APPROVAL SHEET

Title of Dissertation: Where the Jobs Are: Evaluating the Impact of Tax Increment Financing (TIF) on Local Employment and Private Investment in Baltimore City

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ABSTRACT

Title of Document: WHERE THE JOBS ARE: EVALUATING THE IMPACT OF TAX INCREMENT FINANCING (TIF) ON LOCAL EMPLOYMENT AND PRIVATE INVESTMENT IN BALTIMORE CITY

Nichole M. Stewart, Ph.D., 2016

Directed By: Dennis Coates, Professor, Economics

This dissertation examines the impact of designating tax increment financing (TIF) districts in Baltimore City on employment, building permit activity, and residential property sales price appreciation using the difference-in-difference (DID) fixed effects research design together with propensity score estimation to identify economically similar comparison areas. According to the results of this study, TIF designation has no significant impact on employment. The moderate wage job estimate is the only significant job outcome, indicating a decrease in jobs with wages between $15,000 and $40,000 per year. This outcome suggests that TIF designation was not a firewall against a national shift to low-wage jobs during the Great Recession.

With respect to private investment, there is no relationship between TIF designation and building permit activity. The insignificant coefficients suggest that there was no difference in

the number of permits issued and the total permit values in TIF block groups compared to non-TIF block groups after designation. However, there was a large and significant increase in the number of homes sold and the sales prices of homes in TIF block groups. These positive effects are observed for both mixed and residential TIF districts and are likely driven by increased demand for very low-valued homes in the areas surrounding TIF districts that became more desirable after designation.

Finally, this dissertation found no significant TIF spillover effects and therefore TIF designation effects were not biased by economic activity and investment in areas geographically close to TIF districts. The repeat sales estimation also confirms that the sales prices of homes that sold more than once during the study period increased significantly in areas closer to the TIF districts and specifically in emerging and stable housing markets.

WHERE THE JOBS ARE: EVALUATING THE IMPACT OF TAX INCREMENT FINANCING (TIF) ON LOCAL EMPLOYMENT AND PRIVATE INVESTMENT IN BALTIMORE CITY

By

Nichole M. Stewart

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, Baltimore County, in partial fulfillment
of the requirements for the degree of
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Dedication

To all the women in my family, past and present, who toiled, worked, and struggled so that I could have the opportunity, privilege, and courage to believe I could create my own path.

To my late father, Reginald Stewart Sr., who constantly encouraged me to pursue my formal education and also directly (and indirectly) taught me the truth about life so that I was equipped with strength, discipline, and foresight.

To my mother Pauline Stewart, my aunt Angela Brown, and my sister Shanna Stewart for indulging my love of reading as a child, sacrificing their comfort for my benefit as an adult, and caring for my little darlings Spike and Dash.

To East Baltimore, specifically Broadway East, the only place I have ever considered HOME, no matter where I LIVED. From a neighborhood full of families that I still remember by name, to a desolate place I no longer recognized and couldn't wait to escape, to a place I couldn't wait to return to and contribute to its rebuilding. My experiences there informed my personal frame of reference, my opinions about the world, and of course inspired me to see the potential in what others might consider "nowhere places" with "nobody people".

Acknowledgements

Finishing this dissertation at times felt like a quixotic quest! However, there were many people supporting me along the way. First, I would like to thank both my dissertation chairs, Dr. Marvin Mandell for guiding me at the beginning of this endeavor and Dr. Dennis Coates for stepping in to get me over the finish line. Additional thanks to the other members of my dissertation committee, Drs. Dave Marcotte, Gerrit Knapp, Bob Giloth, and Lisa Dickson.

I'd like to acknowledge UMBC's Public Policy department for its many forms of support. Special thanks also to the American Evaluation Association, especially Dr. Stewart Donaldson, Dr. Katrina Bledsoe, and my GEDI cohort.

During this process, I've had the opportunity to work with several Baltimore philanthropies and initiatives over the years, including the Annie E. Casey Foundation, the Association of Baltimore Area Grantmakers, the Baltimore Integration Partnership, and the Baltimore Workforce Funders Collaborative. Their support enabled me to focus on my research while I was also engaged in work that shaped and cultivated my research interests.

Lastly, I must also thank my family, friends, acquaintances, and even the random strangers who supported me, distracted me, checked in on me, connected me with opportunities, conferenced with me, wrote with me, turned on the 4th floor light for me, presented with me, found that rubber band that day in class for my hair, understood when they didn't hear from me, listened to me talk ad nauseam about my dissertation….or simply had ONE word of encouragement.

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1 INTRODUCTION

Tax increment financing (TIF) is currently the most widely used economic development incentive for financing and leveraging public investment (Briffault, 2010). Through this mechanism, a municipality issues bonds and a private developer uses the proceeds from the sale of those bonds for financing public infrastructure, capital improvements, and site preparation in the redevelopment of a TIF designated area.

TIFs are a type of spatially targeted economic development incentive (STEDI) whose advocates contend will attract businesses, eradicate blight, create and retain jobs, raise tax revenue, expand the tax base, and drive investment in and around the redevelopment area. As such, it is essential to measure the impact on an area being designated a TIF district. However there is sparse evidence demonstrating TIF effectiveness and most of what is available is inconclusive due to methodological and data limitations.

Statement of Purpose

The purpose of this dissertation is to estimate the impact of a subset of tax increment financing districts in Baltimore City on employment, building permit activity, and residential property sales price appreciation outcomes. This kind of quantitative study addresses the gap in the literature by using advanced econometric research designs together with data available at small levels of geography to estimate the impact of TIF designation and the spillover effect of TIF designation in surrounding areas.

This dissertation seeks to investigate the following research questions: (1) Does TIF designation facilitate job growth in TIF districts? (2) Does TIF designation increase the employment of local residents? (3) What is the relationship between TIF designation and the distribution of low, moderate, or high-wage jobs? (4) What is the relationship between TIF designation and the distribution of jobs by industry for retail, leisure, and hospitality industries, goods-producing and export driven industries, and educational and health services industries? (5) Does TIF designation induce building permit activity and residential property sales prices? (6) Are the effects of TIF designation on employment, building permit activity, and residential property sales prices biased by the spillover of effects to areas adjacent to TIF districts?

The dissertation examines the first five research questions by analyzing TIF designation effects using a difference-in-difference research design and economically close comparison areas identified with propensity scores derived from various demographic, socioeconomic, and neighborhood indicators. Job outcome measures are derived from the Census Bureau's Longitudinal Employer-Household Origin-Destination Employment Statistic (LODES) data. Previous studies of STEDIs interested in employment primarily focus on the growth of workplace employment, or rather the increase in the number of workers employed in firms in designated areas. However, researchers contend that evaluations of economic development incentives should be viewed through the lens of not only how many jobs are created, if any, but also the types of jobs and whether local workers are employed in them (Peters and Fisher, 2004).

As such, in addition to job growth this dissertation will examine the effects of TIF designation by job type, including the distribution of jobs by wages, jobs by industry, and by local employment, or whether workers in TIF districts also live in Baltimore City. Additionally, building permit activity data and residential property sales transaction data are used to determine the effect of TIF designation on the investment decisions of new and existing private property owners.

The difference-in-difference methodology is also used to address question six which determines whether there are spillover effects of TIF designation. Geographically close comparison areas within varying distances from TIF designated areas are used to estimate the impact of TIFs on employment and private investment in surrounding areas that potentially bias estimated TIF designation effects. Finally, the repeat sales methodology, a variation of hedonic price index regression, is also used to estimate the spillover effects of TIF districts on the sales price appreciation of homes that sold more than once during the study period.

Organization of Chapters

Chapter One presents the historical roots of tax increment financing in federal urban renewal as well as the mechanics of TIF as a financial instrument. The chapter also discusses TIF implementation in Baltimore City. Chapter Two describes the theoretical framework for the justification of TIFs as a government intervention and for estimating the impact of TIFs on job growth, various types of jobs, as well as private investment measures. The chapter also presents a typology of the Baltimore City projects financed with tax increment financing, in addition to the expected effect of TIFs on outcomes based on the type of project financed. Chapter Three outlines the relevant research related to the methodologies used and the employment and private investment outcomes examined in previous evaluations of spatially targeted economic development incentives in general and TIFs specifically. Chapter Four includes the research questions examined in the study, the employment and private investment outcomes of interest, the selection strategy using spatial analysis to identify comparison areas that are economically similar and geographically close to TIF designated areas, and the study's empirical strategies including the difference-in-difference design and the repeat sales methodology. Finally, Chapter Five and Chapter Six present the TIF designation and TIF designation spillover findings, respectively. Chapter Seven concludes with a discussion of how those findings are relevant for future evaluation of local economic development and tax increment financing.

1.1 Waves of Local Economic Development and Spatially Targeted Incentives

Local economic development is distinguished from national macroeconomic approaches that focus on tax reductions, increased government spending, and fewer regulations at the aggregate level. Local economic development is often characterized by a hybrid of strategies, whereby local governments aim to expand the tax base, business activity, and local employment by directly incentivizing private developers and businesses to retain and create jobs, and for property owners to make improvements and investments.

For localities with areas that have experienced significant economic decline, disinvestment, and job loss, politicians and economic developers initiate and implement place-based or spatially targeted economic development incentives to effect economic growth and neighborhood revitalization. While there are debates about the appropriate role for the public sector in local economic development, the theory supporting STEDIs follows the logic that place matters and that physical redevelopment of distressed areas and the provision of employment opportunities for area residents requires location-specific solutions. STEDI strategies include attracting businesses to a specific area, retaining and growing existing firms there, and creating partnerships that catalyze investment and facilitate the institutional capacity to change the trajectory of declining urban areas.

Cray et. al. (2011) identify three significant spatially targeted policies to support those strategies: business attraction and retention, enterprise and empowerment zones, and tax increment financing. Each of these spatially targeted policies reflects the advancement of local economic development policies over time as cities and states responded to changing political considerations and economic conditions. These shifts in theory, strategy, and policy are often characterized as the three waves of economic development. The following discussion describes these waves and the STEDI policies that were prevalent during those periods.

1.1.1 First Wave

The first wave of local economic development focused on business attraction, or assistance to firms through low-interest loans, tax abatements, tax-exempt bonds, and loan guarantees that finance the cost of plant facilities, or limit the costs and risks associated with relocation (Bradshaw and Blakely, 1999). The most widely used direct subsidy, industrial revenue bonds (IRBs), a type of private activity bond, are debt securities issued by state and local governments and governed by federal regulations.

IRBs date back to 1936 when the state of Mississippi authorized the use of municipal tax-exempt bonds for reducing property tax liability for out-of-state firms willing to relocate into the state. When issued by local governments for this purpose, interest income on these bonds is exempt from federal income tax, allowing firms to borrow at below-market interest rates, decreasing the cost of capital and increasing rate of returns at specific locations (Giloth, 1992). Through the 1950s and 1960s, many southern Sun Belt states with relatively cheap land, disorganized labor, and lower wages continued to pursue growing manufacturing plants from the northeastern Rust Belt.

Between 1975 and 1985, the use of private activity bonds increased dramatically from 21 to 68 percent of all tax-exempt bonds. State and local governments were perceived as over-using IRBs as instruments to fund a broader range of private uses, ultimately reducing federal income tax revenue and increasing the federal deficit. In an effort to limit the use of these tax-exempt bonds, the Tax Reform Act of 1986 capped the volume of bonds state and local governments could issue within a state (Zimmerman, 1990).

Local economic development agencies have been criticized as merely smokestack-chasing and engaged in boosterism for expending resources to attract firms. Unclear and conflicting goals and disparate implementation across municipalities hampered continuing support for this kind of direct firm assistance (Peters and Fisher, 2004; Giloth, 1992). In addition, evaluations of IRBs further spurred direct subsidies to grow out of favor. Fisher and Peters (1997) concluded these studies revealed ambiguous outcomes and no statistically significant relationship between IRBs and employment.

1.1.2 Second Wave

The second wave of local economic development advanced in the early 1980s. Instead of attracting new firms from other states or adjacent jurisdictions, the focus of economic developers shifted to business retention strategies directly targeting new and small firms or those in particular sectors of interest to a municipality. The incentives included financial or business management assistance, incubators, investment capital, and technical assistance, often offered to firms within a designated zone.

The concept of enterprise zones as an incentive to increase investment and economic activity in abandoned industrial areas was introduced in the UK by British urban planner Peter Hall. Subsequently, in the U.S. state and local enterprise zones (SEZs) became a popular STEDI designed to encourage businesses to locate in or expand in designated economically distressed communities in an effort to revitalize these areas and provide employment opportunities for local residents. Connecticut became the first state to enact an SEZ in 1981, followed by 36 other states, all with different priorities, program designs, and implementation. SEZs vary in size from a few city blocks to entire states, including Arkansas, Kansas, and South Carolina (Pulsipher, 2005). Wilder and Rubin (1996), Peters and Fisher (2002), and Bartik (1991) offer comprehensive reviews of SEZ evaluations. Notably, more recent research using advanced methodologies do not indicate a significant relationship between enterprise zone designation and employment growth.

Proposals to replicate enterprise zones at the federal level reflected a Reagan-era supply-side entrepreneurial approach for revitalizing distressed areas. Despite bipartisan support from Congressmen Republican Jack Kemp and Democrat Robert Garcia, the early attempts to pass and fund enterprise zone legislation were not successful, likely due to disparate goals for the program. While conservatives focused explicitly on the potential for broad job creation, liberals were interested in inner city revitalization. In addition, enterprise zone opponents were wary that such a federal program would negatively impact other aid to urban communities.

