methods to model the effects that external and internal factors have on transit ridership, both in terms of resolution as well as associated costs.

Direct Demand Modeling

To compensate for the multiple limitations and issues associated with of the four-step model, specifically with respect to predicting and planning for rapid-transit ridership, alternate methods to model the relationships between local land-use, built environment, socio-demographics, transit service characteristics (including multi-modal connectivity), and their effects on transit patronage have been investigated. An alternate methodology that has emerged in the literature in the past few decades is direct-demand modeling (DDM). DDM models require less data intensity (as compared to the four-step method), offer a view of how specific variables interact with transit ridership use while including

control variables, and can be run with fairly ubiquitous and affordable statistical software and GIS programs (Cervero, 2006; Ramos-Santiago, 2018; Ramos-Santiago & Brown, 2016).

Direct demand models typically use multiple regression, though other statistical modeling methods have been tested and used over time (Durning & Townsend, 2015; Ramos-Santiago, 2018). Most direct demand models measure transit ridership at the station level, often using average weekday boardings as the dependent variable. A set of external and internal variables expected to affect ridership are then statistically tested to determine significance and model predictive power. Users of direct demand models have noted that it is not as all-encompassing as the four-step method, but does offer straightforward and easy to interpret results. Direct demand modeling is sometimes referred to as ‘Sketch Planning’ since if being used to assess a new project, quick results and generalizations can be computed and explained to policy makers with a level of simplicity not found in more complicated modeling procedures (Gutiérrez, Cardozo, & García-Palomares, 2011; Zhao, Deng, Song, & Zhu, 2014).

Though the station-level unit of analysis for direct demand ridership models allows for investigations into the effects of land-use and built environment, socioeconomic, and transit service quality factors, there is a significant methodological drawback due to small number of rapid transit stations in any one American transit system. These small numbers of observations pose degrees of freedom constraints on the number of variables that can be included in the analysis, thereby lowering the explanatory

power of the model (Cervero, Murakami, & Miller, 2010; Duduta, 2013). Researchers have worked past this hurdle through a variety of methods including combining cross-sectional data from multiple agencies (Guerra & Cervero, 2011; Kuby, Barranda, & Upchurch, 2004; Parsons Brinkerhoff, 1996; Ramos-Santiago & Brown, 2016), using international rapid transit systems in Korea, Spain, and Mexico with substantially greater number of stations (Duduta, 2013; Gutiérrez et al., 2011; Sohn & Shim, 2010), or applying additional statistical methods such as bootstrapping (Chen & Zegras, 2016; Durning & Townsend, 2015).

Origin – Destination Direct Demand Modeling

As direct-demand models have proliferated through the literature, a small set of studies on transit ridership have shifted from the station-level unit of analysis to an Origin-Destination trip flow analysis. The advantages of this shift in unit of analysis and outcome variable are threefold. First, by using station-to-station passenger flows as opposed to simple boarding counts at a station, those attributes associated with generating trips and those attributes that attract trips can be isolated and evaluated simultaneously in a generalized linear model (Choi, Lee, Kim, & Sohn, 2012; Duncan, 2010; Iseki, Liu, & Knaap, 2018; Zhao et al., 2014). Next, the service quality between stations can be investigated through measures of impedance in travel time or distance that can be factored into the analysis. Finally, in a very practical manner, for a rapid-transit system with roughly 40 stations the analysis would be severely limited in the scope of degrees of freedom. However, for a system of 40 stations, there are 1,560 unique origin-destination pairs, since given N stations, it follows that there are $N(N-1)$ pairs. This near squaring of

the total number of observations allows for more modest sized transit systems to be modeled in a standalone fashion while not sacrificing the exploratory variable capacity of the multivariate regression analysis.

Table 2.1 shows an overview of the four O-D studies. Two of the studies are on American systems: BART in San Francisco, CA and Metrorail in Washington, DC. The other two studies are on Asian metro systems in Nanjing, China and Seoul, South Korea. Three of the studies used average weekday ridership as the dependent variable as is common even among non-origin-destination direct demand models. The Metrorail study instead used passenger miles traveled citing that the utility of a trip grows with distance traveled and therefore has a higher demand. This gives those factors associated with those longer trips greater influence (Iseki et al., 2018). Additionally, three of the studies divided the origin-destination passenger flows through temporal means using morning peak travel, afternoon peak travel, and off-peak travel. This allowed for the significance of the ridership factor in question to be understood as either an attractor (at the destination) or producer (at the origin) of ridership, but also to investigate how those effects change with time of day peak flows.

All four models included some measures of external socioeconomics / demographics, land-use/built environment, and internal transit service quality variables. As expected from the literature, population and employment factors generally showed significant impact on transit ridership, specifically in the expected temporal flows: higher populations at origins and employment at destinations in morning peaks, and vice versa

in afternoon peaks. Special activity generators such as stadiums, universities, and CBD dummy variables also proved significant in studies where they were considered. Transit service quality variables performed generally as expected: bus connectivity was positive and significant in all studies and ridership was higher when traversing the same route by another mode took a greater amount of time.

In the US context, this was compared to automobile travel which is the main competitor of transit. In both of the Asian studies, ridership had a significant negative relationship with total trip distance, but the BART study did not show significance. For all studies that included a park and ride variable (auto in America, bike in China), there was positive trip generation from those stations.

Overall the four O-D models are fairly similar in methodology and findings. The models appear most effective when using averaged weekday riders, a multilevel (mixed-effects) model, and include variables from all three major categories: socio/demographics, land-use/built environment, and transit service quality. They all offer more specific insights from their O-D data than station-level models because they are able to discern the significance of ridership on a specific system with less station observation points (O-D flows instead of stations). This allows origin-destination models to offer a hybrid middle-ground solution between the data and computationally intensive four step model and the sketch planning direct demand ridership models (Duncan, 2010).

Metropolitan Structure, Service Orientation, and Travel Behavior

Sprawl and urban decentralization, though not confined exclusively to those metropolitan American cities who have come of age in the freeway or postindustrial era, have certainly left their mark on their lasting metropolitan structure (Muller, 2017). Gone are the days that cities could be modeled as concentric zones with the CBD at their heart. Instead, dispersed ‘urban realms’ have taken over to describe the poly-centric metropolis (Hartshorn & Muller, 1989). Regions and metro areas have now had many qualities quantified and measured in an attempt to define the elusive ‘sprawl’. One popular method stems from a seminal work by Ewing, Pendall, and Chen (2002) which attempted to quantify sprawl at the metropolitan area level. They created a ‘Sprawl Index’ which uses four factors: residential density, neighborhood mixes (jobs, homes, and services), the relative strength of CBDs and other activity centers, and the overall street network accessibility. Their method has since been adopted by Smart Growth America. Further, and more relevant to this study, a similar methodology was employed shortly after to directly capture the transportation impacts of sprawl on metropolitan areas (Ewing, Pendall, & Chen, 2003). The authors found that sprawling areas underperformed in many categories, including transit patronage, which corroborates the assumptions about external factors from the ridership literature.

This follows the vein of literature and common thinking that suggests that transit demand is mostly tied to those dense, streetcar suburb, walkable cities that developed prior to rise of the automobile (Pucher & Renne, 2003). However, there are authors who take issue with the assessment that transit is doomed to underperform in the suburbs of

sunbelt and postindustrial cities and instead see opportunities and evidence of transit growth (Mees, 2010; Thompson, Brown, Sharma, & Scheib, 2006; Wang & Woo, 2017). Additionally, work by Brown & Thompson (2008) on the performances of multi-destinational versus CBD focused radial transit systems, showed that in metropolitan statistical areas (MSA) between 1-5 million with multi-destinational transit systems fared better on all three performance indicators measured: riding habits, service productivity, and cost-effectiveness.

Brown & Thompson (2008) define radial systems as those whose core function is to connect suburbs to employment in the CBD, while multi-destinational systems attempt to connect all important destinations to one another while understanding the lesser value of the CBD and the greater prevalence of dispersed employment centers. This line of inquiry leads to a suggestion by Brown & Thompson that even with decentralization of employment and increased poly-centricity in metropolitan areas, transit service quality factors should be able to affect transit patronage and potentially serve as effective policy levers. Those factors, as previously discussed in the literature review, often involve providing access to rapid transit stations for patrons who live and work in dispersed metro areas. This means orienting rapid transit networks to sprawling and dispersed metro regions and expanding the overall catchment area served at the station by providing auto-oriented infrastructure (park & ride) and local bus connectivity as opposed to, or in combination with more TOD localized density and land use mix solutions.

