THE ECONOMIC BENEFITS OF BUILT ENVIRONMENT SUPPORTIVE OF ACTIVE LIVING IN DALLAS TAX INCREMENT FINANCING DISTRICTS

A Dissertation

by

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ABSTRACT

This dissertation consists of three studies to systematically evaluate the economic benefits of activity-friendly environmental features in Dallas Tax Increment Financing (TIF) districts, Dallas, Texas, and to examine if TIF developments deliver more walkable/accessible environments, as compared to non-TIF comparison neighborhoods.

Topic 1 employed a quasi-experimental design and the propensity score matching approach to establish a causal inference between TIF development effects and housing value growth and destination accessibility. The findings suggested that the overall TIF development effects accounted for $27,840 (or 95.6%) of the total average SF housing value growth from 2008 to 2014, while the confounding influence of structural attributes and residential locations only accounted for $1,267 (or 4.4%) of the housing value growth, as compared to their counterparts in comparison neighborhoods. In terms of destination accessibility, the overall TIF effects accounted for 8 additional points (of the 100-point scale) on Walk Score, while the other factors only accounted for 2 additional points. The results suggested that TIF developments do stimulate housing value growth, while increasing accessibility to various destinations.

Topic 2 followed a socio-ecological framework to examine the effect of personal, neighborhood, and built environmental factors on active commuting to work in TIF and non-TIF comparison neighborhoods, using fractional logit models with margin effects and margin plots. The findings suggested that the built environmental factors only influenced active commuting to work in the neighborhoods that are already fairly

walkable. The findings also suggested that travel time and personal factors played a consistently important role in influencing the active commuting behavior in both models, regardless of the variation of physical walking environments. In addition, TIF neighborhoods mitigated the negative impact on active commuting from disadvantaged areas.

Topic 3 utilized a 7Ds measurement framework to systematically examine and compare the economic benefits of various activity-friendly environments in TIF and comparison neighborhoods, using ordinary least squares (OLS) regression, spatial regression, and hierarchical linear modeling (HLM) approaches. The finding suggested (1) destination accessibility and transportation facilities were positively associated with appreciation rates, but other activity-friendly environmental features are not associated with higher appreciation rates, and (2) neighborhoods with better walkable environments are associated with higher appreciation rates (1.36% in TIF vs. 0.95% in comparison neighborhoods).

DEDICATION

This dissertation is dedicated

to my parents, Genxing Xu and Miaozhen Zou,

and to my wife, Jianxiong Ji,

Who made all of this possible,

for their endless encouragement and patience.

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NOMENCLATURE

GIS	Geographic Information Systems
HLM	Hierarchical Linear Model
OLS	Ordinal Least Squares
SF	Single-Family
TIF	Tax Increment Financing
TOD	Transit-Oriented Development

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CHAPTER I

INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

According to the 2010 US Census, 80.7% of the US population resides in urban areas (US Census, 2010). The sprawling pattern of urban developments, with low-density and segregated land uses and auto-friendly built environment, have brought serious economic, social, and health burdens to urban residents (Brueckner, 2000; Brueckner & Largey, 2008; Frumkin, 2002). Various policies and initiatives in both governmental and non-governmental (e.g. academic, NGO) sectors, seek to reform land use planning and urban design to rein such sprawling patterns, by either encouraging compact, walkable, transit-orientated, and mixed use developments (Daniels, 2001), or increasing the availability of activity-friendly environmental amenities and urban design features. Understanding the economic consequences of these alternative development strategies is important to provide the legitimate evidence to support recent efforts and initiatives toward promoting more sustainable and healthier neighborhood redevelopments (e.g. smart growth, new urbanism, TIF), especially in the current era of high energy prices, economic uncertainty, demographic changes, and a prevalence of physical inactivity and obesity.

The goal of my dissertation is to systematically evaluate the economic benefits of various activity-friendly environmental features in Dallas TIF districts, and to demonstrate that TIF developments deliver more walkable environments, as compared to non-TIF comparison neighborhoods. In the current era of economic uncertainty and fiscal constraints, TIF is considered one of the most prevalence forms of public-private partnership approaches for urban redevelopments, and has become one of the most active and successfully practiced mechanisms to implement smart growth principles. This dissertation consists of three studies in the city of Dallas to examine different outcomes related to the study goals.

In Chapter 2, I employed a quasi-experimental design to establish a causal inference between TIF development effects and housing value growth and destination accessibility. Propensity score matching was used to remove the price effects of time-constant omitted variable problems, to resemble a random assignment, and to reduce the effects of confounding influence on the observed factors. TIF is one of the commonly suggested policy tools to implement smart growth principles, and it is important to explore its actual effects on supporting smart growth developments. Economic benefits and walkability are two of the major goals that smart growth applications aim to achieve (SmartGrowthToolkit, 2015). Limitations in research design, measurement, and data collection in previous studies have obstructed the comparability and transferability of such analysis. This study provides additional evidence regarding the magnitude and causal direction of the economic benefits originating from TIF programs, which can help support and promote the practical application of smart growth principles.

In Chapter 3, I followed a socio-ecological framework in order to (1) concurrently examine the effect of personal, neighborhood, and built environmental factors on active commuting to work, and (2) compare these relationships between TIF and non-TIF neighborhoods, in the City of Dallas, Texas. I employed the fractional logit models with robust standard errors to adjust for potential correlations across different factors, and utilized margin effects to estimate the magnitude of the significance. Moreover, margin plots were utilized to provide a more complete picture of the non-linear relationships among the variables driven by their interrelations.

In Chapter 4, I employed a 7Ds measurement framework to (1) systematically and concurrently examine the economic benefits of various activity-friendly environmental features in TIF neighborhoods using different analytical methods commonly employed in similar prior studies (OLS, spatial regression, and HLM), and (2) compare the economic benefits of activity-friendly environmental features between TIF and non-TIF comparison neighborhoods. The use of the 7Ds measurement framework helps assess the economic benefits of a variety of activity-friendly elements on residential properties more comprehensively than prior studies which tend to examine only a limited set of environmental variables. The use of spatial error models and hierarchical linear models increased the confidence in reliability and accuracy of the results, and provided insights to guide the selection of appropriate analytical processes and methods to quantify the impact of various environmental features on economic outcomes.

In Chapter 5, I included discussions, remarks on limitations, and suggestions for future investigation on valuating the economic benefits and health benefits of built environmental elements.

1.2 General Literature Review

This section includes generalized literature reviews relevant to all three individual studies carried out in this dissertation. More detailed reviews specific to each individual studies are discussed in corresponding chapters.

1.2.1 Smart Growth and Tax Increment Financing

1.2.1.1 Smart Growth

Smart growth was originally conceived as a reaction to the continuing problems related to "urban sprawl" (Burchell et al., 2000; Burchell et al., 2002; Downs, 2005). The origin of the term, "smart growth", is unclear. The US Environmental Protection Agency launched its smart growth program in 1996, and continued to fund its network to advocate smart growth principles. The American Planning Association launched Growing Smart in 1997, to advocate practical planning tools to help combat urban sprawl, protect farmland, promote affordable housing, and encourage redevelopment.[1] The Natural Resource Defense Council and the Surface Transportation Policy Project published "The Took Kit for Smart Growth" also in 1997.[2] In the same year, the state of Maryland passed the "Smart Growth and Neighborhood Conservation Act" (Knaap & Talen, 2005). After that, the Local Government Commission has co-sponsored Smart Growth related conferences, and the Smart Growth Conference sponsored by New Partner started in 2002. [3] In the same year, Smart Growth America, the largest

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[1] American Planning Association: Growing Smarting, retrieved April, 2015, from https://www.planning.org/growingsmart

[2] Natural Resource Defense Council: The Took Kit for Smart Growth, retrieved April, 2015, from http://www.nrdc.org/reference/topics/smartgrowth.asp

[3] New Partners: the Smart Growth Annual Conference, retrieved April, 2015,

organization devoted to promote smart growth, was founded.[4] Since smart growth was advocated by different programs and organizations, sometimes its advocates tend to promote opposite principles of action. The smart growth principles promulgated by US EPA in 2004 have gained widespread recognitions, which includes the below ten principles: (Knaap & Talen, 2005)

- Mix land uses;
- Take advantage of compact building design;
- Create a range of housing opportunities and choices;
- Create walkable neighborhoods;
- Foster distinctive, attractive communities with a strong sense of place;
- Preserve open space, farmland, natural beauty, and critical environmental areas;
- Strengthen and direct development towards existing communities;
- Provide a variety of transportation choices;
- Make development decisions predictable, fair, and cost effective; and
- Encourage community and stakeholder collaboration in development decisions.

Since then, smart growth has rapidly gained its popularity. Proponents of smart growth include urban and transportation planners, public health professions, environmentalists, and central city advocates, among others. The definition of smart growth has become broader over the years. Many development concepts have been linked with smart growth, such as mixed-use development, Transit-Oriented

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from https://newpartners.org/about-the-event/

[4] Smart Growth America, retrieved April, 2015, from http://www.smartgrowthamerica.org/

Development (TOD), traditional neighborhood development, pedestrian/bicycle-friendly development, etc. Smart growth also became a popular policy tool and has been applied widely in zoning ordinances, urban growth boundaries, transfer of development rights, and environmental impact assessment.(Duany et al., 2010).

Recently, Tax Increment Financing (TIF), a public financing tool originally developed for local governments to stimulate the economy of distressed urban areas, has been considered as an efficient and successful tool to achieve smart growth's goals in municipal level. In many states and local governments, TIF has been proposed or used as an important smart growth implementation tool (e.g. Smart Growth America, Massachusetts, Chicago, Maryland, etc.).

1.2.1.2 Tax Increment Financing

TIF is the most prevalent form of public-private partnerships for urban redevelopment projects conducted by local governments (SmartGrowthToolkit, 2015). It is a public financing mechanism for borrowing money against future gains in tax revenues to subsidize current improvement. By using this tool, local governments can leverage expected growth from property appreciation to finance investments in potential public or private projects, leading to: (1) enhance core assets of the city, (2) provide direct benefits to distressed areas, (3) enhance public investments (e.g. TOD, infrastructure, open space, etc.), (4) improve amenities like parks, green spaces, trails, and urban design, (5) attract business and create jobs, and (6) provide affordable housing (Dallas Economic Development, 2000). Since TIF only targets dedicated tax revenues that are generated by new real estate developments rather than simply increasing property tax rates, it is widely accepted by local governments and public. There are thousands of active TIF districts in the US, from small and mid-sized cities to large metropolitans, and TIF has been acclaimed as an innovative approach to start the improvements in distressed, underdeveloped, or underutilized districts where development might never happen without governmental interventions (Briffault, 2010; Dye & Merriman, 2000; Johnson & Man, 2001).

TIF supports the new developments of residential, retail, commercial, and mixed-use projects in existing urban neighborhoods with incentives. The other major neighborhood improvements that TIF generally financed include: (1) public infrastructures such as sidewalks and curbs, bike lanes, street construction and expansions, street lighting, sewer expansion and repair, storm drainage, utilities, etc.; (2) public recreational uses such as parks and open space improvements, landscaping improvements, environmental remediation, etc.; (3) service facilities such as light rail developments, traffic control, and public buildings; and (4) affordable housing, etc.[5]

The first TIF district appeared in California in 1952. As of 2008, there are over four hundred TIF districts in California with an aggregate of over $10 billion revenues per year with more than $28 billion of long-term debt, and over $674 billion of assessed land valuation (Chiang, 2009). Currently, all the TIFs have been discontinued in California since a couple of lawsuits and local governments will be continuing pay off the debt on old TIFs for years (Antiplanner, 2012; Chiang, 2009). Chicago is the second place to use TIF since the 1990s and still has a significant number of active TIF districts

[5] Information summarized from various sources of TIF projects and definitions.

as of 2013. The city operates 131 TIF districts with total tax revenues of 5.9 billion from 1986 to 2013, and $422 million for 2013 (Cook County Clerk's Office, 2013). TIF has played an important role in the revitalization of Chicago and most of studies on TIF had chosen Chicago as the prime location to discuss the strength and weakness of TIF implementation in large city. As of 2006, the District of Columbia and every state except Arizona had enacted TIF-enabling legislation (Birch et al., 2009). In the current era of economic uncertainty and fiscal constraints, TIF has become recognized as a powerful tool to deliver a stronger local economic future, while improving the built environment to promote active living and sustainable communities for urban residents.

Opponent claimed that TIF has been abused in many situations. There were arguments that new TIF projects were lobbied by developers and have become associated with political favoritism. The spillover effects burdened the public services in nearby neighborhoods without reimbursement, while the redevelopment itself drove out lower-income people leading to gentrification (Lefcoe, 2011; Thompson, 2014).

This dissertation did not focus on the financial and economic mechanism of TIF or civil right issues. Instead, it focused on the economic benefits and walkability improvements because of TIF developments. The brief introduction of TIF history is to provide the background and the linkage with the smart growth principles. TIF has been successfully operated over a thousand projects for six decades. Now it was endowed as one of the valid approaches to implement smart growth strategies by local governments. It is an important planning initiative not only to discuss but also to implement that requires further assessments on its full range of impacts on local communities.

1.2.2 Built Environment and Walkable Neighborhood

1.2.2.1 Built Environment

To study the built environment that facilitates physical activity and influences property values, the specific characteristics of built environment need to be defined first. Broadly defined, the built environment is the spatial, cultural, and physical elements or spaces that are human-made for living, working and recreating on daily basis (Roof & Oleru, 2008). The built environment has been measured differently among different disciplines. Architects and landscape architects often focus on "urban design", which is the design of the physical elements in the built envionrnment, including both appearance and arrangement of them. Urban planners often focus on the "land usage", which includes the distribution of space, density, and the activities associated with it. The land use is usually grouped by coded categories, such as residential, commercial, retail, industrial, and services, etc. Transportation planners often refer to built environment as "transportation system", which includes physical infrastructures of roads, intersections, sidewalks, bike lanes, light rails, and so on, as well as the facilities that support the transportation purpose (e.g. walking, bicycling, driving) (Susan L Handy et al., 2002b). Overall, the built environment being studied in this research refers to the man-made physical environments that provide the setting for human activities, including all the elements of urban design, land use, and transportation systems.

1.2.2.2 Correlations between Built Environment and Physical Activity

The correlations between built environment and physical activity have been discussed in two largely separate bodies of literature. In travel behavior literatures, built environment is studied as factors associated with physical activity as a mode of transportation (e.g. walking, bicycling); while in public health studies, built environment are considered to facilitate physical activity as a form of exercise and recreation (Humpel et al., 2002; Saelens et al., 2003). As a result, the roles of built environment on physical activity have been shown to be slightly different depending on the study purposes. There are different classifications to examine the built environment related to physical activity. One of the most recent and comprehensive classification was summarized by Brian Saelens and Susan Handy. In their review paper, they summarized the elements of built environment that are associated with more physical activity, including accessibility/proximity to non-residential destinations, mixed land use, density, aesthetics, sidewalk/pedestrian infrastructure, street/network connectivity, safety, and the combination of neighborhood amenities (Saelens & Handy, 2008).

1.2.2.3 Neighborhood and Walkable Neighborhood

From one of the early citations, Mumford defined neighborhood as "in some primitive, inchoate fashion exist wherever human beings congregate, in permanent family dwellings; and many of the functions of the city tend to be distributed naturally−that is, without any theoretical preoccupations or political direction−into neighborhoods" (Mumford, 1954). In general, a neighborhood is a spatial and social boundary of a homogeneous group of residents living in a community to maintain a basic social interaction and network. Some scholars defined neighborhood with additional characteristics and specificity. First, a neighborhood is an area where children can play without supervision. Second, a neighborhood is the smallest boundary of "defended neighborhood" to self-identity, contrast, and compete with another area. Third, the liability and social participation for residents in a neighborhood are selective and voluntary (Galster, 2001; Moudon et al., 2006)

The walkable neighborhood concepts are derived from the theory of social reforms and urban growth since the 19^{th} century. A few scholars have attempted to formulate the theory and model of neighborhood based on walkability (Leyden, 2003b; Mumford, 1954). In 1902, Howard modeled new British cities in his "Garden City" on a small district of up to 30,000 people living within a walkable distance that is linked and serviced by railway systems (Howard, 1965). Perry proposed the "neighborhood units" as the areas of children and their families being able to walk safely to elementary schools and community centers from their dwelling in 1929 (Perry et al., 1929). In the mid-20^{th} centuries, Jacobs appealed that streets in a neighborhood should contain three key elements: safety, eyes on the street for the children, and social trust, which were referred to as "street ballet" in her book. The ideal neighborhoods Jacobs considered are the ones with streets serving several primary functions to ensure diverse uses at different times of a day; blocks must be short, to give people alternative routes to reach their destination; buildings must vary in age, condition, and use; and population must be dense to promote visible city life (Jacobs, 1961). From the recent planning movements and initiatives, the supporters of the Smart Growth and New Urbanism have continued to advocate walkable neighborhoods, which have been alternatively characterized as Traditional Neighborhood Design (TND), TOD, Pedestrian Pockets, Transit villages, Urban Villages, and TIF developments, etc. (Duany et al., 2010; SmartGrowthToolkit, 2015).

The concept of walkable neighborhoods is attracting an increasing attention by interdisciplinary scholars. Evidence from planning, public health, and transportation literatures suggests that the modification of physical environments can increase physical activity, and walking in particular, in the neighborhood level (Lee & Moudon, 2006b; Leyden, 2003a; Moudon et al., 2006; Saelens & Handy, 2008). Walking is recognized as one of the most efficient ways to reduce obesity and chronic illness. Built environment that includes rich destinations within walking distance, access and connections to neighborhood recreational amenities and retails, sidewalks and bike lanes, high quality urban design, and safe streets, can form a walkable and health neighborhood (Lee, 2007; Lee & Moudon, 2004, 2006b). In addition to health and physical activity benefits, a growing body of literature has examined that walkable communities can bring various environmental and economic benefits such as reducing carbon emission, air pollution, and climate change (Frank, Greenwald, et al., 2010; Maibach et al., 2009), in additional to reducing auto/energy dependence and traffic congestion (Giles-Corti et al., 2010; Sallis et al., 2004).

The next three chapters examined the benefits of housing value growth and walkability improvement influenced by activity-friendly built environment, focused on aggregated TIF development effects (Chapter 2), active commuting behavior (Chapter 3), and individual built environmental effects (Chapter 4), in the TIF and non-TIF neighborhoods at the City of Dallas, Texas.

CHAPTER II

EXPLORING THE CAUSAL EFFECT OF TAX INCREMENT FINANCING ON SINGLE-FAMILY HOUSING VALUE GROWTH AND DESTINATION ACCESSIBILITY: A PROPENSITY SCORE MATCHING APPROACH

2.1 Introduction

2.1.1 Background

Sprawling patterns of urban expansion have been blamed for low density, segregated land uses and accelerated decline of inner cities. Such development patterns have also shown to be linked with the prevalence of auto-dependent, sedentary lifestyles and obesity (Ewing et al., 2008), accompanying serious economic, social, and health burdens (Brueckner, 2000; Brueckner & Largey, 2008; Frumkin, 2002). Many planning initiatives and policies have been attempted to reverse this trend. Smart growth is one of the most influential theories that support concentrated growth in existing urban communities. It advocates compact, walkable, transit-orientated, and mixed-use developments (Daniels, 2001). Evidence suggests using smart growth principles to remedy sprawl issues is promising; however, smart growth has still been much more talked about in theory than actually carried out in practices (Benfield et al., 2003; Downs, 2005; Duany et al., 2010; Frumkin, 2002).

Tax Increment Financing is one of the most common economic development practices conducted by local governments to make the desirable urban redevelopment a reality. TIF utilizes public financing tools to leverage future gains in tax revenues to subsidize current retrofitting and development on infrastructure, transit-oriented facilities, open spaces, and mixed-use zones in declining urban neighborhoods (Johnson & Man, 2001). Based on the TIF application criteria published by the city of Dallas and the city of Chicago, the primary policy goals of TIF are to: (1) enhance core assets of city, (2) provide direct benefits to distressed areas, (3) enhance public investments (e.g. Transit-Oriented Development (TOD), infrastructure, open space, etc.), (4) improve amenities like park, green space, trail, urban design, (5) attract business and create jobs, and (6) provide affordable housing.[6] These goals are directly and indirectly linked to smart growth principles in order to restrain urban sprawl and revitalize blighted urban areas. In fact, most recent TIFs conducted in US have followed the smart growth principles in their guidelines.

TIF is an important implementation tool in municipal level to achieve the goals of smart growth while stimulating economic development. Exploring the economic benefits of TIF projects could provide evidence to support relevant policy developments and increase financial feasibility for future redevelopment projects, especially to create compact, walkable, and vibrant communities that encourage physical activity, improve overall health and economic vitality, and offer a better quality of life for urban residents.

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[6] The criteria were summarized based on (1) Dallas Economic Development, Criteria for Evaluating Proposed TIF districts, retrieved April, 2015, from http://www.dallas-ecodev.org/incentives/tifs-pids; and (2) Chicago Planning and Development, TIF Application, retrieved April, 2015, from http://www.cityofchicago.org/city/en/depts/dcd/supp_info/tax_increment_financingprogram.html

2.1.2 Significance

Despite the recognized benefits and the growing demand and effort to promote smart growth developments, there was limited understanding in terms of the linkage among smart growth, walkability and economic benefits to the residents. A considerable body of documents has discussed the development and cost benefits of smart growth principles from policy or municipal perspectives. However, no prior work has simultaneously examined the economic benefits and the potential for walkability improvements of such developments from local residents' perspectives. This study is one of the first attempts to examine TIF developments, as a commonly adopted smart growth implementation tool, for their impacts on Single-Family (SF) housing value growth (as a measure to assess economic benefits) and destination accessibility (as a measure of accessibility-based walkability). In particular, the economic benefits measured in this study represented the Single-Family (SF) housing value growth due to TIF developments, and walkability improvement represented the better accessibility of various destinations and amenities (e.g. parks, restaurants, drug stores) measured by Walk Score.

Most previous studies on the economic benefits of smart growth developments (e.g. TIF districts, TOD, mixed-use developments) were based on an observational study design (e.g. cross-sectional design, or case-control design), which lead to relatively weak and inconsistent findings due to the lack of time dimension and random allocation (De Vaus & de Vaus, 2001). This study employed a quasi-experimental design to establish a causal inference between TIF development effects and housing value growth and destination accessibility. Propensity score matching was used to sweep out the price effects of time-constant omitted variable problems, to resemble a random assignment, and to reduce the effects of confounding in observed influence (X. J. Cao et al., 2010; Kuminoff et al., 2010).

2.1.3 Objectives and Hypotheses

2.1.3.1 Objectives

There are great enthusiasms motivated by recent literatures to advocate the smart growth in US. The modification of urban form guided by smart growth principles is the premise to effectively reduce auto and energy dependency and air pollutants, increase residents' physical activity and overall health, relieve climate change, and reduce social isolation. This study responds to the recent calls for combining empirical and theoretical approaches from the planning, health, and economic fields to provide an interdisciplinary approach for understanding the relationship among TIF developments (as an implementation tool of smart growth principle), economic benefits, and walkability (e.g. destination accessibility measured with Walk Score). Two major objective are examined in this study, to help fill in some of the critical gaps remaining in the previous work on this topic.

Objective 1: This study is to advance methodological approaches by incorporating a quasi-experimental design with propensity score matching method to more effectively explore the impact of specific social or environmental effects. This new approach is to provide a possibility to establish causal inference for studies using objective measurements, which is a significant methodological advancement over the previous observational studies.

Objective 2: This study is to apply the new methodology approach (developed as part of Objective 1) to explore the causal effect of TIF on SF housing value growth and destination accessibility (measured with Walk Score).

2.1.3.2 Hypotheses

Since Objective 1 is about the methodological advancement, specific study hypotheses are developed for Objective 2 only.

Hypothesis 1: SF homes located in the TIF neighborhoods have a greater housing value growth from 2008 to 2014 than their matched counterparts in the comparison neighborhoods;

Hypothesis 2: SF homes located in the TIF neighborhoods have a greater Walk Score than their matched counterparts in the comparison neighborhoods in 2014.

To test these hypotheses, I designed a quasi-experimental study in the City of Dallas, Texas utilizing their data on the six years' TIF development (2008-2014). Appraised values and Walk Score were used to represent the property values and destination accessibility respectively in this study. The housing value growth was measured as the difference in appraised values between 2014 and 2008. Since this research focused on the housing value growth in TIF districts, appraised values were used in place of sales values because (1) TIFs are based on appraised values; and (2) appraised values are the only available time-series values that can help fulfil the requirement of quasi-experimental design.

In summary, this study explores whether a SF home has a significant increase in its value and Walk Score if it moved from a non-TIF neighborhood to a TIF neighborhood, controlling for home quality, residential location, socio-demographics, and time dimensional factors. This study also estimates the average treatment effects of TIF developments on housing value growth and Walk Score.

2.2 Literature Review

Complementing the literature review provided in Chapter 1 that offered a brief review of the general literature, this section focuses on the specific body of literature relevant to this first study. This review first discusses property values and walkability, and their relationships with TIF developments. Then it discusses important variables affecting housing values at two different levels, neighborhood level and parcel level. Last, it provides brief discussions on the previous work related to the specific methodology used in this study (quasi-experimental design and propensity score matching method).

2.2.1 Property Values and Walkability, and Their Relationship with TIF

2.2.1.1 The Relationship among TIF, Property Values, and Walkability

Some empirical studies have demonstrated that TIF programs can stimulate residential property value growth in different regions (Byrne, 2006; Man & Rosentraub, 1998; Smith, 2006; Weber et al., 2007). However, a few studies suggested the opposite findings. Merriman found there was no significant increases in aggregated residential property value during 1999-2003 in TIF programs conducted in Wisconsin (Merriman et al., 2011). Using the property value growth data before and after TIF adoption in the

Chicago metropolitan area from 1992 to 1995, Dye found that property values in TIF grew more slowly after adoption than those that did not (Dye & Merriman, 2000). The reasons of the inconsistent findings may be that: (1) the TIF performance and the economic situation varied from case by case; (2) the data used in most studies were old or the duration of the years to study the difference were not long enough to detect the changes; (3) the methodological approaches applied were inappropriate. I was able to locate only one study using a case-control study design during the literature research. Dardia studied matched samples for California TIF parcels, and found the values of parcels in TIF designations grew more rapidly than their matched pairs (Dardia, 1998). However, Dardia did not test or control for the possible sample section bias, and cannot draw a causal inference from the study.

I was not able to find any empirical studies that examined the relationship between TIF designations and walkability. Existing studies on TIF tended to focused primarily on the economic and financial perspectives. However, there were many empirical studies that examined the association between smart growth developments and physical activity. Durand and colleagues conducted a thorough literature review and found 204 articles reporting significant relationships between smart growth related developments and physical activity (Durand et al., 2011). Durand found that five smart growth factors—diverse housing types, mixed land use, housing density, compact development patterns and levels of open space—were associated with increased levels of physical activity, primarily walking. Most of these factors are the similar goals that recent TIF programs target to achieve. As discussed before, smart growth is a toolkit of planning principles including different programs, and TIF is one of the popular implementation tools in this toolkit. However, the relationship between TIF and walkability still remains underexplored.

2.2.1.2 Property Values

Most TIF studies utilized property values to measure the economic growth. This study also used residential property values to represent economic benefits in TIF designations. There are two types of data commonly used to measure property values.

Sales prices refer to the sold prices of residential homes in their last transactions. Sales prices are always the best resources to analyze property values since they reflect the real housing market at a certain time.

Appraised values are assessed and certified by county appraisal district for property taxation purposes. Law requires appraisers to value property's appraisal value at 100% of market value. Land is assessed based on sales information, whether it is from vacant land sales or by extracting a land value based on land to building ratios of improved sales. Most residential improvements are valued on a replacement cost new less depreciation basis. The cost schedules used are market derived cost. The total assessed value is the sum of improvement value and land value. Once a total value has been established, it will be used to compare to the corresponding sales data to determine the ratio to market value and make any necessary adjustments to achieve market value levels.[7]

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[7] Dallas Central Appraisal district: "Dallas CAD Valuation Processes" & "Dallas CAD 2015-2016 Reappraisal Plans", retrieved April, 2015, from http://www.dallascad.org/

This study employed appraised values rather than sales prices because of two reasons. First, Texas state laws prevent the acquisition of sales data for residential homes from being made public available.[8] Second, this study developed a quasi-experimental design to match all the SF homes in TIF designations with the ones in non-TIF neighborhoods, and time-series values were needed to examine the property value growth from 2008 to 2014. Since most homes were sold only for a few times in decades, it was more feasible to apply continuously available appraised values rather than discrete sales prices. In fact, many articles that examined the economic growth in TIF designations used appraised values to measure the changes.

There were several problems associated with using appraised values identified by previous studies (Clapp & Giaccotto, 1992; W. J. Shin et al., 2011b). Appraised values may lead to inaccuracy due to a time lag, missing information, and systematic assessment errors. However, Shin found appraised values to be approximately 95% of the sales prices based on a correlation test and claimed that a large sample size can reduce the drawback. Several empirical studies using Hedonic Price Model suggested the appraisal data to be the only proxy to represent property values when sales data are unavailable (Berry & Bednarz, 1975; Hendon, 1971; Seiler et al., 2001; W. J. Shin et al., 2011b)

[8] Texas House Bill No. 2188, Sec. 552.148 states that "Information relating to real property sales prices, descriptions, characteristics, and other related information received from a private entity by the comptroller or the chief appraiser of an appraisal district remains confidential in the possession of the property owner or agent; and may not be disclosed to a person who is not authorized to receive or inspect the information". April, 2007.

2.2.1.3 Walkability and Walk Score

Measuring walkability requires a systematic measurement of the various built environmental elements/features related to walking, such as sidewalk completeness, accessibility to variety of destinations and amenities, land use density, street connectivity, etc. Cervero and Kockelman proposed the 3Ds (density, diversity, and design) framework in 1997 to guide the measurement of neighborhood and environmental factors related to travel mode choice (Cervero & Kockelman, 1997). Subsequently, a few articles further elaborated his 3Ds approach and included additional domains (Ewing et al., 2014; Frank, Sallis, et al., 2010; Lee & Moudon, 2006a). Lee and Moudon devised the 3Ds + R (density, diversity, and design + route) concept to quantify land use and urban form variables specifically for capturing walkability (Lee & Moudon, 2006a). Ewing et al. developed the 5Ds (density, diversity, design, destination accessibility, distance to transit) model to measure the varying influences of built environment on travel behaviors (Ewing et al., 2014). Frank and colleagues proposed a walkability index to measure the walkability from the neighborhood to the regional level, which included four domains: residential density, commercial density, land use mix, and street connectivity (Frank, Sallis, et al., 2010).

Walk Score is a website and mobile based application developed by a private company found in 2007. It is publicly available and now becoming a popular tool to measure walkability especially in public health and real estate studies. It uses data provided by the Google AJAX Search application program interface, along with a geographically based algorithm to quickly identify neighborhood amenities in close proximity to the entered address, and calculates a walkability score at the parcel level based on a continuous scale. Walk Score algorithm awards points in each of the 13 amenity categories related to walking (grocery store, coffee shop, movie theater, park, bookstore, drug store, clothing and music store, restaurant, bar, school, library, fitness, and hardware store). Destinations get maximum points if they are one quarter mile or less from the residences based on the street-network distance, and the number of points decline as the distance approaches 1 mile, no points are awarded for amenities further than 1 mile. Each category is weighted equally, and scores are summed and normalized to yield a score from 0 to 100, minimum to maximum walkability scores (Carr et al., 2011; Cortright, 2009).

With the popularity and wide availability of Walk Score, it has been launched in almost all major real estate agency websites (e.g., Zillow, Trulia, Redfin, etc.) and has become an important indicator of residential sales and rent prices. Some empirical studies have employed Walk Score in walkability or economic valuation studies and found the significant associations between Walk Score and walking behavior or between Walk Score and property values (S. C. Brown et al., 2013; Carr et al., 2011; Cortright, 2009; Duncan et al., 2013; W. Li, 2013; Talen & Koschinsky, 2014). However, there are several drawbacks for Walk Score. First, it does not capture the actual physical characteristics of walking environments (e.g., sidewalk completeness and street connectivity); second, it only accounts for 13 destination categories, and some important walk-friendly environmental categories (e.g. religion institutions, personal care services) are omitted; third, only the closest destination in each category was evaluated in Walk

Score, and no effects for additional destinations in the same category within one mile are considered. In other words, Walk Score accounts for the distance and diversity, but does not consider the density of destinations and the quality of actual walking environments such as sidewalk, crosswalk, and lighting/shade/traffic conditions. All these issues can trigger underestimation or overestimation of the actual walking environments. Hence, it is important to acknowledge that Walk Score is a limited measure of walkability that is primarily based on destination proximity/accessibility.

This study employed Walk Score as the proxy of destination accessibility because: (a) it is still an efficient proxy of neighborhood walkability with a standardized measurement scale; (b) not all individual walkability-related variables were measurable due to data limitation; and (c) Walk Score is easy to calculate, interpret and compare across different models and with other similar studies later.

2.2.2 Factors Affecting Property Values

This study measured the factors affecting property values in two levels: neighborhood level and parcel level.

2.2.2.1 Neighborhood Level Factors

Neighborhood factors are very important to determine the neighborhood socioeconomic status and account for the variation of social and economic conditions among different neighborhoods. Many empirical studies have demonstrated that population density, race, ethnicity, home occupancy rate, education, and median household income were significantly associated with the overall wealth level, specifically in housing values (Ding et al., 2000; Geoghegan, 2002; Gillard, 1981; Irwin, 2002; M. M. Li & Brown, 1980; W. Li, 2013; Simons et al., 1998). Evidence from these studies suggested that these factors were associated with the degree of homogeneity of the neighborhoods and maintained a consistent relationship with housing values.

2.2.2.2 Parcel Level Factors

Parcel level factors examined in this study included structural factors and location factors.

Structural factors are property attributes reflecting the quality of residential homes. Those factors include house age, square footage of house, number of bedrooms, number of bathrooms (full bath and/or half bath), pool, stories, and so on. Many literatures have demonstrated that structural factors were the most dominating factors that determine housing values (Do & Grudnitski, 1995; Geoghegan, 2002; Gillard, 1981; Irwin, 2002; W. Li, 2013; Lutzenhiser & Netusil, 2001; Palmquist, 1980; Rodriguez & Sirmans, 1994; W.-J. Shin et al., 2011a; Weigher & Zerbst, 1973).

This study employed the CDU rating to measure the overall quality of a residential property. CDU rating is a rating reflecting the physical condition, desirability and utility of a property, and the desirability is measured by the location of property.[9] It is an 8-scale category measurement ranging from Excellent to Unsound (Table 2-1). One empirical study examined that CDU was significantly associated with housing values (Groves & Helland, 2002). However, since CDU rating is based on subjective measures

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[9] Dallas Central Appraisal district: Dallas CAD Valuation Processes, retrieved April, 2015, from http://www.dallascad.org

and sometimes these definitions are not applied uniformly or not applied by the same people to the same properties, which introduce possible bias and discrepancies.

Table 2-1. CDU rating guide (Source: Dallas Central Appraisal district)

CDU Rating of Dwelling	**Definition**
EX-excellent	Building is in perfect condition; very attractive & highly desirable.
VG-very good	Slight evidence of deterioration; still attractive and quite desirable.
GD-good	Minor deterioration visible; slightly less attractive and desirable, but useful.
AV-average	Normal wear and tear is apparent; average attractiveness and desirability.
FR-fair	Marked deterioration but quite useable; rather unattractive and undesirable.
PR-poor	Definite deterioration is obvious; definitely undesirable and barely useable.
VP-very poor	Condition approaches unsoundness; extremely undesirable and barley useable.
UN-unsound	Building is definitely unsound and practically unfit for use or habitation.

Locational factor is another critical factor that determines housing values. In real estate practice, it is always said "location, location, location" when thinking about the value of a house. Many previous studies shown that the distance to Central Business Districts (CBD), Central Activities Districts (CAD), or employment centers is significantly associated with the housing values (Bender & Hwang, 1985; John L Crompton, 2005b; Heikkila et al., 1989; McMillen, 2002). Housing approximately located to CBD, CAD, or employment centers command higher values because it is more accessible to jobs, public services, shopping centers and other amenities. This study applied distance to CAD rather than CBD because for cities with polycentric urban areas like Dallas, CADs more accurately represent the locational advantages that residential properties will have.

Distance to light rail stations and the development around them (TOD) is another important locational factor. However, the relationship between the housing values and distance to light rail stations is still inconsistent. Findings suggested light rail stations had impacts ranging from negative to insignificant or positive on property values based on design, income level, and distance (Al-Mosaind et al., 1993; Debrezion et al., 2007; Hess & Almeida, 2007).

Land-use mix was adopted in this study to control the potential land use effects on housing values. This index was originally developed for measuring the evenness of distribution of different land uses, which value ranging from 0 to 1. Higher values indicate more even distributions of residential, commercial, and office land uses, which were assumed to be more supportive of walking (Frank et al., 2005; Yu, 2014; Zhu & Lee, 2008).

2.2.3 Quasi-Experimental Design, Causal Inference, and Propensity Score Matching

2.2.3.1 Experimental Design, Quasi-Experimental Design, and Random Assignment

From Shadish's book, an experimental design assigns units (e.g. students, patients, homes) to experimental conditions (e.g. treatment groups and control groups) via random assignment. Random assignment ensures that every unit has the same probability of being assigned to a given treatment or condition. As a result, any observed difference between groups on outcome measures (e.g. housing values, Walk Score) are likely to be due to the experimental treatments rather than due to the group differences that existed prior to the assignment, which greatly minimizes the selection bias, increasing internal validity and creating adequate hypothetical counterfactuals. The two major procedures that are used to improve the random assignment process are matching and stratifying (Duke & Mallette, 2011; Shadish et al., 2002).

Despite the merits of experimental design, random assignment of units to conditions is often impossible or cost-prohibitive, especially when involving complex physical conditions (e.g. land use, housing market). The central distinction between experimental design and quasi-experimental design is how the observations are assigned to conditions. Quasi-experimental design resembles similar purposes and structural details of the experimental design, but lacks the random assignment of study units (Duke & Mallette, 2011; Shadish et al., 2002).

2.2.3.2 Causal Inference

The causal inference is another crucial characteristic of experimental design and quasi-experimental design. It is easier to conclude a causal inference in experimental design due to its specialty. However, to establish a causal relationship in quasi-experimental design, three fundamental requirements must be met: (1) that cause precedes effect (in term order), (2) that cause covaries with effect (the cause and effect are statistically associated), and (3) that alternative explanations for the causal relationship are implausible (the confounding variables were well controlled by sampling procedures) (Shadish et al., 2002). Social science studies requires a fourth criterion: the mechanism of the cause influences on the effect is known (S. Handy et al., 2006; Singleton Jr et al., 1993). So far, most economic valuation or walkability studies used non-experimental cross-sectional designs, and have only met the statistical association criterion. Correlation does not mean causality, and ignoring the causality leads to internal validity problems.

2.2.3.3 Propensity Score Matching

Matching techniques have become increasingly popular during last few decades, and propensity score matching (PSM) is one of the most commonly used matching approaches (Figure 2-1). PSM can address the selection bias that occurs within quasi-experimental design, and distributes potential confounding almost equally between the treatment and the control groups (Steiner & Cook, 2013; Thoemmes, 2012). The theory supporting PSM is that if the selection process could be completely modeled by the matching process (e.g. PSM), it would be able to statistically control for any biases that result from the use of nonrandom assignment to condition (Duke & Mallette, 2011; Luellen et al., 2005; Rosenbaum & Rubin, 1983).

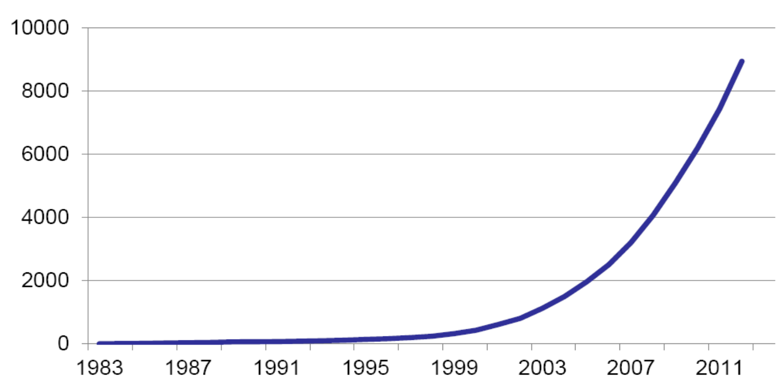

Figure 2-1. Increasing use of propensity scores in recent literatures (Thoemmes, 2012)

PSM is a statistical matching technique to estimate the effect of a treatment (e.g. policy, medication, or other interventions) by accounting for the covariates that predict receiving the treatment effect. It examines the conditional probability of a unit (e.g. students, patients, homes) to be assigned to a particular treatment given a set of observed covariates, and reduces the selection bias by equating groups based on these covariates. Similar to other matching methods, PSM estimates an average treatment effect (ATE) from covariates. The major advantage of PSM is that it can balance treatment and control groups on a large number of covariates without losing many observations, by using a linear combination of covariates with a single score (Steiner & Cook, 2013; Thoemmes, 2012).

PSM basic formula**:** $e(x) = p\ (z=1 \mid x)$

Where $e(x)$ = propensity score, z=treatment assignment (0=control/comparison group, 1=treatment/case group), | = conditional on, x = vector of covariate.

Propensity score is a single number summary based on the values of the set of observed covariates. The value is assembled based on all available covariates that expressed the probability that a given subject was assigned to the treatment condition (Thoemmes, 2012).

There are also two major disadvantages of PSM argued from relevant studies: (1) PSM can only accounts for observed (and observable) covariates, and any hidden bias due to latent variables may still exist after matching; and (2) PSM requires a large sample size (Garrido et al., 2014; Pearl, 2000). However, PSM is still one of the best alternative methods to resemble a random assignment when random assignment of treatments to control subjects is not feasible.

PSM is widely used in the evaluation of social epidemiology studies (Oakes & Johnson, 2006). There are also a few studies in social science using PSM to roughly resemble random assignment of treatment, and found PSM to be a valid method for reducing the effects of confounding in observational studies (X. Cao, 2010; X. J. Cao, 2009; X. J. Cao et al., 2010; Dehejia & Wahba, 2002; Jalan & Ravallion, 2003; O'Keefe, 2004).

2.2.3.4 Examples Using Quasi-experimental Design and Propensity Score Matching

The first application of a quasi-experimental design in social science studies I found was published in 1936 by Hartmann. Hartmann studied the effects of emotionally versus rationally based political leaflets on election results in Pennsylvania. He matched voting wards that received the emotional leaflets with wards that received the rational leaflets, by matching the sizes of wards, previous voting patterns, assessed real-estate values, density of population, and socioeconomic status (Hartmann, 1936; Shadish et al., 2002). Rodriguez applied a quasi-experimental design to compare the residents' physical activity levels between new urbanist neighborhoods and conventional communities in North Carolina, and found residents living in new urbanist neighborhoods were more active (Rodríguez et al., 2006). Cao conducted a propensity score matching to establish a causal relationship between residential location and travel behavior also in North Carolina. He calculated the magnitude of residential location effects and self-selection effects on walking and driving behaviors, and found that residential location effects played a more important role than self-selection effects on influencing travel hehavior (X. Cao, 2010; X. J. Cao et al., 2010)

2.2.4 Summary and Conceptual Framework

Overall, research examining the effects of smart growth and its applications on economic benefits and walkability is still underdeveloped. There was no study that simultaneously examined economic benefits and walkability (destination accessibility) resulting from smart growth practices such as TIF developments. It is important to explore the actual effects of smart growth developments, moving forward from the current advocacy and theory driven debates. Economic benefits and walkability are two major goals that smart growth applications aim to achieve. Limitations in research design, measurement, and data collection methods obstruct the comparability and transferability of previous empirical work on this topic. Additional evidence regarding to the magnitude and causal direction of the benefits of smart growth programs can help promote more widespread applications of smart growth practices.

Empirical studies with tailored hypotheses, well-developed study designs, and rigorous statistical methods are needed to address such knowledge gaps. The following sections developed a quasi-experimental design to effectively explore the causal effect of TIF developments on housing value growth and destination accessibility, by using a propensity score matching approach.

Based on the research objective and the literature reviewed so far, a broad conceptual foundation is developed and presented in Figure 2-2 to show the overview background of smart growth and TIF. Within the large framework, smart growth is a planning toolkit/toolbox and TIF development is one of the implementation tools to achieve smart growth principles. This study only focuses on two outcomes, economic benefits and walkability, that smart growth targets, and examine the causal effects of TIF development effects on the two outcomes.

