EVALUATION OF THE EFFECT OF RAIL INTRA-URBAN TRANSIT STATIONS ON NEIGHBORHOOD CHANGE

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To Mama i Tata

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SUMMARY

Development of heavy rail intra-urban public transportation systems is an economically expensive policy tool for State and Local Governments that is often justified with the promise of economic development and neighborhood revitalization around station areas. However, the literature on the effects of rail intra-urban transit stations on neighborhoods is relatively thin, particularly on the socioeconomic effects. This quasi-experimental study evaluated the effect of heavy rail intra-urban transit stations on surrounding neighborhoods, using Atlanta, Georgia and its transit authority, the Metropolitan Atlanta Rapid Transit Authority (MARTA), as a case study. Atlanta is an expansive American city, with a large public transportation system, but low population density and no large-scale policies promoting growth around MARTA rail stations. The study period, 1970 to 2014, covers the entire period of MARTA's existence – stations opened between 1979 and 2000. Neighborhood change was operationalized with a neighborhood change index (NCI), built on the Neighborhood Life-Cycle framework, with an adaptation that incorporates both the filtering (negative NCI) and gentrification (positive NCI) models of neighborhood change. The study differentiates between an initial effect of new MARTA rail stations, and a long-term effect. Control groups were formed using one and three mile buffers, as well as a matching strategy. Difference-in-difference (DID) models find very little evidence of a positive relationship of NCI with the opening of new MARTA rail stations. The economic recovery that began in 2010 is of special interest for housing research. To address this time-period this study utilized two models, with mixed results. The DID model suggested a negative effect of stations on the

NCI. To control for selection bias in the 2010 to 2014 economic time-period, this study utilized propensity score matching to balance the treatment and control group on observed characteristics. A time and tract fixed effects model using the matched treatment and control groups found a significant positive effect of stations on neighborhood change. To test the long-term effect, a time and tract fixed effects model (1970-2014) with the NCI as the dependent variable found a positive NCI effect of MARTA stations on neighborhoods. Therefore, overall, positive neighborhood change (on the NCI scale) can be attributed to MARTA transit stations. Since 2002 MARTA ridership has slightly declined; therefore, the study concludes that given stagnant ridership, lack of supporting policy, and the finding of a positive relationship between MARTA transit stations and gentrification, the stations are a positive amenity, and are a significant contributor to neighborhood change. However, neighborhoods are heterogeneous on many dimensions, and the effect of rail intra-urban transit stations on neighborhoods may depend on the tract's location, service characteristics, accessibility, and many other unobserved characteristics. Future research will supplement this methodology with additional data and compare the effect of intra-urban transit stations on neighborhood change in other cities to better address potential neighborhood heterogeneity.

CHAPTER 1

INTRODUCTION

Urban form and land use are largely shaped by the technology people use for mobility and their housing choice. Historically, in cities worldwide, the introduction of rail and streetcar technology, and later the automobile and roads, facilitated urban sprawl patterns in newly built suburbs, resulting in declining populations in central cities. The predominance of the automobile as a primary mode of transportation over the past half century, has had a sharp negative effect on density in cities. This effect is particularly strong in cities that developed more recently, such as polycentric cities in the Southern United States of America (e.g., Atlanta, Los Angeles, or Phoenix).

The relationship between transit and housing is also critically important for low income populations, which constitute well over 50% of public transit users (Grube-Cavers & Patterson, 2014). Rail intra-urban transportation systems and other public transportation systems, which require high population densities to function efficiently, provide an important transportation amenity to low income populations. They also provide a solution to alleviate congestion and pollution caused by pervasive automobile use, but at a high capital cost.[1]

After housing, transportation is the next critical urban necessity for personal budgets, but also an important component of municipal budgets. Public transportation is a

[1] Heavy rail construction cost projections vary by location, but can range from $50 million to $2 billion per mile (MacKechnie, 2016)

public good subsidized by the state[2,3] and housing is a private good subject to economic market conditions. Both, however, can have an effect on the other. Neighborhoods can change as a result of a public transportation investment, and the location of transportation investments may be driven by existing housing infrastructure.

The policy impact of public transportation on neighborhoods is important to understand given the high cost and permanence of transit infrastructure. Both housing stock and public transportation systems (i.e., rail transportation) can be characterized as durable components of neighborhoods. That is, once they are put in place the local land use is effectively fixed over long periods of time. Public transit rail systems will maintain their same use almost indefinitely, while land parcels can switch uses. However, it is a slow process for an entire neighborhood to change land use completely, barring some major external shock. In addition to land use changes over time, neighborhoods can undergo changes in the demographic and socioeconomic characteristics of residents, as well as population density changes and property value changes.

Urban studies literature has defined two socially important types of neighborhood change that represent opposing directions of change: filtering and gentrification. Filtering is a process by which the value and socio-economic status of residents of a neighborhood declines over time. Filtering symbolizes decline, but also an increase in affordable housing for low-income populations. Gentrification is a type of neighborhood change that symbolizes renewal and renovation, but also displacement of low-income populations. If

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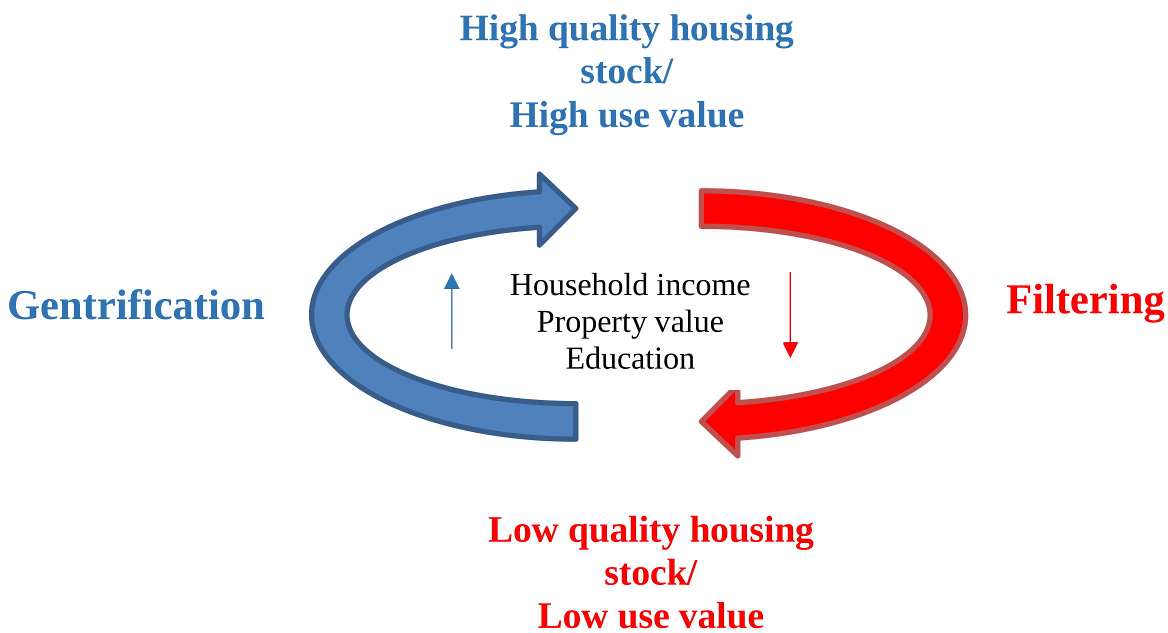
[2] In the U.S., no transit system that operates rail transit covers its full operating costs with fares, and only 2% of the 1,800 public transit systems in the U.S. that don't operate rail systems are profitable (Kearney, Hershbein & Nantz, 2015).
[3] On average, fare revenues make up 33% of operating funds, local (28%) and state (26%) funds make up the majority of the remainder (National Transit Database, 2012).

public transit infrastructure leads to neighborhood changes, such as gentrification, then policy has to address the social justice aspect of taxpayers subsidizing developers and local land owners. To address such social justice issues, it is important to evaluate neighborhood change not only on changes in neighborhood economic indicators (i.e., real estate prices), but also on socio-economic and demographic indicators. If public transportation systems affect who lives in a neighborhood and how land use is allocated over a neighborhood life-cycle, they are an important policy tool in urban development, in addition to being a transportation amenity.

1.1 What is the Neighborhood Life-Cycle?

The principal framework for the operationalization of change in this study is the neighborhood life-cycle. The neighborhood life-cycle framework suggests that a neighborhood’s value and its residents’ socio-economic status continually changes, declining as the use of the neighborhood housing *filters* to successively lower income groups over time (Lees, Slater, & Wyly, 2008; McDonald & McMillen, 2011; Metzger, 2000; Rosenthal, 2014). Early stages of neighborhood life-cycle models were based on the idea of filtering, which describes neighborhood decline (Hoyt, 1939; Metzger, 2000). In these models the process of decline is marked by an influx of progressively lower socioeconomic populations, ultimately ending in abandonment; revitalization was not included as a stage in a cyclical process. But, the “back to the city movement” that started in the 1970s has led to urban renewal and regeneration largely through the process of gentrification (Lees, et al., 2008). Combining the process of filtering and gentrification into one concept and augmenting it to the existing neighborhood life-cycle theory, results in a theoretical neighborhood life-cycle that integrates decline and revival (Figure 1.1).



Source: Author's contribution

Figure 1.1 Neighborhood Life-Cycle

In general, neighborhood change can have three states along the neighborhood life- cycle; ascending, declining, or stable. Evidence suggests that the filtering process is dominant, which has particularly important implications for low income populations, who rely on the decline in quality of real estate over time to increase the amount of available affordable housing (Rosenthal, 2014). Studies suggest a back to the city movement of relatively affluent and highly educated people results in urban reinvestment, but at the cost of displacement or reduced housing opportunities and quality of life for low income dwellers (Zuk et al., 2015; Smith, 1982).

Economic disparities create price gradients between and within urban neighborhoods. Gentrification is an exploitation of these price gradients, or 'rent gaps' (Smith, 1979; 1982), as investors purchase low cost properties and resell the upgraded properties at high profits. The period from 2010 to 2014 was marked by a housing market recovery in the United States (Immergluck, 2016). The period was marked with initially high residential housing foreclosures and unemployment, which then gradually declined. The growing population in the city of Atlanta along with economic recovery of the region generates an environment conducive for gentrification. If public transit stations are an amenity, then this period should show relatively higher levels of gentrification near train stations.

1.2 Rail Intra-Urban Transportation Systems and Neighborhood Change

The presence and scale of public transportation systems alters many characteristics of surrounding neighborhoods. Primarily measured as a change in the cost of housing, the literature is mixed on the results (Zuk et al., 2015), and the literature on changes in other aspects of neighborhood change as a result of the presence of a public transportation system is thin (Billings, 2011; Bowes & Ihlanfeldt, 2001; Debrezion, Peels & Rietveld, 2007; Du & Mulley, 2007; Glaeser et al., 2008; Grube-Cavers & Patterson, 2014). The literature generally examines changes in neighborhoods over short time frames, around the time when new stations are put in place – with only a few exceptions (Glaeser et al., 2008; Kahn, 2007). But, there are more than 3,000 already existing neighborhoods with access to a rail transit station in the United States (Pollack, Bluestone & Billingham, 2010), and the impact and economic cost of rail public transit infrastructure is large and long-lived. Such large public expenditures are important aspects of public policy and should be better understood longitudinally, and not only at one point in time after implementation. Furthermore, although it is important to understand the capitalization of public transit infrastructure investment in increasing property values, policy makers may be interested in neighborhood change in dimensions other than the economic dimension. Therefore, improving the methodology of measuring the effect of existing rail intra-urban transit stations on surrounding neighborhoods and the time frame over which that effect remains, requires academic attention.

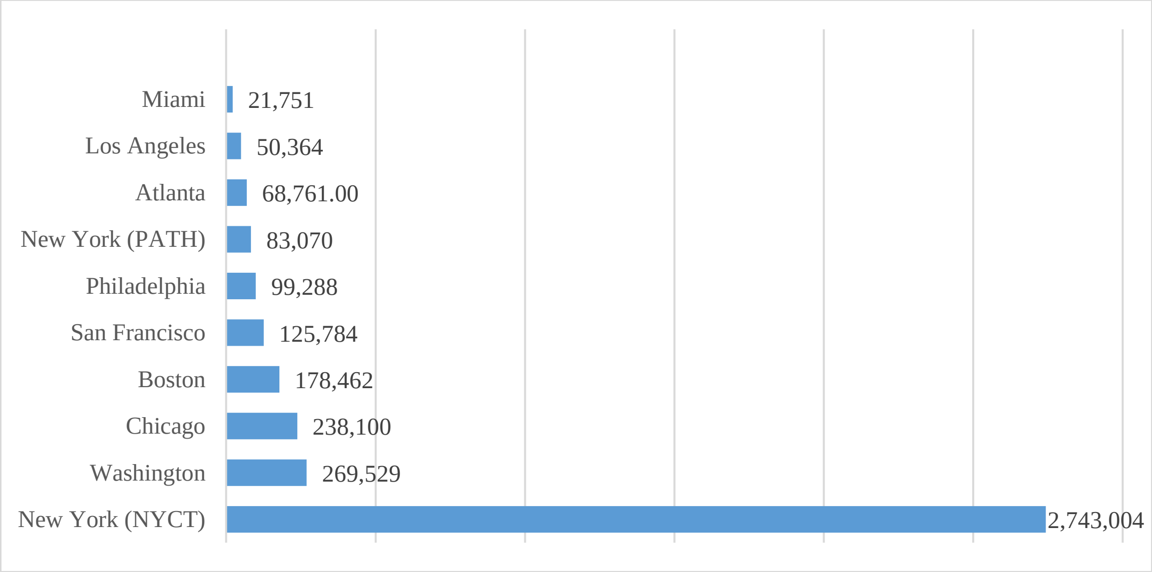
Public transportation infrastructure financial investments have important long-term effects and long-term urban policy consequences for urban areas, and should be factored into neighborhood change research on land redevelopment, social justice, and economic development. Neighborhood change can be represented on a continuum of socio-economic values, following the gentrification literature, measured as economic wealth (e.g. income, housing values) or level of education of neighborhood residents. This study adds to understanding the effect of public transportation investment on neighborhoods, operationalization of neighborhood change, as well as the methodology of the evaluation of urban transit system on neighborhood change, and should be of significance to researchers, planners, and policy advocates.

1.3 Study Area and Analytical Approaches

Atlanta, Georgia lies at the center of the ninth largest metropolitan area in the United States, and contains the nation's ninth largest public transit system.[4](APTA,

[4] MARTA is ranked ninth in vehicle boardings (Unlinked Passenger Trips) and thirteenth in passenger miles

2016). In terms of Unlinked Passenger Trips (UPT)[5] on heavy rail systems, Atlanta ranks eighth (Figure 1.2). The scope of this study covers the lifetime of the Metropolitan Atlanta Rapid Transit (MARTA) system, whose first stations opened in 1978. The study uses census tract level data from 1970 to 2014. The period from 2010 to 2014, during which the housing market began to undergo a period of recovery, is particularly worth noting. During the recovery people were less economically constrained in their residential choice. If there was going to be an effect of transportation on the process of gentrification or filtering in Atlanta it is reasonable to expect it to be most pronounced during that period.



Source: APTA (2016)

Figure 1.2 Top ten U.S. heavy rail transportation agencies by Unlinked Passenger Trips (UPT)

[5] Unlinked Passenger Trips (UPT) are individual vehicle boardings

Atlanta has a racial history that dates to before Martin Luther King Jr., and pre-Civil War times, and the city remains economically and socially polarized. The East-West section of the MARTA line was planned in the 1960s to be a busway based on the lack of sufficient density for rail along the planned route. However, the local political climate would only coalesce in support of the public transit system if both the North-South line serving the white communities, and the East-West line serving the black communities would be the same heavy rail system. Furthermore, the city of Atlanta reached peak population in the early 1970s, when the period of 'white flight' from the city began.

Atlanta has never had sufficient population density for a heavy rail public transportation system, but equally importantly, over time it has not enacted zoning nor other housing density friendly policies focused on public transportation. Therefore, in a low-density environment and with a lack of policy support, if heavy rail intra-urban public transit stations have an effect on surrounding neighborhoods, the Atlanta case study provides a unique environment by removing many potentially confounding policy factors in the evaluation.

1.4 Research Questions and Hypotheses

This study aims to answer three principal questions. First, do intra-urban rail transit stations have an effect on the way neighborhoods change after opening for public service? Second, does that effect persist over the long term? Third, does that effect change during recovery periods when gentrification is expected to be high? The evaluation framework is based on the idea that neighborhood change is driven by public policy, the movement of people, and flows of private capital (Zuk et. al., 2015). This study asks if these changes exist using two types of neighborhood change indicators: individual indicators (e.g. housing values), composite economic and socioeconomic indicators (i.e., the Neighborhood Change Index).

The effect of public transportation stations on neighborhood change is evaluated using a robust set of models, with a time-period predating the formation of the MARTA transit system. To capture the effects in both the short-term after the initial station opening, and long term effects over time, a set of methodologies are employed: Fixed Effects (FE) models, a set of difference-in-difference (DID) models, and a propensity score matching methodology.

Quasi-experimental methodology attempts to replicate experimental design, relies on the selection of unbiased control groups, and assumes no spillover effects from the treatment groups. The treatment in this study is the accessibility of a rail intra-urban transit station to a neighborhood. Neighborhood and access are defined as any census tract that has a centroid within one and a half miles of a MARTA rail station[6]. Control groups are generated based on proximity, as well as using propensity score matching methodology.

The FE method used census tract level census data from 1970 to 2014, modeling the effect of rail intra-urban transit stations in a neighborhood on neighborhood change. Neighborhood change is operationalized with a neighborhood change index (NCI),

[6] Census tracts in Atlanta are very large due to the low population density. A one and a half mile distance was necessary to consistently capture as treatment the tracts surrounding the station. Studies that utilize parcel data as the unit of analysis are able to construct smaller treatment areas. However, parcel data does not provide socioeconomic characteristics, a critical aspect of this dissertation.

building on studies by Smith (1979), Hackworth & Smith (2001), Freeman (2005), Grube-Cavers (2014) and many others.

FE models, however, do not control for selection bias – stations are not necessarily randomly assigned, so any affect attributed to stations could be the result of this unobserved factor – thus, a quasi-experimental approach is used to generate an experimental and control group to address this bias.

The control group selection method used two specifications, proximity and propensity score matching. First, control group census tracts were selected as tracts with a boundary within one mile and three miles of the treated tracts. Difference-in-difference models, capturing a before and after effect, were utilized in the analysis. The propensity scores methodology utilized a logistic regression to create a single indicator that can be used to balance treatment with control groups on observable characteristics. This method theoretically results in two identical groups with exposure to treatment as the only difference. The control group was sampled from census tracts in the five-county study region.[7] A census tract and year fixed effect model was fitted using the treatment and propensity score matched control groups for years 1970 to 2010 using normalized to 2010 geographies census data from the Longitudinal Tract Database (LTDB). A separate analysis was carried out using 5-year American Community Survey (ACS) data for years 2010 to 2014.

This research exploits census tract level historical trends to establish within neighborhood patterns of change over time, using the life-cycle framework. The data covers the lifespan of the MARTA rail system, and the analysis isolates the period of

[7] Fulton, DeKalb, Cobb, Clayton, and Gwinnett, the counties originally planned to participate in MARTA.

housing recovery from the ‘Great Recession’, which ended June 2009 (Bureau of Labor Statistics, 2012). The findings indicate the presence of gentrification in census tracts near MARTA stations, versus control groups. Interestingly, there is some indication that during periods of recovery, MARTA rail accessible areas have gentrified less than MARTA non-accessible areas, but that evidence is mixed. The evidence in this study supports the hypothesis that rail intra-urban transit investments generate gentrification, even without other policy intervention, and thus support the idea that intra-urban rail transit stations are a positive amenity. To maximize the effect, policies promoting rail public transportation systems should include other mechanisms such as Transit Oriented Development (TOD), or regional zoning changes that lead to densification. For example, the region could zone certain high density projects only near transit stations.

It should be noted that this study did not directly address the social issue of displacement that some literature argues is brought on by gentrification (Lees, Slater & Wyly, 2008; Zuk et al., 2015). If rents are rising,[8] it can be assumed that at least at the margin, families will be forced to move, and if they are, they will have to relocate to an area inaccessible to rail transit. Therefore, large scale public development should address low income housing options at the planning stages of the projects, otherwise higher income groups will outbid lower income groups for access to the amenity.

A principal limitation of the study is the data unit of aggregation. Although the census tract unit of analysis makes a long study period possible, Atlanta’s low density makes the census tracts spatially large and oddly shaped. Using such large tracts as treatment units potentially introduces significant measurement error. Longitudinal

[8] Rent is used as a proxy for housing values in this study.

individual housing data would be superior to census tract aggregations, however those data, over a large area and covering a long time-period, are not accessible at this time.

1.5 Chapter Contents

The remainder of the study is organized as follows. Chapter Two examines the existing literature on neighborhood change, transportation system evaluations, methodological approaches. Chapter Three presents the support for using Atlanta as a case study. Chapter Four describes the data, states the hypotheses, and presents the methodology. Chapter Five presents the results, and finally, Chapter Six concludes and summarizes the study and findings. The Appendices contain descriptive statistics and results of the analyses.

CHAPTER 2

BACKGROUND AND CONCEPTUAL FRAMEWORK

Neighborhoods are spatial entities composed of people and infrastructure. People can choose to move, and although the infrastructure is fixed in place, it can be abandoned, restored, or replaced. The infrastructure is shaped by the investment of the people who live there, but neighborhood infrastructure also attracts people and capital, private and public. Therefore, neighborhoods represent a mixture of socioeconomic and infrastructural attributes that change over time, driven by the movement of people, capital, and policy (Zuk et al., 2015).

Transportation is the largest cost to a household after housing; it is an important public good for urban residents, particularly low income populations. Economic models of residential location, such as the Alonso/Muth/Mills Model (AMM) (Alonso, 1964; McDonald & McMillen, 2011; Mills, 1972; Muth, 1969) suggest that transportation access is an important factor in residential location choice. The spatial mismatch hypothesis suggests that residential segregation of minorities in central cities keeps them away from jobs, which have migrated to the suburbs (Arnott, 1998; Ihlanfeldt & Sjoquist, 1998), and access to public transportation is one reason that the poor live in cities (Glaeser et al., 2008).

This dissertation work addresses the gap in the literature suggested by Zuk, et al. (2015); there has been little written about the effects of public transit on the neighborhood life-cycle. The task of Chapter Two is to present scholarship that supports the theoretical framework and methodological approaches employed in this study. The chapter is organized as two sections. The first section presents the Neighborhood Change Framework and examines the literature on the operationalization of neighborhood change, including gentrification and filtering. The second section describes the methodological approaches to the evaluation of public transportation on the urban form.

2.1 Neighborhood Change Framework

In a review of literature, Zuk et al. (2015) identified the neighborhood as the primary unit of analysis in urban research. In the literature, the change in neighborhoods over time has been measured using individual indicators, or using a variety of composite measures. The most commonly used individual measure of neighborhood change is housing value, operating under the assumption that any local amenities or other attributes of a location are capitalized into property values. However, neighborhoods are multi-faceted entities, and measuring neighborhood change on one dimension may not accurately capture the phenomenon (Hanlon, 2009; Wei & Knox, 2014). In the literature, there are two primary frameworks utilized for the study of neighborhood change: (i) a neighborhood life-cycle framework (Downs, 1981; Hoover & Vernon, 1959; Metzger, 2000), and (ii) a typology of neighborhoods framework (Wei & Knox, 2014; Mikelbank, 2011).

The literature suggests several mechanisms and variables that influence neighborhood change. The classic Alonso-Muth-Mills monocentric city model predicts the spatial distribution of households based on transportation costs, population density, land price, distance to the central business district, and household income (Alonso, 1964;

McDonald & McMillen, 2011; Mills, 1972; Muth, 1969). However, neighborhoods don't have to settle into a static state. A change in any one factor produces changes in the others. Macro- and micro-economic changes can have an impact on household income and house prices, and the changing needs and incomes of households over their lifetime may also cause changes in residential choice (Freeman & Barconi, 2004; Rossi, 1980). With the building of new highways and addition of capacity on existing highways transportation cost is reduced. Near the Central Business District (CBD) where density is high, housing demand is expected to be reduced (McDonald & McMillen, 2011). Wealthier households prefer low-density suburban locations, while low income groups live in dense inner city environments, where the high cost of land is offset by smaller, denser development, and lower transportation costs. Factors, such as proximity to public transportation, amenities (e.g., beachfront, riverfront, monuments, parks, historical buildings), and age of housing stock, are other important contributors in the location patterns of high and low income households (Brueckner & Rosenthal, 2009; Brueckner, Thisse & Zenou, 1999). Filtering models starting with Hoyt (1939) suggested a downward socioeconomic transition of neighborhoods over time, as housing *filters* from higher to lower income groups, over time. In the 1970s, researchers began studying gentrification, an upgrading of neighborhoods as higher income residents move in (Lees, Slater & Wyly, 2008).

The Neighborhood Life-Cycle framework describes neighborhood changes over time in the value and quality of the neighborhood's housing stock, and the socio-economic standing of the neighborhood's residents (Downs, 1981; Metzger, 2000). This study augments the Neighborhood Life-Cycle concept (Downs, 1981; Metzger, 2000), to include gentrification. The stages and filtering models predict a decline to abandonment, when Neil Smith' s (1979) 'rent gap' would be the largest. However, gentrification doesn't always begin where the 'rent gap' is largest (Lees, Slater & Wyly, 2008). This revised Neighborhood Life-Cycle framework does not restrict the point at which a neighborhood declines or regenerates; a neighborhood does not have to fully decline to begin regenerating. Some neighborhoods[9] stopped declining somewhere mid-cycle and revitalized through various pathways and catalysts in what is termed gentrification (Lees, Slater & Wyly, 2008). Having identified the revised Neighborhood Life-Cycle to serve as the framework for the dependent variable (i.e. neighborhood change) of this study, the next key task to operationalize it. The following sections describe the literature on the operationalization of key aspects of the Neighborhood Life-Cycle framework.

2.1.1 Filtering

2.1.1.1 Filtering Background

In the United States, there has been very little new housing built since the 1920s specifically to serve low income populations; costs of labor, materials, and the profit motive mandate that new unsubsidized housing is built for higher income groups (Rosenthal, 2014). As demand for the originally new housing changes as a result of material deterioration, changes in neighborhood inhabitants, social tastes, and technology, the housing is passed on to lower income groups – this is the process of filtering (Ohls, 1975). Filtering was first introduced by Hoyt (1939), and refers to the

[9] I use the term neighborhoods as a spatial entity, made up of housing, amenities, and people. Over time, housing, amenities, and people change, but the spatial entity remains the same. As in the old tale of my great-grandfathers knife. My grandfather replaced the handle, my father replaced the blade. But, the identity of the knife remains (Unknown).

change in social class of the residents of a specific housing unit, or more broadly neighborhood, brought on by the dilapidation and devaluation of local real estate and other urban infrastructure over time (Metzger, 2000). Several scholars suggest that low income housing is generated through the filtering process (Harris, 2013; Ohls, 1975; Rosenthal, 2014; Sands, 1979). However, other authors have argued that construction in high quality submarkets will not yield benefits to low quality sub-markets (Galster, 1996).

Similarly, the early filtering 'stages' models (Hackworth & Smith, 2001; Metzger, 2000), all predicted a decline over time, ending in abandonment (Hackworth & Smith, 2001; Metzger, 2000). These models defined distinct stages of neighborhood decline, starting with new construction and ending in abandonment[10]. The U.S. Housing and Urban Development 1970's era neighborhood life-cycle model, because it did not have a natural revitalization component, was used to promote inner city revitalization through slum clearing (Metzger, 2000).

In the 19th century Baron Haussmann cleared the slums in Paris, and in the 20th century Robert Moses attempted a similar feat in New York City - both using the same neighborhood life-cycle logic. The neighborhood life-cycle ends with abandonment and a need for state intervention to rebuild the neighborhood (Metzger, 2000). In the

[10] For example, the "U.S. Home Owners Loan Corp. (1940): First Stage: new residential construction; Second Stage: Normal use and maintenance; Third Stage: Age, obsolescence, structural neglect; Fourth Stage: Falling investment and rent values, neglect of maintenance, district-wide deterioration; Fifth Stage: Slum area with depreciated values, substandard housing, social problems." (p. 9, Metzger, 2000).

neighborhood life-cycle stages models, the stages of decline are marked by an influx of lower income inhabitants, and African Americans of any income group (Metzger, 2000). Demographic shifts determine locational advantages, rather than local amenities or disamenities, such as the decline of the industrial base (Metzger, 2000). Therefore, these models may be oversimplified, in addition to not permitting a market driven renovation of inner cities.

2.1.1.2 Operationalization of Filtering

Filtering exists primarily as a concept and the literature makes few attempts at its operationalization. Two operationalization frameworks exist, change in the socioeconomic status of residents and capital value deterioration. Rosenthal (2014) operationalized filtering as a socioeconomic change, operationalized as a reduction in the income of successive occupants of a property over time. He observed the income of residential in-movers over time and calculated the rate at which the incomes of same-housing unit residents change over time. Filtering was found to occur at a rate of 0.5% per year for owner occupied properties, and 2.5% for rental properties. Some properties change from owner occupied to renter occupied as the property ages, producing an overall blended filtering rate of 1.9%. The study utilized 1985 – 2011 American Housing Survey (AHS) data, which contains data on housing and its occupants. This allows for the observation of housing changes, occupancy status (renter or owner) changes, and changes in the incomes of occupants. AHS provides data on about 55,000 households which are a representative sample of the population of the United States. Rosenthal's (2014) approach utilized a representative sample of the entire United States, thereby ignoring local effects that drive change at the neighborhood level. Cities are not created equally, and there is heterogeneity not only between, but also within cities (Grube-Cavers and Patterson, 2014; Kahn, 2007; Pollack et al. 2010; Swanstrom, 2017). Therefore, although Rosenthal (2014) may capture an overall rate of filtering, the study cannot control for local amenities and preferences that drive neighborhood change in specific neighborhoods. However, the filtering rate measured by Rosenthal (2014) is consistent with a building replacement rate of about 2% in the United States (McDonald & McMillen, 2000).

Other studies operationalized filtering using depreciation rates (Margolis, 1982), and hedonic analysis (Armstrong and Rodriquez, 2006; Bowes and Ihlanfeldt, 2001; Gatzlaff and Smith, 1993; Coulson and Bond, 1990). Coulson and Bond (1990) used a two-stage hedonic model of housing attributes and demographic characteristics of census tracts across six American cities in 1979 and 1980. The study did not find evidence of filtering caused by depreciation by age. Rather, their findings were consistent with higher income households demanding larger lot sizes. The hedonic model captures changes in demand for neighborhood characteristics, not the change in the people who live there. The findings in hedonic model studies very greatly based upon location and model specification (Zuk et al., 2015).

2.1.2 Gentrification

Existing at the sticky intersection of economic development and social justice, the concept of gentrification continues to receive media airtime and academic attention. Hailed for renewal, but derided for increased costs of living and displacement of lower income groups, gentrification also creates a paradox for economic theory, which expects wealthier people to head for the suburbs (Alonso, 1964; McDonald & McMillen, 2011; Smith, 1982; Mills, 1972; Muth, 1969). There are many specific ways to operationalize gentrification, but the core of the idea is that relatively higher income residents move into a lower income neighborhood and invest in the housing stock. The key facet of the definition of gentrification is that of a class transformation of a place (Freeman, 2005; Hackworth, 2002; McKinnish, Walsh, & White, 2010; Slater, 2006).

2.1.2.1 Gentrification Background

Gentrification is a neighborhood change process of reinvestment, and socio-economic change. It is marked by increasing home values, and income and education levels of the residents – three key indicators from the literature (Freeman, 2005). Gentrification research seems to fall into two camps. One camp is led by the likes of Richard Florida’s creative class concept, which celebrates gentrification as breathing new life into cities. The other camp is wary of the effects of gentrification and displacement on the poor (Freeman, 2005; Lees, Slater, & Wyly, 2008; Slater, 2006). These concepts represent key perspectives of economic development and social justice that play a role in public policy debates. Data paucity has restricted research to decadal intervals; therefore, little is known about the speed of gentrification or its pervasiveness.

Local governments are interested in solutions to the opposing fiscal goals of providing social programs and increasing tax revenue. Gentrifying neighborhoods increase the tax base and revenue, whereas social housing programs are a cost, and possibly decrease the tax base. A paradox also materializes at the neighborhood level. Neighborhoods survive by resisting the influx of ‘less desirable residents or businesses’

(Swanstrom, 2017, p. 6), and it is counterintuitive for a collective neighborhood to get behind resisting an influx of more desirable amenities, or for landowners to resist rising land values. However, gentrification introduces just such a problem, as rising property values make it more economically advantageous for local governments to pursue gentrification strategies, to the potential detriment of some of its citizens.

The literature on gentrification tends to be largely preoccupied with stopping or slowing the onset of gentrification, fearing gentrification will displace the poor (Freeman, 2005; Lees et al., 2008; Slater, 2006). Therefore, the operationalization of neighborhood change in gentrification literature is often restricted to changes in low income neighborhoods (Freeman, 2005). Even with restricted focus, there is no consensus on whether gentrification causes displacement. Quantitative studies by Freeman (2005) and McKinnish, Walsh, and White (2010) failed to find any displacement. However, qualitative case studies find high rates of displacement in gentrifying areas (Zuk et al., 2015). The research question in this dissertation is on broad neighborhood change, and is equally interested in change over the spectrum of neighborhood types, not just low income neighborhoods.

Displacement is not the only potential negative outcome of gentrification. Increasing rents, for example, even if not leading to displacement, can cause financial hardships for low income residents. Even so, there are positive economic outcomes produced by gentrification that are easy to accept. These include: increased tax base; integration of classes; integration of schools; reduced and deconcentrated poverty; renovation in housing, cultural, and retail infrastructure; and, employment opportunities for existing residents (Freeman & Braconi, 2004; Lees et al., 2008). Governments are eager to increase their tax revenues, which are correlated with property values, and therefore produce many policies supporting gentrification. An influx of more affluent, younger, and more educated residents of a neighborhood increases the diversity of the neighborhood. Neighborhood schools benefit from diversity, increased funding, as well as more engaged parents. An increased demand for services may potentially lead to new local jobs.

There are scenarios under which gentrification is impeded (Ley & Dobson, 2008), which may be of interest to policymakers. Gentrification does not always start in the lowest land rent areas, contrary to Neil Smith's rent gap hypothesis; rather, gentrification appears to be at least partially caused by the location of amenities (Ley & Dobson, 2008). Public housing, rent control neighborhoods, areas with high crime rates, and areas with subsidized housing provide a disincentive for gentrification. Further, immigrant pockets may resist gentrification by selling or renting to a specific subset of society (Jacobs, 1961; Ley & Dobson, 2008). There are a multitude of policy responses that attempt to tame gentrification, including: demolition controls, rent controls, zoning to maintain neighborhood character loans to aid in housing renovation, and social housing programs (Ley & Dobson, 2008). The remainder of this section briefly addresses the theories of the formations of gentrification and its operationalization.

There are two key competing theories for the genesis of gentrification: (i) consumer preference, and (ii) profit drive (O'Sullivan, 2005). These concepts are also known as production and consumption theories (Lees et al., 2008), and this is where a lot of friction in the literature resides: which process dominates? The consumption theorists suggest that various mechanisms are creating new gentrifiers. The main theses are based on the professionalization and deindustrialization of cities, which are creating a new type of middle class that is demanding urban housing. The production side of the argument is generally based around Neil Smith's (1979) rent gap theory, which posits that capitalists take advantage when properties become worthwhile to renovate based on the properties' best use rent generating potential, versus its current rental income. When the 'rent gap' between the current use and best use becomes large enough, capitalists invest capital in an attempt to reap profits. Other theories of gentrification utilize the 'gap' idea including the value gap and the price gap (Lees et al., 2008), but the general concept is much the same. Buildings are obviously built new, generally with the best technology that exists at the time of construction. Over time, new buildings deteriorate and the technology with which they were built becomes outdated. As capital is deployed to progressively newer buildings, the older buildings become devalorized at a faster rate. Land parcels retain their form and use until the rent gap is once again large enough to warrant reinvestment. This is a valorization/de-valorization cycle according to Smith (1982; 1979), which is similar to the neighborhood life-cycle model, in which neighborhoods deteriorate over time (Metzger, 2001).

Barnsbury, London is a case study in a neighborhood life-cycle (Lees et al., 2008, p. 10-14). Barnsbury began in 1820 as an upper-middle class suburb, about two miles from the city center of London. It went into decline after World War II, and its residents fled the encroaching working class residents into the suburbs. The housing stock, composed of freestanding villas, became over-occupied as the working classes created more demand than there was supply of housing. Approximately twenty-one percent of households had more than 1.5 people per room in 1961. The area turned quickly between

1961 and 1981. In 1981 only 6 percent of housing units were rentals, compared with 61 percent in 1961. In theory, the value gap between unrenovated and best-use of the neighborhood had become large enough for investors to take action.

According to Lees, Slater, and Wiley (2008), the process of gentrification in central cities started in about the 1950's, and has changed in intensity over time, resulting in waves of gentrification in many Western cities. Hackworth and Smith (2001) compiled a chronology on gentrification and broke the phenomenon down into three waves. The first wave, marked by sporadic and isolated gentrifying activity in only the major cities, such as New York City, ended in about the early 1970's. The second wave, coinciding approximately with the decade of the 1980's, marked an increase in gentrification that began reaching smaller cities. A key differentiator between the waves is the role of the private market. In the first wave (1950s) the public sector was a sponsor of gentrification, whereas in the second wave the government sector aimed to spur private development. The third wave of gentrification started post-recession, in the late 1990's. The third wave was marked not only by larger corporate players beginning to lead gentrification, rather than follow, but also larger involvement on the part of the local government. Gentrification is an ongoing process of revival in central cities, driven by a variety of forces over time.

2.1.2.2 Operationalization of Gentrification

Gentrification is a term denoting a change in the socio-economic makeup of a neighborhood, from low to high socio-economic status. The literature is virtually unanimous in defining gentrification as such, but the definition diverges when there is an attempt to more finely define and operationalize it. Operationalization choices in the literature are largely driven by data availability. The primary indicators of gentrification are household income, housing value, level of education of the residents, and age of housing (Freeman, 2005; Freeman & Barconi, 2006; Landis, 2016; McKinnish, Walsh & White, 2010; Wyly & Hammel, 1999).

The simplest operationalization of gentrification is of the I-know-it-when-I-see-it variety. Freeman and Barconi (2004) analyzed the effect of a variety of socio-economic indicators on the probability of moving. The key independent variable was a binary indicator of gentrification, coded through the authors' intimate knowledge of the area. The descriptive statistics showed gentrifying tracts to be higher in the percentage of White residents, average monthly rent, percentage of college graduates, and average annual income. The authors could not find a difference in the number of people moving across income groups, concluding that gentrification does not cause displacement (Freeman & Barconi, 2004). Although the definition of gentrification used by Freeman and Barconi (2004) is not very replicable, and neighborhood size (average population = 46,000) is large for a neighborhood, their findings are aligned with that of McKinnish, Walsh, and White (2010) who utilized census tract geography and a multi-component indicator of gentrification, and also did not find evidence of displacement.

McKinnish, Walsh & White (2010) created a more complex operationalization, defining gentrification as a $10,000 or more increase in the median income of a census tract that started in the bottom quintile for median income in the region at the beginning of the period (1990-2000). Likewise, Landis (2016) defined gentrification as a change in median household income, but using a shift in deciles. His model identified 'gentrifying tracts as those that experienced substantial socioeconomic upgrading starting from an initial (1990) income level that put them within the first four income deciles of their respective metropolitan area' (p. 6, Landis, 2016). Socioeconomic upgrading was defined as a two-decile shift in median household income between 1990 and 2000. Although these definitions of gentrification capture change, it only addresses the change in income aspect of gentrification[11].