Under the Clinton administration, a newly renamed federal Empowerment Zone program (EZ) was finally authorized in 1993 with designations for Renewal Communities, Enterprise Communities, and Empowerment Zones through three rounds. During Round I six out of 78 distressed urban communities were competitively selected to participate over a period of ten years, including Baltimore, Chicago, Atlanta, Detroit, New York City, and Philadelphia/Camden. Firms located in EZs have access to four major types of grants, financing, and tax incentives (McDonald and McMillan, 2011).

- **Investment incentives for purchasing business equipment**— Business located in EZs are allowed to increase the amount of depreciable business equipment, land, and property expenses that can be written off as a deduction in the first year, postpone declaration of capital gains on qualified assets, and increase exclusion of gains from sales of small business stock.
- **Labor incentives to encourage EZ firms to hire local workers**— Firms could take wage tax credits of up to 20% of the first $15,000 in wages paid per qualified employee living in the designated zone. The Work Opportunity Tax Credit (WOTC) is available for businesses hiring disadvantaged and hard-to-employ workers.

- **Financing programs**—Zone businesses have access to low-interest tax-exempt bond financing for qualified expenditures in EZs.
- **Social Services Block Grant (SSBG)—**Each urban EZ was awarded and responsible for administrating $100 million in SSBG funds for a variety of uses including job training, financial education, youth services, business assistance, transportation, homeownership counseling, and supportive services such as drug treatment and after-school programming. The SSBG also facilitated the leveraging of other sources of funds by way of funding the administration of strategic plans.

Critics suggest EZ tax credits may not have been large enough to incentivize employers to hire local workers (Zhou, 2014). This is supported by the fact that most of the businesses taking advantage of the tax credit were large existing businesses with taxable income, higher tax liabilities, and the expertise to utilize them (U.S. General Accounting Office, 1999; U.S. Department of HUD, 2001). This finding is important since EZs were intended to assist new and existing small businesses in designated EZs that would most likely be accommodated by available business space and that would be more willing to hire local low-skill residents in urban neighborhoods (Birch, 1981; Ladd, 1994; Butler, 1991). Also, the utilization of the tax credits might suggest the block grants had a larger impact than the other mechanisms offered by Empowerment Zones to influence employment (Busso, Gregory, and Kline, 2010).

While SEZ and EZ initiatives are credited with creating jobs through business development, connecting area residents to jobs, increasing homeownership, and building community capacity, there exists a mixed body of literature about the impacts of the 3,000 state and federally designated enterprise zones and empowerment zones. The existing research used varied econometric approaches and thus produced mixed evidence suggesting that business attraction and retention policies primarily focused on "place" or indirect incentives do not necessarily increase employment or improve outcomes for residents in targeted areas (Zhou, 2014). These studies are further discussed in Chapter Two.

1.1.3 Third Wave

Third-wave strategies adopted through the 1990s are not as well defined as first and second wave strategies for two reasons. First, rather than specific incentives, the strategies are about affecting the business climate and building institutional capacity, public-private partnerships, and organizational structure to grow the economy. These strategies largely focus on improving quality of life and community-level economic development (Zheng and Warner, 2010).

With its focus on revitalization of urban areas through public-private partnerships, tax increment financing is considered a third-wave strategy whose usage increased through the 1990s. Immergluck (2009) refers to TIFs as third-wave gentrification as they have become associated with large scale redevelopment projects requiring significant infrastructure improvements. While there are some econometric studies estimating TIF impacts, there is more to explore. We need to identify and understand the relevant outcomes of interest and determine whether they are sufficient to increase the employment of local residents and revitalize neighborhoods. The history of TIFs will be discussed in a subsequent section.

The second factor contributing to the vagueness of third wave strategies is that the waves of economic development represent more of a continuum of polices as the use of IRBs, SEZs or EZs, and TIFs certainly overlapped the three wave periods. IRBs are still used for manufacturing facilities and in conjunction with property tax abatements (Kenyon et. al, 2012). In addition, other business attraction strategies remain popular despite criticisms. They resemble big-bang redevelopment projects and stadium-chasing strategies in the pursuit of landing professional sports facilities (Coates and Humphreys, 2003; Giloth, 1991 and 1997). Lastly, after the initial round of the federal EZ in 1994, two subsequent rounds were awarded in 1998 and

2001. While funding for all three rounds was initially set to discontinue at the end of 2011 it was extended through 2013 for the thirty active federal EZs. Also, state and local governments continue to implement enterprise zones.

Ultimately, third wave strategies are designed to strategically focus these first and second wave strategies of attracting and retaining businesses and improve their efficiency (Bradshaw and Blakely, 1999; Eisinger, 1995). While top-down first and second wave strategies are lower priorities for states and localities, they are still relevant in the economic development toolbox.

1.2 Tax Increment Financing

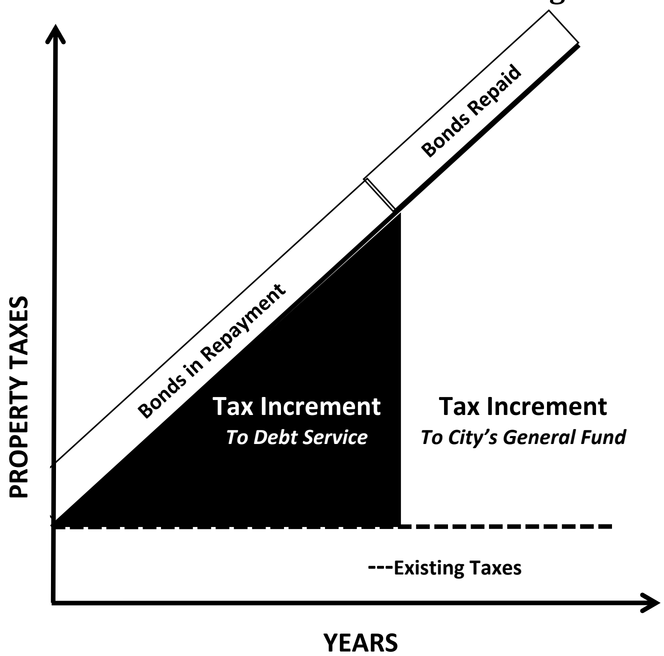
1.2.1 The Mechanism, History, and Critique of Tax Increment Financing

Tax increment financing is essentially a financing mechanism that allows a municipality to borrow funds by issuing bonds in the amount of the incremental or future ad valorem property tax revenue that a TIF designated area is expected to generate after redevelopment. The private developer uses the funds from the sale of those bonds to finance allowable costs and expenses for public infrastructure, capital improvements and site preparation such as roads, water and sewer systems, utilities, land acquisition, roads, lighting, parking, and other facilities within the designated TIF boundaries.

Property tax revenues based on the assessed value of existing properties in the area collected by the municipality continues to flow to the normal taxing bodies, such as a city's general fund, and remains the same through the life of the TIF (see dotted line in figure 1.1). While the bonds are in repayment, the incremental (or increased) property tax revenue resulting from expected property value growth as a result of redevelopment is used to repay the bondholders over time, often for periods as long as 30 years (shaded area). After the borrowed funds are fully repaid, the

TIF district dissolves and the redeveloped area's assessed property taxes are then paid directly to overlapping tax entities (i.e. state, school district) and the city's general fund.

Figure 1.1. Mechanism of Tax Increment Financing



TIFs can be funded as float revenue bonds whereby the debt service on those bonds is paid with the increment through the repayment period. In this way, no other taxes need to be levied. In contrast, with a "pay as you go" (PAYGO) TIF the initial investment is paid by the private investor and the municipality reimburses the developer with the incremental property taxes collected every year (Weber, 2003).

In tandem with changing priorities and policies that facilitated third wave economic development strategies, public distaste for new taxes and direct subsidies to businesses increased public support for TIFs. TIFs are neither a direct tax nor a direct tax subsidy so are favorable to the politicians held accountable for public spending by local taxpayers. Similar to IRBs, TIFs are a form of debt financing. This financing mechanism is also flexible as it avoids municipal debt limits and the need for voter approval for various kinds of economic development expenditures.

Critics have long questioned the usefulness and effectiveness of STEDIs generally, and tax increment financing specifically. A main criticism is that local economic development is a zero-sum game where incentives only serve to lure businesses from the next region and merely shifts rather than actually creates economic growth (Blair and Kumar, 1997). Municipalities are pressured to provide tax increment financing and have engaged in bidding wars to compete for businesses to relocate (Smith, 2009). However, Bartik (1990) and Porter (1994) offer that the relocation of businesses and the redistribution of investment increases efficiency which addresses the market failures of local economic development.

Crowding out is another concern as directing public resources to incentives has fiscal implications for other local public spending, such as transportation and education. TIFs reallocate property tax revenue from a city's general fund to the TIF district. In this way TIFs could represent a tax capture for municipalities that would otherwise be due to states and other jurisdictions, such as school districts (Anderson, 1990). This could potentially create a shortfall and require increased personal property or income taxes. However, there is no easy way to measure the impact of alternative spending.

Critics of TIFs also cite the use of TIFs for development in existing city commercial centers rather than for blighted urban areas as an indication of a lack of accountability and misuse of TIFs. When TIFs were created in 1952 in California, one of the primary rationales was that the financing mechanism facilitates the redevelopment of blighted urban areas. Blight removal and slum clearance as policy goals are directly linked to economic and social transformations that defined the mid-19th and early 20th centuries.

The Housing Act of 1949 provided funds for building low-income housing while allowing states to pass legislation enabling eminent domain to clear substandard housing. The law provided two-thirds of the net costs for buying and clearing abandoned and deteriorating buildings and allowed the sale or lease of land to private developers at reduced costs. TIFs were initially created to match these federal urban renewal funds.

However, TIFs are no longer primarily associated with blight, as increased interest in economic development at the local level through partnerships between local government and business led to TIF's emergence as the most widely used economic development incentive for financing and leveraging public investment (Briffault, 2010).

1.2.2 Implementation in Baltimore City

While TIFs have been authorized for use locally since 1994, Baltimore City was granted authority to issue TIF bonds without a referendum under an amendment of Article II, Section 62 of the Baltimore City Charter in 2000 (Baltimore City Council, 2011). Over the past decade TIFs have increasingly been used in Baltimore City as a place-based strategy for leveraging public investment.

In a July 2013 hearing of Baltimore City's Taxation, Finance and Economic Development Committee, City Council President Bernard C. "Jack" Young's expressed support for a $107 million tax increment financing (TIF) proposal for Harbor Point developers based on one main criteria: "Jobs, jobs, jobs!" (Young, 2013). This reflects the motivation for using tax increment financing for local stakeholders across the country tasked with creating jobs in a sluggish post-recession economy (Courant, 1994).

Increases in the number of employed city residents, local businesses, and retail activity are aligned with the city's priority of achieving a growing economy and are especially desirable goals in Baltimore, a city with an unemployment rate of 8.2 percent in July 2015 compared to 5.2 percent in Maryland and 5.3 for the U.S. during the same period (U.S. Bureau of Labor Statistics, 2016). In addition, just under a quarter of residents had incomes below the poverty line and median household income was $42,266 in 2013 (U.S. Census Bureau, 2015).

Baltimore City uses a hybrid of property tax incentives such as tax abatements, subsidies, empowerment/enterprise zones and tax increment financing to facilitate private development intended to benefit the local economy, spur job growth, and attract new businesses.

Baltimore Development Corporation (BDC) is the quasi-governmental agency primarily responsible for managing economic development projects in Baltimore. [1] A TIF can be initiated by BDC once a developer of a redevelopment site submits a request for tax increment financing. TIF requests are then reviewed by the Board of Finance. Legislation to create a TIF district is then presented to the City Council, approved into legislation by the Board of Estimates, and the Mayor is required to sign the legislation into law.

Proposed TIF projects in Baltimore must meet two main underwriting criteria— the "but-why" and the "but-for" test. The "but-why" test establishes that the project advances the city's goals regarding strategic land use, economic development and public improvement outlined in Baltimore's Comprehensive Plan (Baltimore City Planning Department, 2006) and that there is a return on investment for the city. The "but-for" test establishes that the development project is not feasible save for the TIF or would not have occurred were it not for the public investment in the TIF district. This is demonstrated by financial analysis that shows high development costs, a below market rate of return on investment, and the absence of private funds or other public assistance available for a development project.

As of 2015, 13 TIF districts have been established in Baltimore City. These projects represent a mix of residential, commercial, retail, hotel, and office developments, as well as

[1] The Baltimore Housing Department initiated the EBDI TIF and the Maryland Economic Development Corporation *(MEDCO)* is expected to initiate TIFs in the future.

streetscape improvements in neighborhoods throughout the city (figure 1.2). TIF bond issues range between $2 million for upgrades to the Belvedere Square retail shopping and entertainment center in North Baltimore to the $301 million development of the 757-room Convention Center Hilton Hotel.