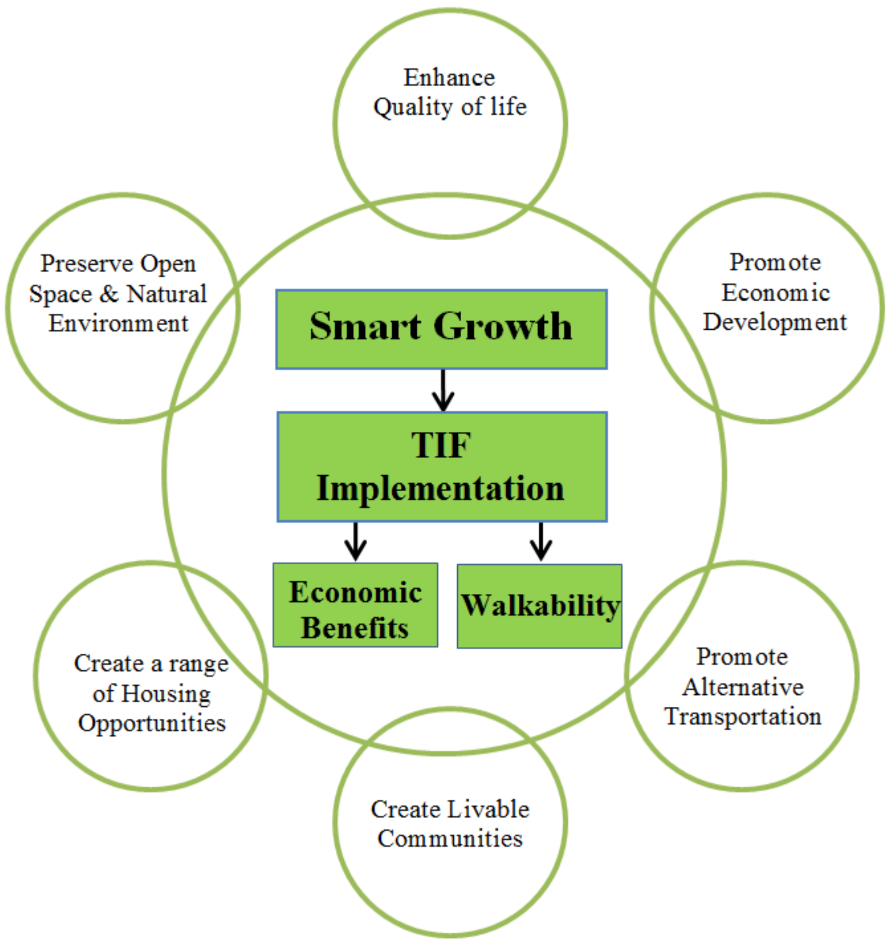

Figure 2-2. Conceptual foundation
(modified based on the principles of smart growth) (Duany et al., 2010)

2.3 Methods

2.3.1 Research Design

2.3.1.1 Study Setting

Most of studies on TIF developments were conducted in the city of Chicago, and few study has been done in the city of Dallas, Texas. To differentiate from previous studies, this study was carried out in the TIF districts and their comparison neighborhoods in Dallas. Dallas is the third largest urban center in Texas and the 8th most populous city in US, with an estimated population of 1,257,676 in 2014 (US census, 2015). Based on the 2008-2012 American Community Survey and the 2010 Census data, Dallas features a high percentage of Hispanic or Latinos population with 42.2% and 28.8% non-Hispanic White population, with $42,436 median household income, 23.6% poverty rate, and 89.2% home occupancy rate. Dallas was ranked the second fastest-growing city in the US, with a projected economic growth rate of 5% and a population growth rate of 2.2% from 2011 to 2016[10].

There are currently 19 active TIF districts in Dallas that continued to experience increased activity and success (check TIF map in Appendix A). In 2013, the growth in property values compared to the TIF's base year (the year TIF initiated), previous year, and entire city was consistently strong. The overall taxable real estate values in TIF districts increased by 139.6% from the base year to 2013, 14.3% from 2012 to 2013, and

[10] Forbes News: America's Fastest-Growing Cities. retrieved April, 2015, from http://www.forbes.com/pictures/mlj45hfdf/1-austin-texas

4.3% compared to the city as a whole (See Appendix C for the full list of TIF with summary statistics).

Dallas is a traditional auto-dependent city with sprawling boundary. It has a citywide Walk Score of 44, which is the 23rd most walkable city among 50 large cities in the US[11]. Through these 19 TIF projects, Dallas is improving its transit service with several light rail lines, as well as its walking and recreational environments. Examining the effects of these TIF designations on housing value growth and destination accessibility can help better understand the benefits and achievements of TIF projects.

2.3.1.2 Study Design and Dataset

The main research question of this study is to examine whether SF homes in TIF neighborhoods have different housing value growth and Walk Score, compare to their matched non-TIF comparison neighborhoods, due to six years of TIF treatment. To accomplish this goal, I followed a quasi-experimental design (Shadish et al., 2002) and used propensity score matching (PSM) approach to conduct a two-level matching study. In neighborhood level (based on Census block groups), I matched each TIF district with a corresponding comparison neighborhood using PSM. Based on the 2014 land use map, compared to the comparison neighborhoods, the TIF neighborhoods generally feature shorter walking distances to office and commercial space from most residences, better infrastructure and amenities for pedestrian, and more compact and mixed land uses (Figure 2-3). In parcel level, I matched housing units in each TIF with the ones in their comparison neighborhood by controlling for structural attributes and residential location

[11] Walk Score, retrieved April, 2015, from https://www.walkscore.com/TX/Dallas

based on the 2014 parcel data. Figure 2-4 shows the research flow of the two-level matching procedure. More details about the two-level matching are discussed in the following section.

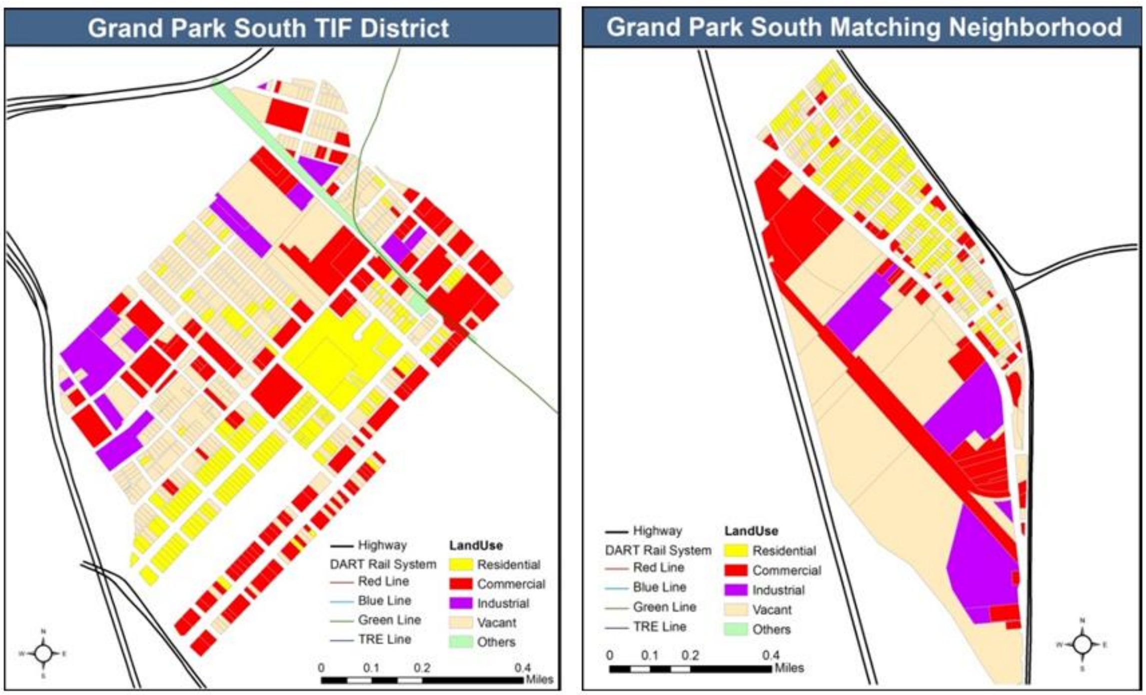

Figure 2-3. 2014 parcel maps example of one TIF neighborhood and its comparison neighborhood (Data source: Dallas Central Appraisal district)

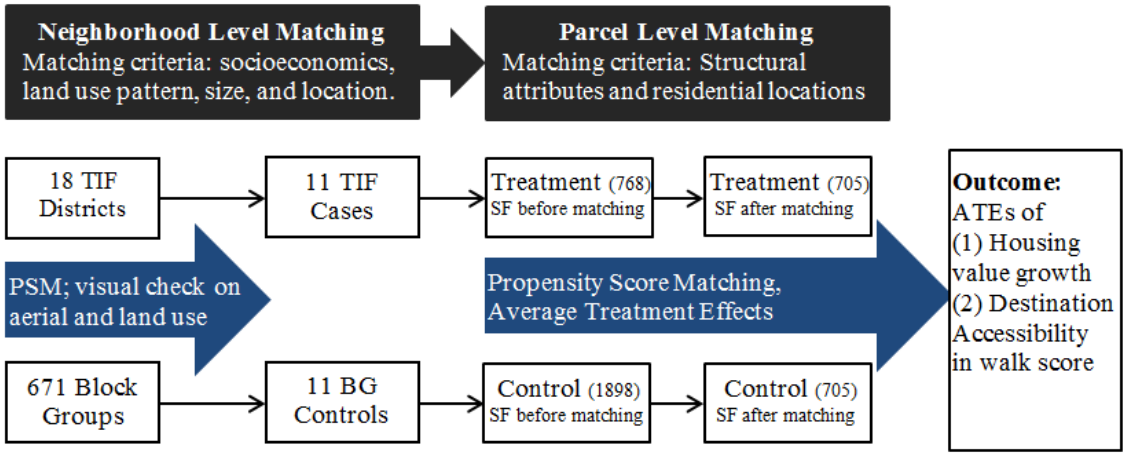

Figure 2-4. Research flow chart for two-level matching procedures

In terms of housing data in parcel level, one of the important steps was to establish a causal relationship that "cause precedes the effect" in time order. Three criteria were considered to determine the beginning and ending times for the housing data to resemble the causal scenario.

First, from Appendix C, all TIFs were launched before 2008 except Maple-Mockingbird (Maple-Mockingbird was initiated in 2009; Cypress Waters was established in 2010 and excluded from this study in data cleaning process)

Second, only the last six years' appraisal data were publicly available from Dallas Central Appraisal district.

Third, the subprime mortgage crisis struck US during 2008-2012 and resulted in the collapse of real estate bubbles. However, Texas real estate market was relatively stable and did not experience a significant impact until the beginning of 2009.[12] However, the real estate prices in Dallas still dropped approximately 15% from 2009 to 2012 (a rough estimate based on Real Estate Index Trend data in Figure 2-5). The subprime mortgage crisis is a major confounding factor, which is difficult to control in housing market studies. There are three potential ways to solve this problem, including: (1) creating a complex index to control the crisis factor, (2) skipping this period with subprime mortgage crisis, or (3) selecting the start and end periods long enough to offset the crisis impacts. The US housing market, including Texas, began to recover since 2012, and there was a general agreement that in 2014 the housing market has recovered from the subprime mortgage crisis.[13] Therefore, I chose the option (3) listed above and selected the time range of 2008 (pre-crisis) to 2014 (post-crisis) for this study to minimize the impact of the subprime mortgage crisis in assessing the potential housing value growth caused by TIF.

Hence, this study employed 2008 and 2014 appraisal data and calculated the difference of housing values between these two years to represent the housing value growth.

The neighborhood level data were acquired from Dallas Economic Development, 2010 US Census, and 2008-2012 American Community Survey. The parcel level data were collected from Dallas Central Appraisal Districts, Dallas Planning Office, and

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[12] Source: Get the real facts about the Texas real estate market. retrieved April, 2015, from www.thekukercompany.com/professional4.shtml

[13] Fortune: Why the housing recovery is over, in four charts. retrieved April, 2015, from http://fortune.com/2014/07/18/housing-recovery-us

Walk Score website. Geographic Information Systems (GIS) was utilized to calculate the study variables.

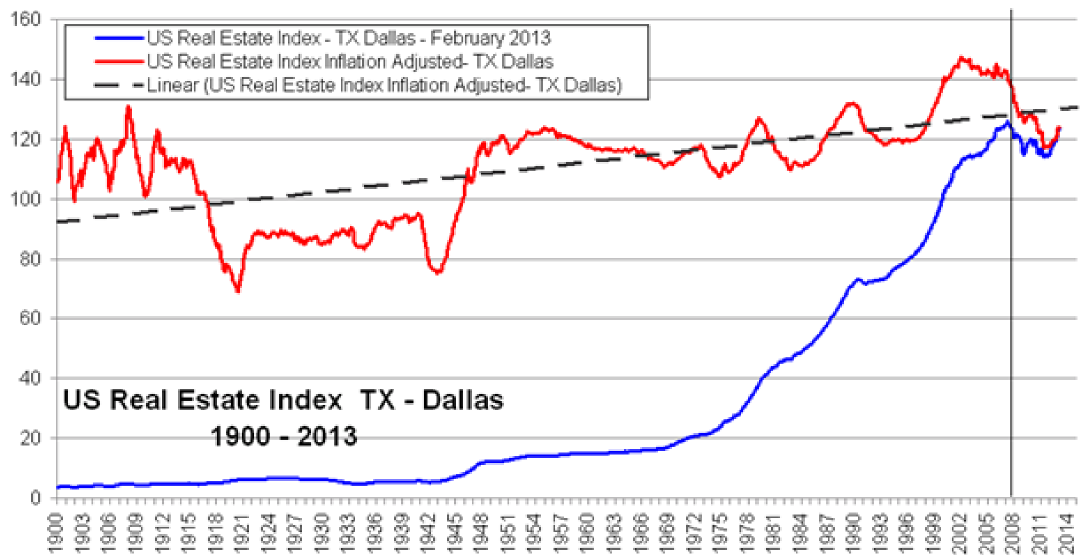


Figure 2-5. City of Dallas, Texas, Real Estate Index trend historical chart (Source: www.aboutinflation.com)

2.3.2 Variable and Measurement

2.3.2.1 Neighborhood Level

To identify suitable matches to the TIF designations, I inventoried all Census block groups in the City of Dallas, to control for neighborhood size, socioeconomic status, location, and land use pattern. All the variables were measured and calculated in ArcGIS.

<u>Neighborhood size</u> was measured by the area in acres. Some TIF districts have much larger sizes than normal block groups. In this case, I selected a group of spatially

clustered block groups (based on a single or multiple Census block groups) that together provide a similar area to match.

Socioeconomics variables were gathered from US Census in block group level, and were recalculated in TIF level based on the proportion of area intersecting with each TIF district. This study evaluated six most important socioeconomics variables based on the previous literature: (1) population density, which was calculated based on the population per acre in 2010; (2) median household income, based on ACS 08-12 estimated; (3) ethnicity, which was calculated based on the percentage of Hispanic or Latinos population in 2010; (4) race, which is calculated based on the percentage of White population without Hispanic or Latinos origin in 2010; (5) education, which was calculated based on the percentage of population aged 25 and over under high school education (ACS 08-12 estimated); and (6) home occupancy rate in 2010.

Location variables were evaluated based on the proximity to highway, light rail stations and Central Activities districts.

Land use pattern variables were calculated based on the percentage of residential land use and the percentage of commercial land use from Dallas 2008 land use data. Appendix B displays a table with detailed descriptive statistics of the neighborhood level variables for TIF districts, block groups, and the City of Dallas.

2.3.2.2 Parcel Level

All the variables in parcel level have been discussed in literature review section. CAD proximity, light rail station proximity, employment number, and land-use mix were examined as the important factors to affect both SF housing price and walkability by previous studies. Table 2-2 displays a detail summary for the parcel level variables and measurements. All the residential location variables were measured by ArcGIS.

Table 2-2. Variable list and measurement methods for parcel level data

Variable List	Measurement Methods
Outcome Variable	
Property values	The difference between 2008 and 2014 appraised values
Walk Score	Walk Score for each home location (2014 cross-sectional data)
explanatory variables	
Structural Attributes (based on 2014 data)	
House age	Number of years the home was built (years)
Total living area	Square feet of the building area (feet)
Bedroom	Number of bedrooms (continuous)
Full bath	Number of bathrooms (continuous)
Half bath	Have half bathroom or not (binary 1/0)
CDU rating	CDU – A rating reflecting the physical condition, utility and desirability of a property; location is an important element of desirability; CDU ratings range from Excellent to Unsound. (categorical variable: excellent = 8, very good = 7, good = 6, average = 5, fair = 4, poor = 3, very poor = 2, unsound = 1)
Residential Locations (based on 2014 data if not specify)	
CAD proximity	The Euclidean distance to the Central Activities Districts (CADs refers to Dallas downtown, uptown, and midtown)
Light rail station proximity	The property within in 0.5 mile radius of light rail stations or not (binary 1/0)
Employment	Number of jobs within 0.25 miles radius from the property in 2011 (continuous)
Land-use mix*	The evenness of residential, commercial and office uses (continuous)

Note:
The land-use mix was calculated based on the equation: (-1) * [(area of R/total area of R, C, and O) * ln(area of R/total area of R, C, and O) + (area of C/total area of R, C, and O) * ln (area of C/total area of R, C, and O) + (area of O/total area of R, C, and O) * ln (area of O/total area of R, C, and O)] / ln (number of land uses present)

In terms of measurements, the CAD proximity was measured as the Euclidean distance to the nearest CAD (downtown, uptown, and midtown) in mile. This study applied distance to CAD rather than CBD because for cities with polycentric urban areas like Dallas, measuring the distance to the closest CAD is more accurate to capture the locational effects on housing values. The proximity to light rail stations was measured as a dichotomous variable to indicate whether the home is within 0.5 mile radius from a light rail station or not. I applied 0.5 mile as the threshold because it is a conventional distance for TOD developments, and has been examined as a positive threshold to affect property values and walkability. Employment and land-use mix were measured within a quarter-mile radius of circular buffer from each property, because a quarter mile buffer is a desirable area range to interpret adequate spatial variation while not to incur serious spatial dependence problems. The land-use mix variable was measured as the evenness of distribution of residential, commercial, and office land use (Yu, 2014; Zhu & Lee, 2008).

2.3.3 Matching Process

2.3.3.1 Propensity Score Matching Logic

Generally, it is difficult to measure the specific neighborhood impact on housing values in observational studies because the effects are always confounded by other factors (e.g. residential location, residential self-selection). Most case-control studies cannot control all confounding factors well since the assignments of treatment are not random. Therefore, the observations in the treatment group are likely to differ systematically from those in the control group (X. J. Cao et al., 2010). In the context of urban economics, residential homes in TIF designations tend to be closer to employment centers and transportation facilities, within higher development densities and with smaller lot size, compared to their counterparts without TIF designations. Accordingly, lack of an elaborate matching procedure to control these confounding factors would cause a statistically biased estimate (X. J. Cao et al., 2010; d'Agostino, 1998).

PSM has been widely used to overcome problems resulting from the nonrandom assignment of treatment. In PSM theory, if an almost "identical" observation in the control group is paired with an observation in the treatment group, conceptually this matching is approximately equivalent to the process, in which one of the two "same" observations are assigned into the treatment group and control group at the same time. If the process is repeated for all observations in the treatment group, there should be no difference between the observations paired in the treatment and the control group. Therefore, the matching approximately resembles an experiment with random assignment of treatment (X. J. Cao et al., 2010; d'Agostino, 1998).

2.3.3.2 Propensity Score Matching Strategies

In this study, the analysis of PSM was carried out using function "MatchIt ( )" in R and "PSM" in SPSS (Hansen & Bowers, 2008; Ho, 2007; Thoemmes, 2012). Propensity score was calculated based on a logistic regression and it is a single number ranging from 0 to 1 calculated based on the values of a set of observed covariates.

Creating a PSM dataset involved three main decisions. The first decision is the choice of a distance metric on observed covariates to quantify the dissimilarity between each pair of treatment and control group. The second decision is the specific matching strategies, which include: (1) the number of matches for each unit (1:1 matching or 1: multiple matching); (2) the caliper coefficient (standard deviation) for preventing poor matches; and (3) matching with or without replacement. The third decision is the matching algorithm to perform the matching and create the matched dataset (Steiner & Cook, 2013).

The Euclidean metric is the default setting in the PSM programs utilized in this study. Matching with replacement was not allowed because it may cause different homes in the treatment group matched with the same home in the control group, which was not appropriate in this study. Hence, this study only considered the number of match, caliper, and matching algorithm for the setup of the PSM in both neighborhood and parcel levels.

2.3.3.3 Matching Procedure for Neighborhood Level

Before conducting PSM for neighborhood level, a few steps were taken: (1) All block groups which intersecting with TIF districts were removed to avoid double counting; (2) the Downtown Connection TIF and the City Center TIF were merged as one TIF unit since they are nested together in the downtown area; (3) A binary treatment indicator was created to represent 1= TIF designations and 0=non-TIF, block groups. Finally, there were 18 TIF neighborhoods and 671 non-TIF block groups available for matching.

The neighborhood level matching involved three steps. First, I developed a logistic regression to estimate the propensity scores for all TIF neighborhoods and block groups, based on the covariates of population density, median household income, ethnicity, race, home occupancy rate, education, residential land use percentage, and commercial land use percentage.

Second, I matched each TIF neighborhood with five most “identical” block groups based on the propensity scores, by conducting PSM with the setting of nearest neighborhood matching algorithms and 1 to 5 matching without replacement (an block group in comparison neighborhood can only be used at most once). Appendix D displays a full list of 1 to 5 matching results. Two limitations were found in this step: (1) 1 to 5 matching was conducted to provide more choices for matching, and that was because the unobserved errors existed due to the data inaccuracy and needed to be manually corrected based on the visual investigation on aerial and land use pattern maps (e.g. a large vacant land was miscoded as commercial or residential use); (2) Area and location factors were removed from the matching covariates since they introduced too many variations causing convergence problems during PSM process. However, these limitations could be addressed by taking the following third step.

Third, this step involves a final check with a visual investigation and comparison on the aerial images and land use patterns for each TIF neighborhood and its five matched comparison neighborhoods. By assessing the actual land use patterns in aerial maps, the location factors (e.g. proximity to highway, light rail, CAD), and the density of residential units, the final selection of the most appropriate matching comparison neighborhood for each TIF neighborhood was made.

There were several TIF designations with unusual characteristics, for which no single block group can be identified as the comparison block based on the matching process specified above. The following individually customized strategies were used to identify their matching comparison groups. In most cases, a group of spatially clustered block groups, instead of a single block group, were selected based on the propensity scores, which together provided a suitable match.

1. Downtown Connection and City Center: These two TIF districts are nested together and hence they are combined as one single TIF neighborhood in this study. Comparing the socio-demographic status, the only comparable neighborhoods for this special case were the uptown and the midtown. Since the uptown was located within another TIF area, the only matching selection was the midtown.
2. TOD: TOD TIF district is a special district designated around light rail stations, which are located across the entire city, and it intersects with 58 block groups. The final matching neighborhoods included all other block groups that contained light rail stations (a total of 42 block groups after excluding 8 block groups selected as comparisons for other TIF cases)
3. Cityplace, Oak Cliff Gateway, Skillman Corridor, Fort Worth Avenue, Davis Garden, Cedars: No single block group has the comparable area that can match these six large TIF districts. Therefore, the block groups with the closest propensity scores and similar land use patterns were selected first, and then grouped with adjacent spatially clustered block groups, to assemble the comparisons with similar sizes.

4. Cypress Water, Vickery Meadow, Southwestern Medical district, Deep Ellum, and Design district: No matched block groups were identified because of the extremely low residential density of these TIF neighborhoods. Therefore, these four TIF designations were excluded from this study.
5. Farmer Market: No matched block group was identified because of the extremely high multi-family residential density in this TIF neighborhood. Therefore, Farmer Market was excluded from this study.

After removing five unqualified TIF designations and combining two downtown TIF districts as one, a total of 12 TIF neighborhoods were selected for this study. The final aerial and land use map with the descriptive statistics for each of the matched pairs for neighborhood level matching are shown in Appendices E1 to E18.

2.3.3.4 Matching Procedure for Parcel Level

In terms of PSM in parcel level, I conducted a logistic regression to quantify the propensity scores first. Then I conducted PSM using nearest neighborhood matching algorithms, imposed with caliper of 0.1 of standard deviation, and 1:1 matching without replacement.

After PSM, the randomly assignment was roughly resembled to assign residential homes from each pair of TIF and comparison neighborhood to the corresponding treatment groups and control groups, by controlling the 10 selected covariates of structural attributes and residential locations; that is, matching every SF homes in each TIF district with the most “identical” one in its corresponding comparison neighborhood, and assigned them to the treatment group and control group.

2.3.4 Data Analysis

2.3.4.1 Neighborhood Level Analysis

Table 2-3 compared the covariates between TIF neighborhoods and comparison neighborhoods before and after the matching. Before matching, the residential and commercial land uses differed significantly, as well as the home occupancy rate. After matching, none of the covariates were significantly different at the 0.05 level. The before-after mean comparison also indicated the differences between the means of covariates were much closer after matching.

Table 2-3. Descriptive statistics and mean comparison test for the covariates of TIF neighborhoods and comparison neighborhoods (before matching vs. after matching)

Covariates	TIF Districts (case) Mean		Non-TIF, Comparison Neighborhoods (control) Mean		*t* Test Before & after matching	
	Before (N=18)	After (N=12)	Before (N=671)	After (N=12)	Before *t*-statistics	After *t*-statistics
Population Density	7.698	8.652	12.678	8.279	-1.394	0.224
Hispanic (%)	32.001	34.350	39.254	32.735	-1.500	0.502
White Alone (%)	44.854	41.097	31.131	43.277	1.779	-0.423
Home Occupancy (%)	90.944	89.863	89.178	91.113	2.340**	-1.073
Education (% under high School)	20.457	22.880	26.518	25.861	-1.519	1.154
Median Household Income	70815.337	65357.306	52930.599	60145.698	1.763	0.920
Residential Land Use (%)	21.968	21.900	49.328	24.033	-5.109**	-0.761
Commercial Land Use (%)	43.299	38.977	14.753	36.094	5.566**	1.132

*: p<0.05 / **: p<0.01

Hence, from the aerial photo and the land use map (Appendix E1- Appendix E18) and Table 2-3, I can conclude that after controlling for neighborhood size, socioeconomic status, location, and land use pattern, the 12 comparison neighborhoods matched appropriately with their corresponding 12 TIF neighborhoods.

2.3.4.2 Parcel Level Analysis

There are a total of 2,908 residential homes in 12 TIF neighborhoods, of which 2,334 are Single-Family detached homes (SF homes), and 574 are non-detached homes (Non-SF homes) including townhouses, condominiums, and duplex. Apartments and mobile homes were excluded from this study to avoid the potential heterogeneity problem, since apartments are more likely to be renter occupied than owned, and mobile homes are more likely to have much lower housing quality. Through the data cleaning process, I removed the residential units with missing structural attributes. I also removed the properties with 2008 appraised values lower than 5 percentile ($20,980) or higher than 95 percentile ($689,000), which were more likely to be the outliers that can skew the results. Since one TIF designation (Skillman Corridor) included a large residential area with a large number of residential homes (account for 73.3% in total sample size), in order to avoid sample bias that the total sample is over-represent by individual TIF subsample, I conducted a random sampling to make sure no single TIF neighborhood has a sample size exceeding 50% of the total sample size. Finally, in 12 TIF neighborhoods, a total of 768 SF homes and 529 Non-SF homes were selected for parcel level matching. The same data cleaning procedure was conducted for residential homes in the 12 comparison neighborhoods, and finally 1,898 SF homes and 710 Non-SF houses were selected for matching. Table 2-4 displays the number of observations for each pair of treatment and control groups. I also conducted the tests to ensure that the random sampling on the TIF and its comparison neighborhoods did not unduly influence the final results.

Table 2-4. Data sample for residential homes and Walk Score in parcel level matching

TIF Name	Treatment Groups				Control Groups			
	# Home subtotal	# SF	# Non-SF*	Walk Score	# Home subtotal	# SF	# Non-SF *	Walk Score
Sports Arena (excluded)	34	34	0		207	0	207	
CityPlace	105	2	103	86	15	15	0	64
Grand Park South	61	54	7	64	199	183	16	30
State Thomas	206	2	204	85	10	10	0	61
Oak Cliff Gateway	82	37	45	42	231	188	43	38
Skillman Corridor	477	384	93	43	814	634	180	39
Fort Worth Avenue	16	11	5	52	44	44	0	36
Davis Garden	74	47	27	76	119	119	0	29
Cedars	69	24	45	70	49	49	0	15
Maple-Mockingbird	11	11	0	48	155	155	0	29
Downtown Connection	15	15	0	86	264	64	200	49
TOD	147	147	0	35	501	437	64	44
Number of observations :	1297	768	529		2608	1898	710	
Average 2008 appraised values:	$243,456	$181,569	$315,291		$127,821	$121,488	$147,312	
Average 2014 appraised values:	$238,765	$200,959	$300,315		$119,724	$111,772	$144,196	
2008-2014 value growth (Δ):	$4,691	$19,391	-$14,976		-$8,097	-$9716	-$3,117	

Note:
The SF-home represented the single-family detached home only, while the non-SF house represented other type of houses include townhouses, condominiums, and duplex

From Table 2-4, there was no matching for SF homes in Sport Arena and its control; therefore, all samples in Sport Arena were dropped from the analysis. Also, for the non-SF home category, there were only 3 treatment-control pairs that could make desirable matching. Hence, the matching for non-detached homes was excluded from the analysis. Therefore, the final samples used in this study were SF detached homes in 11 Dallas TIF districts (treatments) and their comparison neighborhoods (controls).

Table 2-4 also included Walk Score for each TIF and comparison neighborhood, which were calculated based on the average Walk Score of each homes within the neighborhood. From the first glance of the data structure, before matching, SF homes in the TIF group reflected a higher value growth from 2008 to 2014 compared to those in the control group. Also, Walk Score in TIF groups were relatively higher than their corresponding comparison neighborhoods. However, these differences will likely be reduced after the PSM process.

2.3.4.3 Correlations between TIF Developments and Housing Value Growth and Walk Score

Table 2-5 presents a binary logit model with the dependent variable showing the choice of SF homes located in TIF neighborhoods vs. non-TIF, comparison neighborhoods. This model was a predicted model to estimate propensity scores, while also examining the statistical associations between TIF designations and housing value growth or Walk Score.

Table 2-5. Predicted logit model for the choice of SF homes located in TIF neighborhoods vs. comparison neighborhoods (SF located in comparison neighborhood as reference group)

Variable	Coefficients	S.E.
Constant	-2.886	0.557
2008-2014 appraised value growth (in $1,000)	0.043**	0.003
Walk Score	0.029**	0.004
Housing structural attributes		
House age	0.005	0.004
Total living area	0.001**	0.000
Number of bedrooms	0.547**	0.104
Number of full baths	-0.080	0.118
Number of half baths	-0.226	0.155
CDU rating	-0.296**	0.050
Residential locations		
CAD proximity	-0.329**	0.034
Light rail station proximity (within ½ mile radius or not, 1/0)	0.955**	0.141
Employment (in 1,000 person)	0.258*	0.115
Land use mix	0.475*	0.229
Number of observations	2666	
-2 Log likelihood	2300.635	
Cox & Snell's pseudo R Square	0.307	

*: p<0.05 / **: p<0.01

Note:

1. CDU rating: A rating reflecting the physical condition, utility and desirability of a property; location is an important element of desirability; CDU ratings range from Excellent to Unsound. (categorical variable: excellent = 8, very good = 7, good = 6, average = 5, fair = 4, poor = 3, very poor = 2, unsound = 1)
2. CAD proximity is measured as the Euclidean distance to the Central Activities Districts (CADs refers to Dallas downtown, uptown, and midtown)

From the results, the signs of significant variables were consistent with the hypotheses and expectations. Both associations between TIF and the property value growth, and between TIF and Walk Score for these homes, are statistically significant. Therefore, compared to SF homes in the comparison neighborhoods, SF homes located in the TIF neighborhoods were more likely to have a higher value growth and a more walkable/accessible environment. In terms of housing attributes and residential locations, compared to the homes in the comparison neighborhoods, homes located in the TIF neighborhoods tended to have worse building quality, closer distance to both CAD and light rail stations, and higher density of employment and mixed-use development. This model predicted the observed conditions of living in TIF or in comparison neighborhoods for all SF homes (768 in case and 1898 in control) before matching.

2.4 Results

2.4.1 Matching Results for Single-Family Homes

After applying PSM in parcel level, a total of 63 SF homes were dropped from the treatment groups, and a total of 705 pairs of homes were matched by controlling for the structural attributes and residential location factors.

Table 2-6 presents the descriptive results before and after matching. Before matching, all the structural attributes and residential location covariates differed significantly. After matching, none of the covariates were significantly different. The average absolute standardized mean difference reduced from 0.290 (before matching) to 0.021 (after matching). Expect the CAD proximity variable (d=0.061, still a rather small standardized difference), the standardized mean difference for all other covariates were less than 0.05 after matching. Moreover, the overall χ^2 balance test was not significant, with χ^2 (10) = 4.579, p = 0.917, suggesting that overall matching is satisfied. In sum, all observed covariates were well balanced after matching. Figure 2-6 is the distribution of propensity scores dot plot to display whether the SF homes were matched or discarded after matching. Figure 2-7 is a diagnostic plot to display the standardized mean differences for all balanced covariates.

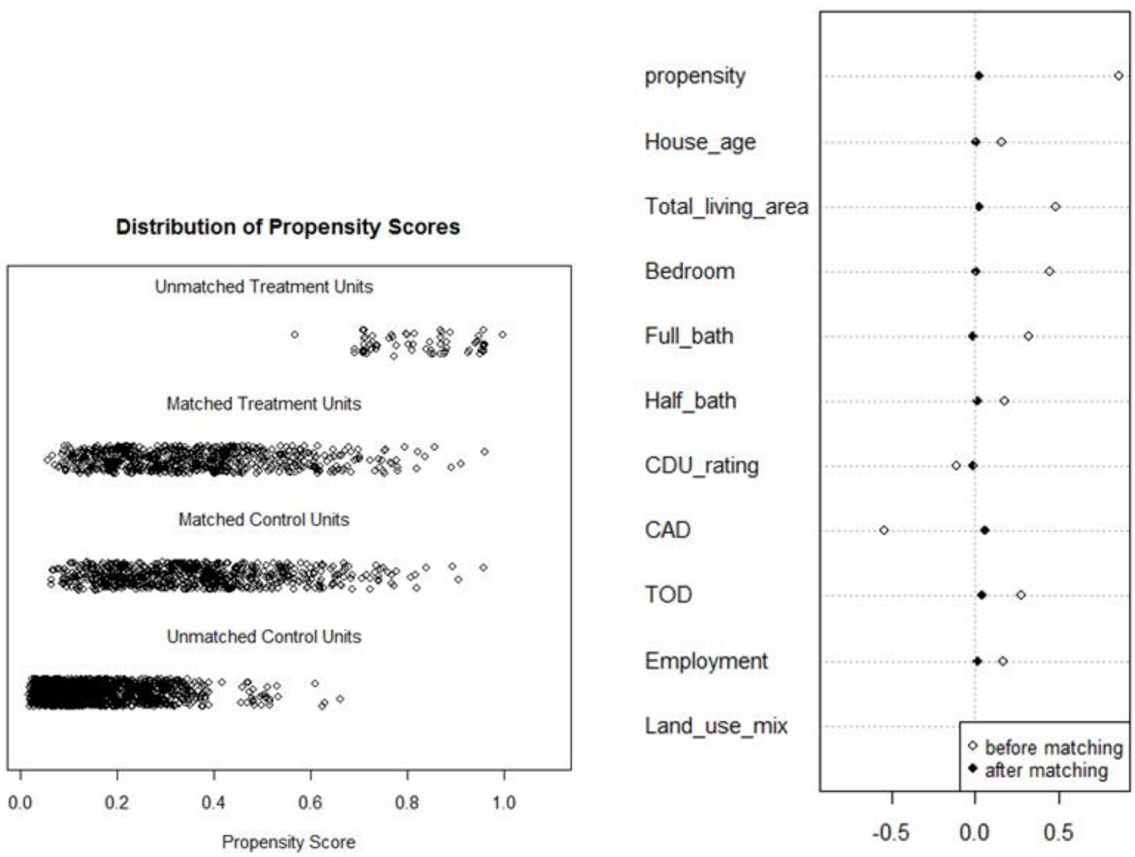


Figure 2-6. Dot plot of distribution of propensity scores (left) and diagnostic plot of standardized mean differences for all balanced covariates (right)

Table 2-6. The descriptive statistics and mean comparison test for the covariates of SF properties in case and control groups (before PSM vs. after PSM)

Covariates	Treatment (TIFs) Mean (SD)		Control (comparison neighborhoods) Mean (SD)		Standardized mean difference		*t* Test for Treatment-control Before & after matching	
	Before (N=768)	After (N=705)	Before (N=1898)	After (N=705)	Before	After	Before *t*-statistics	After *t*-statistics
House age	55.822 (20.355)	54.898 (18.965)	52.606 (21.740)	54.684 (23.228)	0.158	0.011	-3.699**	0.187
Total living area	2141.902 (838.521)	2106.115 (827.980)	1738.423 (759.673)	2088.726 (804.477)	0.481	0.021	-12.316**	0.431
Bedroom	3.254 (0.696)	3.240 (0.708)	2.940 (0.674)	3.233 (0.605)	0.451	0.010	-10.837**	0.218
Full bath	2.010 (0.717)	2.010 (0.708)	1.783 (0.755)	2.021 (0.784)	0.318	-0.016	-7.471**	-0.290
Half bath	0.406 (0.491)	0.409 (0.492)	0.320 (0.467)	0.401 (0.491)	0.176	0.014	-4.243**	0.267
CDU rating	5.319 (1.419)	5.362 (1.399)	5.472 (1.146)	5.373 (1.190)	-0.108	-0.008	2.700**	-0.167
CAD proximity	3.543 (1.862)	3.745 (1.748)	4.559 (1.873)	3.632 (1.738)	-0.545	0.061	12.943**	1.269
Light rail station proximity	0.268 (0.443)	0.251 (0.434)	0.146 (0.353)	0.234 (0.424)	0.277	0.038	-6.937**	0.798
Employment	422.427 (1391.281)	244.494 (700.100)	186.217 (332.641)	226.382 (344.177)	0.170	0.013	-4.658**	0.627
Land use mix	0.344 (0.260)	0.323 (0.255)	0.289 (0.251)	0.319 (0.263)	0.212	0.015	-5.170**	0.272

Overall balance test (Hansen & Bowers, 2010)

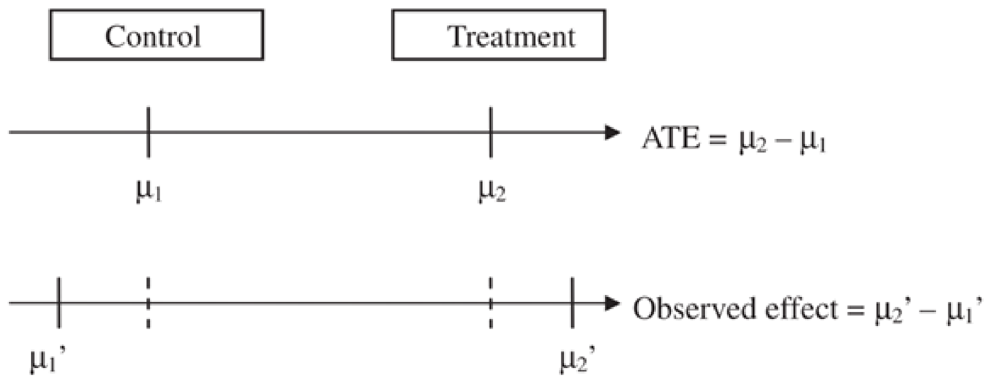
	Chi-Square	*df*	*p*.value
Overall	4.579	10.000	0.917

*: p<0.05 / **: p<0.01

From the final results, the balanced SF homes had an approximately average age of 55, with 2,000 square feet of total living area, 3 bedrooms, 2 full baths, and 0.5 half bath. The housing quality and desirability were slightly below the average. In terms of residential location, the average distance from SF homes to CAD was about 3.7 miles, and most of them were not within 0.5 mile distance from light rail stations. The average employment number within a quarter mile distance from these homes was around 230-240, and most homes were located in somewhat mixed land use environments.

2.4.2 The Estimation and Results of TIF Effects on Housing Value Growth and Walk Score

The final goal of this study was to estimate the "true" impact of TIF development effects on the SF housing value growth and Walk Score. I calculated the average treatment effects (ATE) to indicate the causal effect of TIF developments on the outcomes after six years of TIF treatment. By controlling for the structural attributes and residential location factors, the ATE for housing value growth was assessed as the difference in average housing value growth between the treatment group and the control group after matching. In addition, the mean difference of housing value growth between the treatment group and the control group before matching was the observed effect (unmatched mean). The difference between observed influence and ATE was the observed confounding influences (structural attribute and residential location on property values). Figure 2-7 illustrates the relationship among ATE, observed effect, and confounding influences.



Note:

3. μ_1 and μ_2 represents the mean difference between 2008 and 2014 in control and treatment groups after matching;
4. μ_1' and μ_2' represents the mean difference between 2008 and 2014 in control and treatment before matching; Confounding influence = Observe effect – ATE.

Figure 2-7. The relationship between observed effect and average treatment effect

Table 2-7. Descriptive statistics for outcome variables

Pair	Group description	2008 value mean		2014 value mean		Value growth		t-test	Walk Score		t-test
		Before	After	Before	After	Before	After		Before	After	
1.Total Sample	Treatment	$181,569	$178,830	$200,959	$198,728	$19,391	$19,899	14.788**	47	45	10.469**
	Control	$121,488	$149,441	$111,772	$141,500	-$9716	-$7,941		37	37	
2. Sub-Sample1	Skillman Corridor	$266,794	$269,916	$308,203	$307,852	$41,409	$37,936	17.495**	41	41	5.115**
	Control	$197,454	$201,733	$195,412	$197,150	-$2,042	-$4,583		34	35	
3. Sub-Sample2	Other TIFs	$93,716	$77,376	$96,344	$80,905	$2,628	$3,529	8.462**	52	50	15.564**
	Control	$90,435	$105,945	$77,582	$96,250	-$12,853	-$9,694		39	38	

*: p<0.05 / **: p<0.01

Based on the Pair 1 (Total Sample) in Table 2-7, the ATE for housing value growth was $19,899 – (–$7,941) = $27,840. That is, after controlling for structural attributes and residential location, on average, SF homes in TIF neighborhoods tend to have $27,840 more in housing value growth than their counterparts in comparison neighborhoods during six years' of TIF treatment. In other words, if a randomly-selected SF home moved from a neighborhood without TIF treatment to a similar neighborhood in TIF treatment, it was expected to have an increase of $27,840 on its housing value growth than if it did not move during 2008-2014. The paired t-test for all three groups suggested consistently positive differences of housing value growth and Walk Score for TIF samples compared to non-TIF samples.

Due to the lack of longitudinal data for Walk Score, the causal effect between TIF developments and destination accessibility is quasi or partial, and the interpretation of the Walk Score's ATE is slightly different. That is, after controlling for the observed confounding influences, on average, SF homes in TIF neighborhoods tend to have 8 points more in Walk Score than their counterparts in comparison neighborhoods in 2014. In other words, if a randomly-selected SF home moved from a similar neighborhood without TIF treatment to a TIF neighborhood in 2014, it was expected to have eight points more on Walk Score.

From Table 2-8, the observed confounding influences accounted for $1,267 on housing value growth, which means the value growth attributable to structural attributes and residential locations was shown to be much smaller than the TIF-related value growth ($1,267 vs. $27,840). Moreover, the observed confounding influences accounted for only 2 points on Walk Score, which indicated a minor effect due to the residential location factors on destination accessibility (structural attributes did not affect Walk Score, the significant correlations between TIF/non-TIF and residential location can be found in Table 2-5). Therefore, it demonstrated the matching process in neighborhood level was well balanced once again.

Table 2-8. The effect of TIF developments on housing value growth and Walk Score

Pair	Treatment	Control	Observed effect		ATE		Confounding influence	
			Value	Score	Value	Score	Value	Score
1	SFs in all TIFs	SFs in comparison	$29,107	10	$27,840	8	$1,267	2
2	SFs in Skillman Corridor	SFs in comparison	$43,451	7	$42,519	6	$932	1
3	SFs in other TIFs	SFs in comparison	$15,481	13	$13,223	12	$2,258	1

Note:

1. ATE = Average Treatment Effect = effects of TIF on housing value or Walk Score = outcome in TIF (after matching) – outcome in control (after matching);
2. Observed effect = Total effects on property values or Walk Score (controlled for neighborhood level factors) = outcome in TIF (before matching) – outcome in comparison (before matching);
3. Confounding = the effects of home quality and residential location = Observed effect – ATE.