A comprehensive operationalization of gentrification uses a multi-dimensional index (Freeman, 2005; Ley & Dobson, 2008). Ley and Dobson (2008) set up an index of gentrification based on the equally weighted average of the percentage of residents who have a professional occupation, and the percentage of people with a post-secondary education in districts in Vancouver, Canada. The index values from 2001 were subtracted from the index values in 1971 and the differences were broken into quintiles. Distances to amenities[12] were then correlated with the gentrification score to determine whether gentrification increases or decreases in proximity to these amenities. Change was measured over a 30-year period, and findings were that positive amenities such as shortness of distance to the beach or an expensive residential enclave are conducive to gentrification.

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[11] The authors refined their sample to include the census tracts in the top 15,040 most populous Consolidated Metropolitan Statistical Areas (CMSA) in 1990.

[12] e.g., parks, waterfront sites, views, museums, or theatres (Ley & Dobson, 2008)

Freeman (2005) utilized the following criteria for a census tract to be gentrifying:

1. Be located in the central city at the beginning of the intercensal period.
2. Have a median income less than the median (40^{th} percentile) for that metropolitan area at the of the intercensal period.
3. Have a proportion of housing built within the past 20 years lower than the proportion found at the median (40^{th} percentile) for the respective metropolitan area.
4. Have a percentage increase in educational attainment greater than the median increase in educational attainment for that metropolitan area
5. Have an increase in real housing prices during the intercensal period

Source: (p. 471-472, Freeman, 2005)

These definitional criteria compared a census tract to the metropolitan area and determined gentrification based on median income, age of housing, educational attainment, and housing economic values. Tracts meeting all five criteria were considered gentrifying. Freeman (2005) tested periods 1980 to 1990, and 1990 to 2000.

The understanding of the process of gentrification has changed over time. The stage models of the 1970s suggest that gentrification is a linear process, whereby old inner city neighborhoods (previously prosperous) are 'reclaimed' by the middle class and become 'mature' gentrified places. However, in some places hyper-gentrification has put in question the idea that gentrified can become a final state. Land parcels near amenities have been taken over by successively wealthier groups until in places such as Miami, London, Boston, or New York some high rises are affordable for but the wealthiest few. High rises in Miami, London, New York City, and Boston have been taken over by successively higher classes (Lees et al., 2006). Therefore, the process of neighborhood upgrading is not limited to low-income neighborhoods, or central cities.

The concept of gentrification is the opposite of filtering, which denotes a decline in the income and socioeconomic status of neighborhood residents, and the value and quality of neighborhood attributes. The concepts of filtering and gentrification are complementary concepts, forming opposite ends of the neighborhood change spectrum.

2.1.3 Gentrification and Filtering Cycle

This study adopts the concepts of filtering and gentrification to operationalize a bidirectional concept of neighborhood change; gentrification and filtering are two socially important typologies of neighborhood change with important implications for city renovation, tax base, and low-income housing (Skaburskis & Nelson, 2014). Together, the processes of decline (filtering) and renewal (gentrification) form the Neighborhood Life-Cycle and provide a framework for understanding neighborhood change dynamics in this study. Filtering represents the decline in value and socio-economic status, while gentrification is associated with an increase in values, the age of housing, and rents, and the socio-economic characteristics (e.g., income, education) of the residents (Figure 1.1).

The literature suggests that filtering is a broad process that dominates urban housing infrastructure (Rosenthal, 2014). From the moment a house is built it begins to depreciate. Over time this generates housing for lower income groups. However, when a ‘rent gap’ becomes large enough, either because the actual rent decreases or some amenity is introduced to the system and the potential rent increases, capital will reinvest in the area. Over time, neighborhood change can be observed to display either a gentrifying or filtering quality. Public transportation systems are an important amenity in cities that have an effect on neighborhood characteristics and may affect the neighborhood life-cycle. However, other conceptualizations of neighborhood change may exist (Wei & Knox, 2014; Mikelbank, 2011).

2.1.4 Typology

Value based measures of neighborhood change dominate the literature on neighborhood change. However, neighborhoods can change along dimensions not captured by economic value and several studies have generated typologies of neighborhoods based on cluster analysis rather than a priori classification (Hanlon, 2009; Mikelbank, 2011; Morenoff and Tienda, 1997; Wei and Knox, 2014; Wyly and DeFilippis, 2010). In a study of neighborhood change in Chicago, Morenoff and Tienda (1997) generated a neighborhood typology to capture change during the decadal period of 1970 to 1990. The authors applied a cluster analysis to 10 census tracts (n=825) characteristics: poverty, public assistance, unemployment, education, profession, female households, owner occupancy, tenure, and age of resident. Four neighborhood clusters were generated, using Ward's minimum variance algorithm. The algorithm groups the census tracts based on the similarity of their characteristics, but does not provide a group label. Based on the mean characteristics of each cluster, the clusters were labeled "(1) stable middle class-neighborhoods; (2) gentrifying yuppie neighborhoods; (3) transitional working-class neighborhoods; and (4) ghetto underclass neighborhoods." (p. 64, Morenoff & Tienda, 1997). The census tract clusters allowed the authors to track cluster changes over time and analyze their socioeconomic trajectories.

Expanding on Morenoff and Tienda (1997), Owens (2012) generated a neighborhood typology that included race over all U.S. Metropolitan Statistical Areas

(MSAs). The study utilizes U.S. Census data from 1970 to 2000.[13] Principal Component Analysis (PCA) was utilized to generate factor scores from a set of fourteen neighborhood characteristics. These factor scores were then analyzed to produce eight clusters, labeled: minority urban neighborhoods, affluent neighborhoods, diverse urban neighborhoods, population, new white suburbs, upper-middle-class with suburbs, booming suburbs, Hispanic enclave neighborhoods. A key finding was that certain neighborhood types fall outside of the gentrification framework.

Mikelbank (2011) utilized the cluster analysis methodology on census tracts in Cleveland. For the census years 1970 to 2000[14] a cluster analysis was conducted on the pooled sample of all years, i.e. 848 tracts were recorded four times, once for each census year. All data were converted to z-scores centered on the respective census year, and Hierarchical Cluster Analysis (HCA) was utilized to form the neighborhood types. The advantage of HCA over k-means[15] is that HCA does not require a priori assignment of the number of clusters, but it may not be consistent in the clustering output depending on the arrangement of the data points. The outcome was five clusters: struggling; struggling African American; stable; new starts; and suburbia.

Wei and Knox (2014) generated seven neighborhood types (middle class, white/lower, mix/renter, black/poor, white/aging, elite, and immigrant). Their methodology utilized k-means cluster analysis of 16 socioeconomic and housing variables for all metropolitan and micropolitan areas in the U.S. for the census years

[13] Owens (2012) used Neighborhood Change Database (NCDB) to standardize the data to consistent census tract geographies.
[14] Standardized census tracts through the Neighborhood Change Database.
[15] K-means clustering is a method for grouping data into k clusters based on the distance from each data point to one of the k centroids.

1990, 2000, and 2010. Rather than pre-determined clusters, Wei and Knox (2014) used repeat runs of a clustergram to analyze the stability of the clusters and determine the optimum number to use in the analysis. K-means was used to generate the clusters, following previous research. The findings suggest that neighborhood change tends to be very slow. However, Wei and Knox (2014) included all metropolitan and micropolitan areas in their sample; therefore, their generalization is relying on the unreasonable assumption of a homogeneous change across all types of neighborhoods in the United States.

Neighborhoods can also be typologized into socioeconomic and housing characteristics, such as age of housing, median income of residents, racial composition, percentage of immigrants, and housing ownership (Wei & Knox, 2014). Past studies that attempted to identify neighborhood types generated between 4 and 10 unique types of neighborhoods (Wei & Knox, 2014). Rather than assigning an economic value, a typology allows for the study of a different set of characteristics that may change within a neighborhood over time.

Past scholarship on the operationalization of neighborhood change, using both the neighborhood change or typology approach, provides a framework for this research. In the literature, filtering and gentrification are operationalized in a framework using four primary variables: income and education of residents, value of housing, and age of housing. This study will utilize the continuous indicator of neighborhood change for ease of use in analysis.

2.2 Public transportation system effects and methodological approaches

Intra-urban rail systems are a common public infrastructure amenity in large cities around the world. Given the salience of the topic for urban development and policy, relatively few studies on the effects of public transportation systems have on neighborhood change have been performed.

A broader view of the literature on public transportation system effects on the urban environment can be categorized into foci on health outcomes (Brown & Werner, 2009; MacDonald et al., 2010; Stokes et al, 2008), transportation mode choice (Baum-Snow & Kahn, 2000; Brown & Werner, 2009; Cao & Cao, 2014; Litman, 2007), crime (Billings, Leland & Swindell, 2011; Bowes and Ihlanfeldt, 2001), and economic outcomes, such as on land values (Billings, 2011; Du & Mulley, 2007; Ryan, 1999; Pagliara & Papa, 2011), commercial values (Cervero & Landis, 1993; Debrezion, Pels and Piet, 2007), land use (Cervero & Landis, 1997), and the focus here, neighborhood change (Billings, 2011; Bollinger & Ihlanfeldt, 1997; Bowes & Ihalnfeldt, 2001; Glaeser et al., 2008; Grube-Cavers & Patterson, 2014; Kahn, 2007). Many studies focus on measuring change around a station on one dimension, such as property value, but a neighborhood is a '*bundle* of spatially based attributes' (p. 2111, Galster, 2001). The bundle consists of characteristics of people and infrastructure. Therefore, to capture neighborhood change it must be operationalized on multiple dimensions. This Section reviews the literature on the effects of transportation systems on neighborhoods, with a focus on neighborhood identification, formation of control groups, analysis, dependent variable operationalization.

There are several methodologies that can be employed to study the effects of intra-urban rail transit on neighborhood change. The primary methodologies include pre- and post- quasi-experimental designs (Cervero & Landis, 1993; Du and Mulley, 2007; Pagliara & Papa, 2011), and hedonic regression (Armstrong and Rodriquez, 2006; Bowes and Ihlanfeldt, 2001; Coulson and Bond, 1990; Gatzlaff and Smith, 1993). Although hedonic models are more commonly employed in the literature than pre- and post- models (Zuk et al., 2015), they have limitations as causal designs.

The unit of analysis in transportation studies depends on the analysis method used, and the length of the time-period required for analysis. Hedonic studies use a parcel unit of analysis, because property value is publicly available data. Population based studies that rely on U.S. Census data use a higher level of aggregation for the unit of analysis. However, U.S. Census is available going back to 1970. Furthermore, the unit of analysis is also constrained by data availability. The literature covers studies that use a range of units of analysis, including census tracts (Bollinger & Ihlanfeldt, 1997; Kahn, 2007), self-defined geographical areas (Cervero & Landis, 1993), as well as case studies with individual level analysis (Brown & Werner, 2006). However, other studies have used parcel sales data to supplement census data (Immergluck, 2009), or utilized zip-code level data (Raymond, Wang & Immergluck, 2015). Following Kahn (2007), who found heterogenous effects of ‘Walk and Ride’ and ‘Park and Ride’ stations on gentrification, this dissertation research utilized standardized census tracts as the unit of analysis.

2.2.1 Hedonic Regression Studies

Hedonic regression evaluates the effect of a set of land use characteristics on the value of real estate to determine which variables have an effect. However, hedonic regression ignores geographic factors, and can be biased by omitted factors in model specification. Further, stated well by Swanstrom (2017): Ultimately, researchers can never isolate the effect of urban design on neighborhood trajectories because it is impossible to separate physical design from all the other factors that are varying simultaneously, including location in a metropolitan area, the racial and socioeconomic mix of a neighborhood, its political pull, and its social organization. Even if we could isolate the effect of physical design on neighborhood change, it would not be particularly helpful. In the real world, physical design always interacts with other factors. We *can* say with great certainty that good physical design, whether modernist or urbanist, is never sufficient to guarantee a successful neighborhood. (p. 37)

Bollinger and Ihlanfeldt (1997) conducted an evaluation of the effect of Metropolitan Atlanta Rapid Transit Authority (MARTA) on the population and employment changes around station areas. The study area comprised of 299 census tracts in 1980 geographies that made up the seven county Atlanta region at that time. Using census tract level data for years 1980 and 1990, the study constructed simultaneous equations of population and employment. The operationalization of the treatment was based on a percentage of a tract that fell within a quarter mile radius of a MARTA rail station, and treated tracts were those that partially fell within that ring. The quarter mile constraint was imposed because the downtown stations that were studied were an average of 0.5 miles apart, therefore larger treatment radius would create substantial overlap between stations. Stations further out are approximately two and a half miles apart (Bollinger and Ihlanfeldt, 1997). Such a small treatment area is susceptible to a spillover effect, as areas further than a quarter mile are both within walking distance and within a distance that could be affected by traffic and noise negative externalities. The study did not find an effect on either population or employment growth associated with proximity to the station. The study only looked at one time-period, and it assumed a homogeneous effect across all neighborhoods in Atlanta, but neighborhood characteristics are not the same in all sections of Atlanta.

One limitation of the hedonic approach (Armstrong & Rodriguez, 2006; Billings, 2011; Bowes & Ihlanfeldt, 2001; Du & Mulley, 2012; Immergluck, 2009) is selection bias. Locations with public transportation systems (particularly rail stations) may have unobserved or unobservable characteristics that make them different from locations that were not treated with a transit station. These unobserved characteristics may be responsible for any effect the studies ascribe to public transit infrastructure. A Geographically Weighted Regression (GWR) method advances the hedonic model to consider local effects; however, a disaggregated unit of analysis is needed to capture the local effect (Du and Mulley, 2012). The study by Du and Mulley (2012) used newspaper data at the British postcode level of aggregation at three points in time the period December to October 1999, July to September 2002, and April to June 2003. The ending time-period corresponded to about one year after station opening, which was probably too soon to capture real estate price changes as a result of the station opening. It can take four years for a station to have an effect (Bollinger and Ihlanfeldt, 1997), the results have to be treated with caution. The study relies on a matching strategy to compare catchment areas within 500 meters of a station to similar areas, but at least 1000 meters from the station. Such small catchment areas are based on the assumption that the only effect of a station is driven by accessibility, but negative externalities of increased traffic, crime, or noise (Bollinger and Ihlanfeldt, 1997; Bowes and Ihlanfeldt, 2001) could spillover beyond 1000 meters, compromising the results. The findings suggest that there was no change in prices caused by the announcement of station construction, but also no changes in prices caused by station opening. Again, the findings could be confounded by the short time-period of the study, small size of the treatment area, or the definition of the control tracts.

Bowes and Ihlanfeldt (2001) also use a hedonic price model to test the effect of transit on neighborhoods, but they estimated models with crime and retail activity as the dependent variables in Atlanta[16] in 1991 to 1994. County assessment data at the parcel level were used for housing prices, while the crime and retail variables unit of analysis was the census tract. The control for MARTA transit station accessibility was operationalized using distance contour rings of within ¼ mile, ¼ to ½ mile, ½ to 1 mile, 1 to 2 miles, and 2 to 3 miles. The study area was DeKalb County and the City of Atlanta. A hedonic model of price and regression models were fitted for both the price and crime dependent variable. The models were controlled for population density, poverty, Black percentage, age, education, median income, vacant housing, police officers per jurisdiction, types of employment, distance to CBD, highway access, and MARTA station distance. The study found that house prices near MARTA stations further from the CBD are higher than house prices near MARTA stations closer to the CBD. Using

[16] Crime data was not available for Fulton county, outside of the city of Atlanta. This eliminated 2 of the 33 stations existing at the time.

random effects models on crime and retail activity the study found that crime generally increases near stations, retail activity is negatively affected within a half mile of a station. Using the ¼ mile to 3 mile rings, the census tracts within the ring are compared to census tracts outside the ring. However, using census tract data such small rings cannot be formed.

2.2.2 Quasi-Experimental Approaches

Quasi-experimental matching methods generate control groups that are similar to treatment groups on all observable characteristics, except treatment. The effect is estimated as the difference in the dependent variable observed in a neighborhood before and after the implementation of an urban rail-transit station. The effect is obtained by calculating the difference in certain outcome characteristics, pre- and post- the implementation, between matched sets of neighborhoods that are observationally similar prior to the implementation of the rail-transit treatment to the experimental group (Cervero & Landis, 1993; Du and Mulley, 2007; Pagliara & Papa, 2011).

Cervero and Landis (1993) compared commercial values and indicators in office markets in areas that had new rail intra-urban transit stations with those that didn't have new transit stations. The study matched treated office markets with control areas in Atlanta and Washington D.C. In Atlanta, the Lenox Square station area was matched with Perimeter Center and the Northeast Atlanta corridor, and the Arts Center station was matched with the Northwest Atlanta corridor. In Washington D.C., Ballston was compared to Tysons Corner, and Bethesda and Silver Spring area was compared to Rock Springs. The geographic boundaries of the areas containing the treatment and control groups were established by the transit system authority, local planners, or real estate professionals. The groups were matched on the basis of "(a) type, density and mix of land uses prior to the extension of rail transit; (b) type and quality of available office space; (c) number and type of jobs at the site; (d) distance to the downtown and regional accessibility via auto and other forms of transit; and (e) current city regulatory policies" (p. 14, Cervero & Landis, 2013), as well as interviews with realtors. The analysis consisted of commercial real estate market performance variables: "average office rents; net absorption rates; vacancy rates; annual office space additions; average building size; percent of new regional office floor space" (p. 15, Cervero & Landis, 1993). Transit stations were found to have positive effects on commercial property indicators of economic value. While there is value in understanding the short-term effects of a new station, the long-term effects of rail urban transit stations on neighborhoods may be even more important given the permanence of heavy rail transit infrastructure.

Pagliara and Papa (2011) also utilized a matching strategy to examine the changes in population, residential prices, and office prices around new transit stations and matched control groups in Naples Italy between 2001 and 2008 with a pre- and post-design. Although matching is a strength of the study, the algorithm is ad hoc, and would be difficult to replicate elsewhere. The treatment areas are tracts located 500 meters from the station exit. The control areas are similar to the treatment areas in observed characteristics, and don't lie close to other transit stations. The dependent variables were housing, retail, and office property values. The findings were mixed.

Transportation may affect neighborhoods by reducing dependence on car, and capitalizing the savings into land prices. Other economic impact literature describes the *compensation principle,* which suggests that households can spend more on housing when transportation costs are lower (Kilpatrick et al., 2007). Kilpatrick et al. (2007) utilized a natural experiment to separate the effects of highway accessibility comparing areas adjacent to I-90 with and without access to separate the amenity from the disamenity effect. They found that without access to a highway, a transportation amenity, house prices are lower than with access (Kilpatrick et al., 2007) indicating that a transportation disamenity can affect house prices. Public transit stations will also have disamenity effects, such as crime, noise, pollution, and traffic (Zuk et al., 2015).

The supply side suggests that transportation will affect gentrification only when there is a large-scale reinvestment in the neighborhood where the transit exists (Zuk et al., 2015). In a literature review, Zuk et al. (2015) found that new intra-urban rail stations positively affect value of surrounding real estate. This holds true for new stations, but what about existing stations? Stations spend more time being old than being new, but the literature does not address this distinction. How do neighborhoods change once they have a station?

2.2.3 Other Studies

Kahn (2007) examined the effect of transit stations across fourteen cities over the period 1970 to 2000 using census tract panel data from Geolytics' Neighborhood Change Database (NCDB). The study area consists of census tracts within 20 miles of each city's respective CBD. Census tracts within one mile of a treated tract are considered treated. The findings include heterogeneous effects of transit. The study disaggregated 'park and ride' versus 'walk and ride' stations, finding that household income and level of education increases with treatment in ‘walk and ride’ stations, but decreases in ‘walk and ride’ stations. Overall, the findings point to gentrification, based on low income tracts increasing housing prices after treatment, around ‘walk and ride’ stations and decline around ‘park and ride’ stations.

Recent work by Grube-Cavers and Patterson (2014) examined the effect of public transportation infrastructure on case studies of gentrification in Vancouver (1986-2006), Montreal (1961-2006), and Toronto (1961-2006). Toronto’s stations were built from 1954 to 2002, Montreal built their stations from 1966-1988, and Vancouver from 1986 to 2003. The methodology relied on survival analysis, “a method that makes statistical inferences about how a given independent variable affects the probability of an event occurring at a given time” (p. 9, Grube-Cavers and Patterson, 2014). Essentially, the study was measuring the time it took for a census tract to gentrify, after the introduction of a transit system. Gentrification was operationalized using the following variables: average monthly rent; proportion of people in professional occupations; percentage of owner occupied dwellings; average family income; number of academic degrees per capita. For a tract to be considered gentrified, all variables had to be better than the city average for that time-period. However, first a tract had to be considered gentrifiable by having income and academic degrees per capita lower than the city average. Overall, tracts with public transit station access and proximity to other gentrifying tracts were found to gentrify faster, but not in all cases (Grube-Cavers and Patterson, 2014). Survival analysis is a useful approach to capture an initial wave of gentrification, but it is not useful for studying ongoing neighborhood change, because once a tract is gentrified, this methodology does not allow for any further change. Although this study is well designed to identify an association between transit and the occurrence of gentrification, without a control group, it cannot rule out unobserved variable bias – the possibility that something uncontrolled is driving the affect ascribed to rail transit stations.

In the literature, studies utilize regression analysis and quasi-experimental matching methods with the census tract as the unit of analysis. The effects of stations can be heterogeneous across time and space, as new stations may have different effects than existing stations in different locations. Finally, neighborhoods are made up of multiple characteristics and operationalization of neighborhood change should reflect this complexity.

CHAPTER 3

CASE STUDY: ATLANTA, GEORGIA

This study examines the effect of intra-urban transit stations on neighborhood change using Atlanta, Georgia as a case study. The city of Atlanta is the fortieth most populous city in the U.S.[17] Although the City of Atlanta only makes up 8% of the Metropolitan Statistical Area (MSA) population (U.S. Census, 2016), it is the ninth largest[18] MSA[19], second largest in geographic area, but 198th in population density (Table 3.1). No geographic boundaries, such as major rivers, mountains or coastlines, and lenient regulations have allowed the city to sprawl in all directions. The seemingly limitless supply of land outpaces demand and keeps the region affordable. Since 1991, except for a brief period between about 1995 and 2000, the Metropolitan Atlanta region house price index has consistently been below the top ten U.S. cities index (Carnathan, 2014).

The Metropolitan Atlanta Rapid Transit Authority (MARTA) is ranked the ninth largest transit system in the U.S. by unlinked passenger trips[20], and thirteenth largest by passenger miles traveled (MARTA, 2011; Neff & Dickens, 2014). The city's transit system is managed by the Metropolitan Atlanta Rapid Transit Authority (MARTA), which runs a heavy rail system in conjunction with a bus system. The bus system, in cooperation with several other county based agencies, covers the 29 county Atlanta-

[17] Atlanta population 420,003 (U.S. Census, 2010)
[18] Atlanta Metropolitan Statistical Area has a population of 5,514,323 (BEA, 2015).
[19] The Atlanta-Sandy Springs-Roswell, GA MSA (Atlanta MSA) encompasses 29 counties (Metro Atlanta Chamber, 2013; U.S. Census, 2013).
[20] Also known as passenger boardings (APTA, 2017)

Sandy Springs-Roswell Metropolitan Statistical Area (MSA). The rail system, as constructed, only covers parts of Fulton and DeKalb counties. The MARTA system has 39 stations and 47 miles of rail - 31.6 in Fulton County; 14.7 miles in DeKalb County; and 0.7 miles in Clayton County[21] (MARTA, 2011).

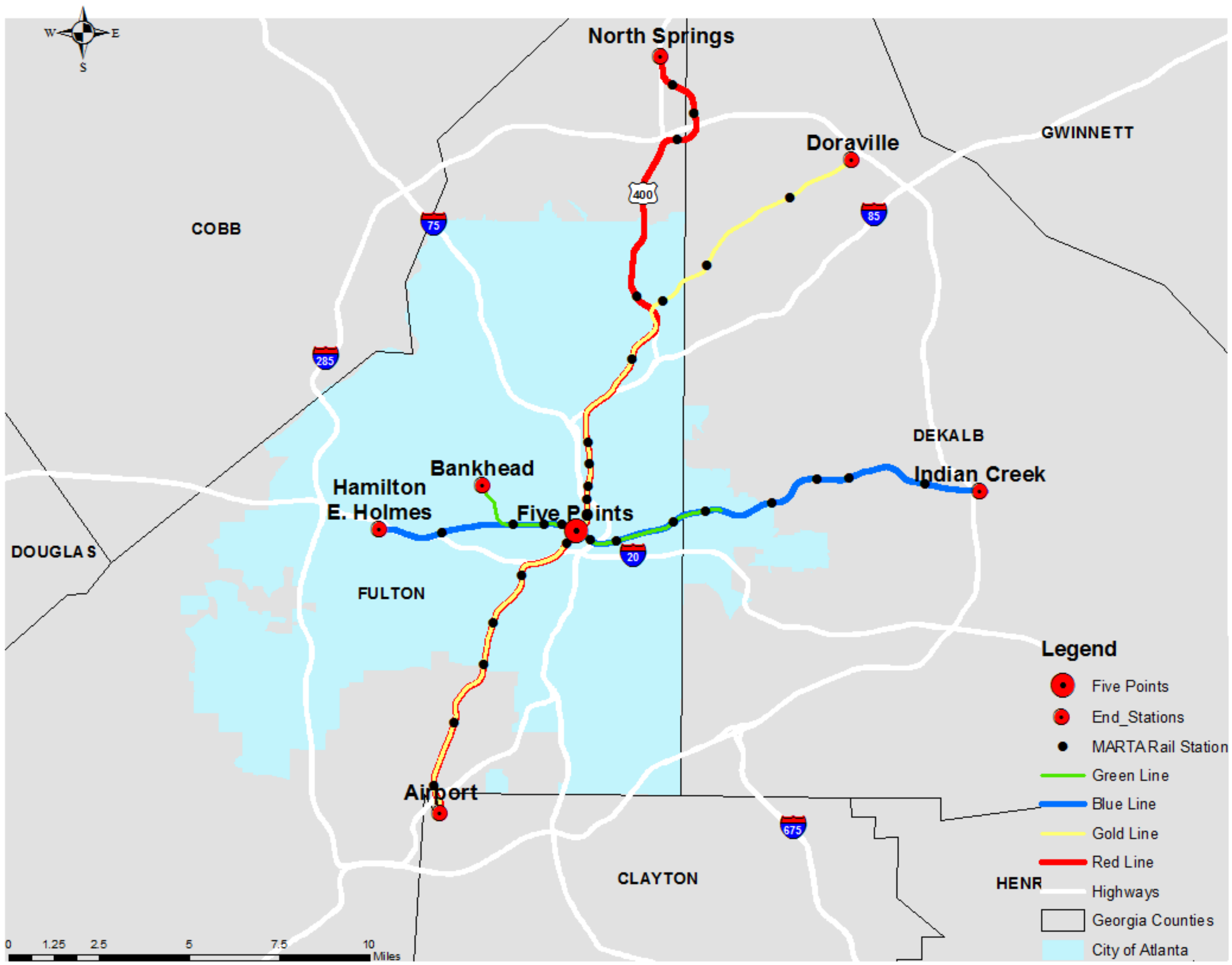
Three major interstates (I-20, I-75, and I-85) intersect in Atlanta, and these are connected by I-285, the city perimeter highway located at a radius of about 15 miles from city center (Figure 3.1). The MARTA rail network operates a North–South line and an East-West line. The North–South line (Red Line and Gold Line) has the southern terminus at the Airport Station, in the vicinity of the I-285 highway. The north end of the line has two end points, the Red line ends in North Springs station, just outside of the I-285 highway and the Gold line ends at the Doraville station, just inside the I-285 perimeter. The East – West line consists of the shorter Green line and the longer Blue line that both share the same track; the green line is an additional train that runs part way along the blue line. On the east side, the Green line ends at Edgewood/Candler Park station, while the Blue line continues to Indian Creek station, just outside I-285. On the west side, the Blue line runs to Hamilton E. Homes station, while the Green line forks northwest and ends at Bankhead, both inside I-285 (Figure 3.1). The Bankhead station was at one point to have been extended to Perry Homes, an African American neighborhood several miles further northwest, but MARTA decided to expand the northern line to the majority white suburbs.

[21] Clayton County became a part of MARTA in 2014, after rejecting MARTA in a 1971 referendum

Table 3.1 Top 10 urbanized areas in the United States

Urbanized Area (2010)	Area	Population Density	Population	Area Rank	Population Rank	Density Rank
New York--Newark, NY--NJ--CT	3,656	5,019	18,351,295	1	1	4
Atlanta, GA	**2,681**	**1,684**	**4,515,419**	**2**	**9**	**198**
Chicago, IL--IN	2,484	3,466	8,608,208	3	3	27
Philadelphia, PA--NJ--DE--MD	2,031	2,680	5,441,567	4	5	65
Boston, MA--NH--RI	1,951	2,143	4,181,019	5	10	119
Dallas--Fort Worth--Arlington, TX	1,815	2,821	5,121,892	6	6	59
Los Angeles--Long Beach--Anaheim, CA	1,760	6,905	12,150,996	7	2	1
Houston, TX	1,694	2,919	4,944,332	8	7	50
Detroit, MI	1,373	2,720	3,734,090	9	11	62
Washington, DC--VA--MD	1,349	3,401	4,586,770	10	8	30

Source: U.S. Census (201



Source: Atlanta Regional Commission (2015)

Figure 3.1. Atlanta, GA Rail Intra Urban Rail and Highway Networks

Atlanta's transit system was built to take advantage of a matching Federal subsidy[22], despite inadequate population density to support efficient use of a heavy rail system (Keating, 2001). Although actual ridership has never approached the initial projections, the stations were built with optimistic ridership projections based on anticipated economic development around the stations (Bollinger, 1997). Land use regulation and densification around stations were promised, neither the city of Atlanta nor the broader Atlanta MSA have responded with any significant policies promoting densification around MARTA stations (Bollinger and Ihlanfeldt, 1997; Keating, 2001; West, 2014). Also significant is the fact that public transportation has received very modest political support, and no State of Georgia funding (West, 2014; Keating, 2001). The Atlanta MSA is not dense, causing the road and highway network necessary for the metro area to function to be extensive. The road network[23] is significantly larger in scale than the public transportation system[24] and the MARTA rail system is almost completely within the I-285 perimeter highway. Therefore, changes in characteristics of neighborhoods near rail intra-urban transit stations are likely to be attributable to the transit system, rather than other public policy or highway transportation amenity.

This chapter provides the background historical information on the City of Atlanta and the MARTA transportation system. Section 3.1 describes the development of

[22] Building MARTA "was an effort to enhance the city's image, not a realistic solution to the region's transportation needs" (Keating, 2001)
[23] Atlanta Metro ranks 2nd in road miles per person (Bureau of Transportation Statistics, 2015)
[24] Atlanta Metro ranked 11th in unlinked passenger trips, half of the trips were on the rail system

the City of Atlanta. Section 3.2 describes the formation and development of the MARTA transportation system, and Section 3.3 briefly identifies the station areas.

3.1 The Metro Atlanta region: growth and development

The City of Atlanta lies along the eastern continental divide, known as Peachtree ridge,[25] which splits the rainfall watershed between the Atlantic Ocean and the Gulf of Mexico, Terminus, the original name for the settlement where Atlanta began in 1836, was located at a 20-acre plain that crossed Peachtree ridge (Allen, 2014). This area was identified as an ideal place for a railroad junction[26] to connect the Western & Atlantic Railroad, to the northwest of Atlanta, the Georgia Railroad to the East, and the Macon & Western Railroad to the south (Allen, 2014). The city's name was changed several times, finally settling on Atlanta, as the feminine form of Atlantic. In 1847, Atlanta was incorporated in a one mile radius area around the zero-mile post, between the Georgia Southern railway to the east and the Western & Atlantic Railroad to the northwest (Allen, 2014). In 1850, the year of Atlanta's first census, the population was 2,569, and the city was an intersection of two railroads. A third railroad to the south of the Atlanta junction, the Macon & Western Railroad was completed in 1851. The Atlanta & LaGrange Railroad was added in 1854, creating a connection to the Southwest, and cementing Atlanta as a regional rail hub (Allen, 2014).

Atlanta continued to develop around the railroads, which left an indelible mark on future urban form, particularly because the City lacked any central planning and a business friendly regulatory climate throughout its history (Allen, 2014). Early

[25] Atlanta's iconic Peachtree road lies along this ridge, and was named for it (Allen, 2014)
[26] The location is near present day MARTA Five Points Station

landowners created uncoordinated street grids of various sizes and orientations. Figure 3.2 is an 1864 map of early Atlanta, where the strange orientation of the grid can be observed. Each landowner shaped the land at his choosing. The land use of the parcels was shaped by their connection to each other, but more importantly their relative location to the railroads, which ran along naturally curving elevated ridges.

The regional rail hub precipitated Atlanta's growth, but also made it a target during the American Civil War when it became a military transportation hub. On July 20, 1864, General Sherman of the Union Army began a five-week bombardment of Atlanta. On September 2, 1864 Sherman captured Atlanta, after having cut off all railroad access. During retreat, just before the Union forces arrived, General Hood, the commanding Confederate officer of forces defending Atlanta, blew up 5 locomotives and 81 railcars, 28 full of ammunition. The explosion destroyed a railroad roundhouse, military infrastructure, and many buildings within a quarter mile. Sherman sponsored the destruction of military facilities, but the majority of the damage was caused just prior to the November departure. Against Sherman's orders, men who had been conditioned to burn cities on the approach to Atlanta, took it upon themselves to continue the tradition. Of 3,600 houses before Sherman attacked, only 400 remained after his army left (Allen, 2014; Leigh, 2014).

Despite the Civil War setback, Atlanta's population increased by 128% between 1860 and 1870. The City's population continued to increase through population growth, as well as a series of annexations in the 1950s. Between 1960 and 1970 the population was essentially flat, only growing by 2%, and reaching a peak of 496,973 in 1970 (Figure 3.3). The decline in population started in 1970 and lasted until 1990; the population having dropped by over 100,000 people. During this same period the Atlanta region gained about 1,000,000 people (Heath & Heath, 2014). After 1990, the City's population started to increase partly due to massive reinvestment in preparation for the 1996 Atlanta Olympic Games, but also encouraged by the expanding highway system. The decline also changed the demographic characteristics of the city Figure 3.4 and Figure 3.5. In 1960 the city of Atlanta was 61.7% white and 38.3 % black. By 1990, the bottom of the decline, the racial mix was nearly reversed with whites constituting 31% and blacks 67.1% of the city population. After 1990, the racial change reversed along with the population. As of the 2010 Census the white/black ratio was 38.4/54.0 percent, with a population of 420,003 (Heath & Heath, 2014; U.S. Census, 2016). Although the dominant racial group has changed over time, both groups remain the dominant groups in the region. Figure 3.5 displays the percentage of white occupants per census tract. In 1970 minorities were concentrated in the center of the city, but increased in surrounding tracts over time.

The Atlanta Regional Commission (ARC) identifies the Atlanta region as a ten-county area, consisting of Cherokee, Clayton, Cobb, DeKalb, Douglas, Fayette, Fulton, and Gwinnett Counties.[27] The ten-county region had a 1970 population of 1,500,823 which increased to 4,107,750 by 2010 (Heath & Heath, 2014). The 2010 racial breakdown of the region was 57% white, 34% black, and only 10% Hispanic (Heath and Heath, 2014). Approximately 82% of the population of the region are English only speakers, 9% speak Spanish, but no other language accounts for over 1% of speakers in Atlanta (Heath & Heath, 2014). Atlanta remains a primarily black and white city and

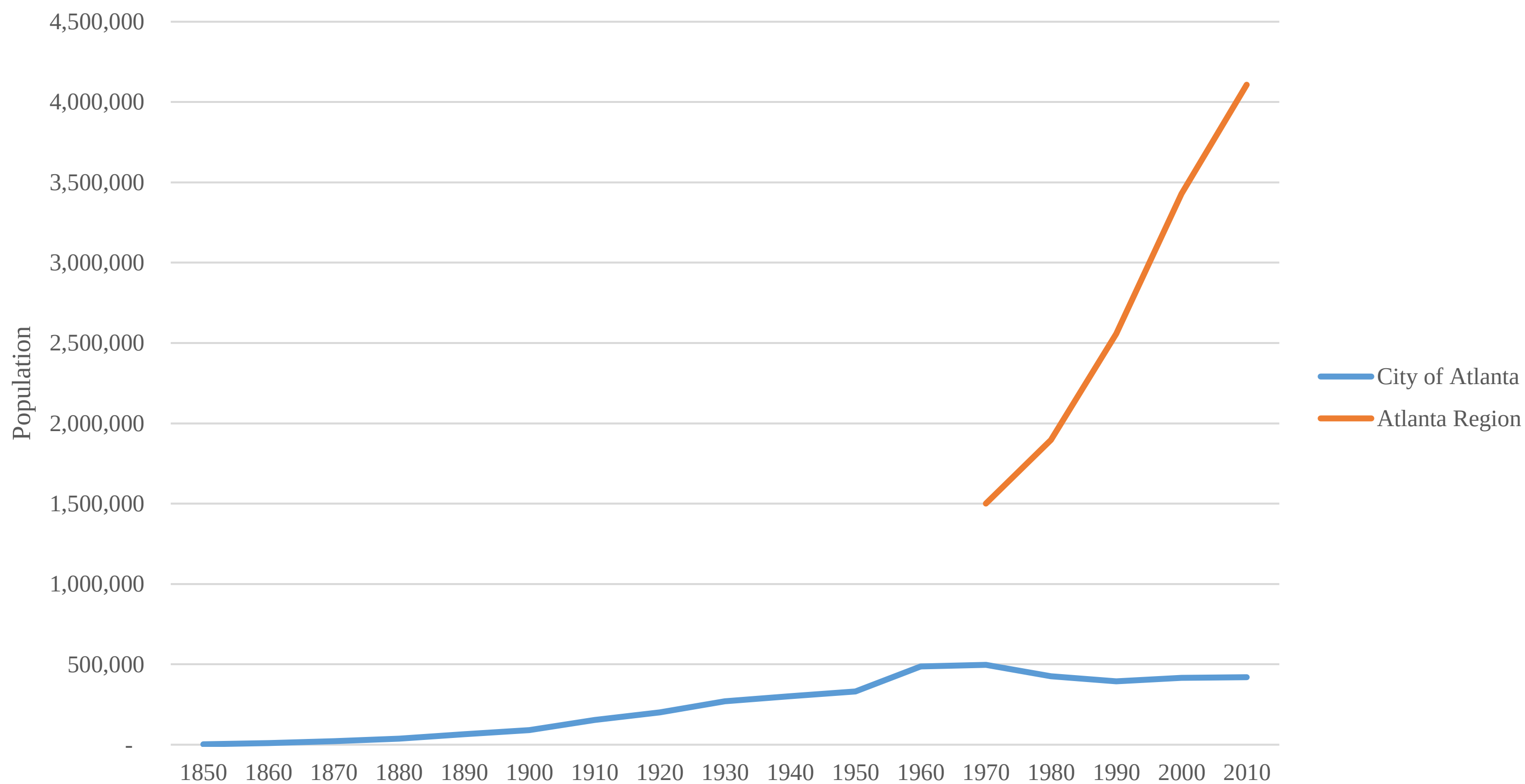
[27] The Atlanta 10 county region (ARC, 2014) is smaller than the Atlanta-Sandy Springs-Roswell Metropolitan Statistical Area (MSA), which is made up of 29 counties (Metro Atlanta Chamber, 2013).

region. Although the Hispanic and Asian foreign born populations are expanding, this growth is largely driven by Gwinnett County (Heath & Heath, 2014), a county which is not a part of the MARTA rail network.