Table 2.1 - O-D Ridership Factors from the International Literature

	Authors: System	Duncan 2010	Choi, et al. 2012			Zhao, et al. 2014		Iseki, et al. 2018		
		BART, California, USA	Seoul Metro, Seoul, South Korea			Nanjing Metro, Jiangsu Province, China		Metrorail, Washington DC, USA		
	Dependent Variable	ln(averaged weekday riders)	Averaged Weekday riders			Averaged Weekday Riders		ln(Passenger Miles Traveled)		
	Time of Day		AM Peak	Midday	PM Peak	AM Peak	PM Peak	AM Peak	Off Peak	PM Peak
	Number of Observations	1,482	2,000	2,000	2,000	2970	2970	6904	6720	6949
	Time Period of Analysis	2002	2010			2011	2012	2014		
	Methodology	Multiplicative & Multilevel- []	Multiplicative - [] , (Poisson aslo)			Multiplicative - []		Multiplicative - []		
	Station Buffer Delimitation	1 mi, Distance Decay	500 meters			800mt Euclidean		0.5 mile walkshed		
	Power of Model (R ²)		0.769	0.772	0.793	0.811	0.829	0.486	0.528	0.447
DEMOGRAPHIC / SOCIOECONOMIC	Population		+.o		+.d	+	+			
	Employment		+.d	+	+	+.d	+.o			
	Night & weekend Jobs								+	
	Employment Density	+.d						+.d	n.s	+.o
	% Nonwhite, Renters	n.s								
	Median Household Income	n.s								-
LAND USE / BUILT ENVIRONMENT	Office Area		+.d		+.o	+.d	+.o			
	Commercial Area			+.d						
	Residential Density	+	+.o			+.o	+.d	+.o	+	+.d
	Special Activity Generators	+.d, Stadium	+.d - Uni	+- Uni	+- Uni	+.d - educ	+- educ- /shop			
	Road Denisty (linear mt. w/n PCA)						+			
	Pedestrian Conn.(intersection density)	n.s								
	CBD (dummy)		+.d	+.d		+.d	+.o			
TRANSIT SERVICE QUALITY	Pedestrian Friendly Intersections		+							
	Service Frequency	+						+.d	+.d	
	Travel Time	n.s	-	-	-	-	-			
	Auto Travel Time/Transit Travel Time	+								
	Transfer Time					-	-			
	Alternate: Bus Travel Time		+	+	+			+	n.s	+
	Alterantaive: Aut Travel Time		+	+	+			+	+	+
	Alternative: Auto Travel Time per mile									
	Bus conections (# of routes)	+	+	+	+	+	+	+	+	+
	Terminal Station (dummy)	n.s						+.d	+	+
	Transfer Station (dummy)					+	+			
	Transfers (#)	-	-		-					
	1/ Road Distance between Stations	+								
	Distance to CBD					o, - +.d		+.o	n.s	n.s
	Interstation Spacing						d, - +.o			
	Fare, *Fare per track mile	-						* -	* -	* -
	Bicycle Park and Ride	n.s				+	+			
	Number of Park&Ride Spaces	+.o, - .d						+.o	n.s	n.s
	Number of Park & Ride Users							+	+	+
	Parking Cost at Destination Station	n.s				+	+			
		+	-	n.s.		.o		.d		
		Positive and Significant,	Negative and Significant	Not Significant, p > 0.10		At Origin Only		At Dest Only		

CHAPTER THREE

STUDY AREA AND RESEARCH QUESTIONS

Case selection Criteria and Description

The focus of this study will be on the Metro Atlanta Rapid Transit Authority (MARTA) in Atlanta, GA. Atlanta is Georgia's capital and most populous city, and is the principal city of both the Atlanta-Sandy Springs-Roswell, GA metro statistical area and the Atlanta urbanized area. The Atlanta-Sandy Springs-Roswell MSA ranks 220th out of 221 for the most sprawling MSA in the Smart Growth America Measuring Sprawl Report (2014). Also, Atlanta ranks 4th in North America for the worst traffic congestion in 2017 (INRIX, 2018) with drivers spending 10% of their total driving time in congestion. The Atlanta urbanized area includes 2,645 square miles with a population of 4.5 million, and is the 9th largest UZA in the US (US Census, 2010). Atlanta is considered the capitol of the 'New South' and is at the core of the Piedmont Atlantic Megaregion (Regional Plan Association, 2008). Atlanta is the epitome of a sprawling, auto-oriented, decentralized sunbelt metropolis and therefore poses a useful case-study for heavy-rail rapid transit ridership factors in a large polycentric dispersed region.

MARTA was created by an act of the Georgia General Assembly in 1965 and is the primary provider of transportation in the Atlanta metro area. MARTA operates 4 heavy rail rapid transit lines, 38 stations, and over 100 local bus routes. The service area stretches across 3 counties (Fulton, DeKalb, and Clayton) and covers an area of 573 miles

and a population of 1.5 million (MARTA, 2018). A schematic transit map of the MARTA heavy rail System can be seen in Figure 3.1.

Research Questions

This study attempts to answer three research questions about transit ridership factors and characteristics of the MARTA system.

RQ1. Using an origin-destination direct demand model, what factors significantly influence MARTA rapid transit ridership?

As cited by Duncan (2010), origin destination data is exceptionally rare among US transit systems. At the time of his writing, Metrorail, BART, and MARTA were the only heavy-rail operators that used automated fare card technology that capture both boarding and alighting stations. As cited in the literature review, origin-destination models have recently been constructed for both BART and Metrorail, but no such model exists for MARTA.

RQ2. Do non-pedestrian access factors to MARTA stations (e.g. Park & Ride, Bus Connectivity) show a stronger effect on ridership than TOD factors (e.g. Pedestrian friendliness, Densities)?

Using the results of the O-D direct demand model, and given that the Atlanta-Sandy Springs MSA ranks 220th out of 221 for sprawling MSAs, do the ideas that Brown, et al. (2012; 2014) suggest as being most important for transit ridership – serving as many dispersed population and employment centers – hold true? Or, does the model suggest

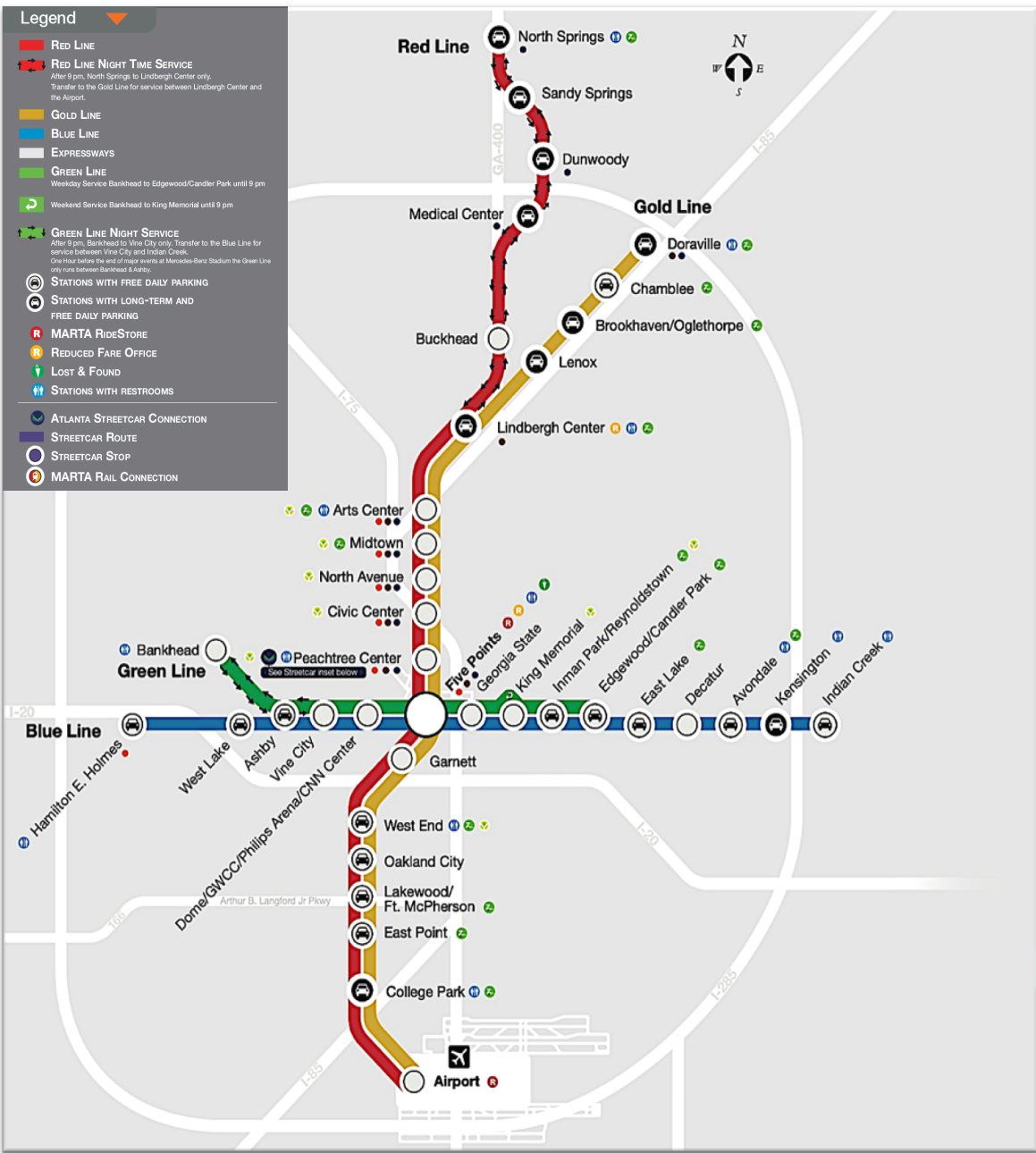
that TOD related factors still seem to be most influential in determining overall rapid-transit heavy-rail ridership? Atlanta is a useful case study in this respect due to its sprawl and several specific characteristics of the MARTA system: bus connectivity is provided at almost every station, large park and ride facilities are available at some, and high densities exist at others.

RQ3. What significance does the downtown Central Business District (CBD) play in predicting ridership in Atlanta?

The literature and travel theory suggest that the CBD should play a major role in transit ridership, especially given the cross shaped structure of the MARTA where the CBD is the geometric center of the system. However, a previous investigation of Atlanta by Brown et al. (2014) highlights the falling importance of the CBD in a region with major suburbanization and dispersal of employment centers.

The answers to these research questions will result in policy suggestions to increase the rapid-transit ridership of MARTA. Either MARTA should embrace its decentralized nature and seek to maximize access via park and ride and bus connectivity, attempt to improve and increase its TODs and the strength of the CBD, or possibly a combination of both.