One major problem in parcel level matching was the extremely large samples for one particular TIF designation (Skillman Corridor). To avoid the potential sampling bias, I did two subsample tests for that TIF designation only and all other TIF separately. From Table 2-7, Pair 2 was the subsample of treatment and control group for the Skillman Corridor TIF district (holding 50% of total samples). Pair 3 was the subsample of treatment and control group for the other 10 TIF designations (together holding another 50% of total samples). After PSM, although the housing value growth had much higher variation in Pair 2 compared to Pair 3, the trend of TIFs' effect is the same (positive effect). In other words, in Pair 2 and Pair 3, the average housing value growth in TIF neighborhoods was $42,519 and $13,223 higher than their counterparts from

2008 to 2014, respectively. The purpose of this study was to evaluate the average treatment effects in aggregated TIF designation level. Therefore, although the Skillman Corridor TIF district was more affluent and experienced a higher appreciation on its housing value growth than other TIF neighborhoods, combining Pair 2 and Pair 3 would not lead to different results.

In summary, according to the literature review, to examine the causal effect of TIF developments, three criteria needed to be satisfied. This study used longitudinal data to ensure that: (1) the ‘cause’ (e.g. TIF designation) precedes the ‘effect’ (e.g. housing value growth) (sufficient time lag of 6 years was considered for TIF effects to occur on housing value growth), (2) the ‘cause’ covaries with the effect (significant associations between the causes and the effects were examined in Table 2-5 and Table 2-7), (3) alternative explanations for the causal relationship are implausible (the major observable confounding factors were controlled).

The results also supported the hypotheses presented earlier. In terms of Hypotheses 1 and 2, this study has found that the SF homes in TIF neighborhoods had a significantly higher housing value growth and significantly higher Walk Score, compared to their counterparts in comparison neighborhoods. In terms of average treatment effects of TIF developments on housing value growth, this study has shown that on average, the overall TIF effects accounted for $27,840 (or 95.6%) more on average SF housing value growth during 2008-2014, while the observed structural attributes and residential location only accounted for $1,267 (or 4.4%) more on value growth. In terms of destination accessibility measured by Walk Score, the overall TIF effects accounted for 8 additional points on average Walk Score, while the confounding influences only accounted for 2 additional points.

2.5 Discussions and Conclusion

2.5.1 Discussions

Overall, research examining the effects of TIF related to economic benefits and destination accessibility is still underdeveloped. Findings from previous studies regarding the TIF effects on housing value growth have been inconsistent (Byrne, 2006; Man & Rosentraub, 1998; Merriman et al., 2011; Smith, 2006; Weber et al., 2007). The existing studies on TIF still focused on the economic and financial perspectives, and rarely addressed other important dimensions such as walkability which can bring important health and transportation benefits. There was no study simultaneously examining the economic benefits and walkability (destination accessibility) expected from TIF developments. TIF is one of the commonly employed implementation tool for smart growth developments and it is important to explore the actual effects of smart growth practices. Economic benefits and walkability are two major goals that smart growth applications aim to achieve. Limitations in research design, measurement, and data collection obstruct the comparability and transferability of such analysis. This study provided additional evidence regarding to the magnitude and causal direction of the benefits of TIF programs can greatly enhance and promote the practicability of smart growth applications.

TIF developments have been recognized as one of the most effective implementation tools with great potential to redevelop and revitalize the recession of urban areas from municipal standpoint and has been carried out in a thousand times during last five decades. Also, this study empirically demonstrated the economic and destination accessibility benefits due to the TIF developments. However, this tool still has long been criticized to be abused as corporate welfare for wealthy developers, politically motivated giveaways, or risky public funds on an uncertain real estate market (Versel, 2012). Other arguments stated the TIF spillover effects burdened the public services in nearby neighborhoods without reimbursement, while the redevelopment itself drove out lower-income people leading to gentrification (Lefcoe, 2011; Thompson, 2014). Downs listed eight major problems that might hinder the implementation of smart growth principles, and most of the cases also applied to TIF implement (Downs, 2005)

(1) Redistributing benefits and costs of development;

(2) Shifting power and authority from community to local/regional level;

(3) Increasing residential density;

(4) Raising housing prices

(5) Failing to reduce traffic congestion

(6) Increasing the "Red Tape" of New Development

(7) Restricting profits for owners of outlying land

(8) Replacing "Disjointed Incrementalism" with regional planning

There is always a dilemma to balance pros and cons for implementing the neighborhood redevelopment projects. This study suggested three possible ways to minimize these conflicts that might appear in TIF projects:

First, substantial works should be prepared before the launch of TIF projects, to reconcile the costs and benefits, services and allowances, and obligations and reliabilities among local governments and districts, private developers, neighborhood associations, and local residents, since the well-established public-private partnerships hold the key to successful urban revitalization.

Second, local governments need to carefully apply the TIF tool appropriately to the neighborhoods where the need is greatest, in order to avoid the overuse of TIF that incur a bad reputation associated with political favoritism. The original purpose of TIF developments was to relieve the blighted neighborhoods. In this study, a similar situation was also found that TIF might not relocate the funds to the most needed place (e.g. one substantially affluent neighborhood was supported by TIF developments).

Third, local governments should pay more attention to keep the housing affordable for residents living or hoping to live in TIF neighborhoods. Although most TIF projects claimed the housing affordability as one of the goals, it conflicted with the economic development purpose. Obviously it was difficult to pursue affordable housing and economic development simultaneously. Indeed, the success of TIF projects do raise the prices of existing housing units, and the quality of TIF can be considered as an advantage from the viewpoint of homeowners seeking greater wealth in their home equities. However, the housing value growth drove out the lower-income people who lived or want to move into these neighborhoods. Local governments should supervise the private sectors to implement affordable housing projects that are associated with TIF developments more efficiently. In this study, high density of non-SF units in several TIF designations indicated Dallas TIF projects do provide a range of housing opportunities.

2.5.2 Limitations

This study has four limitations. First, this study only considered the average treatment effect among the TIF districts, without capturing the variation within individual TIFs. Topic 3 of this dissertation will use the hierarchical linear model to consider the variation of TIF effects on housing values based on the TIF performance. Second, the limitation related to data availability should be noted. For example, variables had slight variations in their time frame due to data availability; also there was no time-series data for Walk Score. Third, the selection of correlates of housing value in both neighborhood level and parcel level relied on the findings from previous studies and data availability. It is possible that there are additional unobserved confounding influences, which might have caused to overestimate the causal effect of TIF developments on the housing value outcomes. Fourth, 7 TIF districts were excluded from this study due to no matching controls that could be identified. Also, the non-SF house category was also excluded due to the inability to identify appropriate matches in comparison neighborhoods. Hence, this study could not capture the TIF effects on SF homes in these particular TIF districts or on non-SF houses. However, Topic 3 would address this issue by including these excluded samples in the Hedonic Price Models. In addition, high density of non-SF units in several TIF designations also indicated TIFs do provide a range of housing opportunities.

2.5.3 Conclusion

In this study, I estimated the causal effects of Dallas TIF developments on SF housing value growth and their destination accessibility. I found that the overall TIF effects accounted for $27,840 (or 95.6%) more on average SF housing value growth during 2008-2014, while the observed structural attributes and residential location only accounted for $1,267 (or 4.4%) on value growth. In terms of destination accessibility, the overall TIF effects accounted for 8 additional points (on a 100-point scale) on Walk Score, while the confounding influences only accounted for 2 points. The results suggested that TIF developments do stimulate housing value growth through providing various built environmental improvements, while providing more walkable environments by increasing accessibility to routine destinations.

Existing evidence on the economic benefits and walkability of TIF developments were inconsistent and limited. This study added to this body of literature by providing new evidence to support the significant role of TIF programs in increasing SF housing value growth and destination accessibility simultaneously. The key question is how to apply this tool appropriately to the neighborhoods where the need is greatest. There have been arguments that TIF is somewhat overused and has become associated with political favoritism. The spillover effects of TIF burden the public services in nearby neighborhoods without reimbursement, while the redevelopment itself drives out lower-income people leading to gentrification. However, in the current era of economic uncertainty and fiscal constraints, TIF is still a powerful tool to deliver a stronger local economic future, while improving the built environments to promote active living and sustainable communities for urban residents.

This study supports TIF programs as an effective mechanism for increasing the economic vitality while improving the overall walkable environments in urban communities. It offered methodological insights to guide the selection of appropriate analytical approaches to conduct matching in both neighborhood level and parcel level, by applying a quasi-experimental design and propensity score matching to establish the causal inference and increase internal validity of the results. The findings also suggested a beneficial extension of the existing literature on smart growth, and these results provided evidence to support local governments, policy makers, and planers for implementing TIF as a way to improve existing urban neighborhoods and to implement smart growth principles at the neighborhood level.

CHAPTER III

IMPACT OF TAX INCREMENT FINANCING DEVELOPMENTS ON ACTIVE COMMUTING BEHAVIOR: A SOCIAL ECOLOGICAL APPROACH

3.1 Introduction

3.1.1 Background

Walking and bicycling are two of the most common forms of physical activity that people choose for health-related, recreational, or transportation purposes. Two largely separate bodies of literature documented the benefits of walking and bicycling from different perspectives. In the physical activity literatures, walking and bicycling have been studied to demonstrate the significant health benefits, such as preventing or reducing the risk of developing obesity (Ewing et al., 2008; McCormack & Shiell, 2011), cardiovascular disease (Ahmed et al., 2012; Pucher & Buehler, 2006), and mental health disorders (Dunn & Jewell, 2010; Paluska & Schwenk, 2000). The Centers for Disease Control and Prevention (CDC) announced that "adults who engage in at least 150 min of moderate-intensity aerobic activity (e.g. walking and bicycling) a week are more likely to obtain greater health benefits than individuals who do not engage".[14] In other body of transportation/planning literature, walking and bicycling have been considered as non-motorized modes of transportation to reach destinations (e.g. shopping, work), which can bring various environmental and economic benefits such as

[14] Centers for Disease Control and Prevention, 2008 Physical Activity Guidelines for Americans, retrieved April, 2015, from http://www.health.gov/paguidelines/guidelines

reducing carbon emission, if some of those trips replace existing automobile trips air pollution, and climate change (Frank, Greenwald, et al., 2010; Maibach et al., 2009), in additional to reducing auto/energy dependence and traffic congestion (Giles-Corti et al., 2010; Sallis et al., 2004).

Active commuting can provide health-related, environmental and economic benefits to both the users and the general public. It is necessary to understand the factors influencing active commuting behavior. A growing body of studies has utilized the socio-ecological model to investigate the multi-level influences of personal, social, and built environmental factors on active commute (Giles-Corti & Donovan, 2002; Giles-Corti et al., 2005; Saelens et al., 2003; Yu, 2014; Zhu et al., 2008). A number of studies have examined the effect of the specific characteristics of built environment on non-motorized travel behavior at a disaggregate level. These studies found that communities with high population and road densities, street connectivity, mixed land uses, transit access, and complete non-motorized infrastructure produced more non-motorized transport mode users (McCormack & Shiell, 2011; Saelens & Handy, 2008; Saelens et al., 2003). Inconsistent findings were also found that the distance to destinations was the most important factor for active transportation, while built environment alone cannot promote active transportation. However, built environmental features still plays an important role influencing one’s decision to walk or bicycle often as a barrier (S. Handy et al., 2006; Saelens et al., 2003).

3.1.2 Significance

Previous studies on the built environmental and active travel relationships have reported both consistent and inconsistent findings depending on study community setting, socioeconomic status, and travel distance or time (Saelens & Handy, 2008; Saelens et al., 2003). Most prior research examined the built environmental correlates to active transportation without considering the interrelations of personal effect, neighborhood effect, and other travel factors (e.g. travel time, travel distance). Few studies, however, simultaneously examined the impacts of these factors on active transportation using aggregated measurements among neighborhoods with diverse socioeconomic characteristics and built environmental elements, such as walkable neighborhood vs. less walkable neighborhood, or new urbanist neighborhood vs. conventional neighborhoods. Moreover, most empirical studies placed a strong emphasis on the statistical significance of the effects, while placing little emphasis on the substantive magnitude of the significant effects.

In response to the continuing development of the smart growth movement and the concept of new urbanism to inhibit the issues of urban sprawl and to shape the built environment to reduce automobile dependency, this study developed an adapted socio-ecological framework to compare the interrelations of personal, neighborhood, and built environmental effects on active commuting in TIF neighborhoods and non-TIF neighborhoods in the City of Dallas. Following the smart growth principles, TIF programs are community redevelopment practices conducted by local governments to retrofit compact, walkable, transit-oriented, and mixed use developments in distressed areas where the changes would not likely occur without such governmental intervention. This study examines the significance and magnitude of personal, neighborhood and built environmental impacts on active commuting in both TIF and non-TIF neighborhoods.

3.1.3 Objectives, Conceptual Framework and Hypotheses

3.1.3.1 Objective and Conceptual Framework

I proposed an adapted socio-ecological framework to estimate the interrelations of personal, neighborhood, and built environmental factors that influence active commuting (walking and bicycling) to work in both TIF neighborhoods and non-TIF neighborhoods in the City of Dallas. I utilized fractional logit models with robust standard errors to adjust for potential correlations across different factors. I also calculated the average effects of each factor on active commuting by estimating the marginal effects. Margin plots were utilized to draw the interrelations of personal, neighborhood, and built environmental effects on active commuting.

The original socio-ecological framework often applied in travel behavior studies does not include the neighborhood factors. Social factor (e.g. social support, social engagement, peers' attitude) are often captured as subjective measures from individuals, but are not available for this study that use the Census block group data. Therefore, neighborhood factors (e.g. residential density, employment, traffic crash rate) were used to replace social factors in this study as previous studies suggested (Saelens et al., 2003; Yu, 2014).

Figure 3-1 is the conceptual framework developed to illustrate the interrelations of personal, neighborhood, and built environmental factors that influence active commuting. Travel time is a critical control as well as a moderator variable that affects the strength of the relationships between predictor variables and dependent variable.

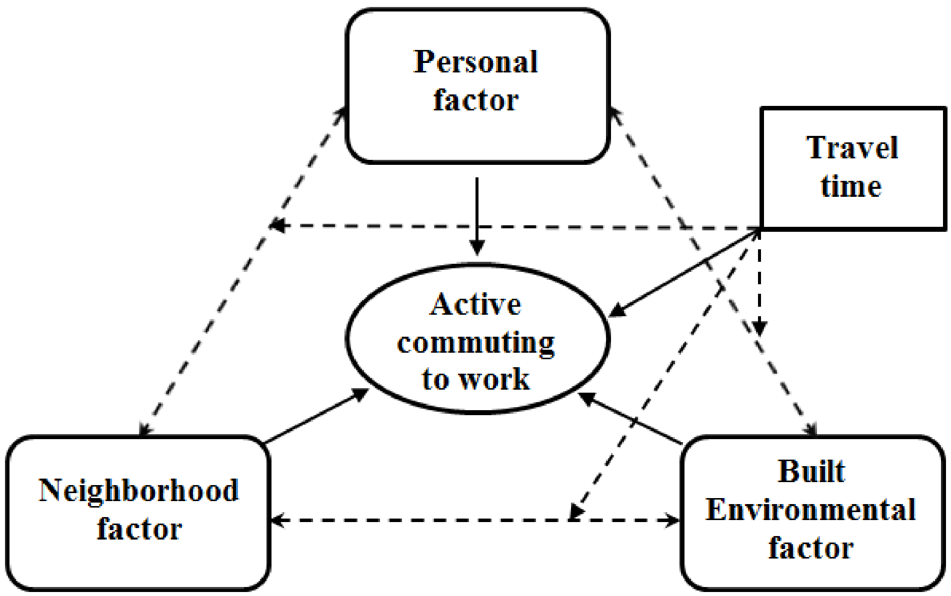


Figure 3-1. Socio-ecological framework for analyzing personal, neighborhood, built environmental, and travel effects on active commuting to work

3.1.3.2 Hypotheses

In an effort to examine if the hypotheses that activity-friendly built environmental features can help to reduce automobile travel and increase active commuting to work, two hypotheses are developed.

Hypothesis 1: Built environmental factors are positively associated with active commuting to work in TIF neighborhoods;

Hypothesis 2: Non-TIF neighborhoods are less walkable, and the relationships between built environmental factors and active commuting to work are less significant or neutral, compared to TIF neighborhoods. Further, the travel time and personal factors account for the most of effects on active commuting to work in non-TIF neighborhoods.

3.2 Literature Review

Complementing the literature review provided in Chapter 1 that offered a brief review of the general literature, this section focuses on the specific body of literature relevant to this study.

3.2.1 Research Designs and Measurements of Previous Studies

Based on the three thorough literature reviews, most previous studies used a cross-sectional design to examine the relationship between walking/bicycling and built environmental factors (McCormack & Shiell, 2011; Saelens & Handy, 2008; Saelens et al., 2003). The majority of studies were undertaken in the US, and approximately one third of the studies used public use surveys (e.g. national travel survey, census) and the remaining two-thirds conducted their own surveys. Among these studies, walking and bicycling variables were assessed ranging from travel to a specific location, to a specific type of travel (e.g. transportation walking, recreational walking), to total or general walking and bicycling behaviors. Most studies included socio-demographic factors as covariates. Few studies, however, examined personal, social/neighborhood, and built environmental factors together (McCormack & Shiell, 2011; Saelens & Handy, 2008; Saelens et al., 2003).

The Socio-Ecological Framework was developed to understand the dynamic interrelations (interacting, interrelated, or interdependent relationship) among various personal and environmental factors, often to study their influences on health-related behavior. Recently, socio-ecological approaches have become popular in physical activity research, facilitating the investigation of the multi-level influences that personal, social, and built environmental factors have on physical activity behaviors (Giles-Corti & Donovan, 2002; Giles-Corti et al., 2005; Saelens et al., 2003; Yu, 2014; Zhu et al., 2008). This study employed marginal plots to show the interrelated relationship among these factors.

In terms of measurements, most studies have quantified personal and environmental factors at the micro-level, often captured from surveys asking about personal characteristics and perceptions of their neighborhood environment (neighborhood often defined as an area walkable, e.g. 10-20-minute walking distance, from home). However, these measurements could be challenged because of (1) the different strategies used to evaluate perceived environmental factors, (2) the lack of information about how individuals may actually define their neighborhood despite given instructions, and (3) the potential problems of spatial dependence caused by the fact that households within the same neighborhood sharing the same built environmental characteristics (Saelens & Handy, 2008).

Some studies utilized objective measures to assess the neighborhood environment by incorporating ArcGIS and census data to measure population density, street connectivity, sidewalk completeness, personal safety and traffic safety, accessibility to variety of destinations and amenities, and land use mix, etc. These measures were usually taken at an aggregated spatial unit (e.g. block groups, census tracts, cities), which provided greater diversity in the personal and built environmental factors studied in neighborhood or regional level rather than individual level, with more specific and diverse samples of demographic variables (e.g. race, ethnicity, occupancy rate, income, education).

In terms of objective measurements, Cervero and Kockelman proposed the 3Ds (density, diversity, and design) framework in 1997 to guide the measurement of neighborhood and environmental factors related to travel mode choice (Cervero & Kockelman, 1997). Subsequently, a few articles further elaborated his 3Ds approach and included additional domains (Ewing et al., 2014; Frank, Sallis, et al., 2010; Lee & Moudon, 2006a). Lee and Moudon devised the 3Ds + R (density, diversity, and design + route) concept to quantify land use and urban form variables specifically for capturing walkability (Lee & Moudon, 2006a). Ewing et al. developed the 5Ds (density, diversity, design, destination accessibility, distance to transit) model to measure the varying influences of built environment on travel behaviors (Ewing et al., 2014). Frank and colleagues proposed a walkability index to measure the walkability from the neighborhood to the regional level, which included four domains: residential density, commercial density, land use mix, and street connectivity (Frank, Sallis, et al., 2010).

3.2.2 Research Methods of Previous Studies

It was difficult to synthesize the research methods from previous empirical studies because they differed significantly in terms of study designs (e.g. cross-sectional vs. quasi-experimental), study settings and population (e.g. individual based vs. community/regional based), data structure (e.g. dependent variables measured in continuous vs. in dichotomous/categorical), factors examined (e.g. individual vs. composite), measurements (e.g. objective vs. subjective), analysis structure (e.g. bivariate vs. multi-level), and statistical models (e.g. OLS vs. logistic, etc.) . The lack of more complete and relevant conceptual models also resulted in the inconsistent and ambiguous methodological approaches used in previous studies.

Most studies did not consider the causality and its affiliated self-selection issues in examining the relationships between physical activity and built environment, because it requires costly and complex causal design as well as the longitudinal data and rigorous quantitative approaches. Cross-sectional studies have been criticized for their failure to account for neighborhood self-selection, which would likely inflate the associations between physical activity and built environment (Boone-Heinonen et al., 2011; McCormack & Shiell, 2011; Saelens & Handy, 2008). Nevertheless, self-selection issues still can be somewhat adjusted in cross-sectional studies using methods such as direct questioning, statistical control, sample selection models, structural equation models, and quasi-experimental design, in order to reduce bias in estimating associations of personal, neighborhood, or built environmental factors with physical activity (McCormack & Shiell, 2011; Mokhtarian & Cao, 2008).

This study used fractional logit model to account for variation across the block groups by involving personal, neighborhood, built environmental and travel factors; robust standard errors were also applied to adjust for potential correlations across these factors to reduce the potential biases. This study also examined the marginal effects which explain the partial effect of each factor on active commuting; this also helped to reduce the biases.

3.2.3 Findings from Previous Studies

This study focuses on active (walking and bicycling) commuting to work. Previous studies have identified two dominant factors that influence non-motorized transportation, which were travel distance and street connectivity (Frank, 2000; Saelens et al., 2003). Most studies using objective or subjective measures found negative impacts of longer travel distance or travel time on active commuting. However, the findings about impacts of street connectivity, which included road density and street intersection density, were still somewhat ambiguous. Saelens and handy summarized transportation walking literature and concluded that consistent positive relationships were found between walking for transportation and density, distance to non-residential destinations, and land use mix, while the relationship between walking for transportation and route/network connectivity, parks and open space, and personal safety were equivocal (Saelens & Handy, 2008).

Personal factors influencing physical activity have been studied broadly in public health literature, and the results have been shown to vary depending on the type of activity carried out for various purposes such as transportation, recreation, or exercise. Trost reviewed 38 studies examining the personal, social, or environmental factors associated with physical activity in adults, and found that physical activity participation was consistently higher in men than in women and inversely associated with age. He also found in most studies that income, occupational status and educational attainment were also positively associated with physical activity, and race/ethnicity (nonwhite) was negatively associated with physical activity (Trost et al., 2002). Yu found that areas with high poverty rates had more walking and biking trips to work, while areas with a high percentage of white population generated more walking trips in the city of Austin census tract level (Yu, 2014). Other transportation scholars also found that low-income and minority groups were more likely to walk to transit stations and more likely to attain the recommended level of daily physical activity if the public transits were accessible by walking (Besser & Dannenberg, 2005; Freeland et al., 2013).

3.2.4 Summary

In sum, while certain correlates appear to have fairly consistent relationships with active commuting such as travel time and ethnicity, inconsistencies have also been reported in terms of personal, neighborhood and built environmental impacts on active transportation due to different study settings and different purposes of physical activities studied. The two primary purposes of this study are to (1) concurrently examine the effect of personal, neighborhood, and built environmental factors on active commuting to work, and (2) compare and quantify their associations between TIF and non-TIF neighborhoods, in the City of Dallas, Texas.

3.3 Methods

3.3.1 Study Design and Setting

This was a cross-sectional study. The city of Dallas was chosen as the study area because (1) the city of Dallas is a typical auto-dependent city with sprawled boundary and its Walk Score is 44, which is the 23rd most walkable large city in the US;[15] (2) its variability in development patterns, with 18 TIF districts containing more walkable environments (46.8% sidewalk completeness, 0.314 street intersection density, and 0.54 land use mix, on average) vs. other block groups with less walkable environments (19.8% sidewalk completeness, 0.221 intersection density, and 0.408 land use mix, correspondingly); (3) the city's diverse income levels and ethnicity profiles across block groups, with the average median household income ranging from less than $10,000 to over $200,000 and the percentage of Hispanic population ranging from 0 to 98.2%; and (4) the availability of rich GIS datasets, including various parcel level land use data and street level data.

The unit of analysis of this study is the Census block group. Block group is the smallest unit with comprehensive socio-demographic data and travel data. Based on the 2010 Census data, there were 855 block groups within the boundary of the Dallas city limit. After removing five block groups with missing population and income data, 850 block groups were analyzed. There are 18 active TIF districts and the latest TIF was established in 2009. According to the GIS analysis, there were 183 block groups intersecting with the 18 TIFs. After removing the block groups that only touched the boundary of TIF districts, 116 block groups completely or partially within TIF districts were identified. Therefore, the 116 block groups were defined as TIF neighborhoods and the remaining 734 block groups were defined as non-TIF neighborhoods. A dummy

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[15] Walk Score, retrieved April, 2015, from https://www.walkscore.com/TX/Dallas

variable (0/1) was created to represent whether the block group was a TIF block group or not. Figure 3-2 displays the active commuting mode share in all Dallas block groups and TIF block groups.

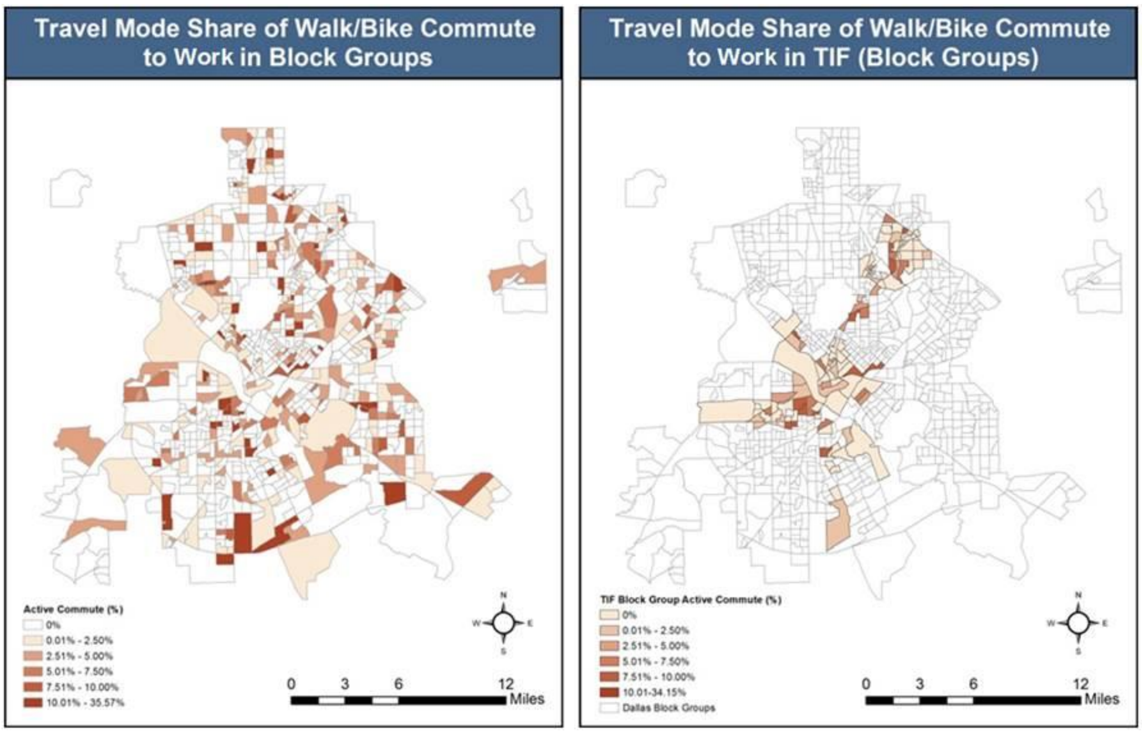

Figure 3-2: Graduated color maps for active commuting mode share in all Dallas block groups and TIF block groups

3.3.2 Variables and Measurements

This study used the percentage of workers (age 16 years or older) who either walked or biked to work in each block group as the dependent variable. The data were gathered from the 2008-2012 American Community Survey (ACS) 5-year estimates (Means of Transportation to Work section) and coded as a fraction ranging from 0-1.

The average percentage of workers who actively commutes to work in Dallas block groups was 1.8%, with a maximum value of 35.6% and minimum of 0%.

In terms of control and independent variables, four domains including travel time, personal factors, neighborhood factors, and built environmental factors are included. Travel distance is the most important factor determining active commuting behavior. Since the travel distance data were not available, I utilized travel time as the proxy. Travel time variable was calculated as the percentage of workers whose travel time to work was less than 20 minutes (included all travel modes). The logic is, if the travel time is than less than 20 minutes (which is equivalent to one mile walking distance), people are more likely to walk or bike to work (Pisarski, 2006; Walker, 2011). The average percentage of population whose travel time is less than 20 minutes in all block groups was 37.5%, with a maximum value of 80.7%, and minimum of 0%.

The personal factors included five aggregative socio-demographic data in block group level. Race, ethnicity, occupancy rate and education were measured by the average percentage of white population, Hispanic or Latino population, occupied housing units and undereducated population and the income was measured as the average median household income. All the personal variables were gathered from 2010 Census SF1 and 2008-2012 ACS. In terms of neighborhood factors, ArcGIS was utilized to calculate residential density, employment count, and pedestrians and bicyclists involved in traffic crashes in each block group. The employment data were based on the 2011 business employment data to aggregate employees from each business in point shapes, which were downloaded from "On the Map" and analyzed in ArcGIS.[16] The crash data were acquired from Texas Department of Transportation and geocoded in ArcGIS.

In terms of built environmental variables, the 3Ds (density, diversity, and design) framework (Cervero & Kockelman, 1997) and walkability index (Frank, Sallis, et al., 2010) were utilized to guide the variable selection and measurements. Density was measured by road density, street intersection density, transit stop density, retail floor area ratio, and industrial density. Diversity was measured by land use mix. Design was measured by sidewalk completeness, bike lane completeness, and average speed limit. All built environmental variables were collected from Dallas Planning Office and Dallas Central Appraisal district, and calculated in ArcGIS. Table 3-1 shows the definition, measurements, descriptive statistics, and data source of the study variables.

Table 3-1. The definition, measurements, descriptive statistics, and data source of study variables

Variable List	Measurement Methods	Mean (SD) Min.-Max.	Data Source and Time Period
Dependent variables			
Active commuting	Percentage of workers (aged 16 years or older) who walked or biked to work/Number of workers	0.018 (0.039) 0 – 0.356	08-12 ACS 5-years estimates
Control variables			
TIF	TIF block group or non-TIF block group (binary, 1/0)	0.136 (0.343) 0 - 1	Dallas ED, 2014
Travel time	Percentage of workers whose travel time to work was less than 20 minutes (%)	37.502 (15.448) 0 – 80.690	08-12 ACS 5-years estimates

[16] On the Map, retrieved April, 2015, from http://onthemap.ces.census.gov/

Table 3-1. Continued.

Variable List	Measurement Methods	Mean (SD) Min.-Max.	Data Source and Time Period
Independent variables			
Personal Factors			
White race	Percentage of White population (without Hispanic or Latinos origin) (%)	32.500 (30.819) 0 - 97.955	2010 US Census
Latino ethnicity	Percentage of Hispanic or Latinos population (%)	38.695 (28.737) 0 - 98.210	2010 US Census
Income	Average median household income ($)	54,922 (41,108) 9,745- 250,001	08-12 ACS 5-years estimates
Occupancy rate	Percentage of occupied housing units (%)	89.635 (7.612) 0 - 100	08-12 ACS 5-years estimates
Education	Percentage of age in 25 and over under high school education (%)	25.849 (21.003) 0 - 88.594	08-12 ACS 5-years estimates
Neighborhood Factors			
Residential density	Number of population/residential area in acres	34.677 (52.035) 1.005 - 583.341	2010 US Census Dallas CAD, 2014
Employment	Number of employment in each block group	876 (3791) 0 - 59002	On The Map, 2011
Crash	Number of pedestrians or cyclists involved crashes in each block group	3.131 (4.939) 0 - 69	Texas DOT, 2010-2014
Built Environmental Factors			
Sidewalk completeness	Total miles of sidewalks/total miles of streets	0.235 (0.341) 0 – 0.988	Dallas planning office, 2008-2014
Bike Lane completeness	Total miles of bike lanes/total miles of streets	0.226 (0.210) 0 – 0.921	
Road density	Total miles of streets/total area (square mile)	20.341 (7.418) 0.021 - 50.374	
Intersection density	Number of street intersections (≥3)/total area (acres)	0.234 (0.131) 0 – 0.967	
Average speed limit	Average speed limit within the block group	28.472 (4.206) 1 - 51.204	
Transit stop density	Number of transit stops (sum of light rail station and bus stops)/total area (acres)	0.062 (0.054) 0 – 0.515	
Retail floor area ratio	Total net lease area/total commercial land area	0.360 (0.512) 0 – 8.094	Dallas CAD, 2014
Industrial density	Area of industrial land use/area of block group	0.005 (0.031) 0 - 0.581	
Land use mix	The evenness of residential, commercial, and office uses	0.425 (0.260) 0 – 0.998	

Note:

1. Dallas ED = Dallas Economic Development Department, Texas DOT = Texas Department of Transportation, Dallas CAD = Dallas Central Appraisal district;
2. The land-use mix was calculated based on the equation: (-1) * [(area of R/total area of R, C, and O) * ln(area of R/total area of R, C, and O) + (area of C/total area of R, C, and O) * ln (area of C/total area of R, C, and O) + (area of O/total area of R, C, and O) * ln (area of O/total area of R, C, and O)] / ln (number of land uses present).

3.3.3 Data Analysis

When modeling a dependent variable representing a proportion or fraction, the bounded nature should be taken into account. A linear probability model on fractional data will generate predictions outside the unit interval. Therefore, using a proportion in a linear regression model will generally yield nonsensical predictions for extreme values of the regression (Baum, 2008). To deal with the limited outcomes of continuous fractions between [0, 1], the fractional logit model was developed by Papke and Wooldridge (Papke & Wooldridge, 1996). Another advantage of using a fractional logit model over other approaches is that it allows recovery of the marginal effects of interest, which resembles a good approximation of the amount of change in the dependent variable produced by a 1-unit of conditional mean change in independent variables; other approaches such as semi-log regression on dependent regression cannot estimate marginal effects (McDonald et al., 2014; Papke & Wooldridge, 1996; Williams, 2011).

In the analysis, first, I created three fractional logit models to estimate the effects of personal, neighborhood, and built environmental factors on active commuting to work among all Dallas block groups, TIF block groups, and non-TIF block groups, respectively. The models were estimated with STATA using generalized linear models with the logit link function and binomial distribution, and robust standard errors were also estimated to adjust for potential correlations across different variables. Second, I calculated the average effects of each factor on active commuting by estimating the marginal effects at the mean (MEMs). The marginal effect is a partial effect or discrete effect measured based on the relevant slope coefficient. Last, I generated the margin plots to reflect the predictive interrelations of personal, neighborhood, and built environmental effects on active commuting to work.

Normalized measurements were applied to all built environmental variables when using marginal effects to represent the amount of change in active commuting based on one percentage change of each built environmental variable. The percentage change of a built environmental variable was calculated based on the mean and marginal effect of each variable. For instance, if one unit change in sidewalk completeness reflected a marginal effect of 0.017, and the mean of sidewalk completeness was 0.468, the normalized values of marginal effect for each one percentage change in sidewalk completeness would be $0.017 \div (1 \div 0.468 \times 100) = 0.008\%$. Because of the varying sizes and measurements among different built environmental variables, this method simplifies the comparisons of marginal effects on built environmental variables by using normalized values.

Table 3-2 displays descriptive statistics and bivariate tests for the total block group, TIF block group and non-TIF block group samples. For active commuting, TIF samples have an average of 2.6% of the population who walked or biked to work, which is 0.9% higher than non-TIF samples (1.7%). In terms of personal factors, TIF samples have a higher percentage of white population and occupancy rate and a higher average median income, with a lower percentage of Hispanic or Latino population and undereducated population, as compared to non-TIF samples. For neighborhood factors, the average value of residential density, employment, and crash in TIF samples was much higher than non-TIF samples, which implied a higher population density and social activity. In terms of built environmental factors, all variables in TIF block groups have higher average values than non-TIF block groups except industrial density, which indicated TIF neighborhoods generally have more walkable environments. The t test indicated that the neighborhood factors and built environmental factors were significantly different between TIF samples and non-TIF samples. In terms of personal factors, significant differences existed in race, ethnicity, and income.

Table 3-2. The descriptive statistics and bivariate test for total samples, TIF samples and non-TIF samples

Bivariate Test	Total Sample	TIF Block Group	Non-TIF Block Group	TIF vs. Non-TIF
	Mean (SD) Min.-Max.	Mean (SD) Min.-Max.	Mean (SD) Min.-Max.	*t* Test
Dependent variables				
Active commuting	0.018 (0.039) 0 – 0.356	0.026 (0.053) 0 - 0.341	0.017 (0.036) 0 - 0.356	1.717
Control variables				
Travel time less than 20 minutes (%)	37.502 (15.448) 0 – 80.690	39.404 (15.017) 0 - 77.840	37.202 (15.504) 0 - 80.690	1.427
Independent variables				
Personal Factors				
White race (%)	32.500 (30.819) 0 - 97.955	39.261 (32.429) 0.467 - 95.829	31.432 (30.464) 0 - 97.95	2.436*
Latino ethnicity (%)	38.695 (28.737) 0 - 98.210	33.110 (28.474) 1.594 - 97.651	39.578 (28.718) 0 - 98.210	-2.257*
Income ($)	54,922 (41,108) 9,745- 250,001	63,705 (47,908) 10,333 - 250,001	53,534 (39,816) 9,745 - 250,001	2.171*
Occupancy rate (%)	89.635 (7.612) 0 - 100	90.004 (7.006) 61.080 - 98.489	89.576 (7.711) 0 – 100	0.562
Education (%)	25.849 (21.003) 0 - 88.594	22.720 (22.375) 0 - 88.594	26.343 (20.766) 0 - 85.032	-1.728
neighborhood Factors				
Residential density	34.677 (52.035) 1.005 - 583.341	64.413 (99.581) 3.000 - 583.341	29.978 (37.709) 1.005 - 410.374	3.683**
Employment	876 (3791) 0 - 59002	2614 (7016) 0 - 55215	602 (2896) 0 - 59002	3.048**
Crash (pedestrians or cyclists involved)	3.131 (4.939) 0 - 69	6.250 (9.373) 0 - 69	2.638 (3.566) 0 - 50	4.104**

Table 3-2. Continued.

Bivariate Test	Total Sample	TIF Block Group	Non-TIF Block Group	TIF vs. Non-TIF
	Mean (SD) Min.-Max.	Mean (SD) Min.-Max.	Mean (SD) Min.-Max.	*t* Test
Built Environmental Factors				
Sidewalk completeness	0.235 (0.341) 0 – 0.988	0.468 (0.599) 0 – 0.988	0.198 (0.262) 0 – 0.909	10.454**
Bike Lane completeness	0.226 (0.210) 0 – 0.921	0.300 (0.216) 0 – 0.828	0.214 (0.207) 0 – 0.921	4.124**
Road density	20.341 (7.418) 0.021 - 50.374	23.217 (8.823) 2.098 - 50.374	19.887 (7.072) 0.021 - 44.163	3.874**
Intersection density	0.234 (0.131) 0.000 – 0.967	0.314 (0.188) 0.005 - 0.967	0.221 (0.114) 0.000 – 0.752	4.764**
Average speed limit	28.472 (4.206) 1 - 51.204	29.284 (3.853) 17.837 - 41.517	28.343 (4.250) 1 - 51.204	2.243*
Transit stop density	0.062 (0.054) 0 – 0.515	0.100 (0.081) 0 - 0.515	0.055 (0.045) 0 - 0.277	5.829**
Retail floor area ratio	0.360 (0.512) 0 – 8.094	0.583 (1.132) 0 - 8.094	0.240 (0.223) 0 - 1.992	3.252**
Industrial density	0.005 (0.031) 0 - 0.581	0.004 (0.013) 0 - 0.089	0.005 (0.033) 0 - 0.581	-0.173
Land use mix	0.425 (0.260) 0 – 0.998	0.535 (0.272) 0 - 0.993	0.408 (0.254) 0 - 0.998	4.949**
N (Sample Size)	850	116	734	

*: p<0.05 / **: p<0.01

Note: Refer to Table 3-1 for the information on the variable definition and measurement unit

3.4 Results

3.4.1 The Predictive Marginal Effects of Personal, Neighborhood, and Built Environmental Factors on Active Commuting to Work

Table 3-3 presents coefficients generated from the fractional logit models and marginal effects generated from the MEMs. In this section, I only discuss the marginal effects for each variable to simplify the explanation of significant effects.

Table 3-3. Coefficients and marginal effects of study variables on active commuting to work in Dallas total block groups, TIF only block groups, and non-TIF block groups

Bivariate Test	Model 1: Dallas Total Block Groups		Model 2: TIF Only Block Groups		Model 3: Non-TIF Block Groups	
	Coefficient	Marginal effect	Coefficient	Marginal effect	Coefficient	Marginal effect
Control Factor						
Block Group (ref. = Non-TIF)	0.553*	0.010*	n/a	n/a	n/a	n/a
% Travel time < 20Mins (×10)	0.291**	0.004**	0.313*	0.005*	0.323**	0.004**
Personal Factors						
White race (×10)	0.082	0.001	0.025	0.001	0.010*	0.001*
Latino ethnicity (×10)	-0.117*	-0.002*	-0.346**	-0.005**	-0.009*	-0.001*
Income (×$10,000)	-0.140**	-0.002**	-0.045	-0.001	-0.018**	-0.002**
Occupancy rate (×10)	-0.206*	-0.003*	-0.489*	-0.007*	-0.020*	-0.003*
Education (×10)	0.147*	0.002*	0.359*	0.005*	0.010	0.001
neighborhood Factors						
Residential density (×1000)	-0.324	0.005	-1.316	0.020	0.003*	0.038*
Employment (×10000)	-0.100	0.001	0.180	0.001	-0.060	0.001
Crash	0.002	0.001	-0.0131	-0.001	0.006	0.001
BE Factors						
Sidewalk completeness	0.453	-0.006	1.130*	0.017*	0.110	-0.001
Bike Lane completeness	0.163	0.002	1.548	0.023	-0.268	-0.003
Road density (×10)	0.420*	0.006*	1.540**	0.023**	0.172	0.002
Intersection density	1.996	0.028	8.241**	0.123**	0.024	0.001
Average speed limit	0.002	0.001	-0.149*	-0.002*	0.024	-0.001
Transit stop density	1.500	0.021	3.939	0.059	-0.630	-0.008
Retail floor area ratio	-0.066	-0.001	0.081	0.001	-0.774	-0.010
Industrial density	-2.999	-0.042	-22.352	-0.334	-1.903	-0.025
Land use mix	-0.054	-0.001	-0.195	-0.003	-0.094	-0.001
No. observations	850		116		734	
Pseudo LL	-59.525		-9.884		-48.473	
AIC	0.187		0.498		0.184	
BIC	-5562.036		-455.571		-4689.286	

*: p<0.05 / **: p<0.01

Note: Refer to Table 3-1 for the information on the variable definition and measurement unit

3.4.1.1 Findings from Model 1 (All Block Groups)

From Model 1, the marginal effect of TIF block groups on active commuting was 0.01 ($p < 0.05$). On average, the predicted percentage of workers who walked and biked to work in TIF block groups was one percentage point higher than in non-TIF block groups, which represented a relative increase of 58.82%, as compared to the mean of active commuting in non-TIF block groups. The marginal effect for travel time was 0.004 ($p < 0.01$). That is, on average (after holding other independent variables constant in their means), the predicted proportion of active commuters in total samples rose by 0.4 percentage point with each ten percentage increase in workers whose travel time less than 20 minutes. This finding suggested a linear dose–response relationship between travel time and active commuting. In other words, on average, each additional one percentage increase in commuters with short travel time led to an absolute increase of 0.04 percentage point, or relatively 2.22% more in the proportion of active commuters in the all block groups in the city of Dallas.

Personal factors played an important role in explaining active commuting behavior. The marginal effects from income, occupancy rate and education suggested consistent and positive associations between active commuting and disadvantaged population in disadvantaged areas. Hispanic or Latinos was negatively associated with active commuting. The result suggested that, on average, each additional one percentage increase in Hispanic or Latinos population, average median household income and occupancy rate led to an absolute decrease of 0.02, 0.01, and 0.03 percentage points, or a relative decrease of 1.11%, 0.61%, and 1.67%, respectively, in the proportion of workers walking and bicycling to work. If the percentage of undereducated population rose by one percentage, the expected absolute increase for the proportion of active commuters would be 0.02 percentage points, or a relative increase of 1.11%.