A discussion of Atlanta is not complete without a discussion of traffic problems, for which it has been seeking solutions since the 1960s. Atlanta's booming regional growth happened at the expense of the central city, partly due to highway expansion (Baum-Snow, 2008). The city is crossed by four major highways, (I-20 running east and west, I-85 running northeast and southwest, I-75 running north and south, and GA-400 connecting the northern suburbs to the central business district), and surrounded by a perimeter highway (I-285). In 2016, Atlanta ranked 4th in the United States and 9th in the world on an index of traffic congestion (INRIX, 2016). Building highways did not alleviate the traffic congestion, so Atlanta built a heavy rail public transportation system.

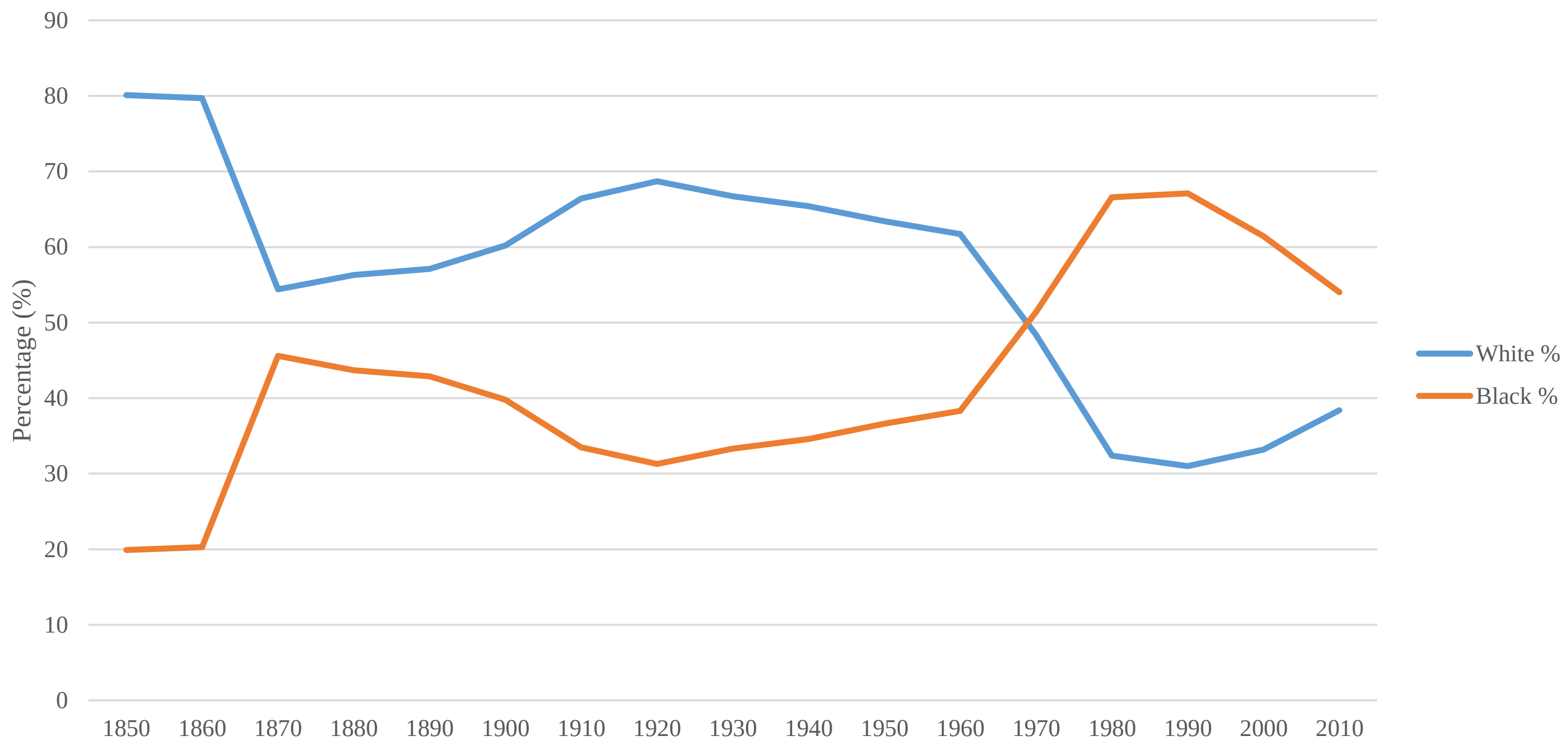
Special Collections and Archives, Georgia State University Library

Figure 3.2 Atlanta Street Patterns 1864



Data source: U.S. Census, 2010; Heath & Heath, 2014

Figure 3.3 City of Atlanta and Ten County population over time



Data source: U.S. Census, 2010; Heath & Heath, 2014

Figure 3.4 City of Atlanta black/white demographic change

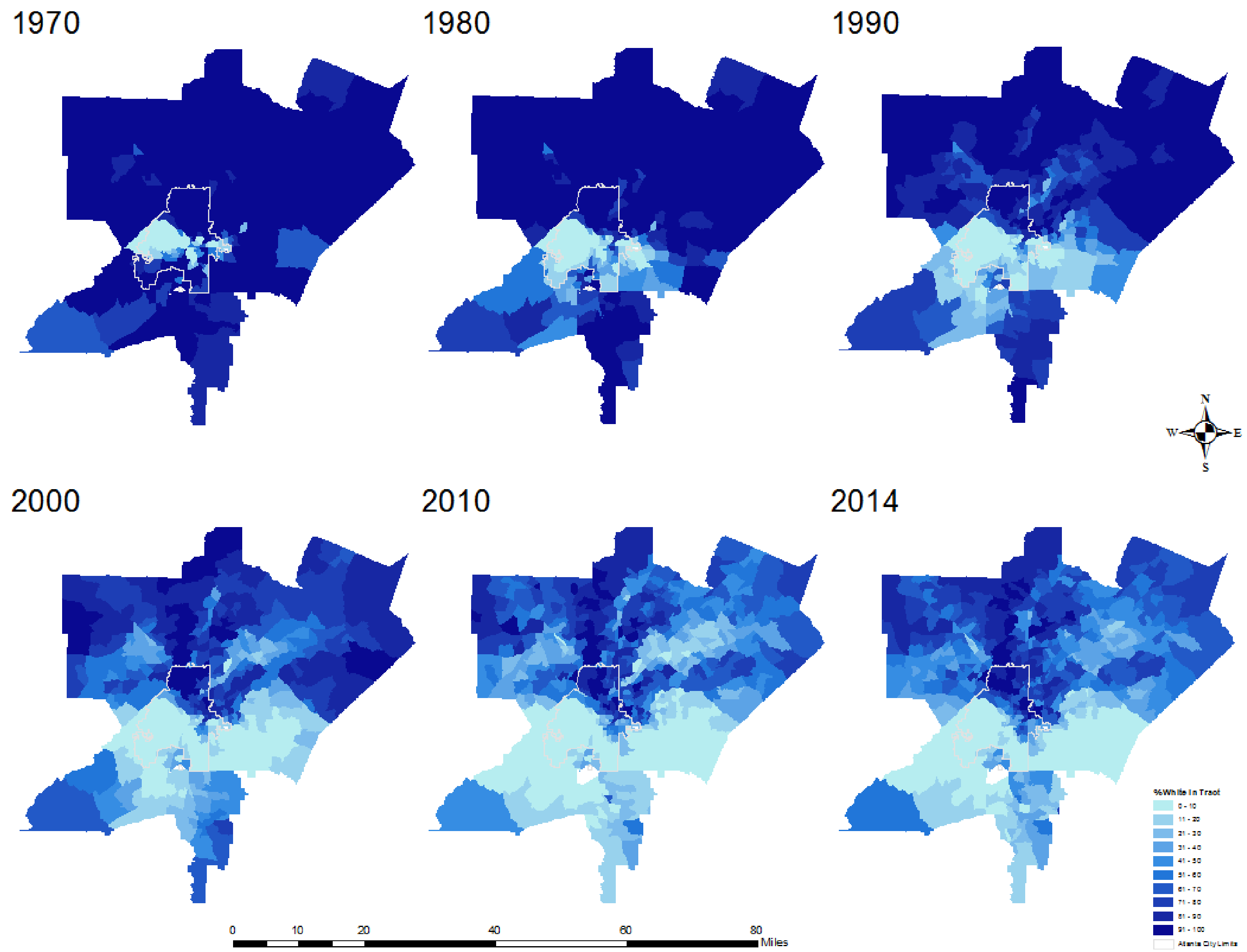


Figure 3.5 Study Area % White residents per census tract

3.2 MARTA – Genesis and Evolution

> *"The most striking feature of this undertaking [MARTA] was that it was essentially an effort to enhance the city's image, not a realistic solution to the region's transportation needs." – Keating (2001)*

MARTA was formed in 1965 by the Georgia General Assembly to build and operate a rapid rail transit system for the core counties that comprised the Atlanta region at the time: Fulton, DeKalb, Clayton, Gwinnett, and Cobb counties (West, 2014). However, full implementation required a separate referendum, which only passed in Fulton, DeKalb, and Gwinnett counties in 1971 (Kain, 1997). MARTA opened rail stations starting in 1979, with the final new station to date opening in 2000.

One of the most important aspects of the Atlanta case study is that the system probably should not have been built (Kain, 1997). Studies at the time of planning and inception indicated that Atlanta, because of its low density, would have been better served by a fleet of buses, and subsequent analysis confirmed those early projections (Kain, 1997). The ridership projections in 1971 for rail passenger trips for 1983 and 1995, respectively, was 83,640,000 and 153,990,000 (PBTB, 1971). The actual unlinked passenger trips on MARTA rail for 2016 was approximately 68,678,000 (NTD, 2017). In terms of train operations, based on these projections, the estimated times between trains on all lines by 1995 were planned to be 90 seconds. As of 2017, peak time headways on the rail line are 10 minutes,[28] stretching to 20 minutes on the weekends (MARTA, 2017). This is a significant shortfall from the projections, with the caveat that the 1995

[28] On segments where the Green and Blue overlap, and Red and Gold lines overlap, there is an additional train, reducing the headways to 5 minutes for travel to certain locations.

projections included 52.6 miles of track (ARC, 1971), not all of which have been built. Furthermore, the projections under which MARTA was planned included land use regulations to help spur high density development around MARTA stations, but no such legislation was ever enacted. In fact, in 1976 a city zoning plan to allow the highest density zoning to be around MARTA stations was reversed, in favor of a more hands off approach to land use planning (Keating, 2001).

Planning for the MARTA system unofficially began in 1954, when the Atlanta Region Metropolitan Planning Commission (ARMPC) released a report indicating that in the future Atlanta needed a rapid-transit system. Officially, ARMPC initiated the study in February, 1960 (Keating, 2001; ARC, 1977). The initial recommended network was composed of 60 miles of track and six lines radiating from a central station, along existing rail right of ways (ARC, 1977). These six lines include three northern lines and one each on the eastern, western, and southern sides. Although this design did not survive, the idea of cost savings by building the system along existing rights of way did.

Atlanta, which got its start as a rail hub, had nine potential rights of way available for the design (Keating, 2001). Therefore, very little had to be disturbed in existing neighborhoods to construct the system. The original plan for the fixed rail rapid transit system and associated funding was defeated by voters in November 1968 (Davis, 1972; Kain, 1997; Stone, 2001; Keating, 2001). The defeat was caused by residential segregation between black and white groups. Political tensions arose around the placement of the rail lines, which were planned to be more concentrated in white parts of the city (Keating, 2001). Atlanta has a black/white racial dichotomy, as described in Section 3.1. Since the 1970s the mayor has been African American, but historically policy has been dictated by white business interests (Saporta, 2014). Had the 1968 resolution passed, the plan called for a 52.1 mile heavy rail transit system and 40 stations, 17.6 miles of dedicated busway, and a takeover and expansion of the existing bus system by 86%, in a four-county area (Keating, 2001).

MARTA is laid out in a cross shape, with a North-South and East-West lines. The South and East lines were placed to serve both white and black areas, the West line served predominantly black areas, and the three lines going north were to serve white areas (Keating, 2001). Without the support of the black community, which wanted equal treatment with rail rather than bus transit, the 1968 bond referendum to fund MARTA failed (Allen, 2014; Keating, 2001; Paget-Seekins, 2014). Jesse Hill,[29] a leader of the African American community (Huie, 2016; Keating, 2001) demanded that the same type and quality of transit be implemented going North-South and East-West. A subsequent citizen's vote on November 9, 1971, succeeded, but only in DeKalb and Fulton Counties. This time the referendum was supported by leaders of the black community[30], who were promised future rail line extensions to historically black residential areas on the west side of the city. The referendum, in addition to approving MARTA to operate, increased the local sales tax by a penny to fund the system.[31] [32] In 1972, MARTA bought the assets of the Atlanta Transit System company for $12.8 million. This was the bus

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[29] Jesse Hill was a progressive leader of the black community in Atlanta and across the South in the 1950s and 1960s. (Myers, 2006)

[30] The 1971 referendum promised rail to black residential areas, minority contracts, and reduced fares for a fixed time period (Keating, 2001)

[31] MARTA remains the largest transit system in the United States that does not receive State funding, but relies on a penny sales tax for operations. However, half of this revenue is required to be spent on capital projects and cannot be used for operations (Paget-Seekings, 2014).

[32] In a referendum in November 2016 a 0.5% sales tax was approved by voters to increase MARTA funding for system upgrades and expansion. The tax went into effect in March 2017. (City of Atlanta, 2017)

only fleet remnant of the streetcar system that provided the transportation for one of Atlanta's early growth spurts. In conjunction, fares were lowered from $0.40 to $0.15 per trip (Kain, 1997).

The scope of the MARTA system plan has been greatly reduced over time from its ambitious beginnings. Each departure from the original MARTA plan is documented as an amendment to the original 1971 Engineering Report. The Engineering report, along with the Rapid Transit Contract and Assistance Agreement MARTA has with the City of Atlanta, and Fulton and DeKalb counties, governs and documents the expansion of the MARTA system. The MARTA rail transit system was designed to have its own right of way, following existing rail line right of ways, which were prevalent, given that Atlanta was built on rail road junction (Keating, 2001). Stations were planned to account local station needs, and in anticipation of increasing ridership, including planning for growth that was expected as a result of the new public transit infrastructure (Huie, 2016; ARC (1977). However, from the beginning the plans for all but the northern rail line were along existing rail right of ways (Keating, 2011). Transit Station Area Development Studies (TSADS) were implemented (ARC, 1977) and expected to develop land use and plan for growth around each station, prioritizing development and conservation of existing neighborhoods. From the report, "rapid transit can literally shape our region and neighborhoods into what we want them to become. The TSADS program has been concerned with identifying ways to use the system as a catalyst" (p. 4, ARC, 1977). For example, the Decatur station was originally planned to be located on the rail corridor at Agnes Scott College. It was rerouted to Decatur Square in hopes of spurring economic development, based on results of a local planning program (ARC, 1977). The planning efforts in Decatur seemed to have been successful, but the majority of the recommendations for development and policy were not adopted (Keating, 2001).

The initial set of MARTA rail stations opened on the East-West line in June of 1979, followed by the opening of the North-South line in December, 1981 with four stations, followed by another four stations in December 1982. The North-South line was further built out in the 1980's with the opening of five stations – in December, 1984; East Point in August, 1986; Chamblee in December, 1987; and finally, the Airport station along with College Park station opened in June, 1988 (Table 3.2). The East-West line further expanded in 1992, and 1993, then the final stations on the North-South lines were put in place in 1996 and 2000. The 2017 MARTA system has 47 miles of rail and 39 stations, but no dedicated busways.[33]

Since 2002, MARTA rail ridership has declined. In January 2002, the monthly ridership. in unlinked passenger trips (UPT), was 6,767,476 and 5,804,663 in March, 2017. Peak ridership was in October, 2008 with 7,982,627 UPT (Figure 3.6).

This brief historical overview is important because is highlights the uniqueness of the Atlanta case study and highlights several main themes. First, Atlanta is a large American MSA with a representatively large population, and age and size of the transportation system. Second, Atlanta's public transit system is small compared to the roadway system. Third, historically, no major regional policies have been passed to entice development around transit stations. Fourth, the system was created based on political motivations not need. MARTA was created with a 'build it and they will come' strategy, built with the promise of policy support by the City of Atlanta for development around MARTA stations. The city did not have the requisite density to

[33] MARTA and regional buses share HOV lanes on certain sections of the Atlanta interstate system.

support a system when it was conceived in the 1960s, when the city of Atlanta had a higher population than it has even in 2010 (Allen, 2014). Atlanta region has such low density that it is questionable whether the City should have built a rail transit system in the first place. Fifth, the location of the MARTA rail system was built primarily along existing railroad right of ways, and the final segment in conjunction with GA 400, a roadway connecting north Atlanta to the northern suburbs; therefore, although not random, its location was largely predetermined and already ingrained in the fabric of the neighborhood. Finally, it is worth noting that there was a bias in more development in the white northern areas than in the other portions of the city.

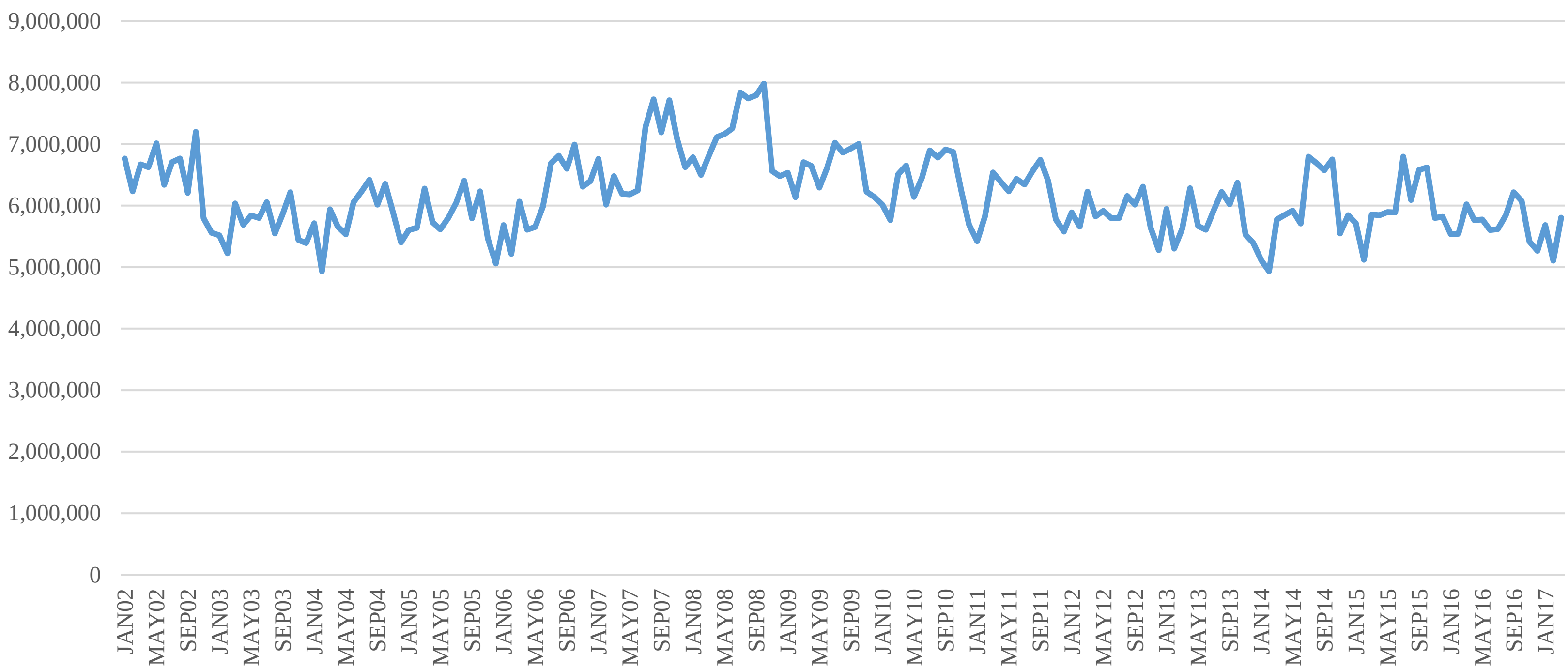
Table 3.2. MARTA Station Names, Type, and Date Opened

Station	**Station**	**Type**	**Opened**	**Station Entries/Day (2013)**
Indian Creek	E9	Commuter	26-Jun-93	5,612
Kensington	E8	Community Center	26-Jun-93	5,950
Avondale	E7	Community Center	30-Jun-79	4,327
Decatur	E6	Mixed Use	30-Jun-79	3,821
East Lake	E5	Neighborhood	30-Jun-79	1,241
Edgewood/Candler Park	E4	Neighborhood	30-Jun-79	1,143
Inman Park/Reynoldstown	E3	Neighborhood	30-Jun-79	2,525
King Memorial	E2	Neighborhood	30-Jun-79	1,517
Georgia State ⸸	E1	High Intensity	30-Jun-79	4,055
Five Points East/West ⸸		High Intensity	22-Dec-79	19,447
Dome/GWCC/Philips/CNN Center⸸	W1	High Intensity	22-Dec-79	2,107
Vine City	W2	Neighborhood	22-Dec-79	821
Ashby	W3	Mixed Use	22-Dec-79	1,791
West Lake	W4	Neighborhood	22-Dec-79	1,378

Table 3.2 (continued)

Station	Station	Type	Opened	Station Entries/Day (2013)
H. E. Holmes (Hightower)	W5	Commuter	22-Dec-79	6,480
Bankhead	P4	Neighborhood	12-Dec-92	1,903
North Springs	N11	Commuter	16-Dec-00	6,436
Sandy Springs	N10	Community Center	16-Dec-00	2,322
Dunwoody ⸸	N9	High Intensity	8-Jun-96	3,545
Medical Center ⸸	N8	High Intensity	8-Jun-96	1,629
Buckhead ⸸	N7	Mixed Use	8-Jun-96	2,643
Doraville	NE10	Commuter	12-Dec-92	5,521
Chamblee	NE9	Commuter	19-Dec-87	3,785
Brookhaven/Oglethorpe	NE8	Community Center	15-Dec-84	2,357
Lenox ⸸	NE7	Mixed Use	15-Dec-84	3,284
Lindbergh Center	N6	Mixed Use	15-Dec-84	8,604
Arts Center ⸸	N5	High Intensity	18-Dec-82	6,605
Midtown ⸸	N4	High Intensity	18-Dec-82	5,664
North Avenue ⸸	N3	High Intensity	4-Dec-81	5,045
Civic Center ⸸	N2	High Intensity	4-Dec-81	2,692
Peachtree Center ⸸	N1	High Intensity	11-Sep-82	7,453
Five Points North/South ⸸		High Intensity	4-Dec-81	
Garnett ⸸	S1	High Intensity	4-Dec-81	1,516
West End	S2	Community Center	11-Sep-82	7,056
Oakland City	S3	Neighborhood	15-Dec-84	4,432
Lakewood/Fort McPherson	S4	Commuter	15-Dec-84	2,207
East Point	S5	Community Center	16-Aug-86	4,571
College Park	S6	Community Center	18-Jun-88	9,026
Airport ⸸	S7	Commuter	18-Jun-88	9,173

Source: ARC, 2014
⸸ Dropped from the analysis



Source: FTA (2017)

Figure 3.6 MARTA Rail Monthly Ridership

3.3 Types of MARTA Stations in Neighborhoods

Census tracts are geographical units assigned to the United States by the US Census, and serve as a common proxy for neighborhoods in the literature. Census tract boundaries are periodically adjusted to contain approximately 4,000 people (U.S. Census, 2010); therefore, areas that have low density will have geographically large census tracts. Figure 3.7 depicts the population density within the five-county study region (Fulton, DeKalb, Clayton, Cobb, and Gwinnett). Density in Atlanta is located primarily in the center of the city, but the region has become denser over time. However, there remains a clear white-black north-south divide in the city. The five-county area is both the original metropolitan area, and the region initially proposed to be served by MARTA.

MARTA stations were placed in a variety of neighborhood settings along existing railroad right of ways. Figure 3.8 is a photograph of the elevated east line along an existing freight right-of-way, with a view looking west towards downtown.

Transit Station Area Development Studies (TSADS), created prior to the opening of stations, presented policy, concept (land use), and design plans around the stations in an effort at holistic transportation and land use planning (ARC, 1977). Policy plans included both broad and minute policy concerns. Broad policy issues included the function of the areas surrounding the stations and the function that stations serve in shaping the neighborhoods, as well as coordination with planned major improvements of an area. Minute policy factors were concerned with redevelopment and preservation of local land uses. Concept plans are land use plans that led to design plans, which describe the form of the station (ARC, 1977).

TSADS developed five types of stations are useful in understanding the characteristics of neighborhoods in which the stations were placed. In order of declining emphasis on development, the station types were: High-intensity, Mixed-use regional node, Commuter station, Community center, and Neighborhood station (Bollinger and Ihlanfeldt, 2001) (Table 3.2). In general, high intensity stations are in the city center, and commuter stations are at the ends of the system, with neighborhood and community center type stations existing in between. Table 3.3 presents the definitions from the TSADS studies. Stations that were built after the publication of the TSADS were assigned a type, based on the categorization of similar stations.

The current system configuration is depicted on Figure 3.9, but the system opened in stages. The East line is the first line constructed in 1979, with the following stations: Georgia State University, Grant Street[34], Moreland Avenue[35], Candler Park, East Lake Drive, Decatur, and Avondale Stations. Memorial Drive[36], and Indian Creek stations were added in the 90s and are considered higher intensity than the Neighborhood stations closer to in-town Atlanta. The East Line primarily consists of residential neighborhoods with Neighborhood and Community Center type stations. An extension from the East Line, going north between Candler Park and East Lake stations was never built.

A portion of the West line was completed next, in the same year, and runs through historically black residential areas, composed of the following stations: Techwood[37], Vine City, Ashby Street, Westlake Avenue, Hightower Road[38]. The Fairburn Road

[34] Later renamed King Memorial
[35] Later renamed Inman Park
[36] Later renamed Kensington
[37] Later renamed Dome/GWCC/Philips Arena/CNN Center
[38] Renamed Hamilton E. Homes

station was planned west of Hightower Road Station, but never built. The Perry Homes spur was not fully built either, stopping at Bankhead station, which was built in 1992 as the final station built on the West Line. The Perry Homes station was one of the broken promises made to gain community support for the 1971 referendum.

Initially opened in 1981 and 1982, the North Line runs through the downtown, Midtown, and Buckhead districts, the heart of Atlanta. The stations on the North line are higher intensity than the East/West line, with no Neighborhood type stations. The Cain Street[39], Civic Center, North Avenue, 10th Street, and Arts Center Stations are all High Intensity stations with significant commercial activity, located in the business districts. Subsequently in the 1980s the Lindbergh station was built on the North Line, and on the Northeast spur, Lenox, Brookhaven and Chamblee Stations were opened. The North and Northeast line stations are either Mixed Use, Community Center, or Commuter stations. In the 90s, the North Line was again extended to include Buckhead, Medical Center, and Dunwoody stations, followed by North Springs and Sandy Springs stations in 2000. None of these were Neighborhood type stations. The initial set of South Line stations were opened in conjunction with the first set of North Line Stations. Garnett, in 1981, West End in 1982, Lakewood and Oakland City in 1984, East Point in 1986, and finally College Park and Airport station in 1988. The South Line consists of Neighborhood, Commuter, and Community Center stations, with the Airport station, which lies inside the World's busiest airport and is therefore a special case (ARC, 1977; DeCosta, 2014; MARTA, 2017).

[39] Renamed Peachtree Center

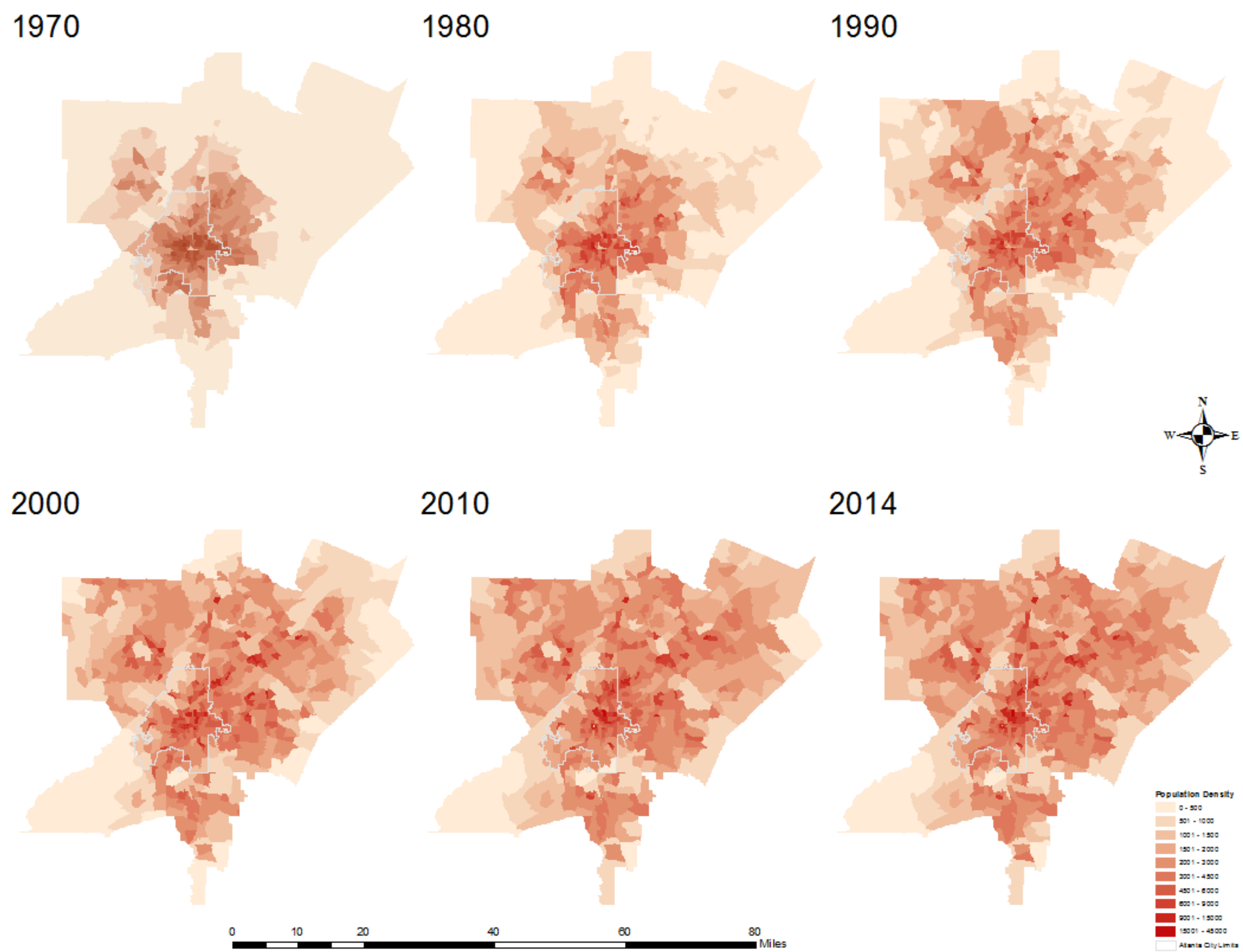


Figure 3.7 Study Area population density (1980-2010)

Table 3.3 TSADS Station Types

High-intensity urban node	High-intensity urban node stations are found primarily in the Atlanta Central Business District and areas with related high-intensity commercial uses. The development objects guiding planning at the stations include the promotion of the highest intensities of mutually supportive uses in close proximity to the MARTA stations while providing for light and air at street level. Aesthetic and functional relationships are sought among structures, utilities, and the rapid transit system. Private automobiles are discouraged, are mass transit facilities encouraged. Pedestrian networkers separated from vehicular traffic between buildings and public ways through buildings are planned. Mixed uses of land are stressed.
Mixed-use regional node	In areas where stations are near existing or prospective community or regional shopping and office centers, mixed-use regional node stations are planned. Enlargement of or addition to such centers as planned development rather than strip commercialism is encouraged. New housing is planned at medium and high densities. At suitable locations office users are encouraged. Protection of adjacent low-density residential uses is stressed for many such station areas.
Commuter station	In areas where commuter stations are located, policies encourage development or expansion of local employment opportunities wherever possible to allow for reverse commuter patterns, thereby more fully utilizing the rapid transit system.
Community center	Community center stations function as centers of activity for several surrounding neighborhoods. A ‘‘feeling of community’’ is pursued in these station area plans. Development plans for these areas designate places to live, work, and shop with a variety of community facilities and services. Residential preservation and redevelopment are encouraged with supportive office and distribution activities.
Neighborhood station	Neighborhood stations serve established low- or medium-density neighborhoods. The plans for these station areas stress the protection of such neighborhoods by prohibiting new commercial or industrial development in the vicinity of stations except where compatible. Where there are opportunities for development or redevelopment, low- or medium-density residential uses are usually recommended.

Source: ARC (1977), *Transit Station Area Development Studies Summary, September 1977*.

Data Source: AJCP229-015w, Atlanta Journal-Constitution Photographic Archives. Special Collections and Archives, Georgia State University Library

Figure 3.8 MARTA East Line Construction 1979

Source: MARTA, 2017

Figure 3.9 MARTA Rail Map

CHAPTER 4

DATA AND METHODOLOGY

The effect of rail intra-urban transit stations on neighborhood change is evaluated using a quasi-experimental evaluation design, informed by both the neighborhood change literature, and literature on the evaluation of the effect transportation systems have on their surrounding neighborhoods, as described in Chapter Two.

Treatment and control groups, the critical aspect of a quasi-experimental design, were formed by two methods; proximity to treatment, and through matching. Neighborhood change was operationalized as indices of the neighborhood life-cycle framework. The analysis consists of difference-in-difference and fixed effects models, over the time frame encompassing the entire existence of the MARTA rail system. This chapter presents the hypotheses, data, and methodology. The hypotheses address the research question of whether transit stations have short-term and long-term effects on neighborhood change, and are stated formally in Section 4.4. First, to provide context, Section 4.1 presents the data and unit of analysis used in the study. Sections 4.2 and 4.3, respectively, address the critical aspect of treatment and control group selection. Section 4.5 describes the operationalization of neighborhood change indicators. Finally, Section 4.6 identifies the methods used in the analysis.

Figure 4.1 provides an outline of the analysis. The research question, is there an effect of intra-urban rail transit stations on neighborhood change, is divided into new station short term effects and long term effects. New station effects are analyzed with difference-in-difference (DID) models in Step 1, addressing Hypothesis 1. Long term effects are analyzed with a Fixed Effects model in Step 2, addressing Hypotheses 2a and 2b. To control for potential unobserved characteristics a matching methodology is employed in Step 3. In Step 4, a Fixed Effect (FE) model is fitted on the matched data to test the effect during a housing recovery period.

Step 1	DID Model
Time	1970-1980; 1980-1990; 1990-2000; 2000-2010; 2010-2014
Y	Individual measures, NCI2
Model	$\delta = (\bar{y}_{t,2} - \bar{y}_{t,1}) - (\bar{y}_{c,2} - \bar{y}_{c,1}) \longrightarrow Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 P2_{it} + \beta_3 (T_{it} * P2_{it}) + \varepsilon_{it}$
Step 2	Fixed Effects Model
Time	1970 - 2014
Y	NCI2
Model	$Y_{it} = \beta_0 + \alpha_i + \beta_1 T_{it} + \beta_1 X1_{it} + \beta_2 X2_{it} + \varepsilon_{it}$
Step 3	Match treatment and control groups on propensity scores
Time	2010
Y	Treatment
Model	$T_{it} = \beta_0 + \beta_1 X1_{it} + \beta_2 X2_{it} + \varepsilon_{it}$
Step 4	Fixed Effects model matched data
Time	2010 - 2014
Y	NCI2
Model	$Y_{it} = \beta_0 + \alpha_i + \beta_1 T_{it} + \beta_1 X1_{it} + \beta_2 X2_{it} + \varepsilon_{it}$

Note: Y = Dependent Variable
T = Treatment
P2 = Period 2
X1 = Population characteristics
X2 = Physical characteristics

Figure 4.1 Analysis Flow Chart

4.1 Data and Unit of Analysis

In census year 1970 the city of Atlanta was at its population peak, MARTA rail transit was non-existent, and Atlanta's public transportation needs were served by a bus fleet operated by the Atlanta Transit System (ATS) (Keating, 2001). MARTA became operational in 1972, when it purchased ATS, followed by the development and opening of the first rail station in 1979. Census data is available at the census tract level of aggregation, spanning the entire life-span of the MARTA heavy rail transit system, starting in census year 1970. Since the MARTA referendum didn't pass until 1971, 1970 Census data can be assumed to predate any MARTA transit station effects. Unfortunately, census tract boundaries change as a function of population change over time. Atlanta has experienced population shifts over time, as was discussed in Chapter Three, leading to shifting census tract boundaries. Therefore, longitudinal analysis would be very imprecise with the raw U.S. Census data. To address this issue, the Longitudinal Tract Data Base (LTDB) provides standardized longitudinal data, using aerial weighting method, at the census tract level for a period from 1970 to 2010 (Logan, Xu & Stults, 2014)[40]. In this study LTDB data standardized to 2010 census tract boundaries is utilized.

To capture effects during the economic recovery from the Great Recession of the late 2000s, this study utilizes 2010-2014 5-year American Community Survey (ACS) data, also with 2010 geographic census tract boundaries. Starting in 2005 the U.S. Census Bureau began collecting long form data[2] from a random sampling of households. Starting

[40] The aerial interpolation using census blocks is used to standardized tracts that may have split or consolidated over time. The assumption of a homogenous distribution of characteristics across blocks introduce measurement error. The Neighborhood Change Database (NCDB) is a commercially available alternative, uses a slightly different weighting process and ancillary data. It produces results that diverge from the LTDB model, but the results for rates and percentages are similar between the two models (Logan, Xu & Stults, 2014).

in 2009, a 5-year aggregation was published spanning the five-year period 2005 to 2009. Here, I utilize 5-year ACS data for years 2010 and 2014.[41] ACS 2010 is based on data collected from 2006 to 2010, and ACS 2014 is based on years 2010 to 2014. The interpretation of the differences between variable values in consecutive sets (i.e., 5-year ACS 2010 and 5-year ACS 2011) is complicated, since the differences are driven only by two years, the other years being the same. Nevertheless, the differences are indicative of changes, though the absolute magnitude of the differences should be interpreted with caution. In this dissertation research, the ACS 5-year sets 2010 and 2014 only overlap by one year (i.e., 2010); therefore, the interpretation is only minimally problematic, and is more likely to be an underestimate. Future studies will have access to the 2015 5-year ACS data, which will eliminate this problem.

MARTA rail station spatial data (in GIS shapefile format) was obtained from the Atlanta Regional Commission (2016). Table 4.1 summarizes the data sources.