Figure 3.1 - MARTA Rail System Map



(MARTA, 2018)

CHAPTER FOUR

RESEARCH DESIGN, METHODOLOGY, & DATA

The research design for this study is quantitative and focuses on a single case-study to investigate the three research questions. The research will seek first to determine what factors affect heavy-rail transit ridership in a sprawling American sunbelt metropolis. Second, it will attempt to determine whether internal factors related to decentralized access to stations (e.g. connecting bus service, park & ride) prove more significant than traditional TOD external factors. Finally, it will seek to gauge the importance of the CBD on ridership. Ridership factors chosen from the transit literature were identified, modeled, and then were iteratively tested for significance and magnitude through statistical analysis – specifically, a cross-classified multi-level generalized linear regression model using station OD ridership flow data as the outcome variable.

The study focuses on the MARTA Transit system, in Atlanta, GA. Atlanta is a major sprawling sunbelt metro area that came of age in the automobile era. However, different than many other sunbelt cities, Atlanta began constructing the MARTA heavy-rail rapid transit system in the 1970s. Today, MARTA consists of 4 heavy-rail transit lines that bisect the city North-South and East-West roughly paralleling major interstates, and also operates an extensive network of connecting local bus service. The system services multiple counties and cities throughout the sprawling polycentric metro Atlanta area.

The sample for this analysis includes 1406 O-D pair flows based on all 38 heavy-rail rapid transit stations in the MARTA system. Since the sample size would be far too small to investigate the numerous explanatory factors of interest if only station level data were used, and since MARTA collects origin and destination flow data through automated fare collection, ridership was sampled as unlinked passenger trip flows between all possible combinations of origin and destination stations. These origin-destination flows serve as the unit of analysis for this study. Ridership, for the purposes of this study, will be defined as the one-way flow, or count, of unlinked trips between MARTA heavy-rail transit station O-D pairs. Average daily ridership data in the form of unlinked trip flows between station pairs were obtained for the entire 2017 year, the most recent year of data available at the time of this study.

To answer research question 1, a cross-classified multi-level (mixed-effects) linear regression model is constructed with average daily ridership between O-D station pairs during 2017 as the dependent variable. This model follows the statistical methodology employed by both Duncan (2010) and Iseki et al (2018). As both studies note, the nature of OD data poses statistical complexity different than that of typical direct demand model. A multi-level model is employed to deal with the two types (levels) of explanatory factors.

The first level relates to the explicit OD pair explanatory variables (like travel time between the pair), whereas the second level relates to the specific station variables within the pair (like employment or park & ride spaces). In addition to this complexity,

each individual OD pair nests into two sets of observational clusters on the second level: one with all other pairs that share the same origin station, and one with all other pairs that share the destination station. This nesting requires statistical cross-classification to be used in the model and is done so by including random effects terms for both the origin and destination station clusters. Therefore, the model will take generalized form given by equation 1, taking the same form used by Iseki et al (2018), but lacking their stratification by time of day specification.

$$R_{ij} = \theta + \alpha * X_{ij} + \beta * Y_i + \gamma * W_j + b_{0i} + c_{0i} + d_{ij}$$

Where:

- R_{ij} is the dependent variable, passenger counts between Origin (i) and Destination (j)
- θ is the model intercept
- α is the vector of OD pair variable coefficients (level 1)
- X_{ij} is the vector of OD pair variables, like travel time between the OD pair (level 1)
- β is the vector of Origin station variable coefficients (level 2 – class 1)
- Y_i is the vector of Origin station variables, like station area population (level 2 – class 1)
- γ is the vector of Destination station variable coefficients (level 2 – class 2)
- W_j is the vector of Destination station variables, like intersection density (level 2 – class 2)
- b_{0i} , c_{0i} , and d_{ij} are the origin, destination, and OD pair residuals vectors

To construct the model, a set of explanatory variables are chosen from a review of the transit ridership theory and literature, then others are iteratively tested to produce a robust generalized linear regression that has strong predictive power and variables with high significance and low collinearity. Candidate explanatory variables are listed in Table 4.1 and are informed by the literature review.

The explanatory variables are divided into three vectors found throughout the ridership literature: external land-use built-environment variables (6 candidate variables), external socioeconomic/demographic variables (4 candidate variables), and internal transit service quality variables (12 candidate variables). The variables are expressed at one of two levels. Level 1 variables are ‘OD pair’ specific variables like travel time between the specific pair. Level 2 variables are ‘station’ variables and are expressed for both origin and destination stations. The model assumes that average weekday O-D pair trip flows are a function of these three explanatory variable vectors and provides an understanding of statistical significance, direction of association, and magnitude.

Table 4.1 – Candidate Explanatory Variables

Dependent Variable		Level	Data Source
Average Weekday Trips between Station Pairs		OD Pair	MARTA (2017)
Independent Variables	Explanatory Vector Category	Level	Data Source
Population in 0.5mi walkshed	External - Land Use/Built Environment	Station	US Census ACS 5yr (2016)
Jobs in 0.5 walkshed	External - Land Use/Built Environment	Station	US DOL OnTheMap (2017)
WalkScore®	External - Land Use/Built Environment	Station	WalkScore® (2018)
Airport Station (0-1 binary)	External - Land Use/Built Environment	Station	MARTA (2017)
Special Generator Count	External - Land Use/Built Environment	Station	MARTA (2017)
CBD Station (0-1 binary)	External - Land Use/Built Environment	Station	MARTA (2017)
NonWhite Population Percentage	External - Socioecon/Demographics	Station	US Census ACS 5yr (2016)
0 Vehicle Household Availability	External - Socioecon/Demographics	Station	US Census ACS 5yr (2016)
Avg. Household Auto Availability	External - Socioecon/Demographics	Station	US Census ACS 5yr (2016)
Median Household Income	External - Socioecon/Demographics	Station	US Census ACS 5yr (2016)
MARTA Station Pair Travel Time	Internal - Transit Service	OD Pair	MARTA GTFS (2017)
MARTA Station Pair Travel Distance	Internal - Transit Service	OD Pair	MARTA (2017)
Auto Travel Time between Stations	Internal - Transit Service	OD Pair	CDX Technologies (2019)
Auto Travel Time / MARTA Travel Time	Internal - Transit Service	OD Pair	CDX Technologies (2019)/ MARTA
MARTA Transfer Required (0-1 binary)	Internal - Transit Service	OD Pair	MARTA (2017)
Number of Park & Ride Spaces Available	Internal - Transit Service	Station	MARTA (2017)
Average Weekday Parking Spaces Utilized	Internal - Transit Service	Station	MARTA R&A Survey (2017)
Number of connecting Bus Lines to station	Internal - Transit Service	Station	MARTA GTFS (2017)
Number of Buses per day	Internal - Transit Service	Station	MARTA GTFS (2017)
Route Miles of connecting Bus Lines to station	Internal - Transit Service	Station	MARTA GTFS (2017)
Bus Miles Driven connecting to Station (VMT)	Internal - Transit Service	Station	MARTA GTFS (2017)
Terminal Station (0-1 binary)	Internal - Transit Service	Station	MARTA (2017)

*Bold variables included in initial model specification

The data for the explanatory variables were collected to correspond to the most recent available data and to match the 2017 MARTA heavy-rail transit ridership data. For the land-use built-environment variables, the station catchment and delineation areas are computed by using network distance of 0.5 mi as suggested throughout the literature (Gutiérrez et al., 2011; Kuby et al., 2004). This is accomplished using GIS software to produce a network using ESRI Business Analysts streets data to create 0.5-mile walksheds surrounding each station. This method is chosen over a Euclidean buffer

delineation which can produce less favorable results by ignoring local street networks and including data that is not in the real pedestrian walkshed service area.

These walksheds are then used in tandem with US Census population and US Department of Labor ‘On the Map’ employment data to calculate station area populations and jobs to be included in the model. These factors are included extensively throughout the ridership literature and are especially relevant to the question of whether TOD factors are most important. Next, WalkScore® data will be used as an index measure of built environment pedestrian friendliness in a similar manner as used by Ramos-Santiago (2018). Additionally, a count of special generators including sports venues, conference centers, museums, hospitals, and major universities were included.

The Hartsfield-Jackson Atlanta airport is included as a stand-alone binary (dummy) variable as its own special generator. The airport is a massive influence on the southeastern US region as a whole, and is hypothesized to be a strong special generator for the MARTA system, and therefore should be separated and controlled for in the model. Finally, to address research question 3, a dummy variable to delineate the 6 CBD stations at the core of the MARTA system is included.

Socioeconomic and demographic factors are found significant intermittently throughout the station-level ridership literature. They are included in the model as candidate control variables since they do not directly apply to the research questions of the study. Four station level variables are included: non-white population percentage, average household auto availability, 0 vehicle households, and median household income

as informed by the literature review. All of the data for these factors comes from the US Census American Community Survey (ACS) 2016 which is the most recent year data is available. These factors were measured for the populations inside the 0.5 mile pedestrian walkshed area surrounding each station.

The largest number of candidate variables falls into the 3rd ridership factors vector – internal transit service quality variables. This category contains two levels of variables – OD pair specific variables and station level variables.

The OD pair specific variables describe the quality of the transit (and their alternatives) between the specific two stations. There are 5 candidate variables in this group: MARTA travel time, MARTA travel distance, Auto travel time between stations, Auto travel time divided by MARTA travel time, and a binary variable for whether a transfer is required on the trip. The MARTA data for these variables comes from MARTA General Transit Feed Specification (GTFS) 2017 data and the drive time was calculated with the CDX Technologies software and Bing maps.

These candidate variables which relate to travel time/distance and auto competition are especially unique to OD pair modeling. They allow for comparison between the competitive modes, and since the auto is the main competitor in large sprawling US metropolises the travel time between stations is a necessary and useful inclusion. Transfers are also continually cited as highly important (if not the most important) to transit riders (Walker, 2011), above and beyond simple travel time

calculations. Due to the layout of the MARTA, only 1 heavy-rail transfer is ever required to complete a journey so transfers are measured as a binary variable in the model.