In terms of neighborhood factors and built environmental factors, only road density was statistically significant, with a marginal effect of 0.006 ($p<0.05$). That is, on average, if the road density increased by one percentage, the expected absolute increase for the proportion of active commuters would be 0.012 percentage point, or a relative increase of 0.68%. This finding suggested that built environment has a very small impact on promoting active commuting at the overall city level. Other neighborhood and built environmental factors did not show a significant relationship with active commuting, either.

3.4.1.2 Finding from TIF Samples (Hypothesis 1)

Compared to the full model, half of the built environmental factors in the TIF model became significant, which suggested that built environmental variables were more strongly associated with active commuting to work in walkable neighborhoods. On average, each additional one percentage increase in sidewalk completeness, road density, and street intersection density led to an absolute increase of 0.008, 0.053, and 0.039 percentage points, or relative increases of 0.31%, 2.05%, and 1.49% in the proportion of active commuters. The average speed limit played a negative role on active commuting. For each one percentage rose in speed limit, on average, the expected absolute decrease for the proportion of active commuters would be 0.059 percentage point, or a relative decrease of 2.25%, which was the relatively highest effect on active commuting compared to other significant built environmental variables.

In terms of personal factors, ethnicity, occupancy rate and education had significant marginal effects on active commuting to work. On average, each one percentage increase in Hispanic or Latinos population and occupancy rate led to an absolute decrease of 0.05 and 0.07 percentage points, or a relative decrease of 1.92% and 2.69% in the proportion of workers walking and bicycling to work. For education, on average, if the percentage of undereducated population rose by one percentage, the expected absolute increase for the proportion of active commuters would be 0.05 percentage point, or a relative increase of 1.92%. In TIF samples, compared to the built environmental factors, the personal factors still had slightly higher average marginal effects on active commuting to work. Similar to Model 1, the neighborhood factors were not significantly associated with active commuting to work.

The findings from Model 2 supported Hypothesis 1 that physical activity related built environmental factors to be significantly associated with active commuting to work in TIF neighborhoods. Findings suggested that greater sidewalk completeness, road density and street intersection density can promote active commuting, while higher average speed limit would discourage active commuting.

3.4.1.3 Finding from Non-TIF Samples (Hypothesis 2)

Contrasting to TIF model (Model 2), none of the built environmental factors were significantly associated with active commuting in the non-TIF model (Model 3). However, residential density considered as a neighborhood factor was significant. On average, each additional one percentage increase in residential density led to an absolute increase of 0.001 percentage point, or a 0.07% relative increase in the proportion of workers walking and bicycling to work. This finding echoed findings in previous studies (Saelens & Handy, 2008; Saelens et al., 2003); that is, urban areas with higher residential density had more active trips than suburban areas with low residential density.

In terms of personal factors, white population was positively associated with active commuting to work, while ethnicity, income and occupancy rate were negatively associated with active commuting. On average, each additional one percentage increase in Hispanic or Latinos population, average median household income, and occupancy rate led to an absolute decrease of 0.01, 0.01, and 0.03 percentage points, or a relative decrease of 0.59%, 0.63%, and 1.76%, respectively, in the proportion of active commuters. For race, on average, if the percentage of white population rose by one percentage, the expected absolute increase for the proportion of active commuters would be 0.01 percentage point, or a 0.59% relative increase.

The findings from Model 3 supported Hypothesis 2. In less walkable neighborhoods, the built environment factors tended to be insignificant associated with active commuting to work, while the travel time and personal factors accounted for the majority of the effects on the proportion of active commuters.

3.4.2 The Interrelations of Personal, Neighborhood, and Built Environmental Effects on Active Commuting to Work

The marginal effects provide a way to substantively quantify the significance, which estimate the average effects based on the slope coefficient from each point, controlling for all other variables in their mean values. However, marginal effects cannot help provide a complete understanding of non-linear relationships and interrelations of personal, neighborhood, and built environmental effects on active commuting. This section employed the marginal plots to illustrate the tendency of interrelations among two or three dimensions. However, these figures do not compare the magnitude of the effects among different built environmental variables on active commuting because they were measured based on absolute values, not relative values.

Figure 3-3 illustrates the predicted relationship between travel time and active commuting to work in total block groups. It shows a nonlinear U-shape relationship, which indicates a sharp increase in active trips with the increased percentage of short trip commuters.

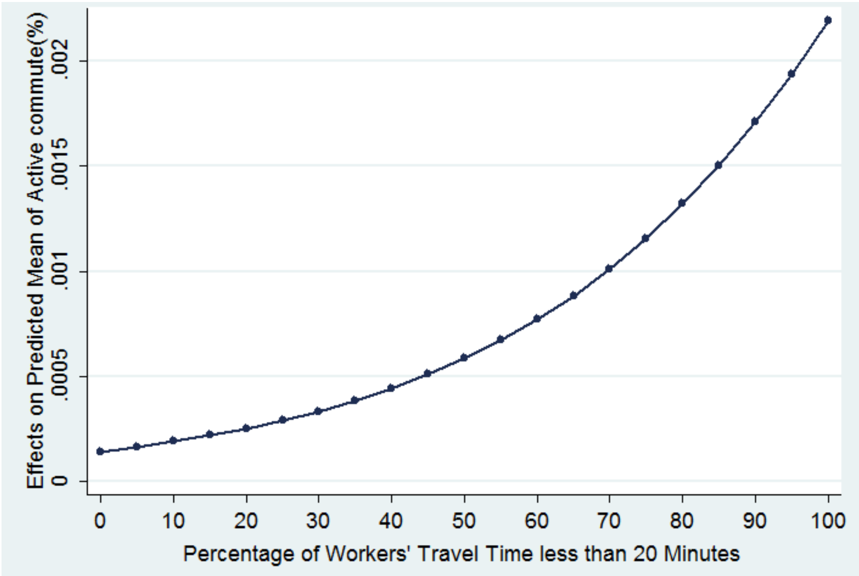

Figure 3-3. Marginal effects of short commuters (percentage of workers traveling < 20 minutes) on active commuting in total block groups

Figure 3-4 illustrates the influence of travel time on the relationship between active commuting and each of the social factors in total block groups. Higher percentage of commuters with short travel time (<20 minutes) magnified the positive effects of undereducated population and road density on active commuting, and also magnified the negative effects of Hispanic population and occupancy rate on active commuting. The effect of income on active commuting was not affected by the variation of the travel time variable.

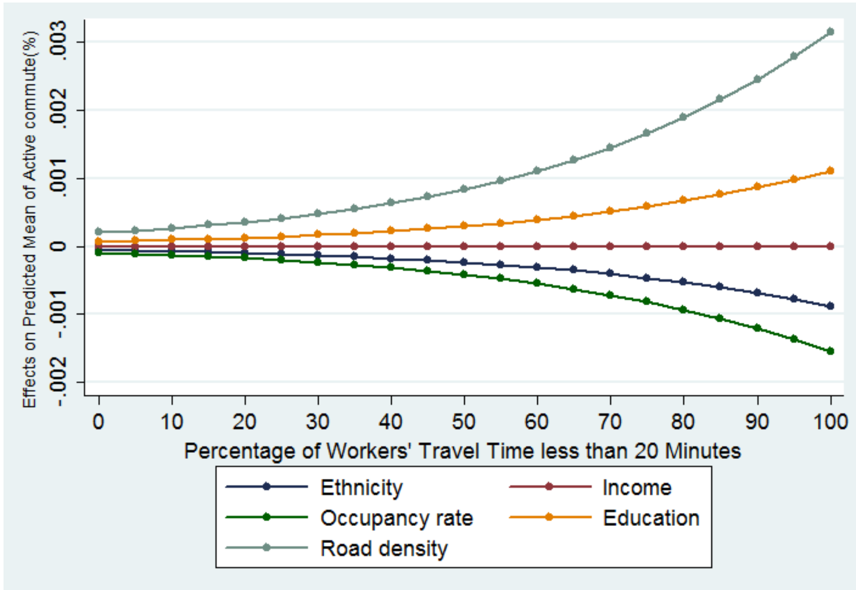

Figure 3-4. Marginal effects of significant variables on active commuting by short commuters (percentage of workers traveling < 20 minutes) in total block groups

Figures 3-5 to 3-8 illustrate the interrelated effects of variables on active commuting for TIF block group samples. Figure 3-5 illustrates the influence of travel time on the relationship between active commuting and each of the built environmental factors. Among them, only street intersection density and sidewalk completeness were magnified in their impact on active commuting with increased percentage of short-time commuters. The relationship between active commuting and road density and average speed limit was not affected or only slightly affected by the travel time factor.

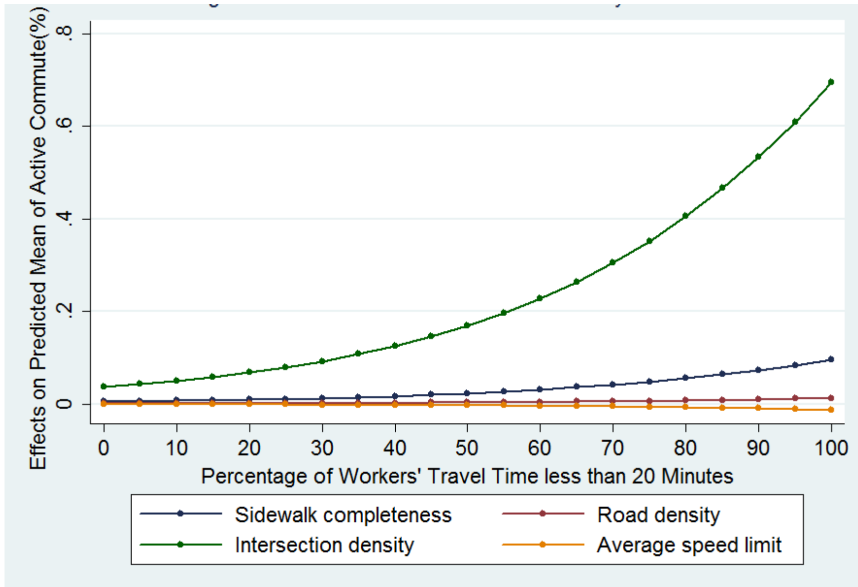

Figure 3-5. Marginal effects of significant built environmental variables on active commuting by short commuters (percentage of workers traveling < 20 minutes) in TIF block groups

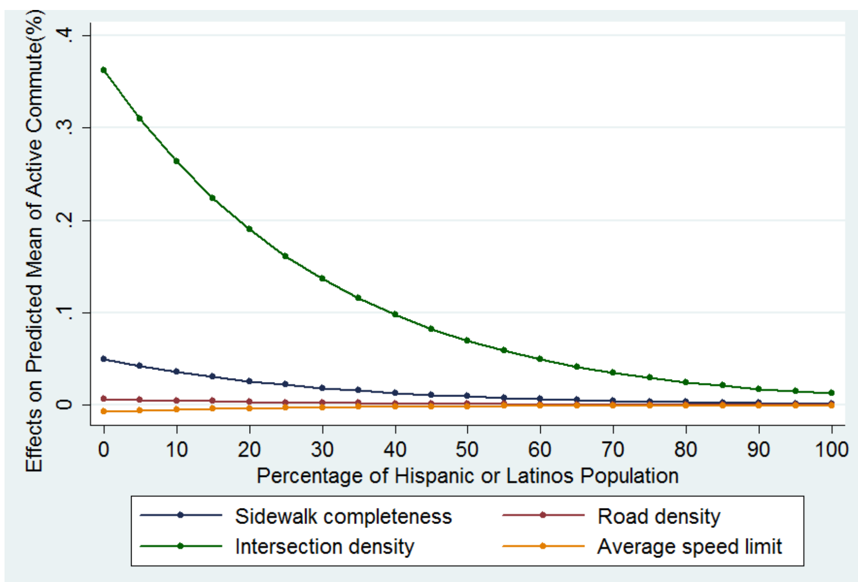

Figure 3-6. Marginal effects of significant built environmental variables on active commuting by percentage of Hispanic or Latinos population in TIF block groups

Figures 3-6 and 3-7 illustrate the influence of ethnicity and occupancy rate on the relationship between active commuting and each built environmental factor. Overall, the greater the percentage of Hispanic or Latino population and occupancy rate, the less the effects of street intersection density and sidewalk completeness were on active commuting. The relationship between active commuting and road density and average speed limit were not be affected or minimally affected by ethnicity and occupancy rate.

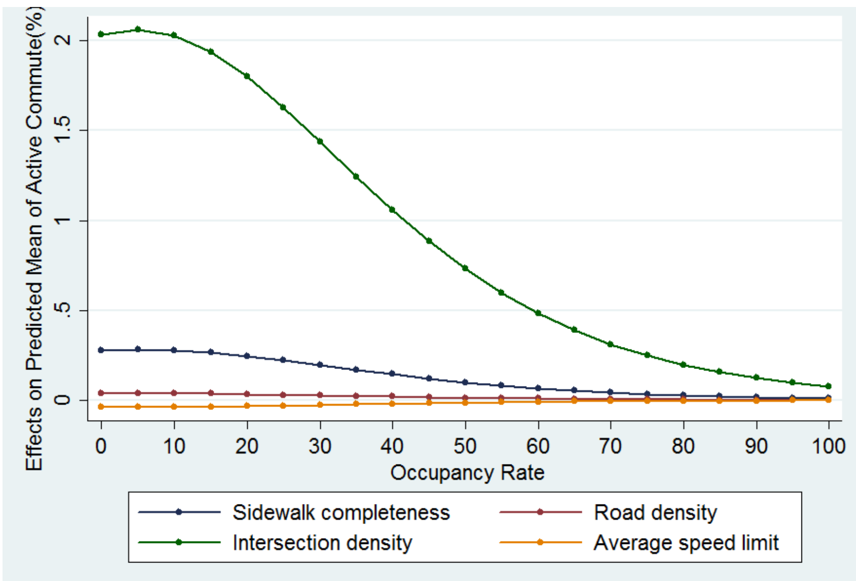

Figure 3-7. Marginal effects of significant built environmental variables on active commuting by home occupancy rate in TIF block groups

Figure 3-8 illustrates the influence of education on the relationship between active commuting and each of the built environmental factors. Greater percentage of undereducated population would enhance the effects of street intersection density and sidewalk completeness on active commuting. The relationship between active commuting and road density and average speed limit was not be affected or slightly affected by education.

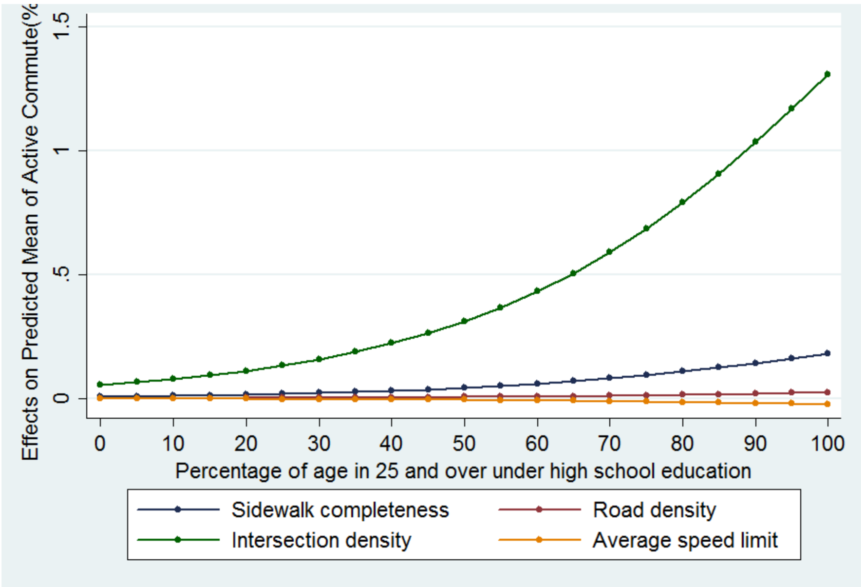

Figure 3-8. Marginal effects of significant built environmental variables on active commuting by percentage of undereducated population in TIF block groups

Figures 3-9, 3-10 and 3-11 compare the predictive margins of the same significant factors in both TIF samples and non-TIF samples. Figure 3-9 illustrates similar pattern of relationships between travel time and active commuting in both TIF samples and non-TIF samples. Figure 3-10 illustrates the overall negative effects of ethnicity on active commuting in both groups. However, the pattern displayed that gradually reduced negative effects were associated with the increase of Hispanic or Latino population, and that the reduction trend in TIF block groups was much greater than non-TIF block groups. The finding suggests that active commuting had a marginal increase when the Hispanic or Latino population increases, especially in TIF block groups, although the overall effect was still negative. Figure 3.11 illustrates the same tendency as Figure 3-10 displays. Although the overall effect was negative, occupancy rate had a marginally positive effect on active commuting, especially in TIF block groups.

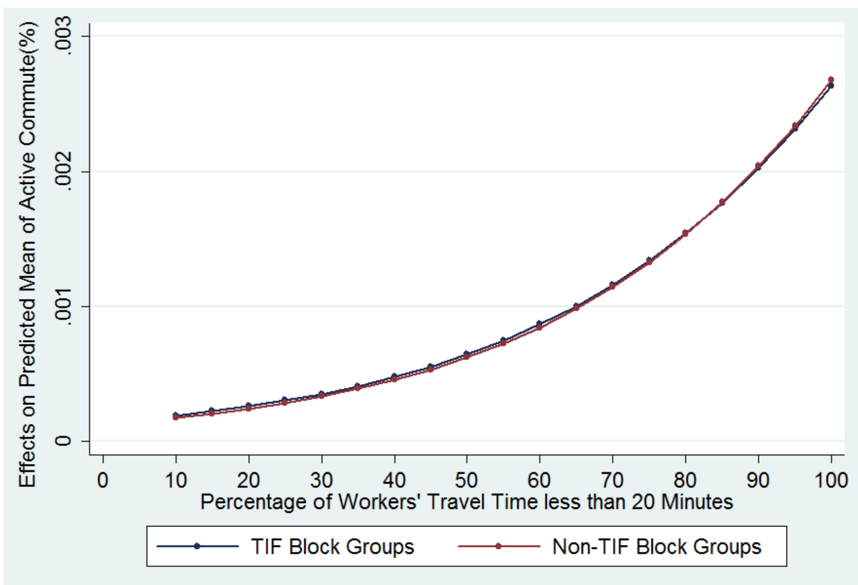

Figure 3-9. Marginal effects of short commuters (percentage of workers traveling < 20 minutes) on active commuting in TIF block groups vs. Non-TIF block groups

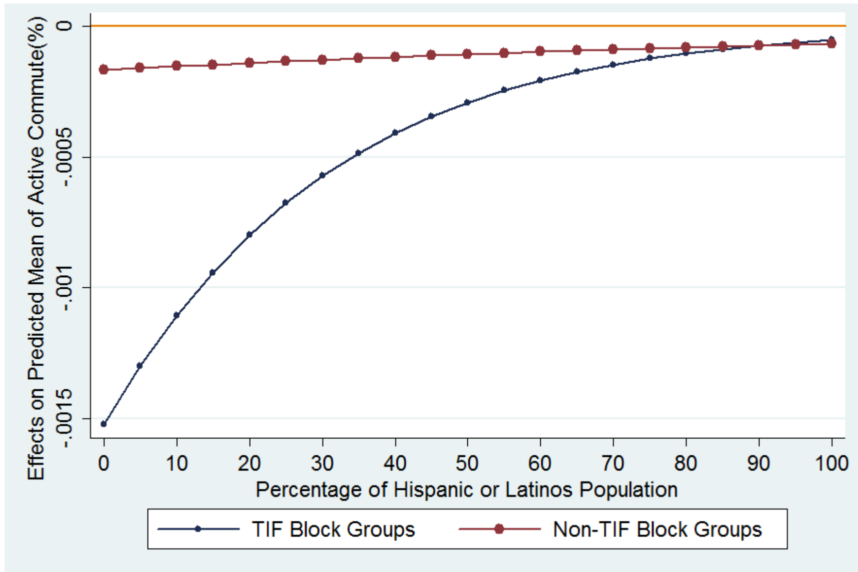

Figure 3-10. Margins effects of Hispanic population on active commuting in TIF block groups vs. Non-TIF block groups

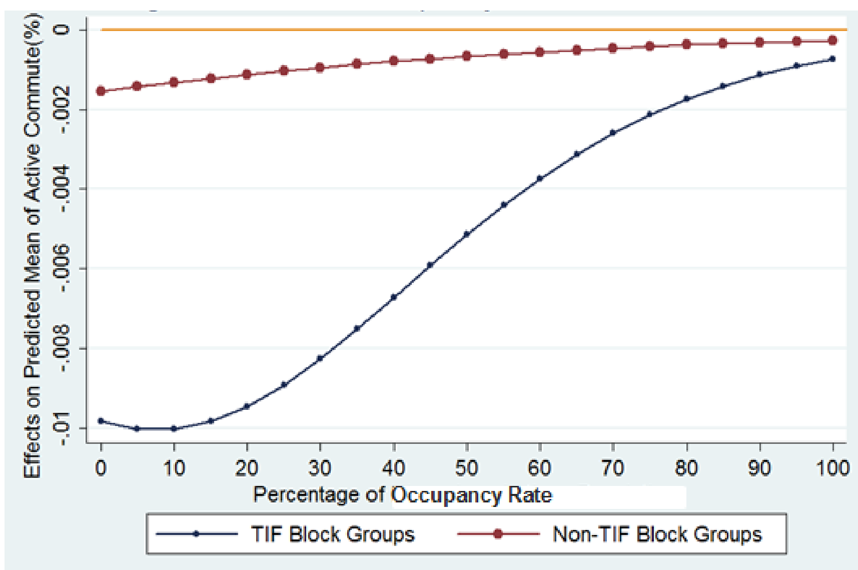

Figure 3-11. Margins effects of occupancy rate on active commuting in TIF block groups vs. Non-TIF block groups

3.5 Discussions and Conclusion

3.5.1 Discussions

In summary, I found the predicted walking and bicycling trips to work in TIF block groups were relatively higher than non-TIF block groups by 58.82%. The descriptive statistics showed TIF block groups have greater activity-friendly built environmental features (e.g. sidewalk completeness, intersection density). Both results indicated TIF neighborhoods were more walkable and generated more active trips.

In the overall model, travel time and personal factors were significantly associated with active commuting, while road density was the only built environmental factor that had a significant relationship with active commuting. None of the neighborhood factors was significantly associated with active commuting. Overall, each additional one percentage increase in short travel time (<20 minutes, one way), Hispanic and Latino population, income, occupancy rate, undereducated population, and road density led to a relative change of 2.22%, -1.11%, -0.61%, -1.67%, 1.11%, and 0.68%, respectively, in the proportion of active commuters.

Most of the built environmental factors were significantly associated with active commuting in the TIF block groups only. On average, if the sidewalk completeness, road density, street intersection density, and average speed limit rose by one percentage, the expected relative increase for the proportion of active commuters would be 0.31%, 2.05%, 1.49%, and -2.25% in TIF block groups. The neighborhood factor was only significantly associated with active commuting in non-TIF block groups, which represented a 0.59% relative increase in the proportion of active commuter with one percentage increase in residential density. In both TIF and non-TIF models, short travel time and personal factors were still the dominant factors predicting active commuting.

The results from the fractional logit models and marginal effects revealed the inconsistencies across neighborhoods with different levels of walkability. The findings suggested that the built environmental factors only impacted the active commuting to work in the walkable neighborhoods that with more walkable environmental features. If the walking environments were in less desirable condition, the built environmental factors would not impact the active commuting. The findings also suggested that travel time and personal factors played consistently important roles in influencing the active commuting behavior in all three models (total, TIF and non-TIF block group samples), regardless of the variation in physical environments. Previous studies also found that travel distance (travel time) is the most important factor in the selection of active commuting mode, while the built environment alone does not play a determining role. However, the built environmental factors still appear to play a role as a barrier and facilitator of active travel behavior especially in neighborhoods that are at least somewhat walkable.

In terms of the marginal plots, there were three interesting findings. First, for all block group samples, the greater the percentage of commuters with short travel time, the greater the original effects (positive or negative) of social and built environmental factors were on active commuting to work. This suggested that travel time played one of the most important roles on active trips to work, which has been verified in previous studies. Second, for TIF block group samples, the associations of active commuting with sidewalk completeness and street intersection density were stronger interrelated with travel time and personal factors than the associations with other built environmental factors, suggesting that the modification of these two built environmental factors will more likely lead to changes in active commuting behavior more strongly than others. Third, by comparing the same significant variables in both TIF and non-TIF block groups, the marginal positive effects were found for ethnicity and occupancy rate on active commuting, especially for TIF block groups, although the overall effects were still negative. This finding implied that the negative impact from disadvantaged areas on active commuting could be mitigated by a more walkable environment.

3.5.2 Limitations

This study has four limitations. First, only active commuting to work, that is, the percentage of workers commuting to work by walking and bicycling, was examined in this study. The results cannot represent other physical activity types such as active transportation to other destinations and recreational activities. Also, the results might over-represent the influence of personal factors (e.g. median household income) on active commuting, since people who cannot afford automobiles have to walk or bike more frequently to their workplace. Second, this study examined active commuting at the neighborhood level and could not control for the self-selection issue which occurs at the individual level. This was considered to be the major confounding factor impacting physical activity in previous studies. Moreover, this study was a cross-sectional study with no ability to assess causal relationships between study variables. Third, the selection of independent variables was based on previous empirical studies and available data, and therefore findings are subject to potential biases related to omitted variables. For the built environmental factors, micro-scale environmental characteristics such as the quality and maintenance of infrastructure, were not considered in this study due to the lack of available data. Furthermore, the GIS and census data for measuring social, neighborhood, and built environmental factors had slight variations of their time frames. Fourth, the sample sizes for TIF and non-TIF groups are quite different. There were only 116 observations in TIF groups, which add potential biases on the results of this comparison study.

3.5.3 Conclusion

In this study, I employed an adapted socio-ecological framework to examine the effects of personal, neighborhood, and built environmental effects on active commuting (walking and bicycling) to work, as well as the interrelations of these factors, in TIF neighborhoods, non-TIF neighborhoods, and the entire city of Dallas. I employed the fractional logit models with robust standard errors to adjust for potential correlations across different factors, and utilized margin effects to estimate the magnitude of the significant variables. Moreover, the use of margin plots helped gain a more complete understanding of the non-linear relationships resulting from the interrelations of different factors.

Existing evidence for impacts of built environment on active commuting was equivocal. This study added to this body of literature by providing new evidence to support the significant role of built environmental factors on promoting active commuting in more walkable environments. It dose so by emphasizing their substantive normalized significance effects with rigorous statistical analysis. The evidence from margin plots also suggested a more walkable environment could mitigate the negative impact of personal factors (e.g. Hispanic and Latino population, occupancy rate) on active commuting from areas with lower socioeconomic status, providing the basis for initiating important policy debates related to equity/disparity.

Built environmental factors are essential elements of the neighborhood context. It is important for planners to learn, whether or not varying conditions of the built environment lead to differential impacts on active commuting in neighborhoods with different social and physical characteristics. The evidence from this study showed that, by a wide margin, different types of built environmental factors need to be considered together when assessing their impacts on active travel. However, considering the fiscal constraints most local governments face and cost benefits, making improvements on sidewalk and street intersection a priority will provide more opportunities to encourage active commuting; they are relatively easy to engineer, and more closely associated with the personal factors than other built environmental factors, which showed in the margin plots.

Previous studies have demonstrated that disadvantaged populations are more vulnerable to obesity and obesity-related illnesses (Lovasi et al., 2009), and they are also associated with physical inactivity for recreational and exercise purpose (Trost et al., 2002). To mitigate the health disparities, changing the built environment to be more supportive for active commuting is a crucial factor for disadvantaged populations who lived in those less walkable neighborhoods.

In response to the growing interest in the smart growth movement and the concept of new urbanism as means to inhibit the problems of urban sprawl, to reduce automobile dependency, to promote physical activity, and to bring the vitality back to inner city, an increasing number of neighborhood redevelopment projects (e.g. TIF, urban renewal, TOD) has targeted the modification of the built environment in distressed urban areas. The findings from this study suggested the overall built environmental conditions should be considered as an additional and essential factor when studying active commuting behavior, and their varying implications for neighborhoods with different levels of walkability should be explored. Also importantly, local governments and planners must understand how to shape the built environment with a special attention to the disadvantaged segments of populations to ensure sufficient access to safe, convenient, and walkable environments.

CHAPTER IV

A SYSTEMATIC EVALUATION OF THE ECONOMIC BENEFITS OF ACTIVITY-FRIENDLY BUILT ENVIRONMENT ON RESIDENTIAL PROPERTIES: A 7DS MEASUREMENTS APPROACH

4.1 Introduction

4.1.1 Background

In the era of high energy price, economic uncertainty, demographic changes, and a prevalence of physical inactivity and obesity, a growing number of Americans are showing the interest in urban living as an alternative to the traditional auto-dependent suburban living. Recent financial, physical, and environmental constraints have begun to limit additional roadway expansions in congested urban areas, and many residents are concerned about reducing their annual vehicle miles traveled (VMT) and instead increasing walking and biking (Campoli, 2012).

The issue of urban sprawl, that cities were primarily auto-centric, with low-density, fragmented, and disaggregated land uses, and comprised of high-speed and disconnected roadways, is the primary obstacle to physical activity for many urban residents (Ewing et al., 2008). These characteristics also attributed to serious economic, environmental, social and health problems in US cities (Brueckner, 2000; Brueckner & Largey, 2008; Frumkin, 2002), prompting states and local governments to reform land use planning and urban design to rein such a sprawled trend. The development of compact, walkable, and convenient neighborhoods with various built environment that encouraging walking and biking are being promoted by recent planning movements and initiatives (e.g. Smart Growth, New Urbanism, Transit-oriented Development, etc.).

Walkable neighborhoods are about the quality: the quality of life and the quality of real estate. As the constructed suburban neighborhoods have become homogeneous with limited functions, walkable neighborhoods equipped with activity-friendly amenities are now favored and advocated by realtors for marketing and advertising purposes. The popularity of the Walk Score is a successful example to conveniently measure walkability of the neighborhoods that is widely utilized in many businesses. In construction field, many developers have begun to provide neighborhood amenities as a package in their new developments to compete with other projects with similar elevations and floor plans (Benefield, 2009). The benefits of the activity-friendly environments have been widely accepted by new home buyers and, ultimately, will provide a more walkable neighborhood and increasing appreciation rates for homeowners who seek greater active living environments while gaining greater wealth in their home equities.

This study utilized TIF districts in the city of Dallas as a mechanism to facilitate the creation of walkable neighborhoods, to examine the economic benefits of activity-friendly environments on home values appreciation during the six years of TIF retrofitting treatment. TIF is one of the most prevalent public-private partnership approaches for urban redevelopment conducted by local governments. TIF employed public financing tools to leverage future gains in tax revenues to subsidize the redevelopment projects in declined neighborhoods, attract small businesses, enhance real estate market, improve public amenities and infrastructure, and make the desirable urban revitalization become reality.[17]

The TIF districts in Dallas support the new development of residential, retail, commercial, and mixed-use projects in existing urban neighborhoods. The other major public infrastructure and amenities, and service facilities that Dallas TIF generally financed are: (1) public infrastructure such as sidewalks and curbs, bike lanes, street construction and expansions, street lighting, sewer expansion and repair, storm drainage, utilities, etc.; (2) public recreational uses such as parks and open space improvements, landscaping improvements, environmental remediation, etc.; and (3) service facilities such as light rail developments, traffic control, and public buildings, etc.[18] These improvements are directly and indirectly linked to the reform of walkable neighborhoods, and help create active and vibrant communities to encourage physical activity, improve overall health and community economic vitality, and offer a better quality of life for urban residents. Appendix C presents a summary of Dallas TIF project information.

4.1.2 Significance

Despite the significant relationships between BE and physical activity that have been were well-documented in previous studies, the economic implications of such relationships are relatively unknown. Few studies have examined the economic benefits of recent neighborhood redevelopment projects guided by smart growth and new

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[17] Data summarized from various sources of TIF projects and definitions.

[18] Data source: Dallas Economic Development, TIFs & PIDs, http://www.dallas-ecodev.org/incentives/tifs-pids

urbanism principles. More specifically, the potential property value appreciation due to better provision or condition of activity-friendly features in retrofitted neighborhoods is understudied.

According to the methods used to evaluate the economic valuation of activity-friendly environments in previous studies, there were three major limitations. First, almost all of previous studies used a cross-sectional design to examine the associations between the built environment and property values. Ignoring the time-constant variable can caused serious biases in the hedonic pricing studies (Wooldridge, 2012).

Second, a limited range of built environmental variables were measured in previous studies. Most of studies examined particular types of built environment (e.g. parks, greenways, trails) or a group of common neighborhood amenities. The values of BE will vary depending on the specific built environmental variables used in the study, and therefore careful selection and measurements of the BE variables are important to draw valid conclusions on their roles.

Third, the use of analytical approach remains a limitation in many previous studies. A growing number of studies have employed advanced statistical models to overcome the potential problems of heteroskedasticity, spatial autocorrelation, and nested data structure that traditional hedonic pricing regression often encounters. However, there was neither a clear comparison among different models, nor a systematic discussion about the model selection.

Inspired by previous transportation research (Cervero & Kockelman, 1997; Ewing et al., 2014; Lee & Moudon, 2006a), this study employs the 7Ds measurement framework (Density, Diversity, Design, Distance, Destination accessibility, Demographics, and district) to comprehensively measure the potential economic benefits of activity-friendly environments for residential properties. By conducting a systematic assessment with a variety of activity-friendly elements identified from previous physical activity studies, this study enhanced the studies examining the economic valuation of built environmental features. To compare and discuss the different model approaches, this study employed three different models commonly employed in this type of study − OLS regression, spatial regression, and hierarchical linear model (HLM) − to provide insights to guide the selection of appropriate analytical processes and methods for quantifying the impact of various environments on home value appreciation.

Examining the economic benefits of activity-friendly environments in TIF districts help offer insights about how modification of built environment increase property values, and deliver policy implications and financial feasibility for local governments. Moreover, the findings provide evidence to guide future neighborhood improvement strategies to create activity-friendly environments and promote active living among urban residents.

4.1.3 Objectives

The primary goal of this study was to examine the economic effects of various activity-friendly environmental features on the appreciation rates of residential homes in Dallas TIF districts. I also conducted neighborhood level matching to pair each TIF district with a non-TIF comparison neighborhood with similar socio-demographic characteristics, to compare the differences in economic benefits of various built environmental features between walkable (TIF) neighborhoods and less-walkable (non-TIF) neighborhoods.

Informed by the reveal preference theory, I established two sets of hedonic price models (HPM) to examine the following objectives and hypotheses.

Objective 1: This study is to examine the economic benefits of various activity-friendly environmental features on home appreciation rates in TIF districts using different analytical methods (OLS, spatial regression, and HLM).

Hypothesis 1: Differences in the built environment are associated with differences in home value appreciation rates. Specifically, environments that provide better opportunities for physical activity are associated with higher appreciation rates.

Objective 2: This study is to compare the economic benefits of activity-friendly environments on home appreciation rates between TIF districts and matched non-TIF comparison neighborhoods.

Hypothesis 2: Neighborhoods with more walkable environments are associated with higher appreciation rates.

4.2 Literature Review

Complementing the literature review provided in Chapter 1 that offered a brief review of the general literature, this section focuses on the specific body of literature relevant to this study.

4.2.1 Methods on Evaluating the Economic Values of Environments

4.2.1.1 Revealed Preference Theory

In economic theories, the way to measure the value of goods can be broadly defined in two categories: those which value a commodity via a demand curve; and those goods that fail to provide “true” valuation information and welfare measures. The first category refers to the traditional demand and supply theory based on the assumption that people make consumption decisions to maximize their utility. The second category is based on the preference theory that assumes consumers’ consumption decisions are based on their purchasing habits. Revealed Preference is the key theory established by economists to study consumers’ preference on purchasing habits, especially for environmental goods (Adamowicz et al., 1994; Garrod & Willis, 1999; Pearce & Turner, 1990). In other words, the demand for activity-friendly built environmental goods can be revealed by examining the purchases of related goods (residential property) in the private marketplace. Figure 4-1 depicted a whole picture of conventional valuation techniques for environmental features.

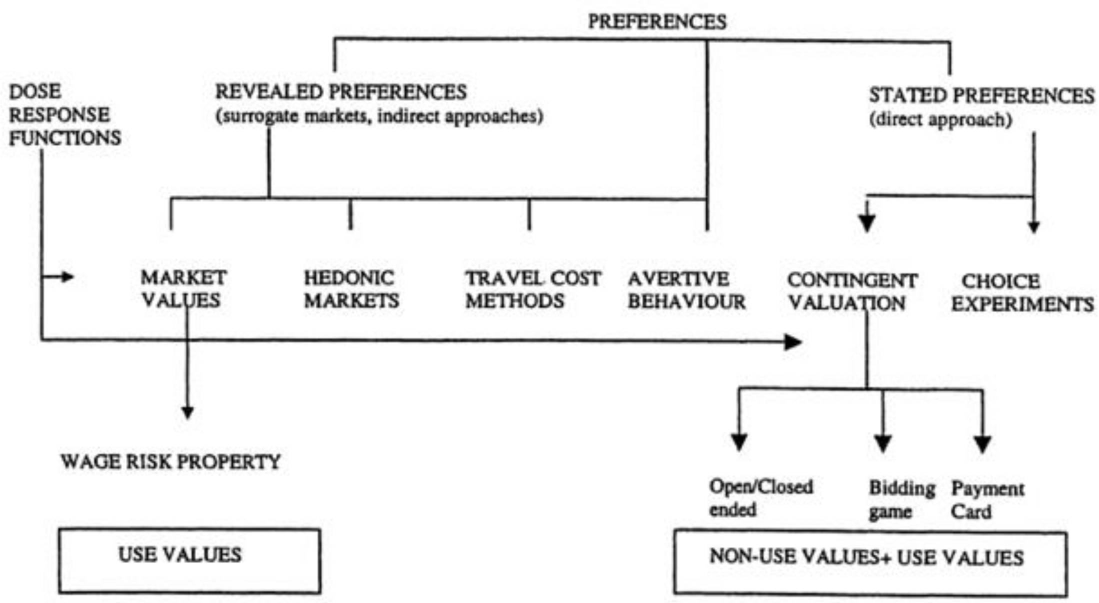

Figure 4-1. Conventional valuation techniques for environmental features (Garrod & Willis, 1999)

4.2.1.2 Hedonic Price Model

HPM is widely used to measure consumer valuations of various attributes or characteristics of property in real estate and economics literature. It is based on the consumer theory that postulates every good provides a bundle of characteristics or attributes, and the use values of goods are from the market of close substitutes. Market goods can be considered as intermediate inputs into the production of the more basic attributes that individuals really demand. The demand for goods, like housing, can be considered a derived demand (Lancaster, 1966; Rosen, 1974). Therefore, a house yields shelter, but through its location it also yields access to different quantities and qualities of built environment and public services. The HPM extends the theory that the price of a house is determined by a number of factors: structural, neighborhood, locational, environmental, and financial characteristics. The HPM estimates the values consumers attach to a variety of characteristics and rely on the assumptions about markets, pricing, and consumer behavior (Cortright, 2009; DiPasquale & Wheaton, 1996). Figure 4-2 depicted the important factors considered in hedonic price model to reveal property values.

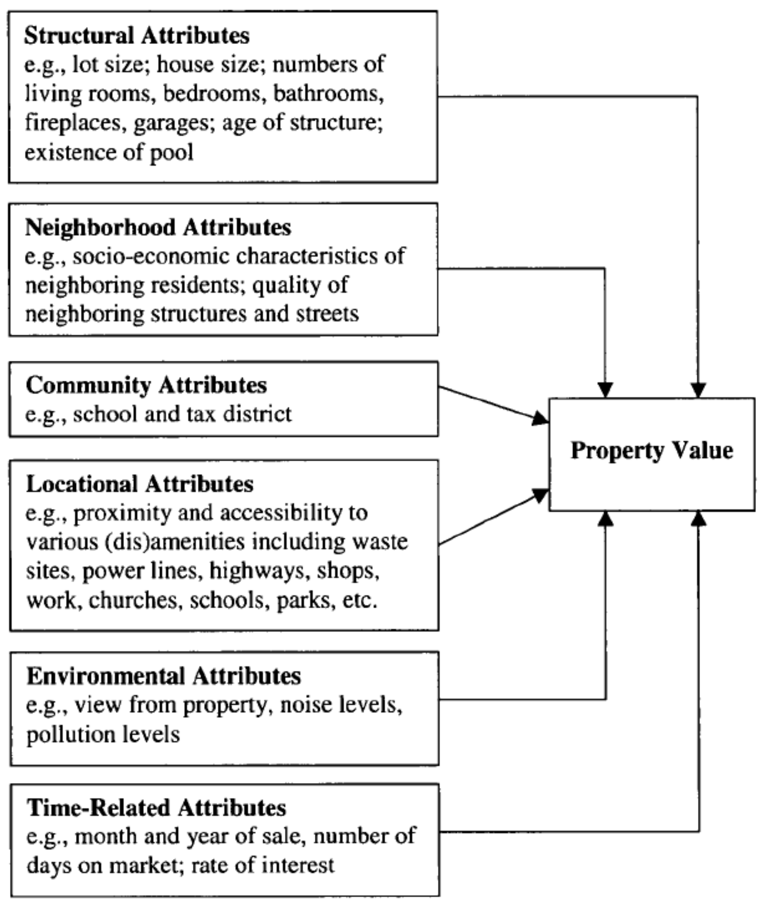

Figure 4-2. Diagram of hedonic price model (John L Crompton, 2005b)

4.2.1.3 Spatial Regression Model

The instantiation of Tobler's first law of geography suggested "Everything is related to everything else, but near things are more related than distant things" (Miller, 2004). Most statistical analyses are based on the assumption that the values of observations in each sample are independent of one another, but spatial autocorrelation violates this assumption, because samples taken from the nearby area are related to each other and are not independent. Spatial autocorrelation is a universal problem when geographic data, either physical or human, are involved in analysis (F Dormann et al., 2007). One significant example of spatial autocorrelation is often found in housing data, that homes that are located close to each other always have similar housing values compared to those further apart. If this spatial pattern remains present in the residuals of a statistical model, one of the key assumptions of standard statistical analysis, that residuals are independent and identically distributed (i.i.d) is violated. The violation of the assumption may cause biased parameter estimates and increase type I error (falsely rejecting the null hypothesis of no effect) (F Dormann et al., 2007; Miller, 2004).

Spatial autocorrelation suggests the operation of a spatial process to deal with two primary types of spatial dependence: spatial error and spatial lag. With spatial error in OLS regression, the assumption of uncorrelated error terms is violated, resulting in inefficient estimates. Spatial error model is suggested to handle the omitted spatially correlated covariates. With spatial lag in OLS regression, the assumption of both uncorrelated error terms and independent observations are violated, resulting in biased and inefficient estimates. Spatial lag model is suggested to reduce the diffusion process

(Anselin et al., 2005; Brown, 2015). Figure 4-3 depicts the spatial mechanism of spatial error and spatial lag.

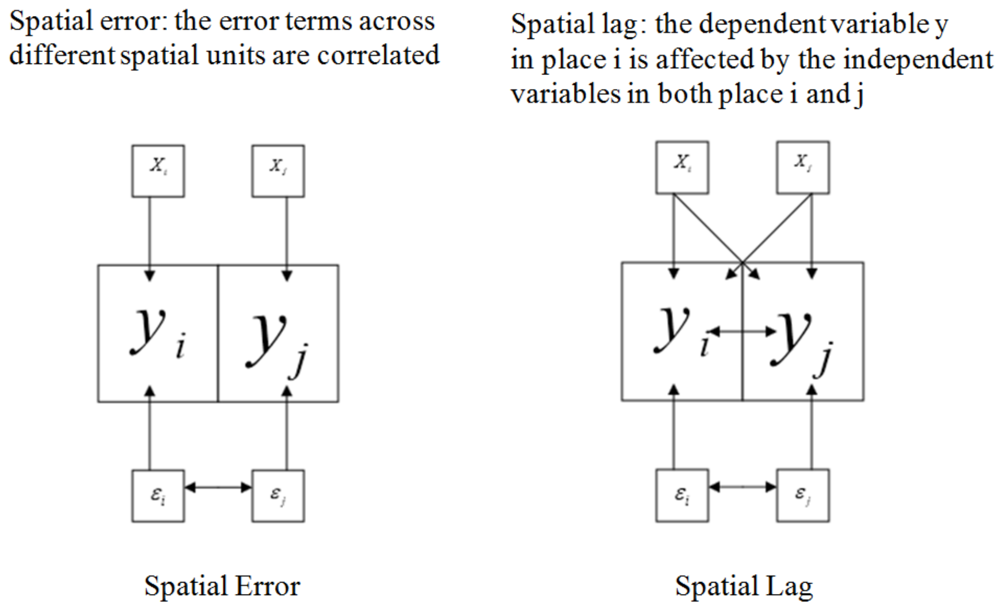

Figure 4-3. The mechanism of spatial error and spatial lag (Anselin et al., 2005)

This study used GeoDa developed by Luc Anselin to handle the spatial autocorrelation issue. Geoda provides a range of diagnostics to detect spatial dependence. Figure 4-4 presents a flow process for spatial regression decision based on Lagrange Multiplier (LM) test statistics.