Table 4.1 Data sources

Name	**Time frame**	**Data Source**
Longitudinal Tract Data Base	1970 to 2010	Brown University[42]
American Community Survey 5-year estimates	2006-2010 2010-2014	U.S. Census[43]
MARTA rail intra-urban transit stations	2015	Atlanta Regional Commission (ARC)

[41] There are two surveys that the Census uses to collect information. The short form is designed to account for every resident living in the United States, but collecting data on only: name, sex, age, date of birth, race, ethnicity, relationship and housing tenure. Long form data contains additional socioeconomic and housing information, but is now collected through the American Community Survey (ACS) on samples of the population over time. No household is sampled more than once every five years (American Census, 2016).
[42] Spatial structures in the social sciences – Brown University
[43] American Fact Finder

4.2 Treatment Group Selection

In an experimental research design the treatment is applied randomly; therefore, the treatment and control groups are assumed to be equal in all other characteristics, except the treatment, and a difference in means of the response variable can be interpreted as the causal effect. The critical aspect of a quasi-experimental design is the assignment of treatment and control groups. The validity of the design greatly depends on the similarity of the control group with the treatment group (Bingham & Felbinger, 2002). If a valid treatment and control group can be established, then the pre/post control group design can be analyzed with a difference-in-difference model to obtain a measure of the causal effect of interest (Angrist and Pischke, 2008).

The first step is identification of the treatment, with the census tract as the unit of analysis. In treatment design, spillover effect is a source of concern that is dealt with here by operationalizing a large buffer zone around station locations, described below. The other concern is about unique characteristics of tracts near the center of the city.

This study is focused on the effect of MARTA rail stations on the more traditional notion of a residential neighborhood, rather than commercial district. Some central city tracts have access to MARTA rail stations, but are denser than outlying tracts, with a different mix of residential and commercial real estate property than can be expected in other parts of Atlanta. A better measure for the effect of public transit on such areas may be commercial values, local restaurant/retail sales volume, or traffic alleviation, or some index of indicators. To keep focus on housing and residential neighborhoods, which are a better fit for the Neighborhood Life-Cycle framework employed here, some stations have been excluded from the study. Bollinger & Ihlanfeldt (1997) in a study of transit effects in Atlanta utilized a typology of MARTA rail stations[44] based on Transit Station Area Development Studies (TSADS) (ARC, 1977), and these were useful for selecting stations to include in this study. As described in Chapter 3, the types of stations were Commuter, Neighborhood, Mixed use, High intensity, and Community center (Table 3.3). Stations that were rated High Intensity (Table 3.2) were excluded from the present analysis, because in these areas it is not clear that access to public transit is the central policy lever leading to neighborhood change. It is more likely that existing development led to neighborhood change, and possibly the location of the stations. Similarly, several other stations near existing large scale development were excluded to avoid this same bias. The Airport MARTA rail station is located in the main terminal at the Hartsfield International Airport, the world's busiest airport [45]; therefore, it is an outlier. The airport amenity will have a larger effect on the neighborhood than the transit station, and is essentially its own census tract. Likewise, the Lenox and Buckhead MARTA Stations straddle Lenox Square, a major shopping attraction since 1958, and neighboring boutique mall Phipps Plaza, which opened in 1969. The Medical Center station is adjacent to a large hospital and office park complex, and the area is on one side bordered by a massive highway interchange of I-285 and GA 400, which is a major artery connecting sprawling northern suburbs to Downtown, Midtown, and Buckhead office districts[46]. One station north of the Medical Center station is Dunwoody Station, which is within the parking

[44] Bollinger and Ihlanfeldt (1997) presented a typology of MARTA stations – Commuter, Neighborhood, Mixed use, High intensity, and Community center.
[45] Atlanta served over 94 million passengers in 2013, more than any other airport in the world. The other cities in the top 5 in volume in 2013 were Beijing (83 million), London (72 million), Tokyo (69 million), and Chicago (66 million) (API, 2014).
[46] Downtown, Midtown, and Buckhead are the major business district in the Atlanta Central Business District all located along Peachtree Street, which is oriented north and south and is essentially the spine of the City of Atlanta.

area of Perimeter Mall[47]. Built in 1971, the mall and surrounding restaurants and office parks dominate the area, and predate the Dunwoody Station by 25 years. Therefore, the Airport, Lennox, Buckhead, Medical Station, and Dunwoody stations in addition to the High Intensity stations were dropped because the MARTA transit station in these areas may be an effect of the existing urban form, and any effect of transit stations back on the urban environment is difficult to isolate. In other words, any effects of a transit station are likely to be overpowered by the effects of the surrounding infrastructure.

To operationalize the treatment, census tracts must be selected in some proximity to the transit stations. In the Atlanta case, neighborhoods are relatively large and oddly shaped (Bowes and Ihlanfeldt, 2001) (Figure 4.2). Additionally, there is no consistency in the location of a MARTA rail transit station relative to the center and boundaries of the tracts where they are located. The treatment tracts could be defined to only consist of tracts that contain a station. In these cases, spillover effect becomes a threat to validity, because many stations are close to the edge of the census tract where they are located[48]. Therefore, a distance from the station has to be used. To measure distance of a tract from a station a tract centroid is used. A tract centroid is a point which is on average the closest linear distance to all other points in the tract, making it a good measure of distance from a tract to a MARTA station (Bowes and Ihlanfeldt, 2001). Billings (2011) found an increase on the value of real estate within 1 mile of a Light Rail station. Kahn (2007) also used a 1 mile distance for the station treatment area. Immergluck (2009) even found positive house price effects within a quarter mile of a train station of a transit amenity

[47] Perimeter mall is a large regional mall located in Dunwoody a wealthy northern suburb of Atlanta
[48] The positive externality of mass transit is associated with increased mobility and reduced transit cost. The negative externality is traffic congestion and noise.

that has not yet been built[49]. However, in the Atlanta case, using a one mile distance from station to centroid left some tracts that actually contained a station untreated. Again, due to the relatively large size and odd shape of the tract geographic area. Therefore, the treatment group was selected as census tracts that have a centroid within 1.5 miles of a MARTA station. This essentially creates a buffer of treated tracts around the station beyond which a spillover effect of positive or negative externalities, is unlikely. In the present study the concern is primarily with spillover of the effect, that control areas are also affected by the transit station. Beyond 1.5 miles walking becomes inefficient[50], and any negative externalities such as traffic, crime, or noise associated with transit should be unlikely. It should be noted that because of the large size of the treatment area the effect estimated here may be muted, as some areas within the treated census tract are not accessible to the transit station, but are treated in the study (Type 2 error – failing to reject a false null hypothesis).

[49] Atlanta Beltline is a planned multi-modal 22-mile greenway circumscribing the city of Atlanta. Only a few miles of the Beltline have been completed to date, and the majority of the project is still in the planning stage.
[50] At a speed of 3 miles per hour, one and a half miles equates to 30 minutes.

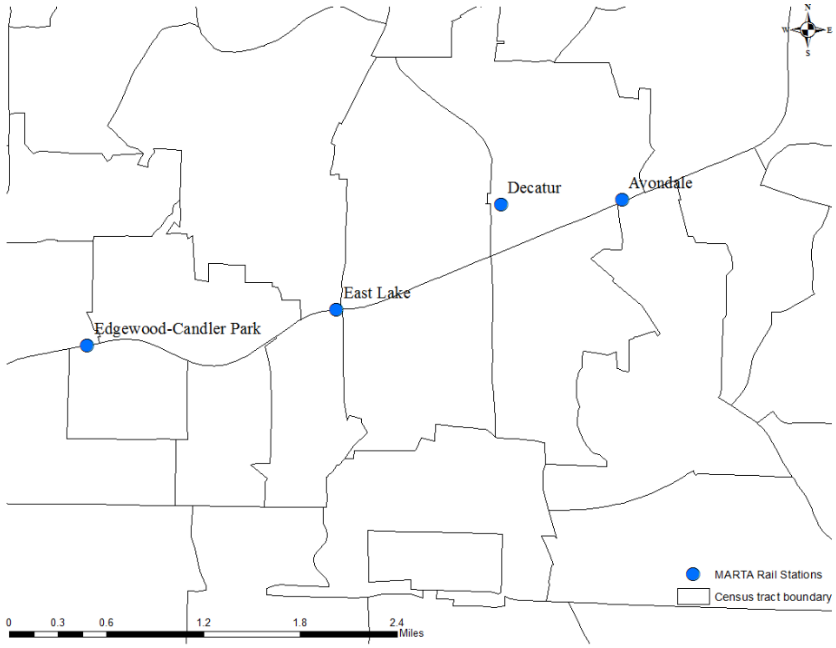


Figure 4.2 MARTA Stations and Census Tracts East Line

4.3 Control group selection

A quasi-experimental approach requires control group selection that closely matches treatment groups on relevant characteristics (Bingham & Felbinger, 2002). Atlanta contains two heavy rail transit lines that run North-South, and East-West in the city. The lines cross downtown, with regular stops primarily in residential neighborhoods (Figure 3.1). The MARTA rail service area is also covered by a robust highway system, which enables the automobile to serve as the primary mode of transportation in Atlanta, even for those living within the study area and working downtown. [51] The MARTA rail system has not increased ridership since 2002, thus the MARTA rail stations may not

[51] A survey of downtown Atlanta employees and students who live in Fulton, DeKalb, Gwinnett, Cobb, and Clayton counties found 54% drive alone (Shapiro Group, 2015)

increase accessibility, except for the low-income groups who are captive MARTA users. Nelson (1992) found a positive effect on housing values for low income neighborhoods near transit, but a decrease in high income neighborhoods in a study that contrasted South versus North Atlanta using 1986 data. Census tracts treated with a rail transit stop will have nearby, comparable, tracts that do not have exposure to the transit station, but are similar in other characteristics. Importantly, accessibility to a highway will be very similar on this scale. In this dissertation control tracts were selected using proximity to treatment and a matching methodology. The primary assumptions to be met for the quasi-experimental design to be valid are that there is no spillover effect from the treatment, and that the treated and control tracts are similar in observable and unobservable characteristics.

Tracts proximate to treatment groups are the first control specification. Tracts with boundaries within one mile of the treatment tract boundary were used to define treatment in this analysis. One mile represents a distance that can be covered easily be any mode of transportation (walking, biking, public transit, automobile), so it represents a reasonable distance within which tracts could be expected to be similar to each other on many locational and potentially other characteristics; however, this approach yields a very small control group in terms of the number of census tracts, which serve as the unit of analysis. A three-mile distance increases the sample size of the control group, so it was used for a robustness check. The effect of public transit stations wanes with distance (Grube-Cavers & Patterson, 2014), especially given the low-density environment in Atlanta, and low mode share of public transportation; therefore, minimal spillover is expected between treated and untreated census tracts. Figure 4.3 presents the census tracts and control groups for each decadal treatment period: 1970s, 1980s, 1990s, and 2000. The interstate highway network and Atlanta city limits are presented, as well. Green dots represent stations that were newly opened in that decade. Dark red indicates a tract was newly treated in the decade, light red indicates a previously treated tract, dark blue indicates one mile control tracts around the newly treated tracts (dark red), and light blue indicates corresponding three-mile control tracts. Table 3.2 presents the dates of opening for each of MARTAs 39 stations. Five Points station is at the center of the system and is shared by all lines.

MARTA rail stations were opened simultaneously on the East and West side in the 1970s, the North and South sides in the 1980s, and the North, East, and West sides in the 2000s. However, Atlanta is not homogenous, racially or economically, with a lot of variation moving in any direction from downtown. The effect of MARTA stations on neighborhoods may be heterogeneous across the city, as is suggested in the literature (Kahn, 2007; Nelson, 1992; Ryan, 1999; Zuk et al., 2015). Several studies with an Atlanta focus found geographic variation in neighborhood change related to public transportation (Bowes & Ihlanfeldt, 2001; Bollinger & Ihlanfeldt, 1997; Nelson, 1992). To account for the potentially heterogeneous effect, the regions were divided into geographic groupings relative to downtown for each decade. Lee and Immergluck (2012), in a foreclosure study divided Atlanta into similar type quadrants centered on downtown. In the 1970s the treatment group was divided at the Five Points MARTA Station into East and West control groups. The 1980s had North and South segments, also divided at Five Points. In the 1990s there were distinct North, East, and West clusters.   A tract could be used in an earlier period as a control tract, then as a treatment tract. However, once a tract was treated it was not used as a control tract in subsequent years. This had the effect of reducing the sample sizes in later years. The descriptive statistics are presented Appendix A. High Intensity station tracts and other stations that were dropped are not used as either treatment or control tracts.

4.4 Hypotheses

Neighborhoods are defined by their housing infrastructure, "a spatially immobile, highly durable, highly expensive, multidimensionally heterogeneous and physically modifiable commodity" (p, 1798, Galster, 1996); however, neighborhoods are also composed of people, who are mobile, and who choose to reside in or utilize available and accessible neighborhood amenities (McDonald & McMillen, 2011; Tiebout, 1956). Neighborhood change, therefore, is driven by the movement of people and capital. The capital can be private investment or public policy. These three factors interact to create change in a neighborhood (Zuk et al., 2015) (Figure 4.4a). In Atlanta, public policy to implement a rail intra-urban transit system was guided by factors other than population density and the region's transportation needs (Keating, 2001). Atlanta's transportation policy was politically motivated to take advantage of Federal matching grants, but succeeding political administrations did not follow through on policies in support of densification or development around MARTA stations, as discussed in Chapter 3. Therefore, the MARTA transit station, a creation of public transportation policy, is assumed to have preceded any investment in, or movement of people to, neighborhoods that have a station. In other words, in the case of Atlanta, the effect runs from Policy, through Private Capital and People, to Neighborhood change. The analysis measures the effect of transportation policy on neighborhood change, controlling for the movement of people and capital Figure 4.4b.

Public Transportation Policy is the treatment variable, operationalized as census tracts with centroids within 1.5 miles of the location of a MARTA rail transit station. In Figure 4.4a, three factors interact to produce neighborhood change: public policy, movement of people, and investment by private capital (Zuk et al., 2015). In Figure 4.4b shows the Atlanta case. In Atlanta, the transportation policy (implementation of MARTA rail service) was the only significant economic development policy affecting the treated areas, and it was created for political gain not as a result of the movement of people or private capital. Therefore, the implementation of the MARTA rail system had an effect on neighborhood change through private investment and the movement of people. In the Fixed Effects model (Section 4.6.2) the controls for Population Characteristics and Physical Characteristics are proxies for the movement of people and the private capital investment. Neighborhood change is operationalized with the Neighborhood Life-Cycle framework using rent, median income, educational attainment, and age of housing, as discussed in Section 4.3.

This study evaluated the effect of rail intra-urban transit stations on neighborhood change, answering the question of whether MARTA rail stations have an effect on neighborhoods over time. Neighborhood change is operationalized with data predating MARTA formation, using indices based on the Neighborhood Life-Cycle framework.

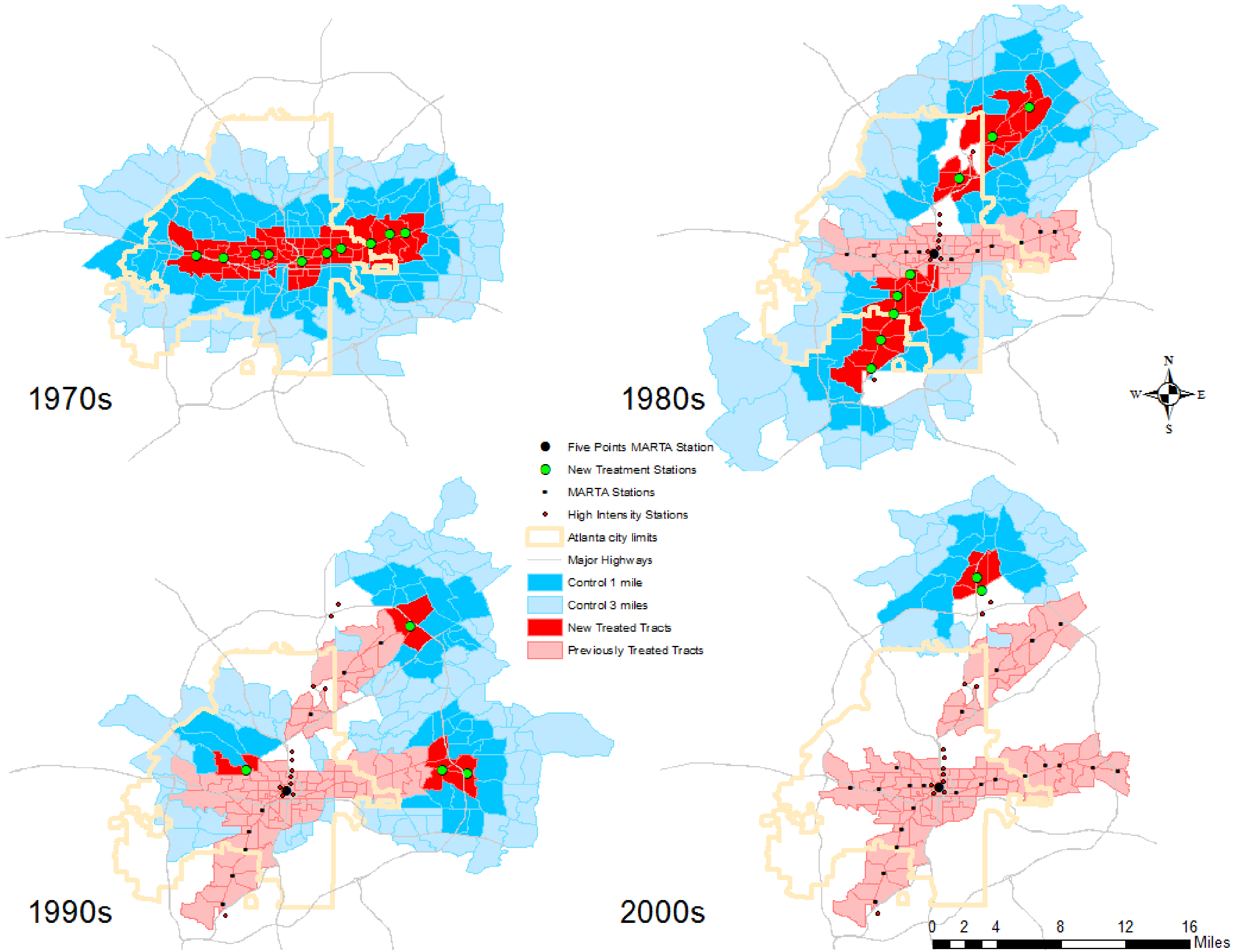
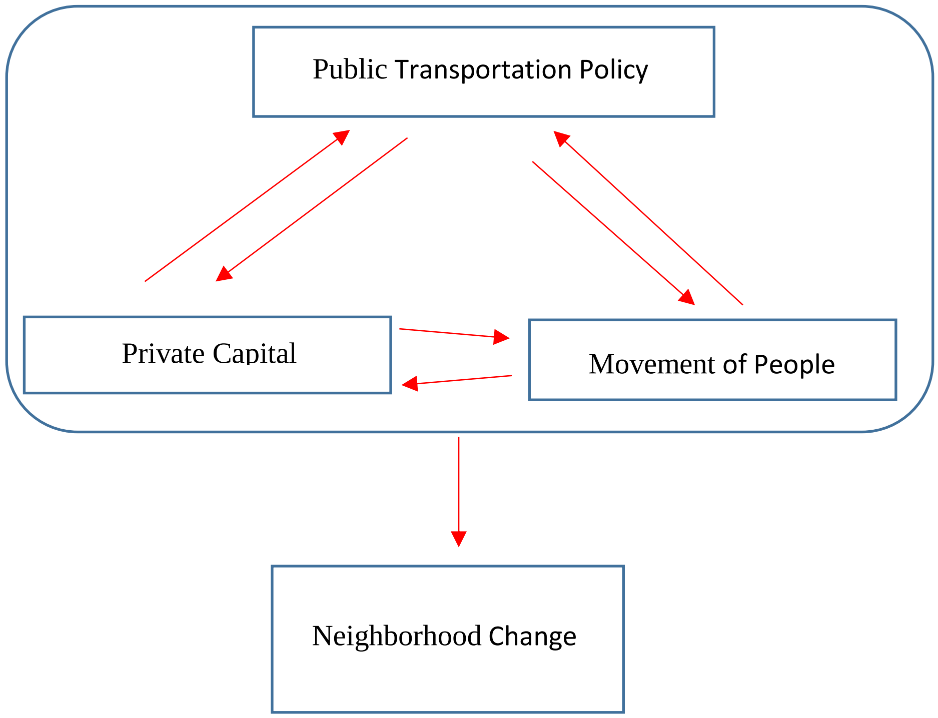


Figure 4.3 Treatment and Control Groups Around New Neighborhood MARTA Stations

a)



b)

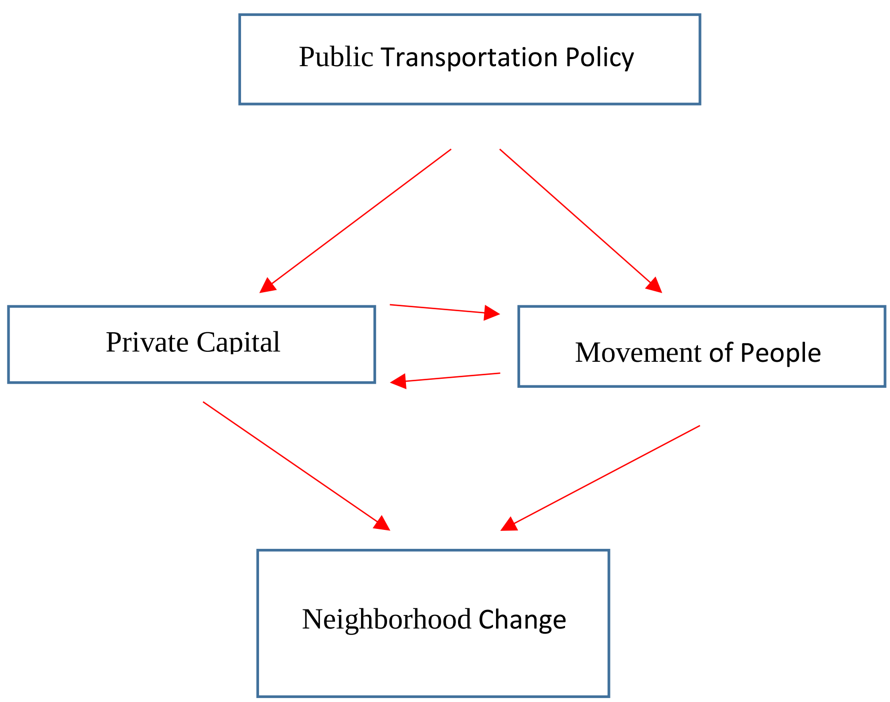


Figure 4.4 Factors affecting neighborhood change

Hypothesis 1: Neighborhoods with access to rail intra-urban transit stations will gentrify more than equivalent neighborhoods without access, within a decade after a new station is opened

The majority of studies evaluating the effect to public transportation systems test an increase in housing values, not any comprehensive operationalization of neighborhood change. Even so, the literature is ambiguous with regard to the direction of the effect (Zuk et al., 2015). In a literature review Ryan (1999) found positive price effects associated with newly implemented stations. New stations increase the accessibility to the surrounding neighborhood. Following economic theory, positive externalities should be capitalized into real estate values in the short-term after station opening (Du & Mulley, 2012).

To test for the effect of a new station[52] this study utilized a quasi-experimental pre- and post- design. The control group is composed of tracts within 1 mile of treatment, with the assumption that proximate census tracts (within 1 mile) will have similar characteristics. A three-mile radius is also used as a robustness check. Hypothesis 1a is tested with difference-in-difference (DID) models:

$$\delta = (\bar{y}_{t,2} - \bar{y}_{t,1}) - (\bar{y}_{c,2} - \bar{y}_{c,1}) \qquad \text{(Equation 1)}$$

Where, $\bar{y}$ is the average of the NCI2 value for the treated (t) or control (c) in periods 1 and 2. δ is the difference-in-difference coefficient. A positive value indicates that gentrification increased more for the treatment group than the control group between

[52] Short-term refers to the effect of a MARTA station from the inception of service to the end of the decade. A limitation of this approach is that the time from opening to the end of the decade varies.

periods 1 and 2. Only newly treated tracts were considered in each DID model; therefore, some of the models have very small sample sizes.

Hypothesis 2a: Neighborhoods with access to rail intra-urban transit stations will gentrify less than equivalent neighborhoods without access, over long time-periods after the station is opened

Neighborhoods with access to rail intra-urban transit stations are a negative amenity, because of the higher traffic they introduce to the area (Kahn, 2007). However, the effect that a rail intra-urban transit station has on a neighborhood may change over time. People may sort themselves depending on whether they find the transit station useful, or a nuisance, following Tiebout's (1956) theory of neighborhood sorting. Once externalities are capitalized into the land price, land values reach equilibrium, they are not expected to change further (Ryan, 1999). Further, Bollinger and Ihlanfeldt (1997) did not find any effects of MARTA rail stations on population and employment.

Public transportation access may spur gentrification when transit increases accessibility, or it provides an anchor to reverse disinvestment (Zuk et al., 2015). Although the evidence is mixed, some studies have found increased housing values and gentrification in neighborhoods accessible to rail intra-urban transit stations (Ryan, 1999; Zuk et al., 2015).

There has not been an increase in MARTA rail ridership with the full system in place (Figure 3.1), so it is likely that accessibility has not been improved by MARTA stations, on average. Atlanta also has low population density and a cultural opposition to transit, evidenced by the lack of supportive policy, vast road network, cheap suburban land, and ubiquitous parking. All factors not favoring MARTA utilization. Therefore, MARTA transit stations are expected to have a net negative effect on neighborhood change (i.e., filtering, towards disinvestment as people choose areas away from the mass transportation disamenity).

To test Hypothesis 2a this study generated control groups using all tracts that are not treated, but lie within the study area. This is a commonly used control group assignment in transit studies (Kahn, 2007; Bowes and Ihlanfeldt, 2001; Bollinger and Ihlanfeldt, 1997). The larger sample size allows for the use of statistical controls.

The framework described in Figure 4.4 is operationalized in the Atlanta context (Figure 4.4b). MARTA rail stations were built as a public policy, and people and capital responded, generating neighborhood change. The movement of people is operationalized using socioeconomic characteristics (X2), and the invested capital is proxied with Physical Characteristics (X1) (Table 4.2).

A fixed effects model enables within tract analysis; therefore, controlling for unobserved and time invariant characteristics of a tract (Long and Freese, 2006). The year and tract Fixed Effects model is:

$$Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 X1_{it} + \beta_3 X2_{it} + \alpha_i + \varepsilon_{it} \qquad \text{(Equation 2)}$$

The Dependent variable (Y) is the NCI2, at time t and period i. The key independent variable is the treatment (T) variable, followed by a set of control variables for physical characteristics (X1) and socioeconomic characteristics (X2) (Table 4.2), as described in Figure 4.4. α_i is the term representing the time invariant characteristics of census tract i, and ε_{it} is the error term.

Table 4.2 Variables in the Fixed Effects Model

Physical Characteristics (X1)
Population density
% Vacant properties
% Households have not moved in last 10 years
% Housing units over 30 years old
% Multi-family housing units
Socioeconomic Characteristics (X2)
% of population that is White
% of population over 60 years old
% of population foreign born
% of adult population in a professional occupation
% of adult population that is unemployed

In the fixed effects model, a significant coefficient value on β_1 would indicate that, controlling for characteristics of a tract that are fixed over time and other observed characteristics, tracts with and without a rail intra-urban transit station have a differing effect on neighborhood change as operationalized here.

Hypothesis 2b: During periods of economic recovery, neighborhoods with access to rail intra-urban transit stations will gentrify more than equivalent neighborhoods without access.

Gentrification is affected by economic cycles (Hackworth & Smith, 2001), and Atlanta experienced strong economic fluctuations in its history. In the 1995 to 2005 period, Atlanta led the nation in residential building permits (Carnathan, 2014). The housing market troubles leading to the Great Recession started arguably in 2006 or 2007 (Immergluck, 2015). Between 2006 and 2011, the Atlanta Metropolitan Statistical Area (MSA) was last among American MSAs by an even larger margin (Carnathan, 2014). Of the neighborhoods with the highest foreclosures in the Atlanta 20 county region, 66% were within the I-285 'perimeter'[53] (Carnathan, 2014), which corresponds well to the extent of the MARTA intra-urban rail service area. In 2008 the American federal government began to respond to the foreclosure and housing crisis, launching the Housing and Economic Recovery Act (HERA) in 2008, which included the Neighborhood Stabilization Program, followed by Obama's Making Home Affordable (MHA), which included Home Affordable Refinancing Program (HARP) and the Home Affordable Modification Program (HAMP) in March 2009, followed by Home Affordable Foreclosure Alternatives (HAFA) in 2010 (Immergluck, 2015; Carnathan, 2014). By the end of 2010, foreclosures had begun to decline (Immergluck, 2015). The recession ended in June 2009, and the unemployment rate began to decline in 2010 (Center on Budget and Policy Priorities, 2016). By 2012, the area inside the I-285 perimeter represented only 43% of foreclosures in the 20 county Atlanta region (Carnathan, 2014). The increase in foreclosures inside I-285 provided an opportunity for gentrifiers to take advantage of the rent gap (Smith, 1979), and the subsequent decline in

[53] I-285 is referred to as the 'perimeter' by Atlantans because it completely circumscribes the city, with about a fifteen-mile radius. A common colloquialism for describing location in Atlanta is 'OTP' and 'ITP', meaning 'outside the perimeter' and 'inside the perimeter', respectively. It opened in October 15, 1969 (UGA, 2017)

foreclosures suggests that may be the case. If transportation is a positive amenity for gentrifiers, then it can be expected that during periods of economic recovery gentrification would be more likely to occur near MARTA transit stations.

Hypothesis 2b was tested using a DID model, propensity score matching, and FE model. In the DID model β_3 indicates a difference in the mean of the neighborhood change outcome variables between treatment and control groups over time. A significant positive difference in a neighborhood change indicator β_3 will be evidence that the treatment has an effect on gentrification.

Propensity score matching was another quasi-experimental approach used to generate control tracts that were similar, on observable characteristics, except the treatment. The propensity score is based on a logistic regression predicting the probability of treatment (Morgan & Winship, 2007). The MARTA system was put in place along existing right of ways, and were chosen on a racially discriminatory basis, in Atlanta's black/white biracial environment (Keating, 2001). However, the stations were placed in locations where there was anticipation of development (ARC, 1977). The two most important variables predicting MARTA treatment are percentage of white residents and population density, and these were used as variables in the matching model. A Fixed Effects model was fitted both before and after matching. A significant coefficient on the Treatment coefficient is an indication that stations have an effect.

4.5 Operationalization of Neighborhood Change

Operationalization of neighborhood change is a critical aspect of evaluating the effect of transit stations. The economic approach suggests that an amenity would be capitalized in the real estate values (Du & Mulley, 2012), making housing values a key variable of neighborhood change. However, the literature also suggests that neighborhood change is a multi-dimensional concept, and can be observed with the combination of neighborhood socio-economic and physical characteristics, and real estate value (Freeman, 2005). Therefore, this study utilizes multiple dependent variables in each model specification: Individual indicators, and a neighborhood change index.

Outside of individual economic measures of neighborhood change, the literature provides a framework for neighborhood change around the concepts of gentrification and filtering. Methods in the literature for capturing gentrification and filtering rely on change over time, often using decadal data (Hanlon, 2009; Owens, 2012; Wei and Knox, 2014). The primary ways to operationalize gentrification involve increase over time of one or more indicators, including household income, educational attainment, and real estate values, typically relative to the overall city or MSA change (Freeman, 2005; Hackworth, 2002; Lees et al, 2008; McKinnish, Walsh & White, 2010; Slater, 2006;). Filtering is a general decline, operationalized in the literature in a similar fashion as gentrification, but in reverse, with household income and property values (Coulson & Bond, 1990; Margolis, 1982; Rosenthal, 2014). As described in Chapter 2, the concept of gentrification is growth and reinvestment, and filtering is a measure of decline. Together they form the basis of the theoretical framework applied in this study – the Neighborhood Life-Cycle framework.

Two indexes and associated nomenclature were developed to operationalize neighborhood change using the Neighborhood Life-Cycle framework. The indexes serve as key variables in the analysis. Neighborhood Change Index 1 (NCI1) is on a categorical scale, and defines three conditions of change in a census tract over time: gentrifying, stable, and filtering. The condition is identified in each neighborhood for each time-period between 1970 to 2010, plus 2014, so that a pattern of change can be observed over time. Neighborhood Change Index 2 (NCI2) is a continuous index, with gentrification at one extreme and filtering at the other. NCI2 is the Dependent Variable in the evaluation.

4.5.1 Individual Indicators

The Neighborhood Life-Cycle is composed of periods of decline and renewal; filtering and gentrification, respectively. The primary indicators of gentrification found in the literature are housing values, household income, age of housing, and education (Kahn, 2007; Freeman, 2005; Owens, 2012). Filtering has been operationalized as changes in the income of residents, and changes in housing values (Coulson & Bond, 1990; Margolis 1982; Rosenthal, 2014).

Housing value can be obtained from several sources, among them assessed value from the County, sales value from actual sales, and the U.S. Census provides median home values and rental costs. Assessed value is a trailing measure, as Counties react to market rises in prices, so there can be some price distortion. Sales and predicted values can be obtained from private market sources such as Zillow (Raymond, Wang & Immergluck, 2015), but these data are unavailable going back to the 1970s. The Census provides estimates of rental rates and median home values, and both could be utilized as measures of value. Low income neighborhood values may be particularly biased because of low transaction character of those markets (Margolis, 1982). Further, U.S. Census home and rent values are estimates provided by the respondent to the Census questionnaire. Since every tenant will know their rental rate, but not every homeowner will have a good sense of the market value of their home. For these reasons rental rate is used in this study as a proxy for home values. Household income can be obtained from the U.S. Census[54] as the median income for each census tract in each time-period. Percentage of housing that is over 30 years old is a proxy for new construction, and is also available from the US Census. Education is coded as percentage of people 25 years or older with a college education. Education is an interesting measure in the Atlanta context, because the Atlanta Public School system has struggled. In 2012 the federal standard for attaining graduate status was applied to Atlanta Public School students, the graduation rate fell from 70% to 52%. That's compared to the State of Georgia which had a drop from 81% to 67% (Clark, 2014).

The median house value and median rent variables are coded in respective year dollars. However, since dollar value changes over time due to inflation, the value variables were adjusted to 2010 dollars using the CPI index (BLS, 2016).

4.5.2 Neighborhood Change Index 1

The first step in this study is to observe neighborhood change. There are several methods used to capture the phenomena of gentrification and filtering from available socio-economic indicators, as discussed in Chapter 2. The framework established by Freeman (2005) and others operationalized gentrification with housing values, income, and education, as described in the Neighborhood Life-Cycle (Figure 1.1). Filtering is the opposite of gentrification, and is operationalized here using the same framework. For a

[54] Source: American Fact Finder; https://factfinder.census.gov

decadal period a tract can be gentrifying, filtering, or remaining stable. If a tract does not meet the definition of gentrification or filtering, as described below, it is considered stable.

<u>Gentrification</u>:

- Change in ***median income*** for the census tract is **greater** than the increase in median income for the five-county area
- Change in the ***percent of college graduates*** in a census tract is **greater** than the increase in the percent of college graduates in the five-county area
- Change in ***real housing prices*** is **greater** than the increase in real housing prices in the five-county area

<u>Filtering</u>:

- Change in ***median income*** for the census tract is **lower** than the increase in median income for the five-county area
- Change in the ***percent of college graduates*** in a census tract is **lower** than the increase in percent of college graduates in the five-county area
- Change in ***real housing prices*** is **lower** than the increase in housing prices in the five-county area

Freeman's criterion for tracts having to be 'gentrifiable' (i.e. relatively low value) is relaxed, because the study is interested in continuing neighborhood change. A gentrifiable tract, according to Freeman's (2005) definition, is one that starts out being of low economic value. Freeman's (2005) central question is regarding displacement; therefore, his operationalization has to focus on low income populations. Under such a definition, neighborhood change would not be captured at higher valued properties, although neighborhoods could certainly be expected to change. In this study the question is about broad neighborhood change, not specifically focused on any one type of neighborhood.

Once filtering, gentrifying, and stable tracts were identified, in the next step each census tract was coded to identify whether it changed categories between periods to identify the direction of change. The coding identifies the direction and intensity of change in the gentrification index between two periods of time on a 1-9 scale, shown below. Codes 1-3 indicate filtering. Codes 4-6 indicate stability, Codes 7-9 indicate gentrification.

- 1 the change is from gentrification to filtering,
- 2 gentrification to stable
- 3 stable to filtering
- 4 filtering to filtering
- 5 stable to stable
- 6 gentrification to gentrification
- 7 filtering to stable
- 8 stable to gentrification
- 9 filtering to gentrification

Change is scaled from strongest filtering (1) to strongest gentrification (9). 1 represents the strongest change towards filtering, from gentrification at the beginning of a period to filtering at the end – a two-step movement. Likewise, 9 represents a two-step movement from filtering to gentrification. Steps 2 and 3 and steps 7 and 8 represent a one-step movement towards filtering and gentrification, respectively. Step 2 is ranked above step 3 because gentrification starts at a higher level, so it is a stronger movement towards filtering. To maintain symmetry with steps 2 and 3 in the scale, step 8 is placed below step 7. The three middle positions are grouped together because they all represent stability. This is the Neighborhood Change Index 1 (NCI1). 1990 is the first year that data is available because the index measures the change in the index level. The neighborhood change index is calculated between the years 1970 and 1980; therefore, to measure a change in the index one more time-period is necessary. Rather than indicating filtering or gentrification, NCI1 indicates the change of the index over time.

4.5.3 Neighborhood Change Index 2

The first operationalization of neighborhood change was an individual indicator. The second was a categorical index. A third operationalization of the Neighborhood Life-Cycle is generated as a continuous change index. The Neighborhood Life-Cycle framework defines gentrification and filtering to be composed of four variables. Accordingly, median income, educational attainment, age of housing, and rental value changes between successive decades in a census tract are normalized relative to the regional average (i.e., Fulton, DeKalb, Clayton, Cobb, and Gwinnett Counties) using z-scores. Z - scores are weighted, then summed to produce the Neighborhood Change Index 2 (NCI2). The literature does not provide guidance related to the weighting of the variables, so three specifications of the index were generated. In the first specification, income, education and house value variables were equally weighted ($NCI2_1$). In the second specification income and education were each weighted 25%, and house rent weighted 50%, to produce an index weighted 50% characteristics of residents, and 50%

characteristics of the housing ($NCI2_2$). A third specification adds percentage housing over age 30 to the index, with each of the four variables having a 25% weighting ($NCI2_3$).[55] Figure 4.5 presents the flow chart of the NCI2 construction. The decadal periods utilized are 1970 to 1980, 1980 to 1990, 1990 to 2000, 2000 to 2010, and the period from 2010 to 2014.

[55] The four factor NCI2 contains age of housing as a factor in the index construction. Age of housing is removed from the control variables in the analysis model.

Indicators: **Income** ($), **Education** (% College Degree), **House Rent** ($), **Housing Age** (Years)

Compute change over time: $X_t - X_{t-1}$

Convert to z –scores: $z = (\Delta X_i - \Delta \mu_{region})/\sigma$

μ = regional county average and σ = st dev

Weight the z – scores : Income (25%), Education (25%), Value (50%)

Income (33.33%), Education (33.33%), Value (33.33%)

Income (25%), Education (25%), Value (25%), Housing Age (25%)

NCI2: SUM of weighted scores

Figure 4.5 Neighborhood Change Index 2 (NCI2) Construction

4.6 Methods

The objective of this research is to evaluate the short-term and long-term effects of MARTA rail stations on neighborhoods, and along a typology of neighborhoods. The analysis consists of DID and FE models. Statistical analysis was conducted using RStudio 1.0.136, 'plm' package (Croissant & Millo, 2008) and Stata 11.2. [56]

4.6.1 Measuring short-term effects of new intra-urban transit stations on neighborhood change

The MARTA rail network was opened in stages from 1979 to 2000 (Table 3.2), making it possible to evaluate Hypothesis 1, the effect of stations when they were first opened, using a pre- and post- quasi-experimental design. To capture the short-term new station effects of MARTA rail stations on neighborhoods, this study utilizes a difference-in-difference model (DID) with the treatment and proximity based (one mile and three mile) control groups clustered by geography, as described in Section 4.3.