The remaining 7 candidate variables are especially relevant to this study as they not only apply to research question 1, but include variables of interest for research question 2 – since they include those explanatory variables that relate to the non-pedestrian access to the rapid transit stations. The variables are: utilization of park & ride spaces, the number of connecting bus lines to the station, the number of buses that arrive at the station per day, a summation of the bus-route miles that connect to the station, and binary variables for if the station is a terminal or CBD station.

Park & ride availability and usage are found in the literature to reflect the much greater catchment area than the auto provides. The data comes from MARTA Research & Analysis (2017) which tracks parking availability and utilization as required by Federal Transit Authority. The next three variables, number of bus lines, number of buses per day, and number of route miles of connecting bus lines, seek to measure the non-pedestrian access to the system via MARTA local buses. For connecting bus access to the station, the traditional measures found throughout the direct-demand literature are the number of connecting bus routes to the station or the number of buses that arrive at the station per day. That data is included in the MARTA GTFS 2017 data and is included in this study. However, to further investigate the effects of connecting a decentralized and sprawling metro area via multi-destinational transit service a new candidate variable is proposed for this study. In addition to simply counting the routes or buses serving a

station, the route-miles of bus service, as determined from GIS software and MARTA GTFS data for 2017, is included. This measure should capture those stations that serve as the portal to larger MARTA local bus service catchment areas being served by the longer and more frequent routes. Finally, a binary variable for terminal stations is included to serve as a control variable as it appears significant through some of the literature. This data comes from MARTA.

The data was collected and compiled for all of the specified variables. Due to the nature of the variables, both Duncan (2010) and Iseki et al. (2018) natural log transformed both their dependent and continuous independent variables before modeling. They found that this gave better model fits as well as allowed for log-log interpretations of the results. Tests were performed on the data to determine if there existed unacceptable multicollinearity which would violate the regression model assumptions and skew the results. It was determined that several variables were unacceptably collinear. This included obvious cases such as MARTA travel time and MARTA travel distance, and number of connecting bus lines, buses per day, bus route miles, and bus miles traveled, but it also included other less obvious relationships like the one between population and number of 0 vehicle households. After selecting a single variable for those cases of collinearity, a subset of the candidate variables were designated for the initial model and specific collinear variables were noted as to be only individually included in the model during the iterative process.

After the initial modeling, an iterative process of adding, examining, and removing or modifying variables was used to determine what combination of factors should be included for the best fit model. The best fit model was identified as the most parsimonious model with strong predictive power, fit, variable significance, and theoretical backing. The best fit model then was used to offer answers to the research questions by analyzing the final inclusion, significance, magnitudes, and directionality between variables.

In regards to research design validity, issues of internal and external validity could arise in this research design under a few scenarios. If the model had produced results that were exclusively and exceptionally different than what the literature suggests, face validity could be an issue since the transit ridership theory literature is well documented. Internal validity should not pose an issue unless the explanatory variables display high degrees of collinearity. Finally, the study could suffer from issues of construct validity, as not all of the phenomenon under question lend themselves to easy measurement. Specifically, the concept of ‘pedestrian friendliness’ is captured through the use of a composite and proprietary WalkScore® index, however it is possible that the design ‘D’ as examined in the literature review is not being appropriately captured through this score.

As noted in previous DDM studies collinearity was an issue with some variables, but no two collinear variables were included in models simultaneously. Instead, variables that measured similar phenomena were iterated through the model to determine which

best fit. Additionally, especially low power of prediction models should be noted as such, with additional interest in what explanatory factors were missed in the candidate ridership variables. Finally, though this study seeks to generalize about decentralized station access factors like auto and bus connectivity as opposed to traditional TOD factors, the interest is in those cities that are similar in sprawl and polycentricism to Atlanta. Generalizing further than that, or to cities with vastly different transit infrastructure (like no tunneled heavy-rail), would likely increase issues of external validity.

The results of the modeling process are documented in the following section.

CHAPTER FIVE

RESULTS

Data was obtained for all the candidate variables of interest. Table 5.1 presents descriptive statistics for the variables of interest. An initial model was specified, coded, and run using the Lme4 and LmeTest packages in R which are designed to handle generalized linear multi-level (mixed-effects) models. The initial model included all of the variables included in Table 5.1, with the exception of Avg. HH vehicles, Buses per Day, and Bus miles traveled, each of which was excluded due to issues of high correlation (>0.7). The variables that offered a better fit were instead used – Median HH income and connecting bus lines. This model also included random effects terms based on the origin station clustering and the destination clustering (to account for the cross-classification of the data).

This initial model had an Akaike Information Criteria (AIC) score of 2027 which is an estimator used in multi-level (mixed-effect) modeling to describe the quality of the model in terms relative to other models. It also had a marginal R^2 value of 0.495 which describes the predictive power of the fixed effects (the variables of interest included), and a conditional R^2 of 0.855 which describes the power of the model as a whole (including both the fixed effects and the cross-classified random effects). Though the initial model was not poor in terms of power and fit, few of the variables showed statistical significance. This led to an iterative process of removing those variables that did not seem to be significant to the model to find a best fit model.

Table 5.1 - Descriptive Statistics of Variables of Interest

Descriptive Statistics of Variables of Interest									
Variable	Level	Count	Mean	Median	Std. Dev.	Min	Max	Count	1/0
Dependent Variable									
Average Daily Ridership	OD	1406	86	44	116	2	1098	-	-
Independent Variables									
MARTA Travel Time [min]	OD	1406	21.9	21.0	12.1	1.0	56.0	-	-
Drive Time [min]	OD	1406	15.0	15.5	6.2	1.7	29.5	-	-
Population in 0.5 mi Walkshed	Station	38	2967	2622	1754	4	7953	-	-
Jobs in 0.5 mi Walkshed	Station	38	9778	3309	12233	8	40694	-	-
WalkScore®	Station	38	65.0	68.5	24.7	2.0	98.0	-	-
Med. HH Income in 0.5 mi Walkshed	Station	38	\$55,092	\$48,962	\$27,966	\$216	\$107,144	-	-
Avg. HH Vehicles in Walkshed	Station	38	1.22	1.24	0.26	0.78	1.69	-	-
Nonwhite Percentage in Walkshed	Station	38	54.8%	51.9%	27.9%	0.6%	98.1%	-	-
Parking Spaces Utilized	Station	38	384	209	510	0	2217	-	-
Num. Connecting Bus Lines	Station	38	4	4	3	0	11	-	-
Connecting Buses per day	Station	38	179	161	148	0	744	-	-
Connecting Bus Miles Traveled	Station	38	1709	1423	1496	0	5850	-	-
MARTA Transfer Required [0-1]	OD	1406	-	-	-	-	-	714	-
Airport Station [0-1]	Station	38	-	-	-	-	-	1	-
Downtown CBD Station [0-1]	Station	38	-	-	-	-	-	6	-
Terminal Station [0-1]	Station	38	-	-	-	-	-	6	-

The results of the best fit model are shown in Table 5.2. The best fit model has predictive power values, R^2 marginal and conditional, very similar to the initial model, but offers a better overall fit via the AIC score of 2015 (and a much better AIC than the null, 2859) Also, the model is composed of variables that all (but one) offer statistical significance at the 0.05 level or greater. The decision to include the random effects terms to capture the nesting of the cross-classified origin station and destination station is also validated in the results. In the best fit model, the R^2 marginal shows that the fixed effects variables provide 48% of the power, but by including the random effects terms the R^2 conditional rises to 85%, meaning that the random effects offer the model a substantially better predictive power and fit.

Table 5.2 - Best Fit Model Results

Model Results

Random Effects		Variance	St. Dev.		
Origin Station		0.227	0.4764		
Desintation Station		0.2843	0.5332		
Residual		0.1954	0.4421		

Fixed Effects: Ind. Variables	Level	Coef	Std. Error	t Value	Pr (> t)
(Intercept)		7.593	1.399	5.428	0.000 ***
OD Pair Variables					
Transfer Required [0-1]	OD	-0.786	0.032	-24.854	0.000 ***
ln (MARTA Travel Time) [min]	OD	-0.068	0.022	-3.083	0.002 **
Origin Station Variables					
ln (Jobs in 0.5 mi walkshed)	Station	0.170	0.052	3.244	0.002 **
ln (WalkScore®)	Station	-0.282	0.127	-2.216	0.033 *
ln (Med. HH Income in walkshed)	Station	-0.274	0.080	-3.404	0.002 **
ln (Num. Bus Lines)	Station	0.616	0.135	4.574	0.000 ***
Desintation Station Variables					
ln (Jobs in 0.5 mi walkshed)	Station	0.181	0.059	3.091	0.004 **
ln (WalkScore®)	Station	-0.286	0.142	-2.014	0.051 -
ln (Med. HH Income in walkshed)	Station	-0.249	0.090	-2.771	0.009 **
ln (Num. Bus Lines)	Station	0.597	0.150	3.972	0.000 ***

Model	AIC	BIC	R ² _m	R ² _c
Null Model (Rand. Eff. Only)	2859.5	2880.5	-	0.748
Fitted Model	2015.4	2088.9	0.479	0.856

The strongest predictor of the dependent variable, average daily ridership, is whether or not a MARTA transfer is required to complete the trip. It had the highest *t*-score, and the expected negative sign, as transfers are cited in the literature as a major detractor to ridership. Following transfers, the number of bus lines connecting to the station at both the origin and destination were significant, had expected (+) signs, and had high coefficients. All of the bus related variables were tried in the modeling process

(number of connecting bus lines, buses per day, bus route miles, and the constructed bus miles traveled), but the number of connecting bus lines proved to fit best in the model. Since both the dependent and independent variables have been log transformed, the coefficient can be interpreted as an elasticity. This means that an increase in the number of bus lines connecting to the origin station by 10% would correspond with an increase in daily ridership of 6.16%.