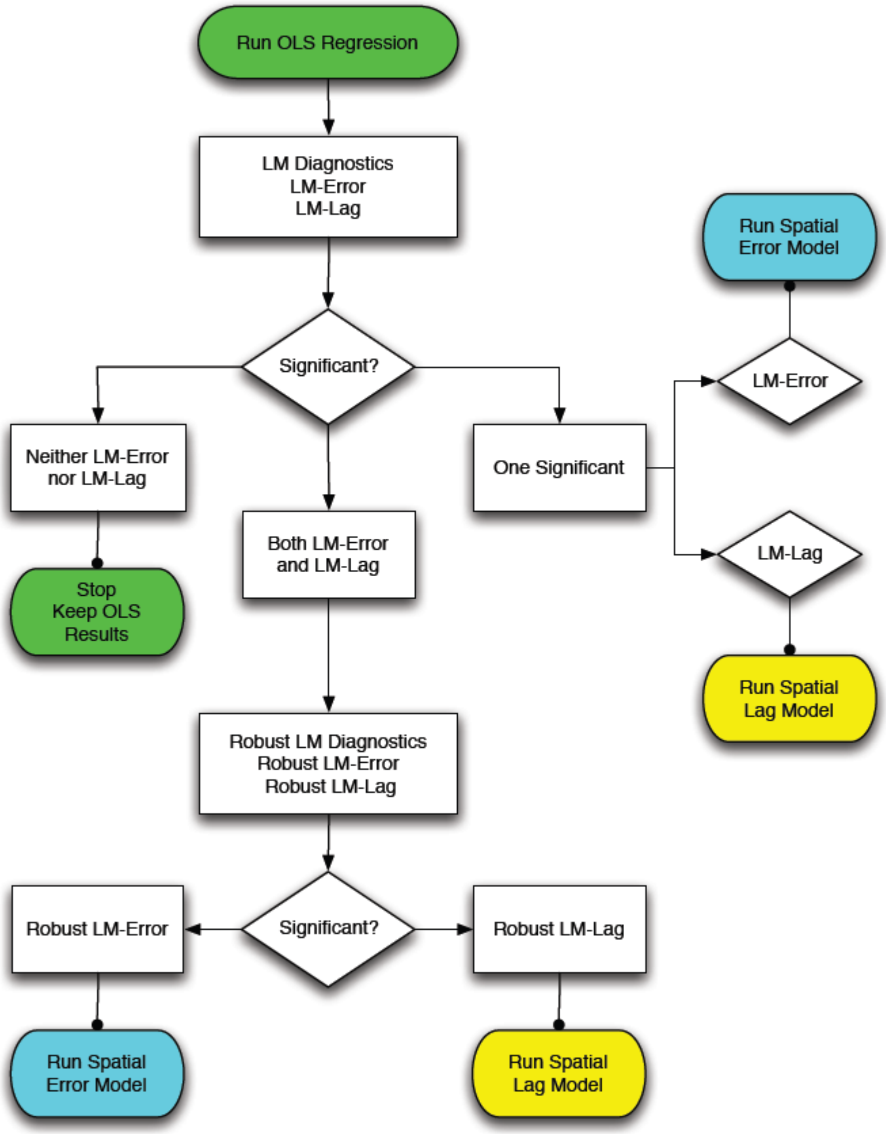

Figure 4-4. Spatial regression model selection process (Anselin, 2004)

4.2.1.4 Hierarchical Linear Model

Although the use of spatial regression approach to estimate hedonic price model improved regression estimates (Cohen & Coughlin, 2008; Lipscomb, 2004). However, the potential problems due to nested or hierarchical structure still exist. The spatial weight matrix measured in spatial regression only controlled for spatial dependence in certain criteria (e.g. contiguity weight, distance weight, k-nearest neighborhood); however, it cannot capture the extent and context of particular characteristics of neighborhoods.

Dwellings are located within a large spatial unit often called a neighborhood or district, such as census block groups, school attendance zone, TIF district, etc. The dwellings with a specified neighborhood often share the economic, demographic, environmental, social structures, and even have similar structural features. Therefore, dwellings grouped within a neighborhood are likely to be more similar to each other than those from other neighborhoods. This type of hierarchical data violates the assumption of independent observations. Hence, using traditional methods such as OLS would yield statistically biased estimates and increase the risk of committing a Type I error (Osborne, 2000; Raudenbush & Bryk, 2002).

Neglecting the statistical reliability discussed above, OLS may consider the neighborhood by using a series of dummy variables representing neighborhood attributes. But this approach assumed that all of the samples in one neighborhood are affected in the same way by neighborhood attributes without variation. Therefore, it cannot measure the interaction between individual variables and neighborhood variables (Osborne, 2000; Raudenbush & Bryk, 2002). For data with two or more hierarchies, hierarchical linear model (HLM) could treat data from each level in its own sub-model. These sub-models express relationships among variables within the given level, specifically how variables at one level influence the relations occurring at other levels.

In other words, HLM can account for interactions across levels (e.g. students and schools, dwellings and TIF) (Raudenbush & Bryk, 2002).

4.2.2 Economic Benefit of Activity-Friendly Environments

Previous studies on the relationship between built environment and physical activity has been primarily focused on the transportation and public health purposes. Despite the activity-friendly environments have been well classified and documented, there were only a few empirical studies that discussed the economic benefit of these environments. Crompton conducted the proximity principle to explore the economic benefits of recreational neighborhood amenities, by capturing the increased housing values from nearby residential properties. He found relatively higher housing values for homes close to the recreational amenities, such as parks, open spaces, greenways, and trails (J Crompton & Nicholls, 2006; John L Crompton, 2001b, 2005b). He also found that SF properties near parks and open spaces gain 20% value premiums in the city of Austin (J.L. Crompton, 2001a). Nicholls demonstrated that greenways have significantly positive impacts on nearby SF homes' sales prices in the city of Austin (Nicholls & Crompton, 2005). Council of Tree and Landscape Appraisers (CTLA) reported that as much as 10 to 30 percent of residential property values could be assigned to the entire landscape that includes trees (Cullen, 2007). Li found that the premium of condominium housing is influenced by street connectivity, length of sidewalks, and speed limit (W. Li, 2013). Benefield found that neighborhood sport fields and golf courses significantly impact property values (Benefield, 2009). Table 4-1 presents a more deep and comprehensive literature reviews about the benefits and risks of activity-friendly built environments.

4.2.3 Summary and Conceptual Framework

The findings discussed above demonstrated the economic benefits do exist in recreational amenities, and these amenities were approved as the activity-friendly environments by physical activity studies. However, there are only a few studies that systematically examine the economic benefits of activity-friendly environments. Based on 90,000 SF home sales in 15 metropolitan areas, Cortright found housing values were significantly associated with Walk Score, which are the normalized scores generated based on the network distance to 13 destinations (grocery store, coffee shop, movie theater, park, bookstore, drug store, clothing and music store, restaurant, bar, school, library, fitness, and hardware store). He found on average, every one point increase in Walk Score led to $1,500 increase in sales prices (Cortright, 2009). However, Walk Score only represents the destination accessibility and does not include other important activity-friendly environmental features (e.g. sidewalk, street connectivity, land use mix, etc.).

This study established a 7Ds measurement framework to systematically and concurrently examine the economic benefits of various activity-friendly environmental features. Based on the research objective and literature review, Figure 4-5 is the tailored conceptual framework to guide the study.

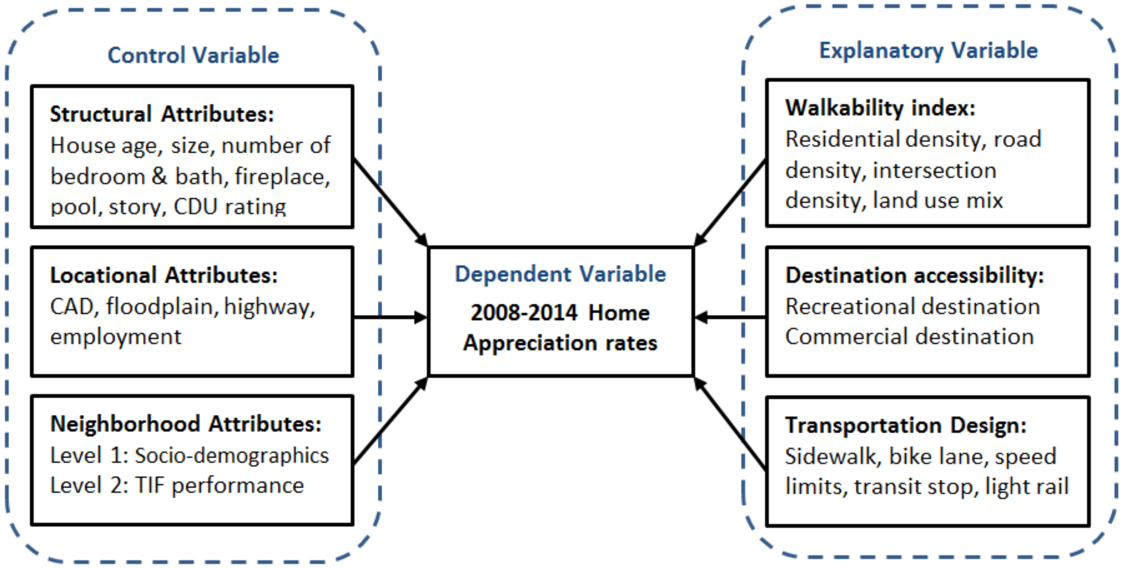

Figure 4-5. Conceptual framework for systematic evaluation of the economic benefits of activity-friendly environments

Table 4-1. The benefits and risks of neighborhood built environments based on literature review

BE category	Typical Variables	Benefits	Risks	Literature
Activity-Friendly Built Environment: Recreation				
Urban open space	Parks, green spaces, recreation areas	Physical activity, physical and psychological health, quality of life, property values, aesthetics, air quality, climate change, social interactions Crompton (2005) confirmed a positive impact of 20% on property values abutting or fronting a passive park is a reasonable starting point guideline.	Noise, traffic, park crime, more strangers/homeless	(Bedimo-Rung et al., 2005; J. Crompton, 2005a; J.L. Crompton, 2001a; John L Crompton, 2005b; Marans, 2003; Orsega-Smith et al., 2004; Parsons, 1995)
Trails	Byway, hiking trail, nature trail, bicycle trail	Physical activity, health, quality of life, income, neighborhood population, vegetative health, property values	Noise, traffic(to age groups of 64+ and < 5), litter, higher vegetation density	(Asabere & Huffman, 2009; John L Crompton, 2001b; Krizek, 2006; Greg Lindsey et al., 2006; G. Lindsey et al., 2004; Reynolds et al., 2007)
Greenway	street trees, green belt	Health, quality of life, positive attitude to own community, the longevity of senior citizens, urban form, recreation, property values, ecological biodiversity and services, amenity visual/aesthetic, economic development, solar shading, reduce air pollution. Orland (1992) found tree size was not a main effect on property value. CTLA (Council of Tree and Landscape Appraisers, 2000) found as much as 10 to 30 percent of residential property values can be assigned to the entire landscape that includes trees.	allergenic properties, infrastructure/property damage and injure people associated with tree failure, messy fruits	(Asabere & Huffman, 2009; John L Crompton, 2001b; Gill et al., 2007; G. Lindsey et al., 2004; Luttik, 2000; Nicholls & Crompton, 2005; Orland et al., 1992; Payton et al., 2008; Takano et al., 2002; Walmsley, 1995)
Water features	Lake, pools, ponds, streams, creeks	Physical activity, quality of life, property values, aesthetics	Recreation conflicts among users, water management cost, flood risk	(Deller et al., 2001; Lansford Jr & Jones, 1995; Leggett & Bockstael, 2000; McDaniels et al., 1999; Wang & Dawson, 2005; Young & Loomis, 2014)
Activity-Friendly Built Environments: Destinations				
Restaurants or food retails	Full-service restaurants, grocery stores	Physical activity, cost saving, travel convenience, consuming goods, property values, activities in destinations (work, shopping, recreation, etc.)	Noise, traffic, messy garbage	(Cerin et al., 2007; Cortright, 2009; S. Handy et al., 2006; Susan L Handy et al., 2002b; Hoehner et al., 2005; McCormack et al., 2008)
Stores and shops	convenience stores, drug stores, clothing/book/ sports stores, etc.	Physical activity, health, cost saving, travel convenience, consuming goods, property values, activities in destinations (work, shopping, recreation, etc.)	Noise, traffic, strangers	

Table 4-1. Continued.

Stores and shops	convenience stores, drug stores, clothing/book/ sports stores, etc.	Physical activity, health, cost saving, travel convenience, consuming goods, property values, activities in destinations (work, shopping, recreation, etc.)	Noise, traffic, strangers	(Cerin et al., 2007; Cortright, 2009; S. Handy et al., 2006; Susan L Handy et al., 2002b; Hoehner et al., 2005; McCormack et al., 2008)
Services	clinics, banks, post offices, dry cleaners	Physical activity, health, cost saving, travel convenience, consuming goods, property values, activities in destinations (work, shopping, recreation, etc.)	Tax, traffic, noise	
School or Institutional facilities	libraries, school playgrounds	Physical activity, health, cost saving, travel convenience, consuming goods, property values, activities in destinations (work, shopping, recreation, etc.)	Noise, traffic	
Religious institutions	Church	Physical activity, travel convenience, consuming goods, activities in destinations (work, shopping, recreation, etc.)	Traffic	
Activity-Friendly Built Environment: Transportation/Infrastructure Design				
Bus/transit stops	bus stop	Physical activity, cost saving, environmental protection, employment (job access), property values (residential and commercial), land development, residential density	Noise, traffic, slower travel speed and longer travel times, suburban sprawl	(Al-Mosaind et al., 1993; Cervero & Duncan, 2002; Hess & Almeida, 2007; McCormack et al., 2008; McMillen & McDonald, 2004; Murray & Wu, 2003)
Sidewalks	Sidewalks	Physical activity, safety, neighborhood accessibility	Soil moisture, sidewalk failure/crack, redirection of street tree roots	(Marlon G Boarnet et al., 2005; M.G. Boarnet et al., 2008; Davison & Lawson, 2006; Hoehner et al., 2005; Krizek, 2006; Landis et al., 2001; Sydnor et al., 2000)
Bike lanes	On-street bicycle lane, off-road bike trail, has parking adjacent to it	Physical activity(bicycling and walking), safety, motorist behavior	Bike-related accidents(e.g., the left-side lane); Krizek found suburban home values were most reduced by proximity to roadside bike trails	(Hunter et al., 2000; Krizek, 2006; Smith Jr & Walsh, 1988; Tilahun et al., 2007; V.R. et al., 2011)
Intersection	pedestrian crossing	Safety, physical activity, pedestrian visibility at crossing points.	Higher collision risk (with no signal/stop sign)	(Marlon G Boarnet et al., 2005; Marlon G Boarnet et al., 2011; S.L. Handy et al., 2002a; Koepsell et al., 2002; Saelens & Handy, 2008; Zegeer et al., 2001)

4.3 Methods

4.3.1 Data and Study Design

This study was carried out in the 14 currently active TIF districts and 14 non-TIF comparison neighborhoods in city of Dallas (the discussion about the selection of comparison neighborhoods could be found in Chapter 2). There are 2,908 residential homes in these 14 TIF districts and 6,703 homes in 14 non-TIF comparison neighborhoods, after removing the ones with missing attributes. Next, for TIF districts, I removed 12 homes with appreciation rates less than 0.5 and 21 homes with appreciation rates more than 2.0. For comparison neighborhoods, I removed 76 homes with appreciation rates less than 0.5 and 5 homes with appreciation rates more than 2.0. The final samples sizes for residential properties in TIF districts and their comparison neighborhoods are 2875 and 6622, respectively.

The dependent variable is the appreciation rates for each of residential homes, which was calculated as the 2014 appraisal values divided by 2008 appraisal values. The appraisal values were assessed as 100% of market values by Dallas Central Appraisal district, and is the only longitudinal and systematic property data available for this study, and has been approved as the legitimate data to measure hedonic price model by previous studies (Berry & Bednarz, 1975; Hendon, 1971; Seiler et al., 2001; W. J. Shin et al., 2011b) (More discussion could be found in Chapter 2). The ratio was transformed into natural log form when it was used as the dependent variable in the analysis. Figure 4-6 presented the distribution of appreciation rates before and after log-transformation. From the figure, the distributions of appreciation rates for both samples were positively skewed (skewed to the right). The log-transformation reached approximate Gaussian distributions.

The reasons to use appreciation rates instead of actual value growth are: (1) to avoid the negative and zero values, which are invalid for log-transformation; (2) Similar practice in previous studies applied appreciation rates to represent the longitudinal housing value changes (Dong, 2014).

The reasons to use 0.5 and 2 as the cut off appreciation rates are: (1) the distribution of samples suggested that removing the values below 0.5 and above 2 would not impact the samples sizes (reduce total 114 homes, only account for 1.19% of original samples); (2) the appreciation values larger than 2 times or less than half during six years were abnormal conditions and considered as outliers in this study; (3) using 0.5 and 1.5 as the cut off values seems more legitimate for non-TIF sample distribution; however, TIF samples have relatively higher appreciation rates and using 1.5 led to a risk of reducing the sample variation (132 samples dropped, which account for 4.54% of original TIF samples). To keep the measurement consistent between two groups, I used 0.5 and 2 as the cut off values for appreciation rates.

Three additional tests were conducted to confirm the log-transformation of dependent variable between 0.5 and 2 has the best model fit and can better express the variation for study variables. I used (1) cut off values of 0.5-1.5, (2) cut off values of 0.5-1.5 in log-transformed, (3) cut off values of 0.5-2 in log-transformed as dependent variable respectively with the final OLS model variables, and the results suggested these models have less significance and lower R squares compared to the cut off values of 0.5-2 in log-transformed.

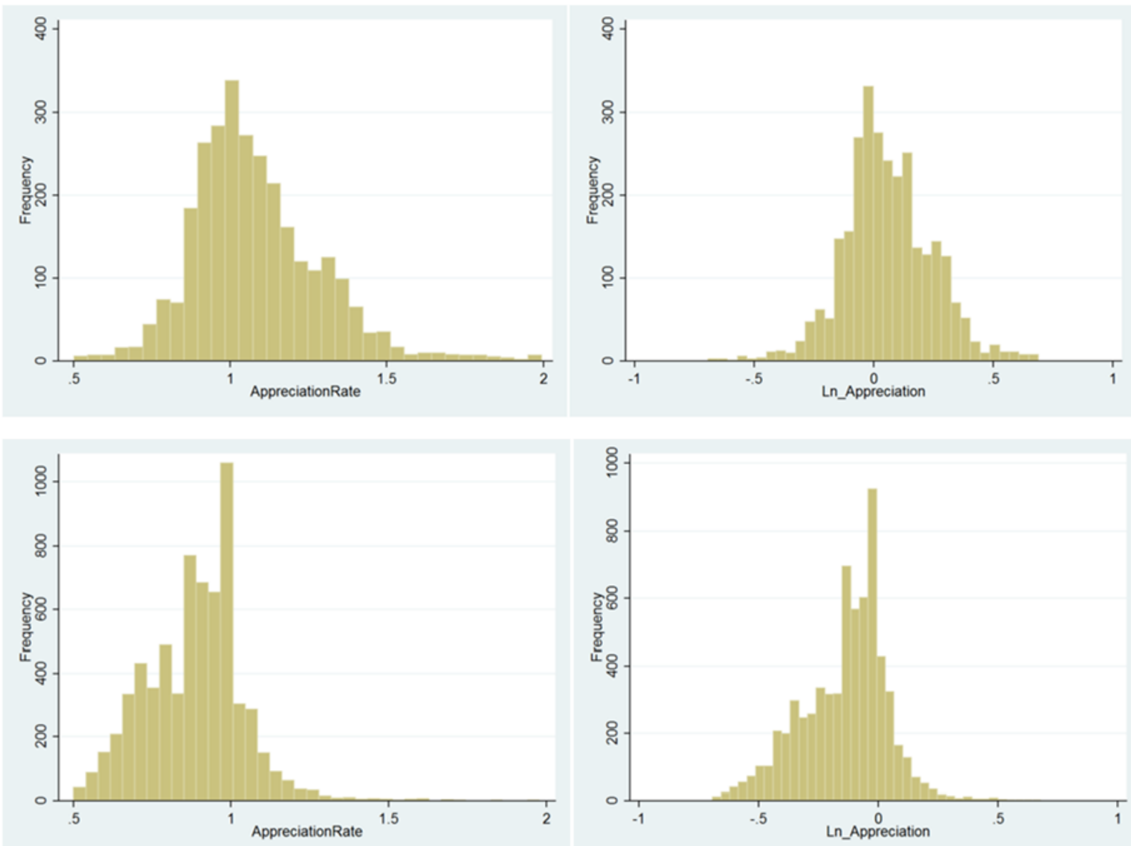

Figure 4-6. Distribution of appreciation rates in TIF districts (top) and comparison neighborhoods (below) before and after log-transformation

4.3.2 Variables and Measurements

To systematically identify the economic benefits for activity-friendly environments, I established 7Ds measurement framework to measure the study variables. The 7Ds measurement framework was inspired by previous transportation and physical activity studies. Cervero and Kockelman proposed the 3Ds (density, diversity, and design) framework in 1997 to guide the measurement of neighborhood and environmental factors related to travel mode choice (Cervero & Kockelman, 1997). Subsequently, a few articles further elaborated his 3Ds approach and included additional domains (Ewing et al., 2014; Frank, Sallis, et al., 2010; Lee & Moudon, 2006a). Lee and Moudon devised the 3Ds + R (density, diversity, and design + route) concept to quantify land use and urban form variables specifically for capturing walkability (Lee & Moudon, 2006a). Ewing et al. developed the 5Ds (density, diversity, design, destination accessibility, distance to transit) model to measure the varying influences of built environment on travel behaviors (Ewing et al., 2014). Frank and colleagues proposed a walkability index to measure the walkability from the neighborhood to the regional level, which included four domains: residential density, commercial density, land use mix, and street connectivity (Frank, Sallis, et al., 2010). Walk Score measured the destination accessibility based on the closest network distance to each of the 13 destinations (grocery store, coffee shop, movie theater, park, bookstore, drug store, clothing and music store, restaurant, bar, school, library, fitness, and hardware store) (Cortright, 2009).

Based on Ewing's 5Ds, this study added two additional Ds to 7Ds framework, which includes Density, Diversity, Design, Distance, Destination accessibility, Demographics, and District. All the Ds were measured in ArcGIS. The following paragraphs briefly introduced the process of 7Ds measurements applied in this study.

In terms of density, the variables in polygon shape were measured by the proportion of area or count per area (e.g. parks), while the variables in polyline shape were measured by the proportion of length (e.g. roads), and the variables in point level were measured as the count per area (e.g. total employment in buffer).

Diversity was measured by land use mix, which is the evenness of residential, commercial, and office land uses. It could be also measured by the availability of various destination types.

Design measured infrastructure characteristics, such as street connectivity, sidewalk/bike lane completeness, or other measurable physical variables.

Destination accessibility measured the ease of access to trip destinations, such as the shortest distance from home to park, coffee shop or school.

Distance measured regional locations or environments, such as the proximity to CADs (Dallas is a polycentric urban area which has three CADs located in downtown, uptown, and midtown), highway, floodplain, etc.

Demographics measured socio-demographic characteristics (in density or counts) within certain areas (e.g. buffers or neighborhoods), such as population, race, ethnicity, income, education level, housing characteristics, etc.

District measured attribute-specific variable interactions across hierarchies, such as students across different schools, SF homes across different school districts. This measurement usually prepares for further analysis such as hierarchical linear models or mixed effect models. In this study, for TIF districts, district measured the random effect of TIF performance, which was the average annual growth rate for each TIF districts, that was calculated based on the total growth rate divided by the years of that TIF has been operated (Appendix C). For comparison neighborhoods, district measured the fixed effect, which only account for the variation among comparison neighborhoods.

In terms of study variables, the activity-friendly environmental features were considered as explanatory variables, including the walkability indices, the destination accessibility variables of 13 types of destinations defined by Walk Score, as well as the additional variables of recreational, commercial and service destinations, and transportation/infrastructure design defined from previous physical activity studies and measured by the 7Ds framework (Table 4-1). The structural variables, locational variables and socio-demographic variables were considered as control variables in the analysis. All the explanatory variables and control variables were categorized into six variable domains. Except structural domain, each of domains belongs to one or more Ds measurements.

Another issue in measurement needs to be addressed is how to define the boundary of neighborhoods. The modifiable areal unit problem (MAUP) is a classic problem in statistical analysis of geographical data suggests that the same basic data generate different results when aggregated in different neighborhood sizes (Gehlke & Biehl, 1934). Flowerdrew empirical identified MAUP does matter where researchers draw the boundaries of neighborhoods, however, the difference is not too worrying (Flowerdew et al., 2008). Several studies suggested the use of 400-meters (equal to a quarter mile) radius of circular buffers to reflect an individuals' immediate neighborhoods has helped to manage the MAUP, because this distance can capture suitable variations of specific neighborhood characteristics, and would not cause much problem due to spatial autocorrelation (Brownson et al., 2009; Duncan et al., 2012; James et al., 2014). Therefore, I applied a quarter mile straight-line buffers to all the variables in density measurement. Table 4-2 presented the definition, measurements, and data sources of each study variable and its domain.

Table 4-2. The definition, measurements, and data sources of study variables

Variable	Measurement	Data sources and time period
DEPENDENT VARIABLE		
Home appreciation rates (log)	(2014 values ÷ 2008 values) in log transformation	Dallas CAD, 2008 & 2014 appraisal
CONTROL VARIABLES		
Subsample neighborhood	The home is in subsample neighborhood or not (1/0)	Dallas ED, 2014;
SF detached home	The home is SF detached or not (1/0)	Dallas CAD, 2008 & 2014 appraisal (same as below)
House age	Number of years the home was built (years)	
Total living area	Square feet of the building area (feet)	
Bedroom	Number of bedrooms (continuous)	
Full bath	Number of bathrooms (continuous)	
Half bath	Have half/wet bathroom or not (1/0)	
Story	Have 1.5 stories and more or one story only (1/0)	
Fireplace	Have fireplace or not (1/0)	
Pool	Have swimming pool or not (binary, 1/0)	
CDU rating	Rating reflecting the physical condition, utility and desirability of a property (8-scale treat as continuous)	
Locational Attributes (Distance)		
Floodplain	Property within 100/500 year floodplain or not (1/0)	Dallas planning office, 2014;
Traffic crash	Number of pedestrians or cyclists involved crashes in buffer	Texas DOT, 2010-2014
CAD proximity	Euclidean distance to the Central Activities Districts (CADs refers to Dallas downtown, uptown, and midtown)	Google map
Highway	Euclidean distance to the closest highway	Dallas planning office, 2014

Table 4-2. Continued.

Variable	Measurement	Data sources and time period
Highway proximity	Have highway within a quarter mile or not (0/1)	Dallas planning office, 2014
Socio-Demographics (Demographics)		
Employment	Number of employees within buffer	On The Map,2011
Occupancy rate	Percentage of occupied housing units in buffer	2010 US Census; 08-12 ACS 5-years estimates (same as below)
Race	Percentage of White only population in buffer	
Ethnicity	Percentage of Hispanic or Latinos population in buffer	
Education	Percentage of population aged in 25 and over under high school education in buffer	
Income	Average median household income in buffer	
EXPLANATORY VARIABLES		
Neighborhood Walkability Indices (Density & Design & Diversity)		
Residential density	Number of population / residential area in buffer	2010 US Census; Dallas CAD, 2014
Intersection density	Number of street intersections (≥3) in buffer	Dallas planning office, 2014; Dallas CAD, 2014
Road density	Total miles of streets in buffer	
Land use mix	Evenness of residential, commercial, and office uses	
Recreational Uses (Diversity & Destination Accessibility)		
Park	Euclidean distance to the closest one (same as below)	Dallas planning office, 2008-2014
Water feature		
Trail		
Golf courses & country clubs	Network distance to the closest one	Reference USA, 2014; ArcGIS Business Analysis (same as below)
Destinations (Diversity & Destination Accessibility)		
Grocery store/supermarket	Network distance to the closest one (same as below)	
Coffee and snack shop		
Sports good/book/music store		
Drug store		
Clothing store		
Full-service restaurant		
Bar/tavern/pub		
School and education service		
Library		
Fitness center		
Hardware store		
Specialty food store		

Table 4-2. Continued.

Variable	Measurement	Data sources and time period
Child Day Care Service		Reference USA, 2014; ArcGIS Business Analysis (same as below)
Religious institution		
Office/stationery/gift store		
Arts/entertainment/recreation facilities service		
Personal care service		
Dry cleaning/laundry service		
Destination density	Total number of destinations in buffer	
Average network distance	Average network distance of destinations	
Transportation/Infrastructure Design (Density & Design)		
Sidewalk completeness	Total miles of sidewalks in buffer / total mile of streets in buffer	Dallas planning office, 2008-2014 (same as below)
Bike lane completeness	Total miles of bike lanes in buffer/ total mile of streets in buffer	
Traffic signal	Number of traffic signals within buffer	
Speed limit	Average speed limit within buffer	
Transit stop	Number of transit stops within buffer	
Light rail station proximity	The property within in 0.5 mile radius of light rail stations or not (1/0)	
Level Two Variable (District)		
TIF annual growth rate	Average annual growth rate for each TIF districts	Dallas ED, 2013

Note:

1. Dallas ED = Dallas Economic Development Department, Texas DOT = Texas Department of Transportation, Dallas CAD = Dallas Central Appraisal district;
2. The land-use mix was calculated based on the equation: (-1) * [(area of R/total area of R, C, and O) * ln(area of R/total area of R, C, and O) + (area of C/total area of R, C, and O) * ln (area of C/total area of R, C, and O) + (area of O/total area of R, C, and O) * ln (area of O/total area of R, C, and O)] / ln (number of land uses present).
3. The circular buffer was measured based on a quarter mile radius from each home, area was measured in acres, and distance was measured in miles

Table 4-3. The descriptive statistics and bivariate test for residential homes in TIF districts and comparison neighborhoods

Variables	Homes in TIF (N = 2875)	Homes in Non-TIF (N=6622)	TIF vs. Non-TIF
	Mean (SD) / Freq. (% of 1)	Mean (SD) / Freq. (% of 1)	*t* Test
Dependent variables			
Home appreciation rates	1.089 (0.255)	0.881 (0.169)	40.279**
Control Variables			
Subsample neighborhood (Skillman Corridor=1)	2025 (70.43%)	1950 (29.45%)	40.243**
SF detached home (0/1)	2334 (80.3%)	5469 (81.6%)	-1.515
House age (years)	43.293 (18.708)	48.737 (20.563)	-12.711**
Total living area (square feet)	2234.330 (719.923)	1684.495 (683.604)	48.603**
Bedroom (continuous)	3.362 (0.703)	2.867 (0.662)	32.290**
Full bath (continuous)	2.294 (0.644)	1.814 (0.734)	32.129**
Half bath (0/1)	1897 (65.2%)	2393 (35.7%)	27.808**
Story (0/1)	1322 (45.5%)	1486 (22.2%)	22.104**
Fireplace (0/1)	2479 (85.2%)	3623 (54.1%)	34.810**
Pool (0/1)	668 (23.0%)	583 (8.7%)	16.738**
CDU rating (categorical)	5.810 (1.390)	5.518 (1.155)	9.947**
Locational Attributes (Distance)			
Floodplain (0/1)	195 (6.7%)	179 (2.7%)	8.007**
Traffic crash (continuous)	2.380 (3.942)	1.900 (2.508)	6.051**
CAD proximity (continuous)	3.819 (2.017)	4.354 (1.782)	-12.360**
Highway (continuous)	0.760 (0.436)	0.792 (0.605)	-2.872**
Highway proximity (0/1)	461 (15.9%)	1349 (20.1%)	-5.111**
Employment (continuous)	341.852 (905.002)	332.766 (628.046)	0.566
Socio-Demographics (Demographics)			
Occupancy rate	91.652 (5.319)	88.750 (8.640)	20.090**
Race	37.706 (31.857)	30.875 (27.452)	10.056**
Ethnicity	35.031 (28.822)	35.737 (27.264)	-1.121
Education	20.781 (17.286)	20.897 (19.281)	-0.291
Income	58610.876 (31522.738)	56753.971 (32787.329)	2.621**
Explanatory Variables (continuous)			
Neighborhood Walkability Indices (Density & Design & Diversity)			
Residential density	22.027 (28.281)	24.296 (13.513)	-4.127**
Intersection density	34.318 (21.333)	30.500 (16.548)	8.594**
Road density	4.655 (1.275)	4.103 (1.298)	19.399**
Land use mix	0.285 (0.260)	0.296 (0.262)	-1.859

Table 4-3. Continued.

Variables	Homes in TIF (N = 2875)	Homes in Non-TIF (N=6622)	TIF vs. Non-TIF
	Mean (SD) / Freq. (% of 1)	**Mean (SD) / Freq. (% of 1)**	***t* Test**
Recreational Uses (Diversity & Destination Accessibility)			
Park	0.246 (0.164)	0.415 (0.264)	-38.176**
Water feature	0.048 (0.076)	0.103 (0.106)	-29.181**
Trail	0.483 (0.305)	0.518 (0.296)	-5.275**
Golf courses & country clubs	2.449 (0.830)	2.599 (1.258)	-6.898**
Destinations (Density & Diversity & Destination Accessibility)			
Grocery store/supermarket	0.491 (0.262)	0.681 (0.341)	-29.689**
Coffee and snack shop	0.588 (0.311)	0.907 (0.362)	-43.827**
Sports good/book/music store	0.606 (0.295)	0.767 (0.484)	-20.032**
Drug store	0.589 (0.220)	1.116 (0.416)	-80.908**
Clothing store	0.593 (0.253)	0.588 (0.259)	0.853
Restaurant	0.427 (0.216)	0.526 (0.392)	-15.879**
Bar/tavern/pub	1.422 (0.686)	1.308 (0.662)	7.707**
School and education service	0.337 (0.154)	0.559 (0.297)	-48.040**
Library	1.023 (0.413)	1.693 (0.925)	-49.067**
Fitness center	0.865 (0.473)	0.911 (0.469)	-4.437**
Hardware store	2.202 (0.722)	2.053 (1.021)	8.163**
Specialty food store	0.734 (0.424)	0.808 (0.347)	-8.259**
Child Day Care Service	0.648 (0.325)	0.713 (0.334)	-8.724**
Religious institution	0.439 (0.219)	0.395 (0.274)	8.297**
Office/stationery/gift store	0.536 (0.277)	0.989 (0.455)	-59.958**
Arts/entertainment/recreation facilities	0.541 (0.248)	0.738 (0.411)	-28.884**
Personal care service	0.412 (0.193)	0.460 (0.227)	-10.521**
Dry cleaning/laundry service	0.494 (0.293)	0.692 (0.281)	-30.791**
Destination density	11.695 (18.478)	6.527 (8.249)	14.468**
Average network distance	0.735 (0.131)	0.888 (0.210)	-43.315**
Transportation/Infrastructure Design (Density & Design)			
Sidewalk completeness	0.225 (0.271)	0.212 (0.285)	2.029*
Bike lane completeness	0.217 (0.134)	0.178 (0.123)	13.362**
Traffic signal	1.274 (1.688)	0.787 (0.977)	14.544**
Speed limit	27.104 (2.020)	29.202 (2.854)	-41.004**
Transit stop	6.614 (6.264)	5.787 (5.132)	6.268**
Light rail station proximity (0/1)	757 (26.0%)	1445 (21.6%)	4.678**
Level Two Variable (District)			
TIF annual growth rate (%)	10.559 (14.398)	n/a	n/a

*: p<0.05 / **: p<0.01

4.3.3 Analysis

Table 4-3 presented the descriptive statistics and bivariate test for study variables in both TIF districts and comparison neighborhoods. The average of appreciation rates for TIF is 1.089, which is significantly higher than comparison neighborhoods (0.881). There is one TIF with substantial amount of residential homes, which account for 70.43% of total samples. To control for the potential sampling bias due to the overrepresentation, I created a dummy variable to present the homes located in this TIF and its comparison neighborhood. I also created another dummy variable to control for the difference of whether the residential homes are SF detached homes or SF non-detached homes. Only townhouses, condominiums, and duplex were considered as non-detached homes; apartments and mobile homes were excluded from this study to avoid heterogeneity problem. From the statistics, both groups had high percentages of SF detached homes (80.3% and 81.6%). After controlling the socioeconomic characteristics in neighborhood level, on average, the residential homes in TIF districts were newer, with more space and rooms, better utility (with higher percentage of fireplace and pools), and better structural conditions (5.810 vs. 5.518 in CDU).

Table 4-4 shows unadjusted analyses comparing the relationship between appreciation rates and each of study variables in both groups. Without controlling for other variables and spatial patterns, most of the variables were significantly associated with appreciation rates. However, the findings were different between two groups. In terms of control variables, SF detached homes had relatively higher appreciation rates in TIF districts while relatively lower appreciation rates in comparison neighborhood, compared to SF non-detached homes. Most of the differences appeared in destination, which indicated the effect of destination accessibility on appreciation rates has the largest variation among neighborhoods with different development pattern. More total destinations within buffer and less average destination distance were associated with higher appreciation rates in both groups, indicating the density of accessible destinations significantly impact the property values of nearby homes. Unadjusted analyses provided a first glance of the simplest relationships among variables. Next I conducted several multiple regression analyses by controlling multicollinearity, spatial autocorrelation, and nested data structure, to examine the more complex relationships among study variables.

The variable selection for the final OLS regression model followed sequential steps, including (1) construction of a base model incorporating two dummy variables (subsample and SF detached home) and structural attributes, all the variables in base model are locked and included as important control variables for the rest of analyses (Table 4-5); (2) selection of the significant subset of variables in each domain modeled with base model; (3) Adding the significant variables from each domain together and modeled with the base model and kept only significant variable; (4) To reduce the multicollinearity issue, I removed all the significant variables with a Variance inflation factor (VIF) larger than 5.

Table 4-4. Unadjusted relationship between homes appreciation rates and study variables for both TIF samples and non-TIF samples

Variables	Homes in TIF (N = 2875)		Homes in Non-TIF (N=6622)	
	Unadjusted Coefficient	Association (+/-)	Unadjusted Coefficient	Association (+/-)
Control Variables				
Subsample neighborhood (Skillman Corridor=1)	0.190**	+	0.128**	+
SF detached home	0.143**	+	-0.076**	—
House age	0.001**	+	-0.002**	—
Total living area (×1,000)	0.038**	+	0.113**	+
Bedroom	0.069**	+	0.048**	+
Full bath	0.016**	+	0.091**	+
Half bath	-0.027		0.139**	+
Story	-0.001		0.057**	+
Fireplace	0.158**	+	0.100**	+
Pool	0.022**	+	0.134**	+
CDU rating	0.029**	+	0.047**	+
Locational Attributes				
Floodplain	0.082**	+	-0.166**	—
Traffic crash	-0.009**	—	-0.010**	—
CAD proximity	0.044**	—	-0.015**	+
Highway	0.158**	—	0.003	
Highway proximity	-0.124**	—	-0.075**	—
Employment (×1,000)	-0.028**	—	0.009**	+
Socio-Demographics				
Occupancy rate	0.002**	+	0.002**	+
Race	0.001**	+	0.002**	+
Ethnicity	-0.001**	—	0.001**	+
Education	-0.001**	+	0.002	
Income (×10,000)	-0.003**	—	-0.011**	—
Explanatory Variables				
Neighborhood Walkability Indices				
Residential density	-0.002**	—	-0.002**	—
Intersection density	-0.002**	—	-0.002**	—
Road density	-0.031**	—	-0.030**	—
Land use mix	-0.133**	—	0.011	

Table 4-4. Continued.

Variables	Homes in TIF (N = 2875)		Homes in Non-TIF (N=6622)	
	Unadjusted Coefficient	Association (+/-)	Unadjusted Coefficient	Association (+/-)
Recreational Uses				
Park	0.218**	—	-0.012	
Water feature	-0.836**	+	-0.674**	+
Trail	0.027*	—	0.134**	—
Golf courses & country clubs	0.036**	—	0.011**	—
Destinations				
Grocery store/supermarket	0.015		0.009	
Coffee and snack shop	-0.060**	+	-0.080**	+
Sports good/book/music store	0.089**	—	-0.094**	+
Drug store	-0.165**	+	0.002	
Clothing store	0.010		-0.124**	+
Full-service restaurant	0.200**	—	-0.056**	+
Bar/tavern/pub	0.085**	—	0.010**	—
School and education service	-0.233**	+	-0.068**	+
Library	-0.110**	+	0.035**	—
Fitness center	-0.062**	+	-0.034**	+
Hardware store	-0.026**	+	0.051**	—
Specialty food store	-0.071**	+	-0.048**	+
Child Day Care Service	-0.100**	+	0.060**	—
Religious institution	0.256**	—	0.114**	—
Office/stationery/gift store	-0.076**	+	-0.043**	+
Arts/entertainment/recreation facilities	0.166**	—	0.002	
Personal care service	0.121**	—	-0.026**	+
Dry cleaning/laundry service	0.004		-0.090**	+
Destination density	0.001**	+	0.002**	+
Average network distance	-0.078**	+	-0.094**	+
Transportation/Infrastructure Design				
Sidewalk completeness	-0.275**	—	-0.057**	—
Bike lane completeness	-0.396**	—	-0.041*	—
Traffic signal	-0.022**	—	0.012**	+
Speed limit	-0.009**	—	-0.008**	—
Transit stop	-0.010**	—	-0.008**	—
Light rail station proximity	0.035**	+	-0.140**	—
Level Two Variable (District)				
TIF annual growth rate	0.001**	+	n/a	n/a

*: p<0.05 / **: p<0.01

Table 4-5. The base model for multi-level analysis (HPM, Spatial error, and HLM)

Variables	Homes in TIF		Homes in Non-TIF	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**
Subsample with large units	0.216**	0.010	0.011	0.006
SF detached home	0.021	0.012	-0.075**	0.007
House age	0.001**	0.001	0.001*	0.001
Total living area (×1,000)	-0.021**	0.007	0.096**	0.001
Bedroom	-0.001**	0.006	-0.023**	0.004
Full bath	-0.019	0.006	0.017**	0.005
Half bath	-0.050**	0.008	0.052**	0.005
Story	0.065**	0.007	-0.052**	0.006
Fireplace	0.039**	0.010	-0.035**	0.005
Pool	-0.054**	0.007	0.017*	0.008
CDU rating	0.042**	0.002	0.033**	0.002
No. Observations	2875		6622	
Adjusted R Square	0.343		0.275	

*: p<0.05 / **: p<0.01

In order to select appropriate spatial model approach to mitigate the spatial autocorrelation problems, I performed the Lagrange Multiplier (LM) test based on Figure 4-4. The Robust LM test for spatial lag was not significant for TIF samples, which suggested spatial error model is more appropriate for TIF samples. For the non-TIF samples, both spatial lag and spatial error were suitable suggested by LM test. Finally the spatial error models were utilized for both models for two reasons: (1) to ensure model consistency in both samples; (2) unlike spatial Durbin and spatial lag models that have partial derivative for indirect effects, there are no spillover effects (indirect effects or higher order direct effects) for spatial error models. Hence, spatial error model can be interpreted like OLS in the usual way (Glass, 2012; Elhorst, 2014).

The spatial weight matrix was constructed based on Euclidean distance of 660 feet, that is, all neighbors located within 660 feet from each home would have the same weight of impact on each other's property values. There are three justifications to apply 660 feet as spatial weight distance instead of 1320 feet: (1) the spatial weight distance of 1320 feet over-captured the spatial autocorrelation issue and reduced the variations of specific characteristics, which caused only a few exploratory variables were significant in final spatial models; (2) this study included all the residential types (except apartments and mobile homes) in TIF neighborhoods, which densely nested together. Therefore, 660 feet threshold of spatial weight matrix is enough to account for spatial dependence; and (3) the variations of TIF neighborhoods would capture the spatial dependence issue in large scale distance measured in HLM, which is a different spatial procedure but targeting the similar goals.

The spatial error regressions were generated with the maximum likelihood estimation, and the variable selection was based on the significant variables measured in OLS estimates, after the consideration of VIF tolerance.