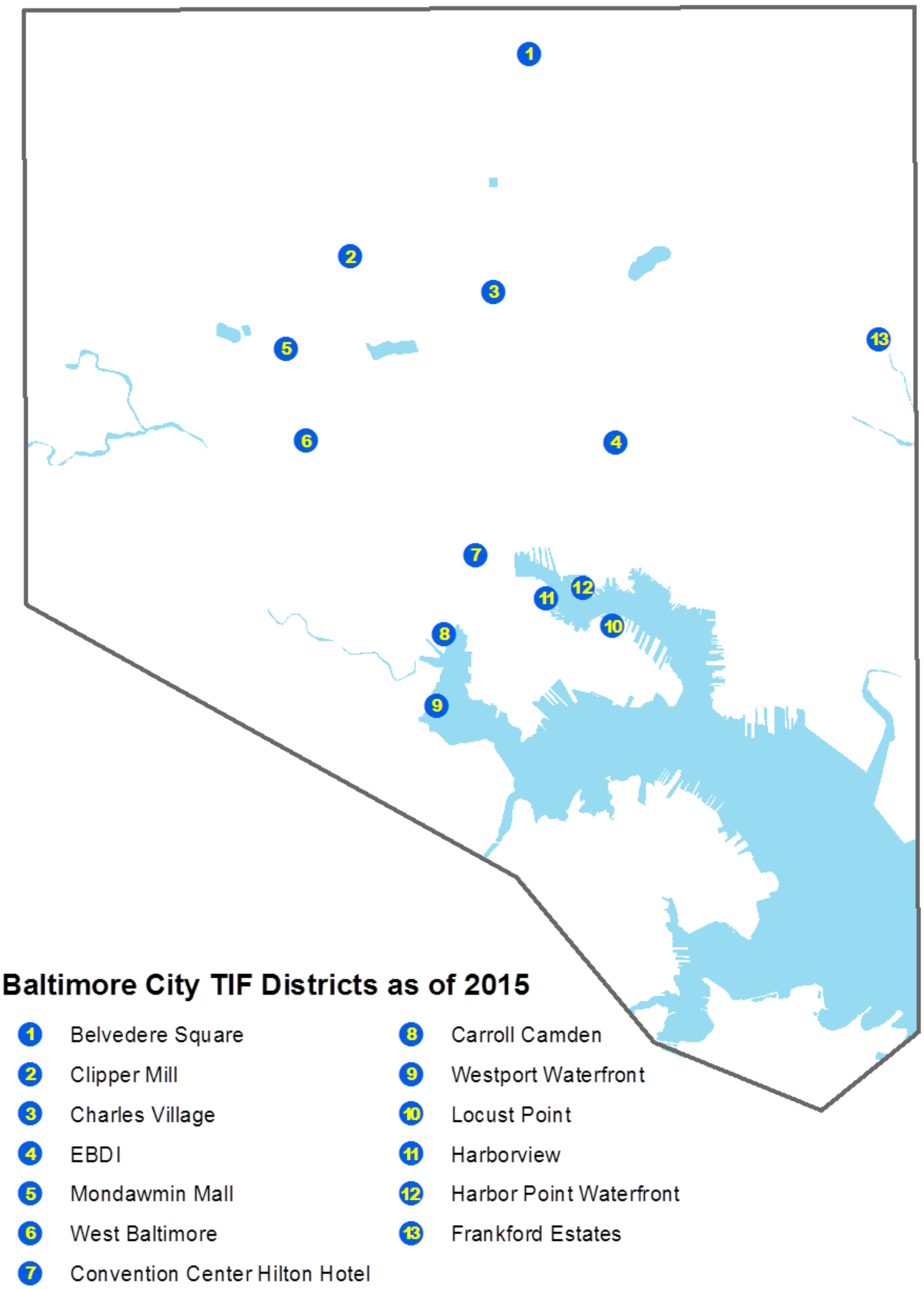
EBDI, the multi-phase redevelopment of an entire neighborhood covering 88 acres north of Johns Hopkins Hospital is the largest TIF district. The TIF proceeds have been used to fund acquisition and development of land as well as the relocation of residents in Phase II of the project area. It is important to note that many of the parcels are still in development. Since 2003, the project acquired through eminent domain the homes of 584 families who have been relocated from the area with benefit packages that include assistance for renters and homeowners. New development in the TIF district includes the Rangos Life Science Building opened in 2008, JHU graduate student housing opened in 2012, the 7-acre Henderson Hopkins school campus opened in 2013, and 215 residential units in mixed-income and senior housing developments with nearly 33 percent of units affordable to renters earning between 50-80 percent of area median income.

Frankford Estates and Harborview are housing developments in northeast Baltimore and adjacent to Baltimore’s Inner Harbor, respectively. The Mondawmin Mall renovation and expansion in West Baltimore includes the first Target store in the city. About 2 miles away, tax increment financing was used to finance the mixed-use redevelopment of Clipper Mill, an historically significant site in the Jones Falls Valley that has been on the National Register of Historic Places since 1972.

As of late 2015, the Harbor Point Waterfront mixed-use project funded with $107 million in TIF proceeds is under construction and the Poppleton Center/West Baltimore TIF near the University of Maryland BioPark was recently approved. No bonds have been issued for the

Carroll Camden TIF slated to redevelop the vacant Acme warehouse in Rosemont or the proposed 4.8 million square foot mixed-use development on the Westport Waterfront. For active TIF districts, the debt service paid to bond holders was $12.3 million in fiscal year 2014 (Baltimore City Finance Department, 2015).

Figure 1.2. Baltimore City TIF Districts as of 2015



2 THEORETICAL FRAMEWORK FOR EVALUATING STEDIS AND TIFS

The following section outlines the theoretical framework justifying STEDIs as government intervention. In addition, the theoretical framework for evaluating the relationship between TIF designation and job outcomes as well as private investment outcomes is discussed.

2.1 STEDIs and the Justification for Government Intervention

The common thread among STEDIs is that they are targeted to specific geographic areas. Economic geography, the relationship between location and the spatial organization of economic activities is produced by factors as broad as trends in globalization and as local as the consumption of goods and services by neighborhood families. There are consequences for the resulting spatial distribution of investment and business activity in a geographic area. The long-term goals of spatially targeted economic development incentives, economic efficiency and the equitable distribution of income, attempt to mitigate these consequences through government intervention.

2.1.1 Efficiency and Market Failures

The confluence and interaction of actors and motivations ultimately influence the location decisions made by firms and households, creating a market. In a competitive market, businesses act in their own self-interest. According to location theory businesses will locate where they can obtain some competitive advantage, maximize profits, and minimize the costs of business inputs, including land, labor and capital (Blair and Premus, 1993).

While these location decisions are optimal for individual firms, they diminish economic efficiency or the efficient allocation of resources where no one market participant would be better or worse off. This results in inefficient market allocation or failures in the private market.

Market failures exist where the market equilibrium between producers and consumers results in a loss of social surplus and alternate allocations are more efficient (Weimer and Vining, 2005).

As such, spatially targeted economic development programs and incentives are designed to address market failures and other limitations of the competitive market by improving economic efficiency and the allocation of resources (Kline and Moretti, 2014). Rationales justifying the government's role in STEDIs include agglomeration economies, negative externalities, and capital markets.

<u>Agglomeration Economies and Uneven Development</u>

Cities are natural agglomeration economies where businesses concentrate. In urban areas firms in close proximity or firms within the same industry expect to experience growth and innovation by generating economies of scale that reduce transportation, labor, and communication costs (Porter, 2000).

However, capital is highly mobile. As the built environment expands, capital, or investment, has a tendency to accumulate and produce uneven development (Smith, 2008). In the instance of the U.S. post-World War II, uneven development manifested as businesses fled the cities for the suburbs. Dye and Merriman (2006) assert that competitive markets do not exploit the potential for agglomeration economies in urban areas and decline and disinvestment is therefore a market failure. Local governments have the resources to serve as a catalyst for innovation to improve competitive advantage and indirectly foster growth in disadvantaged areas (Porter, 1994).

<u>Spatial Mismatch as a Negative Externality</u>

An externality is defined as an impact resulting from the production or consumption of a good that affects someone who did not consent to it through participation in voluntary exchange (Weimer and Vining, 2005). The seemingly benign location decisions of firms ultimately led to the overwhelming suburbanization of employment (Gobillion, Selod and Zenou, 2007). This affected many minorities who could not afford to move or who were excluded from suburbia through discriminatory housing policies (Wilson, 1987). As a result spatial mismatch acted as an externality that severely limited city residents' access to jobs and contributed to high unemployment rates and concentrated urban poverty in urban areas (Kain, 1968, 1992).

The Coase theorem (Frank, 2010) suggests that actors in the market will address externalities through bargaining, in other words they will eventually reach an efficient equilibrium price and quantity, provided there are no transaction costs involved in the bargaining. With regard to the spatial mismatch, labor has followed capital to the suburbs to some extent as a result of the negative externality yet unemployment rates in general and specifically for African Americans remains consistently high. Therefore negative externalities are a compelling argument for local economic development as a reasonable market-compatible form of government intervention (Weimer and Vining, 2005).

Urban Development and Capital Markets

In a perfectly competitive market, the capital markets supply sufficient loan funding to satisfy the demand for borrowing and the interest rate represents the price that clears the capital market. However, investment in urban areas is a risky endeavor. Porter (1994) outlined several disadvantages associated with hollowed cities that fuel the riskiness and serve to repel businesses from locating in an area. They include underutilized land and difficulty assembling vacant parcels, high building costs, aging infrastructure, capital, inadequate talent and labor, safety and security; other costs, i.e. taxes, and a weak business climate. These disadvantages represent costs that private companies would not likely choose to bear where feasible alternative sites exist.

Therefore site preparation for redevelopment will likely require large initial outlays for public infrastructure and other costs (Brueggeman and Fisher, 2008). As a result of this increased risk and within the context of a capital market still recovering from the recent financial crisis, lenders will charge higher interest rates for this redevelopment project than interest rates at the market equilibrium.

In this imperfect capital market, the increased market interest rate exceeds the social rate of time preference. As people value short term and long term benefits differently, this is the rate at which everyone is indifferent between exchanging current consumption for future consumption. Investors and developers will pursue investments with lower interest rates and risk, and thus higher rates of return (Weimer and Vining, 2005). As a result, private investment falls short of an efficient level and locating in urban areas is cost prohibitive for the private market.

Public funding in the form of tax abatement and subsidies serves to fund the gap between the cost of the redevelopment and the level of investment the market will bear. Incentives shift the demand curve outward so that the level of investment increases and also reduce the costs associated with siting a business in a distressed area where it otherwise would not locate. Otherwise, the social gains expected from the redevelopment will be diminished.

2.1.2 Equity and the Distribution of Jobs and Income

The theory that STEDIs should benefit local workers has been debated in the literature (Mier, 1993). However, incentivizing investment in a place does not necessarily address or achieve equity through the employment of local residents. In addition, the implementation of STEDIs could result in various unintended consequences, including increased rents (Kline and Moreti, 2014). The justifications for government intervention to achieve equity include positive externalities and social welfare.

Social Benefits as Positive Externalities

The anticipated positive externalities of urban development include social benefits in the form of jobs, increased property value and property tax revenue, housing, improved environmental quality, and an expanded tax base (Brueggeman and Fisher, 2008). Where these benefits materialize, developers and businesses have no way of internalizing the value of these social benefits as profit or otherwise. Therefore businesses would only relocate and investors would only redevelop in cities to the extent their marginal private benefit (demand) intersected with the supply schedule for investment at market equilibrium.

However, the marginal social benefit of redevelopment includes both the marginal private benefit to real estate developers and investors and the external marginal benefit that beneficiaries assign to redevelopment. Therefore, the private investment that would occur by the private market at a level reflecting only marginal private benefit represents an undersupply and loss of efficiency as the private market fails to provide the socially efficient investment at a level reflecting the marginal social benefit (Weimer and Vining, 2005). Relocation and urban redevelopment remains cost prohibitive for businesses and developers as transaction costs continue to be quite large due to the scope and magnitude of the issue.

Neighborhood Effects and Social Welfare

Sociological theories about the causes and consequences of inequality clearly espouse the importance of space and place in generating and sustaining socioeconomic outcomes related to employment concentrating away from cities and workers (Soja, 2010). Overall quality of life and life outcomes are impacted by and based on the spatial access to opportunities and resources.

Low-income families are thus isolated from educational and employment opportunities often determined by one's neighborhood. These neighborhood effects are a burden on society and decrease the quality of life for the low-income families who live in these neighborhoods (Jencks and Mayer, 1990).

2.2 Theoretical Underpinnings for Evaluating Employment Outcomes of Local Incentives

The previously outlined justifications for government intervention related to addressing uneven development by increasing public investments in deteriorated areas represent valid arguments. Similarly, there are sound justifications for evaluating the employment impacts of tax increment financing and a growing demand for evidence-based practices to accomplish that task. Of course, these factors do not make it an easy endeavor or one that is completely supported by all stakeholders.

Storey (1990) presented early theoretical underpinnings for evaluating local incentives designed to increase employment and his rebuttals for the arguments against such evaluation still ring true. A common criticism of evaluations of local economic development incentives is that policy goals often reach beyond job creation to the distribution of employment among disadvantaged group, reducing unemployment, job quality, and community development. Therefore evaluations can't evaluate these multiple goals with the same intensity. However Storey argues that the process of evaluation requires stakeholders to explicitly identify these goals, their priority, and how costs to target goals with a social impact may vary.