Job counts in the station walkshed at both the origin and destination are also positive and significant, with coefficients of 0.17 and 0.18 respectively. Median household income was found to be significant and negative, which corresponds with the transit literature. MARTA travel time was also found to be significant and negative as expected from the transit theory. Finally, WalkScore® was found to be negative and significant at the origin, but just over the threshold to insignificant in the model at the destination. It was retained in the model since it was very close, and when an Anova test for type III error in mixed-effect models was performed in R on the model (another statistical method to approximate significance of a mixed-effects model), it did show significance at the 0.05 level. The WalkScore® result was the only variable to remain in the model that performed differently than expected by lowering expected ridership rather than increasing it, though the literature was more mixed on its effect than with the other variables. There is no clear answer in this study as to why the contribution to ridership would be negative for a higher WalkScore®. However, it is possible that there was some issue with collinearity (0.56) between WalkScore® and job counts which produced the

negative relationship, or simply the score did not adequately capture the design phenomenon as described in the transit ridership literature.

Post processing diagnostics tests and plots were performed on the results of the model. Figure 5.1 shows the Normal Q-Q plot and the Fitted vs Residuals plots. The Q-Q plot follows the linear trend line closely and the Fitted vs. Residuals plot shows a tight band around the horizontal 0 with a random but equal dispersal. These diagnostic plots show that the results are acceptable and do not violate the assumptions of the modeling process. Additionally, the correlation chart for the independent variables is presented in Figure 5.2. None of the variables are unacceptably correlated, with the highest correlation value being 0.57.

A discussion of the implications of the results of the modeling process follows in the next section.

Figure 5.1 - Normal Q-Q Plot & Fitted vs Residuals Plot

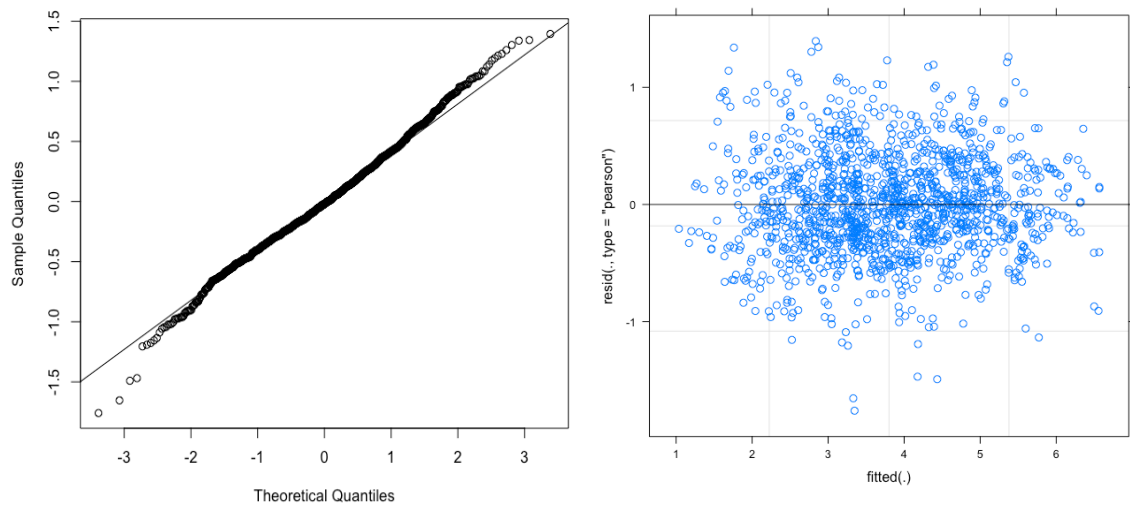
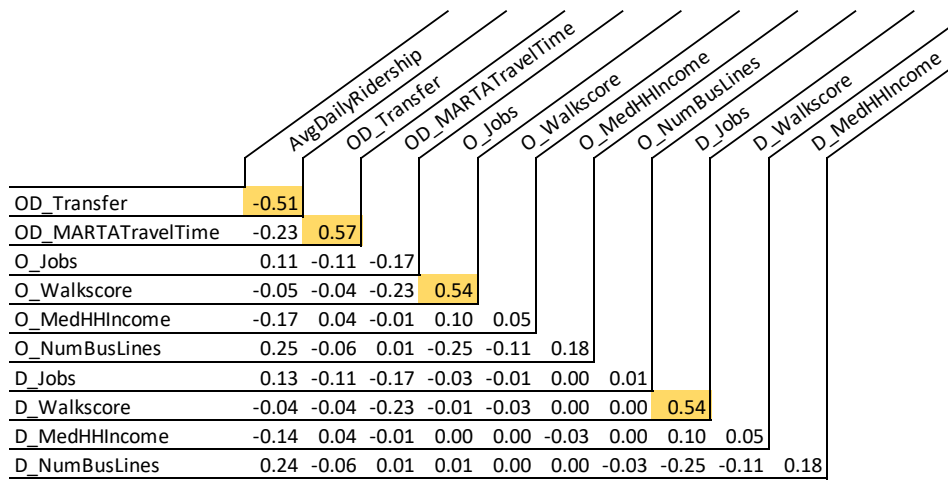


Figure 5.2 - Correlation Chart



CHAPTER SIX

DISCUSSION

In the previous section the results of the best fit model are described numerically and with respect to the modeling process. This section will interpret the findings in terms of the research questions, as well as address those variables that did not prove significant and worth inclusion in the best fit model.

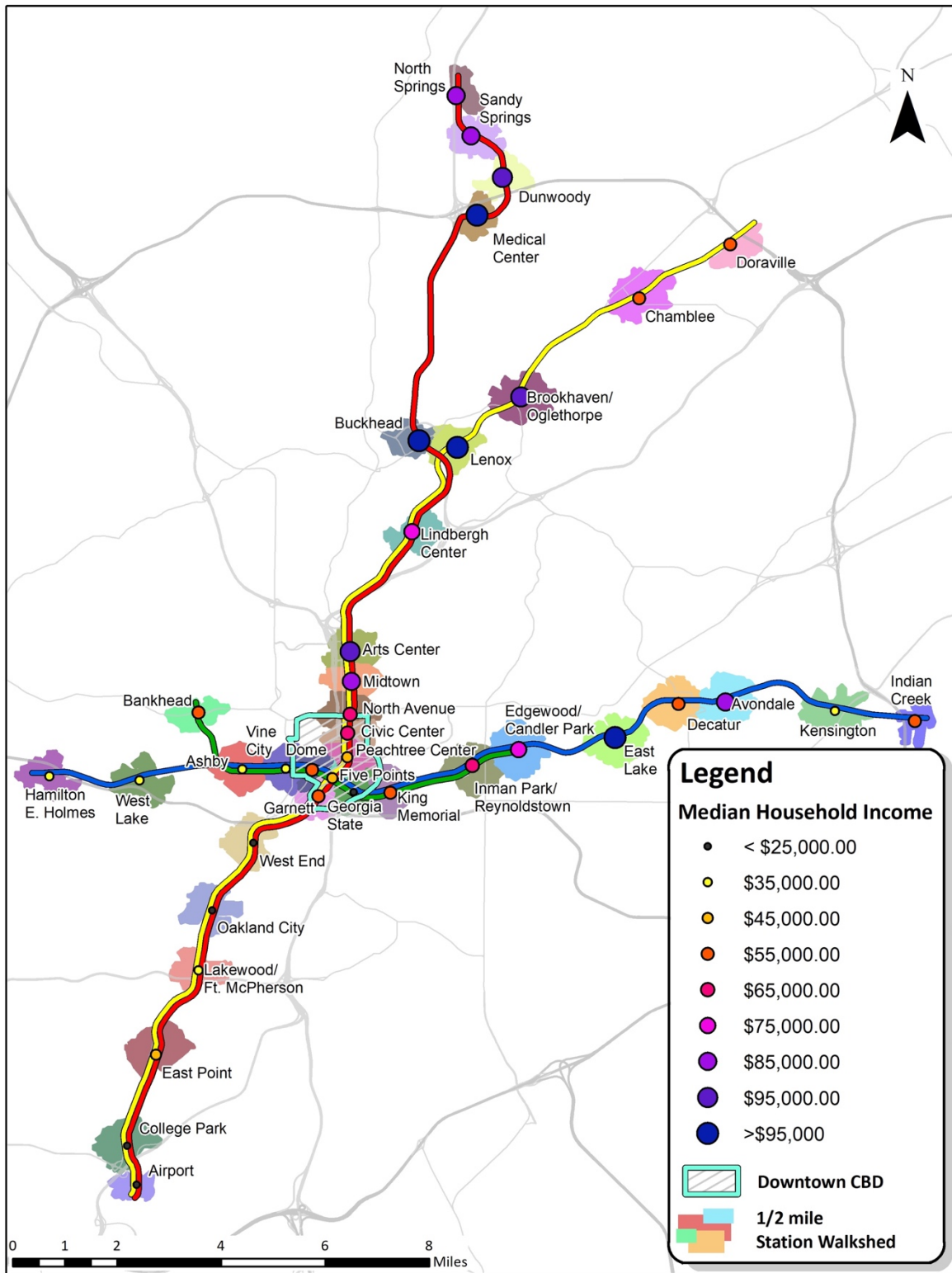
The best fit model serves as the primary answer to research question 1: What factors significantly influence MARTA ridership. The model showed that jobs in the station walkshed and the number of connecting bus routes both are significant and positive factors predicting MARTA ridership, with the strongest positive elasticity going to number of bus lines. The MARTA travel time, whether or not a transfer was required, median household income, and WalkScore® were all found to be significant and negative. Transfers were far more powerful in dissuading trips than overall MARTA travel time, and median household income had the expected negative effect that the literature suggested.