Quasi-experimental pre- and post- designs (Figure 4.6) are often used to evaluate the effect of the inception of a public policy, since they can capture the before and after effect of policy implementation (Angrist & Pischke, 2009; Bingham & Felbinger, 2002). MARTA opened stations every decade starting in the 1970s and ending in 2000. Therefore, data from 1970 was used to form the pre-treatment conditions for the 13 stations that opened in 1979, and data from 1980 was used to form the post-treatment conditions. Likewise, for each subsequent decade, census data from the beginning of the decade was used as the pre-conditions, and data from the subsequent decade were used as

[56] RStudio was utilized for all statistical analysis reported here. Stata 11.2 was used as a robustness check and to calculate robust standard errors

the post conditions. There were 17 stations opened in the 1980s, another 7 in the 1990s, and finally 2 more in 2000.

	Pre-test	Treatment	Post-test
Treatment Group	O	X	O
Control Group	O		O

Source: Bingham & Felbinger, 2002

Figure 4.6 Pre- and post- quasi-experimental design

Matched by proximity, treatment and control tracts were compared on Y, the outcome variables. O represents the observation. X is the treatment, allocation of rail intra-urban transit station. The DID equation is:

$$(TREAT_t - TREAT_{t-1}) - (CONTROL_t - CONTROL_{t-1}) \qquad \text{(Equation 3)}$$

or

$$\delta = (\bar{y}_{e,t} - \bar{y}_{e,t-1}) - (\bar{y}_{c,t} - \bar{y}_{c,t-1}) \qquad \text{(Equation 4)}$$

δ is the DID estimator. $\bar{y}$ is the average Y for each group, e is the experimental treatment group, c is the control group, at time t and t-1. The changes in the treatment outcome are subtracted from the control group outcome to arrive at δ, the effect of treatment, for each census tract, i.

This difference-in-difference model was calculated using and interaction term in a regression:

$$Y = \beta_0 + \beta_1 T + \beta_2 P2 + \beta_3 T * P2 + \varepsilon \qquad \text{(Equation 5)}$$

Where T is a dummy for Treatment and P2 is a dummy for the second decade in each time-period. β_3 represents the difference-in-difference coefficient. The DID treatment effect is the average of all census tracts (Angrist & Pischke, 2007). A significant β_3 coefficient indicates that the transit station had an effect on the outcome variable. The DID approach addresses selection bias and larger scale effects within a metro area, but it does not control for other factors. Results of the models with one and three mile controls are presented in Section 5.1.

4.6.2 Measuring long-term effects of intra-urban transit stations on neighborhood change

Stations are new only once, so they are old for much longer than they are new. Two types of models are fitted to evaluate the long-term effect of rail intra-urban transit stations on neighborhood change; a FE model and a DID model. Control groups based on proximity and matching.

Model specifications are plagued by unobserved and unknowable factors. A time and census tract FE model can control for unobserved characteristics of a census tract that do not change over time. This model captures the association between rail intra-urban transit stations and neighborhood change, controlling for several observed variables.

FE model:

$$Y_{it} = \beta_0 + \alpha_i + \beta_1 T_{it} + \beta_2 X1_{it} + \beta_3 X2_{it} + \varepsilon_{it} \qquad \text{(Equation 6)}$$

Y is the neighborhood change variable at the census tract level of observation for each census tract i, and time-period t. T is the treatment, the primary independent variable, a binary indicator of tracts that had a rail intra-urban station. X1 and X2 are respectively, physical characteristics and socioeconomic characteristics, corresponding to the framework in Figure 4.4. α_i is the term representing the time invariant characteristics of census tract i. The error term is represented by ε_{it}.

The first 13 MARTA rail transit stations opened in 1979, the next 4 in 1981, followed by 4 in 1982, 5 in 1984, 1 in 1986 and 1987, 2 in 1988, 2 in 1992, 2 in 1993, 3 in 1996, and 2 in 2000. For the purposes of the FE model, tracts with transit in 1979 will be considered treated in 1980, tracts that received transit in the 1980s will be considered treated in 1990, the tracts treated in the 1990s will be considered treated in 2000. The last stations were put into service in December 2000, this is practically 2001. It could be argued that the station's effect started when construction began, as Immergluck (2009) showed is possible. However, it is difficult to figure out when planning for each individual station would have started, and when it would have become public knowledge. In this study, it is assumed the effect on actual riders begins when trains start to carry passengers. The tracts receiving a rail MARTA station in 2000 will be considered to be treated in 2010.

Five periods are included in the FE model: 1970 - 1980, 1980 - 1990, 1990 - 2000, 2000 - 2010, 2010 - 2014. However, this model does not address selection bias; the stations were not randomly assigned. There may be properties associated with the location of the stations, omitted variables, that could be the reason that is driving neighborhood change. Neighborhood change could be driving assignment of the treatment (i.e., transit stations). Propensity score matching is used to balance the data. A FE model was fitted using the matched data.

If following an experimental approach, neighborhood treatment would be assigned randomly (i.e. rail intra-urban transit stations would be randomly placed within a metro area), so any change in neighborhood characteristics after the assignment of treatment would be captured by the difference in Y between treatment and control groups.

To overcome the selection bias without random assignment of rail intra-urban transit stations, which is impossible in an actual city, matching strategies have been employed in the literature (Cervero and Landis, 1993; Freeman & Barconi, 2006; Morgan and Winship, 2007; Pagliara and Papa, 2011). Matching strategies overcome selection issues by identifying members of a population that are the same in all observable respects except treatment. In the intra-urban transit effects literature, the studies generally form matches partly based on qualitative criteria that would be difficult to replicate. Control areas are identified with arbitrary geographies, based partly on interviews, or the author's local knowledge. Treatment and control areas are compared on socioeconomic and other characteristics. Propensity score matching provides a single parameter as a function of a set of predictor variables. The propensity score can then be used to reduce selection bias, by improving balance between the treatment and control group on selected characteristics (i.e., match).

The propensity score matching model predicts the probability of treatment, theoretically matching census tracts with access to a rail intra-urban transit station to census tracts without access to transit, but with a similar propensity score. The differences between the treatment and control tracts on other observable characteristics can then be ascribed to the effect of the treatment.

Any selection bias in the treatment in Atlanta was limited to racial bias, and population density. Keating (2001) described the political climate in which public money was used to build a better system in the mostly white north of the city, than the other sections. The selection for location of the rail lines was limited, since they were to be built along existing right-of-ways. The intention of the early leadership guiding MARTA's creation was for economic development around the stations, which would have been driven by population density. The matching variables are % white and population density.

The propensity matching model:

$$T_{it} = \beta_0 + \beta_1 X1_{it} + \beta_2 X2_{it} + \varepsilon_{it} \qquad \text{(Equation 7)}$$

The unit of analysis remains the census tract. T is the probability of treatment of census tract i at time t. X1 is the population density, and X2 is the percentage of population that is white. The matched treatment-control data is analyzed using a FE model, Equation 6.

CHAPTER 5

RESULTS

This analysis attempts to detect a causal effect of rail intra-urban transit stations on neighborhoods using a quasi-experimental approach. This chapter first presents the results of the neighborhood change indexes to descriptively show neighborhood change over time, followed by sections 5.1, and 5.2, which address Hypotheses 1, 2a, and 2b. Hypothesis 2a and 2b are jointly presented in Section 5.2.

The first step is to show that neighborhoods change over time within the Neighborhood Life-Cycle framework, as operationalized here. Neighborhood Change Index 1 (NCI1), described in Section 4.5.2, is composed of two steps. First, each tract is assigned a category, gentrifying, stable, or filtering. If the percentage change in a tract is above or below the median for the study area in all three categories education, median income, and median rent, the tract is labeled as gentrifying or filtering, respectively. All others are labeled stable. Figure 5.1 depicts this first stage of NCI1 construction. Gentrification, filtering, and stable tracts are represented with blue, red, and yellow, respectively.

In Figure 5.1 the patterns of gentrification and filtering shift over time, but there are clear geographic clusters. In the 1970 to 1980 period filtering was prevalent in the southern portions of the study area, as well as the city of Atlanta. Gentrification was localized in the north and northeastern suburbs. Between 1980 and 1990 the southern suburbs filtered, while the northern suburbs gentrified. Between 1990 and 2000 the same general north – south pattern held, however some gentrification moved south. Inside the city of Atlanta gentrification appeared in the eastern portion of the city, partially along the path of the East MARTA rail line. Between 2000 and 2010, gentrification spread across the city of Atlanta, as well as the southeastern suburbs. However, filtering now appeared in the previously gentrifying areas and largely continued into 2014.

Stage 2 of the NCI1 captures the change between time-periods in terms of the change in each neighborhood category over time between filtering, stable, and gentrifying. In Figure 5.2, the choropleth map is based on the 9 categories of change. The blue end of the scale represents movement towards gentrification, and red denotes filtering. The darker the color the higher the intensity of the change. Yellow hues denote stability. The starting decade on the maps is 1990, because it takes two time-periods to operationalize the NCI1 scale, then another period to observe change in the index. The map labeled 1990 indicates change between the period 1970 to 1980, and the period 1980 to 1990.

In 1990, the category with the highest count of census tracts in the five-county study area was Category 4, neighborhood change from filtering to filtering (Figure 5.3). In the north part of the City of Atlanta tracts were moving towards gentrification, and primarily remained stable elsewhere. Stable to stable had the second highest count of census tracts. A filtering trend is observed in the northeast portion of the study area, but stability and movement towards gentrification is present throughout the northern sections of the study area. In 2000, the north part of the City of Atlanta reverses, and moves to filtering, while the remainder of the city remains stable with the exception of a few census tracts in the center of the city that are gentrifying. The overall pattern is mixed, but the majority of the stations in 2000 are Category 5, stable to stable. In 2010, there are even more Category 5 tracts, and the number of filtering to gentrification tracts (Category 1) doubles from the previous two decades. South Atlanta is showing a gentrification trend that extends south of the city. In the northern sections of the study area a filtering pattern is observed in the 2000 to 2010 period. The NCI1 provides an interesting picture because it calculates change on change. It indicates that the largest number of tracts tend to be stable, but presents evidence that many neighborhoods change over time along the Neighborhood life cycle.

Overall, most tracts are stable and stay stable over time. The extreme categories one and nine have the fewest tracts. In Figure 5.3 the left end of the scale represents gentrification. The graph looks like a normal distribution, but the left side has higher counts, indicating that gentrification may be producing an overall stronger effect.

Figure 5.4 shows only the tracts that change from gentrification to filtering or filtering from gentrification (the extremes) and notes the locations of MARTA stations. In the 1980 to 1990 period, tracts moving to gentrification from filtering were located in the northeastern section of the study area, as well as in the north part of the city. In the 1990 to 2000 period there is scattered gentrification along the east MARTA rail stations. In the 2000 to 2010 period filtering is scattered along the northern suburbs, and gentrification in the southern parts of the city. There is no discernable pattern in the 2010 to 2014 period.

Figure 5.5 identifies the stable areas, showing changes from gentrification to gentrification, stable to stable, and filtering to filtering. In the 1980 to 1990 period, the eastern part of the study area and southern part of the city showed persisting filtering. There were areas of persistent gentrification in the northeastern suburbs. From 1990 to

2000 the pattern remained the same, but there were fewer census tracts with persistent filtering, while there were more tracts with persistent gentrification in the northern suburbs. In the 2000 to 2010 period persistent gentrification tracts exist in the far northern suburbs and in the south and west sections of the city of Atlanta. Some of the persistently gentrifying tracts lie along MARTA rail stations over several periods, particularly the 2000 to 2010 period. During all of the periods there is some strong neighborhood change indicated near some MARTA stations.

Figure 5.6 presents the results of the NCI2 index, as discussed in Section 4.5.3. The year 1970 is not shown because gentrification is based on change between two time-periods. Since the 1960 Census data is not available, 1970 NCI2 cannot be calculated. The choropleth map shows the distribution of values for each decade. Gentrification is noted as dark blue and, and on the other extreme, filtering is coded as dark red. Yellow indicates stability. The choropleth map is based on the natural breaks classification scheme using ArcMap 10.4. The maximum and minimum values are not consistent for each decade, so the classifications are unique for each decade. The choropleth colors in Figure 5.6 are relative to the values within each decade; however, the colors are representative across decades and can be used for a same-tract interdecadal comparison using the maps, but carefully. The tracts in white have missing data or were dropped from the analysis.

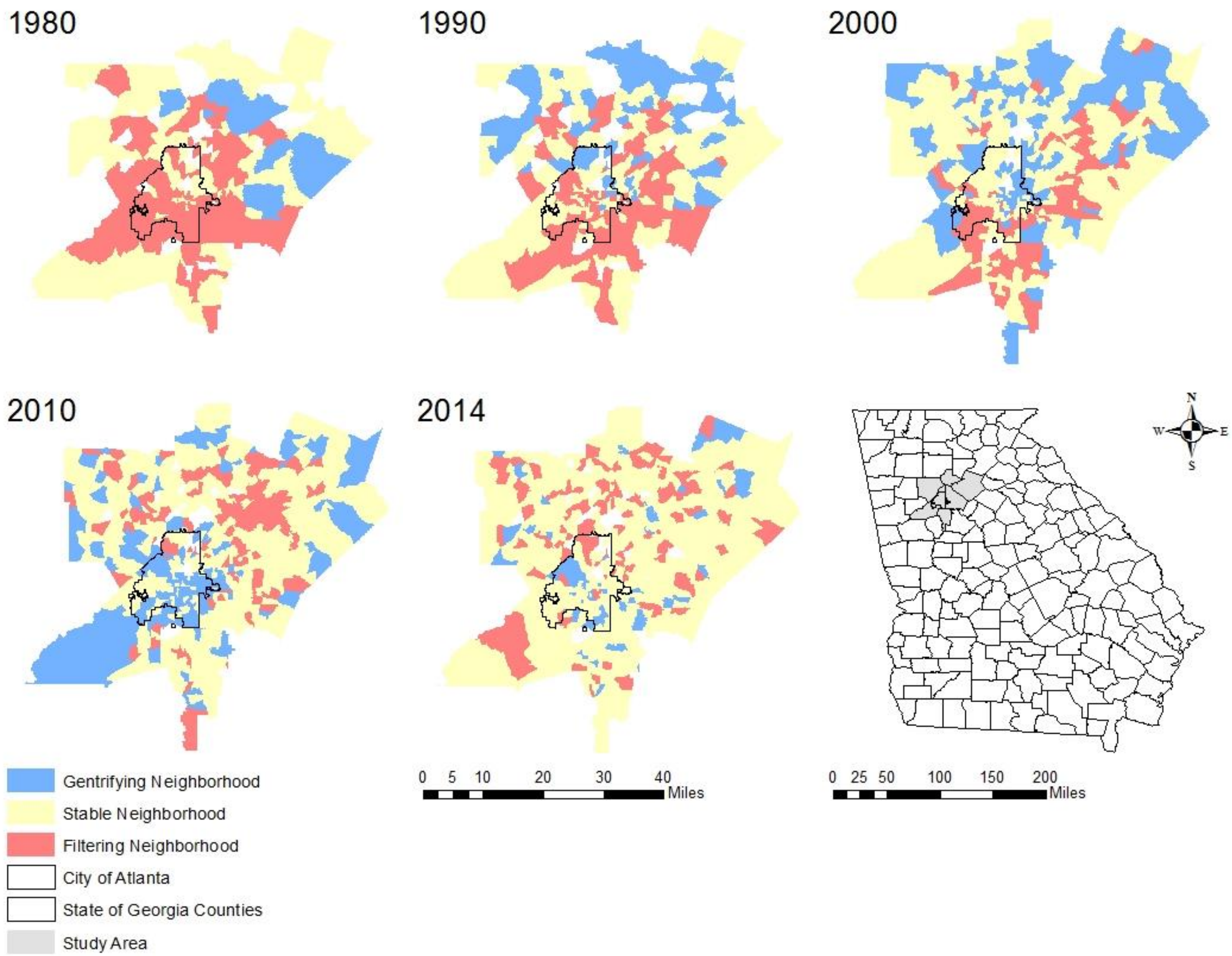


Figure 5.1 Neighborhood Change Index 1 – Stage 1

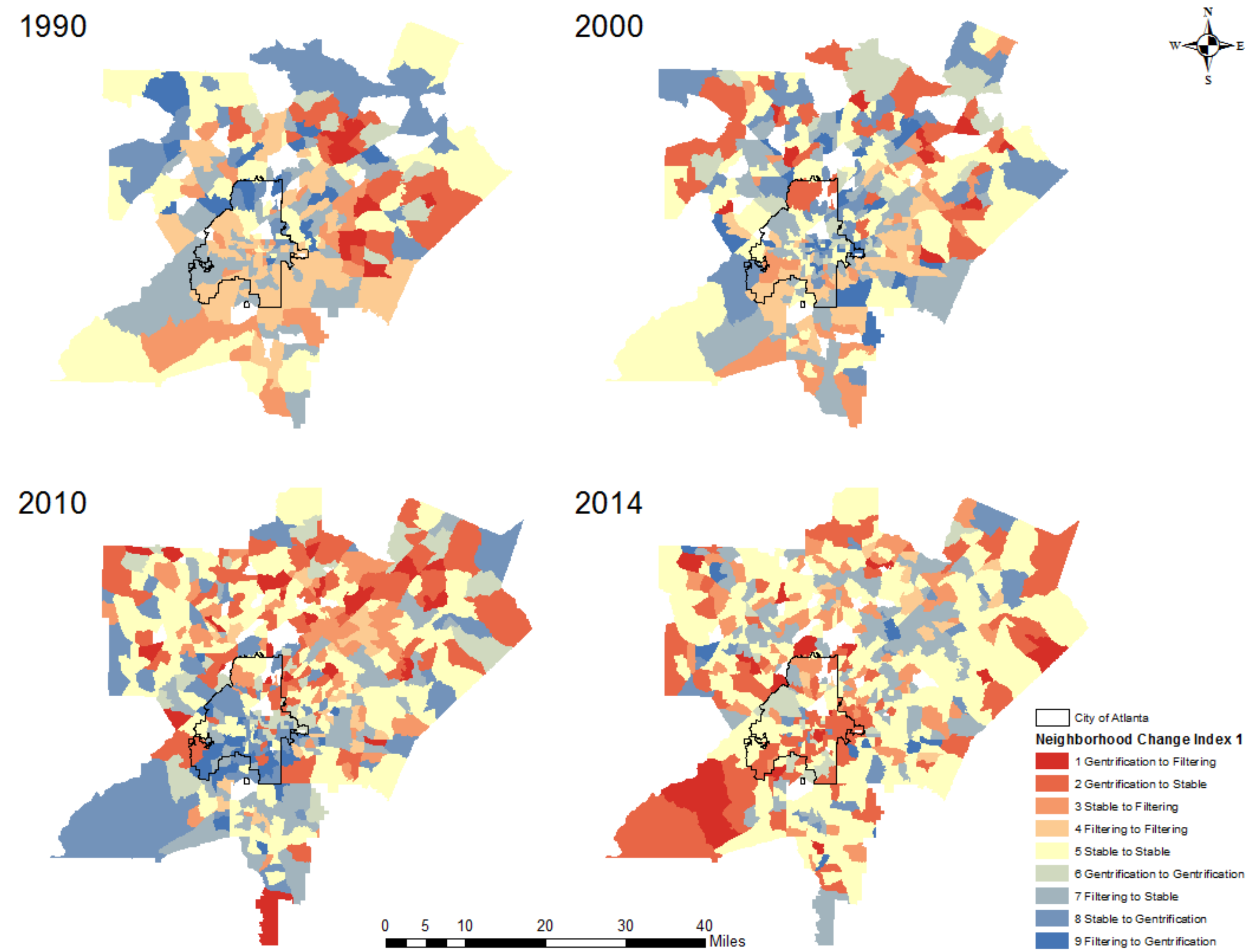


Figure 5.2 Neighborhood Change Index 1 – Stage 2

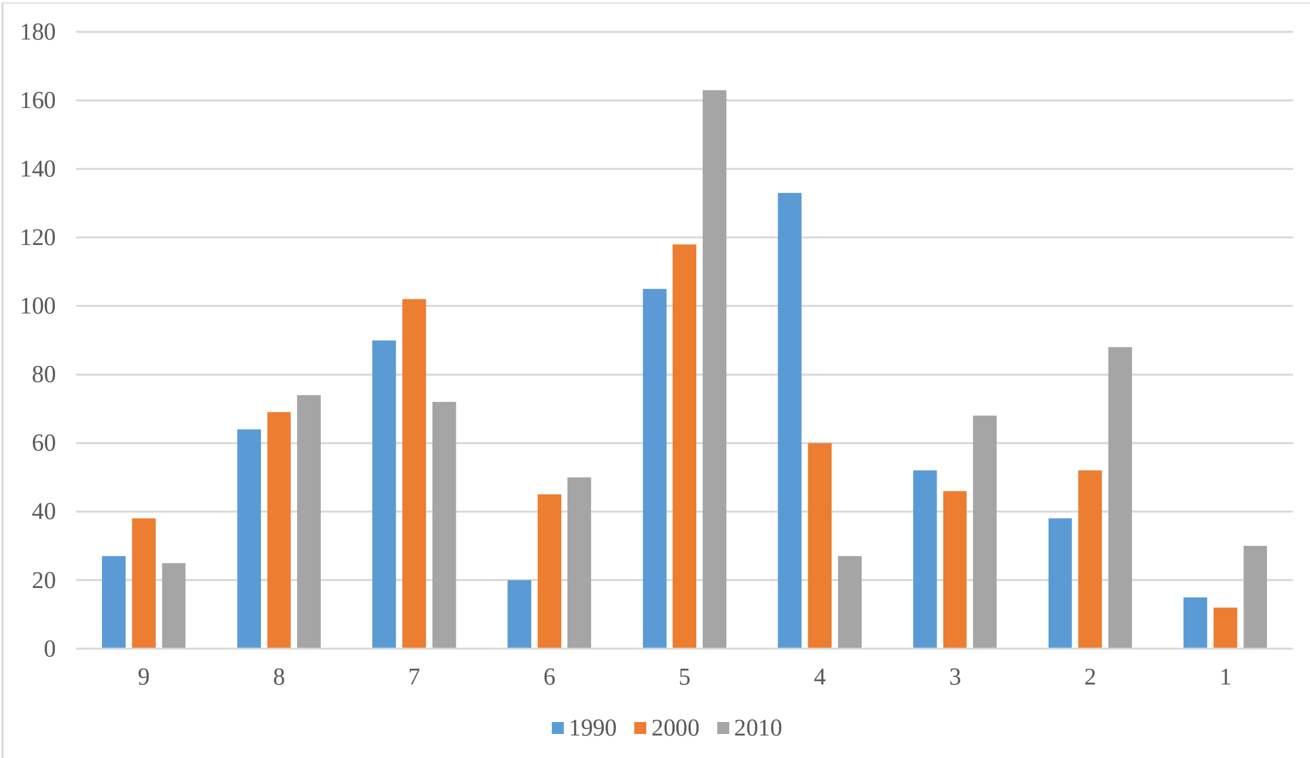


Figure 5.3 Neighborhood Change Index 1 Count of Tracts for Each Category

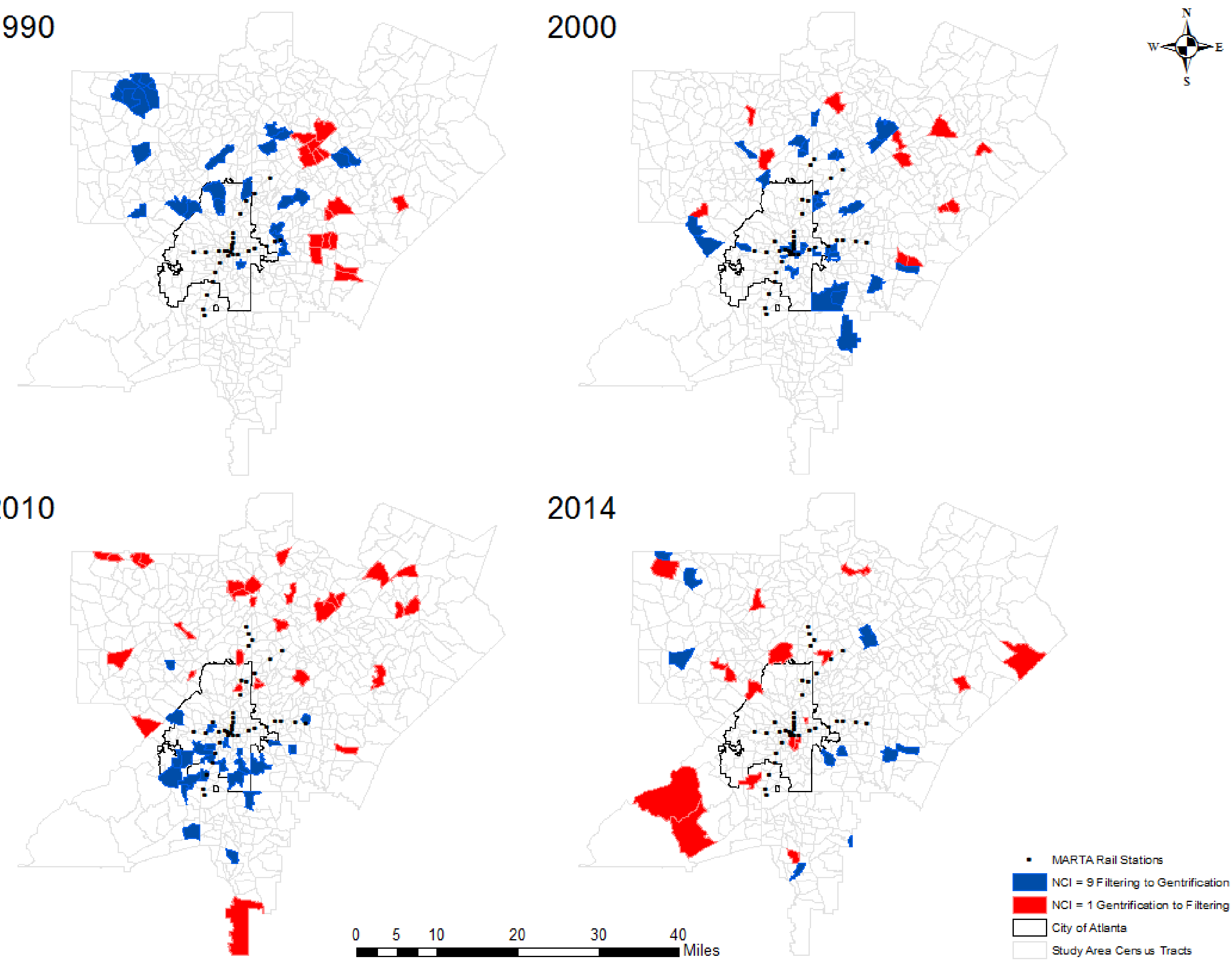


Figure 5.4 NCI1 Change Gentrification to Filtering/Filtering to Gentrification

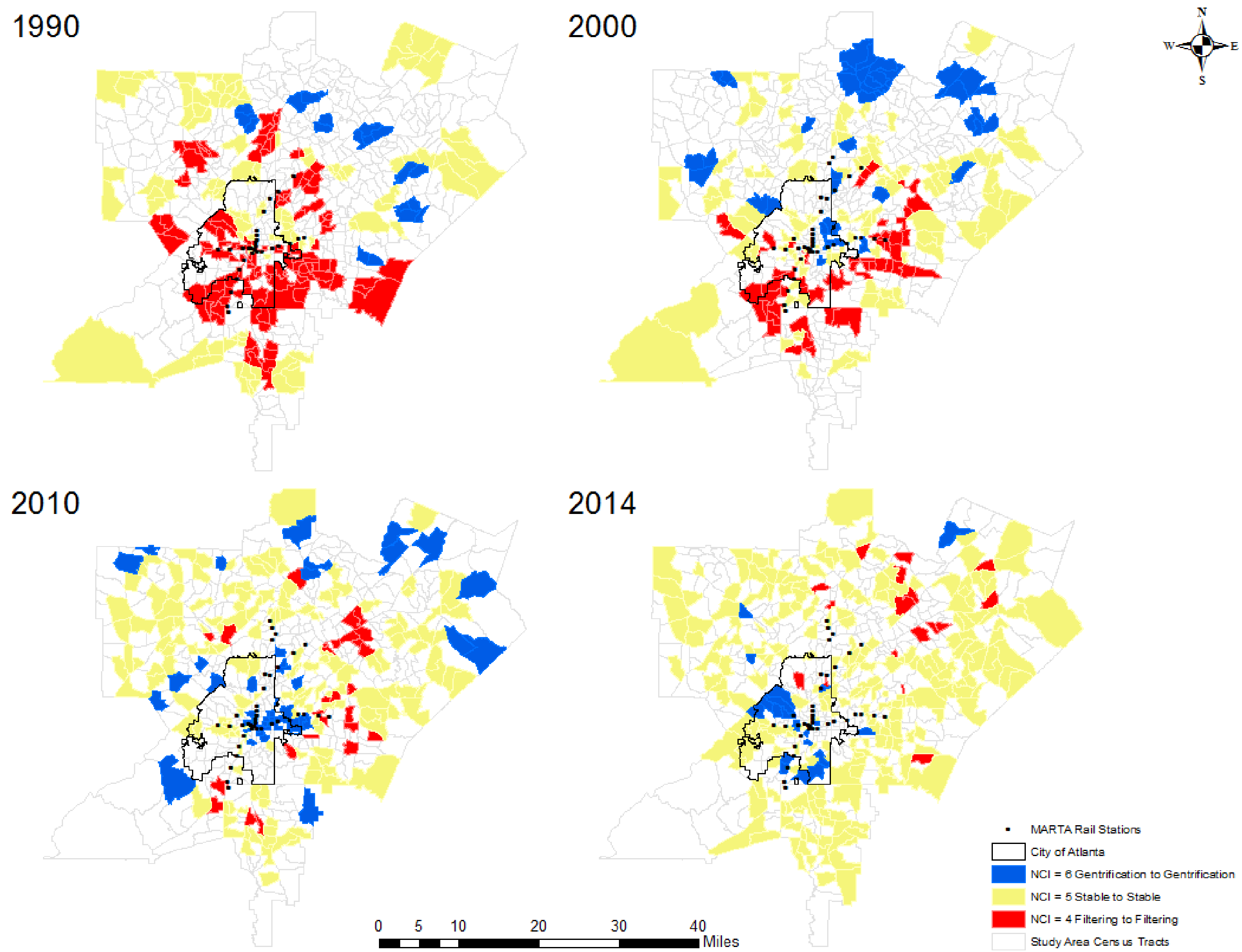


Figure 5.5 NCI1 Stable Tracts

In 1980, the city of Atlanta had an overwhelming filtering effect, with a negative mean $NCI2_1$ score (Table 5.1). All specifications of the NCI2 variable were consistent, and the equally weighted, three variable index ($NCI2_1$) was utilized for mapping. In Figure 5.6 red represents maximum filtering for the period, and orange represents more modest filtering. The city boundary is almost entirely filtering, with only a few tracts showing stability and gentrification. Modest gentrification for the period in the city is confined to a very small section of eastern Atlanta. Strong filtering in 1980 extended in all directions from the city except in the southwestern region of the study area. Gentrification is strongly indicated in the extreme north and northeastern portions of the study area.

In 1990, gentrification is much stronger than in 1980. The maximum gentrification score in 1990 is 5.19, but only 1.72 in 1980. The negative end of the scale is also shifted towards gentrification; in 1990 the minimum value was -0.78, while it was -1.64 in 1980. In 1990 stable tracts (i.e., those with an index score near 0.00) are coded blue. In the 1990 period, relatively strong gentrification formed in the north sections of the city of Atlanta as well as the extreme north sections of the study area. The results for the decades ending in 1980 and 1990 are consistent with expectation, as the City of Atlanta experienced population declines, while the Northern suburbs grew, as discussed in Chapter 3.

In 2000, the city of Atlanta in the south continues to filter. The Jenks classification in 2000 is skewed because of an outlying tract with -5.43 value. However, the green color captures the gentrification, and yellow represents stability. Filtering is present in the south sections of the city and surrounding census tracts. Gentrification is notable in the central and northeastern sections of the city, and extreme north, northeast and northwest sections of the study area.

In 2010, tracts in the city of Atlanta are primarily weakly gentrifying or stable, but eastern and northern tracts are strongly gentrifying. Northeastern sections of the study area are filtering, while the southwestern sections and extreme northeastern sections are gentrifying.

Table 5.1 NCI2 1 Descriptive Statistics by Decade

Year	Mean	SD	Min	Max
1980	-0.103	0.778	-1.641	1.715
1990	0.565	0.739	-0.777	5.195
2000	0.104	0.608	-5.432	2.681
2010	-0.389	0.699	-3.793	2.394
2014	-0.189	0.521	-3.449	1.773

The NCI2 index is continuous, with zero indicating no change, gentrification is indicated with positive values and filtering with negative values. There are two primary differences between NCI1 and NCI2. First the former is categorical, while the latter is continuous. Secondly, NCI1 measures the second order of change. Gentrification and filtering are calculated as the first order, then the index captures whether those tracts change in the next period. NCI1 and NCI2 indices indicate that there is variation in neighborhood change across the study area and across time, and both find a similar pattern. Northern suburbs gentrified during the period of 1970 to 1990, while the City of Atlanta languished. Subsequently, possibly due to investment for the 1996 Atlanta

Olympic games, increased ‘rent gap’, and/or an overall change in the demand for urban space, the center of the city began to gentrify. By 2010 the northeastern suburbs are filtering, but the City of Atlanta, were MARTA rail stations are primarily located, is gentrifying.

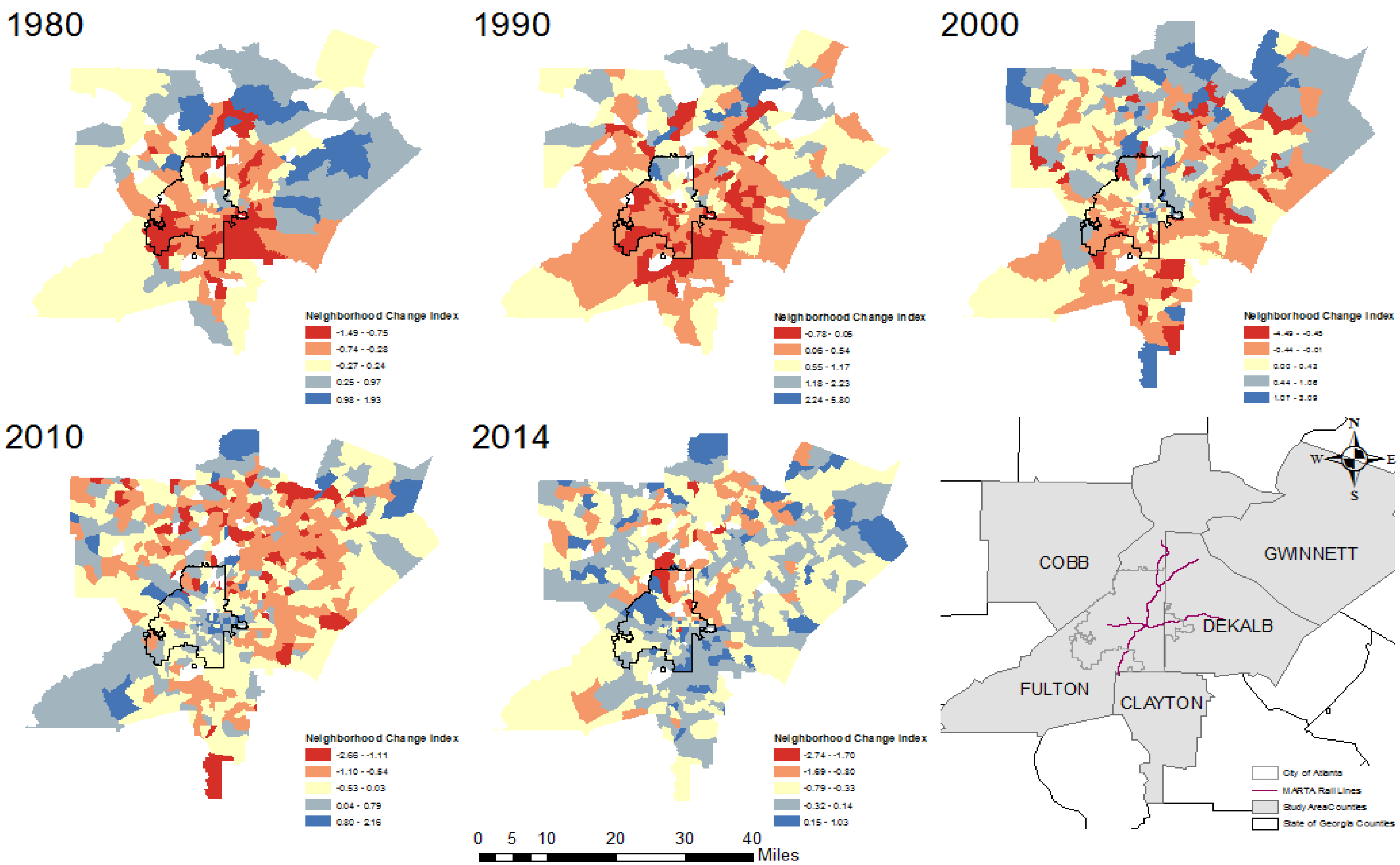


Figure 5.6 Neighborhood Change Index 2 Natural Breaks Classification

5.1 Do New MARTA Stations have Short-Term Effects on Neighborhood Change?

Station opening provides a natural experiment, and studies exploit it to evaluate an effect of stations on urban form (Cervero & Landis, 1996; Pagliara & Papa, 2014). Thus, the first step in the analysis compares the changes in key neighborhood variables between the treatment and control tracts using a difference-in-difference model (DID) to test Hypothesis 1 - *Neighborhoods with access to rail intra-urban transit stations will gentrify more than equivalent neighborhoods without access, within a decade after a new station is opened.* DID models for individual indicators are presented first, followed by models utilizing NCI2 as the dependent variable.

The control tracts include one and three mile distances. Further, control and treatment tracts were broken up by geography (North, South, East, and West) for each period, centered at the central station, Five Points. The DID models are constructed with a pre- and post- period. For example, tracts that received treatment in the 1970s are identified as treatment tracts, and control tracts are assigned as discussed in Section 4.3. The same tracts are identified and merged with U.S. Census date with the year 1970 and 1980, forming the pre- and post- periods. Descriptive statistics for each set of treatment and control tracts are presented in Appendix A. The included statistics are means of the key variables for the DID models, grouped by time-period, treatment versus control, and size of control (i.e., one-mile, three-mile).