Critics also argue that evaluations detract resources from addressing employment growth and unemployment. Within a framework of multiple strategies and policies, maintaining the status quo without understanding the impacts of policy interventions exacerbates disparate employment outcomes for groups and within disadvantaged areas. To this point Bartik and Bingham (1997) add that more sophisticated research designs are not employed not only due to costs, but also concerns about political consequences of explicit evaluation results measuring the benefits of public incentives.

A third argument against evaluations interested in employment outcomes is that unlike policies with comparably quicker wins, those targeted to improving employment outcomes can only be examined over the long-term. Evaluations could miss the true impact of an initiative if implemented in early stages of implementation. Storey rejects this notion and acknowledges that there are short term outcomes that can be measured. These could include more immediate goals of identifying networks for accessing employment networks and employer efforts to target various populations.

The last argument that Storey (1990) identifies is that there are methodological challenges associated with measuring employment impacts directly attributable to local incentives. His contention that pursuing a common framework for evaluating the impact of local incentives on local employment is a worthy goal to work towards is the impetus behind this study.

Evaluating the employment impact of TIF developments in Baltimore City contributes to the literature since the existing research on TIFs focuses on the legal structures of TIFs, the fiscal impacts, or the political factors that lead to TIF adoption across municipalities (Anderson 1990). In addition, this study addresses the methodological challenges associated with evaluating the employment outcomes associated with TIFs as well as other spatially targeted economic development incentives.

At the same time, this study recognizes the limitations of this econometric approach. Giloth (1992) posits that even the most careful and rigorous of evaluation methodologies may not lead to improved economic development programs. Bartik and Bingham (1997) echo this concern, suggesting that process and outcome evaluations be conducted along with empirical investigations. Greenbaum and Landers (2009) and Boarnet (2001) go further, challenging researchers studying the impacts of these incentives to not only improve methods but also understand the motivations of both political and private sector stakeholders to make the findings more accessible to the policy community by emphasizing policy implications and making recommendations for program improvement.

2.3 The Rationale for Distributional Impacts

The success of STEDIs is often viewed in the context of the physical transformation of a neighborhood and an influx of new and more affluent residents rather than improvements in existing residents' circumstances.

However, STEDIs are outlays of public subsidies and incentives by municipalities that have varying degrees of impact and distributional effects (Partridge and Rickman, 2003). STEDIs are either explicitly or implicitly expected to improve the welfare of these residents and provide job opportunities for a jurisdiction's workforce.

In addition, the socioeconomic status of existing residents is directly tied to the economic well-being of the city. STEDIs generally, and TIFs specifically, are a major investment and the justification for the incentive includes providing access to employment opportunities to residents and increasing services and revenue that supports these services and improves the overall quality of life. Many underemployed and unemployed existing residents receive public benefits such as food stamps and other assistance because they do not make a family-supporting wage. This translates into high social costs.

There are competing expectations and theories about how tax incentives might benefit residents in targeted neighborhoods. Bartik (1991, p. 77) offers the normative argument that incentives can be viewed as a labor market shock that produces "hysteresis effects." This means that households are immobile in the short run and therefore existing unemployed residents will obtain jobs and skills that improve their long-term employment outcomes and labor market attachment.

This is supported by the theory of nearby jobs and "local working" or residents working within or near their home as discussed by Immergluck (1998). Most importantly, neighborhoods with higher concentrations of jobs tend to have higher local working rates. This is important since labor markets of lower-income urban residents are highly localized, with both firms and residents focusing their job search and recruiting on nearby areas.

At the same time, Bartik (1991) observes that in high unemployment neighborhoods, many residents have been unemployed for a significant time which may limit future job prospects that might become available. In addition, just as firms might move in and out of an area with incentives, workers will migrate to areas experiencing economic growth. Researchers conclude that any new jobs created in EZs will be filled by commuters or in-migrants instead of existing residents (Peters and Fisher, 2004; Blanchard et. al, 1992).

The extent to which local workers or in-migrant commuters pursue local jobs depends on preferences of mobile workers for residential location and commutes. Therefore the number of local workers is an important measure of job quality and a way to focus on the distributional impacts of STEDIs.

Gobillion, Selod, and Zenou (2007) outline the mechanics of spatial mismatch from the perspective of the worker that makes local employment an outcome of interest in this study. These include the high costs of searching for a long distance job and then commuting to it, as well as the likelihood that worker's job search efficiency and intensity decreases as distance to job increases. Persky, Felsenstein, and Wiewel (1997) suggest that decreased commuting resulting from local job creation should be viewed as a neighborhood spillover benefit of such activity.

Interpreting wage impacts related to STEDIs can be complicated. An increase in the percentage of jobs that are low-wage might limit the economic benefit of job growth associated with an incentive. However, low-wage jobs or part-time opportunities might serve as on-ramps for unemployed residents. In an urban setting like Baltimore City, this is of specific concern because of the city's high unemployment rate compared to the region.

Job growth within particular industries has also been studied as a measure of job quality. According to Kenyon et. al (2012) the return on property tax incentives supporting firms engaged in industries that export goods out of the region will have a larger economic impact as job growth would not have occurred save for the incentive, compared with job growth in industries that serve local residents. In addition, Byrne (2010) offers that TIF districts supporting industrial development may increase employment, while TIF districts supporting retail development decrease employment. Courant (1994) suggests that economic development policy has tended to focus on manufacturing jobs as "good jobs" as the sector has experienced severe decline.

In summary, STEDIs can potentially create or reinforce disparities in opportunities and access to employment as benefits (jobs and revenue) accrue disproportionately to communities. Therefore measuring these kinds of distributional impacts is important to understand the overall impact on target areas and the residents who live in them.

2.4 The Rationale of TIFs and Private Investment Outcomes

Like job creation, catalyzing private investment is an indirect target of local economic development incentives and is therefore a basic measure of success for TIFs (Foley, 1992). The premise of TIFs as a tool for local governments is that due to various neighborhood factors in the case of blighted neighborhoods or financing considerations including development costs with interest rates unfavorable to the investors, projects would not be financially feasible without the subsidy to finance infrastructure. It is logical then that these same neighborhood conditions and financing considerations affect the investment decisions made by investors, existing home owners making repairs to their property, and buyers seeking to purchase property.

As a public investment in the form of a subsidy of development costs, TIFs produce what Lester (2014) calls a signaling effect. Just as employers may make decisions about locating their businesses in or around a TIF district, the presence of a nearby TIF district may be a positive signal to private investors to improve existing or purchase new property.

Existing property owners in and around TIF districts may experience some hesitation when choosing to make improvements. They may not have confidence that any improvements made would be realized as profit in an otherwise depressed property market. This is especially relevant since TIFs have been associated with the removal of blight. Although blight is not a requirement for Baltimore City TIF designation, there are approximately 20,000 vacant properties in Baltimore City and to the extent that TIFs assist in redeveloping these structures might encourage these existing property owners to invest and make improvements (Ellen et. al, 2001).

With regard to property sales, TIFs are designated based on the assumption that the assessed value of property in the district will increase. Assessed value is determined by the county and/or state tax assessor for the purpose of levying property taxes. This amount could be less or more than the market value or the price the market indicates a property is worth which is only realized once the property sells.

The overall sales trend in a neighborhood with a TIF district and the sales price of residential properties in areas around TIF districts are expected to increase after designation as land prices are bid up in anticipation of the future development financed by the incentive (Weber, Bhatta, and Merriman, 2007). Potential homeowners may pay higher prices for homes in proximity to TIF districts where they may have been reluctant to purchase homes prior to designation. On the other hand, TIF designation and the associated development activity could negatively impact private investment as there is often substantial time between designation and project completion. In addition, considerable effort is necessary to assemble parcels of land that could suppress non-speculative improvements and sales. TIF districts could also facilitate gentrification in neighborhoods where increased demand crowds out existing residents and affordable housing in and around the district. As such, the impact of TIF designation depends on the overall trajectory and timing of a project. This dissertation ultimately seeks to determine whether this theorized impact of TIF designation on private investment exists and how far-reaching this effect is in the areas surrounding the district.

2.5 TIF Typology and the Relationship to Outcomes

Baltimore City TIF districts differ in scope and size, but can be stratified into a more general typology: residential, mixed, and infrastructure TIF districts (table 2.1). For the purposes of this research, mixed TIF districts are those that include non-residential development (commercial, retail, hotel, industrial, and office) alone or in some combination with residential development. Residential TIF districts include multi-family housing developments and developments with single-family homes, townhomes, or condominiums. Infrastructure TIF districts fund streetscaping, lighting, sewer improvements and other infrastructure improvements.

Following this typology, Belvedere Square, Clipper Mill, EBDI, the Convention Center Hilton Hotel, and Mondawmin Mall are mixed TIF districts as they represent retail, commercial and industrial office space, and both new development and redevelopment projects. With these kinds of developments there is often an explicit expectation of job growth as the TIF finances the infrastructure necessary to complete the project. New businesses and tenants are attracted into the developments themselves and to surrounding areas; these businesses intend to serve the new workers and take advantage of improved markets, thereby increasing permanent employment.

Mixed TIF districts are expected to also induce developers and existing property owners to make improvements to existing property and invest in new developments as TIF redevelopment raises the neighborhood's profile. Likewise, property sales and the selling price of properties are expected to increase after TIF designation.

While there is no expectation of job growth in the residential TIF districts, Harborview and Frankford Estates, considering the theory of agglomeration economies, other businesses are expected to locate in the areas surrounding the residential TIF districts as businesses locate in the area seeking to serve new residents. Estimating TIF designation effects at the block group, a large geographic unit that covers areas beyond the TIF district, would capture employment in the surrounding areas, as does an estimation of TIF spillover effects.

In contrast to mixed and residential TIF districts, infrastructure TIF districts which fund streetscaping, lighting, sewer and other infrastructure improvements, may improve or expand ease of access, but their contribution is not likely to be significant enough to expect job growth or private investment. As such, this study excludes TIF districts that were used to fund infrastructure projects, including the Locust Point Key Highway extension and the Charles Village TIFs. Also excluded are those Baltimore City TIFs that have not issued bonds to date (the Westport Waterfront and Carroll Camden TIFs) and TIFs that were only recently approved (Harbor Point TIF was approved in 2013 and Poppleton Center/West Baltimore in 2015). The seven mixed and residential TIF districts included in this study are Belvedere Square, Clipper Mill, EBDI, the Convention Center Hilton Hotel, Mondawmin Mall, Harborview, and Frankford Estates. The type of project and the year the project was funded or approved are provided in table 2.1.

Previous TIF studies take a similar approach in distinguishing between TIF types. In an examination of property rates Dye and Merriman (2000) conduct different analyses for industrial, commercial, housing and mixed-use TIF designation in Illinois and conclude that while commercial activity shifts within a municipality, increases in industrial activity in TIFs is due to growth in the municipality. Scholars have also examined the spillover effect of mixed use TIFs specifically on residential property appreciation (Weber, Bhatta, and Merriman, 2007) and on industrial properties (Weber, Bhatta, and Merriman, 2003). In one of the few TIF evaluations of employment impacts, Byrne (2010) studied industrial TIF districts and found an insignificant relationship between tax increment financing and employment.

While this study does not limit analysis to a certain type of TIF district, distinguishing between mixed and residential TIF districts is important as the study differentiates TIF designation effect estimates according to the type of development that characterize the TIF districts.

Table 2.1. Summary of Projects within Baltimore City TIF Districts

Geographic Area/ Project	Project Description	TIF Bond Issue	Year Project Funded or Approved
Mixed TIFs Included in Study			
Belvedere Square	Retail shopping and entertainment center	$2 million	2003
Clipper Mill	90k SF of office and artisan/industrial space; 120 market rate apartments and 101 for-sale condominiums, townhouses and detached homes	$8 million	2004
Convention Center Hilton Hotel	757-room hotel, part of the Baltimore Convention Center	$301 million	2005
EBDI	88 acre redevelopment project including the East Baltimore Research Park with 2,100 mixed income housing units, 1.1m SF of life science technology space, 400k SF of office and retail space, hotel, parking and a seven-acre school campus	$78 million	2008
Mondawmin Mall Redevelopment	Redevelopment of retail shopping center (127k SF Target, 67k SF Shoppers Food grocery store; and renovation of the existing mall	$15 million	2008
Residential TIFs Included in Study			
Harborview	88 for-sale waterfront townhouses	$7.5 million	2003
Frankford Estates	177 for-sale homes	$6 million	2003
Recent TIFs Excluded from Study			
Poppleton Center/West Baltimore	1,600 apartments and other residences, 52k SF of commercial space, park, and neighborhood school	$58.3 million	2015
Harbor Point Waterfront	1.8m SF of office and retail space; 270 residential condominium units; 346 rental apartments; a 260 hotel key and 2,990 structured parking spaces	$107 million	2013
Infrastructure TIFs Excluded from Study			
Locust Point	Development of Key Highway extension	$2.9 million	2005
Charles Village	Streetscape improvements in Charles Village	$2 million	2010
TIFs with No Bonds Issued to Date Excluded from Study			

Geographic Area/ Project	Project Description	TIF Bond Issue	Year Project Funded or Approved
Westport Waterfront	Proposed 4.8m SF mixed-use development including 2m SF of office; 300k SF retail; 2,000 housing units; 500 hotel rooms, and 10,000+ parking spaces	No Bonds Issued	2008
Carroll Camden	Redevelopment of former Acme warehouse in Rosemont	No Bonds Issued	2004

Source: Adapted from Baltimore City Council (2011).