Those candidate variables that were not found to be statistically significant are also a component of the answer to RQ1. Population in the walkshed was tested as a count variable, a density variable, and with categorization by Jenks natural breaks, but never came up as significant in any model. Neither the airport station binary variable nor the CBD station variable showed significance either, though they were hypothesized to be important in the Atlanta context. It is possible that since the Atlanta airport has such

notoriety (being the world's busiest airport) the perception of transit to and from it is greater than the actual reality of the effect it has on the MARTA system.

Nonwhite percentage and vehicle availability factors also did not appear in the best fit model. They were iterated through the model both while including and excluding median household income, but ultimately they did not improve the fit nor show significance in any iteration. This once again differentiates the MARTA/Atlanta case from those in the literature that find that race and auto availability are major predictors of transit ridership. Figure 6.1 shows the median household income by station, as well as the ½ mile station walksheds used throughout the analysis.

Figure 6.1 - Median Household Income and 1/2-mile Station Walksheds Map



Author: J.Luke Derochers March 2019 Source: MARTA

Also conspicuously absent from the final model is any factor related to driving or parking. Drive time was not found significant, nor was a hybrid variable of drive time divided by the MARTA travel time which would attempt to capture the time penalty that MARTA riders incur versus those who drive. Parking utilization was also not found to be significant, even though a large percentage of stations have parking areas and some are used thoroughly (one station had 2,217 out of 2,341 parking spaces utilized, or 90%). This suggests that even though there exists rather large parking infrastructure and the 4th worst traffic in North America (INRIX, 2018), the MARTA system performance does not depend on travel mode substitution from the auto. This aligns with the lack of significance of the drive time divided by MARTA travel time variable in the model.

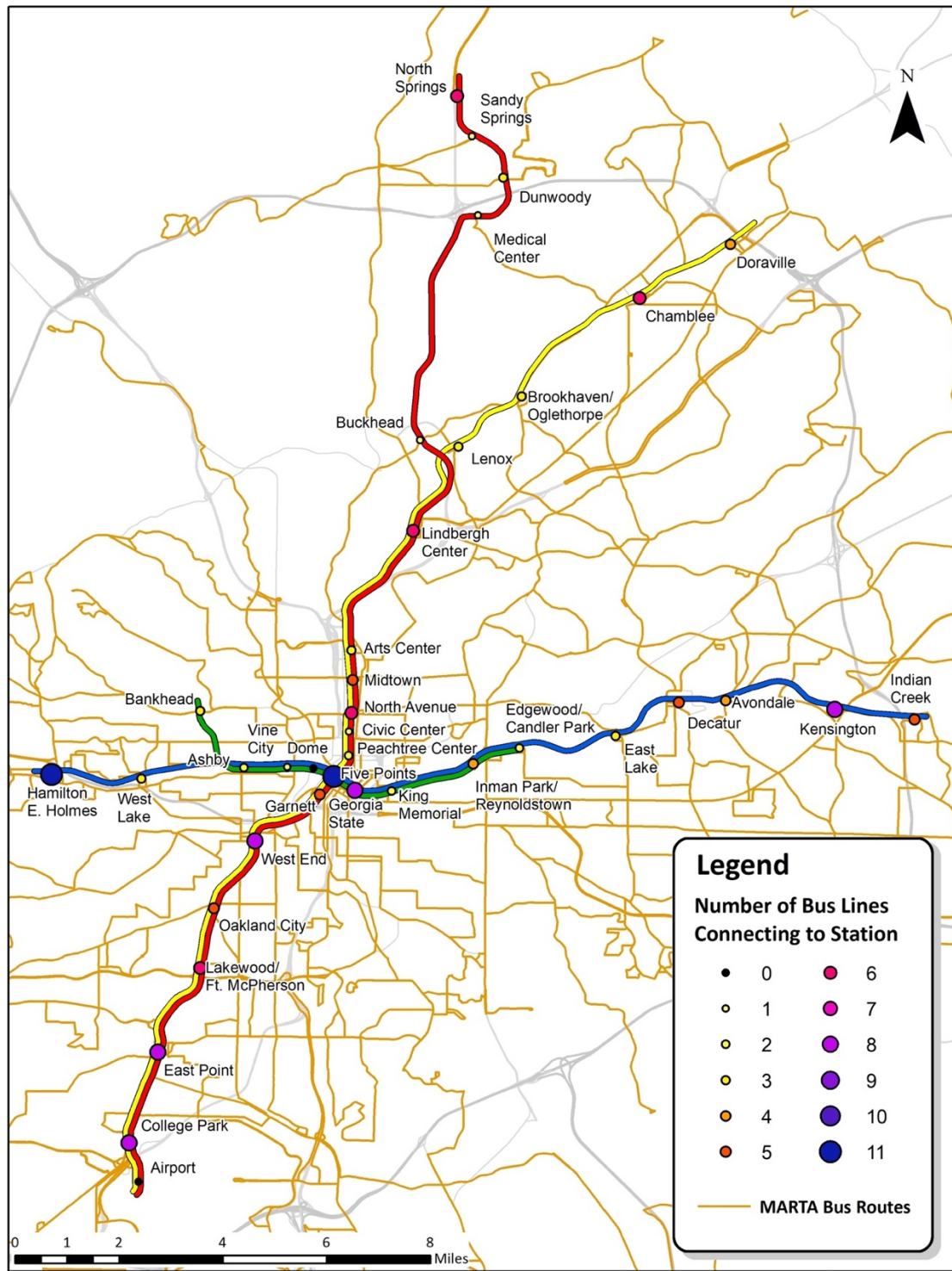
Research question 2: *Do non-pedestrian access factors to MARTA stations show a stronger effect on ridership than TOD factors*, was framed to be an either-or answer, however the findings from this study fall somewhere in between. Non-pedestrian access was defined as arriving at the station via a car and using the park and ride or by MARTA bus. The model strongly suggests that many riders are utilizing the bus system to reach main-haul rapid-transit service, and that the greater the number of connecting bus lines, the higher the ridership both at the origin and destination stations. However, by parking not showing significance (nor any of the auto variables), it appears that parking infrastructure doesn't play a significant role in overall system ridership. Figure 6.2 shows the MARTA heavy rail system as well as the connecting bus routes to the stations.

It is appropriate to note that the structure of the MARTA bus system is specifically designed to function as the model predicted. Almost all of the 100+ bus lines originate from and then return to a MARTA heavy rail station (or connect multiple stations), allowing those who need to transfer direct non-pedestrian access to the main trunk heavy rail lines. In other cities where the feeder bus system has a different service orientation, it would be expected that the bus system may not have such a direct and positive effect on rail transit ridership.

On the other side of the question, TOD factors were defined as population density, job density, and pedestrian friendliness (estimated by WalkScore® in this study). Population did not show significance in any form (total count, density, or categorization by Jenks natural), but is considered a major component of TODs. However, jobs in the walkshed showed significance and the expected positive sign and correlation, following the TOD expectations. Interestingly, WalkScore® showed a negative effect, insinuating that the pedestrian friendliness of the area is not of importance to ridership, and in a small way may substitute for transit or dissuade riders. It is also possible that WalkScore® may not be a suitable measure of the land-use / built-environment as the design 'D' is trying to capture and creates a construct validity issue. In future research it would be useful to either break the WalkScore® index into its constituent parts and test them independently, or to use a more direct measure such as intersection density inside the station walkshed.

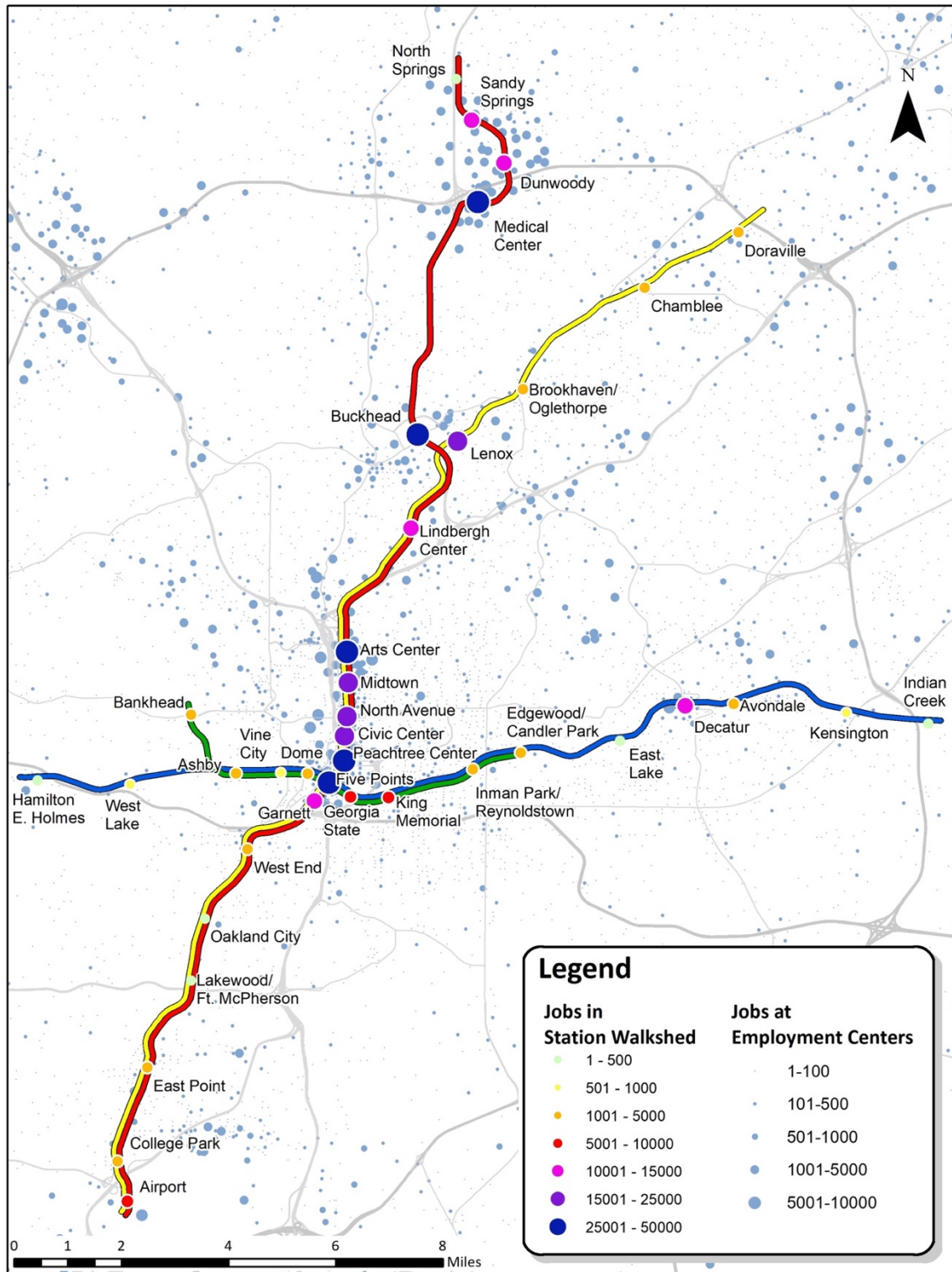
Figure 6.3 shows the jobs within the station walksheds, as well as the jobs throughout the metro Atlanta region. Figure 6.4 shows the Station WalkScore®.