I also conducted two HLMs for each groups to control for the nested data structure. Based on the Interclass Correlation Coefficient (ICC) and Design Effect test (Raudenbush & Bryk, 2002; Satorra & Muthen, 1995), the ICC for TIF samples was 0.242, and the Design Effect was 51.024; the ICC for comparison neighborhood samples was 0.416 and the Design Effect was 232.96. Both results suggested using HLM as a solution to deal with the nested structure and intraclass correlations. The variable selection was based on the significant variables measured in OLS estimates, with VIF tolerance considered. The statistical analyses were carried out in STATA, GeoDa, and HLM software.

4.4 Results

4.4.1 The Economic Benefits of Activity-Friendly Environments in TIF Districts

This study considered a conservative estimates and only discussed the variables that were significant in all three models (OLS regression, spatial error regression, and HLM).

In regard to Objective 1, the TIF models in Table 4-6 shows the final estimates of economic benefits of activity-friendly environmental feature reflected in appreciation rates in TIF districts. In terms of the control variables, for structural attributes, the TIF models presented consistent findings. Housing age, presence of fireplace and CDU rating were positively associated with appreciation rates, while presence of swimming pool was negatively associated with appreciation rates. For locational attributes, only one variable, being away from highway, was associated with higher appreciation rates in all three models. For socio-demographic variables, the percentage of Hispanic or Latino population and the average household income were negatively associated with appreciation rate.

Table 4-6. The models comparison for the effects of study variables on residential homes' appreciation rates in both TIF districts and comparison neighborhoods

Variables	Homes in TIF (N = 2875) TIF Models			Homes in Non-TIF (N=6622) Non-TIF Models		
	OLS	Spatial Error	HLM	OLS	Spatial Error	HLM
Control Variables						
Subsample neighborhood (Skillman Corridor=1)	0.208**	0.186**	0.202*	0.031**	0.072**	0.111
SF detached home	-0.002	0.001	0.010	-0.055**	-0.062**	-0.044**
House age	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**
Total living area (×1,000)	-0.008	-0.001	-0.001	0.062**	0.048**	0.052**
Bedroom	-0.002	-0.002	-0.005	-0.004	0.001	-0.001
Full bath	-0.005	-0.005	-0.003	0.002	0.003	0.001
Half bath	-0.002	0.002	-0.002	0.003	-0.005	-0.004
Story	0.002	-0.005	-0.002	-0.030**	-0.029**	-0.026**
Fireplace	0.027**	0.035**	0.023*	-0.019**	-0.015**	-0.020**
Pool	-0.023**	-0.016*	-0.018**	0.004	-0.003	-0.002
CDU rating	0.043**	0.045**	0.043**	0.035**	0.038	0.034**
Locational Attributes						
Floodplain				-0.049**	-0.007	-0.033*
Traffic crash				-0.004**	-0.005**	-0.001
Highway	0.126**	0.131**	0.133**			
Highway proximity				-0.022**	-0.045**	-0.023**
Employment (×1,000)	0.012**	0.005	0.005			
Socio-Demographics						
Occupancy rate				0.002**	0.001	0.003**
Ethnicity	-0.001**	-0.001**	-0.001**			
Income (×10,000)	-0.003*	-0.002	-0.001**	-0.012**	-0.001**	-0.020**
Explanatory Variables						
Neighborhood Walkability Indices						
Residential density	0.001*	0.001	0.001	-0.001**	-0.001	-0.001**
Road density				-0.016**	-0.006	-0.018**
Land use mix	0.031*	0.010	0.025	0.023**	0.014	0.026**
Recreational Uses						
Park				-0.068**	-0.078**	-0.038**
Water feature	-0.348**	-0.348**	-0.178*			
Trail	-0.071**	-0.065*	-0.076**	0.059**	0.045	0.034**

Table 4-6. Continued.

Variables	Homes in TIF (N = 2875) TIF Models			Homes in Non-TIF (N=6622) Non-TIF Models		
	OLS	Spatial Error	HLM	OLS	Spatial Error	HLM
Destinations						
Coffee and snack shop				-0.088**	-0.124**	-0.128**
Sports good/book/music store	0.079**	0.010**	0.092**			
Drug store	0.097**	0.100**	0.055	-0.018**	0.008	0.008
Clothing store				-0.120**	-0.066*	-0.088**
Full-service restaurant	-0.078**	-0.102*	-0.036	-0.150**	-0.148**	-0.100**
School and education service	-0.070**	-0.043	-0.020	0.061**	0.072**	0.029**
Fitness center				0.032**	0.010**	0.011
Hardware store				0.032**	0.031**	0.009
Specialty food store	-0.116**	-0.108**	-0.084**			
Child Day Care Service				0.069**	0.085**	0.094**
Religious institution	-0.055**	-0.072**	-0.077**	-0.069**	-0.093**	-0.088**
Arts/entertainment/recreation facilities	0.052**	0.047*	0.061**			
Personal care service	-0.114**	-0.095*	-0.093**	0.184**	0.199**	0.181**
Transportation/Infrastructure Design						
Sidewalk completeness	-0.092**	-0.094**	-0.087**	0.035**	0.028	0.002
Bike lane completeness				-0.075**	-0.070	-0.058**
Traffic signal	0.004*	0.007*	0.012**	0.008**	0.001	0.005
Speed limit				-0.002**	-0.001	0.001
Transit stop				0.003**	0.003**	0.002*
Light rail station proximity				-0.088**	-0.070**	-0.095**
Level Two Variable (District)						
TIF annual growth rate	n/a	n/a	0.001	n/a	n/a	n/a
Adjusted R square	0.526	0.558		0.480	0.547	
Spatial error coeff. (LAMBDA)		0.544**			0.805**	
-2 Log likelihood		-1916.572			-4583.637	
σ^2			0.017			0.016

*: p<0.05 / **: p<0.01

In terms of the explanatory variables, none of the neighborhood walkability index variables were significant in all TIF models. For recreational uses, closer to water feature and trails were associated with higher appreciation rates. For destinations, closer to specialty food stores, religious institutions, and personal care services were associated with higher appreciation rates; while away from sport good/book/music stores and arts/entertainment/recreation facilities were associated with higher appreciation rates. For transportation/infrastructure design, sidewalk completeness was negatively associated with appreciation rates, while the density of traffic signal was positively associated with appreciation rates.

In terms of the overall model fit, the adjusted R-squared for OLS regression was 0.526. The adjusted R-squared for spatial error regression was 0.558, indicating the general model fit improved. Further, the spatial correlated errors (LAMBDA) was highly significant, indicating the spatial error issue was controlled. For hierarchical linear model, the level-2 TIF variable was not significant, indicating the variation of home appreciation rates among TIF districts were not associated with the annual TIF growth rate and were only impacted by the nested structure. In other words, the HLM played a similar role as spatial error model did in this study, but with different statistical mechanisms and spatial ranges.

4.4.2 The Comparison of Economic Benefits of Activity-Friendly Environments between TIF Districts and Comparison Neighborhoods

In regard to Objective 2, I compared the results between TIF models and non-TIF models shown in Table 4-6. In terms of control variables, the SF detached homes had lower predicted appreciation rates than non-detached homes in comparison neighborhoods, while it was not significant in TIF models. For structural attributes, compared to TIF models, there were more variables significantly related to the home appreciation rates in non-TIF models, suggesting structural attributes accounted for more effects on home appreciation rates in comparison neighborhoods. For locational attributes, homes within a quarter mile distance from highway were associated with lower appreciation rates in non-TIF models, which is similar with findings from TIF models. For socio-demographic variables, only median household income was negatively associated with appreciation rates, and ethnicity was not significant, compared to TIF models.

In terms of the explanatory variables, for neighborhood walkability indices, same as TIF models, none of the variables were significant in non-TIF models. For recreational uses, park proximity was positively related to appreciation rates. This was the similar findings as TIF models because parks, water features, and trails are always clustered together. The major differences between TIF and non-TIF models were the associations of destinations and transportation/infrastructure design with home appreciation rates. For non-TIF models, closer to coffee and snack shops, clothing stores, full-services restaurants, religious institutions were associated with higher appreciation rates; while away from school and education services, day care services, and personal care services were associated with lower appreciation rates. For transportation/infrastructure design, bike lane completeness and homes within quarter mile distance from light rail stations were negatively associated with appreciation rates, while the transit stop density was positively associated with appreciation rates.

In terms of the overall model fit, for non-TIF models, the adjusted R-squared for OLS regression and spatial error regression were 0.480 and 0.547; both indicating a weaker model fit compare to the TIF models. The spatial correlated errors (LAMBDA) was highly significant, indicating the spatial error issue was controlled. There was no level-2 variable and HLM only controlled the fixed effects for homes nested in different comparison neighborhoods.

4.5 Discussions and Conclusion

4.5.1 Discussions

4.5.1.1 The Economic Benefits of Activity-Friendly Environments in TIF Districts

Findings from TIF models supported the Hypothesis 1 that differences in the built environment are associated with differences in the economic benefits on home value appreciation rates. However, environments that provide better opportunities for physical activity are not necessarily associated with higher appreciation rates.

In terms of control variables, controlling for other factors, all the results followed the real estate and socioeconomics rules. SF detached home was not significantly associated with appreciation rates, suggesting non-SF detached homes, which often located in mixed-use areas, have equal opportunities on home value appreciation as SF homes in TIF neighborhoods. The newer dwellings and dwellings with swimming pools often considered as the positive factors on home sales prices; however, they were associated with lower appreciation rates in this study, suggesting in the current financial constraints, the older dwellings without pools have higher demands in housing market which lead to higher appreciation rates, controlling for other factors. Highway is usually considered as an undesirable built environmental factor for dwellings to close with, that was negatively associated with appreciation rates. Hispanic or Latino population was negatively associated with appreciation rates in this study.

Regional proximity (e.g. proximate to CBD or CAD) was examined as one of the most important variable to influence home value appreciation rates (Dong, 2014). Dong found the positive effects of proximity to the CBD on SF appreciation rates in the Portland, Oregon, using 3,940 repeat SF home sales data from 2006 to 2012. This study also found a positive association between home appreciation rates and distance close to CAD. However, the CAD proximity variable was finally dropped from the final model due to the high multicollinearity issue. This study involved a comprehensive set of built environmental variables, it is not surprising that some variables such as residential density and land use mix captured the same regional proximity characteristics as CAD proximity does.

In terms of activity-friendly variables, for neighborhood walkability indices, none of the variables were significantly associated with appreciation rates in all TIF models. Residential density and land use mix were only positively associated with appreciation rates in the OLS model, suggesting environments that provide better opportunities for physical activity are not necessarily associated with appreciation rates in Dallas TIF districts. Considering the city of Dallas is still an auto-dependent city with an overall Walk Score of 44, which is the 23rd most walkable large city in the US[19], such findings should not necessarily come as a surprise. In addition, considering the long-time

[19] Walk Score, retrieved April, 2015, from https://www.walkscore.com/TX/Dallas

favor on traditional neighborhood design with private cul-de-sacs and limited access by many developers and residents, the economic benefits of walkability index factors were still underestimated by public and cannot reflect in home appreciation rates.

Destination accessibility for recreational and commercial amenities was the most important activity-friendly elements to promote housing values. For recreational uses, proximity to water features and trails would increase the home appreciation rates, which echoed with previous studies (J. Crompton, 2005a; G. Lindsey et al., 2004). For destinations, the first finding was close to neighborhood based amenities, such as specialty food stores, religious institutions, and personal care services, would promote the housing values. However, due to the high multicollinearity, several significant neighborhood based amenities were removed from the final models. In addition, due to the spatial autocorrelation and nested data structure, full-service restaurants and schools, which were significantly associated high appreciation rates in OLS regression, were removed from the results. Another finding was the shopping center based destinations were negatively associated with home appreciation rates, such as sport goods/ book/ music stores and arts/entertainment/recreation facilities. The possible reason is that these destinations usually clustered in commercial only land uses surround by highways and vacant lands, which lowered the property values of nearby homes.

For transportation/infrastructure design, sidewalk completeness was negatively associated with home appreciation rates, while the density of traffic signal was positively associated with appreciation rates. Previous studies found the positive economic benefits of sidewalk completeness and traffic signal density. Boarnet found that those less-expensive projects, such as a projects capped at $450,000 including sidewalk improvements and traffic signalization, increased walking in the context of the California Safe Routes to School program, while brought a range of monetized benefits due to the economic growth (e.g. increase of population density, retail employment) and health impacts (Marlon G Boarnet et al., 2005; M.G. Boarnet et al., 2008). Guo found that an investment of $450 million to make sidewalks available to all Dane County residents in Wisconsin would avoid approximately $90.93 million saving for annual medical cost associated with weight gain and obesity ($560 per person), which was estimated to yield a cost-benefit ratio of 1.87 over a 10-year life cycle (Guo & Gandavarapu, 2010). Dong found one percentage increases in sidewalk completeness was associated with a 0.13% greater appreciation rate of a typical SF home in Portland (Dong, 2014), while Shin found sidewalk connectivity and length of cul-de-sac have positive effects on SF appraisal values (W. J. Shin et al., 2011b).

There are two possible explanations for the negative effects of sidewalk completeness on home appreciation rates found in this study. First, it is possible that residents dislike greater access to their property and neighborhood by strangers. Krizek found negative impacts of bicycle trails on housing values, resulting $250-$1059 decrease on home sales prices (Krizek, 2006). Second, the association between sidewalk completeness and home appreciation rates does not necessarily follow a linear relationship. Sidewalk completeness in non-walkable neighborhoods might cause a negative impact on home appreciation rates, but a positive impact in walkable neighborhoods. Li found that to get a positive walkability premium on condominiums' sales prices in the city of Austin, they must locate in neighborhoods that are at least somewhat walkable. Condominium properties located in auto-dependent neighborhoods would generally not benefit from improve walkability (W. Li, 2013). Crompton applied a squared term on home distance to park to explore the non-linear relationship between home values and park proximity. He found that even though being close to a park has a positive effect on the value of properties, the association became negative when the distance are within 1-2 blocks (Figure 4-7) (John L Crompton, 2000). To test the potential reversed non-linear relationship based on empirical justification, I included a square terms for sidewalk completeness in spatial error model and got the significant results in both interaction terms. Figure 4-8 illustrates an inverted U-shaped parabola interpreting the non-linear effects of sidewalk completeness on home appreciation rates. It verified that sidewalk completeness only positively impacted home appreciation rates in walkable neighborhoods; otherwise, it is a negative factor on property value growth. The cut off value for walkable neighborhood determined by sidewalk completeness is 0.842, or 84.2%.

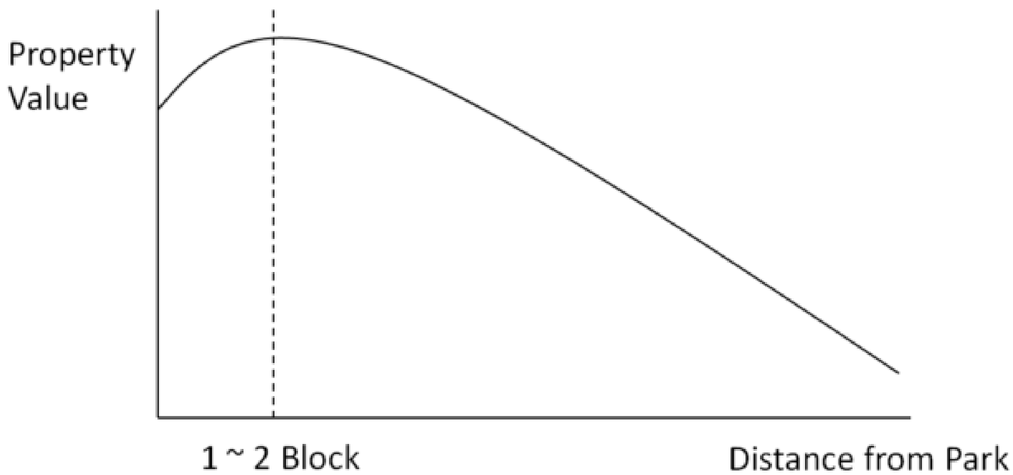

Figure 4-7. Relationship between distance from a park and housing value (John L Crompton, 2000)

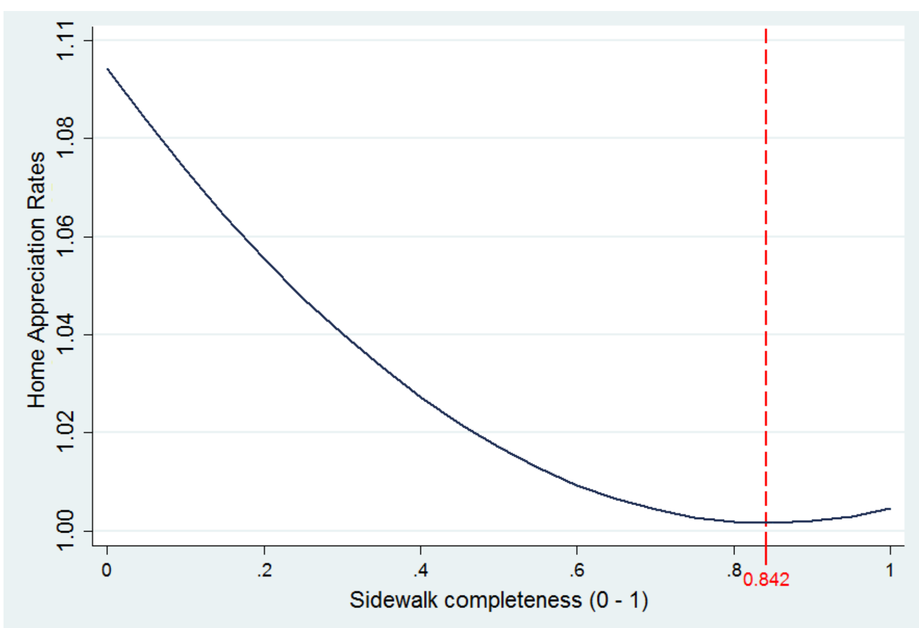

Figure 4-8. The predicted effects of sidewalk completeness with squared term on home appreciation rates

I also included a square terms for other significant built environmental variables to examine the potential non-linear relationships based on the results in spatial error model, and found four variables are significant in both interaction terms. Figures 4.9 – 4.11 illustrate an inverted U-shaped parabola interpreting the non-linear the effects of distance to water feature, arts/entertainment/recreation facilities and personal care services on home appreciation rates. Assuming the distance gradually close to these environmental features, the predicted home appreciation rates would firstly decrease and then increase, with the cut off distance of 0.383, 0.511, and 0.606 miles, respectively. The finding suggested these activity-friendly environmental features only promote home appreciation rates within certain walking distance. Figure 4.10 illustrates the predicted relationship between home value appreciation rates and distance to religious institution with squared term. The figure suggested a consistently positive effect of religious institution proximity on home value appreciation rates, by examining the non-linear relationship.

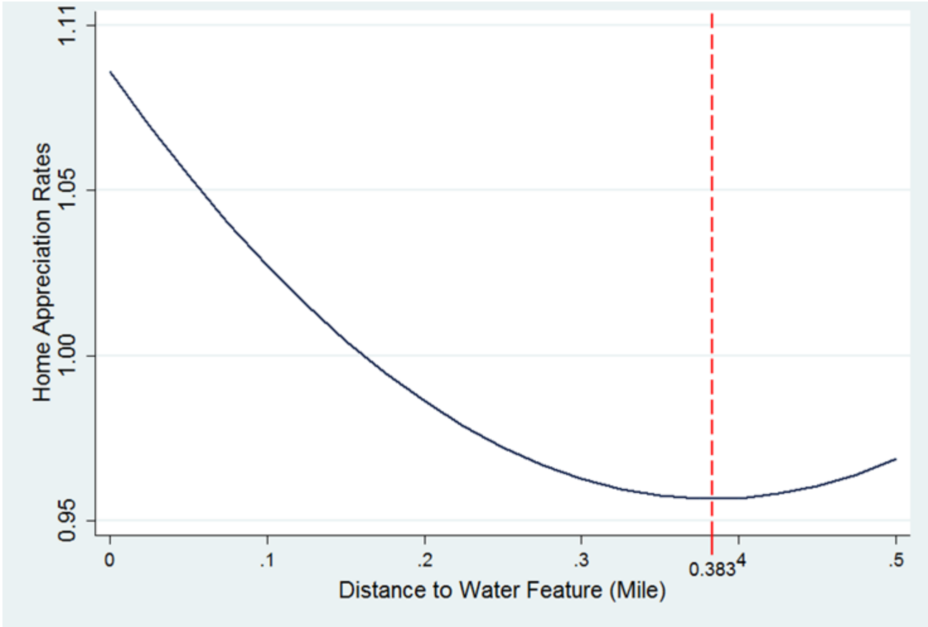

Figure 4-9. The predicted effects of distance to water features with squared term on home appreciation rates

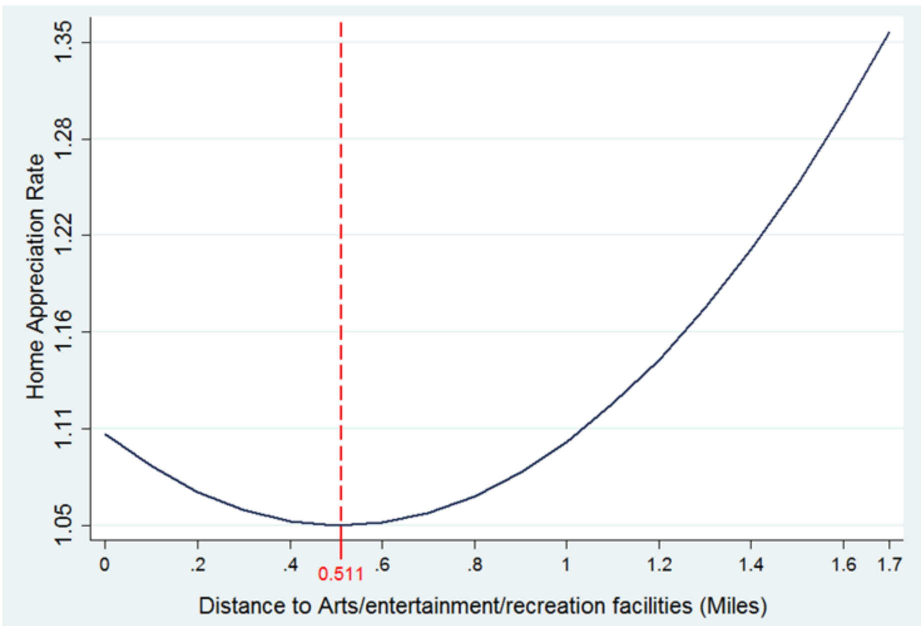

Figure 4-10. The predicted effects of distance to arts/entertainment/recreation facilities with squared term on home appreciation rates

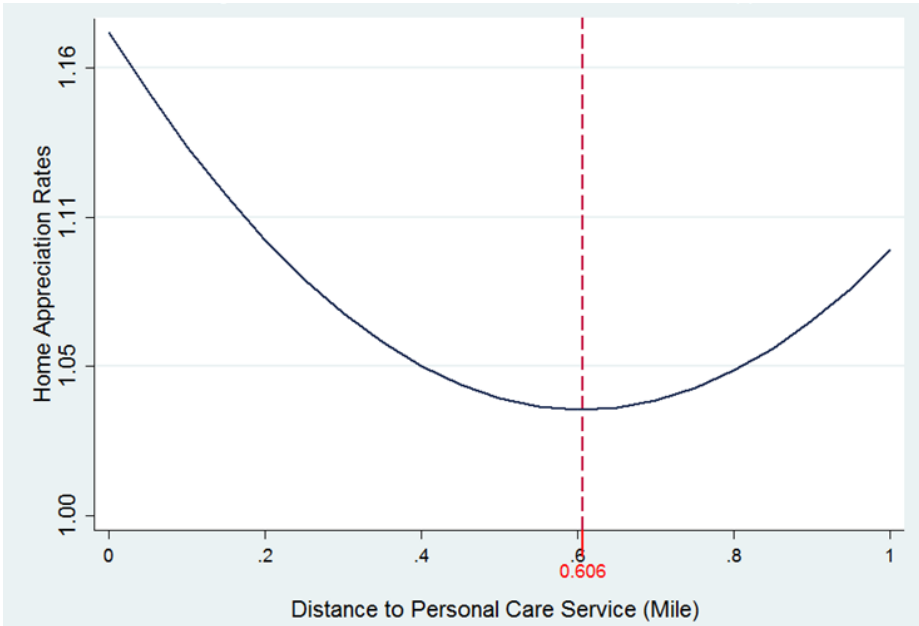

Figure 4-11. The predicted effects of distance to personal care services with squared term on home appreciation rates

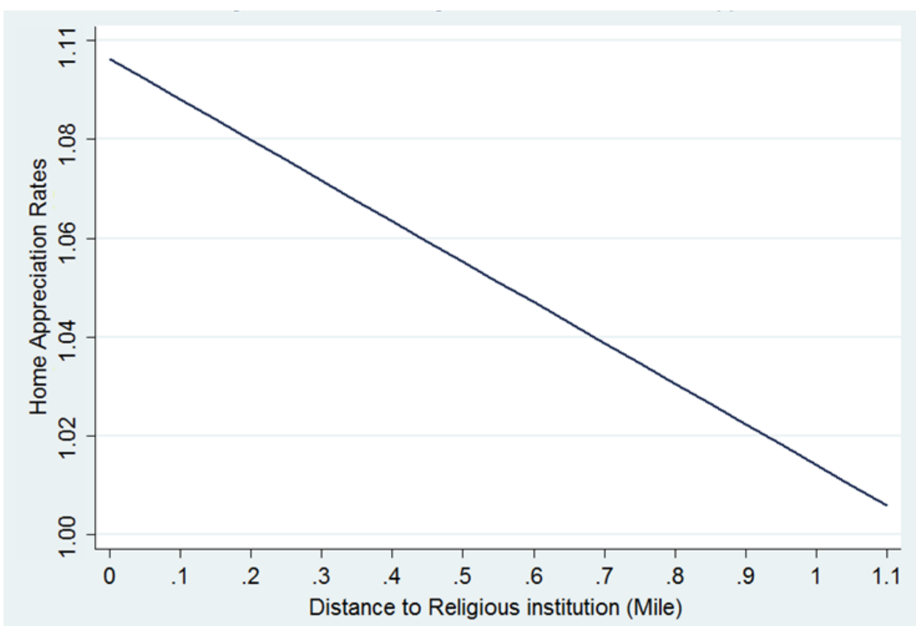

Figure 4-12. The predicted effects of distance to religious institution with squared term on home appreciation rates

In regard to choosing the best model to measure the economic benefits of activity-friendly environments, two suggestions were concluded from this study. First, if level-2 variables (e.g. performance of school attendance zones, socioeconomic status of neighborhoods) are theoretically important and empirically justified, and the intraclass correlation with outcome is significant, HLM is a better choice for such data structure. Second, if the level-2 variable is not significant and the intraclass correlation is not a hypothetic study interest, spatial regression models are more appropriate to measure the built environmental effects on properties, with the ability to provide more accurate estimates to control for spatial dependence from a range of adjustable spatial weight matrix (e.g. contiguity weight, distance weight, k-nearest neighborhood).

4.5.1.2 The Comparison of Economic Benefits of Activity-Friendly Environments between TIF Districts and Comparison Neighborhood

Chapter 2 and Chapter 3 have examined that the comparison neighborhoods were less walkable than TIF districts. Compared to comparison neighborhoods, TIF districts have better walkable environments and were associated with higher appreciation rates.

In terms of control variables, compared to TIF models, there were more structural variables significantly related to the home appreciation rates in non-TIF models, suggesting structural attributes accounted for more effects on home appreciation rates in non-TIF neighborhoods. Highway was also examined as the undesirable environmental feature for dwellings to be close with. The median household income was negatively associated with appreciation rates, suggesting the expensive residential homes in high income areas tend to have lower appreciation rates.

In terms of explanatory variables, the descriptive statistics in Table 4-3 shows TIF districts have better walkable environments. For walkability indices, none of the variables were significant in both groups. For recreational uses, based on the coefficient in spatial error model, on average, being 0.1 mile closer to water features and trails led to 4.16% and 0.67% increases in home appreciation rates for TIF samples, respectively; while being 0.1 mile closer to parks led to 0.81% increases in home appreciation rates for non-TIF samples, respectively, controlling for other factors.

For destination variables, based on the spatial error model, on average, being 0.1 mile closer to full-service restaurants, specialty food stores, religious institutions, and personal care services led to 1.07%, 1.14%, 0.75%, and 1.00% increases in home appreciation rates for TIF samples, respectively; while being 0.1 mile closer to coffee and snack shops, clothing stores, full-services restaurants, and religious institutions led to 1.32%, 0.68%, 1.60% and 0.97% increases in home appreciation rates for non-TIF samples, respectively, controlling for other factors.

For transportation and infrastructure facilities, based on the spatial error model, on average, each additional traffic signal added within a quarter mile of homes led to 0.70% increases in home appreciation rates for TIF samples; while each additional transit stop added within a quarter mile of homes led to 0.30% increases in home appreciation rates for non-TIF samples, controlling for other factors.

In summary, based on the spatial error model, Table 4-7 presents the comparison of the economic benefits of activity-friendly environments on home appreciation rates between TIF districts and comparison neighborhoods. TIF samples have 7 types of activity-friendly environmental features that were positively associated with home appreciation rates, with one unit increase leading to an average of 1.36% appreciation rate increase. Non-TIF samples have 6 types of activity-friendly environmental features that were positively associated with home appreciation rates, with one unit increase leading to an average of 0.95% appreciation rate increase. The findings suggested neighborhoods with better walkable environments are associated with higher appreciation rates.

Table 4-7. The comparison of the economic benefits of activity-friendly environments on home appreciation rates between TIF samples and non-TIF samples

Activity-Friendly Environments	Homes in TIF (N = 2875)	Homes in Non-TIF (N=6622)	Measurements
Park		0.81%	- 0.1 mile (Distance)
Water feature	4.16%		- 0.1 mile (Distance)
Trail	0.67%		- 0.1 mile (Distance)
Coffee and snack shop		1.32%	- 0.1 mile (Distance)
Clothing store		0.68%	- 0.1 mile (Distance)
Full-service restaurant	1.07%	1.60%	- 0.1 mile (Distance)
Specialty food store	1.14%		- 0.1 mile (Distance)
Religious institution	0.75%	0.97%	- 0.1 mile (Distance)
Personal care service	1.00%		- 0.1 mile (Distance)
Traffic signal	0.70%		+1 unit (count)
Transit stop		0.30%	+1 unit (count)
Average appreciation rate increase	1.36%	0.95%	

Note: The results were generated based on the coefficients in spatial error models

4.5.2 Limitations

This study has five limitations. First, due to the model limitation, I have to control spatial autocorrelation and nested data structure in separate models. Although this study suggested spatial regression is more appropriate to measure the activity-friendly environments, there were no additional studies that can back this conclusion. There was no way to combine spatial regression with hierarchical linear model yet. Future method may be developed to estimate the spatial dependence in level-1, while considering the neighborhood characteristics in level-2. Second, the data limitation may cause the measurement bias. The GIS data, appraisal data and census data had slight variations in their time frames, while the use of appraisal data may cause the problems of time lag and systematic errors. Third, the study design was unable to establish a causal inference between activity-friendly environments and home appreciation rates. Although the outcome was longitudinal values, and the necessary matching was conducted in neighborhood level, the lack of random assignment in parcel level made it illegitimate to conclude a causal inference that changes in the built environment cause changes in the economic benefits on home values. Therefore, all the relationships examined in this study are associations but not causality. Future studies are needed to test the causal relationship among study variables. Fourth, for measurement, this study only considered a quarter-mile radius of circular buffer for all the density variables measured in parcel level, which may lead to the problem of Modifiable areal unit problem (MAUP). Fifth, although this study attempted to eliminate the common problems such as measurement error, omitted variable bias and simultaneous bias often exist in studies using hedonic pricing method, unobserved and uncaptured errors may still existed.

4.5.3 Conclusion

This study found that in Dallas TIF districts, differences in the built environment are associated with differences in the economic benefits on home values. However, environments that provide better opportunities for physical activity are not necessarily associated with higher appreciation rates. None of the walkability indices were significantly associated with home appreciation rates. The most significant activity-friendly factors are destination accessibility (recreational, commercial, services) and the density of transportation/infrastructure design. This study also found that sidewalk completeness was only positively associated with home appreciation rates in walkable neighborhoods, but was negatively associated with the home appreciation rates in auto-dependent neighborhoods. Also, proximate to activity-friendly destinations (e.g. water features, personal care services) only positively influence the home appreciation rates within certain range (e.g. the cut off value for water features is 0.383 mile); beyond the certain distance cause the association become negative, which suggested the activity-friendly environmental features only promote home appreciation rates within walking accessible distance.

This study employed a 7Ds measurement framework to measure the economic benefits of activity-friendly environmental features on home appreciation rates, which is innovative, and thereby made the systematic and simultaneous economic assessment of various activity-friendly elements feasible, and greatly enhances the economic valuation studies on environmental features. The use of spatial error models and hierarchical linear models increase the confidence in reliability and accuracy of the results, and provide insights to guide the selection of appropriate analytical processes and methods to quantify the impact of various environments on economic outcomes. This study suggested if the level-2 variable is not significant and the intraclass correlation is not a hypothetic study interest, spatial regression models are more appropriate to measure the built environmental effects on properties because of the better control for spatial dependence with a range of adjustable spatial weight matrix.

Existing evidence on the economic benefits of activity-friendly environments were inconsistent and limited. This study added to this body of literature by providing new evidence to offer insights about how modifications of built environment increase property values. By examining the economic benefits of various activity-friendly environments in TIF districts and comparing such relationships between TIF districts and non-TIF neighborhoods, evidence suggested the improvements of built environment such as destination accessibility and transportation infrastructure facilities do increase the home appreciation rates, while raising future tax revenues and delivering policy implications and financial feasibility for local governments.

By offering robust methodologies and solid results, I hope the evidence provided in this study could promote more practice of improving activity-friendly environmental features in urban neighborhoods from discussion to real projects. I also hope the findings could guide future neighborhood improvements to shape urban developments that better structure the activity-friendly environmental features, to bring economic benefits to the community, to facilitate healthy outdoor activities, and to build healthy and economically vibrant communities.

CHAPTER V

CONCLUSION AND DISCUSSION

In this dissertation, I conducted three studies to systematically evaluate the economic benefits of various activity-friendly environments in Dallas TIF districts, and to demonstrate TIF developments deliver more walkable environments, as compared to comparison neighborhoods. Innovative approaches in study designs, measurements, and analytic methods were employed, which greatly enhanced the reliability, validity and accuracy of the final results. The evidence-based findings add significant contributions to the existing body of literature and provide insightful implications for policy and future studies.

5.1 Contribution to Previous Literature

In terms of study design, Topic 1 (Chapter 2) applied the quasi-experimental design and the propensity score matching approach to conduct a two-level study of matching in both neighborhood level and parcel level. The advanced research design resembled a random assignment and thus provided the feasibility to establish a causal inference between TIF development effects and the housing value growth, which has not been done before, and thereby increased confidence in the causality and internal validity of the results. The findings greatly enhance the body of similar literature on TIF evaluation studies.

In terms of measurements, Topic 3 (Chapter 4) established a 7Ds measurement framework to measure the economic benefits for activity-friendly environments, which is innovative, and thereby make the systematic and simultaneous assessment of economic benefits of various activity-friendly elements on residential properties become feasible. This is an improvement compared to previous economic valuation studies on environments with limited variables.

In terms of analytic methods, Topic 2 (Chapter 3) utilized the fractional logit models with the margin effects to estimate the substantive magnitude of the significance of personal, neighborhood, and built environmental effects on active commuting, which enhance the previous studies which placed a strong emphasis on the statistical significance of effects but with little emphasis on examining the magnitude of the significant effects. Further, the margin plots were utilized to draw the whole pictures of non-linear relationships driven by the interrelations of different factors, which were seldom examined in previous studies. In addition, the use of spatial error model and hierarchical linear model in Topic 3 (Chapter 4) increased the confidence in reliability and accuracy of the results, and provided insights to guide the selection of appropriate analytical processes and methods to quantify the impact of various environments on economic outcomes.

5.2 Policy Implication

In regard to Topic 1, sufficient evidence suggested using smart growth principles to remedy urban sprawl issues. However, smart growth has still been much more talked about in theory rather than actually carried out in practices. TIF is one of the common tools considered to implement smart growth principles, according to explore the causal effects of TIF on housing value growth, this study provided evidence of the economic and health implications of TIF developments in order to (1) demonstrate TIF is a powerful tool to deliver a stronger local economic future, while improving the built environments to promote active living and sustainable communities for urban residents, and (2) support local governments, policy makers, and planers to further implementing neighborhood retrofitting programs (e.g. TIF) guided by smart growth principles.

In regard to Topic 2, the evidence from rigorous statistic models and margin plots suggested a more walkable environment could mitigate the negative impact on active commuting from areas with lower socioeconomic status. Previous studies have demonstrated disadvantaged population are more vulnerable to obesity and obesity-related illnesses (Lovasi et al., 2009), and they are also associated with less physical activity for recreational and exercise purpose (Trost et al., 2002). To mitigate the health disparities, this study suggested the changes of built environment to be more supportive for active commuting is the crucial factor for disadvantaged population who lived in those less walkable neighborhoods. Local governments and planners must understand how to shape the built environment for disadvantaged residents in order to provide a safe, convenient, and walkable neighborhood.

According to the elaborate measurements, robust methodologies, and solid results provided in Topic 3, the results suggested that TIF developments do stimulate housing value appreciation rates through providing various built environmental improvements, while providing more walkable environments, compared to non-TIF comparison neighborhood. The findings provided the evidence to guide future neighborhood improvement to shape urban development that better structure the activity-friendly environments, to bring economic benefits to the community, to facilitate healthy outdoor activities, and to build healthy and economically vibrant communities. I also hope the evidence-based results could help to move more practice of activity-friendly environments for walkable neighborhoods from discussion to real projects.

5.3 Future Study

In terms of study design, future research on the economic and walkable evaluation of the environments should consider the causal effects because correlation does not necessarily mean causality. This study only considered the causal effect by estimating the average treatment effects on housing value growth and Walk Score increase caused by the overall TIF level. Future analyses should further explore the causal effects from individual activity-friendly environments on housing value appreciation based on Topic 3.

In terms of measurements, Topic 2 examined the active commuting on the neighborhood level using cross-sectional data and couldn't fully control for the self-selection issue on an individual level, which may cause the overestimation bias. Future travel behavior studies could adjust for the self-section bias using methods such as direct questioning, statistical control, sample selection models, structural equation models, and quasi-experimental design, to reduce the bias in estimating associations of personal, neighborhood, or built environmental factors with physical activity.

In terms of analytic methods, because of the model limitation, Topic 3 was unable to concurrently control the spatial autocorrelation and the neighborhood level variation in the one model. Future study may overcome this limitation once the new methodology approach is developed.

Overall, my dissertation work has greatly improved the previous literature with innovative methodology approaches and meaningful findings. Examining the economic benefits of activity-friendly environments in TIF districts help offer insights about how modification of BE increase property values, and deliver policy implications and financial feasibility for local governments. Moreover, the evidence-based findings can help to enhance public favor on housing market demand for walkable communities, and facilitate the developments of appropriate policies for funding and designing/planning interventions from public/private sectors to promote healthier, livable communities.

The author hope more active living studies are developed to further assess the full and varying ranges of values and costs associated with individual and combinations of activity-friendly environments, to help develop more effective design and policy interventions to promote walkable communities.