3 EVALUATING SPATIALLY TARGETED ECONOMIC DEVELOPMENT INCENTIVES

This chapter will investigate the existing literature related to evaluating TIFs and other spatially targeted economic development incentives including the methodological approaches, the data and geographical units used in the analysis, and the outcomes that have been studied. This review will focus on the limitations of previous studies to identify gaps in the body of literature and to guide this study of the causal relationship between tax increment financing and employment, building permit activity, and residential property sales in Baltimore City.

This study addresses these limitations through the use of 1) difference-in-difference, a quasi-experimental research design that identifies the counterfactual to address unobserved heterogeneity in the estimation of the impact of TIF designation, 2) propensity score estimation to identify economically similar untreated units based on demographic and socioeconomic neighborhood characteristics, 3) data available at the census block geography to estimate the spillover effects of TIF designation on employment and permit activity outcomes, and 4) the repeat sales methodology, a variation of the hedonic price index that models the TIF spillover effect on residential property sales price appreciation using homes that have been sold at least twice.

3.1 Econometric Analyses and STEDI Literature Review

3.1.1 Evolving Methodologies

Early STEDI studies are largely based on firm and stakeholder surveys and case studies about how spatially targeted economic development incentives affected hiring and business relocation decisions (Bartik, 1991 and 2002). In addition, this kind of analysis often includes descriptive findings measuring short-term program activity outputs such as the number of jobs, housing units, and the tax revenue produced before and after an incentive (Bartik and Bingham, 1997; Byrne, 2010).

As an example, Rubin (1990) used a survey to evaluate New Jersey Urban Enterprise Zone (UEZ) incentives that included questions about the extent UEZ tax benefits influenced a firm's decision to expand or locate their business in the designated area. Survey responses and input-output projections estimate 9,193 new jobs created in the New Jersey UEZ over two years among 976 participating firms.

The Baltimore Development Corporation's Report of the Task Force on Baltimore City Public/Private Development Financing Efforts-Appendix A contained job counts and other performance outcomes for many of the completed TIF projects (Baltimore City Council, 2011). According to the report, the Mondawmin Mall Redevelopment project financed with TIF produced 930 jobs with 70 percent of employees living in the city. The Belvedere Square TIF project produced 385 jobs, 65 percent of which represent City residents.

While surveys and program monitoring output data can be useful, the result is findings that inflate the importance of locational incentives. Survey responses from administrators or agencies implementing a program might not be objective if they believe it reflects their own performance or affects the likelihood of receiving future incentives.

Similarly, job counts and other program outcomes collected through performance monitoring and management often overstate the impacts of STEDIs as it is assumed that any change over time in jobs, wages, or property tax revenue can be attributed to the project. In addition, these data are usually derived from participating firms in an area designated to receive an incentive and therefore likely undercount the effect on the surrounding neighborhood.

As a result of these methodological shortcomings, many studies in the 1980s and early 1990s reported positive impacts on employment outcomes for STEDIs in general (Wilder and Rubin, 1996) and positive impacts on property value outcomes for TIFs (Anderson, 1990; Man and Rosentraub, 1998; Dardia, 1998). Since then, empirical evaluations of STEDIs have evolved as researchers and local governments explore more rigorous local economic development evaluation and the effectiveness of these incentives, yielding largely insignificant effect estimates. This has led to the overall inconclusiveness of results from research attempting to measure the impact of spatially targeted economic development policies.

The following sections of this study will present the existing literature on the use of quasi-experimental research designs including difference-in-difference and propensity score analysis for estimating the effects of STEDIs.

3.1.2 *Difference in Difference*

Identifying the Counterfactual – The Other "But For"

Recent studies have sought to address the most significant factor underlying the justification for local economic development and determining its effectiveness— whether there is a causal relationship between an incentive and observable outcomes (Rubin, 1986). Causality, or causal inference, indicates that an incentive is not only related or associated with outcomes but that there is a cause and effect relationship. There are three criteria for causality. A causal relationship has a temporal order where the incentive, or cause, precedes the outcome, or effect, in time. In addition, the incentive and outcome must be correlated with each other. Finally, the correlation must not be a result of other spurious, mediating, or moderating factors. The extent to which a causal relationship meets these criteria is called internal validity (Campbell, 1957; Cook and Campbell, 1979).

In program evaluation, the Neyman-Rubin Causal model is a framework whereby establishing causality between an incentive and outcomes involves identifying the counterfactual (Neyman, 1923; Rubin, 1986). With respect to STEDIs, an area designated to receive an incentive represents the treatment condition. The counterfactual is the "but for" condition, or what would have happened in the area without an incentive. The causal effect of an incentive is conceptualized as the difference in outcomes for an area experiencing both conditions at the same point in time. Of course, it is impossible to observe outcomes for the same area with both the treatment and counterfactual conditions. It is therefore impossible to observe the true causal effect in a real world setting, essentially the fundamental problem of causal inference (Holland, 1986).

This problem of observing causal effect is addressed by assigning an area to either a treatment group that receives the incentive or a non-treatment or comparison group that does not receive the incentive. The counterfactual can then be estimated by observing the difference in the mean outcomes between the groups, which is the average treatment effect of an intervention. The key assumption associated with this causality framework is exogeneity, whereby assignment to a treatment or non-treatment group is independent of outcomes if other factors are held constant (Imbens, 2004). Experiments manipulate a cause to observe an effect by randomly assigning a unit to the treatment group or non-treatment (control) group.

The random assignment mechanism represents an exogenous change that controls for other factors by balancing the treatment and control groups in a way that makes the treatment assignment independent of the outcomes. This essentially rules out confounders that might otherwise explain a causal relationship between treatment and outcomes. As such, the exogeneity assumption holds for randomized experiments and produces unbiased estimates of impact. The randomized experiment therefore has the strongest internal validity and is considered the gold standard of evaluation.

Federal, state and local government have increasingly used experiments with random assignment. However, a true experiment is often not feasible due to costs or ethical concerns. In economic development, randomly assigning individual businesses or targeted areas to a treatment or control group is rare. Evaluations of tax subsidies and firm location have consistently used econometric methods (Boarnet and Bogart, 1996). Similarly, a growing body of research has emphasized quasi-experimental research designs as a methodological development in econometric studies of STEDIs (Bartik, 2002).

Addressing Unobserved Heterogeneity with Difference-in-Difference

Campbell, Stanley and Gage (1963) coined the term "quasi-experiment" which has since been used across many fields of study to determine causal inferences where a random experiment design is not possible or practical. In quasi-experimental research designs, a treatment is intentional like an experiment but assignment to treatment or non-treatment groups is non-random. The non-treatment group in quasi-experimental studies is a comparison group rather than a control group due to nonrandom assignment. A comparison group has not been exposed to the treatment and is similar to the treatment group based on characteristics observed prior to the treatment.

Difference-in-difference is the most often used quasi-experimental research design and has grown in popularity since Ashenfelter and Card (1985) used it to study the earnings impact of the Comprehensive Employment and Training Act. Card and Krueger's (1994) study of the impact of a minimum wage increase in New Jersey is one of the most well-known uses of DID in policy research. The authors measured employment in the fast food industry before and after the increase in New Jersey compared to Pennsylvania where an increase was not implemented.

With respect to STEDIs, the Lincoln Institute of Land Policy's review of property tax incentives for business specifically suggests a DID analysis to determine employment, wage, business creation, and property value outcomes of property tax incentives (Kenyon, et al., 2012). This method is ideal for STEDI studies interested in the impact of designation in targeted areas on outcomes that can be observed longitudinally as DID estimation is conceptualized as combining both time and spatial differencing (O'Keefe, 2004; Greenbaum and Engberg, 2004).

Compared to TIFs there exists a larger research base about the impact of state enterprise zones and federally designated empowerment zones using a DID approach. As discussed in Chapter One, SEZs and EZs are STEDIs that represent an approach similar to TIFs, i.e. tax incentives and a focus on a geographic target area. As such, in addition to TIF studies, SEZ and EZ studies can be used to understand how the impacts of STEDIs have been evaluated.

The main criticism of QEDs in general and the DID research design specifically is the validity of extending the randomization assumption that treatment and comparison groups are comparable. Without randomization, the groups are likely to differ systematically before a treatment in ways that affect outcomes. This selection bias represents the most likely threat to the internal validity of the causal relationship in quasi-experimental designs.

For STEDIs specifically, selection bias often arises due to the fact that the process by which designated areas are selected is likely determined by these prior economic conditions that are likely to be among the major factors affecting the post-treatment outcome of interest for the evaluation. More specifically, TIF designated areas are often selected specifically because they are economically depressed or blighted (Anderson, 1990). To address this selection bias, researchers use quasi-experimental methods of two varieties depending on the assumptions made about how STEDIs are designated and whether these factors are observable or unobservable.

According to Oakley and Tsao (2006), the designation of an area as a STEDI is likely dependent on a range of unobservable factors including expectations about changes in a neighborhood, political factors, as well as strategic aims and local priorities for the STEDI. More specifically, Rogers and Tao (2004) outline two sources of selection bias that may be difficult to measure. First, the choice to adopt and implement an incentive varies across municipalities and the selection process to designate the treatment areas is often based on explicit policy guidelines. Secondly, the choice of a developer or municipality to decide to apply for an incentive indicates factors other than treatment that might affect outcomes. This suggests that STEDI designation is not exogenous, but is rather at least partly the outcome of these processes and decisions that are unobservable (Boarnet and Bogart, 1996; Elvery, 2009).

Further discussed in Chapter Four, unobserved heterogeneity potentially differentiating treatment and comparison areas can be accounted for with the difference-in-difference methodology. DID rules out these threats to internal validity with an assumption that any change over time in the comparison group is the same change that would have happened to the treatment group, if that group did not receive the treatment.

A number of SEZ and EZ researchers have constructed comparison groups from cities that were rejected applicants or areas that were designated in subsequent selection rounds or through zone expansions (Boarnet and Bogart, 1996; Hanson, 2009; U.S. Department of HUD, 2001; Busso, Gregory, and Kline, 2010). As will be later discussed, many studies combine this identification strategy with others to select comparison units. With regard to TIFs, a few studies use fixed effects alone (Merriman, Skidmore, and Kashian, 2011; Byrne, 2010) but the majority of analyses of TIF designation effects largely focuses on comparing economically similar units in the same or different municipality, or geographically close units adjacent to the TIF district. The next two sections of this dissertation outline how existing STEDI studies have used propensity scores and proximity to identify comparison groups in the estimation of designation effects.

3.1.3 Economically Similar Comparisons Using Propensity Scores

While DID addresses unobservable factors affecting designation, if the assumption about how areas are selected for STEDI designation is based on observable characteristics or factors, methods that can explicitly capture and control for the observable systematic differences between treated and untreated areas are appropriate. Propensity score estimation, developed by Rosenbaum and Rubin (1984) is one such approach. Early TIF studies using regression models often use statistical tools such as regression models with covariates or propensity score matching or weighting to attempt to control for selection bias (Dardia, 1998; Man, 1999; Man and Rosentraub, 1998; Anderson, 1990; Byrne, 2010).

Even though propensity score estimation improves cross-sectional regression models, causal impacts cannot be estimated for STEDIs using this technique alone. Therefore, the assumption necessary to use propensity score matching that selection into treatment and comparison groups is strictly based on observable pre-designation characteristics may not hold and is difficult to justify (Smith, 2009). As such, recent TIF studies and a preponderance of SEZ and EZ studies use a combination of DID and propensity score estimation for two purposes.

Using a panel-data fixed effects approach, DID essentially removes unobservable pre-designation differences specific to a unit that do not change over time (fixed) and may be correlated with designation. Propensity score analysis identifies comparison units as similar to the designated area as possible or only randomly different from the treatment group to addresses the self-selection bias inherent in the designation of STEDIs. Bartik (1991) advocates for better methods for choosing comparison groups that are similar to designated areas for the evaluation of STEDIs and combining these quasi-experimental designs is well-suited to that end where panel data are available.

Propensity score estimation requires calculating a propensity score on the basis of pre-designation demographic and socioeconomic characteristics or covariates (excluding the outcome variable). A propensity score reflects the probability of receiving a binary treatment (designation) and is estimated for all units with a probit or logit regression. Untreated units are then matched to treated units based on this score or the score is used to weight observations in the treatment effects model.

STEDI studies using the DID methodology and propensity score estimation compare and contrast by the choice of matching or weighting technique as discussed in Chapter Four, as well as the unit of analysis used, from parcels to census geographies to municipalities. As an example, at one end of the geographical spectrum Smith (2009) calculates propensity scores for parcels in TIF districts and outside TIF districts based on the economic characteristics of the Chicago neighborhood where each home is located. Then both treated and untreated parcels are stratified by propensity scores and the impact of TIF designation on home sales price appreciation is estimated within each strata. Carroll (2008) also calculates propensity scores using property and neighborhood characteristics for each parcel. The propensity scores are ultimately included in the fixed effects model estimating TIF designation effects on property values.

Parcels or other units of analysis can also be aggregated to the TIF district or some other geography. Lester (2014) aggregates firm employment and building permit data to the census block group geography. The author addresses the issue of selection bias by calculating a propensity score to identify Chicago block groups that are likely to receive TIF designation. The effect of TIF designation on employment and permit activity is then estimated with the DID methodology and block groups are weighted by the propensity scores.