Figure 6.2 - Number of Connecting Bus Lines to Station Map



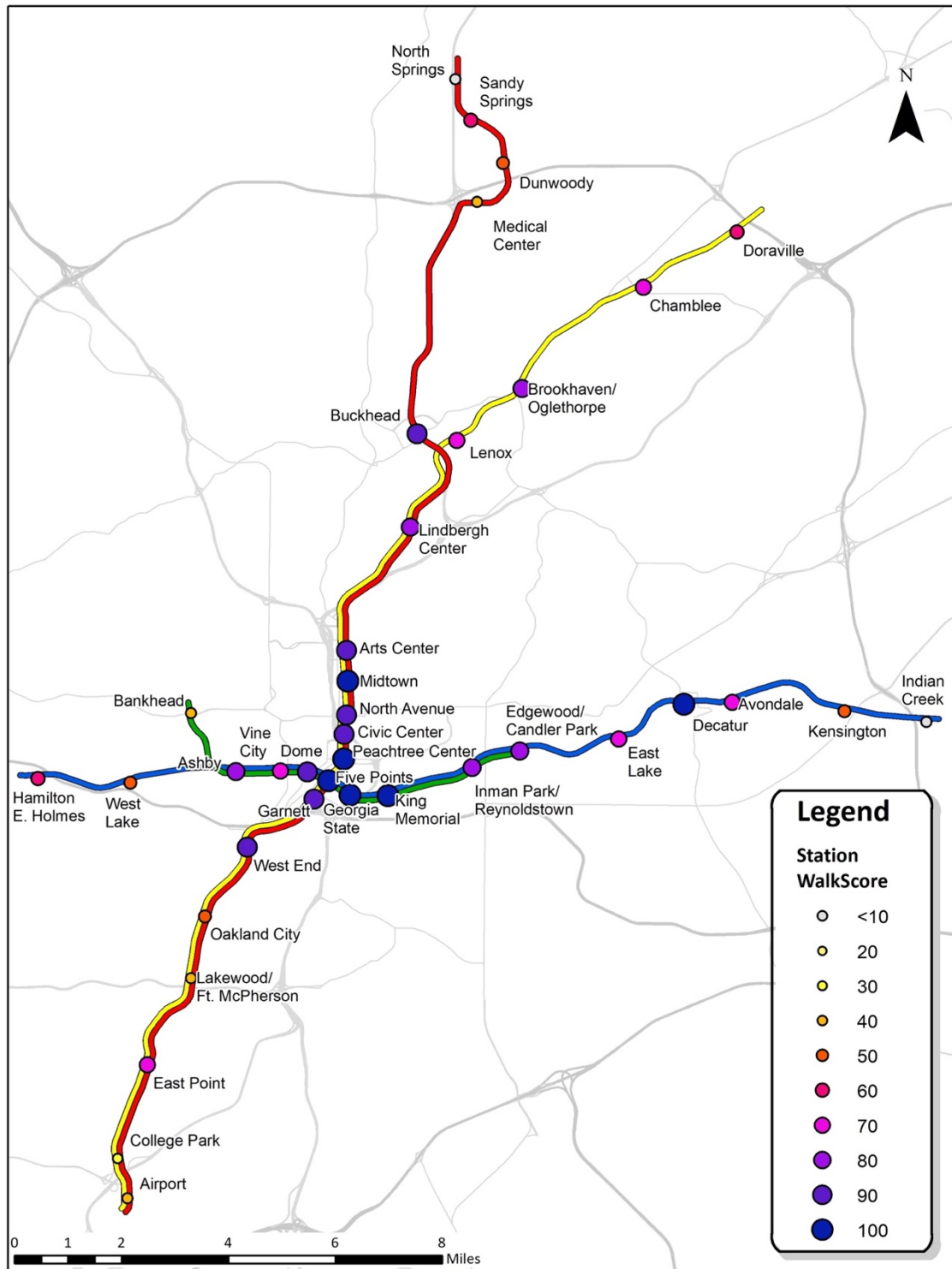
Author: J. Luke Derochers March 2019 Source: MARTA

Figure 6.3 - Jobs in Station Walkshed Map



Author: J.Luke Derochers March 2019 Source: MARTA, OnTheMap Employment Data LEDH 2015

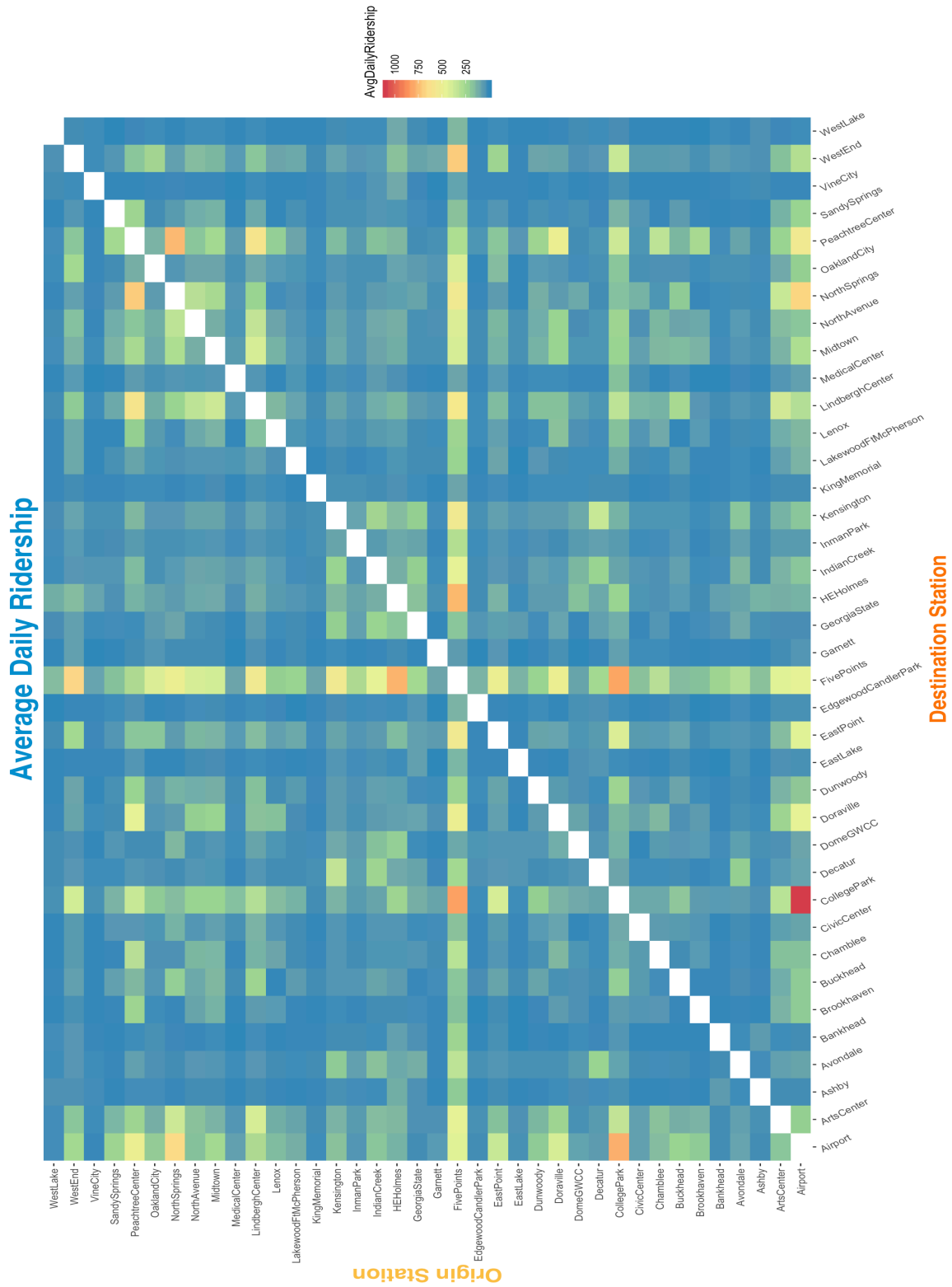
Figure 6.4 - Station WalkScore Map



This study suggests that in the case of Atlanta, the answer is not exclusively TOD or non-pedestrian access specifically that is driving. Instead it seems that MARTA is primarily serving those who use the buses to move throughout the dispersed metro area to get to centers of activity (as measured by the station area job count). This reflects a conclusion much more similar to that of Brown & Thompson (Brown & Thompson, 2008) wherein the utility of a transit system is serving the dispersed centers of activity and jobs, as opposed to the traditional TOD literature. However, this is not to suggest that TODs should be discouraged in the MARTA system, but that TOD development must include strong job creation (as opposed to focusing on housing at a higher rate) and that stations must retain and improve connectivity to the bus system, and thus improve bus service levels as well.