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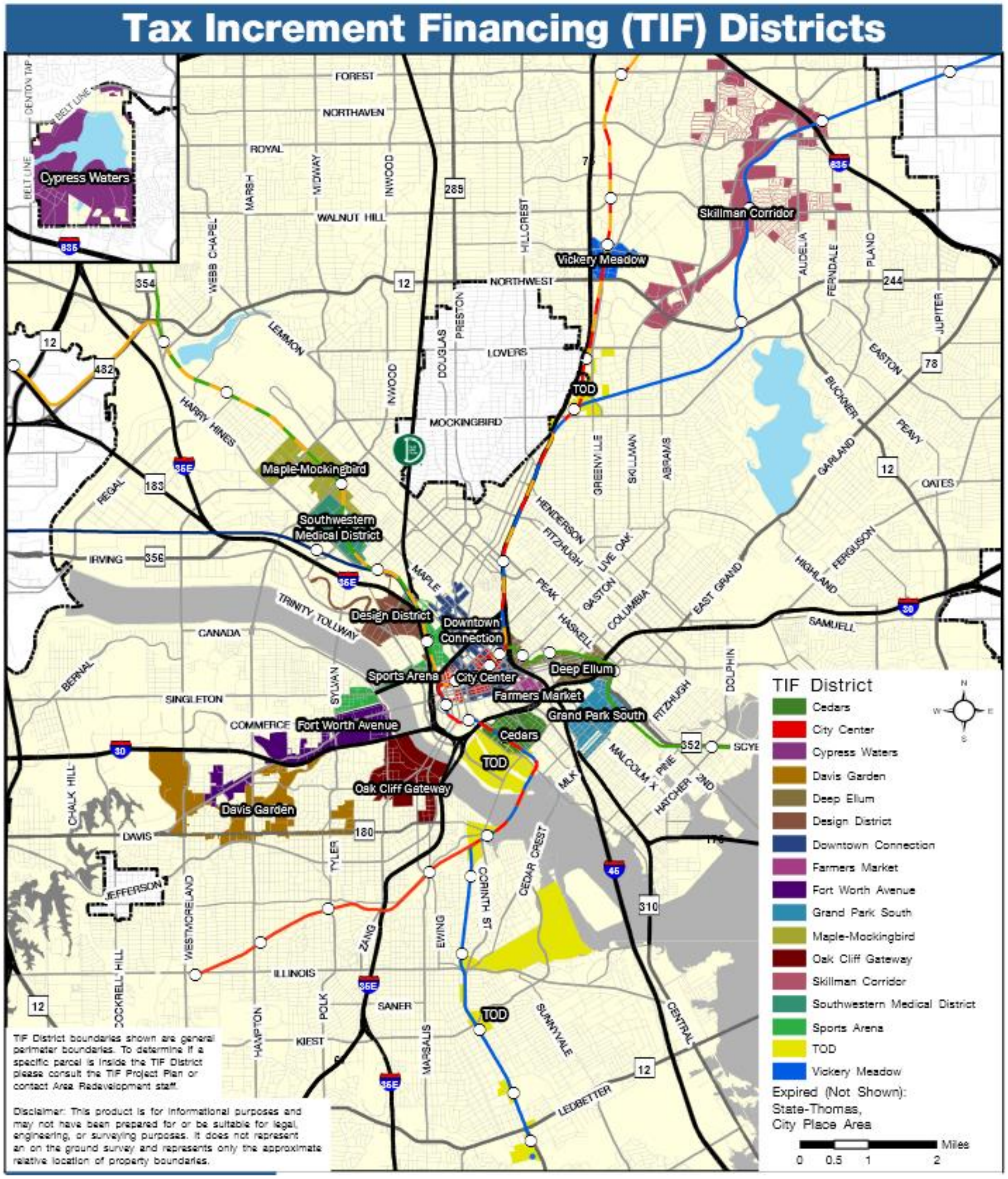
APPENDIX A

Dallas TIF district map

(Source: Dallas Economic Development, http://www.dallas-ecodev.org/resources/maps/tifs, retrieved April, 2015)



APPENDIX B

The Summary of Socio-demographic, Travel to Work Behavior and Distance Variables in TIF Level, City of Dallas, and Block Group Average (Source: 2010 US Census, 2008-2012 American Community Survey, and Dallas Economic Development)

TIF Name	Area (Acres)	Population	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Travel to work by Automobile (%)	Travel to work by Public Transportation (%)	Travel to work by Walk/ Bike (%)	TIF year began	Distance to Light Rail Station (mile)	Distance to Highway (mile)	Residential Land Use (%)	Commercial Land Use (%)
Cypress Waters	939.5	388	3.6	90.0	94.8	0.5	168333	3.9	99.7	0.3	0.0	2010	2.676	1.873	0.77	8.98
Farmers Market	61.4	330	7.4	82.2	97.3	2.6	131174	1.5	82.2	0.1	0.6	1998	0.258	0	69.47	7.19
Sports Arena	394.6	1410	43.2	37.6	93.2	28.7	109778	21.1	90.5	3.4	0.4	1998	0	0	8.60	46.86
Southwestern Medical district	302.0	964	9.5	85.1	97.4	2.1	107155	3.6	87.8	0.3	1.7	2005	0	0.243	8.49	58.97
Grand Park South	338.7	1394	6.3	87.4	94.6	0.1	103964	3.3	93.9	2.5	2.1	2005	0	0.008	18.52	29.74
CityPlace	230.3	1829	31.1	37.6	84.1	26.9	93569	16.3	93.9	2.3	0.0	1992	0	0	42.33	50.97
Deep Ellum	283.9	954	13.8	70.9	92.2	7.0	78672	4.7	92.2	0.7	1.4	2005	0	0	3.69	56.32
Vickery Meadow	172.6	3343	21.5	38.6	93.8	7.3	77011	11.3	90.2	4.6	0.0	2005	0	0	11.00	75.42
Davis Garden	877.9	7809	30.7	42.4	93.4	23.4	75937	17.4	92.3	2.3	0.7	2007	1.088	0	17.41	26.77
Downtown Connection	522.2	6270	39.8	39.9	92.0	26.1	68385	18.8	88.8	3.0	1.3	2005	0	0	13.94	47.14
Fort Worth Avenue	629.9	3538	38.9	28.7	92.4	21.3	58680	12.2	87.4	4.4	1.9	2005	0.804	0	5.74	57.84
Skillman Corridor	1405.5	17325	29.9	37.2	86.3	21.0	58382	20.3	84.6	5.3	1.2	2005	0	0	60.22	25.55
TOD	1641.6	12593	33.3	34.1	90.6	23.3	57899	16.4	91.7	2.9	1.1	2008	0	0	9.60	36.13
Oak Cliff Gateway	515.8	3374	15.1	60.0	87.6	6.6	50707	17.5	81.1	2.7	7.7	1992	0.678	0.011	17.01	32.72
Cedars	249.7	518	42.6	27.8	91.8	33.0	44799	23.6	96.6	1.9	0.0	1992	0	0.001	10.03	47.08
Design district	343.1	188	73.6	8.2	90.9	55.0	42500	40.1	88.5	5.5	0.0	2005	0.027	0	9.98	74.31
City Center	106.6	1594	79.8	4.6	87.0	59.4	30537	29.6	88.7	7.4	1.0	1996	0.007	0	13.94	47.14
Maple-Mockingbird	421.0	2994	59.4	8.4	79.0	35.2	20276	53.8	79.8	18.1	1.7	2009	0	0.616	10.99	56.86
TIF Mean/Median	**524.2**	**3712**	**32.2**	**45.6**	**91.0**	**21.1**	**72161**	**17.5**	**89.4**	**3.8**	**1.3**					
TIF Maximum	1641.6	17325	79.8	90.0	97.4	59.4	168333	53.8	99.7	18.1	7.7					
TIF Minimum	61.4	188.2	3.6	4.6	79.0	0.1	20276	1.5	79.8	0.1	0.0					
City of Dallas	**217932.0**	**1257676**	**42.4**	**28.8**	**89.2**	**25.3**	**42436**	**23.6**	**88.9**	**3.8**	**1.9**					
Block group average	**341.9**	**1370**	**39.0**	**33.3**	**89.3**	**26.2**	**42723**	**21.5**	**87.7**	**4.5**	**1.9**					

APPENDIX C

The Summary of TIF Project Information and Property Value Growth (Source: Dallas Economic Development: TIF Memo-2013 Annual Reports, http://www.dallas-ecodev.org/incentives/tifs-pids, Retrieved April, 2015)

TIF district	Brief Projects Outlines	Base Year	Base Value	2013 Taxable Value	2013 Captured Value	Initial vs. 2013 (% change)	Total years	Average annual growth
State-Thomas	Complete infrastructure replacement and enhancement	1988	$47,506,802	$451,881,035	$404,374,233	929.9%	25	37.196%
City place	Retail, commercial, and multi-family uses	1992	$45,065,342	$668,182,616	$623,117,274	1382.7%	21	65.843%
Oak Cliff Gateway	New residential development and improve the infrastructure	1992	$40,097,623	$153,387,385	$113,289,762	282.5%	21	13.452%
Cedars	New residential development and improve the infrastructure	1992	$35,300,760	$76,227,853	$40,927,093	115.9%	21	5.519%
City Center	Improve street and pedestrian environment and lighting, add parking, Coordinate linkages with the new DART light rail transit	1996	$866,044,996	$1,268,844,704	$402,799,708	31.7%	17	1.865%
Farmers Market	Complete infrastructure replacement and enhancement	1998	$27,706,851	$132,692,290	$104,985,439	378.9%	15	25.260%
Sports Arena	Infrastructure replacement and enhancement for a sports arena	1998	$16,423,773	$494,975,808	$478,552,035	676.6%	15	45.107%
Design district	convert the Design district area from industrial and warehousing land uses to a mixed-use, transit oriented neighborhood	2005	$141,852,062	$363,037,801	$221,185,739	155.9%	8	19.488%
Vickery Meadow	Improve street and pedestrian environment and lighting add parking, Coordinate linkages with the DART Park Lane light rail station	2005	$161,270,320	$352,072,010	$190,801,690	118.3%	8	14.788%
Southwestern Medical	Convert the area from industrial and warehousing land uses to a mixed-use, transit oriented neighborhood	2005	$67,411,054	$152,408,068	$84,997,014	126.1%	8	15.763%
Downtown Connection	Improve access and image between and within Uptown and Downtown areas; Increase open space and recreational opportunities in the zone	2005	$564,917,317	$2,155,282,220	$1,590,364,903	281.5%	8	35.188%
Deep Ellum	Implement appropriate urban design standards, improve pedestrian connections between downtown, Fair Park, and etc.	2005	$113,885,770	$169,042,489	$55,156,719	48.4%	8	6.050%
Grand Park South	Expand parks and open space within the zone by developing pocket parks, plazas, etc.; Improve pedestrian lighting;	2005	$44,850,019	$44,580,824	-$269,195	-0.6%	8	-0.075%
Skillman Corridor	Improve pedestrian environment; Improve access and connections to the DART light rail system and open space system	2005	$335,957,311	$469,102,270	$133,144,959	39.6%	8	4.950%
Fort Worth Avenue	Improve pedestrian environment; Improve access and connections to planned improvement of transit services and open space system	2005	$86,133,447	$113,795,416	$27,661,969	32.1%	8	4.013%
Davis Garden	Environmental remediation and demolition of structurally obsolete structures; New residential and retail development	2007	$137,834,597	$159,035,176	$21,200,579	15.4%	6	2.567%
TOD	New residential and retail development; improve connections to city trails and open space	2008	$202,074,521	$291,947,326	$89,872,805	44.5%	5	8.900%
Maple/Mockingbird	New residential and retail development, redevelop urban design of properties; Improve access and connections to the DART light rail system	2009	$183,140,018	$253,118,069	$69,978,051	37.6%	4	9.400%
Cypress Waters	Attract new private development; improve ridership on DART; Improve recreational opportunities	2010	$73,382	$10,472,389	$10,399,007	14170.9%	3	4723.633%
Total All Districts			$3,262,822,053	$7,817,488,558	$4,554,666,505	139.6%		

APPENDIX D

Propensity score matching results with 1 to 5 matching (the yellow marks indicated the final matched block groups)

TIF Name & matched BG ID	Treatment	Area (Acre)	Population	Population /Acre	Hispanic (%)	White Alone (%)	Occupancy (%)	Education (%)	Income	Poverty Rate (%)	Residential Density (%)	Commercial Density (%)	Industrial Density (%)	PS Score
Sports Arena	1	394.63	1410	3.57	35.77	48.32	92.76	20.74	132611	15.26	8.6	46.86	1.58	0.200
481130136191	0	255.93	1779	6.95	16.69	71.67	90.11	1.05	73849	9.36	16.59	57.5	0	0.200
481130136112	0	694.18	1017	1.47	6.29	79.15	89.59	0	79167	6.16	4.83	46.34	6.43	0.190
481130078255	0	648.3	829	1.28	36.79	7	86.52	8.59	22600	18.08	7	64.57	0	0.230
481130078254	0	59.09	846	14.32	8.39	49.65	94.33	3.11	212604	15.3	25.7	48.61	0	0.180
481130014004	0	90.37	594	6.57	25.25	63.13	88.49	3.13	62500	12.05	2.65	53.52	0	0.230
Farmers Market	1	61.36	330	5.38	9.89	68.58	96.75	5.40	112921	7.12	69.47	7.19	0.00	0.004
481130046001	0	189.67	1064	5.61	48.97	41.73	85.74	37.35	23250	20.50	56.99	12.53	0.00	0.004
481130084001	0	66.04	952	14.42	70.69	17.02	92.70	39.09	50500	21.73	50.73	5.15	0.00	0.004
481130130053	0	103.58	406	3.92	9.36	86.45	96.98	0.00	76389	4.13	66.80	8.46	0.00	0.004
481130003003	0	89.54	1338	14.94	8.97	87.22	93.45	0.00	110185	5.76	68.14	7.12	0.00	0.000
481130096081	0	74.31	732	9.85	11.48	81.28	96.49	3.47	104,821	1.47	67.97	26.79	0.00	0.004
Southwestern Medical district	1	302.01	964	3.19	11.97	81.29	94.59	2.06	97336	3.59	8.49	58.97	2.02	0.299
481130192051	0	701.58	1385	1.97	3.54	83.10	95.02	2.11	96154	1.24	12.55	61.19	0.32	0.285
481130076052	0	193.93	998	5.15	5.41	88.48	92.59	1.10	85938	4.95	13.22	68.84	0.00	0.348
481130136112	0	694.18	1017	1.47	6.29	79.15	89.59	0.00	79167	6.16	4.83	46.34	6.43	0.188
481130078192	0	263.49	481	1.83	83.58	4.78	46.08	71.51	25278	44.31	23.45	66.17	0.00	0.133
481130130082	0	207.18	2630	12.69	30.72	51.63	93.09	5.38	68882	20.38	13.94	33.01	0.00	0.069
City Place	1	230.35	1829	7.94	32.55	36.79	87.54	24.05	89695	14.61	42.33	50.97	0.00	0.061
481130053002	0	650.54	1237	1.90	84.16	14.39	87.78	62.56	38264	52.98	18.77	40.26	0.00	0.058
481130164121	0	442.04	2228	5.04	15.48	39.45	97.80	1.45	109931	1.38	7.82	19.50	10.69	0.057
481130010012	0	212.02	3817	18.00	32.83	57.77	93.96	7.07	73622	27.57	37.84	49.27	0.00	0.054
481130014003	0	603.98	944	1.56	25.85	65.36	87.26	8.35	45845	18.10	14.58	29.59	0.49	0.053
481130002012	0	472.70	1082	2.29	8.41	87.89	94.07	3.24	58973	11.39	13.86	23.85	0.00	0.048

APPENDIX D continued.

TIF Name & matched BG ID	Treatment	Area (Acre)	Population	Population /Acre	Hispanic (%)	White Alone (%)	Occupancy (%)	Education (%)	Income	Poverty Rate (%)	Residential Density (%)	Commercial Density (%)	Industrial Density (%)	PS Score
Grand Park South	1	338.65	1394	4.12	8.02	80.96	90.39	0.27	84687	5.83	18.52	29.74	8.83	0.061
481130164121	0	442.04	2228	5.04	15.48	39.45	97.80	1.45	109931	1.38	7.82	19.50	10.69	0.060
481130127012	0	45.35	982	21.65	72.00	21.18	96.70	43.08	41447	22.68	30.94	51.41	0.00	0.064
481130004044	0	2845.65	520	0.18	18.85	56.15	75.41	11.99	69028	10.89	7.11	26.79	2.77	0.066
481130136192	0	683.72	1664	2.43	6.67	85.64	98.21	6.77	149189	1.05	27.73	30.27	3.29	0.069
481130133001	0	430.02	965	2.24	4.04	90.88	94.43	2.33	215000	0.00	44.10	25.00	0.00	0.049
State-Thomas	1	99.79	2714	27.20	11.83	74.80	90.04	4.14	74594	19.03	48.42	10.08	0.00	0.007
481130101012	0	129.69	1245	9.60	38.55	0.24	91.91	47.88	16214	46.68	43.06	20.65	0.00	0.007
481130078272	0	214.98	480	2.23	15.63	28.96	80.46	6.21	44511	17.40	52.64	19.21	0.00	0.007
481130111043	0	188.23	941	5.00	13.28	1.17	92.75	13.40	35039	30.07	47.64	20.26	0.00	0.007
481130049001	0	80.04	1133	14.16	40.42	2.38	89.00	44.79	27125	17.53	51.76	25.29	0.00	0.007
481130129002	0	52.38	632	12.07	11.55	85.13	93.25	2.58	79018	3.60	49.82	7.96	0.00	0.007
Deep Ellum	1	283.88	954	3.36	24.48	47.89	92.29	12.60	68055	7.99	3.69	56.32	4.25	0.243
481130136081	0	271.62	1293	4.76	2.40	92.03	96.81	2.16	175213	0.93	17.93	49.80	5.31	0.250
481130014004	0	90.37	594	6.57	25.25	63.13	88.49	3.13	62500	12.05	2.65	53.52	0.00	0.234
481130047003	0	146.45	1467	10.02	90.25	5.11	92.84	69.89	34643	34.51	9.60	60.39	0.00	0.171
481130136063	0	321.19	1702	5.30	9.34	72.86	94.58	2.44	72981	6.82	24.83	54.52	0.00	0.132
481130190413	0	99.89	789	7.90	5.07	68.57	99.33	2.15	91875	0.00	42.18	44.77	0.00	0.052
Oak Cliff Gateway	1	515.82	3374	6.54	16.70	64.90	88.80	10.11	58103	13.86	17.01	32.72	4.53	0.058
481130003001	0	75.95	1295	17.05	9.27	85.02	90.00	1.57	89893	5.79	32.24	38.68	0.00	0.058
481130006011	0	318.17	780	2.45	19.74	74.23	90.39	13.75	55647	31.75	12.43	27.89	0.23	0.056
481130130045	0	166.65	1222	7.33	10.64	70.87	96.08	3.72	53882	9.09	12.57	27.77	1.24	0.054
481130079141	0	25.79	1553	60.21	15.97	64.78	87.33	2.15	38775	33.00	38.33	53.30	0.00	0.053
481130004011	0	145.28	1719	11.83	15.82	42.82	81.90	7.10	48388	40.63	20.01	34.12	0.00	0.047
Skillman Corridor	1	1445.23	15356	10.63	34.42	30.01	90.22	18.54	55020	22.62	60.22	25.55	0	0.009
481130071025	0	137.51	784	5.70	31.25	15.18	94.39	22.24	52438	15.63	53.34	22.76	0	0.009

APPENDIX D continued.

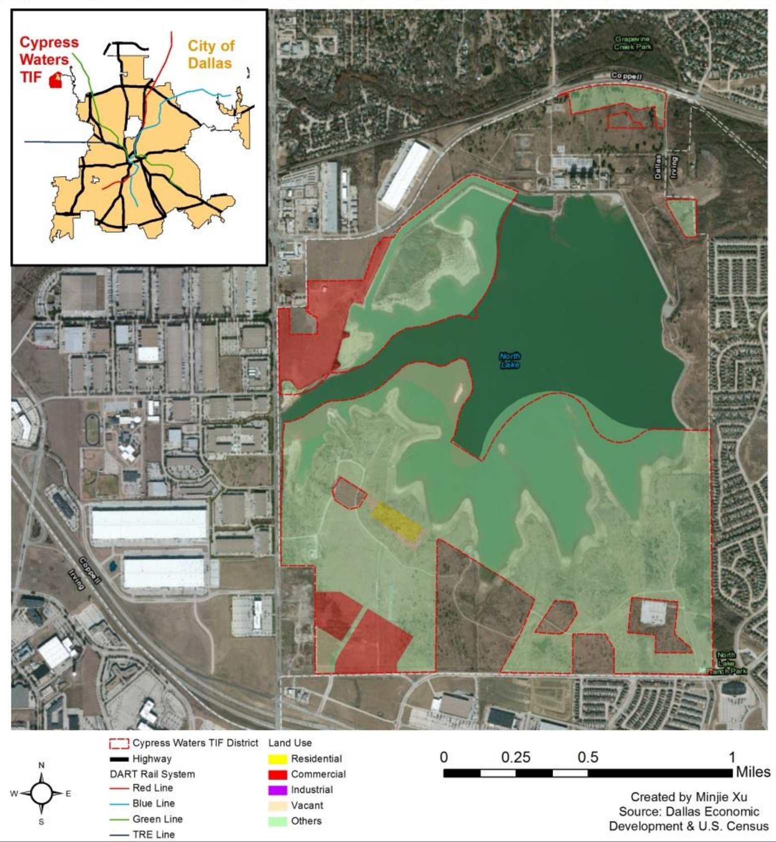
TIF Name & matched BG ID	Treatment	Area (Acre)	Population	Population /Acre	Hispanic (%)	White Alone (%)	Occupancy (%)	Education (%)	Income	Poverty Rate (%)	Residential Density (%)	Commercial Density (%)	Industrial Density (%)	PS Score
481130130071	0	244.26	1541	6.31	21.61	37.77	91.03	24.68	60750	11.96	33.08	7.77	0	0.009
481130122045	0	190.64	1910	10.02	57.23	12.41	84.12	57.22	16129	63.18	47.72	26.58	0	0.010
481130110013	0	94.74	1553	16.39	6.95	1.87	94.36	6.44	20156	43.68	46.30	26.67	0	0.010
481130115004	0	137.66	827	6.01	49.09	0.85	92.24	38.81	12917	48.76	47.05	25.98	0	0.010
Fort Worth Avenue	1	629.95	3538	5.62	45.89	26.65	92.32	24.87	50836	14.32	5.74	57.84	5.88	0.210
481130078254	0	59.09	846	14.32	8.39	49.65	94.33	3.11	212604	15.30	25.70	48.61	0.00	0.203
481130109021	0	115.67	2575	22.26	14.49	2.80	97.41	6.59	58447	6.13	17.23	68.51	0.00	0.203
481130015042	0	222.11	425	1.91	44.94	19.53	88.80	37.59	12143	72.33	10.85	62.21	3.28	0.163
481130117021	0	137.62	1400	10.17	70.57	25.64	93.98	43.23	29722	25.74	12.89	52.25	0.00	0.119
481130088021	0	86.61	576	6.65	32.99	1.39	87.34	55.44	22621	32.61	19.79	44.73	0.00	0.051
Davis Garden	1	877.94	7809	8.90	48.43	23.42	90.62	37.87	48699	22.34	17.41	26.77	0.13	0.035
481130045001	0	108.45	492	4.54	78.46	16.46	89.41	52.25	53145	30.26	39.63	41.87	0.00	0.034
481130124005	0	86.89	596	6.86	16.28	77.52	96.50	5.36	48929	11.04	49.75	46.96	0.00	0.035
481130053004	0	658.85	1696	2.57	92.98	5.19	93.79	50.62	46500	4.09	14.06	22.67	0.10	0.034
481130002022	0	126.24	1170	9.27	8.03	87.69	91.58	2.22	96833	1.25	35.95	27.65	0.40	0.033
481130136233	0	271.07	2362	8.71	63.29	12.45	92.06	37.72	34038	25.88	18.03	27.82	1.19	0.033
Cedars	1	249.71	518	2.07	42.77	27.58	91.62	28.96	44691	23.66	10.03	47.08	4.05	0.114
481130014001	0	293.83	1344	4.57	54.09	24.93	85.63	38.20	36151	29.08	19.78	55.66	0.69	0.112
481130043002	0	292.99	699	2.39	70.82	1.43	84.58	60.07	28409	12.15	26.22	63.51	0.00	0.113
481130118004	0	112.60	1281	11.38	73.85	12.18	92.60	53.75	50660	47.82	5.27	44.89	0.20	0.105
481130107012	0	5465.12	886	0.16	88.26	10.05	93.25	62.05	33214	22.03	0.90	41.02	1.34	0.099
481130122102	0	662.02	2456	3.71	25.29	25.65	87.39	19.99	36151	35.18	9.83	42.36	2.90	0.048
Maple-Mockingbird	1	421.01	2994	7.11	60.02	20.45	86.62	44.22	36862	31.74	10.99	56.86	3.01	0.152
481130136053	0	962.88	1284	1.33	6.46	84.58	98.44	3.11	100156	1.05	0.00	33.74	0.68	0.149
481130005001	0	735.28	1034	1.41	51.45	39.36	86.51	19.50	52083	21.45	8.47	48.20	0.00	0.145
481130202003	0	615.97	1069	1.74	10.29	2.53	92.70	16.97	23333	33.66	19.96	66.70	0.00	0.144
481130136233	0	271.07	2,362	8.71	63.29	12.45	92.06	37.72	34,038	25.88	18.03	35.47	6.58	0.118
481130136193	0	835.46	1429	1.71	4.06	89.08	97.56	1.19	158833	0.30	0.00	0.00	0.00	0.050

APPENDIX E

Appendix E1: Cypress Water TIF district & control block group Aerial and Land Use Map

Cypress Waters TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Cypress Waters	939.47	388	0.41	3.61	89.97	94.84	0.53	168,333	3.93	0.77	8.98	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46

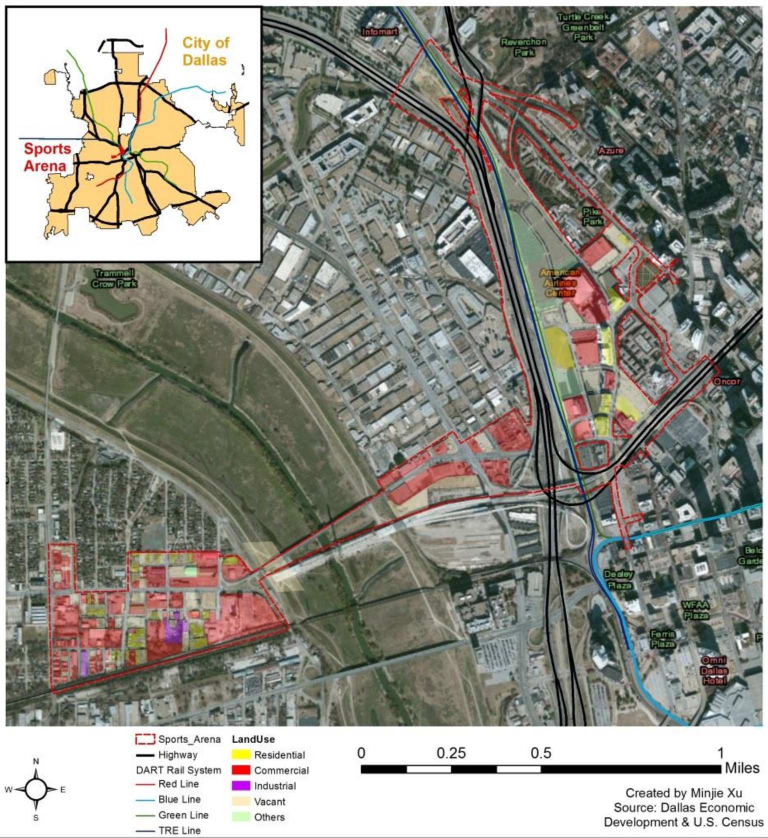


No matched block group was identified with unusually low population density and development density. Therefore, this TIF is excluded from this dissertation study.

Appendix E2: Sports Arena TIF district Aerial and Land Use Map

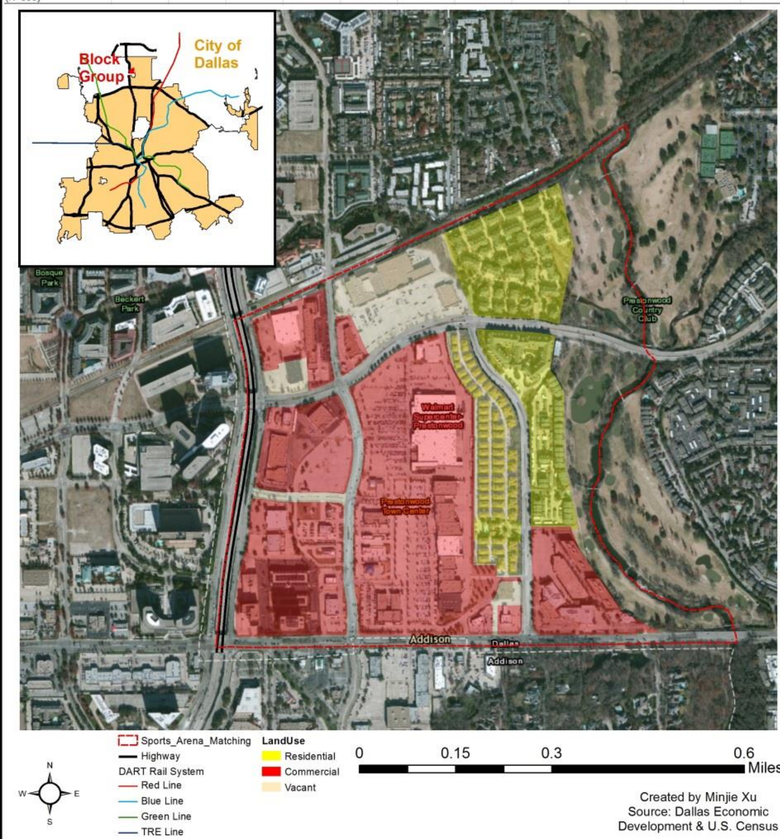
Sports Arena TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Sports Arena	394.63	1,410	3.57	35.77	48.32	92.76	20.74	132,611	15.26	8.60	46.86	1.58
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Sports Arena Matching Block Group

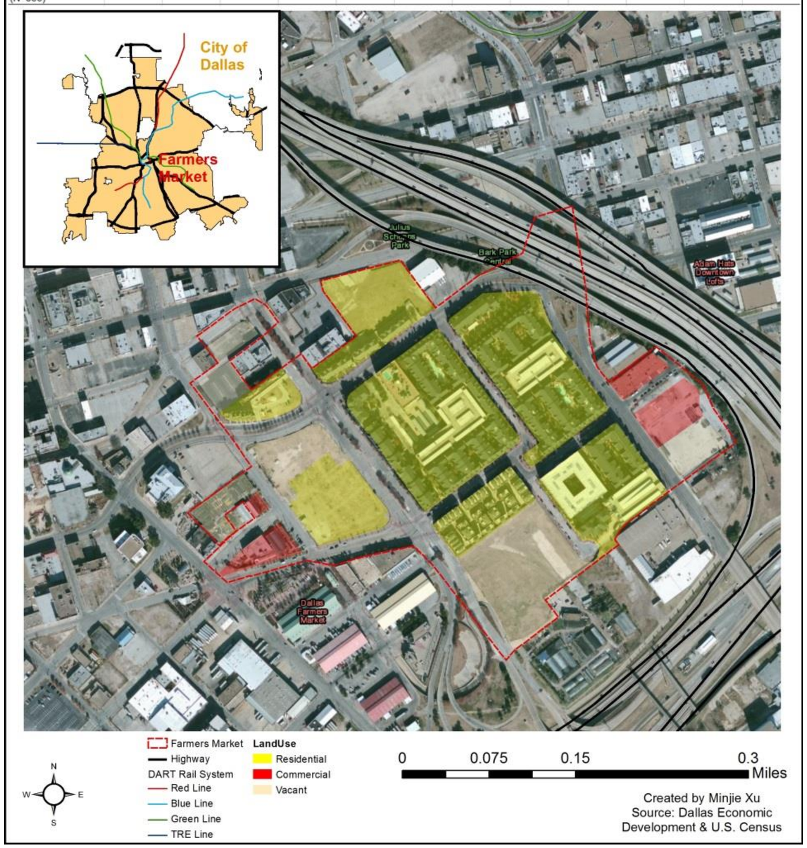
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Sports Arena matching	255.93	1,779	6.95	16.69	71.67	90.11	1.05	73,849	9.36	16.59	57.50	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Appendix E3: Farmers Market TIF district Aerial and Land Use Map

Farmers Market TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Farmers Market	61.36	330	5.38	9.89	68.58	96.75	5.40	112,920	7.12	69.47	7.19	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46

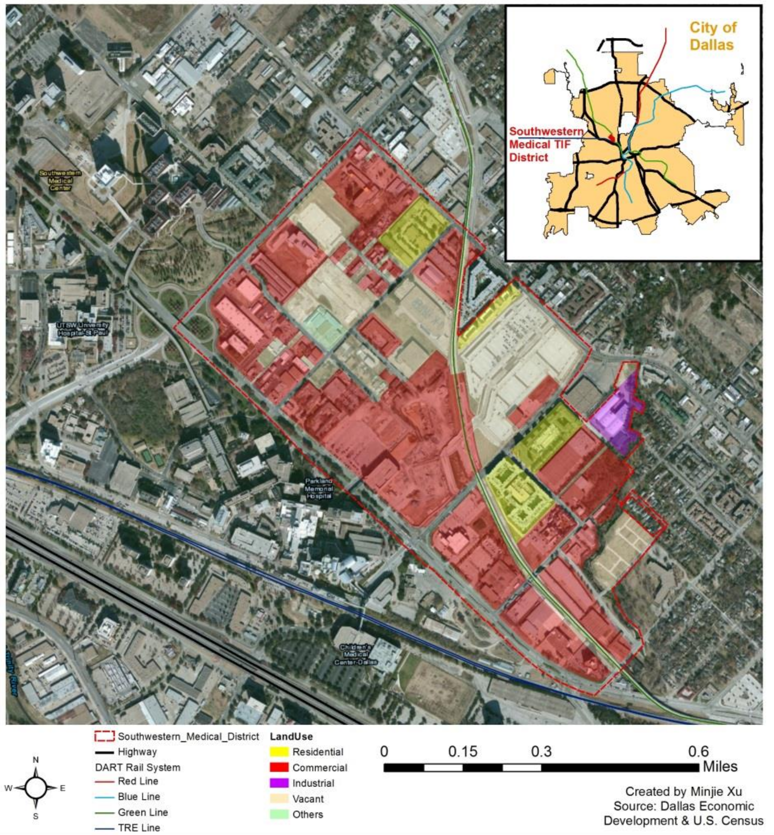


No matched block group was identified because of extremely high multi-family residential density. This TIF is excluded from the analysis.

Appendix E4: Southwestern Medical district TIF district Aerial and Land Use Map

Southwestern Medical TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Southwestern Medical District	302.01	964	3.19	11.97	81.29	94.59	2.06	97,336	3.59	8.49	58.97	2.02
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46

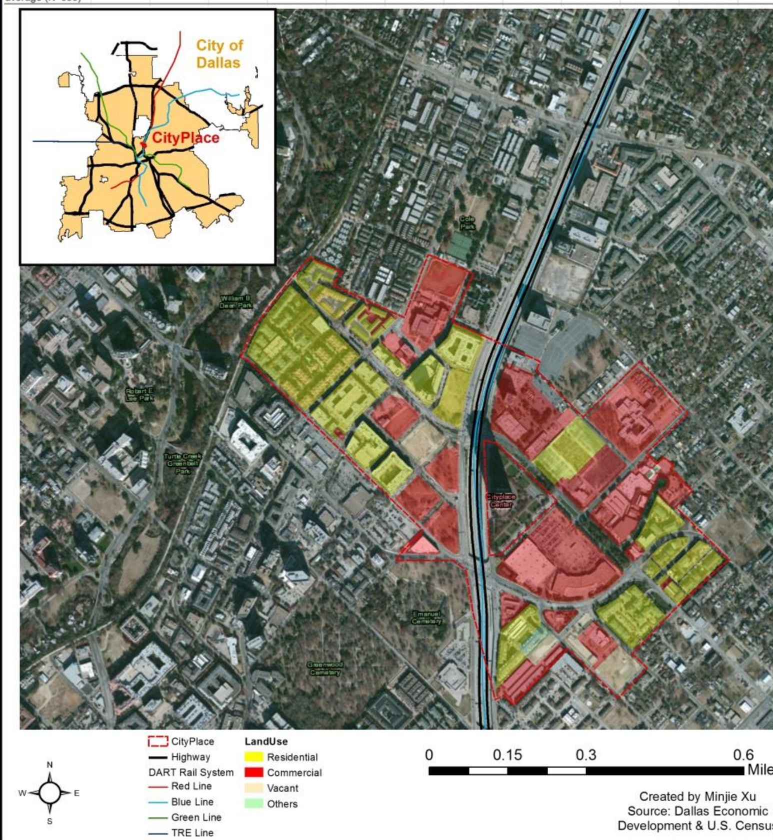


No matched block group was identified because of extremely low residential density. This TIF is excluded from the analysis.

Appendix E5: CityPlace TIF district Aerial and Land Use Map

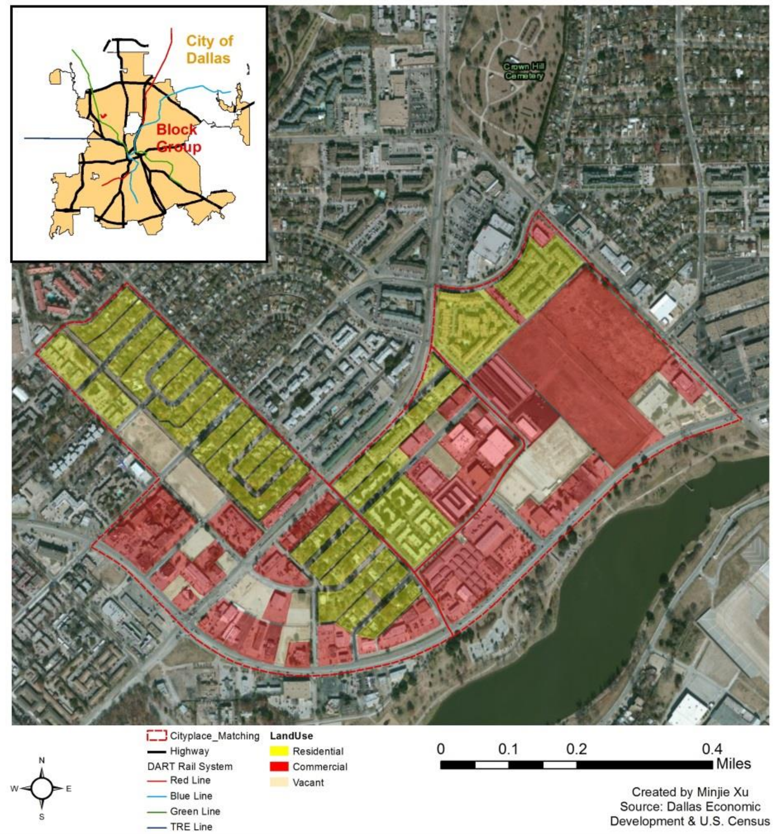
CityPlace TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
CityPlace	230.35	1,829	7.94	32.55	36.79	87.54	24.05	89,695	14.61	42.33	50.97	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



CityPlace Matching Block Group

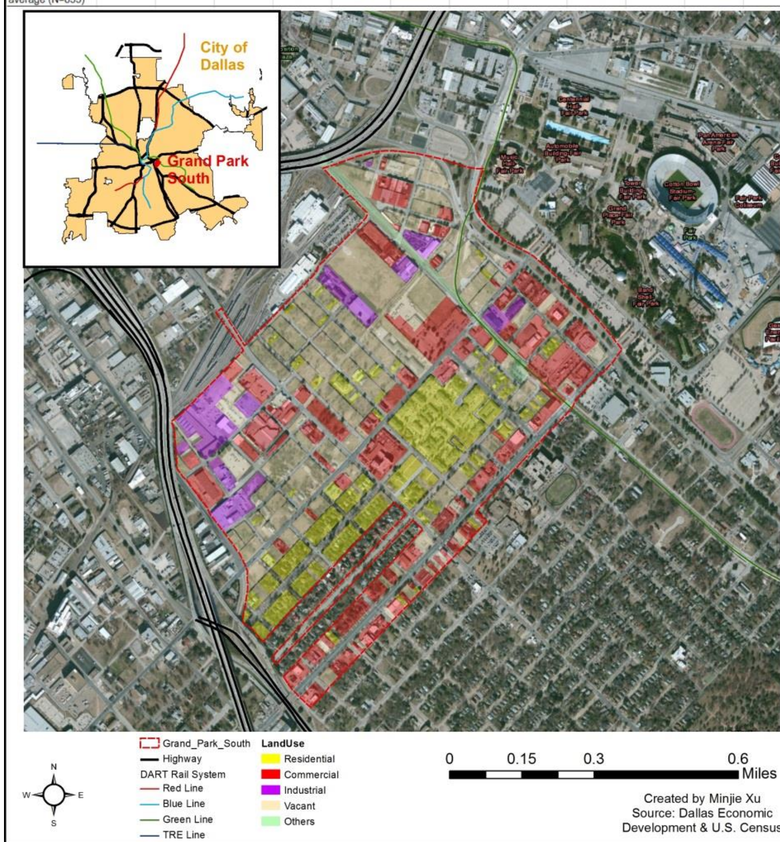
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
CityPlace Matching	212.02	3,817	18.00	32.83	57.77	93.96	7.07	73,622	27.57	37.84	49.27	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Appendix E6: Grand Park South TIF district Aerial and Land Use Map

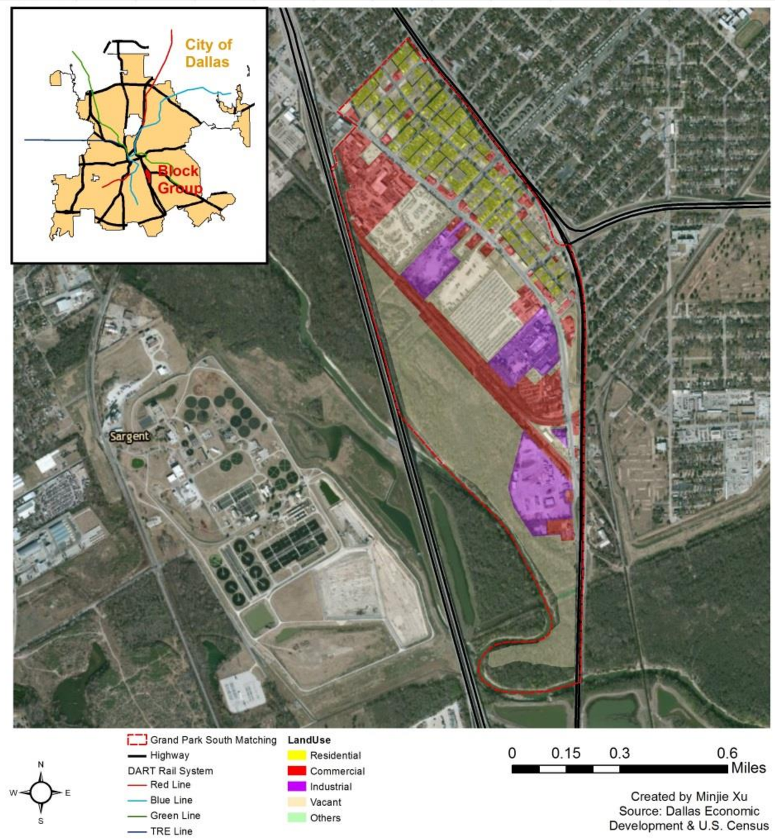
Grand Park South TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Grand Park South	338.65	1,394	4.12	8.02	80.96	90.39	0.27	84,687	5.83	18.52	29.74	8.83
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Grand Park South Matching Block Group

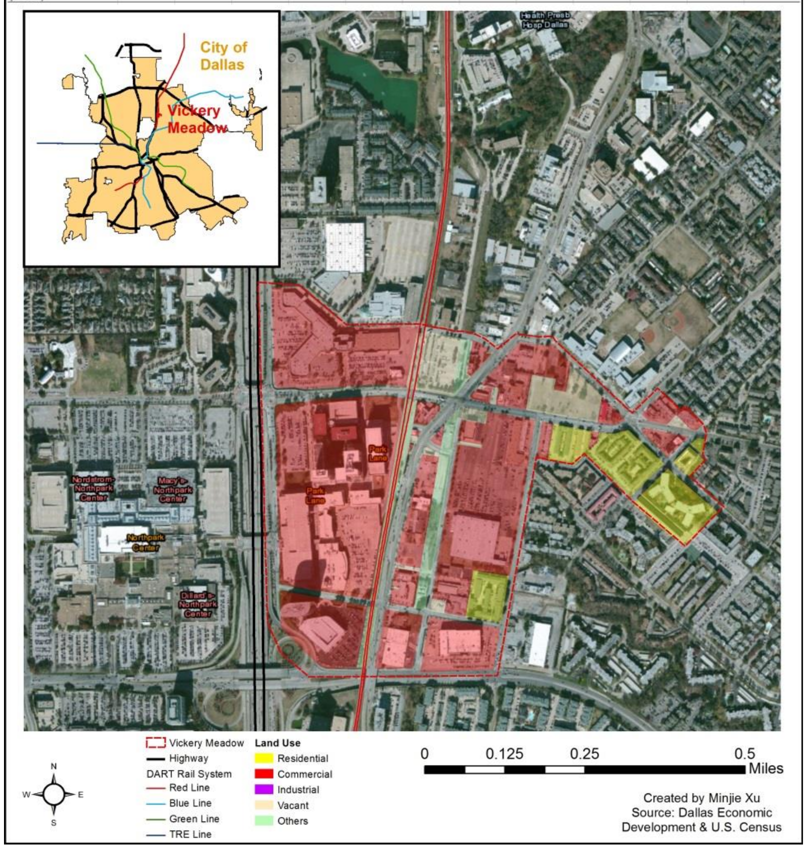
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Grand Park South matching	442.04	2,228	5.04	15.48	39.45	97.80	1.45	109,931	1.38	7.82	19.50	10.69
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Appendix E7: Vickery Meadow TIF district Aerial and Land Use Map

Vickery Meadow TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Vickery Meadow	172.58	3,343	19.37	26.83	41.89	92.35	12.70	76,239	16.70	11.00	75.42	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46

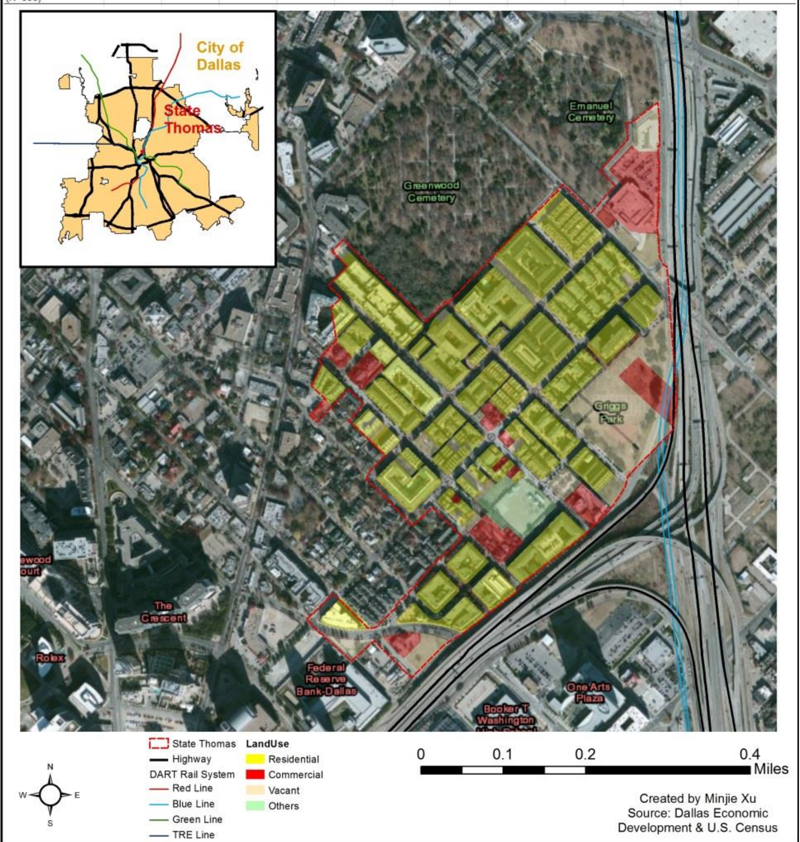


No matched block group was identified because of extremely low residential density. This TIF is excluded from the analysis.