Similarly, many of the SEZ and EZ studies combining the DID research design with propensity score estimation used pre-designation characteristics of census geographies, including zip codes (Bondonio and Engberg, 2000; Greenbaum and Engberg, 2004; Bondonio and Greenbaum, 2007) or census tracts (Elvery, 2009; O'Keefe, 2004; U.S. Department of HUD, 2001; Oakley and Tsao, 2006; Busso and Kline, 2008; Ham et. al., 2011) to estimate the probability of designation and identify comparison geographies that are "economically close" to treatment units based on socioeconomic characteristics (Hanson and Rohlin, 2011, p. 89).

One major advantage of conducting this kind of analysis using these census geographies is the ability to use publicly available decennial and other census data for propensity score estimation with units of analysis more similar in geographic coverage to the targeted incentive than the entire municipality. Researchers of SEZ, EZ, and TIF designation effects suggest that using smaller units of analysis represents a methodological improvement for these kinds of studies. In a discussion about the methodological issues associated with SEZ and EZ evaluations, Boarnet (2001) expressed support for using more geographically detailed data. Likewise, in a paper examining the locations of TIF areas in a city, Gibson (2003) offers that analysis at the census tract level may reveal important differences between areas that are included in TIF districts vs. non-TIF districts compared to studies at the municipal or zip code level of geography.

However, estimating designation effects by identifying economically similar treated and untreated census geographies such as zip codes and census tracts can be complicated as neither TIFs nor EZ/SEZs are designated based on these census geographies. In addition, these census geographies often intersect or extend beyond STEDI boundaries. Researchers have to make determinations about whether and how to assign these geographies when they are only partially in a STEDI.

One option is to identify all geographies that contain a part of an STEDI as being treated. Therefore, the analysis captures the effect of an STEDI not only the designated area but also the surrounding areas. Elvery (2009) notes that using this strategy for zip codes containing SEZs in California and Florida results in a treatment area six times the size of the designated zones. The author found that less than half of the population of residents in census tracts in California and Florida in 1990 that contain SEZs live in SEZs.

Another approach is to identify geographic units as treated when they meet some criteria. Elvery (2009) chose to exclude tracts where less than 25 percent of the population lives in a zone. In various specifications of their model, Bondonio and Greenbaum (2007) identify treated zip codes as those where at least 25, 50, or 75 percent of its land is covered by zones. Similarly, Ham et. al. (2011) exclude census tracts where less than half of the census tract is covered by an EZ. Some studies allocate data of larger geographies to the zones. Hanson and Rohlin (2012) and Dowall (1996) use the percentage of the census geography land area to assign the employment level in an EZ or smaller geography. Both these options can present a challenge for accurately estimating impacts as they approximate the effects of STEDI designation larger than the targeted area. Any misassignment of designated and non-designated areas ultimately introduces upward or downward bias into estimating effects which likely leads to disparate effects across studies.

Bias is also introduced as effects spillover to adjacent areas. This study estimates TIF designation effects using the difference-in-difference analysis and propensity score estimation for employment, permit activity, and residential property sales outcomes. Since Baltimore City TIF districts are parcels or development projects, at the block group level of geography treatment effects could be biased by economic activity in areas surrounding the TIF district, leading to obscured net effects of designation. The next section explores how previous studies have used small area data to observe the spillover effects of STEDIs. Additionally, the literature on the use of a hedonic price regression model and the repeat sales methodology to estimate home sales price appreciation is outlined herein.

3.1.4 Geographically Close Comparisons and Estimating Spillover

TIF studies estimating employment and property value impacts using the city or county as the unit of analysis (Anderson, 1990; Byrne, 2010; Man, 1999; Man and Rosentraub, 1998) generally compare growth in municipalities with TIFs to growth in municipalities without TIFs in a cross-sectional model. However, attempting to estimate the effect of a TIF district at the municipal level presents a challenge. Byrne (2010) acknowledged that there are shortcomings associated with examining TIF impacts at the municipal level when TIFs cover a smaller area within a municipality. Comparisons between treated and untreated areas may not be meaningful or capture the true impact of a TIF that covers a smaller sub-city area.

Small area and individual level data is ideal for estimating TIF designation effects. The increased availability of parcel level property tax data maintained by municipalities and GIS software has allowed researchers to estimate the effects of TIF designation on property tax revenue by comparing parcels located within an established TIF boundary to those in non-TIF designated areas of the same municipality (Smith, 2006; Byrne, 2006; Dye and Merriman, 2000, 2003; Merriman, Skidmore, and Kashian, 2011).

Following Brueckner's (2001) framework theorizing increased support for TIFs where designation increases property values in blighted non-TIF areas, these studies often conceptualize growth across non-TIF areas of a municipality as spillover effects of TIF designation. However, spillover implies that establishing a TIF district could cause the benefits of TIF designation to extend beyond the boundaries and spillover specifically to the adjacent areas. Only two TIF studies use measures of proximity and distance to estimate effects in areas adjacent to TIF districts. Weber, Bhatta, and Merriman (2003) include distance to TIFs as an explanatory variable affecting the sales price of industrial properties in Chicago TIF districts. Weber, Bhatta, and Merriman (2007) extend this observation of TIF effects within areas proximate to TIFs by excluding property sales in the TIF district and focusing on the sales prices of homes within varying distances of TIF districts to estimate TIF spillover effects. A number of SEZ and EZ studies explore employment spillover effects. Spillover of employment effects occurs where employment shifts from non-designated areas to designated areas and offsets growth in designated areas, resulting in zero net impacts and also where the effects of TIF designation spillover to adjacent area (Greenbaum and Engberg, 2004).

Spillover is identified using geographically close comparison units taking into consideration their spatial location within proximity to treated units. This is often accomplished using three different approaches: comparison units within some buffer distance from treated units, comparing treated and untreated units that are located on the opposing sides of some geographic border, or selecting or excluding contiguous geographies for comparison.

As an example of comparison units identified based on the distance to designated areas Neumark and Kolko (2010) created a 1,000 ft. buffer from the outer boundary of California enterprise zones and any of the establishments in the buffer area were identified as the comparison group to estimate spillover. Billings (2009) employs a similar methodology as Neumark and Kolko (2010) to study Colorado enterprise zones. The study goes further in exploiting the EZ border by limiting both the treatment and comparison groups to establishments in commercial areas within a quarter mile of either side the SEZ border.

Busso, Gregory, and Kline's (2010) study uses census tracts from rejected cities approved in subsequent rounds as comparisons in an attempt to avoid capturing spillover effects of federal EZs. In another specification the authors exclude tracts located within a mile of EZs. Ham et. al. (2011) also studied the Round I federal EZs as well as federal Enterprise Communities and 13 SEZs. The authors test for spillover effects with specifications for contiguous (first closest) and second closest tracts that are adjacent to the contiguous tracts. Hanson and Rohlin (2012) use a few different specifications to estimate spillover. The study first compares census tracts contiguous to EZs to census tracts contiguous to Enterprise Communities (ECs) that were rejected EZ applicants (excluding actual EZ and EC designated areas).

While using small geographic units as described above is necessary to examine spillover effects, there are still challenges associated with using census geographies larger than the designated area that could obscure the effects of the spatially targeted economic development incentive and produce disparate results. This is especially true for Baltimore City's TIF districts that are often small development projects or parcels.

Further discussed in Chapter Four, this dissertation borrows from this existing literature. The spillover effects of TIF designation are estimated for jobs and permit data comparing census blocks in spillover prone areas within varying distances from TIF districts to adjacent comparison census blocks. The census block is the smallest geography at which jobs data are available and enable the estimation of spillover effects in areas immediately surrounding the boundaries of the TIF district. Permit activity data are also aggregated to the census block. The spillover effects of TIF designation on residential property sales are estimated using individual parcels in order to include individual property characteristics in the analysis. In addition to difference-in-difference, the appreciation of homes sales prices are estimated using another panel methodology, the repeat sales methodology also used in Weber, Bhatta, and Merriman (2007). The repeat sales methodology is discussed in the next section.

3.1.5 Repeat Sales Methodology

In the hedonic price model the value of a property is estimated as a function of structural and neighborhood characteristics (Rosen, 1974). Structural characteristics are attributes of the home, including square footage, lot size, and age of the building, the number rooms, stories and bathrooms, along with amenities such as the presence of a basement or a garage. Neighborhood characteristics include demographics, socioeconomic conditions, the availability of public services, and the accessibility to amenities and transportation (Can, 1990; Smith, 2006). These characteristics indicate a property's quality and depending on the elasticity of the housing supply, a marginal change in each individual characteristic ultimately determines the change in sales price.

Selection bias is a limitation of cross-sectional OLS hedonic regression models, particularly in the study of spatially targeted incentives where designation could be correlated with unobservable factors. As previously discussed, difference-in-difference estimation is one method to reduce the potential bias caused by time invariant unobservables that contribute to the sales price. Galster, Tatian, and Smith (1999) and Santiago, Galster, and Tatian (2001) investigate the impact of subsidized housing vouchers and dispersed rental programs in Baltimore County, MD and Denver, Colorado, respectively, with the difference-in-difference methodology. These papers compare home sales price trends in areas within a buffer distance from the subsidized homes to trends in areas outside the buffer but in the same census tract before and after occupancy.

The repeat sales method is another analytical approach to panel analysis. The repeat sales methodology is a variation of the hedonic price model that estimates the appreciation of sales prices over time for homes that have sold more than once during a study period. Although hedonic models are more prevalent in the literature, the repeat sales model is the basis of housing price indices beginning with Bailey, Muth and Nourse (1963). The S&P Case-Schiller (SPCS) Home Price Indices subsequently (Case & Schiller, 1987, 1989) expanded its use.

Estimating the sales price change from repeat sales of the same property where the quality of individual homes remains the same between sales controls for selection bias more accurately than the hedonic model (Case and Shiller, 1987). Also, detailed information about a property's characteristics is not necessary to estimate sales price appreciation, avoiding the issue of omitted variable bias (Malpezzi,2002). There are several caveats with this method, including a reduced sample as only properties with more than one sales observation are used in the analysis. In addition, those properties may not be representative in markets where turnover is infrequent. Lastly, there is an assumption that there are no significant structural changes or renovations to a dwelling between sales transactions.

The repeat sales method has been used to determine how proximity to sports stadiums (Humphreys and Lee, 2010), big-box stores (Johnson and Lybecker, 2010), light rail transit

(Billings, Leland, and Swindell 2011), crime (Ihlandfeldt and Mayock, 2010), historical landmarks (Noonan, 2007), low income housing tax credit development (Green, Malpezzi, Seah, 2002), and other kinds of neighborhood investments impact the value of nearby property.

Relative to this dissertation Weber, Bhatta, and Merriman (2007) investigate the spillover effect of TIF designation on the sales price appreciation of single-family homes that sold more than once between 1993 and 1999. The authors employ what could be considered a hybrid approach that estimates the most recent sales price of homes within distance of TIF districts using structural characteristics and neighborhood conditions of individual properties as with a standard hedonic model and the initial sales price of a home as controls.

3.2 Review of STEDI Literature by Outcome

This chapter has discussed the ways in which existing STEDI studies compare and contrast by identification strategies to control for endogeneity and the quasi-experimental methods used to estimate the effect of designation and the spillover of effects into surrounding neighborhoods. The findings of these STEDI studies in the analysis of employment and private investment outcomes are outlined in this section.

3.2.1 Employment Impacts

The following review presents the findings of STEDI studies for several employment outcomes including total employment, local employment, jobs by wages, jobs by industry, along with the spillover effects of designation on employment. Delineating employment outcomes is important for several reasons. STEDI research interested in employment outcomes either focus on the growth of workplace employment or resident employment and unemployment depending on the aims of the study, the type of incentive, and the available data (Freedman, 2013). While most reviews of this literature don't make the distinction between workplace and resident employment, it is important here since this dissertation is interested in both total (workplace) employment, or the number of workers employed in firms in designated and surrounding areas, as well as local employment, workers employed in these designated areas who also live in Baltimore City.

Local employment is a valuation of job quality based on whether jobs provide some social benefit through the increase of employment for targeted populations in targeted areas (Rephann, et. al, 1997; Felsenstein and Persky, 2007; Wilder and Rubin, 1996). Also, since federal EZs and some SEZs specifically incentivize zone firms to hire zone residents, many of the SEZ and EZ studies have attempted to determine the extent to which designating zones is sufficient to improve employment outcomes of zone residents. Wilder and Rubin (1996) summarize that an average of 20-30 percent and for each zone a range between 2-90 percent of new jobs created in EZs go to zone residents. A number of STEDI studies are also interested in the types of jobs created in designated areas and what types of jobs zone residents are employed in. As such, other employment outcomes explored in the research includes the distribution of jobs by wages and by industry. Also, some STEDI studies have estimated employment spillovers effects. Where the STEDI studies in this review analyze these different employment outcomes, the findings are contained herein.

Only a few studies examine the impact of TIF designation on employment, with inconsistent results. Both studies conducted at the municipal level of geography used resident employment information. Man (1999) found that Indiana cities with a TIF experienced increased city employment compared to those without a TIF district. Byrne (2010) used Bureau of Labor Statistics LAUS panel data to determine that there is no evidence of a direct and significant relationship between TIFs and resident employment growth rates in Illinois municipalities.