Building off that conclusion, the answer to research question 3: *What significance does the downtown Central Business District (CBD) play in predicting ridership in Atlanta*, is that the CBD does not play a statistically significant role. It is certainly important from a structural role; Five Points station, which is the center station in the system has the greatest number of riders daily by a large margin, and most riders who transfer lines will do so at Five Points. But when considering the CBD holistically, it does not have a significant effect of the OD ridership flows. Figure 6.5 shows a heatmap of the average daily ridership throughout the entire system.

Figure 6.5 - Average Daily Ridership Heatmap



CHAPTER SEVEN

CONCLUSION

As transit agencies all throughout the US face declining ridership, and impetus for increasing ridership grows due to climate change, congestion, and urbanization, understanding the factors that affect ridership is fundamental to the successful planning, performance, and longevity of US transit. However, the literature and current planning thought is split on the issue of what is the primary driver of transit ridership. Some contend that the aspects of older, historically successful systems are the major components and they seek to replicate these attributes by planning Transit Oriented Developments with high population and job densities, mix of uses, and pedestrian friendliness.

Others contend, especially for younger systems in the Sunbelt, that the historic radial model of the city where jobs and demand were focused on the Central Business District is not accurate. Instead they suggest a view of metro areas as dispersed clusters of activity that transit should attempt to connect. These competing ideals were examined in this study for the metropolitan Atlanta area, focusing on the factors that affect MARTA ridership.

Three research questions were outlined to investigate not only which factors were significant, but also to attempt to understand what the most appropriate approach would be for MARTA when considering TOD vs non-pedestrian connectivity and a dispersed polycentric or CBD focused metro area.

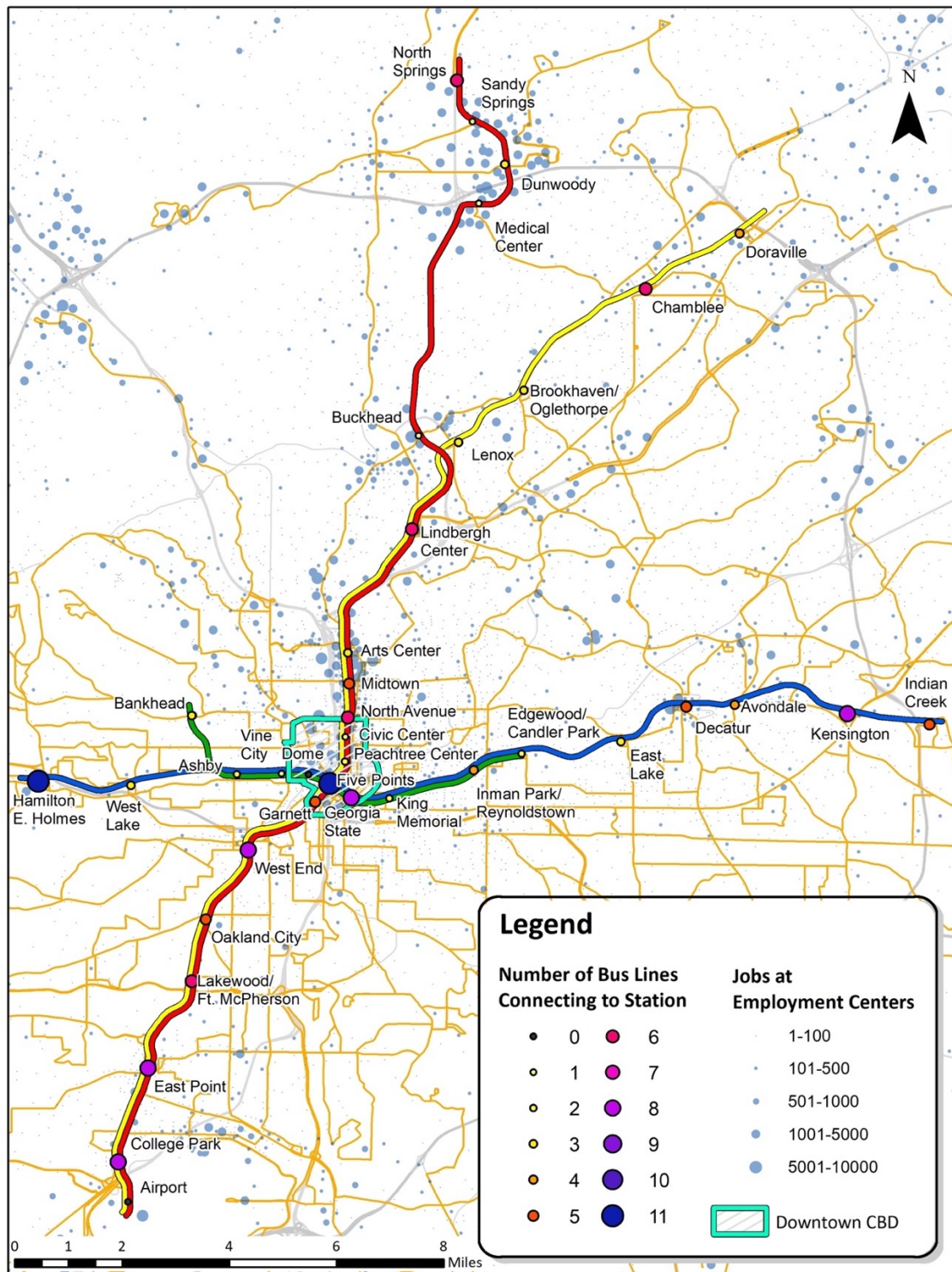
The study utilized an origin-destination direct demand model with average daily ridership as the dependent variable. A multilevel (mixed-effects) cross-classified generalized linear regression model was employed to statistically test candidate variables from the transit ridership literature to determine the factors' significance, magnitude, and directionality. An initial model based in theory was tested, then the model was explored and iterated to develop a best fit model. This best fit model was the best intersection of parsimony, significance of factors, explanatory power, and overall linear fit. The model showed that the number of jobs in a half mile station walkshed and the number of connecting bus lines to the station to be positive and significant factors of ridership. It also showed significantly that transfers, median household income, MARTA travel time, and WalkScore® reduce ridership, although issues of construct validity may exist for the multi-dimensional WalkScore measure. All other candidate variables were found to be insignificant. These notably included drive time, population around stations, parking utilization, and CBD stations.

The findings suggest that it is not an either-or situation in Atlanta when it comes to TOD vs non-pedestrian connectivity. From the model, MARTA is shown to be serving bus riding patrons who are attempting to reach destinations with high densities of jobs (which can also be seen as activity). This finding does not in any way explicitly discourage TOD implementation, but highlights the necessity to ensure that the development is one that includes jobs and activity centers as its primary function (as opposed to population density and proximity to the station, or pedestrian friendliness). It also requires that MARTA continue to provide good connectivity between the heavy-rail

and local bus modes of the transit system. This has been a tenet of MARTA transit planning in the past, and must remain so as MARTA plans new TODs and station and system upgrades.

Finally, the findings do suggest that the dispersed polycentric model of the city more aptly describes the metropolitan Atlanta region where MARTA operates. Figure 7.1 helps to visualize this phenomenon by overlaying the employment data with the connecting bus line data. The CBD variable showed no statistical significance, and employment centers seemed to be the major external factor driving transit demand. Though the results of the O-D direct demand model are specific to the MARTA system, they align with the growing body of evidence that suggests transit in younger cities must respond to the suburbanization of jobs, and attempt to serve as many of the nodes of activity as possible by making good use of their bus networks to avoid further declines in ridership.

Figure 7.1 - Employment and Bus Connectivity Map



Author: J.Luke Derochers March 2019 Source: MARTA, OnTheMap Employment Data LEDH 2015

CHAPTER EIGHT

FUTURE RESEARCH

The findings of this study offer a pair of lines of future research. The first comes from the tension between creating an ‘urban place’ node in the city with tenets of TOD and specifically including high concentrations of jobs, while still proving the ‘transportation node’ aspects of physical capacity to support many intersecting bus lines and smooth transfers from bus to rail. This is often looked past in the literature as the either/or policies tend to focus on creating pedestrian friendly TODs or improving multimodal transportation service quality. However, if the solution exists, it comes from good urban design. Focusing on how to incorporate the most valuable assets of both urban places and transportation hubs simultaneously would be an insightful stand-alone research project.

Another line of further research lies with the connection between bus service connectivity and rail transit ridership. Though this study found that connecting bus service had a significant and positive impact on ridership, it would be interesting to dive deeper into this relationship. Specifically, a study that sought to quantify the increase in rail ridership from various types of bus service improvements would be of great use to transit planners who must make such decisions. A study could assess pre and post rail ridership data from various types of improvements like frequency increases, routing changes, vehicle upgrades, or station/transfer infrastructure and look for differences in the elasticity of resulting rail ridership. The relationship between the bus service and rail

transit ridership is obviously significant, but further study could illuminate the expected results of various improvements.

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