Appendix E8: State Thomas TIF district Aerial and Land Use Map

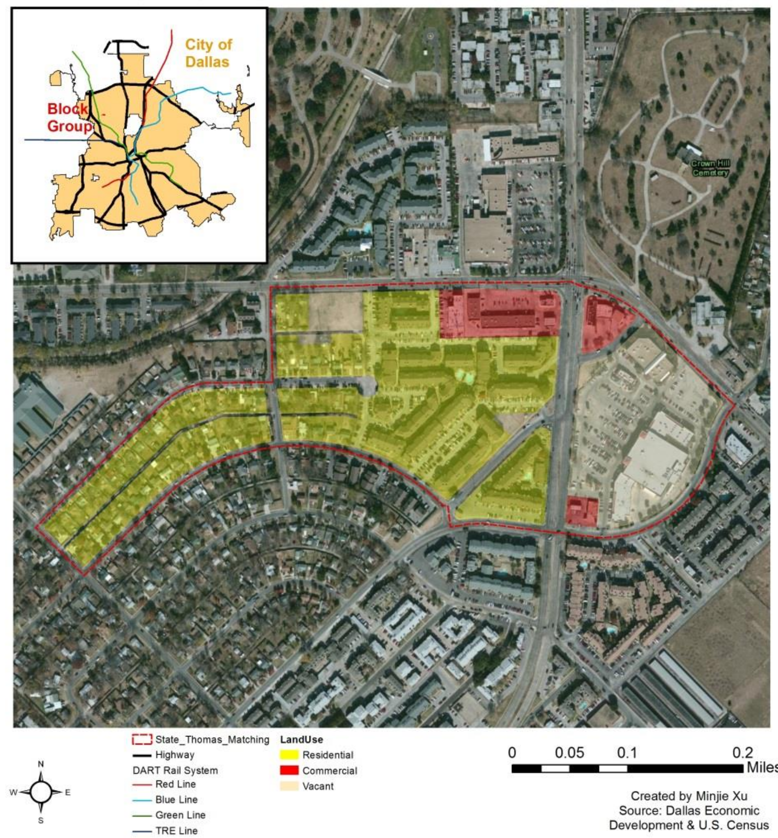
State Thomas TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
State-Thomas	99.79	2,714	27.20	11.83	74.80	90.04	4.14	74,594	19.03	48.42	10.08	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



State Thomas Matching Block Group

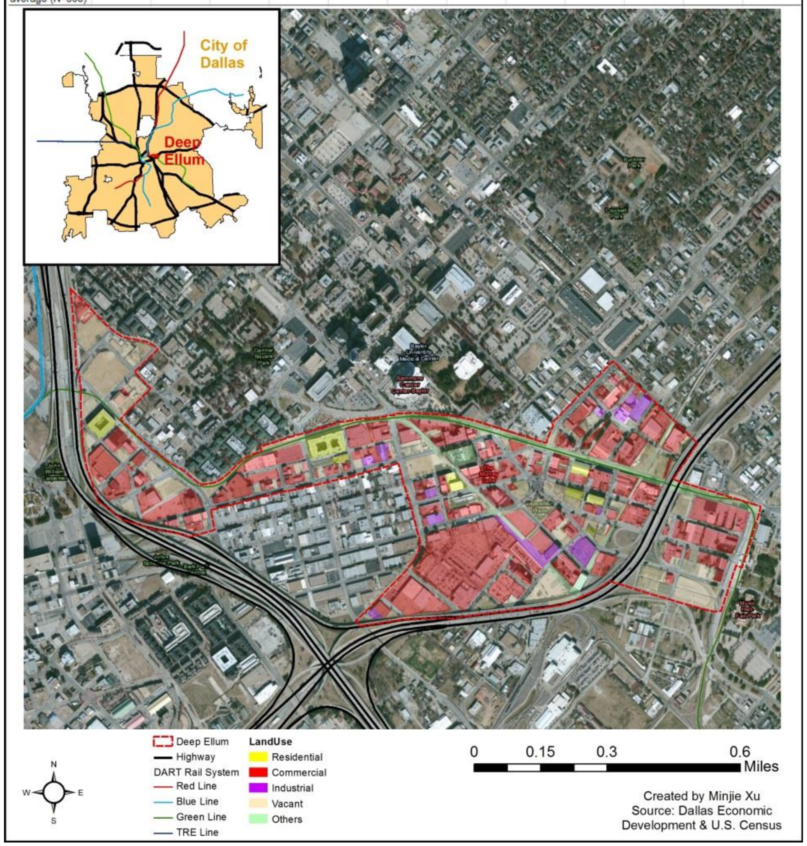
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
State-Thomas Matching	52.38	632	12.07	11.55	85.13	93.25	2.58	79,018	3.60	49.82	7.96	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Appendix E9: Deep Ellum TIF district Aerial and Land Use Map

Deep Ellum TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Deep Ellum	283.88	954	3.36	24.48	47.89	92.29	12.60	68,055	7.99	3.69	56.32	4.25
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46

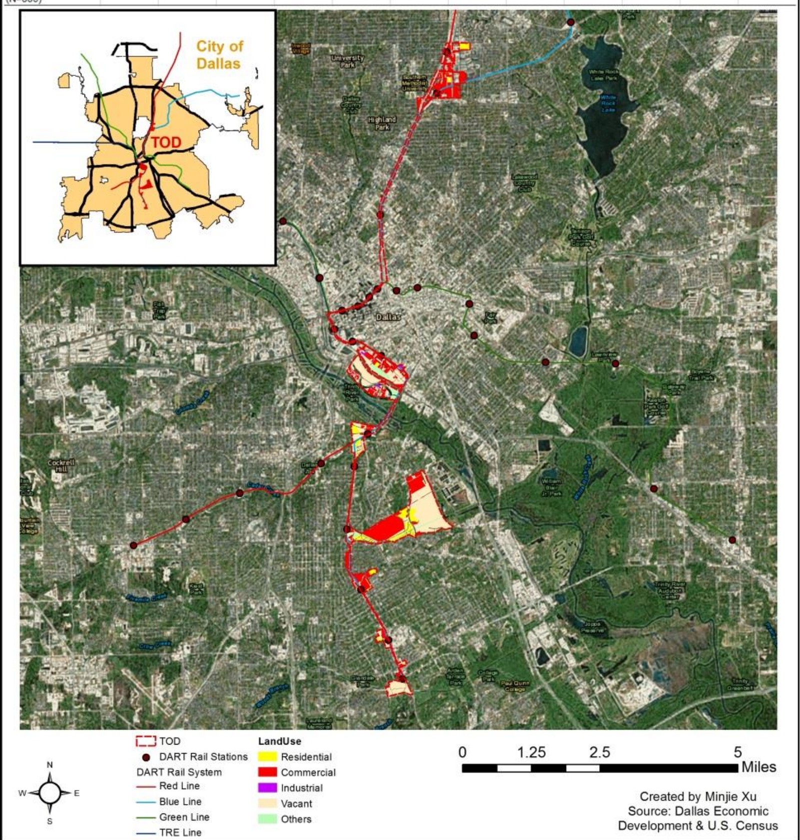


No matched block group was identified because of extremely low residential density. This TIF is excluded from the analysis.

Appendix E10: TOD TIF district Aerial and Land Use Map

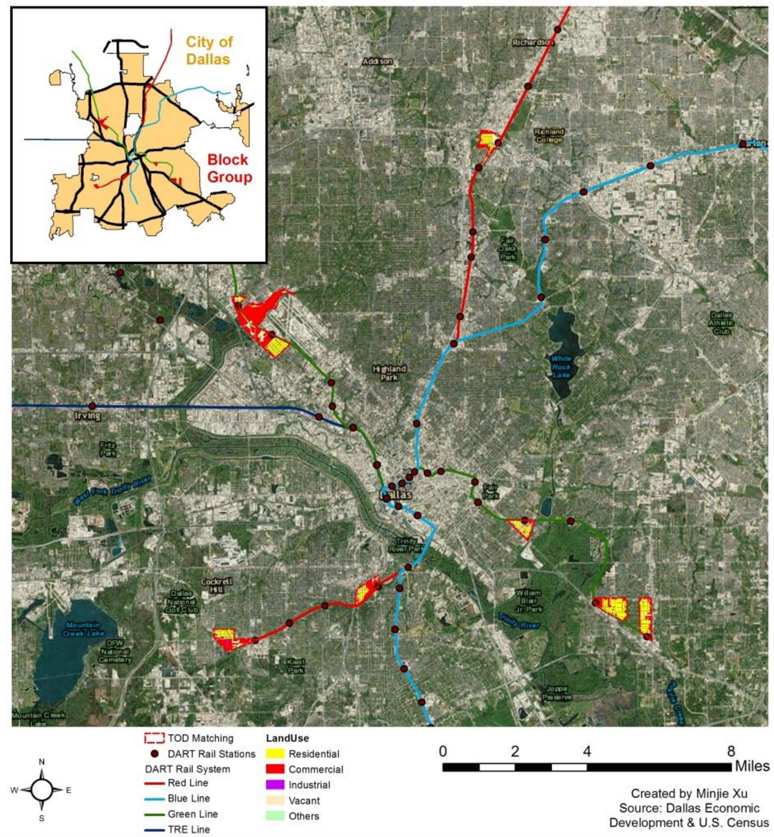
TOD TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
TOD	1636.78	12,482	7.63	28.89	35.96	87.31	25.78	60,195	17.62	9.60	36.13	0.61
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



TOD TIF Matching Block Group

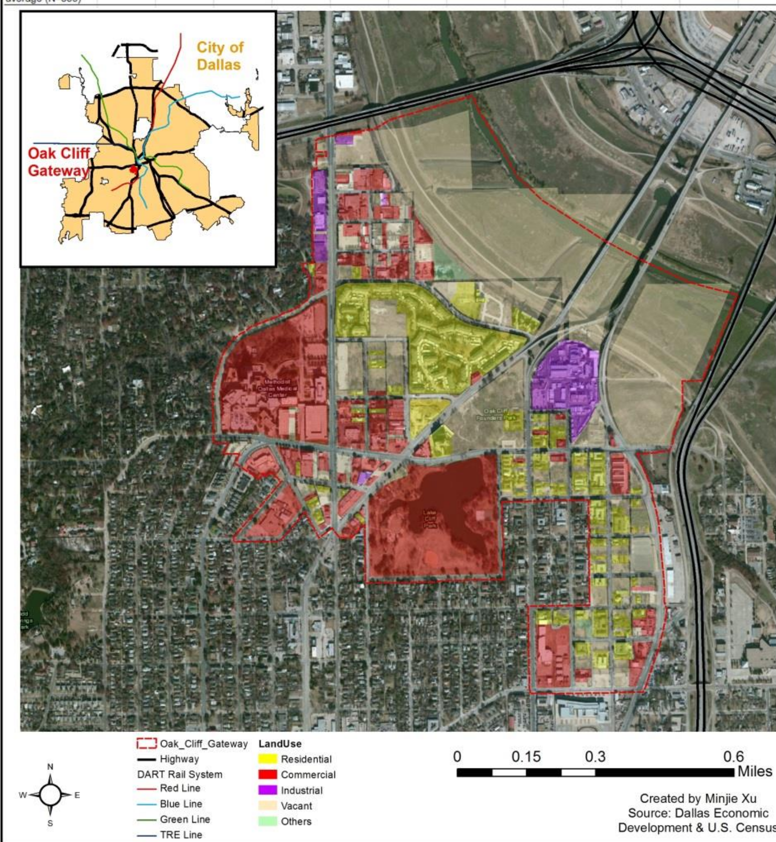
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
TOD Matching	1863.92	13,448	7.21	23.90	41.17	83.52	13.92	66,056	17.84	29.70	38.90	0.68
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Appendix E11: Oak Cliff Gateway TIF district Aerial and Land Use Map

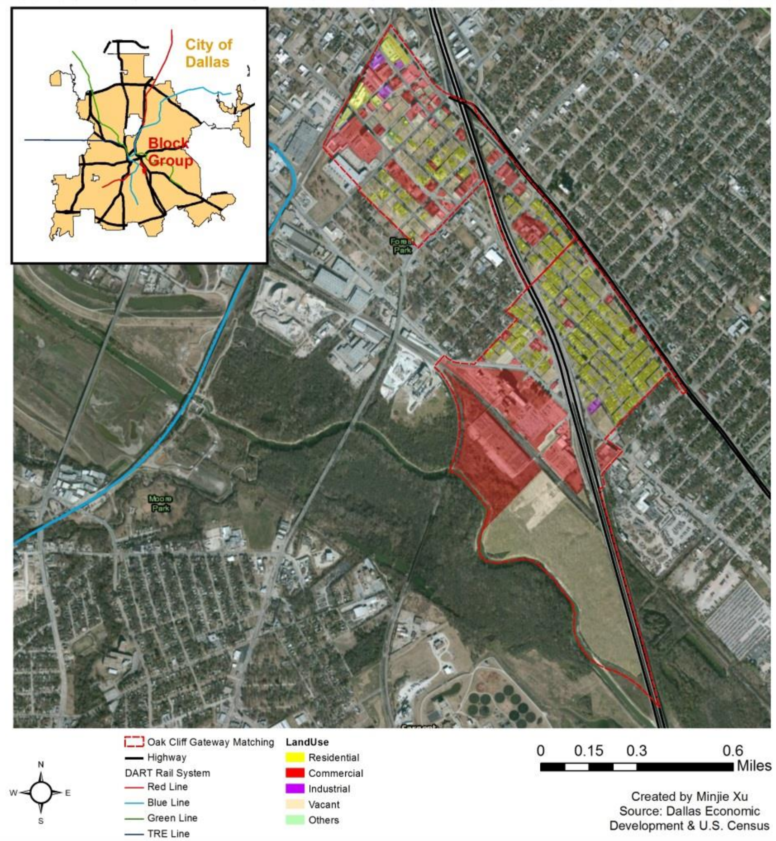
Oak Cliff Gateway TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Oak Cliff Gateway	515.82	3,374	6.54	16.70	64.90	88.80	10.11	58,103	13.86	17.01	32.72	4.53
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Oak Cliff Gateway Matching Block Group

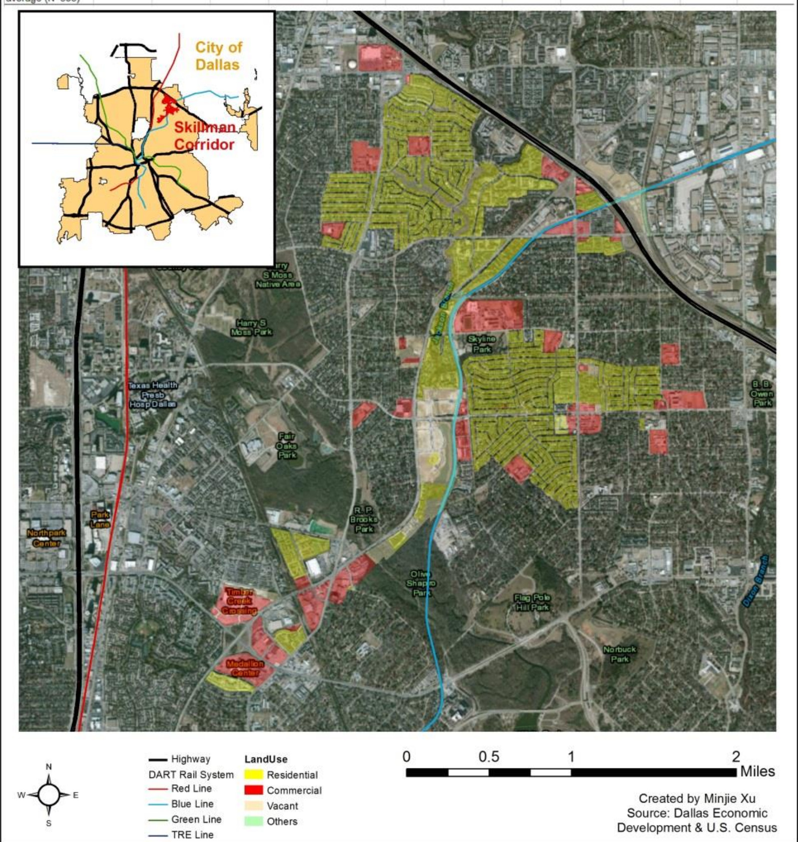
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Oak Cliff Gateway Matching	484.82	2,002	4.13	14.19	72.18	93.61	7.78	54,570	17.92	12.48	27.85	0.58
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Appendix E12: Skillman Corridor TIF district Aerial and Land Use Map

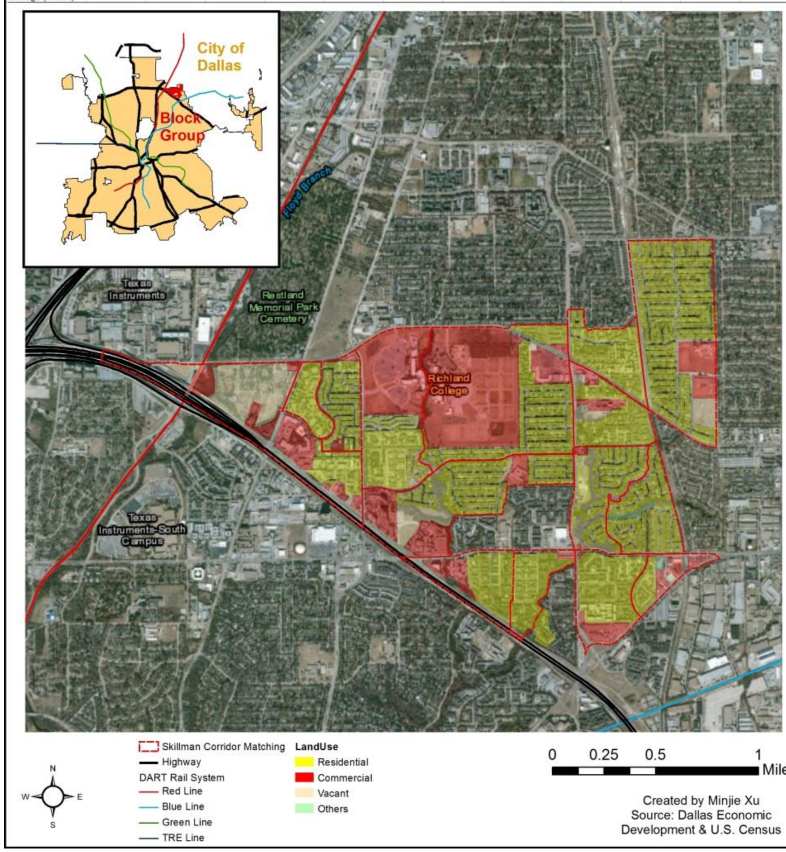
Skillman Corridor TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Skillman Corridor	1445.23	15,356	10.63	34.42	30.01	90.22	18.54	55,020	22.62	60.22	25.55	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Skillman Corridor Matching Block Group

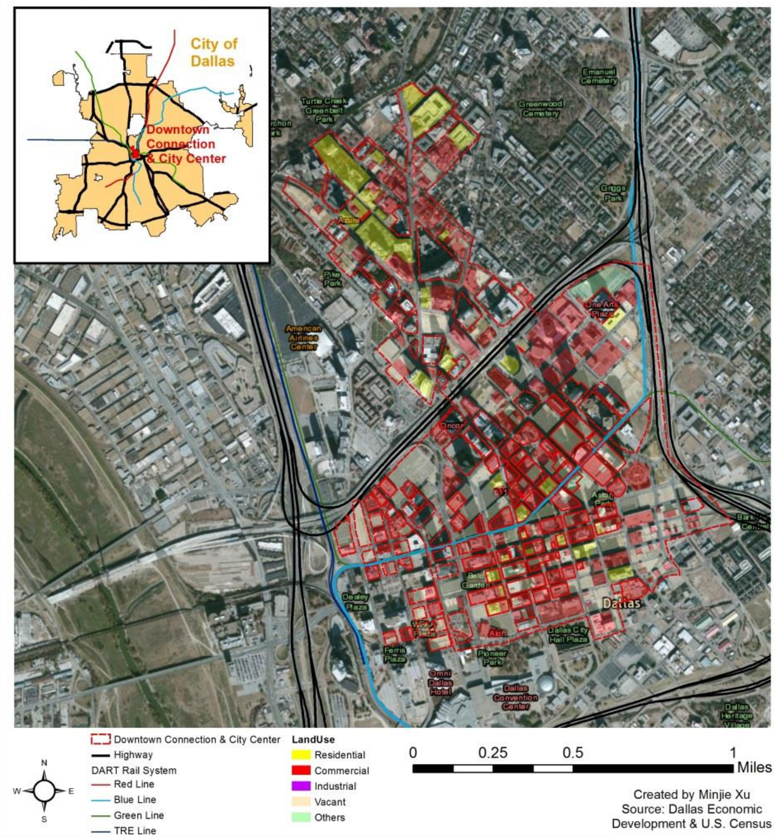
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Skillman Corridor Matching	1653.34	17,263	10.44	42.50	31.03	90.22	22.62	53,213	19.04	46.23	26.38	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Appendix E13: Downtown Connection & City Center TIF district Aerial and Land Use Map

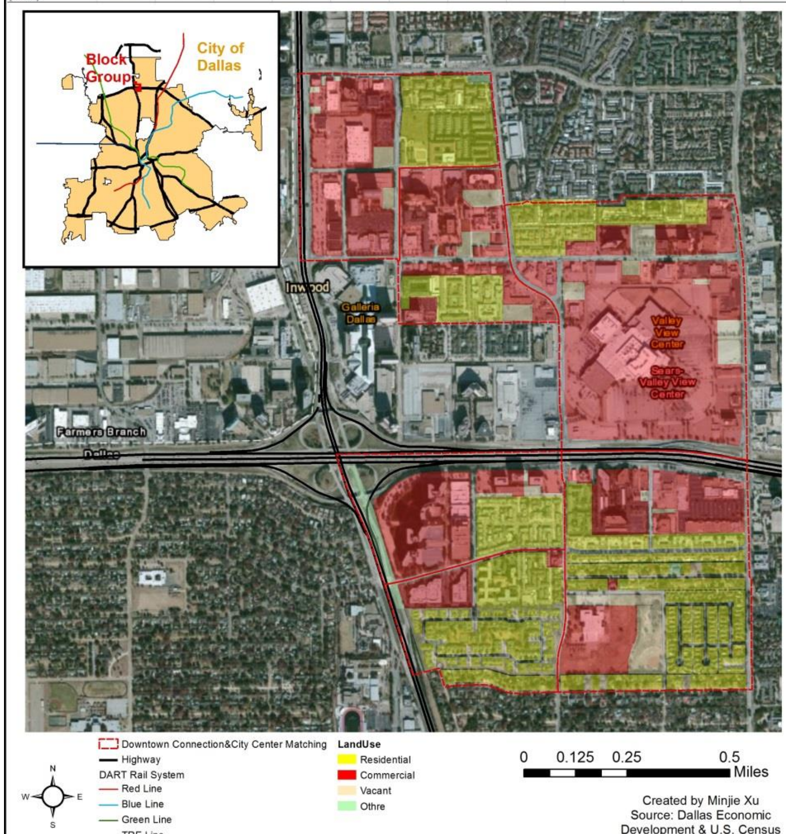
Downtown Connection & City Center TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Downtown Connection + City Center	628.84	7,864	12.51	46.91	23.31	90.12	35.01	48,294	27.07	13.94	47.14	0.02
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46

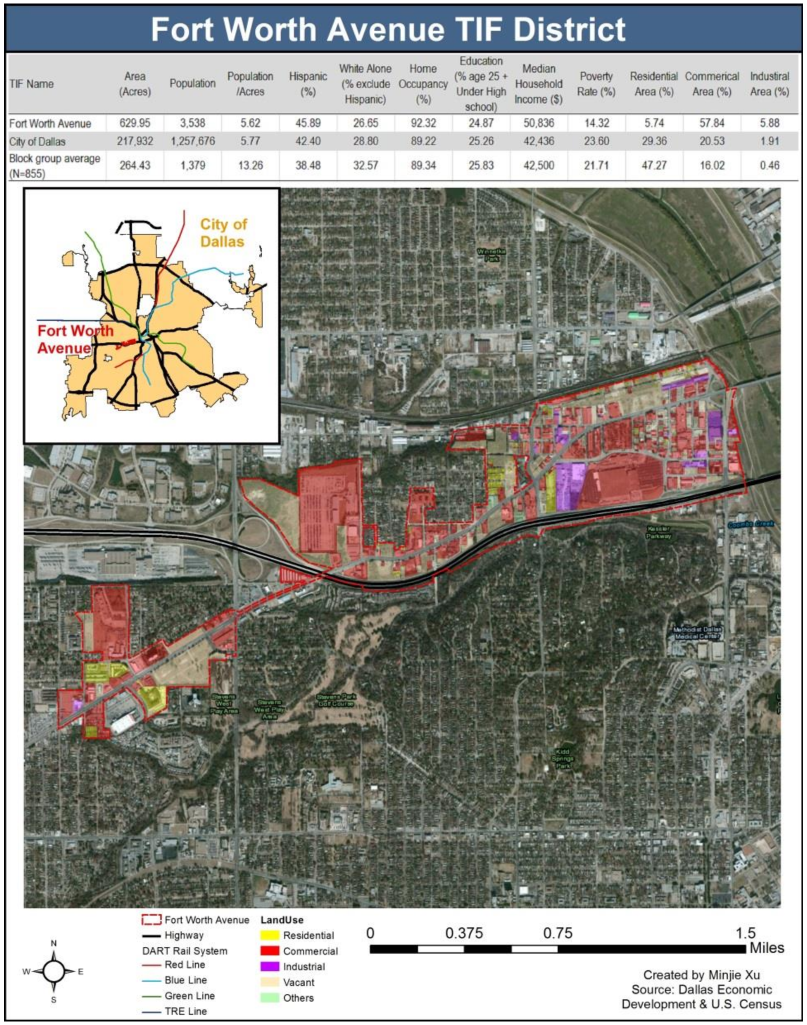


Downtown Connection & City Center Matching Block Group

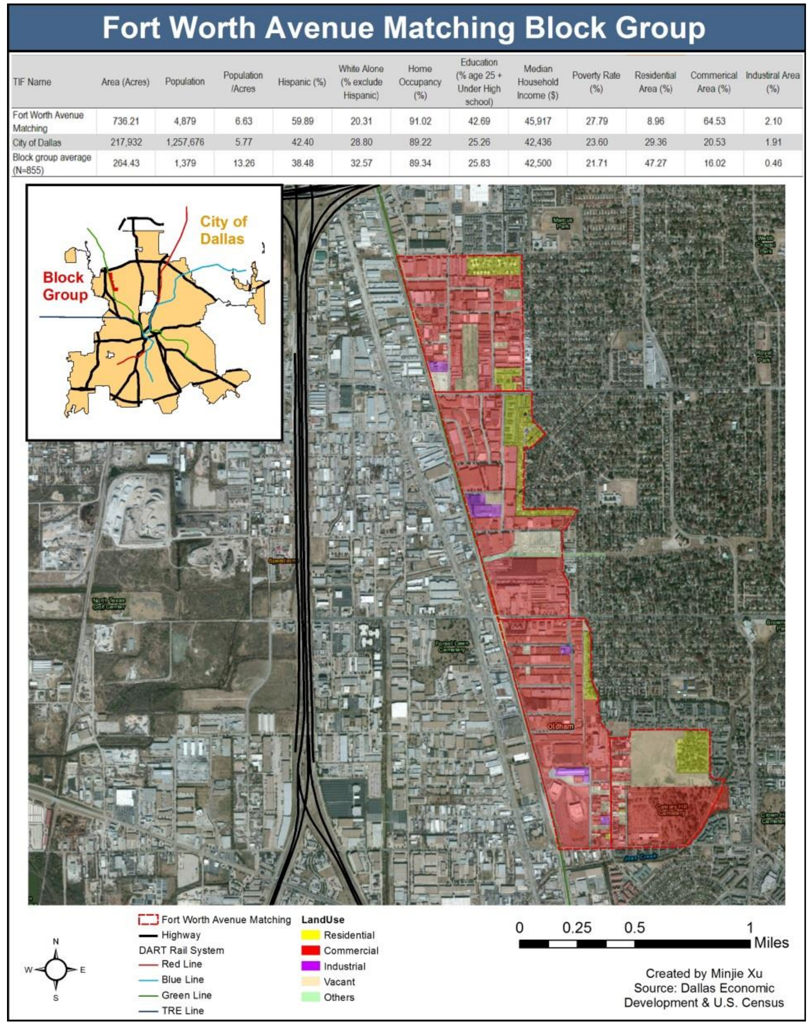
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Downtown Connection + City Center Matching	698.40	6,689	9.58	35.85	46.12	91.03	16.29	50,188	20.71	27.87	46.74	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Appendix E14: Fort Worth Avenue TIF district Aerial and Land Use Map



TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Fort Worth Avenue	629.95	3,538	5.62	45.89	26.65	92.32	24.87	50,836	14.32	5.74	57.84	5.88
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46

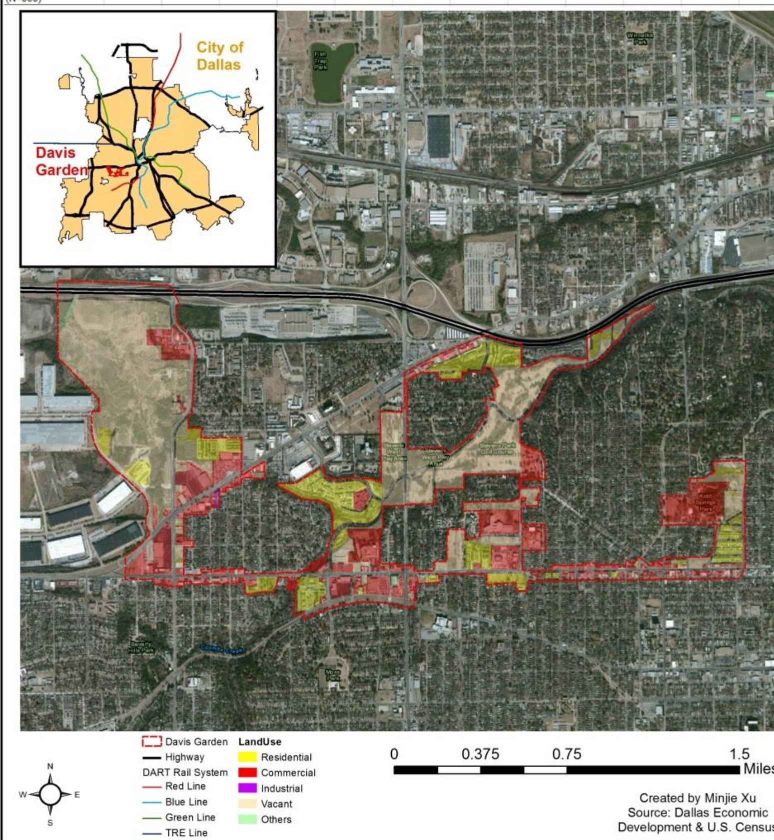


TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Fort Worth Avenue Matching	736.21	4,879	6.63	59.89	20.31	91.02	42.69	45,917	27.79	8.96	64.53	2.10
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46

Appendix E15: Davis Garden TIF district Aerial and Land Use Map

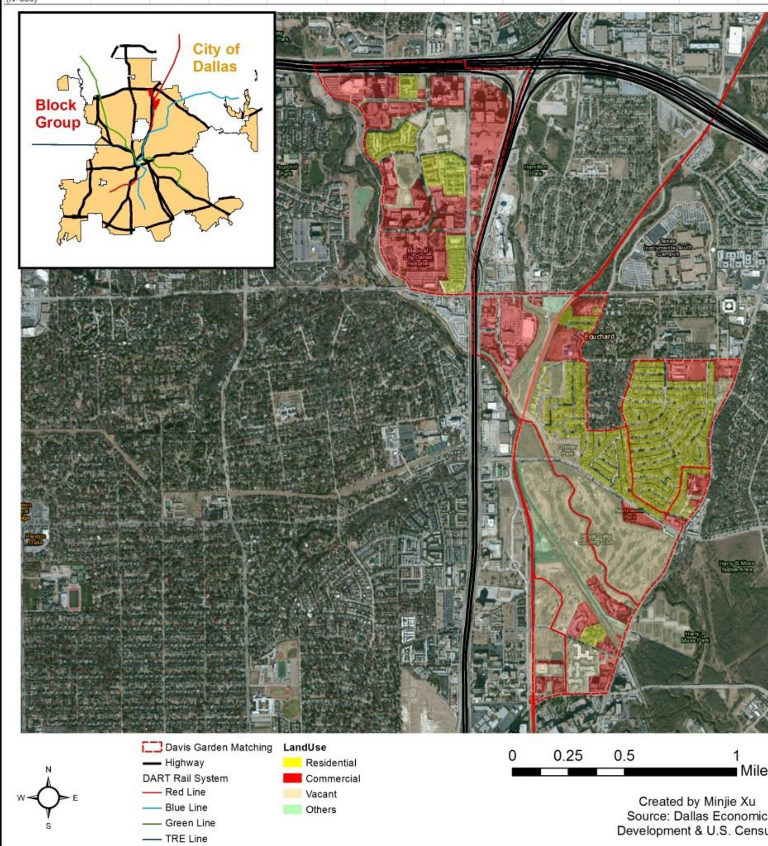
Davis Garden TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Davis Garden	877.94	7,809	8.90	48.43	23.42	90.62	37.87	48,699	22.34	17.41	26.77	0.13
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Davis Garden Matching Block Group

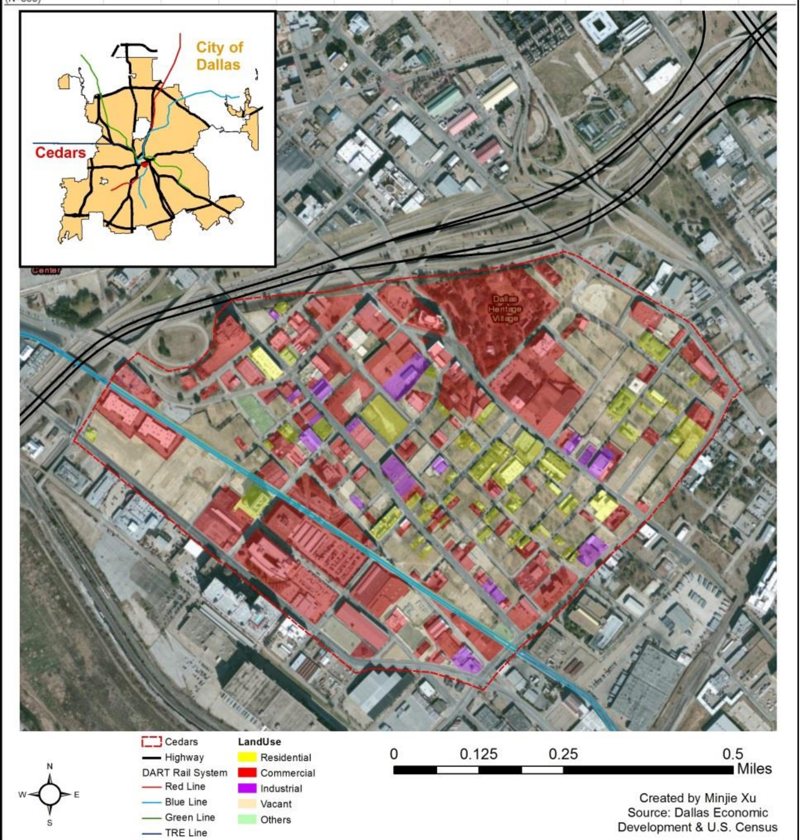
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Davis Garden Matching	1088.95	7,168	6.58	56.12	20.54	88.20	22.98	46,826	23.36	20.56	27.75	0.00
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Appendix E16: Cedars TIF district Aerial and Land Use Map

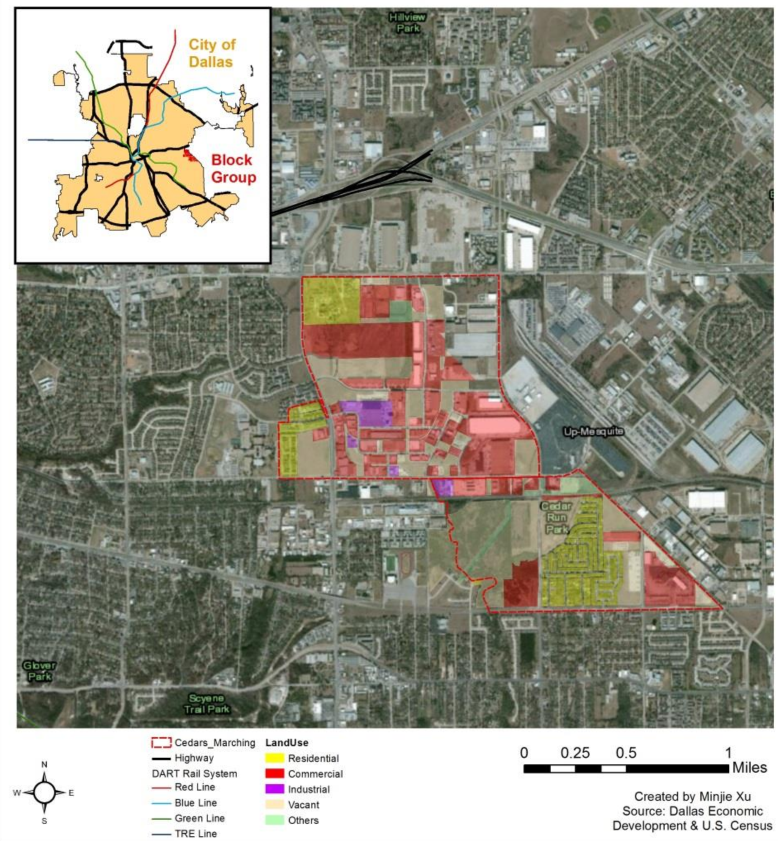
Cedars TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Cedars	249.71	518	2.07	42.77	27.58	91.62	28.96	44,691	23.66	10.03	47.08	4.05
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Cedars Matching Block Group

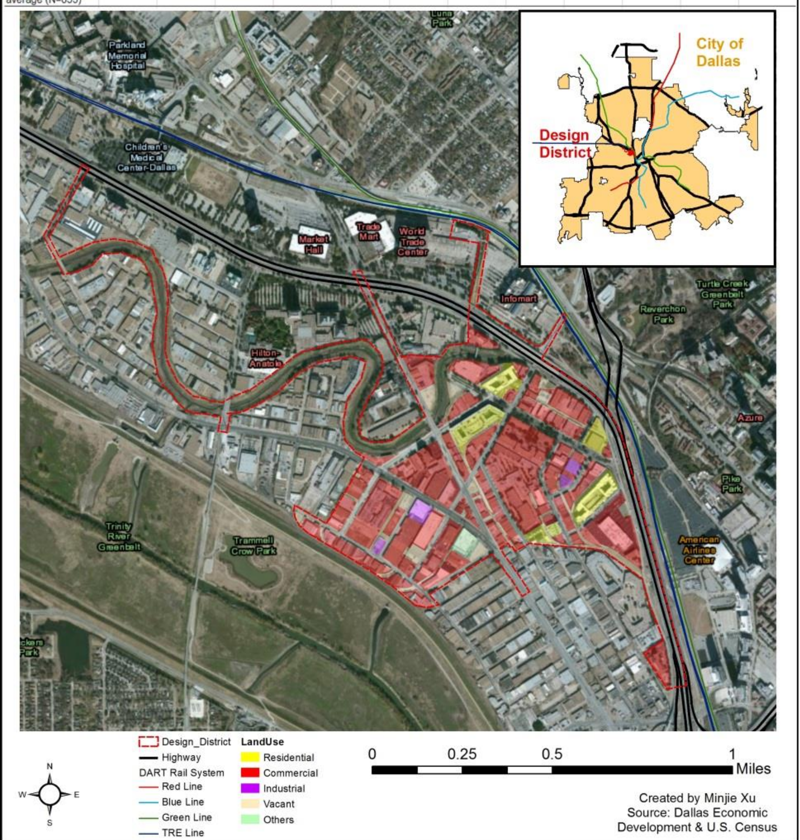
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Cedars Matching	1067.23	4,268	4.00	20.52	21.51	88.58	14.17	34,520	29.89	12.50	35.14	2.27
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Appendix E17: Design district TIF district Aerial and Land Use Map

Design District TIF District

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Design District	343.13	188	0.55	73.57	8.17	90.89	54.99	42,500	40.12	9.98	74.31	2.15
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46

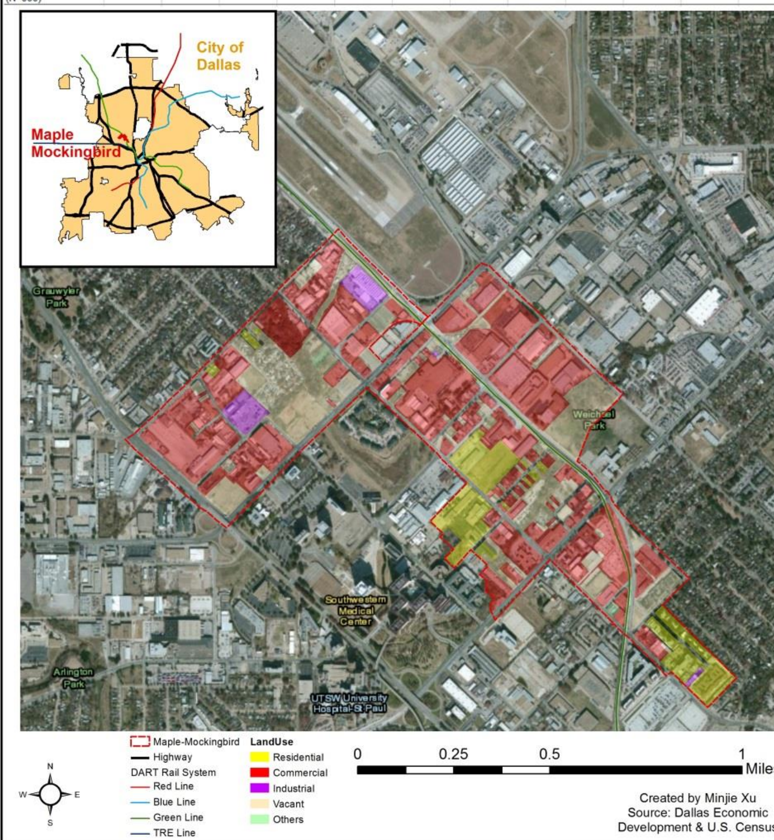


No matched block group was identified because of extremely low residential density. This TIF is excluded from the analysis.

Appendix E18: Maple-Mockingbird TIF district Aerial and Land Use Map

Maple Mockingbird TIF District

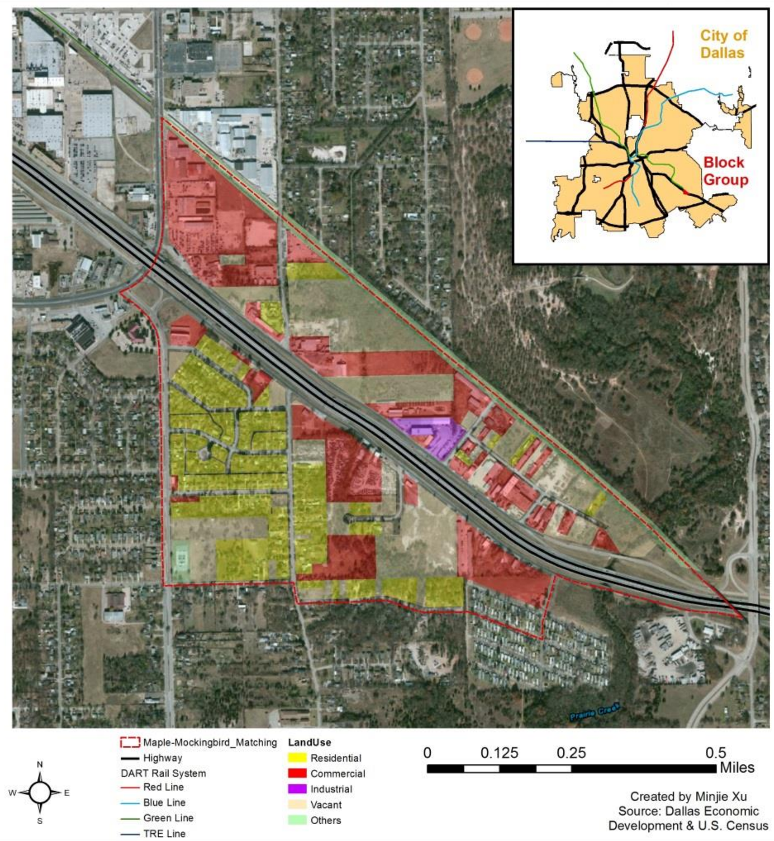
TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Maple Mockingbird	421.01	2,994	7.11	60.02	20.45	86.62	44.22	36,862	31.74	10.99	56.86	3.01
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Created by Minjie Xu
Source: Dallas Economic Development & U.S. Census

Maple-Mockingbird Matching Block Group

TIF Name	Area (Acres)	Population	Population /Acres	Hispanic (%)	White Alone (% exclude Hispanic)	Home Occupancy (%)	Education (% age 25 + Under High school)	Median Household Income ($)	Poverty Rate (%)	Residential Area (%)	Commerical Area (%)	Industiral Area (%)
Maple Mockingbird Matching	271.07	2,362	8.71	63.29	12.45	92.06	37.72	34,038	25.88	18.03	35.47	6.58
City of Dallas	217,932	1,257,676	5.77	42.40	28.80	89.22	25.26	42,436	23.60	29.36	20.53	1.91
Block group average (N=855)	264.43	1,379	13.26	38.48	32.57	89.34	25.83	42,500	21.71	47.27	16.02	0.46



Created by Minjie Xu
Source: Dallas Economic Development & U.S. Census