Using block groups as the unit of analysis along with DID and propensity score weighting. Lester (2014) indicates TIF designation impacts close to zero and not any larger than a 2.7 percentage point increase in workplace employment therefore there is no evidence that any jobs were created beyond what would have occurred without the incentive.

Among single and multi-state SEZ studies, Papke's (1994) study of Indiana enterprise zone job tax credits is one of the earliest and well-known empirical evaluations of SEZs using DID. The study compared unemployment insurance claims in offices in designated areas to non-designated areas and found that SEZ designation reduced unemployment claims by 19 percent. However, the offices all served a much larger area than just the enterprise zones, so it is difficult to attribute this outcome directly to designation. In a subsequent study the author found that enterprise zones in Indiana SEZs increased zone resident employment by approximately 1.5 percentage points (Papke, 1993).

Similar to Papke's work, Elvery (2009) used propensity score matching and a number of other selection criteria to identify comparison tracts for an analysis of resident employment in California and Florida SEZs but found insignificant impacts for SEZ designation. Bondonio and Engberg (2000) studied SEZs designated in California, Kentucky, Pennsylvania, New York, and Virginia between1981 to 1994. Observing separate effects for each state, the authors found no significant changes in employment growth in zip codes that contain designated areas compared to zip codes that include areas that became zones after initial designation.

Greenbaum and Engberg (2004) similarly examined SEZ impacts across six states using DID and matched pairs of zip codes. While there was no significant impact associated with zone designation on manufacturing employment between 1984 through 1993, the study did observe a significant increase in employment growth for new firms in the zones. With respect to the influence of employment shifting on EZ impacts, this study suggests that employment losses among existing firms in non-designated areas offset any growth of new firms in designated areas resulting in zero net impacts. Bondonio and Greenbaum (2007) found consistent outcomes across 64 zones in 10 different states: California, Connecticut, Florida, Indiana, Kentucky, Maryland, New Jersey, New York, Pennsylvania, and Virginia) and the District of Columbia. Overall employment impacts are insignificant but there is an increase in employment in new and existing establishments.

Several studies focus on employment outcomes for California SEZs. Using matched pairs of census tracts, O'Keefe (2004) found that California enterprise zones increased employment growth by 3.1 percent in the first six years. These impacts do not hold for the subsequent six years. Bostic and Prohofsky (2006) used DID and matching to determine the effectiveness of enterprise zones to increase wages for California SEZ program participants. The authors find that relative to comparable taxpayers, SEZ designation positively impacts wages and adjusted gross income (AGI) in the short term for those with initial low wages. Estimating the effects of California enterprise zones between 1992 and 2004, Neumark and Kolko (2010) conclude that SEZ designation in California did not have an impact on overall employment the shift employment in low-wage industries or manufacturing employment. In Billings (2009) the estimated employment impact of SEZ designation was only slightly larger in magnitude for a propensity score matching model and the border matching technique however the increase is small for both identification strategies, ranging between 0.0 to 0.3 and 1.5 and 1.8 for existing and new establishments, respectively. The author speculates that these smaller estimates for the border matching are an indicator that propensity score matching only addresses observable characteristics and that there are unobservable characteristics correlated with SEZ designation that introduce bias.

HUD's (U.S. Department of HUD, 2001) comprehensive evaluation of the first round of federal EZs constructs a comparison group of census tracts in rejected cities that are socioeconomically similar as well as a specification that includes only matched contiguous tracts. For the period roughly prior to designation (1990-1995) and five years after (1995-2000) the study indicates a workplace employment gross growth rate of five percent for comparison areas and 11 percent for contiguous areas. Employment increased in five of six Round I urban EZs and overall for all EZs compared with both adjacent and same-city comparison areas. However, this employment growth cannot be directly attributed to EZ designation. First, the research design can only provide evidence of the relationship between EZ designation and employment but not direct causal impacts. Secondly, during the study period there were significant national and metropolitan trends of economic growth and curbed unemployment rates.

Based on business establishment surveys, the HUD study indicates that the number of local residents employed by EZ businesses across the six sites increased but the change before and after EZ was insignificant. However, other events at local sites likely contributed to job growth such as the new Chrysler plant in the Detroit EZ that increased employment of residents in the area unrelated to EZ designation (Berger, 1997). In addition, EZ employment tax credits reportedly did not affect hiring decisions of employers and were only modestly used by zone businesses: 11 percent used employment tax credit and three percent used the work opportunity tax credit (U.S. Department of HUD, 2001). The majority of increases in zone residents employed in the zones occurred in the service industry and of these resident-workers, 40 percent worked in the service industry, an increase of 10 percentage points. Within manufacturing, the number of zone residents employed in this industry doubled but still represented a small share of overall zone manufacturing jobs. Comparatively, half the retail industry jobs in the zone were taken by zone residents.

Busso, Gregory, and Kline’s (2010) study shares many of the same design elements of HUD’s (2001) evaluation including using tracts from rejected cities approved in subsequent federal EZ rounds and a comparison group made up of contiguous clusters of census tracts with high poverty rates. Here, EZ designation resulted in an estimated 12-21 percentage point increase in employment. The paper also examined employment outcomes of zone employees by residence and found generally larger increases in employment for zone residents compared to residents commuting from outside the zone, however few of the specifications are significant. Lastly, Busso, Gregory, and Kline (2010) conducted a welfare analysis of outcomes for federal EZ residents and concluded EZs increase the wages of residents with caveats about the stability of these benefits.

Across four cities (Baltimore, Chicago, Detroit, and New York City) Oakley and Tsao (2006) found an insignificant impact on unemployment for zone residents based on a comparison of matched federal EZ census tracts. Another examination of resident employment but with a positive result, Hanson (2009) compared federal EZ tracts to tracts in cities with applications that were denied and found a two percentage point increase in the employment rate of residents.

Ham et. al (2011) studied the Round I federal EZs as well as Enterprise Communities and 13 SEZs. The study estimates a significant resident employment level increase of an average of 69 jobs for state EZs at the national level and insignificant impacts at the state level except for Ohio between 1990 and 2000. For the federal EZs, the employment level increased significantly by an average of 238. The paper also tests for spillover effects, finding positive but statistically insignificant spillover effects of SEZ and EZ designation in the nearest non-EZ tract. After excluding the nearest EZ tract and including the second nearest tracts as comparisons, there is an estimated statistically significant increase in employment level by154.

Hanson and Rohlin's (2012) estimate the net impacts of EZ designation and conclude that there is negative spillover associated with EZ designation and that employment in EZs increased at the expense of adjacent areas where employment decreased. This is also the case for employment in the retail and service industry.

Ultimately this review of employment impacts suggests that spatially targeted economic development incentives have not explicitly succeeded in achieving employment growth. Where there are positive effects they are insignificant or small in magnitude. In addition, spillover effects potentially bias designation effects.

3.2.2 Private Investment Impacts

As the use of tax increment financing has expanded to fund local economic development, the body of empirical TIF research examining the impacts of the incentive largely focuses on the effect of TIF designation on the growth in real estate values. Growth in property value is a premise of financing development and infrastructure with TIF bonds. In addition, the appreciation of property values in the surrounding neighborhoods is an indirect outcome of designating TIF districts.

The estimated TIF designation impacts on property values are mixed, but largely negative. There exist a variety of factors that contribute to these mixed results. Most importantly, housing markets vary across and within municipalities. Therefore TIF designation is expected to produce disparate impacts on property value across studies. Previously discussed in this dissertation, TIF research is conducted at units of analyses that vary from whole cities to individual parcels as public property tax data maintained by municipalities or other accessible data sources has become more easily accessible. The refined level of geography more accurately reflects the spatial dimension of the TIF district and thus produces more valid impact estimates. The outcome measure of interest also varies as earlier studies focused on median housing value and property value determined by tax assessment while more recent studies analyzed sales prices.

Both the type of property analyzed in these studies (residential, commercial, or industrial) and the type of TIF projects financed (commercial, industrial, residential, mixed) are also explanatory factors for varied results. Depending on the neighborhood's land use distribution and real estate market, commercial and industrial parcels might have higher property values that are more greatly influenced by location in or in proximity to TIF districts. Likewise, a TIF bond issuance financing a new housing development, as is the case for two TIF districts in this study, compared to a new commercial development or even a TIF designated to revitalize existing housing will all affect sales price appreciation differently. Lastly, TIF studies have also estimated trends in TIF-adopting areas, growth in an entire municipality, the effects within the TIF district, and the spillover of effects outside the TIF district. The following review outlines the different characteristics of these TIF studies estimating property sales and permit activity outcomes.

One of the earliest empirical studies, Anderson (1990) compared aggregate property value growth of Michigan municipalities with TIF districts to growth in municipalities without them. This cross-sectional study found that cities that established TIF districts experienced increased overall assessed value of real property in Michigan cities. Also conducted at the municipal level of geography Man and Rosentraub (1998) explore the effect of TIF designation on median value of owner-occupied housing across 151 Indiana cities. The results indicate growth between 1980 and 1990 in a TIF-adopting city two years after their establishment. In contrast Dye and Merriman (2000) concluded that TIF adoption decreased municipal annualized assessed value in the metropolitan Chicago area. This negative impact was due to growth in the TIF district at the expense of non-TIF areas, suggesting an inefficient relocation of economic activity within a municipality. The follow up to this research focuses on the type of projects financed by the TIF proceeds and find evidence that supports the previous findings of negative impacts for commercial and residential TIF districts but not industrial TIF districts (Dye and Merriman, 2003).

Dardia (1998) is the first TIF study estimating impacts by comparing the TIF district to similar non-TIF areas in the same municipality based on various neighborhood and socioeconomic variables indicating the degree of blight. The author concluded that property values in California TIF districts grew more rapidly. Many of the more recent TIF studies also estimate effects at the level of TIF district using individual parcels in hedonic price models. The studies estimating growth for commercial or industrial properties also attempt to control for selection bias by matching properties in the TIF district with similar properties outside the TIF district. Carroll (2008) analyzed assessed value business property in Milwaukee, Wisconsin TIF districts using a hedonic model with property characteristics, location and neighborhood, and exposure to TIF policy as the explanatory factors. According to the study there was no significant growth from 1980 to 1999.

Both Smith (2009) and Weber, Bhatta, and Merriman (2003) employ a similar methodology to estimate commercial and industrial property value outcomes in Chicago TIF districts, respectively. Smith (2009) concludes that TIF designation has a positive impact on the sales price of commercial parcels in TIF districts between 1992 and 2000 as a result of designation.

According to Weber, Bhatta, and Merriman (2003), the value of industrial parcels located in a mixed-use TIF district that includes industrial properties along with residential or commercial properties was higher than that of similar parcels not located in a TIF district. However, this was not the case for industrial TIF districts as the sales price was unchanged or lower than similar parcels in non-TIF areas using different specifications. The authors suggest that the owners of industrial parcels can redevelop their properties into residential or commercial conversions in mixed-use TIF districts which could be more desirable in the market compared to properties located in other areas with only industrial land uses such as industrial parks.

The findings for residential property values are also estimated with hedonic price regressions. The results of Smith (2006) indicate a positive relationship between the sales price of multifamily housing properties in Chicago and TIF designation. Rather than estimating the impact of designation on properties inside the TIF district, Weber Bhatta, and Merriman (2007) investigate the spillover effect of Chicago TIFs on the sales price appreciation of single-family homes near commercial, industrial, and mixed TIF districts using the repeat sales methodology. To that end, the paper excludes home sales inside TIF districts and those near residential TIF districts from the analysis. Overall, proximity to any TIF yielded an increase in sales prices. Sales prices of homes near mixed TIF districts also appreciated over time, indicating positive spillover effects as this land use can potentially accommodate a mix of new residential developments alongside retail in the same building that is both increasingly popular and profitable. In contrast, negative spillover is observed for commercial and industrial TIF districts. The authors speculate that this is a result of businesses in these kinds of districts such as big-box retailers and the negative externalities that come with them like increased traffic and limited pedestrian access result in suppressed sales prices of nearby homes and lead to negative or no net effect associated with TIF designation. The discussion of this paper focuses on whether the finding that the estimated increased sales prices for mixed TIF districts and for initially lower-priced homes led to gentrification. They conclude that the magnitude of the appreciation is relatively small and may be more likely associated with the presence of urban amenities such as proximity to public transit and rental-to-condo conversions.

In addition to property sales outcomes, this dissertation also estimates permit activity growth as a measure of private investment. Lester (2014) is the only TIF study estimating the impact of TIF designation on this outcome. Using the DID methodology and permits aggregated to the block group geography, the results indicate there is no relationship between the value of permits and TIF designation.

4 RESEARCH DESIGN AND METHODOLOGY

The purpose of this study is to estimate the effects of designating select TIF districts in Baltimore City. As discussed in Chapter Two, existing research on TIF designation effects often examines assessed property tax value and property tax revenue outcomes associated with TIF designation. This study builds on the methodological advancements used in the few TIF studies that focus on what can be considered indirect outcomes of the incentive, as well as studies estimating the impacts of other kinds of spatially targeted economic development incentives. Econometric techniques including the difference-in-difference quasi-experimental design, propensity score estimation, and the repeat sales methodology are used to measure the impact of TIFs on several outcomes including employment, building permit activity, and residential sales prices.