The advantage of using the DID regression model is that the standard errors (SE) are calculated, so statistical significance can be identified if it exists. In the DID model (Equation 5) β_3 represents the key variable, the difference between the treatment and control group over time on the dependent variable (DV). β_0 represents the average of the dependent variable for the control group in Period 1; treatment (T) = 0 and the second period in the models (P2) = 0. β_1 represents the difference between the treatment and control groups before the treatment is applied. β_2 represents the change in the dependent variable before treatment and after treatment for the control group. The first set of DID models with DVs representing neighborhood population, % white, % with a college degree, median rent, and median household income for periods 1970 to 1980; 1980 to 1990; 1990 to 2000; 2000 to 2010; and 2010 to 2014 are presented in Appendix B. Population change was used rather than density because tracts are consistent in size across the data panel, and population change is more natural to interpret. The advantage of using individual components, rather than the NCI2 is that the data can be evaluated going back to 1970. 1970 was pre-MARTA rail, so the 1970 to 1980 time-period is associated with the introduction of MARTA rail to Atlanta. The DID models with NCI2 as the dependent variable, presented later, can only measure gentrification starting in the 1980 to 1990 time-period. The interaction term labeled Diff-in-Diff represents the difference in the value of the average DV between the treatment and control tracts over time. A positive coefficient on β_3 represents an increase of the index value in the treatment tract, versus the control tract, over the decade. A positive Diff-in-Diff value could be caused by a larger increase in the treated versus control tracts, or it could be caused by a smaller decline in the treatment versus control tracts.

The first model is an analysis of the 1970 to 1980 time-period with one mile controls, split into an East and West grouping. This period represents the changes associated with the introduction of the MARTA rail system to Atlanta. In the East model, the coefficient on the Diff-in-Diff indicator is negative, indicating that the average population in the treatment tract declined over the decade relative to the control tract. The coefficients on % college educated, real household income, real rent, and % white were positive. However, none of the Diff-in-Diff coefficients indicated a statistically significant difference. There was a significant increase between 1970 and 1980 in the % college educated within the control group (β_2), but a significant decrease in household income, rent, and % white. In 1970 (Period 1 in the model) there is a significant negative difference between treatment and control groups for income, rent, and % white.

In the West model, none of the coefficients on the Diff-in-Diff indicator are significant. The direction of the effect is negative for population, % college educated, and rent, and positive for household income and % white. The direction of the effect between the East and West groups are not consistent for education and rent, but again none of the results are statistically distinguishable from zero. The differences between Period 2 (1980) and Period 1 (1970) for the control tracts are significant and in the same direction as the 1970 to 1980 East model. Likewise, the difference between treatment and control in Period 1 are consistent with the East model.

In the three-mile control models the results are consistent with the one mile models. The direction of the effect is the same as in the one mile models, with the exception of the coefficient on rent in the 1970-1980 West specification, which is positive in the three-mile specification and negative in the one mile. However, in both cases the results are not statistically distinguishable from zero. There was statistical significance on the population and % white coefficients in the 1980 East 3 mile specification. In the neighborhoods where MARTA opened the first set of stations population declined, versus the control tracts, but the percentage of white population increased. On average, treatment tracts lost almost 1,000 more people than control tracts between 1970 and 1980, and the percentage of white residents increased by about 18 percentage points more for treatment than control groups over the same period. The average population started higher in treatment versus control tracts, but lower in % white by 33 percentage points.

In the 1980 to 1990 timeframe the stations were opened on the North and South lines. In the North, there were no statistically significant differences in the Diff-in-Diff coefficient. Although not statistically significant, in the North only the coefficient on income was positive, while in the South, the coefficients on income and population were negative. In the three mile specifications in the North model, all coefficients indicate a decline, while in the South the population and education have negative coefficients, but income, rent, and % white have positive coefficients.

In the 1990 to 2000 timeframe there were three geographic locations of station openings, North, East, and West. For all three models, none of the interaction terms have a significant coefficient, the coefficients are small in magnitude, and the standard errors are large. Population increased in the North and Western tracts of the City of Atlanta, but declined in the East. The income and % white coefficient had a positive value in all specifications. The three mile specifications were largely consistent.

In the 2000 to 2010 time-period, two stations were built in the northern section of the city. In the DID model none of the coefficients are significant, but all coefficients show a higher increase in the treatment than the control tracts in all variables except % white and population between 2000 and 2010. The % white coefficient changed direction in the three-mile specification, but remained insignificant.

Neighborhoods are complex entities made up of the interaction of policy, people and infrastructure. Therefore, a measure of neighborhood change should be multi-dimensional. The next step in the analysis is to apply the NCI2 as an outcome measure in a DID model with one and three mile controls (Appendix C). The period from 1970 to 1980 is not available for analysis because it was used to calculate NCI2.

In 1980-1990 treated neighborhoods have a positive value on the Diff-in-Diff coefficient in the North, but negative in the South, but neither difference in difference is statistically distinguishable from zero. The three-mile track results are consistent in the South, but reverse in the North. Between 1990 and 2000, in the West and East the NCI2 rose more in treated tracts than in the one mile control tracts. The North declined more in the treated tracts than the control tracts, but the differences are not statistically significant. In the three-mile control specification the North reverses the effect, but the East and West sides stay consistent. Between 2000 to 2010, treated neighborhoods gentrified. The NCI2 declined by .6 fewer index points more in tracts that were treated than in one mile control tracts. The three-mile result is consistent with the one mile control group outcome, but the result is not statistically significant.

However, there is a significant difference between the control groups over time in most specifications. In the 1980 to 1990 specifications, the difference between control groups over time is positive in all specifications. In 1990 to 2000 the coefficients on Period 2 are negative, and only the one mile North and West specifications are not significant. In the subsequent period (2000 to 2010) the differences in Period 2 are negative and significant. The reversal of the direction of the change in the control tract over time indicates potential temporal homogeneity in the effects of stations.

The short-term effects of MARTA rail stations on neighborhood change were analyzed using DID models and control groups chosen by proximity. There is some evidence supporting the causal effect of MARTA stations on neighborhood change in the direction of gentrification, and stations may have a heterogeneous effect on neighborhoods. However, the majority of the models specified cannot reject the null hypothesis that there is no difference between treatment and control tracts.

5.2 Do MARTA stations have long-term effects on neighborhood change?

MARTA stations are only new once, thus Hypothesis 2 addresses the long-term effect of stations on neighborhoods. A set of DID models was estimated for each decade between 1970 and 2010, and the time-period from 2010 to 2014 with NCI2 as the dependent variable. The 2010 to 2014 time-period represents a period of economic recovery. The entire five county area (Fulton, DeKalb, Gwinnett, Cobb, and Clayton) was the control (Table 5.2, Figure 5.7), and the treatment consisted of stations that were open during the time-period of analysis. This is in contrast to Section 5.1, where the treatment consisted only of newly opened stations. Three gentrification independent variables are used. The first, labeled $NCI2_1$ (Table 5.2), uses equal weights for rental rate, median income, and percent of people over 25 with a college degree. The second weights median income and education 25% each, and 50% rent. It is labeled $NCI2_2$. The final specification, labeled $NCI2_3$, adds age of housing and weights the four variables equally. The operationalization on the Neighborhood Change Indexes is documented in Chapter 4.

1970 is in not included because the initial year, 1970, is needed to calculate the change to 1980 in the difference-in-difference model. In the 1980 to 1990 time-period there was not a significant change in the Diff-in-Diff interaction term with any of the DV specifications. The coefficient on the Diff-in-Diff indicator is negative for the equally weighted, three variable index ($NCI2_1$), but positive for the second three variable specification ($NCI2_2$), and the equally weighted four variable specification ($NCI2_3$). The 1990 to 2000 time-period Diff-in-Diff indicator is positive and significant ($p < 0.01$), but β_1 and β_2 are negative. Therefore, $NCI2_1$ decreases 0.4 index points less in MARTA rail station neighborhoods than control tracts. $NCI2_2$ and $NCI2_3$, are consistent indicating a respective negative change of 0.5 and 0.2 index points in treated versus untreated tracts over the 1990 to 2000 period. The NCI_2 2000 to 2010 specifications produce a positive significant result on the Diff-in-Diff coefficient; the treatment tracts declined less than the control tracts during this time-period.

The DID models found an effect on gentrification. DID models using proximity controls focus on minimizing the unobservable characteristics, but do not account for other characteristics that may affect this relationship. Adding control variables can control some of the observable characteristics, but unobserved factors will remain. Fixed effects models can address omitted variable bias by controlling for unobserved factors that do not change within a geographic region over time (Angrist and Pischke, 2009). Table 5.3 shows the output from the Fixed Effects (census tract and year) model, years 1980 to 2014. Again, 1970 does not have a gentrification score. To maximize the size of the sample the entire study area is used as the control (Fulton, DeKalb, Clayton, Cobb, Gwinnett). Four model specifications are conducted, using three specifications of the

NCI2. In all specifications the treatment variable is positive and significant, indicating that the treated census tracts have higher neighborhood change index scores (i.e. gentrification) than the control tracts. Standard errors are reported, models with robust standard errors did not alter the results. Model I is controlled only by population density, the coefficient on the treatment variable (TREAT) indicates that treated tracts have a 0.4 index point higher $NCI2_1$ score than control tracts. Model II includes controls for only housing characteristics of neighborhoods. Model III includes only the characteristics of neighborhood residents. Model IV is the full model for the $NCI2_1$ dependent variable. Model V is the full model, with the $NCI2_2$ dependent variable. The final specification, Model VI, includes age of housing in the construction of the index ($NCI2_3$). In that specification the age of housing variable is removed from the control variables.

Table 5.2 NCI2 DID Models

Index DID Model Years 1980-1990

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	-0.3** (0.1)	-0.3*** (0.1)	-0.1 (0.1)
	p = 0.02	p = 0.003	p = 0.2
Period 2	0.6*** (0.05)	0.7*** (0.05)	0.5*** (0.03)
	p = 0.0	p = 0.0	p = 0.0
Diff-in-Diff	-0.01 (0.1)	0.03 (0.1)	0.01 (0.1)
	p = 1.0	p = 0.9	p = 0.9
Constant	0.03 (0.03)	-0.1** (0.03)	0.04* (0.02)
	p = 0.4	p = 0.04	p = 0.1
N	1,088	1,088	1,087
R^2	0.1	0.2	0.2
Adjusted R^2	0.1	0.2	0.2
Residual Std. Error	0.7 (df = 1084)	0.8 (df = 1084)	0.5 (df = 1083)
F Statistic	57.8*** (df = 3; 1084)	78.2*** (df = 3; 1084)	79.2*** (df = 3; 1083)

Table 5.2 (continued)

Index DID Model Years 1990-2000

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	-0.3*** (0.1)	-0.3*** (0.1)	-0.1 (0.1)
	p = 0.001	p = 0.001	p = 0.2
Period 2	-0.5*** (0.04)	-0.5*** (0.04)	-0.3*** (0.03)
	p = 0.0	p = 0.0	p = 0.0
Diff-in-Diff	0.4*** (0.1)	0.5*** (0.1)	0.2*** (0.1)
	p = 0.000	p = 0.000	p = 0.01
Constant	0.6*** (0.03)	0.6*** (0.03)	0.5*** (0.02)
	p = 0.0	p = 0.0	p = 0.0
N	1,154	1,154	1,154
R^2	0.1	0.1	0.1
Adjusted R^2	0.1	0.1	0.1
Residual Std. Error (df = 1150)	0.7	0.7	0.5
F Statistic (df = 3; 1150)	40.8***	52.3***	33.1***

Index DID Model Years 2000-2010

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	0.2** (0.1)	0.2** (0.1)	0.1** (0.05)
	p = 0.02	p = 0.02	p = 0.02
Period 2	-0.6*** (0.04)	-0.6*** (0.04)	-0.4*** (0.03)
	p = 0.0	p = 0.0	p = 0.0
Diff-in-Diff	0.4*** (0.1)	0.3*** (0.1)	0.1** (0.1)
	p = 0.001	p = 0.001	p = 0.03
Constant	0.1*** (0.03)	0.1*** (0.03)	0.2*** (0.02)
	p = 0.000	p = 0.01	p = 0.0
N	1,207	1,207	1,207
R^2	0.2	0.2	0.2
Adjusted R^2	0.2	0.2	0.2
Residual Std. Error (df = 1203)	0.6	0.6	0.4
F Statistic (df = 3; 1203)	91.4***	79.1***	88.5***
Note:	***p < .01; **p < .05; *p < .1		

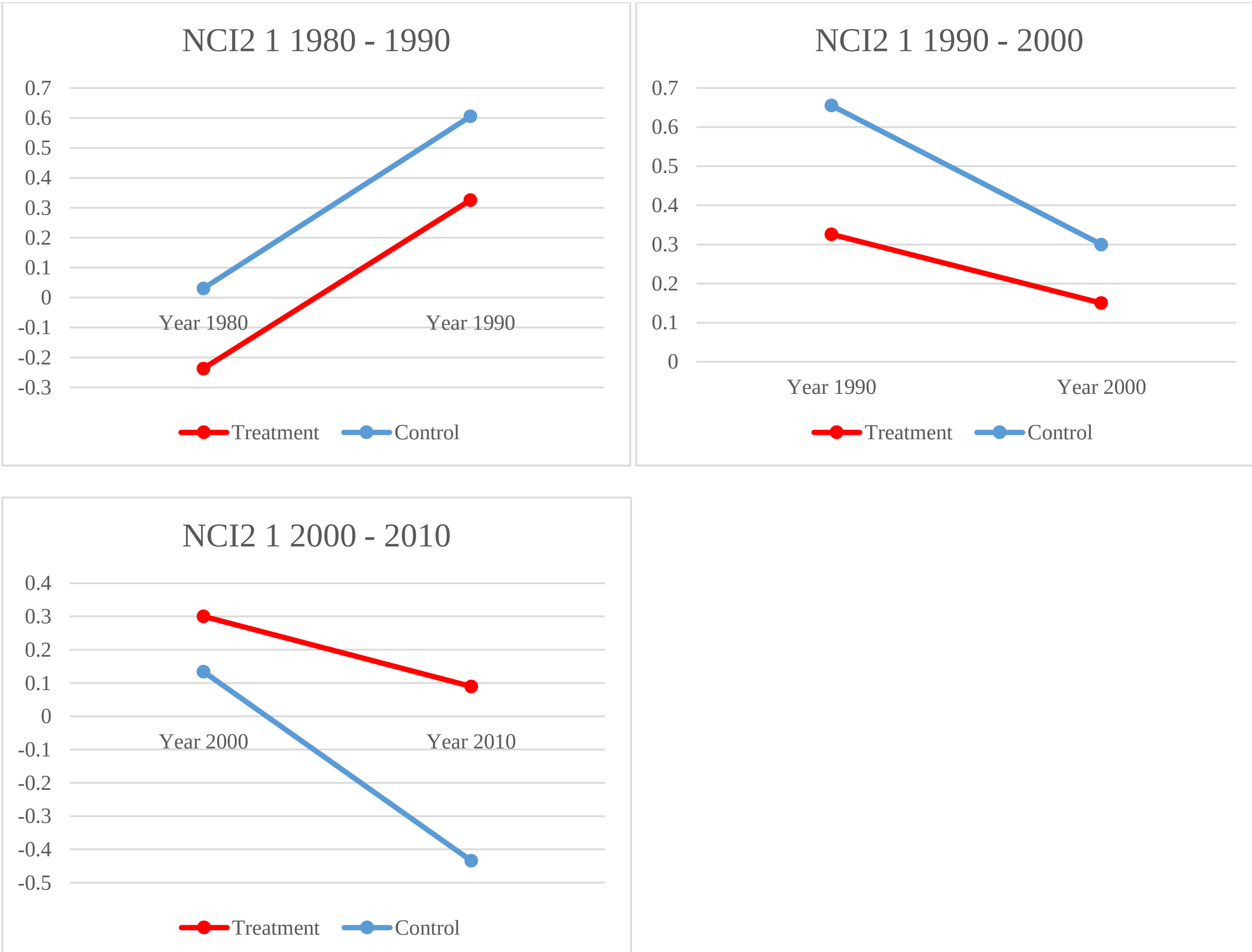


Figure 5.7 DID Models NCI2$_1$

Table 5.3 Fixed Effects Model output

Model output FE 5 county area controls

	NCI2 2				NCI2 1	NCI2 3
	Model I	Model II	Model III	Model IV	Model V	Model VI
Treatment	0.4^{***} (0.1)	0.3^{**} (0.1)	0.6^{***} (0.1)	0.4^{***} (0.1)	0.3^{***} (0.1)	0.2^{***} (0.1)
	p = 0.001	p = 0.02	p = 0.0	p = 0.000	p = 0.001	p = 0.005
Density	-0.000^{***} (0.000)	-0.000^{***} (0.000)		0.000 (0.000)	0.000 (0.000)	-0.000^{***} (0.000)
	p = 0.0	p = 0.0		p = 0.5	p = 1.0	p = 0.000
Vacant		0.01^{**} (0.003)		0.03^{***} (0.003)	0.03^{***} (0.003)	0.002 (0.002)
		p = 0.05		p = 0.0	p = 0.0	p = 0.5
Tenure		0.02^{***} (0.002)		0.01^{***} (0.002)	0.01^{***} (0.002)	-0.01^{***} (0.001)
		p = 0.0		p = 0.0	p = 0.0	p = 0.0
House Age		0.003^{***} (0.001)		0.004^{***} (0.001)	0.01^{***} (0.001)	
		p = 0.000		p = 0.0	p = 0.0	
Multifamily		-0.02^{***} (0.002)		-0.01^{***} (0.001)	-0.01^{***} (0.001)	-0.005^{***} (0.001)
		p = 0.0		p = 0.0	p = 0.0	p = 0.000
White			0.01^{***} (0.001)	0.01^{***} (0.001)	0.01^{***} (0.001)	-0.001 (0.001)
			p = 0.0	p = 0.0	p = 0.0	p = 0.2
Over Age 60			-0.01^{***} (0.003)	-0.004 (0.004)	-0.01^{***} (0.004)	-0.03^{***} (0.003)
			p = 0.003	p = 0.4	p = 0.001	p = 0.0
Foreign			-0.01^{**} (0.002)	-0.004^{*} (0.002)	-0.01^{***} (0.002)	-0.01^{***} (0.002)
			p = 0.03	p = 0.1	p = 0.003	p = 0.000
Professional			0.02^{***} (0.001)	0.02^{***} (0.001)	0.02^{***} (0.001)	0.02^{***} (0.001)
			p = 0.0	p = 0.0	p = 0.0	p = 0.0
Unemployed			0.01^{***} (0.003)	0.01^{*} (0.003)	0.003 (0.003)	-0.01^{***} (0.003)
			p = 0.000	p = 0.1	p = 0.4	p = 0.000
N	2,886	2,885	2,885	2,885	2,885	2,884
R^2	0.1	0.2	0.2	0.3	0.4	0.3
Adjusted R^2	0.04	0.1	0.2	0.2	0.3	0.3
F Statistic	67.5^{***} (df = 2; 2274)	71.9^{***} (df = 6; 2269)	107.1^{***} (df = 6; 2269)	85.2^{***} (df = 11; 2264)	129.7^{***} (df = 11; 2264)	108.8^{***} (df = 10; 2264)

Note: $^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

Hypothesis 2b asks whether treated tracts change differently than control tracts during periods of economic recovery. Two quasi-experimental methods are utilized: a DID model and matching.

Two DID models were specified, one with individual characteristics as the DV and the other with using the NCI2. In the 2010 to 2014 period DID models (Appendix B) the Diff-in-Diff (β_3) coefficients are stable and insignificant between the control group specifications (i.e. one-mile, three-mile, five-mile, and study region). As the control group increases in geographic size only the coefficient on population changes signs. In the one mile control group the population change has a positive significant coefficient, and a negative sign on the treatment coefficient (β_1). The coefficient on β_2 is also significant and negative. This means that treatment tracts started the time-period with, on average, 1,877 fewer people; between 2010 and 2014 control tracts lost 487 people, on average. β_3 indicates that on average a net of 588 fewer people left treatment tracts versus control tracts over the 2010 to 1014 time-period. The coefficient on population turns negative as the control group increases in geographic size, but these differences are not statistically significant. Using the NCI2 specification the effect is reversed (Table 5.4). The Diff-in-Diff coefficient is negative and significant in all control specifications. In the 2010 to 2014 time-period the increase in NCI2 is 0.5 index points higher for control tracts than for treatment tracts. and treatment tracts filter more than control tracts over the time-period. This is the opposite direction expected in Hypothesis 2b.

The second quasi-experimental method utilized was matching. Treated tracts in the year 2010 were matched to control tracts. One-to-one propensity score matching method is utilized for the using the 'matchit' package in R (Ho et al., 2011). The matching model included the percentage of white residents and population density, the critical variables in station location decisions. Matching models with more variables were not able to achieve a significantly improved balance, but were also not important to treatment selection. A chi-square test of the post-match balance fails to reject the null hypothesis that the treated and untreated groups are not different, with a p-value of 0.454.

Pre-matching the null hypothesis was rejected, p-value<0.001. The matched data provides a more balanced sample on covariates than the original data for the year 2010.

The matched data were analyzed using a fixed effects model for the years 2010 and 2014. Appendix D shows the descriptive statistics for the pre- and post- matching models. Table 5.5 shows the post-match output. The Fixed effects output for the matched set indicates a positive and statistically significant coefficient on the TREAT variable, indicating that gentrification is higher in the treatment tracts versus the control tracts between the years 2010 and 2014. The post-match effect is consistent with the pre-match effect; the neighborhood change index increases over the period 2010 to 2014. However, this is contradictory to the effect predicted by the DID model for the same time-period.

To test Hypothesis 2a and 2b DID, Fixed Effects, and matching methodologies were employed. The overall conclusion is that MARTA rail stations have an overall gentrifying effect on neighborhoods in the Atlanta area over the period 1970 to 2010. However, this effect is reversed for the period 2010 to 2014.

Table 5.4 2010 to 2014 NCI2 DID Models

NCI2 1 mile DID Model Years 2010-2014

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	0.4^{***} (0.1)	0.5^{***} (0.1)	0.4^{***} (0.1)
	p = 0.000	p = 0.000	p = 0.000
Period 2	-0.1 (0.1)	0.2^{**} (0.1)	-0.1 (0.1)
	p = 0.3	p = 0.03	p = 0.3
Diff-in-Diff	-0.3^{***} (0.1)	-0.4^{***} (0.1)	-0.3^{***} (0.1)
	p = 0.004	p = 0.002	p = 0.004
Constant	-0.4^{***} (0.1)	-0.4^{***} (0.1)	-0.4^{***} (0.1)
	p = 0.0	p = 0.0	p = 0.0
N	419	419	419
R^2	0.1	0.1	0.1
Adjusted R^2	0.1	0.1	0.1
Residual Std. Error (df = 415)	0.6	0.6	0.6
F Statistic (df = 3; 415)	17.7^{***}	11.2^{***}	17.7^{***}
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

NCI2 3 mile DID Model Years 2010-2014

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	0.5^{***} (0.1)	0.5^{***} (0.1)	0.2^{***} (0.1)
	p = 0.0	p = 0.0	p = 0.000
Period 2	-0.1 (0.1)	0.2^{***} (0.1)	-0.7^{***} (0.05)
	p = 0.2	p = 0.005	p = 0.0
Diff-in-Diff	-0.3^{***} (0.1)	-0.4^{***} (0.1)	-0.2^{***} (0.1)
	p = 0.002	p = 0.001	p = 0.01
Constant	-0.4^{***} (0.05)	-0.4^{***} (0.04)	-0.1^{***} (0.03)
	p = 0.0	p = 0.0	p = 0.001
N	574	574	574
R^2	0.1	0.1	0.5
Adjusted R^2	0.1	0.1	0.5
Residual Std. Error (df = 570)	0.6	0.6	0.4
F Statistic (df = 3; 570)	19.4^{***}	14.5^{***}	168.1^{***}

Table 5.4 (continued)

NCI2 5 mile DID Model Years 2010-2014

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	0.5*** (0.1)	0.5*** (0.1)	0.2*** (0.1)
	p = 0.0	p = 0.0	p = 0.000
Period 2	-0.03 (0.1)	0.2*** (0.1)	-0.6*** (0.04)
	p = 0.6	p = 0.000	p = 0.0
Diff-in-Diff	-0.4*** (0.1)	-0.4*** (0.1)	-0.3*** (0.1)
	p = 0.000	p = 0.001	p = 0.000
Constant	-0.4*** (0.04)	-0.5*** (0.04)	-0.1*** (0.03)
	p = 0.0	p = 0.0	p = 0.000
N	697	697	697
R^2	0.1	0.1	0.4
Adjusted R^2	0.1	0.1	0.4
Residual Std. Error (df = 693)	0.6	0.6	0.4
F Statistic (df = 3; 693)	22.6***	18.9***	166.8***

NCI2 All Area DID Model Years 2010-2014

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	0.5*** (0.1)	0.5*** (0.1)	0.3*** (0.05)
	p = 0.0	p = 0.0	p = 0.0
Period 2	0.04 (0.04)	0.3*** (0.04)	-0.5*** (0.03)
	p = 0.4	p = 0.0	p = 0.0
Diff-in-Diff	-0.5*** (0.1)	-0.5*** (0.1)	-0.5*** (0.1)
	p = 0.000	p = 0.000	p = 0.0
Constant	-0.4*** (0.03)	-0.5*** (0.03)	-0.2*** (0.02)
	p = 0.0	p = 0.0	p = 0.0
N	1,188	1,188	1,188
R^2	0.1	0.1	0.3
Adjusted R^2	0.1	0.1	0.3
Residual Std. Error (df = 1184)	0.6	0.6	0.4
F Statistic (df = 3; 1184)	26.0***	30.7***	175.1***
Note:	***p < .01; **p < .05; *p < .1		

Table 5.5 Post-Match Fixed Effects Model

	Post Match FE Model		
	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	0.4^{***} (0.1)	0.4^{***} (0.1)	0.2^{**} (0.1)
Density	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
% White	0.002 (0.002)	0.000 (0.002)	-0.000 (0.002)
Over 60	-0.01 (0.01)	-0.01 (0.01)	-0.01^{*} (0.01)
Foreign Born	-0.004 (0.004)	-0.005 (0.004)	-0.004 (0.003)
Professional	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Unemployed	-0.01 (0.01)	-0.01 (0.01)	-0.004 (0.01)
Vacant	0.01^{**} (0.01)	0.01^{**} (0.01)	0.004 (0.005)
Tenure 10+	-0.002 (0.01)	-0.005 (0.01)	
House Age	-0.002 (0.003)	-0.002 (0.003)	0.003 (0.002)
Multi-Family	-0.004 (0.003)	-0.003 (0.003)	-0.002^{*} (0.001)
N	420	420	420
R^2	0.1	0.1	0.1
Adjusted R^2	0.1	0.1	0.04
F Statistic	2.7^{***} (df = 11; 199)	2.7^{***} (df = 11; 199)	2.0^{**} (df = 10; 200)
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

CHAPTER 6

DISCUSSION AND CONCLUSION

"Few studies have addressed the role of public investment, and more specifically transit investment, on gentrification. Moreover, little has been written about how transit investment may spur neighborhood disinvestment and decline."

Source: p. 3, Zuk et al. (2015)

Heavy rail intra urban public transportation systems are large capital investments for municipal governments, but also critical investments given the dependence of low income residents on public transportations systems. However, the literature on the effects of rail intra-urban public transportation systems on neighborhoods is limited for such an important topic of urban policy. The literature that does exist is primarily focused on economic impacts, such as housing value. It assumes that all neighborhood change from the addition of a rail transportation station can be understood by the capitalization of amenity effects into real estate. But, neighborhoods are defined by real estate and people. A few studies have looked at race and education level changes in the population, but the effect of rail intra-urban public transportation systems on a multi-dimensional operationalization of a neighborhood remains understudied (Zuk et al., 2015). A measure of neighborhood change should include both socioeconomic and physical urban form characteristics. Few studies have attempted this, but a small stream of literature has begun to explore the effects of public transportation on the multi-dimensional concept of gentrification. The guiding research question in this dissertation seeks to understand whether rail intra-urban transit stations have an effect on neighborhood change.

Atlanta serves as a good case study, because although Atlanta planned the MARTA system in conjunction with supporting land use regulations, but the regulations never materialized. Therefore, local effects of transit stations are not confounded by other policies. MARTA is a reasonably modern transportation system, initially opened in 1979. Publicly available socio-economic data from the U.S. Census is available back to 1970 at the census tract level. The current 39 station MARTA rail system orientation was developed between 1979 and 2000, adding stations over time. Therefore, the effect of the MARTA stations can be measured for new and existing stations over the entire time-period of the MARTA rail system's existence.

The quasi-experimental design, multi-dimensional operationalization of neighborhood change, and comprehensive time-frame of this study, add to the literature on the evaluation of public transportation system effects. Overall, the findings suggest that rail intra-urban transit stations have a gentrifying effect on neighborhoods. This is significant, if social justice is a responsibility of government policy. Low-income groups are sometimes referred to as captive riders because the only form of transit they can afford is public transportation. If rail intra-urban transit stations are a positive amenity, wealthy groups will outbid low-income groups for access. Public transportation policy has to include ways for low-income groups to maintain access to this important amenity.

6.1 Summary of Key Findings

The neighborhood change literature is broad and well established, but gentrification is a relatively new phenomenon that goes against conventional urban economic theory. The earliest theories of neighborhood change expected the life-cycle of a neighborhood to end in abandonment, moving linearly downward in the quality of physical form and socioeconomic standing of the residents, from construction to abandonment. As it ages housing 'filters' down to progressively lower class individuals. At the end of the process, policy intervention is needed to rebuild. Other economic models predict that the tradeoff between transportation and housing costs will lead to wealthy people buying large homes in the distant suburbs, and low income people will populate dense Central Business Districts (CBD). Gentrification violates both theories, as well educated, high income people move into the CBD. To operationalize neighborhood change this study combined the concepts of filtering and gentrification in the Neighborhood Life-Cycle framework.

The findings suggest that rail intra-urban transit stations have a gentrifying effect on neighborhoods. This holds true for long term and short term effects, Hypotheses 1 and 2a. There is mixed evidence on the effects of MARTA rail stations on neighborhood change during economic revival, Hypothesis 2b. The difference-in-difference model is better suited for discrete policy events, and the matching model addresses some of the station location selection bias. Therefore, the effect of new transit stations on neighborhoods is likely towards gentrification.

The question may not be whether transportation has an effect on neighborhood change, but rather, under what conditions does it produce the effects in neighborhoods.

Studies taking into account several cities aim to generalize, but there is heterogeneity between and within cities, in culture, neighborhood make-up, geographic size, density, politics, and many other factors. To address some heterogeneity issues this study focused on residential neighborhoods, dropping stations in more commercial districts. However, much potential heterogeneity remains unexplored.

It should be noted that this study does not directly address the social issue of displacement that some literature argues is brought on by gentrification (Zuk et al., 2015; Lees, Slater & Wyly, 2008). If rents are rising, it can be assumed that at least at the margin, families will be forced to move, and if they are, they will have to relocate to an area inaccessible to rail transit. Therefore, large scale public development should address low income housing options at the planning stages of the projects, otherwise higher income groups will outbid lower income groups for access to the amenity.

6.2 Contributions to Scholarship and Practice

Empirical evaluations of policy outcomes and neighborhood change processes are difficult, particularly because of data availability. There is a paucity of socioeconomic and property value data available, over a long timeframe, and a small geographically identifiable unit of analysis. This research builds on previous neighborhood change literature to make several key contributions to the study of the effects of public transportation systems on neighborhood change.

The literature on the effects of transportation systems on neighborhood change is small. This study provides a link to the broader and more established literature on neighborhood change, and add to our understanding of transportation system effects by capturing change along multiple dimensions. Revising the Neighborhood Life-Cycle framework of neighborhood decline with a gentrification component, this study operationalized a multi-dimensional neighborhood change index. This indicator can be applied to measure transportation effects in other cities, and compare cities, as well as study other policy effects. The natural experiment around the opening of a transit station is commonly used in the literature in a causal evaluation design. Although the short-term effect is an important policy effect to understand, this result says little about what happens to tracts with intra urban rail transit stations over time. Public transit systems are only new once, after all, so it is important to understand the change induced on neighborhoods over the lifetime of the transit system. The effect of stations when they are first put in place may be different then their effect after they are an established part of the neighborhood and have reached equilibrium. Further, there may be heterogeneity across cities or within cities. To address these effects this study focused on a single city, Atlanta, and utilized several control area specifications.

Quasi-experiments rely on similarity between treatment and control groups to address omitted variable bias in an effect estimate. Two specifications of control groups were utilized, based on proximity and a matching approach. The proximity approach may be more useful in urban studies than the matching approach, primarily because of unobservable characteristics of census tracts. There are only a few characteristics of neighborhoods that can be observed, but many more potentially unobservable factors that make up a neighborhood and drive its change. It is more likely that neighborhoods in geographic proximity will have more drivers of change in common than neighborhoods matched on any of the limited observable characteristics.

Gentrification research is largely focused on gentrification's effects on low-income populations. Planners and policy makers must take into account the broad population, not just one income group when making decisions. The revision of the Neighborhood Life-Cycle model of neighborhood change expands the utility of neighborhood change measures by potentially capturing change across neighborhoods at various points in the change cycle.

The policy environment around transportation funding is complicated, because all systems require a subsidy to exist – that includes all modes of transit, pedestrian, cycling, public transit, or automobile. Each system competes with the others for federal, state, and local funding. However, the region is based around the automobile, so support for road subsidies is strong. Evidence of the effects of rail intra-urban transportation system may encourage the implementation of coordinated polices.

Policy responses to stabilize neighborhoods that could be applied in public transportation accessible areas include rent provisions, refinancing laws, reduction in lot size restrictions, and mixing commercial with residential development (Jacobs, 1961). Although it would require regional coordination, building restrictions for certain types of density or land uses could be saved for MARTA rail station accessible neighborhoods. Such a policy was removed early in the history of the MARTA network. Dense development around stations could also be encouraged through tax breaks, at the federal, state, or local level. Additionally, local policy actions such as parking restrictions in dense urban areas served by transit could provide impetus for people to switch to transportation modes to public transit.

6.3 Limitations

The primary limitations in this study are associated with measurement error. The Longitudinal Tract Database (LTDB) standardizes census tract boundaries, which change over time, to a common geography. It utilizes an aerial weighting technique that produces measurement error (Logan, Xu & Stults, 2014).

Another source of measurement error is the ACS 5-year data. The 5-year dataset is composed of data samples collected over a 5-year period. The 5-year ACS 2010 data is composed of years 2006-2010, and the 2014 ACS data is composed of years 2010-2014. A calculated change between the years is only going to be based on 4 years of data, since both sets share the year 2010 sample.

A third measurement problem with Census data is the error from the sampling procedure. In this study data is considered point data; however, there is error in those measurements.

The U.S. Census is administered at the end of each decade. However, MARTA stations opened at various points in time during a decade. This introduces another source of measurement error into the DID model. If a station opened in 1979, the pre- period was 1970 and the post- period is 1980. There are 9 years between the pre- observation and the treatment, but only a year between the treatment and the post- observation. In 2000, the scenario is reversed. The pre- period for the station that opened in December of 2000, was the 2000 census, and the post- observation was 2010.

The treatment assignment uses a 1.5-mile distance from the center of the centroid to a MARTA rail station. However, the odd shapes of Atlanta's census tracts make the buffer zone irregular, and reasonably large. Large treatment zones are more likely to lead to Type 1 error, incorrectly rejecting the effect when it is really there. Heterogeneity in the geographic size of treatment and control zones can also produce measurement error. For example, a filtering effect on in one control tract, but gentrification on the other, as could happen where rail tracts separate wealthy neighborhoods, from neighborhoods 'on the wrong side of the tracks'. Further, the treatment groups shrink over time, primarily because the census tracts get larger as density declines, so stations further away from the CBD will be larger, and fewer tracts will fall within the 1.5-mile radius.

MARTA built the rail system mostly on existing railroad right of ways, with stretches on elevated platforms and underground, so the planners would have little chance to induce a bias by targeting certain types of neighborhoods for treatment. Still, there remains the possibility of selection bias, which could impact results. Given this potential measurement bias, this study did not attempt to interpret the magnitude of the results in any of the analysis. Instead, the focus was on the direction of the effect. Further, the matching methodology at least partially addresses that bias.

6.4 Future Research

The question answered here is very basic, do rail intra-urban transit stations effect neighborhood change. However, a more practical question explores the heterogeneity in the effect; what characteristics of rail MARTA stations are responsible for the gentrification effect. Future research on the effects of transportation and neighborhood change should focus on the heterogeneity within and between cities, which has been suggested by past research and found here. Generalizations are critical for theory construction, however so little is known about the drivers and effects of neighborhood change that generalizing may be premature. Additionally, policy makers will be interested in the interaction of the effects of intra-urban rail policy with the effects of zoning and other local development and social justice policies and programs.

The mixed results in the 2010 to 2014 time period suggest that there may be variation in the effect between decades. The decadal DID models for new stations do not capture conditions in existing stations, and the fixed effects model generalizes the effect over time. The methodology used in this study could be further improved and augmented with additional data. For example, service characteristics, historical street grid patterns, historical streetcar alignment, or durability of housing stock could serve as additional controls. Other socioeconomic characteristics, such as more controls for age, could be important. Additionally, more complex formulations and refinements of the Neighborhood Life-Cycle Framework could be developed.

Future extension of this work will try to understand change at the smaller scale, accounting for conditions around each station. Although MARTA has not seen ridership growth since 2002, service characteristics around each station may be a factor. Some stations have more frequent service than others. Station ridership and the availability of parking may also be factors, and can be controlled for. Accessibility to a station within the neighborhood can also be examined in smaller scale studies. Further, the physical form of the station and proximity to other amenities can be captured as additional data.

In the early 1960s and 1970s Washington D.C., San Francisco and Atlanta all built intra-urban rail transportation systems using Federal matching funds. The outcomes of these systems differ. The methodology presented in this study can be utilized for a comparative analysis of the three cities to understand the policy differences that may have driven the outcome differences. Other associated research will include effects of crime and additional GIS data will be used to better control for land use.

The Neighborhood Life-Cycle framework, as revised here with the inclusion of gentrification, can be useful in the theoretical development of gentrification and neighborhood change and adds to the gentrification and filtering literature. Neil Smith (1982) describes two competing causes for the generation of gentrification. The first is in line with the early Stages and Filtering models that predict eventual neighborhood demise. Gentrification is identified as a localized effect. Smith (1982) asserts that gentrification is the leading edge of a widespread process of renewal caused by uneven urban development. Table 6.1 presents both cases adapted to both theories. The cycle effect does not have to be symmetric, and the thickness of the arrows corresponds to the size of the effect. Panel (a) depicts the theory that filtering is the general condidion of neighborhoods and gentrification is an isolated concept. This is in line with the filtering models. Panels (b) represents strong and balanced change in both directions. Panel (c) illustrates Neil Smith's hypothesis that gentrification is going to intensify over time due to the effects of uneven development (Smith, 1984). Panel (d) suggests there is low neighborhood change. There are theoretical implications for redevelopment and low income housing that can be tested for each version of the model. The neighborhood change indexes can be used to test whether neighborhoods change in a cycle, whether the go through a complete cycle, and the timing of the cycle. If neighborhoods change like panel (a) in Figure 6.1 then we can expect ample low income housing to be available, and policy does not have to address this social need. Although panel (b) and (d) suggest a balance, the implications for low income housing may differ with high supply versus low supply. Finally, panel (c) presents a situation suggested by Neil Smith, where gentrification becomes a stronger process in the cities. It is the process in panel (c) that is most problematic for low income people and communities, but best for the future economic prospects of cities. The ‘strength’ of the filtering and gentrification effects can be heterogenous between cities and over time, and subject to public policy changes. Operationalizing the ‘thickness’ of the arrows could be accomplished with a conversion to prices. However, measurement error would have to be better addressed.

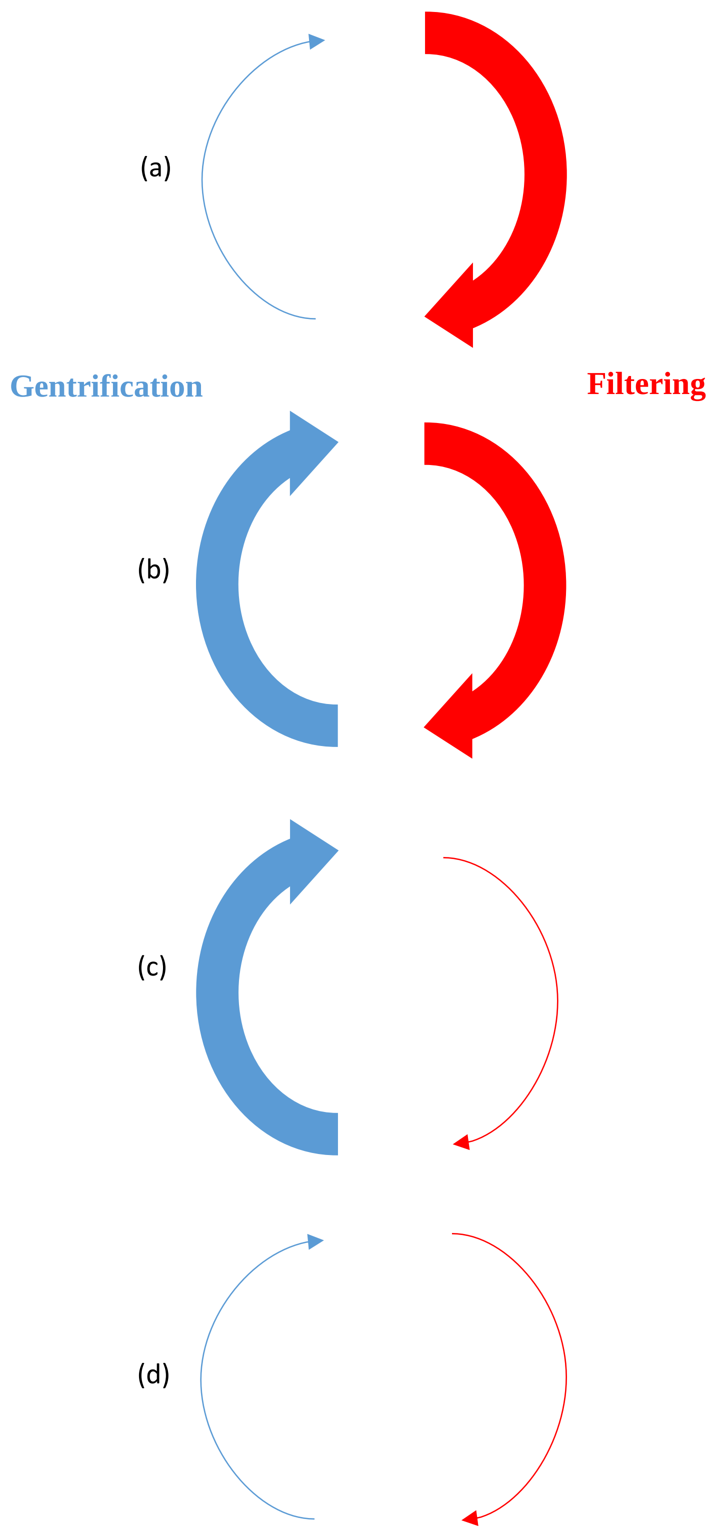


Figure 6.1 Neighborhood Change Theoretical Models

APPENDIX A: DESCRIPTIVE STATISTICS

1970 data Treatment East 1970s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	33	3,851	1,614	771	7,127
% White	33	52	40	0	99
% College Educated	33	9	10	0	44
% Poverty	33	27	18	4	71
Real Household Income (2010)	33	30,774	15,300	8,107	70,253
Real Rent (2010)	33	443	110	232	602
Real Housing Value (2010)	33	79,733	30,435	34,928	174,875

1970 data Control East 1970s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	45	3,976	1,886	761	9,520
% White	45	82	31	1	100
% College Educated	45	14	12	1	57
% Poverty	45	12	11	2	57
Real Household Income (2010)	45	46,474	19,644	8,791	104,447
Real Rent (2010)	45	606	196	283	1,342
Real Housing Value (2010)	45	101,991	37,240	51,914	240,287

1980 data Treatment West 1970s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	24	4,286	2,031	771	7,633
% White	24	20	32	0	95
% College Educated	24	9	7	0	28
% Poverty	24	29	17	3	71
Real Household Income (2010)	24	24,466	15,572	5,719	61,930
Real Rent (2010)	24	400	107	232	623
Real Housing Value (2010)	24	77,401	19,846	39,529	120,615

1980 data Control West 1970s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	32	4,207	2,639	890	11,451
% White	32	52	43	1	99
% College Educated	32	11	10	1	36
% Poverty	32	17	11	4	56
Real Household Income (2010)	32	37,895	14,616	8,791	77,691
Real Rent (2010)	32	488	139	293	856
Real Housing Value (2010)	32	93,899	40,655	54,996	240,287

1980 data Treatment East 1970s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	33	2,888	1,466	708	7,382
% White	33	43	37	0	98
% College Educated	33	18	17	0	58
% Poverty	33	32	19	6	74
Real Household Income (2010)	33	26,977	13,326	9,610	61,268
Real Rent (2010)	33	345	134	143	709
Real Housing Value (2010)	33	83,968	49,876	26,199	203,455

1980 data Control East 1970s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	45	3,535	1,529	866	8,059
% White	45	55	37	2	97
% College Educated	45	23	17	1	54
% Poverty	45	19	15	2	61
Real Household Income (2010)	45	36,901	14,040	11,605	71,601
Real Rent (2010)	45	495	166	164	1,021
Real Housing Value (2010)	45	106,041	60,984	32,615	354,630

1980 data Treatment West 1970s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	24	3,384	1,726	615	7,066
% White	24	9	20	0	86
% College Educated	24	11	11	1	45
% Poverty	24	41	20	10	79
Real Household Income (2010)	24	21,403	12,168	7,388	54,097
Real Rent (2010)	24	301	135	127	675
Real Housing Value (2010)	24	63,264	32,955	28,865	190,365

1980 data Control West 1970s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	31	3,577	2,035	866	8,706
% White	31	33	37	0	94
% College Educated	31	16	17	0	53
% Poverty	31	28	15	5	65
Real Household Income (2010)	31	30,032	11,899	11,605	63,427
Real Rent (2010)	31	398	130	130	714
Real Housing Value (2010)	31	91,751	68,891	32,615	354,630

1980 data Treatment North 1980s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	15	3,072	1,181	1,370	4,818
% White	15	88	7	77	98
% College Educated	15	35	11	15	50
% Poverty	15	11	3	5	16
Real Household Income (2010)	15	46,262	9,847	35,423	75,385
Real Rent (2010)	15	650	71	480	728
Real Housing Value (2010)	15	162,625	47,916	92,864	260,681

1980 data Control North 1980s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	33	3,319	1,231	1,187	6,105
% White	33	93	6	74	98
% College Educated	33	43	10	15	60
% Poverty	33	7	4	1	16
Real Household Income (2010)	33	60,083	19,129	31,702	105,917
Real Rent (2010)	33	720	127	480	1,191
Real Housing Value (2010)	33	184,578	62,585	92,478	385,985

1980 data Treatment South 1980s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	18	3,726	1,596	1,578	7,271
% White	18	38	32	2	92
% College Educated	18	8	5	0	22
% Poverty	18	27	14	11	58
Real Household Income (2010)	18	27,552	8,210	11,605	41,665
Real Rent (2010)	18	380	115	204	622
Real Housing Value (2010)	18	65,010	21,900	32,615	115,191

1980 data Control South 1980s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	18	4,554	1,895	978	7,123
% White	18	37	26	2	92
% College Educated	18	15	9	1	24
% Poverty	18	20	16	5	61
Real Household Income (2010)	18	37,536	12,784	11,806	60,162
Real Rent (2010)	18	502	164	164	685
Real Housing Value (2010)	18	88,219	31,592	38,288	132,573

1990 data Control North 1980s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	33	3,501	1,173	1,192	6,128
% White	33	80	15	42	97
% College Educated	33	49	12	24	70
% Poverty	33	8	5	2	24
Real Household Income (2010)	33	70,141	22,773	29,484	131,829
Real Rent (2010)	33	905	217	673	1,670
Real Housing Value (2010)	33	261,387	127,105	124,266	800,306

1990 data Treatment South 1980s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	18	3,365	1,383	1,426	5,742
% White	18	22	21	1	65
% College Educated	18	10	6	1	19
% Poverty	18	29	13	10	62
Real Household Income (2010)	18	30,045	8,659	11,852	44,169
Real Rent (2010)	18	524	117	318	686
Real Housing Value (2010)	18	83,710	22,605	42,892	140,213

1990 data Control South 1980s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	18	4,265	1,497	1,693	6,722
% White	18	17	17	2	76
% College Educated	18	15	9	0	27
% Poverty	18	22	17	4	69
Real Household Income (2010)	18	40,831	13,979	8,689	63,792
Real Rent (2010)	18	618	142	173	747
Real Housing Value (2010)	18	102,753	26,758	59,548	140,279

1990 data Treatment North 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	3	3,281	839	2,659	4,236
% White	3	63	6	55	68
% College Educated	3	30	6	24	37
% Poverty	3	9	2	8	11
Real Household Income (2010)	3	55,627	4,463	50,721	59,446
Real Rent (2010)	3	837	44	787	867
Real Housing Value (2010)	3	139,401	14,156	124,266	152,316

1990 data Control North 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	14	3,525	1,109	1,359	5,393
% White	14	78	10	62	95
% College Educated	14	40	14	2	58
% Poverty	14	5	4	1	16
Real Household Income (2010)	14	68,903	21,715	52,272	121,487
Real Rent (2010)	14	940	280	719	1,670
Real Housing Value (2010)	14	186,778	62,736	93,083	287,563

1990 Treatment East 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	7	2,806	1,163	1,427	4,709
% White	7	34	10	18	50
% College Educated	7	24	7	8	28
% Poverty	7	13	11	7	37
Real Household Income (2010)	7	45,540	8,450	26,651	49,838
Real Rent (2010)	7	701	113	445	757
Real Housing Value (2010)	7	133,775	23,339	82,236	153,456

1990 Control East 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	16	4,830	1,378	1,737	7,051
% White	16	44	24	13	91
% College Educated	16	25	9	8	41
% Poverty	16	10	5	3	22
Real Household Income (2010)	16	56,691	12,952	41,413	85,540
Real Rent (2010)	16	818	107	659	1,058
Real Housing Value (2010)	16	130,470	22,040	91,573	171,804

1990 Control West 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	4	5,436	1,883	2,731	7,081
% White	4	35	39	1	76
% College Educated	4	16	23	2	51
% Poverty	4	37	19	17	62
Real Household Income (2010)	4	32,045	16,842	13,306	53,767
Real Rent (2010)	4	510	286	188	877
Real Housing Value (2010)	4	98,600	50,340	68,555	173,642

2000 data Treatment North 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	3	4,485	1,153	3,664	5,803
% White	3	33	2	31	35
% College Educated	3	29	6	23	35
% Poverty	3	15	2	12	16
Real Household Income (2010)	3	56,836	1,378	56,014	58,427
Real Rent (2010)	3	887	48	832	918
Real Housing Value (2010)	3	174,725	13,439	160,651	187,423

2000 data Control North 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	14	4,417	1,282	2,222	6,078
% White	14	49	23	22	91
% College Educated	14	40	18	13	65
% Poverty	14	10	5	2	17
Real Household Income (2010)	14	68,809	26,721	46,028	124,972
Real Rent (2010)	14	1,034	375	748	2,080
Real Housing Value (2010)	14	202,864	82,371	111,408	340,301

2000 data Treatment East 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	7	3,506	1,352	1,749	5,769
% White	7	16	9	6	32
% College Educated	7	21	6	12	31
% Poverty	7	19	12	12	46
Real Household Income (2010)	7	45,091	7,283	30,250	50,683
Real Rent (2010)	7	715	154	367	786
Real Housing Value (2010)	7	136,710	34,736	92,038	207,877

2000 data Control East 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	16	5,654	1,584	2,062	7,695
% White	16	19	19	4	76
% College Educated	16	23	9	11	41
% Poverty	16	13	6	3	24
Real Household Income (2010)	16	55,533	10,547	42,960	78,878
Real Rent (2010)	16	819	96	696	995
Real Housing Value (2010)	16	127,290	21,924	94,444	162,048

2000 data Treatment West 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	2	4,174	882	3,551	4,798
% White	2	7	9	1	14
% College Educated	2	4	1	4	5
% Poverty	2	25	1	25	26
Real Household Income (2010)	2	38,671	8,870	32,399	44,943
Real Rent (2010)	2	711	132	618	804
Real Housing Value (2010)	2	122,232	63,111	77,606	166,859

2000 data Control West 1990s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	4	4,517	1,182	2,975	5,811
% White	4	27	33	1	69
% College Educated	4	24	27	4	63
% Poverty	4	33	12	17	43
Real Household Income (2010)	4	33,233	16,606	20,324	56,745
Real Rent (2010)	4	515	305	209	923
Real Housing Value (2010)	4	132,369	93,072	72,922	270,264

2000 data Treatment 2000s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	5	3,270	1,409	1,210	4,653
% White	5	75	13	57	94
% College Educated	5	61	7	51	72
% Poverty	5	6	3	2	8
Real Household Income (2010)	5	88,098	43,879	57,183	165,684
Real Rent (2010)	5	1,112	126	934	1,290
Real Housing Value (2010)	5	292,112	93,854	151,793	416,449

2000 data Control 2000s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	11	4,744	693	3,593	5,653
% White	11	75	17	46	95
% College Educated	11	60	10	42	76
% Poverty	11	6	3	1	12
Real Household Income (2010)	11	92,092	38,286	57,183	175,427
Real Rent (2010)	11	1,291	551	893	2,493
Real Housing Value (2010)	11	347,447	121,362	151,793	502,855

2010 data Treatment 2000s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	5	3,555	1,434	1,648	5,596
% White	5	67	25	34	95
% College Educated	5	62	14	45	78
% Poverty	5	7	6	0	13
Real Household Income (2010)	5	81,111	41,424	50,554	153,977
Real Rent (2010)	5	1,141	482	879	2,001
Real Housing Value (2010)	5	302,780	150,214	115,200	472,800

2010 data Control 2000s 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	10	5,033	584	4,070	5,852
% White	10	64	24	23	92
% College Educated	10	57	15	33	78
% Poverty	10	9	6	2	21
Real Household Income (2010)	10	70,759	27,975	41,335	123,375
Real Rent (2010)	10	902	217	714	1,358
Real Housing Value (2010)	10	357,860	134,853	142,000	527,500

2010 data Treatment All 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	104	3,860	2,046	936	13,362
% White	104	33	30	0	96
% College Educated	104	38	23	3	82
% Poverty	104	23	16	1	79
Real Household Income (2010)	104	51,249	29,929	9,449	196,875
Real Rent (2010)	104	761	218	182	1,466
Real Housing Value (2010)	104	231,695	135,474	38,500	816,300

2010 data Control All 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	104	4,788	2,125	977	15,841
% White	104	39	34	0	97
% College Educated	104	41	25	6	93
% Poverty	104	18	13	1	60
Real Household Income (2010)	104	58,685	35,032	15,893	171,917
Real Rent (2010)	104	796	270	275	2,001
Real Housing Value (2010)	104	267,147	175,944	73,800	1,000,001

2014 Treatment All 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	104	3,308	1,372	987	7,073
% White	104	40	30	0	97
% College Educated	104	25	13	0	54
% Poverty	104	26	15	2	71
Real Household Income (2010)	104	44,422	25,830	8,598	131,140
Real Rent (2010)	104	883	214	438	1,842
Real Housing Value (2010)	104	191,235	121,150	36,659	578,260

2014 Control All 1 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	103	4,597	1,563	1,082	9,014
% White	103	40	32	0	97
% College Educated	103	23	12	2	47
% Poverty	103	25	14	1	69
Real Household Income (2010)	103	46,062	26,626	10,537	132,279
Real Rent (2010)	103	929	239	496	1,842
Real Housing Value (2010)	103	192,132	148,017	53,147	792,690

1970 data Treatment East 1970s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	33	3,851	1,614	771	7,127
% White	33	52	40	0	99
% College Educated	33	9	10	0	44
% Poverty	33	27	18	4	71
Real Household Income (2010)	33	30,774	15,300	8,107	70,253
Real Rent (2010)	33	443	110	232	602
Real Housing Value (2010)	33	79,733	30,435	34,928	174,875

1970 data Control East 1970s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	101	3,668	2,035	506	11,451
% White	101	86	27	1	100
% College Educated	101	16	12	1	57
% Poverty	101	9	9	1	57
Real Household Income (2010)	101	52,658	17,487	8,791	104,447
Real Rent (2010)	101	668	208	283	1,342
Real Housing Value (2010)	101	115,578	39,730	51,914	240,287

1970 data Treatment West 1970s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	24	4,286	2,031	771	7,633
% White	24	20	32	0	95
% College Educated	24	9	7	0	28
% Poverty	24	29	17	3	71
Real Household Income (2010)	24	24,466	15,572	5,719	61,930
Real Rent (2010)	24	400	107	232	623
Real Housing Value (2010)	24	77,401	19,846	39,529	120,615

1970 data Control West 1970s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	76	3,999	2,171	890	11,451
% White	76	74	37	1	100
% College Educated	76	14	13	1	50
% Poverty	76	12	11	2	57
Real Household Income (2010)	76	48,254	21,654	8,791	149,474
Real Rent (2010)	76	571	179	283	1,001
Real Housing Value (2010)	76	110,455	55,975	51,914	315,848

1980 data Treatment East 1970s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	33	2,888	1,466	708	7,382
% White	33	43	37	0	98
% College Educated	33	18	17	0	58
% Poverty	33	32	19	6	74
Real Household Income (2010)	33	26,977	13,326	9,610	61,268
Real Rent (2010)	33	345	134	143	709
Real Housing Value (2010)	33	83,968	49,876	26,199	203,455

1980 data Control East 1970s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	101	3,664	1,611	866	8,706
% White	101	58	36	0	97
% College Educated	101	24	17	0	60
% Poverty	101	16	14	2	61
Real Household Income (2010)	101	41,502	15,064	11,605	79,679
Real Rent (2010)	101	546	178	164	1,021
Real Housing Value (2010)	101	116,124	58,226	32,615	354,630

1980 data Treatment West 1970s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	24	4,286	2,031	771	7,633
% White	24	20	32	0	95
% College Educated	24	9	7	0	28
% Poverty	24	29	17	3	71
Real Household Income (2010)	24	24,466	15,572	5,719	61,930
Real Rent (2010)	24	400	107	232	623
Real Housing Value (2010)	24	77,401	19,846	39,529	120,615

1980 data Control West 1970s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	75	3,639	1,706	866	8,706
% White	75	49	39	0	98
% College Educated	75	21	18	0	60
% Poverty	75	21	15	2	65
Real Household Income (2010)	75	37,153	18,584	11,605	122,306
Real Rent (2010)	75	460	151	130	802
Real Housing Value (2010)	75	112,006	79,377	32,615	385,985

1980 data Treatment North 1980s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	15	3,072	1,181	1,370	4,818
% White	15	88	7	77	98
% College Educated	15	35	11	15	50
% Poverty	15	11	3	5	16
Real Household Income (2010)	15	46,262	9,847	35,423	75,385
Real Rent (2010)	15	650	71	480	728
Real Housing Value (2010)	15	162,625	47,916	92,864	260,681

1980 data Control North 1980s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	73	3,300	1,579	577	8,706
% White	73	91	18	1	98
% College Educated	73	40	13	2	60
% Poverty	73	7	8	1	58
Real Household Income (2010)	73	65,869	23,988	15,506	122,317
Real Rent (2010)	73	734	198	191	1,339
Real Housing Value (2010)	73	195,264	82,207	38,367	394,005

1980 data Treatment South 1980s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	18	3,726	1,596	1,578	7,271
% White	18	38	32	2	92
% College Educated	18	8	5	0	22
% Poverty	18	27	14	11	58
Real Household Income (2010)	18	27,552	8,210	11,605	41,665
Real Rent (2010)	18	380	115	204	622
Real Housing Value (2010)	18	65,010	21,900	32,615	115,191

1980 data Control South 1980s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	53	4,351	1,878	978	8,706
% White	53	40	33	0	94
% College Educated	53	15	11	1	46
% Poverty	53	19	14	5	61
Real Household Income (2010)	53	39,696	13,619	11,806	63,427
Real Rent (2010)	53	475	151	164	714
Real Housing Value (2010)	53	91,740	33,621	38,288	157,617

1990 data Treatment North 1980s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	17	3,153	1,113	1,843	4,760
% White	17	71	21	29	96
% College Educated	17	40	14	13	61
% Poverty	17	13	7	5	33
Real Household Income (2010)	17	56,351	15,695	36,095	101,206
Real Rent (2010)	17	801	148	666	1,249
Real Housing Value (2010)	17	222,872	85,216	127,569	408,994

1990 data Control North 1980s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	73	3,515	1,395	689	7,523
% White	73	80	20	1	97
% College Educated	73	48	14	2	70
% Poverty	73	8	9	0	62
Real Household Income (2010)	73	79,071	39,883	13,306	250,202
Real Rent (2010)	73	939	289	188	1,670
Real Housing Value (2010)	73	268,710	148,245	64,385	800,306

1990 data Treatment South 1980s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	18	3,365	1,383	1,426	5,742
% White	18	22	21	1	65
% College Educated	18	10	6	1	19
% Poverty	18	29	13	10	62
Real Household Income (2010)	18	30,045	8,659	11,852	44,169
Real Rent (2010)	18	524	117	318	686
Real Housing Value (2010)	18	83,710	22,605	42,892	140,213

1990 data Control South 1980s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	53	4,247	1,419	1,596	7,349
% White	53	23	24	0	92
% College Educated	53	17	13	0	59
% Poverty	53	21	16	4	69
Real Household Income (2010)	53	41,787	14,796	8,689	74,234
Real Rent (2010)	53	614	169	165	891
Real Housing Value (2010)	53	110,750	38,798	59,548	272,718

1990 data Treatment North 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	3	3,281	839	2,659	4,236
% White	3	63	6	55	68
% College Educated	3	30	6	24	37
% Poverty	3	9	2	8	11
Real Household Income (2010)	3	55,627	4,463	50,721	59,446
Real Rent (2010)	3	837	44	787	867
Real Housing Value (2010)	3	139,401	14,156	124,266	152,316

1990 data Control North 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	40	3,547	1,332	1,181	6,876
% White	40	79	13	48	96
% College Educated	40	44	13	2	67
% Poverty	40	5	4	0	16
Real Household Income (2010)	40	82,923	40,889	49,304	250,202
Real Rent (2010)	40	977	313	673	1,670
Real Housing Value (2010)	40	231,136	113,705	93,083	681,378

1990 Treatment East 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	7	2,806	1,163	1,427	4,709
% White	7	34	10	18	50
% College Educated	7	24	7	8	28
% Poverty	7	13	11	7	37
Real Household Income (2010)	7	45,540	8,450	26,651	49,838
Real Rent (2010)	7	701	113	445	757
Real Housing Value (2010)	7	133,775	23,339	82,236	153,456

1990 Control East 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	49	4,488	1,445	1,306	9,705
% White	49	48	32	3	95
% College Educated	49	30	14	5	56
% Poverty	49	9	6	1	29
Real Household Income (2010)	49	60,925	15,262	29,484	107,046
Real Rent (2010)	49	818	122	566	1,126
Real Housing Value (2010)	49	151,403	54,626	82,757	399,224

1990 Treatment West 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	2	4,034	774	3,487	4,582
% White	2	9	12	1	18
% College Educated	2	7	0	7	7
% Poverty	2	21	8	15	27
Real Household Income (2010)	2	30,655	3,825	27,951	33,360
Real Rent (2010)	2	517	45	485	549
Real Housing Value (2010)	2	67,471	4,364	64,385	70,556

1990 Control West 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	27	3,779	1,381	1,410	7,081
% White	27	44	41	0	97
% College Educated	27	29	25	0	66
% Poverty	27	24	20	1	69
Real Household Income (2010)	27	52,575	41,889	8,338	200,479
Real Rent (2010)	27	660	268	165	1,251
Real Housing Value (2010)	27	198,262	192,990	59,548	800,306

2000 data Treatment North 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	3	4,485	1,153	3,664	5,803
% White	3	33	2	31	35
% College Educated	3	29	6	23	35
% Poverty	3	15	2	12	16
Real Household Income (2010)	3	56,836	1,378	56,014	58,427
Real Rent (2010)	3	887	48	832	918
Real Housing Value (2010)	3	174,725	13,439	160,651	187,423

2000 data Control North 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	40	4,434	1,402	1,735	7,354
% White	40	57	27	16	94
% College Educated	40	46	18	13	75
% Poverty	40	9	6	1	22
Real Household Income (2010)	40	84,137	38,579	46,028	186,964
Real Rent (2010)	40	974	334	0	2,080
Real Housing Value (2010)	40	252,254	120,104	111,408	614,137

2000 data Treatment East 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	7	3,506	1,352	1,749	5,769
% White	7	16	9	6	32
% College Educated	7	21	6	12	31
% Poverty	7	19	12	12	46
Real Household Income (2010)	7	45,091	7,283	30,250	50,683
Real Rent (2010)	7	715	154	367	786
Real Housing Value (2010)	7	136,710	34,736	92,038	207,877

2000 data Control East 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	49	5,135	1,459	2,062	7,695
% White	49	26	30	2	90
% College Educated	49	31	18	6	75
% Poverty	49	11	7	2	36
Real Household Income (2010)	49	59,618	15,841	31,044	108,816
Real Rent (2010)	49	828	165	308	1,290
Real Housing Value (2010)	49	160,698	67,307	90,772	354,194

2000 data Treatment West 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	2	4,174	882	3,551	4,798
% White	2	7	9	1	14
% College Educated	2	4	1	4	5
% Poverty	2	25	1	25	26
Real Household Income (2010)	2	38,671	8,870	32,399	44,943
Real Rent (2010)	2	711	132	618	804
Real Housing Value (2010)	2	122,232	63,111	77,606	166,859

2000 data Control West 1990s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	27	3,888	1,029	1,229	5,811
% White	27	38	38	0	94
% College Educated	27	36	29	3	84
% Poverty	27	23	18	2	71
Real Household Income (2010)	27	54,774	35,627	12,474	152,818
Real Rent (2010)	27	723	311	186	1,442
Real Housing Value (2010)	27	238,033	219,814	61,654	795,554

2000 data Treatment 2000s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	5	3,270	1,409	1,210	4,653
% White	5	75	13	57	94
% College Educated	5	61	7	51	72
% Poverty	5	6	3	2	8
Real Household Income (2010)	5	88,098	43,879	57,183	165,684
Real Rent (2010)	5	1,112	126	934	1,290
Real Housing Value (2010)	5	292,112	93,854	151,793	416,449

2000 data Control 2000s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	29	4,673	1,586	1,735	7,993
% White	29	76	16	46	95
% College Educated	29	61	10	42	80
% Poverty	29	5	4	1	15
Real Household Income (2010)	29	106,163	42,987	57,183	206,851
Real Rent (2010)	29	1,172	479	0	2,493
Real Housing Value (2010)	29	358,217	135,949	151,793	725,917

2010 data Treatment 2000s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	5	3,555	1,434	1,648	5,596
% White	5	67	25	34	95
% College Educated	5	62	14	45	78
% Poverty	5	7	6	0	13
Real Household Income (2010)	5	81,111	41,424	50,554	153,977
Real Rent (2010)	5	1,141	482	879	2,001
Real Housing Value (2010)	5	302,780	150,214	115,200	472,800

2010 data Control 2000s 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	26	5,025	1,440	2,194	7,588
% White	26	70	19	23	92
% College Educated	26	60	14	33	83
% Poverty	26	7	5	1	21
Real Household Income (2010)	26	90,693	44,240	41,335	207,500
Real Rent (2010)	26	984	267	714	1,644
Real Housing Value (2010)	26	399,858	187,589	142,000	1,000,001

2014 Treatment All 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	104	3,308	1,372	987	7,073
% White	104	40	30	0	97
% College Educated	104	25	13	0	54
% Poverty	104	26	15	2	71
Real Household Income (2010)	104	44,422	25,830	8,598	131,140
Real Rent (2010)	104	883	214	438	1,842
Real Housing Value (2010)	104	191,235	121,150	36,659	578,260

2014 Control All 3 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	181	5,004	2,071	1,082	14,359
% White	181	39	33	0	97
% College Educated	181	23	12	0	47
% Poverty	181	22	15	1	81
Real Household Income (2010)	181	52,428	32,617	2,302	162,678
Real Rent (2010)	181	937	253	175	1,842
Real Housing Value (2010)	181	194,578	164,867	40,528	921,090

2010 data Treatment All 5 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	105	3,171	1,300	914	7,001
% White	105	33	30	0	96
% College Educated	105	38	23	4	85
% Poverty	105	25	16	0	74
Real Household Income (2010)	105	45,979	26,236	10,636	153,977
Real Rent (2010)	105	717	222	182	2,001
Real Housing Value (2010)	105	235,126	136,119	38,500	816,300

2010 data Control All 5 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	242	5,161	2,005	1,285	15,841
% White	242	34	33	0	97
% College Educated	242	38	23	3	93
% Poverty	242	17	13	0	79
Real Household Income (2010)	242	58,961	33,191	9,449	207,500
Real Rent (2010)	242	818	248	275	2,001
Real Housing Value (2010)	242	233,756	157,199	73,800	1,000,001

2014 Treatment All 5 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	104	3,308	1,372	987	7,073
% White	104	40	30	0	97
% College Educated	104	25	13	0	54
% Poverty	104	26	15	2	71
Real Household Income (2010)	104	44,422	25,830	8,598	131,140
Real Rent (2010)	104	883	214	438	1,842
Real Housing Value (2010)	104	191,235	121,150	36,659	578,260

2014 Control All 5 mile

Statistic	N	Mean	SD	Minimum	Maximum
Population	243	5,347	2,159	1,082	15,830
% White	243	40	33	0	97
% College Educated	243	24	13	0	51
% Poverty	243	21	14	1	81
Real Household Income (2010)	243	54,457	31,547	2,302	162,678
Real Rent (2010)	243	972	275	175	1,842
Real Housing Value (2010)	243	189,573	150,086	16,119	921,090

2010 data Treatment All Tracts All

Statistic	N	Mean	SD	Minimum	Maximum
Population	105	3,171	1,300	914	7,001
% White	105	33	30	0	96
% College Educated	105	38	23	4	85
% Poverty	105	25	16	0	74
Real Household Income (2010)	105	45,979	26,236	10,636	153,977
Real Rent (2010)	105	717	222	182	2,001
Real Housing Value (2010)	105	235,126	136,119	38,500	816,300

2010 data Control All Tracts All

Statistic	N	Mean	SD	Minimum	Maximum
Population	488	5,934	2,648	1,027	20,655
% White	488	40	29	0	97
% College Educated	488	37	20	3	93
% Poverty	488	14	11	0	79
Real Household Income (2010)	488	62,707	29,807	9,449	207,500
Real Rent (2010)	488	850	234	275	2,001
Real Housing Value (2010)	488	216,970	126,243	9,999	1,000,001

2014 Treatment All Tracts All

Statistic	N	Mean	SD	Minimum	Maximum
Population	104	3,308	1,372	987	7,073
% White	104	40	30	0	97
% College Educated	104	25	13	0	54
% Poverty	104	26	15	2	71
Real Household Income (2010)	104	44,422	25,830	8,598	131,140
Real Rent (2010)	104	883	214	438	1,842
Real Housing Value (2010)	104	191,235	121,150	36,659	578,260

2014 Control All Tracts All

Statistic	N	Mean	SD	Minimum	Maximum
Population	491	6,129	2,805	851	21,373
% White	491	46	29	0	97
% College Educated	491	24	12	0	56
% Poverty	491	17	13	1	81
Real Household Income (2010)	491	57,267	28,398	2,302	162,678
Real Rent (2010)	491	1,024	269	175	1,842
Real Housing Value (2010)	491	174,043	119,862	9,211	921,090

APPENDIX B: DID MODELS

1980 East 1 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-125.0 (377.1)	-5.5 (3.4)	-15,699.4*** (3,662.9)	-163.7*** (36.5)	-29.5*** (8.2)
	p = 0.8	p = 0.2	p = 0.000	p = 0.000	p = 0.001
Period 2	-440.9 (346.9)	8.6*** (3.1)	-9,572.6*** (3,369.4)	-111.4*** (33.6)	-26.4*** (7.6)
	p = 0.3	p = 0.01	p = 0.01	p = 0.002	p = 0.001
Diff-in-Diff	-522.3 (533.3)	1.0 (4.8)	5,775.0 (5,180.1)	13.8 (51.7)	17.3 (11.7)
	p = 0.4	p = 0.9	p = 0.3	p = 0.8	p = 0.2
Constant	3,976.0*** (245.3)	14.1*** (2.2)	46,473.9*** (2,382.5)	606.3*** (23.8)	81.8*** (5.4)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	156	156	156	156	156
R^2	0.1	0.1	0.2	0.3	0.1
Adjusted R^2	0.04	0.1	0.2	0.2	0.1
Residual Std. Error (df = 152)	1,645.4	14.8	15,982.4	159.4	36.0
F Statistic (df = 3; 152)	3.1**	6.3***	11.2***	18.0***	8.7***
Note:	***p < .01; **p < .05; *p < .1				

1980 West 1 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	79.0 (585.8)	-2.0 (3.3)	-13,429.6*** (3,678.2)	-87.8** (34.9)	-32.2*** (9.4)
	p = 0.9	p = 0.6	p = 0.001	p = 0.02	p = 0.001
Period 2	-629.7 (546.7)	5.9* (3.1)	-7,863.6** (3,432.7)	-89.5*** (32.6)	-18.8** (8.8)
	p = 0.3	p = 0.1	p = 0.03	p = 0.01	p = 0.04
Diff-in-Diff	-272.1 (831.3)	-3.0 (4.6)	4,801.3 (5,219.7)	-9.5 (49.5)	7.6 (13.4)
	p = 0.8	p = 0.6	p = 0.4	p = 0.9	p = 0.6
Constant	4,206.7*** (383.5)	10.5*** (2.1)	37,895.3*** (2,407.9)	488.0*** (22.8)	52.1*** (6.2)
	p = 0.0	p = 0.000	p = 0.0	p = 0.0	p = 0.0
N	111	111	111	111	111
R^2	0.03	0.1	0.2	0.2	0.2
Adjusted R^2	0.004	0.03	0.2	0.2	0.2
Residual Std. Error (df = 107)	2,169.3	12.1	13,621.4	129.2	34.9
F Statistic (df = 3; 107)	1.1	2.2*	8.0***	9.6***	8.1***
Note:	***p < .01; **p < .05; *p < .1				

1980 East 3 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	182.6 (354.6)	-7.5** (2.9)	-21,883.5*** (3,181.0)	-225.6*** (35.9)	-33.5*** (6.8)
	p = 0.7	p = 0.02	p = 0.0	p = 0.0	p = 0.000
Period 2	-4.2 (248.9)	7.6*** (2.1)	-11,155.8*** (2,232.5)	-122.4*** (25.2)	-27.8*** (4.7)
	p = 1.0	p = 0.001	p = 0.000	p = 0.000	p = 0.0
Diff-in-Diff	-959.0* (501.5)	2.0 (4.1)	7,358.2 (4,498.6)	24.7 (50.8)	18.7* (9.6)
	p = 0.1	p = 0.7	p = 0.2	p = 0.7	p = 0.1
Constant	3,668.4*** (176.0)	16.2*** (1.5)	52,658.0*** (1,578.6)	668.1*** (17.8)	85.8*** (3.4)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	268	268	268	268	268
R^2	0.02	0.1	0.3	0.3	0.2
Adjusted R^2	0.01	0.1	0.2	0.3	0.2
Residual Std. Error (df = 264)	1,768.7	14.6	15,864.5	179.1	33.7
F Statistic (df = 3; 264)	2.1	10.3***	30.5***	33.0***	20.4***
Note:	***p < .01; **p < .05; *p < .1				

1980 West 3 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	286.8 (453.7)	-5.4 (3.4)	-23,788.5*** (4,427.0)	-170.3*** (36.6)	-53.7*** (8.4)
	p = 0.6	p = 0.2	p = 0.000	p = 0.000	p = 0.0
Period 2	-359.4 (315.4)	6.8*** (2.4)	-11,101.5*** (3,077.3)	-111.1*** (25.4)	-24.1*** (5.8)
	p = 0.3	p = 0.005	p = 0.001	p = 0.000	p = 0.000
Diff-in-Diff	-542.4 (642.2)	-3.9 (4.8)	8,039.2 (6,265.7)	12.1 (51.8)	12.9 (11.8)
	p = 0.4	p = 0.5	p = 0.3	p = 0.9	p = 0.3
Constant	3,998.9*** (222.3)	13.9*** (1.7)	48,254.3*** (2,168.8)	570.6*** (17.9)	73.6*** (4.1)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	199	199	199	199	199
R^2	0.02	0.1	0.2	0.2	0.3
Adjusted R^2	0.005	0.1	0.2	0.2	0.3
Residual Std. Error (df = 195)	1,937.9	14.6	18,907.0	156.3	35.7
F Statistic (df = 3; 195)	1.3	6.1***	17.8***	21.4***	27.5***
Note:	***p < .01; **p < .05; *p < .1				

1990 North 1 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-247.4 (368.8)	-7.8^{**} (3.6)	$-13,820.9^{**}$ (5,887.8)	-70.4 (50.2)	-5.2 (4.0)
	p = 0.6	p = 0.04	p = 0.03	p = 0.2	p = 0.3
Period 2	181.7 (291.5)	6.8^{**} (2.8)	$10,057.9^{**}$ (4,654.7)	184.8^{***} (39.7)	-13.1^{***} (3.2)
	p = 0.6	p = 0.02	p = 0.04	p = 0.000	p = 0.000
Diff-in-Diff	-100.5 (510.9)	-1.3 (5.0)	30.6 (8,156.5)	-33.7 (69.5)	-3.5 (5.6)
	p = 0.9	p = 0.8	p = 1.0	p = 0.7	p = 0.6
Constant	$3,318.9^{***}$ (206.1)	42.6^{***} (2.0)	$60,083.1^{***}$ (3,291.4)	720.5^{***} (28.0)	92.8^{***} (2.3)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	98	98	98	98	98
R^2	0.02	0.2	0.2	0.3	0.3
Adjusted R^2	-0.01	0.1	0.1	0.2	0.3
Residual Std. Error (df = 94)	1,184.2	11.5	18,907.4	161.1	13.0
F Statistic (df = 3; 94)	0.6	6.2^{***}	6.0^{***}	11.5^{***}	12.3^{***}
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$				

1990 South 1 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-828.7 (534.7)	-6.9^{***} (2.5)	$-9,984.0^{***}$ (3,731.3)	-121.2^{***} (45.3)	1.3 (8.2)
	p = 0.2	p = 0.01	p = 0.01	p = 0.01	p = 0.9
Period 2	-289.3 (534.7)	0.1 (2.5)	3,294.2 (3,731.3)	116.3^{**} (45.3)	-19.9^{**} (8.2)
	p = 0.6	p = 1.0	p = 0.4	p = 0.02	p = 0.02
Diff-in-Diff	-71.7 (756.2)	1.6 (3.5)	-801.7 (5,276.9)	27.0 (64.1)	3.5 (11.6)
	p = 1.0	p = 0.7	p = 0.9	p = 0.7	p = 0.8
Constant	$4,554.4^{***}$ (378.1)	14.7^{***} (1.7)	$37,536.4^{***}$ (2,638.4)	501.5^{***} (32.1)	36.9^{***} (5.8)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.000
N	72	72	72	72	72
R^2	0.1	0.2	0.2	0.3	0.1
Adjusted R^2	0.04	0.1	0.2	0.3	0.1
Residual Std. Error (df = 68)	1,604.2	7.4	11,194.0	136.0	24.5
F Statistic (df = 3; 68)	2.0	4.2^{***}	5.6^{***}	9.3^{***}	3.4^{**}
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$				

1990 North 3 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-228.3 (400.3)	-5.2 (3.6)	-19,606.5** (7,767.0)	-84.1 (60.0)	-2.9 (4.9)
	p = 0.6	p = 0.2	p = 0.02	p = 0.2	p = 0.6
Period 2	215.0 (211.7)	7.9*** (1.9)	13,202.0*** (4,106.3)	205.1*** (31.7)	-10.6*** (2.6)
	p = 0.4	p = 0.000	p = 0.002	p = 0.0	p = 0.000
Diff-in-Diff	-133.8 (564.3)	-2.4 (5.1)	-3,113.5 (10,947.1)	-54.0 (84.6)	-6.0 (6.9)
	p = 0.9	p = 0.7	p = 0.8	p = 0.6	p = 0.4
Constant	3,299.8*** (122.2)	40.1*** (1.1)	65,868.6*** (2,370.8)	734.2*** (18.3)	90.5*** (1.5)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	251	251	251	251	251
R^2	0.01	0.1	0.1	0.2	0.1
Adjusted R^2	-0.004	0.1	0.1	0.2	0.1
Residual Std. Error (df = 247)	1,476.5	13.2	28,646.0	221.3	18.1
F Statistic (df = 3; 247)	0.6	7.5***	7.7***	16.2***	9.7***
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$				

1990 South 3 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-625.1 (443.0)	-6.9** (3.0)	-12,143.1*** (3,556.1)	-94.6** (41.1)	-2.2 (7.8)
	p = 0.2	p = 0.03	p = 0.001	p = 0.03	p = 0.8
Period 2	-104.0 (315.5)	2.1 (2.1)	2,091.9 (2,532.2)	138.6*** (29.3)	-17.8*** (5.5)
	p = 0.8	p = 0.4	p = 0.5	p = 0.000	p = 0.002
Diff-in-Diff	-257.0 (626.5)	-0.3 (4.2)	400.6 (5,029.0)	4.6 (58.2)	1.4 (11.0)
	p = 0.7	p = 1.0	p = 1.0	p = 1.0	p = 0.9
Constant	4,350.8*** (223.1)	14.7*** (1.5)	39,695.6*** (1,790.5)	475.0*** (20.7)	40.3*** (3.9)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	142	142	142	142	142
R^2	0.04	0.1	0.1	0.2	0.1
Adjusted R^2	0.02	0.1	0.1	0.2	0.1
Residual Std. Error (df = 138)	1,624.0	10.9	13,035.1	150.8	28.5
F Statistic (df = 3; 138)	2.1	4.2***	7.9***	13.5***	4.5***
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$				

2000 North 1 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-243.9 (747.5)	-9.5 (9.7)	-13,276.0 (14,440.7)	-102.8 (196.4)	-15.6 (10.7)
	p = 0.8	p = 0.4	p = 0.4	p = 0.7	p = 0.2
Period 2	892.6* (444.1)	0.8 (5.7)	-94.1 (8,579.1)	94.2 (116.7)	-29.4*** (6.4)
	p = 0.1	p = 0.9	p = 1.0	p = 0.5	p = 0.000
Diff-in-Diff	311.7 (1,057.1)	-1.4 (13.7)	1,302.9 (20,422.2)	-43.9 (277.7)	0.2 (15.1)
	p = 0.8	p = 1.0	p = 1.0	p = 0.9	p = 1.0
Constant	3,524.6*** (314.0)	39.5*** (4.1)	68,902.8*** (6,066.3)	939.9*** (82.5)	78.1*** (4.5)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	34	34	34	34	34
R^2	0.2	0.1	0.05	0.05	0.5
Adjusted R^2	0.1	-0.02	-0.05	-0.05	0.5
Residual Std. Error (df = 30)	1,174.9	15.2	22,698.1	308.6	16.8
F Statistic (df = 3; 30)	1.9	0.8	0.5	0.5	10.1***
Note:	***p < .01; **p < .05; *p < .1				

2000 East 1 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-2,023.2*** (645.4)	-0.7 (3.8)	-11,150.6** (4,910.4)	-116.6** (51.0)	-10.3 (8.6)
	p = 0.004	p = 0.9	p = 0.03	p = 0.03	p = 0.3
Period 2	824.4 (503.5)	-1.7 (3.0)	-1,157.4 (3,831.1)	1.5 (39.8)	-25.0*** (6.7)
	p = 0.2	p = 0.6	p = 0.8	p = 1.0	p = 0.001
Diff-in-Diff	-125.0 (912.7)	-1.7 (5.4)	708.2 (6,944.4)	12.0 (72.1)	7.3 (12.2)
	p = 0.9	p = 0.8	p = 1.0	p = 0.9	p = 0.6
Constant	4,829.6*** (356.0)	24.8*** (2.1)	56,690.8*** (2,709.0)	818.0*** (28.1)	44.1*** (4.8)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	46	46	46	46	46
R^2	0.4	0.03	0.2	0.2	0.3
Adjusted R^2	0.3	-0.04	0.1	0.1	0.3
Residual Std. Error (df = 42)	1,424.1	8.4	10,835.9	112.5	19.0
F Statistic (df = 3; 42)	8.1***	0.4	3.3**	3.2**	6.0***
Note:	***p < .01; **p < .05; *p < .1				

2000 West 1 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-1,401.3 (1,232.8)	-9.3 (19.1)	-1,389.3 (12,887.2)	6.9 (225.9)	-25.7 (27.5)
	p = 0.3	p = 0.7	p = 1.0	p = 1.0	p = 0.4
Period 2	-918.5 (1,006.6)	7.7 (15.6)	1,188.6 (10,522.3)	4.9 (184.4)	-7.7 (22.5)
	p = 0.4	p = 0.7	p = 1.0	p = 1.0	p = 0.8
Diff-in-Diff	1,058.5 (1,743.4)	-10.4 (27.1)	6,827.3 (18,225.2)	188.9 (319.5)	6.0 (39.0)
	p = 0.6	p = 0.8	p = 0.8	p = 0.6	p = 0.9
Constant	5,435.8*** (711.8)	16.4 (11.0)	32,044.7*** (7,440.4)	510.2*** (130.4)	34.8* (15.9)
	p = 0.000	p = 0.2	p = 0.003	p = 0.005	p = 0.1
N	12	12	12	12	12
R^2	0.2	0.1	0.04	0.1	0.2
Adjusted R^2	-0.1	-0.2	-0.3	-0.2	-0.2
Residual Std. Error (df = 8)	1,423.5	22.1	14,880.8	260.8	31.8
F Statistic (df = 3; 8)	0.6	0.5	0.1	0.3	0.5

Note: ***p < .01; **p < .05; *p < .1

2000 North 3 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-266.7 (809.2)	-13.9 (9.1)	-27,296.5 (23,211.4)	-140.1 (188.8)	-16.7 (12.5)
	p = 0.8	p = 0.2	p = 0.3	p = 0.5	p = 0.2
Period 2	886.5*** (302.3)	2.1 (3.4)	1,213.2 (8,670.5)	-3.1 (70.5)	-22.1*** (4.7)
	p = 0.005	p = 0.6	p = 0.9	p = 1.0	p = 0.000
Diff-in-Diff	317.7 (1,144.4)	-2.7 (12.8)	-4.4 (32,825.9)	53.3 (267.1)	-7.1 (17.7)
	p = 0.8	p = 0.9	p = 1.0	p = 0.9	p = 0.7
Constant	3,547.4*** (213.7)	43.9*** (2.4)	82,923.4*** (6,131.0)	977.2*** (49.9)	79.3*** (3.3)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	86	86	86	86	86
R^2	0.1	0.1	0.03	0.01	0.3
Adjusted R^2	0.1	0.03	-0.003	-0.03	0.2
Residual Std. Error (df = 82)	1,351.9	15.1	38,775.6	315.5	20.9
F Statistic (df = 3; 82)	3.3**	2.0	0.9	0.3	10.2***

Note: ***p < .01; **p < .05; *p < .1

2000 East 3 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-1,681.4*** (578.7)	-5.9 (6.2)	-15,385.0** (6,019.8)	-116.8** (58.2)	-13.7 (11.8)
	p = 0.005	p = 0.4	p = 0.02	p = 0.05	p = 0.3
Period 2	647.5** (289.3)	0.6 (3.1)	-1,307.5 (3,009.9)	9.6 (29.1)	-21.3*** (5.9)
	p = 0.03	p = 0.9	p = 0.7	p = 0.8	p = 0.001
Diff-in-Diff	51.9 (818.4)	-4.0 (8.8)	858.2 (8,513.3)	4.0 (82.3)	3.5 (16.7)
	p = 1.0	p = 0.7	p = 1.0	p = 1.0	p = 0.9
Constant	4,487.8*** (204.6)	29.9*** (2.2)	60,925.2*** (2,128.3)	818.2*** (20.6)	47.5*** (4.2)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	112	112	112	112	112
R^2	0.2	0.03	0.1	0.1	0.1
Adjusted R^2	0.1	0.004	0.1	0.04	0.1
Residual Std. Error (df = 108)	1,432.2	15.3	14,898.3	144.0	29.3
F Statistic (df = 3; 108)	7.4***	1.1	4.2***	2.6*	5.4***
Note:	***p < .01; **p < .05; *p < .1				

2000 West 3 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	255.6 (883.5)	-22.0 (19.2)	-21,919.9 (27,979.6)	-142.8 (208.9)	-34.7 (28.5)
	p = 0.8	p = 0.3	p = 0.5	p = 0.5	p = 0.3
Period 2	109.2 (328.1)	7.0 (7.1)	2,199.3 (10,391.4)	63.6 (77.6)	-6.2 (10.6)
	p = 0.8	p = 0.4	p = 0.9	p = 0.5	p = 0.6
Diff-in-Diff	30.8 (1,249.5)	-9.7 (27.1)	5,816.6 (39,569.1)	130.2 (295.5)	4.6 (40.2)
	p = 1.0	p = 0.8	p = 0.9	p = 0.7	p = 1.0
Constant	3,778.9*** (232.0)	29.2*** (5.0)	52,575.2*** (7,347.8)	659.8*** (54.9)	43.8*** (7.5)
	p = 0.0	p = 0.000	p = 0.0	p = 0.0	p = 0.000
N	58	58	58	58	58
R^2	0.01	0.1	0.02	0.03	0.1
Adjusted R^2	-0.05	0.03	-0.04	-0.03	-0.001
Residual Std. Error (df = 54)	1,205.7	26.2	38,180.3	285.1	38.8
F Statistic (df = 3; 54)	0.1	1.6	0.3	0.5	1.0
Note:	***p < .01; **p < .05; *p < .1				

2010 1 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-1,474.0*** (508.8)	1.2 (6.5)	-3,994.1 (19,767.5)	-178.2 (219.1)	0.6 (10.9)
	p = 0.01	p = 0.9	p = 0.9	p = 0.5	p = 1.0
Period 2	288.8 (412.2)	-3.1 (5.3)	-21,333.4 (16,013.5)	-388.6** (177.5)	-10.7 (8.8)
	p = 0.5	p = 0.6	p = 0.2	p = 0.04	p = 0.3
Diff-in-Diff	-3.6 (725.2)	3.5 (9.3)	14,345.7 (28,173.0)	417.4 (312.2)	2.5 (15.6)
	p = 1.0	p = 0.8	p = 0.7	p = 0.2	p = 0.9
Constant	4,744.0*** (284.4)	60.2*** (3.6)	92,092.4*** (11,050.3)	1,290.6*** (122.5)	74.6*** (6.1)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	31	31	31	31	31
R^2	0.4	0.03	0.1	0.2	0.1
Adjusted R^2	0.3	-0.1	-0.04	0.1	-0.04
Residual Std. Error (df = 27)	943.4	12.1	36,649.8	406.2	20.2
F Statistic (df = 3; 27)	5.7***	0.2	0.6	1.6	0.6
Note:	***p < .01; **p < .05; *p < .1				

2010 3 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-1,402.6* (729.6)	0.2 (5.8)	-18,065.1 (21,046.7)	-59.9 (188.0)	-1.0 (8.6)
	p = 0.1	p = 1.0	p = 0.4	p = 0.8	p = 1.0
Period 2	351.9 (406.9)	-1.0 (3.2)	-15,470.0 (11,738.8)	-188.5* (104.9)	-6.2 (4.8)
	p = 0.4	p = 0.8	p = 0.2	p = 0.1	p = 0.2
Diff-in-Diff	-66.7 (1,036.1)	1.4 (8.3)	8,482.2 (29,890.6)	217.3 (267.0)	-2.0 (12.2)
	p = 1.0	p = 0.9	p = 0.8	p = 0.5	p = 0.9
Constant	4,672.6*** (279.8)	61.2*** (2.2)	106,163.4*** (8,071.1)	1,172.3*** (72.1)	76.2*** (3.3)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	65	65	65	65	65
R^2	0.1	0.002	0.04	0.1	0.04
Adjusted R^2	0.1	-0.05	-0.005	0.01	-0.01
Residual Std. Error (df = 61)	1,506.6	12.0	43,464.0	388.3	17.7
F Statistic (df = 3; 61)	2.8**	0.05	0.9	1.1	0.8
Note:	***p < .01; **p < .05; *p < .1				

2014 1 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-1,877.7*** (243.9)	0.7 (2.7)	-9,581.5** (4,196.9)	-70.3** (33.5)	-0.2 (4.5)
	p = 0.0	p = 0.9	p = 0.03	p = 0.04	p = 1.0
Period 2	-457.8** (227.5)	-16.9*** (2.6)	-12,636.2*** (3,913.7)	122.4*** (31.2)	3.7 (4.2)
	p = 0.05	p = 0.0	p = 0.002	p = 0.001	p = 0.4
Diff-in-Diff	588.1* (341.1)	1.5 (3.8)	7,941.0 (5,869.2)	24.6 (46.8)	0.4 (6.3)
	p = 0.1	p = 0.8	p = 0.2	p = 0.6	p = 1.0
Constant	5,055.2*** (152.2)	39.4*** (1.7)	58,698.4*** (2,619.0)	806.2*** (20.9)	36.3*** (2.8)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	415	415	415	415	415
R^2	0.2	0.2	0.04	0.1	0.004
Adjusted R^2	0.2	0.1	0.03	0.1	-0.004
Residual Std. Error (df = 411)	1,715.5	19.2	29,514.9	235.2	31.7
F Statistic (df = 3; 411)	31.1***	24.4***	5.5***	12.2***	0.5
Note:	***p < .01; **p < .05; *p < .1				

2014 3 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-1,644.5*** (217.0)	0.8 (2.3)	-10,584.4*** (3,801.8)	-63.2** (28.2)	1.2 (3.9)
	p = 0.0	p = 0.8	p = 0.01	p = 0.03	p = 0.8
Period 2	188.9 (186.0)	-14.3*** (2.0)	-4,135.6 (3,258.9)	156.6*** (24.1)	6.7** (3.3)
	p = 0.4	p = 0.0	p = 0.3	p = 0.0	p = 0.05
Diff-in-Diff	-51.9 (307.2)	0.9 (3.3)	2,578.1 (5,382.0)	9.1 (39.9)	0.3 (5.5)
	p = 0.9	p = 0.8	p = 0.7	p = 0.9	p = 1.0
Constant	4,815.3*** (131.7)	37.2*** (1.4)	56,563.7*** (2,307.6)	780.5*** (17.1)	32.1*** (2.4)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	570	570	570	570	570
R^2	0.2	0.1	0.02	0.1	0.01
Adjusted R^2	0.2	0.1	0.02	0.1	0.01
Residual Std. Error (df = 566)	1,766.9	18.9	30,959.9	229.3	31.7
F Statistic (df = 3; 566)	39.9***	26.0***	4.6***	26.1***	2.2*
Note:	***p < .01; **p < .05; *p < .1				

2014 5 Mile DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-1,989.7*** (220.9)	0.2 (2.2)	-12,982.0*** (3,577.4)	-100.6*** (29.2)	-0.5 (3.7)
	p = 0.0	p = 1.0	p = 0.001	p = 0.001	p = 0.9
Period 2	186.0 (171.7)	-14.2*** (1.7)	-4,504.0 (2,780.2)	154.4*** (22.7)	6.3** (2.9)
	p = 0.3	p = 0.0	p = 0.2	p = 0.0	p = 0.03
Diff-in-Diff	-49.0 (312.9)	0.8 (3.1)	2,946.4 (5,066.2)	11.2 (41.3)	0.6 (5.3)
	p = 0.9	p = 0.8	p = 0.6	p = 0.8	p = 1.0
Constant	5,160.5*** (121.5)	37.9*** (1.2)	58,961.3*** (1,967.9)	817.9*** (16.1)	33.8*** (2.1)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	694	694	694	694	694
R^2	0.2	0.1	0.03	0.1	0.01
Adjusted R^2	0.2	0.1	0.03	0.1	0.01
Residual Std. Error (df = 690)	1,890.6	18.6	30,613.3	249.7	32.0
F Statistic (df = 3; 690)	55.8***	32.5***	7.8***	30.2***	2.4*
Note:	***p < .01; **p < .05; *p < .1				

2014 DID Model

	Population Model I	Education Model II	Income Model III	Rent Model IV	% White Model V
Treatment	-2,763.3*** (273.3)	1.0 (1.8)	-16,727.4*** (3,076.2)	-132.6*** (26.5)	-6.8** (3.1)
	p = 0.0	p = 0.6	p = 0.000	p = 0.000	p = 0.03
Period 2	194.5 (162.4)	-13.1*** (1.1)	-5,439.3*** (1,827.8)	174.5*** (15.8)	5.5*** (1.9)
	p = 0.3	p = 0.0	p = 0.003	p = 0.0	p = 0.004
Diff-in-Diff	-57.5 (387.1)	-0.2 (2.5)	3,881.8 (4,357.9)	-8.8 (37.6)	1.4 (4.4)
	p = 0.9	p = 1.0	p = 0.4	p = 0.9	p = 0.8
Constant	5,934.1*** (115.0)	37.1*** (0.8)	62,706.7*** (1,294.5)	849.9*** (11.2)	40.0*** (1.3)
	p = 0.0	p = 0.0	p = 0.0	p = 0.0	p = 0.0
N	1,188	1,188	1,188	1,188	1,188
R^2	0.2	0.1	0.04	0.1	0.02
Adjusted R^2	0.1	0.1	0.04	0.1	0.01
Residual Std. Error (df = 1184)	2,540.2	16.7	28,595.5	246.5	29.1
F Statistic (df = 3; 1184)	69.9***	61.8***	18.3***	66.7***	6.5***
Note:	***p < .01; **p < .05; *p < .1				

APPENDIX C: DID NCI2 NEW TREATMENT MODELS

New Treatment DID Model North 1980-1990 1 mile Controls

	NCI 2 1	NCI 2 2	NCI 2 3
	Model I	Model II	Model III
Treatment	-0.1 (0.2)	-0.04 (0.2)	-0.04 (0.1)
	p = 0.6	p = 0.9	p = 0.8
Period 2	0.8^{***} (0.1)	1.0^{***} (0.1)	0.7^{***} (0.1)
	p = 0.000	p = 0.0	p = 0.0
Diff-in-Diff	0.1 (0.2)	0.01 (0.2)	0.03 (0.2)
	p = 0.7	p = 1.0	p = 0.9
Constant	-0.3^{***} (0.1)	-0.5^{***} (0.1)	-0.1 (0.1)
	p = 0.003	p = 0.000	p = 0.2
N	88	88	88
R^2	0.4	0.5	0.4
Adjusted R^2	0.4	0.5	0.4
Residual Std. Error (df = 84)	0.5	0.5	0.4
F Statistic (df = 3; 84)	19.5^{***}	28.6^{***}	21.0^{***}
Note:	***p < .01; **p < .05; *p < .1		

New Treatment DID Model South 1980-1990 1 mile Controls

	NCI 2 1	NCI 2 2	NCI 2 3
	Model I	Model II	Model III
Treatment	0.2 (0.1)	0.2^{*} (0.1)	0.2^{**} (0.1)
	p = 0.2	p = 0.1	p = 0.05
Period 2	0.7^{***} (0.1)	0.9^{***} (0.1)	0.7^{***} (0.1)
	p = 0.0	p = 0.0	p = 0.0
Diff-in-Diff	-0.1 (0.1)	-0.1 (0.2)	-0.1 (0.1)
	p = 0.6	p = 0.5	p = 0.4
Constant	-0.7^{***} (0.1)	-0.8^{***} (0.1)	-0.4^{***} (0.1)
	p = 0.0	p = 0.0	p = 0.0
N	72	72	72
R^2	0.6	0.6	0.6
Adjusted R^2	0.6	0.6	0.6
Residual Std. Error (df = 68)	0.3	0.3	0.3
F Statistic (df = 3; 68)	40.0^{***}	40.2^{***}	40.5^{***}
Note:	***p < .01; **p < .05; *p < .1		

New Treatment DID Model North 1990-2000 1 mile Controls

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	0.2 (0.4)	0.1 (0.4)	0.3 (0.3)
	p = 0.6	p = 0.8	p = 0.5
Period 2	-0.1 (0.2)	-0.2 (0.3)	0.1 (0.2)
	p = 0.6	p = 0.5	p = 0.8
Diff-in-Diff	-0.3 (0.6)	-0.3 (0.6)	-0.4 (0.4)
	p = 0.6	p = 0.7	p = 0.4
Constant	0.1 (0.2)	0.2 (0.2)	0.2 (0.1)
	p = 0.5	p = 0.4	p = 0.2
N	34	34	34
R^2	0.04	0.04	0.03
Adjusted R^2	-0.1	-0.1	-0.1
Residual Std. Error (df = 30)	0.6	0.7	0.5
F Statistic (df = 3; 30)	0.4	0.4	0.3
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

New Treatment DID Model East 1990-2000 1 mile Controls

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	-0.2 (0.1)	-0.1 (0.1)	-0.2 (0.1)
	p = 0.2	p = 0.4	p = 0.2
Period 2	-0.3^{***} (0.1)	-0.4^{***} (0.1)	-0.2^{**} (0.1)
	p = 0.002	p = 0.001	p = 0.04
Diff-in-Diff	0.2 (0.2)	0.1 (0.2)	0.1 (0.2)
	p = 0.4	p = 0.5	p = 0.4
Constant	0.1 (0.1)	0.1 (0.1)	0.2^{***} (0.1)
	p = 0.4	p = 0.3	p = 0.001
N	46	46	46
R^2	0.3	0.3	0.1
Adjusted R^2	0.2	0.2	0.1
Residual Std. Error (df = 42)	0.3	0.3	0.2
F Statistic (df = 3; 42)	4.8^{***}	6.0^{***}	2.2^{*}
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

New Treatment DID Model West 1990-2000 1 mile Controls

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	0.01 (0.3)	0.1 (0.3)	-0.1 (0.1)
	p = 1.0	p = 0.7	p = 0.7
Period 2	-0.1 (0.2)	-0.2 (0.2)	-0.02 (0.1)
	p = 0.7	p = 0.5	p = 0.9
Diff-in-Diff	0.2 (0.4)	0.2 (0.4)	0.1 (0.2)
	p = 0.7	p = 0.7	p = 0.6
Constant	0.2 (0.2)	0.1 (0.2)	0.3^{***} (0.1)
	p = 0.4	p = 0.5	p = 0.001
N	12	12	12
R^2	0.1	0.2	0.04
Adjusted R^2	-0.3	-0.1	-0.3
Residual Std. Error (df = 8)	0.3	0.3	0.1
F Statistic (df = 3; 8)	0.2	0.7	0.1
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

New Treatment DID Model 2000-2010 1 mile Controls

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	0.1 (0.2)	-0.2 (0.3)	-0.03 (0.2)
	p = 0.9	p = 0.7	p = 0.9
Period 2	-1.1^{***} (0.2)	-1.4^{***} (0.3)	-0.8^{***} (0.2)
	p = 0.000	p = 0.000	p = 0.000
Diff-in-Diff	0.6^{*} (0.3)	1.0^{**} (0.5)	0.5 (0.3)
	p = 0.1	p = 0.04	p = 0.2
Constant	0.2 (0.1)	0.3 (0.2)	0.4^{***} (0.1)
	p = 0.2	p = 0.2	p = 0.01
N	31	31	31
R^2	0.6	0.5	0.5
Adjusted R^2	0.6	0.5	0.4
Residual Std. Error (df = 27)	0.4	0.6	0.4
F Statistic (df = 3; 27)	14.1^{***}	10.1^{***}	8.1^{***}
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

New Treatment DID Model North 1980-1990 3 mile Controls

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	-0.02 (0.2)	0.02 (0.2)	0.1 (0.2)
	p = 1.0	p = 1.0	p = 0.8
Period 2	1.0^{***} (0.1)	1.2^{***} (0.1)	0.8^{***} (0.1)
	p = 0.0	p = 0.0	p = 0.0
Diff-in-Diff	-0.1 (0.3)	-0.2 (0.3)	-0.1 (0.2)
	p = 0.7	p = 0.6	p = 0.6
Constant	-0.4^{***} (0.1)	-0.6^{***} (0.1)	-0.2^{***} (0.1)
	p = 0.000	p = 0.0	p = 0.005
N	164	164	164
R^2	0.3	0.4	0.3
Adjusted R^2	0.3	0.4	0.3
Residual Std. Error (df = 160)	0.8	0.7	0.6
F Statistic (df = 3; 160)	24.5^{***}	35.5^{***}	28.4^{***}
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

New Treatment DID Model South 1980-1990 3 mile Controls

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	0.03 (0.1)	0.1 (0.1)	0.1 (0.1)
	p = 0.8	p = 0.5	p = 0.3
Period 2	0.7^{***} (0.1)	0.8^{***} (0.1)	0.6^{***} (0.1)
	p = 0.0	p = 0.0	p = 0.0
Diff-in-Diff	-0.03 (0.1)	-0.1 (0.2)	-0.03 (0.1)
	p = 0.9	p = 0.7	p = 0.9
Constant	-0.5^{***} (0.1)	-0.7^{***} (0.1)	-0.3^{***} (0.04)
	p = 0.0	p = 0.0	p = 0.0
N	144	144	143
R^2	0.4	0.5	0.5
Adjusted R^2	0.4	0.5	0.5
Residual Std. Error	0.4 (df = 140)	0.4 (df = 140)	0.3 (df = 139)
F Statistic	37.5^{***} (df = 3; 140)	47.1^{***} (df = 3; 140)	49.1^{***} (df = 3; 139)
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

New Treatment DID Model North 1990-2000 3 mile Controls

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	-0.3 (0.6)	-0.3 (0.7)	-0.1 (0.5)
	p = 0.7	p = 0.7	p = 0.9
Period 2	-0.7*** (0.2)	-0.8*** (0.2)	-0.4** (0.2)
	p = 0.003	p = 0.003	p = 0.02
Diff-in-Diff	0.3 (0.9)	0.3 (0.9)	0.1 (0.7)
	p = 0.8	p = 0.8	p = 0.9
Constant	0.6*** (0.2)	0.6*** (0.2)	0.6*** (0.1)
	p = 0.001	p = 0.002	p = 0.000
N	86	86	86
R^2	0.1	0.1	0.1
Adjusted R^2	0.1	0.1	0.03
Residual Std. Error (df = 82)	1.1	1.1	0.8
F Statistic (df = 3; 82)	3.3**	3.3**	2.0
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

New Treatment DID Model East 1990-2000 3 mile Controls

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	-0.2* (0.1)	-0.2 (0.2)	-0.2 (0.1)
	p = 0.1	p = 0.3	p = 0.2
Period 2	-0.3*** (0.1)	-0.4*** (0.1)	-0.2** (0.1)
	p = 0.000	p = 0.000	p = 0.02
Diff-in-Diff	0.2 (0.2)	0.1 (0.2)	0.1 (0.2)
	p = 0.5	p = 0.6	p = 0.6
Constant	0.1*** (0.1)	0.1** (0.1)	0.3*** (0.05)
	p = 0.01	p = 0.02	p = 0.000
N	112	112	112
R^2	0.2	0.2	0.1
Adjusted R^2	0.1	0.1	0.1
Residual Std. Error (df = 108)	0.4	0.4	0.3
F Statistic (df = 3; 108)	7.2***	7.5***	3.1**
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

New Treatment DID Model West 1990-2000 3 mile Controls

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	-0.3 (0.4)	-0.2 (0.4)	-0.3 (0.3)
	p = 0.5	p = 0.6	p = 0.4
Period 2	-0.4^{**} (0.2)	-0.4^{**} (0.2)	-0.3^{**} (0.1)
	p = 0.04	p = 0.02	p = 0.02
Diff-in-Diff	0.4 (0.6)	0.4 (0.6)	0.3 (0.4)
	p = 0.6	p = 0.5	p = 0.5
Constant	0.5^{***} (0.1)	0.5^{***} (0.1)	0.6^{***} (0.1)
	p = 0.000	p = 0.000	p = 0.0
N	57	57	57
R^2	0.1	0.1	0.1
Adjusted R^2	0.04	0.1	0.1
Residual Std. Error (df = 53)	0.6	0.6	0.4
F Statistic (df = 3; 53)	1.7	2.3^{*}	2.2
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

New Treatment DID Model 2000-2010 3 mile Controls

	NCI 2 1 Model I	NCI 2 2 Model II	NCI 2 3 Model III
Treatment	-0.02 (0.4)	-0.1 (0.5)	-0.05 (0.3)
	p = 1.0	p = 0.9	p = 0.9
Period 2	-0.9^{***} (0.2)	-0.9^{***} (0.3)	-0.6^{***} (0.2)
	p = 0.001	p = 0.002	p = 0.004
Diff-in-Diff	0.3 (0.6)	0.6 (0.7)	0.3 (0.5)
	p = 0.6	p = 0.5	p = 0.6
Constant	0.3^{*} (0.2)	0.2 (0.2)	0.4^{***} (0.1)
	p = 0.1	p = 0.3	p = 0.01
N	65	65	65
R^2	0.2	0.2	0.1
Adjusted R^2	0.1	0.1	0.1
Residual Std. Error (df = 61)	0.9	1.0	0.7
F Statistic (df = 3; 61)	4.7^{***}	3.9^{**}	3.3^{**}
Note:	$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$		

APPENDIX D: DESCRIPTIVE STATISTICS

1970 Descriptive Stats

Statistic	N	Mean	SD	Minimum	Maximum
Treatment	612	0.0	0.0	0	0
% White	610	86.9	25.8	0.0	99.9
% Black	610	12.9	25.8	0.0	99.9
Age over 60	610	9.1	4.8	2.6	38.6
Foreign Born	610	0.9	1.4	0.0	15.2
Vacant	610	4.6	2.8	0.0	20.5
Professional	610	24.9	11.8	2.4	61.2
Unemployed	610	2.6	1.4	0.0	15.8
% College	610	12.4	10.1	0.0	57.4
Income	610	56,353.8	18,058.4	5,719.1	149,474.1
Rent	610	581.5	268.0	191.3	1,342.4
Density	612	1,930.8	2,996.0	0.0	36,658.6
Tenure over 10	609	79.3	9.0	46.5	97.1
Housing Age	609	15.8	14.3	0.0	77.8
Multifamily	610	22.1	20.4	0.0	95.4

1980 Descriptive Stats

Statistic	N	Mean	SD	Minimum	Maximum
Treatment	612	0.1	0.3	0	1
% White	610	77.7	31.7	0.1	99.0
% Black	610	20.2	32.0	0.02	99.1
Age over 60	610	9.8	6.4	0.0	40.7
Foreign Born	571	2.5	2.4	0.0	23.8
Vacant	610	6.1	3.9	0.0	30.0
Professional	571	26.3	11.5	0.0	56.7
Unemployed	571	4.8	3.6	0.0	26.5
% College	571	22.3	14.3	0.0	59.5
Income	590	54,291.4	19,700.7	6,615.0	122,316.6
Rent	569	593.9	214.7	116.4	1,338.9
Density	612	2,012.6	2,346.9	0.0	33,427.5
Tenure over 10	590	77.9	11.2	34.7	100.0
Housing Age	590	15.4	18.4	0.0	100.0
Multifamily	610	29.2	25.4	0.0	98.5
NCI 2 1	544	-0.1	0.8	-1.6	1.7
NCI 2 2	543	0.03	0.5	-1.1	1.4
NCI 2 3	544	0.003	0.7	-1.5	1.9

1990 Descriptive Stats

Statistic	N	Mean	SD	Minimum	Maximum
Treatment	612	0.1	0.4	0	1
% White	610	66.1	33.4	0.2	98.2
% Black	610	29.2	34.2	0.3	99.6
Age over 60	610	10.5	6.0	0.9	38.5
Foreign Born	610	4.9	4.5	0.0	45.3
Vacant	610	10.2	6.6	1.3	83.6
Professional	610	30.1	12.3	0.0	70.6
Unemployed	610	5.7	4.6	0.0	41.0
% College	610	29.3	16.5	0.0	72.3
Income	610	64,855.4	27,912.1	8,338.3	250,201.7
Rent	610	798.6	245.5	165.1	1,669.7
Density	612	2,366.5	1,872.9	0.0	14,469.8
Tenure over 10	610	74.9	13.6	21.3	100.0
Housing Age	610	21.2	24.7	0.0	100.0
Multifamily	610	33.4	27.4	0.0	100.0
NCI 2 1	544	0.6	0.7	-0.8	5.2
NCI 2 2	544	0.5	0.5	-0.9	4.4
NCI 2 3	544	0.6	0.7	-0.8	5.8
GScale	544	5.2	2.1	1	9

2000 Descriptive Stats

Statistic	N	Mean	SD	Minimum	Maximum
Treatment	612	0.2	0.4	0	1
% White	610	48.7	32.1	0.0	95.2
% Black	610	38.5	34.4	1.0	98.9
Age over 60	610	10.2	5.3	0.3	33.7
Foreign Born	610	12.5	11.1	0.0	80.8
Vacant	610	5.3	3.9	0.9	33.3
Professional	610	38.2	15.7	3.8	74.6
Unemployed	610	6.3	7.3	0.0	89.7
% College	610	34.6	19.7	0.0	83.9
Income	610	69,093.7	30,486.0	5,956.5	206,850.5
Rent	610	864.6	280.8	0.0	2,533.3
Density	612	3,071.5	2,614.6	0.0	40,947.8
Tenure over 10	610	75.4	13.0	29.9	100.0
Housing Age	610	31.3	28.0	0.3	100.0
Multifamily	610	33.0	27.9	0.0	100.0
NCI 2 1	610	0.1	0.6	-5.4	2.7
NCI 2 2	610	0.2	0.4	-3.2	2.5
NCI 2 3	610	0.2	0.6	-4.5	3.1
GScale	544	5.5	2.1	1	9

2010 Descriptive Stats

Statistic	N	Mean	SD	Minimum	Maximum
Treatment	612	0.2	0.4	0	1
% White	610	39.4	29.8	0.0	96.8
% Black	610	41.3	33.2	0.0	100.0
Age over 60	609	13.2	6.2	0.2	34.3
Foreign Born	610	16.6	13.3	0.0	73.1
Vacant	609	11.8	7.9	1.0	55.6
Professional	609	7.3	3.7	0.0	29.4
Unemployed	609	10.0	6.1	0.0	58.6
% College	610	37.6	20.7	0.0	92.6
Income	608	60,497.1	30,692.3	9,449	207,500
Rent	597	825.3	237.8	182	2,001
Density	612	3,109.7	2,033.4	0.0	13,774.0
Tenure over 10	609	67.6	15.3	17.2	100.0
Housing Age	609	42.1	26.7	0.0	100.0
Multifamily	609	32.2	28.7	0.0	100.0
NCI 2 2	597	-0.4	0.7	-3.8	2.4
NCI 2 1	597	-0.1	0.5	-1.6	1.6
NCI 2 3	597	-0.3	0.7	-2.7	2.2
GScale	597	4.9	2.2	1	9

2014 Descriptive Stats

Statistic	N	Mean	SD	Minimum	Maximum
Treatment	612	0.2	0.4	0	1
% White	610	44.7	29.1	0.0	96.8
% Black	610	42.3	32.3	0.0	100.0
Age over 60	610	14.5	7.4	0.1	100.0
Foreign Born	610	15.9	12.1	0.0	69.7
Vacant	609	13.0	9.5	0.0	100.0
Professional	607	13.9	6.1	0.6	33.4
Unemployed	607	12.1	7.2	1.4	53.1
% College	610	24.1	12.1	0.0	56.3
Income	607	55,475.4	29,069.7	2,302.0	162,678.3
Rent	600	998.2	265.2	175.0	1,842.2
Density	612	3,212.3	2,108.7	0.0	14,267.3
Tenure over 10	608	74.2	13.7	31.6	100.0
Housing Age	612	0.0	0.0	0	0
Multifamily	609	31.7	28.4	0.0	100.0
NCI 2 2	591	-0.2	0.5	-3.4	1.8
NCI 2 1	591	-0.7	0.4	-2.6	0.5
NCI 2 3	591	-0.4	0.5	-2.7	1.0
GScale	591	4.7	2.0	1	9

Post 2010 Match, 2010 Descriptive Stats

Statistic	N	Mean	SD	Minimum	Maximum
Treatment	210	0.5	0.5	0	1
% White	210	32.0	26.7	0.0	95.6
% Black	210	46.1	32.3	0.6	99.7
Age over 60	210	11.4	6.0	0.2	33.8
Foreign Born	210	18.7	16.0	0.0	73.1
Vacant	210	15.1	9.4	1.9	51.8
Professional	210	6.6	4.1	0.0	29.4
Unemployed	210	10.9	6.7	0.9	34.9
% College	210	36.3	21.2	3.6	85.4
Income	210	48,300.6	23,062.9	10,636	153,977
Rent	210	761.3	194.5	265	2,001
Density	210	4,552.6	2,370.0	1,470.9	13,774.0
Tenure over 10	210	73.8	14.4	21.6	100.0
Housing Age	210	51.2	26.7	1.0	100.0
Multifamily	210	47.2	28.2	0.0	98.3
NCI 2 2	210	-0.4	0.7	-2.1	1.8
NCI 2 1	210	-0.1	0.5	-1.6	1.1
NCI 2 3	210	-0.3	0.7	-2.1	1.9
GScale	210	5.0	2.2	1	9

Post 2010 Match, 2014 Descriptive Stats

Statistic	N	Mean	SD	Minimum	Maximum
Treatment	210	0.5	0.5	0	1
% White	210	40.0	27.0	0.0	96.8
% Black	210	46.1	31.0	0.0	99.6
Age over 60	210	12.3	6.3	0.1	32.7
Foreign Born	210	17.6	14.9	0.0	69.7
Vacant	210	16.7	9.9	0.3	56.5
Professional	210	14.3	6.3	2.9	33.4
Unemployed	210	13.3	7.5	1.6	35.7
% College	210	22.9	12.0	0.0	54.4
Income	210	45,298.7	23,401.2	8,598.4	145,724.7
Rent	210	906.7	192.4	391.5	1,842.2
Density	210	4,725.1	2,495.2	1,529.8	14,267.3
Tenure over 10	210	80.0	12.5	31.6	100.0
Housing Age	210	0.0	0.0	0	0
Multifamily	210	47.0	28.4	0.0	99.2
NCI 2 2	210	-0.2	0.5	-3.0	1.2
NCI 2 1	210	-0.7	0.4	-2.6	0.1
NCI 2 3	210	-0.4	0.5	-2.7	1.0
GScale	210	4.6	2.1	1	9

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