Improving on the previous studies of the influence of TIFs and STEDIs on job outcomes, this analysis measures overall job growth in addition to the job growth of local workers, within industries relevant to Baltimore's economy, and for low, moderate, and high wage jobs. Additionally, the dissertation uses jobs, permit activity, and sales transaction data available at small levels of geography to address a weakness of previous studies, a failure to identify and measure spillover effects associated with the incentive. Omission of spillovers potentially biases the designation effect estimates.

This chapter begins with an outline of the research questions for this study. Next, the Longitudinal Employer-Household Dynamics Origin Destination Employment Statistic (LODES) dataset, permit activity data, and residential property sales transactions are discussed and the outcome measures of interest are defined. Limitations of these datasets are also described. The chapter ends with descriptions of the difference-in-difference quasi-experimental design, propensity score estimation, repeat sales methodology, and the spatial analysis techniques used to identify the spillover effects of TIF districts.

4.1 Research Questions

This dissertation examines six research questions about the relationship between TIF designation and employment, permit activity, and residential property sales outcomes in Baltimore City.

(1) Does TIF designation facilitate job growth in TIF districts?
(2) Does TIF designation increase the employment of local residents?
(3) What is the relationship between TIF designation and the distribution of low, moderate, or high-wage jobs?
(4) What is the relationship between TIF designation and the distribution of jobs by industry for retail, leisure, and hospitality industries, goods-producing and export driven industries, and educational and health services industries?
(5) Does TIF designation induce building permit activity and residential property sales prices?
(6) Are the effects of TIF designation on employment, permit activity, and residential property sales prices biased by the spillover of effects to areas adjacent to TIF districts?

In order to address the first four questions, this study estimates job growth, the distribution of jobs by wages, jobs by industry, and local employment in neighborhoods in and surrounding TIF-designated areas using the Census Bureau's LODES data. Building permit activity data available from Baltimore City's Planning Department and residential property sales transaction data obtained from Maryland's Planning Department are used to answer question five. For question six these datasets are used to estimate TIF spillover effects.

TIF designation effects are estimated at the block group level of geography with the difference-in-difference methodological approach. For the 710 block groups that comprise

Baltimore City, propensity scores are calculated to weight observations based on whether comparison block groups are economically similar to TIF-designated block groups. TIF spillovers, or TIF designation effects observed within areas proximate to TIF districtss, are estimated two ways. For job and permit outcomes, these spillover effects can be observed across the 13,598 census blocks in Baltimore City, comparing areas surrounding TIF districts that are prone to spillover to adjacent census blocks in the next buffer ring of census blocks depending on their distance from TIF districts. The spillover effects of TIF designation on residential property sales are estimated using the difference-in-difference design for all sales transactions and with the repeat sales methodology for properties that sold more than one time during the study period.

4.2 Data Sources

The outcomes of interest in this dissertation are derived from three datasets: the Census Bureau's LODES data for job outcomes, building permit activity data available from Baltimore City's Planning Department, and residential property sales transaction data obtained from the Maryland Department of Planning's MdProperty View database.

4.2.1 LODES Data

The Longitudinal Employer-Household Dynamics Origin Destination Employment Statistic (LODES) dataset is released by the Census Bureau's Center for Economic Studies and available for years 2002-2013. Unemployment Insurance (UI) wage records from state administrative data and Quarterly Census of Employment and Wages (QCEW) data (formerly ES-202) are core datasets from which LODES data are derived.

Employers paying unemployment insurance benefits report UI wage record data to the state. An individual's wage record includes any UI-covered earnings if at least one employer reports earnings of at least one dollar for that individual during the quarter with a six-month lag. QCEW is jointly administered by BLS and the State Employment Security Agencies (SESAs) and consists of establishment employment and wage data subject to statutory payroll taxes for UI-covered workers and those covered by the Unemployment Compensation for Federal Employees (UCFE) program.

While most employers have only one establishment, or the location where employees perform their work, those with multiple establishments submit QCEW data for each establishment. Other federal administrative data, economic censuses, and surveys add demographic data and place of residence information to the dataset.

LODES Data Coverage, Characteristics, and Structure

LODES data are available for years 2002-2013 and for all states and territories including the District of Columbia. LODES data do not include the self-employed nor railroad workers and members of the military. According to Graham and Ong (2007) 10 percent of workers are self-employed. Those working with wages paid in cash and paying no taxes are also excluded.

LODES data include counts of primary or secondary jobs. For multiple job-holders or workers who have multiple jobs in one year because of job changes, primary jobs are the highest wage job a worker holds. This study will use primary jobs to avoid double counting of workers. Recently data on federal workers for 2010 and later from OPM is included in LODES, however this study will use private employment only. LODES data are available by segments, including worker age, earnings category, and industry at the 2-digit NAICS level. Worker characteristics such as race, gender, educational attainment, and firm characteristics such as firm age and size are available for more recent years of LODES data but not the period of interest for this study.

LODES data are released and updated annually. Data users can access data through OnTheMap, an interactive web mapping application, or as raw data files at the census block level of geography. The raw LODES data include three file types in csv format:

- Residence Area Characteristics (RAC)— workers living in an area (home census block)
- Workplace Area Characteristics (WAC)— workers employed in area businesses (workplace census block)
- Origin-Destination (OD)—connects a home census block with a work census block to create a home-work block pair

RAC and WAC files contain total job counts and job counts for each combination of year, job type (private or government), and segment variables. For OD files, there are job counts for each worker/job characteristic for each segment. Due to size, these files are available for each state and split into MAIN vs. AUX files. MAIN files include jobs of workers who are employed in the state and reside in the state. AUX files are jobs of workers who are employed in the state and reside out of state.

LODES Data Adjustments and Limitations

For the purposes of confidentiality, noise infusion is applied to employment data so that individual firms and workers cannot be identified. The amount of noise is small enough not to distort the data. With regard to data accuracy, there are several data limitations. For businesses with more than one establishment, large employers with a headquarters location such as a school district or chain store, as well as job staffing agencies, a worker's job location may not reflect where they actually work since states have varying tolerances for accurate establishment addresses. Also, certain workers such as those using temporary permanent addresses may provide data that does not reflect the actual home-to-work commute.

In addition, the LODES origin-destination data, or job flows, include synthetic data. As previously stated, employers often have multiple establishments. However, the processing of LODES data does not link individual employees by SSN to an exact worksite. Minnesota is the only state that includes data elements that enable this link. A model derived from this Minnesota data is used to distribute workers to a worksite for an employer with multiple establishments. This synthetic data could potentially introduce measurement error that is correlated with TIF designation however these issues are considered systematic and necessitate a review of LODES data, especially at small levels of geography. As such, initial data checks will be performed, visually inspecting job changes across each census block included in the study and using knowledge about the local economy to determine whether observed changes are reasonable.

4.2.2 Permit Activity Data

By request the Baltimore City Planning Department provided building permit activity data for permits over $50,000 for years 2000-2013. Of the permits issued during that period, 17 could not be geocoded because there was no correct address or building number, leaving a total of 16,242 permit records used in the analysis. Each of the permit records include the amount of the permit, the permit type (new or addition, alteration or repair), and information about the land use of the parcel.

The categories used by the Baltimore City Planning Department to record land use information about a permit varies across the years. As such, the land uses were combined into broad categories, i.e. commercial, residential, institutional, parking lot or garage, public utility, and miscellaneous. For example, office, industrial, auto repair shop, and hotel were grouped into the commercial category. Where this information was missing, other information in the permit record such as the permit description was used to categorize the permit. In total, 15,786 permit records were categorized by land use.

4.2.3 Property Sale Data

Residential property sales transactions and additional indicators of property condition are derived from the 2013 release of MdProperty View made available as shapefiles for download through the Maryland Department of Planning. The data cleaning methodology used by the Maryland Department of Planning imposes the following restrictions to delete sales transactions from the residential property sales datasets:

- Non-arms-length transactions
- Transactions with consideration values less than $10,000
- Duplicate sales records with the same parcel account number, transaction date, and consideration value
- Sales records that could not be geocoded
- Sales to an owner that is a business entity, e.g. LLC, that are likely to be properties purchased for redevelopment or a use other than residential sale and occupancy
- Sales to business entities, banks, home builders or mortgage companies were listed as the owner of the property rather than a private individual

Once the shapefile for each year of sales transactions for years 2002 through 2013 were combined in ArcGIS, duplicate records with the same unique parcel identification and sales date that didn't meet the previous criteria were deleted for the purpose of conducting panel analysis with unique sales dates. In total there were 93,275 residential property sales. Each property sale record includes the date of the sales transaction and the amount of consideration for the sale.

MdProperty View also includes the Computer Assisted Mass Appraisal (CAMA) database from the State Department of Assessments and Taxation's (SDAT) Integrated Property Tax Software System. The structural information about each parcel from the CAMA database includes age and square footage of the building, and the presence of a basement, deck, enclosed porch, or a garage.

4.2.4 Other Data

Census Data

In the analysis of TIF designation effects at the block group level of geography Census 2000 data from the SF1 and SF3 files are used to derive propensity scores. Data from Census 1990 are also used to derive some variables denoting change over time between 1990 and 2000.

Planning Data and Shapefiles

Baltimore City's Planning Department provided a georeferenced shapefile of polygons that represent the boundaries of existing TIF districts. The shapefile for the 2005 Baltimore City Housing Market Typology developed in partnership with The Reinvestment Fund includes the typology for all Baltimore City block groups as well as the underlying data used to derive the typology. Other various geographic shapefiles from Baltimore City's Planning Department are used to identify the location and proximity of neighborhood amenities such as public transit stops and university and college anchor institutions, as well as land uses as of the year 2002.

4.3 Measures

The following section outlines the operationalization of the outcome measures of interest in this study estimating the causal impact of TIF designation on employment, building permit activity, and residential property sales. Due to the non-normal distribution of outcomes across all units of analyses used in the study, all dependent variables are natural logs.

4.3.1 Job Outcomes

Job Growth

The various justifications for TIFs outlined in Chapter One suggest that this investment facilitates redevelopment that will create and attract new businesses, and increase employment in existing businesses that surround the redevelopment area. This analysis is interested in the growth of workplace employment rather than resident employment. The LODES data defines a job as Beginning of Quarter Employment, which means the worker was employed by the same employer in both the current (2nd) and previous (1st) quarter. Job growth is defined as an increase in the total number of jobs. Here we are interested in job counts for employees working in these areas. These job counts exist in the WAC file as variable C000.

Local Employment

Existing TIF studies that examine employment outcomes usually focus on total job growth with limited consideration for how TIF designation impacts the employment of local residents. Local employment is often an outcome of interest in previous studies of federal empowerment zones or state enterprise zones that targeted zone residents. However, these studies measure the number of residents living and working within the boundary of a zone. In comparison, TIF districts have a more indirect relationship with employment outcomes and therefore measuring local residents employed in the district is not an appropriate measure of job accessibility or the targeting and employment of local residents. Instead, in this study local employment is the number of workers in a geographic unit who also live in Baltimore City. This is calculated with the number of total workers in a geographic unit as the denominator and the count of "resident-workers" from the OD file as the numerator.

Since the OD file is made up of block-to-block pairs of workplace and residence job counts, this requires some manipulation of the dataset. For each workplace census block, the residence blocks that are located in Baltimore City, identified by the first five numbers of the FIPS code as "24510", need to be aggregated to both the block group and the census block to produce the number of local workers in a geographic unit.

Jobs by Wages

The LODES dataset is segmented by the following earnings categories of jobs: $1,250 per month or less; $1,251 to $3,333 per month and; greater than $3,333 per month. These are variables CE01, CE02, and CE03 in the WAC file, respectively. This analysis uses three different dependent variables for each wage category, defined as low, moderate, and high. This is similar to the measures used by Freedman (2013, 2015) who annualizes the measures to less than $15,000, between $15,000 and $40,000, and more than $40,000 for easier interpretation.

One concern, also recognized by Freeman (2013) is that wage categories don't seem to account for inflation. For instance, between 2002 and 2013 more jobs may be in the moderate or high wage categories, but may not indicate increased buying power for workers as wages overall increased. However, these measures still give an indication of the quality of jobs in and surrounding TIF districts.

Job by Industry

As previously discussed, jobs potentially have different economic impacts based on their industry categorization. Goods-producing firms are expected to have larger economic impacts than professional and service firms. It follows then that estimating the impact of TIFs by job industry would be a measure of the quality of jobs in and surrounding TIF districts.

The LODES data includes job counts for every 2-digit NAICS code in the WAC file (CNS01-CNS20). Job counts for each industry at the census block level of geography in the WAC file are aggregated to the block group level of geography.

Based on the characteristics of Baltimore City TIF districts, residential TIF districts and mixed TIF districts (office, commercial, or hotel developments) in a developed urban setting, this analysis focuses on three groupings of these industry sectors that are relevant to Baltimore City and Maryland's broader economy which are likely to be affected by the developments financed by TIFs.

For TIF districts financing both mixed and residential projects, job growth in retail, leisure, and hospitality industries reflect an increased demand for consumer services and goods within the local economy. In Baltimore City, educational and medical institutions are otherwise known as anchor institutions and are among the largest employers in the city. These institutions contribute to neighborhood stability and are often economic drivers for the surrounding community and beyond. Goods-producing and export driven industries support export industries and supply chains throughout the region or move goods and people both within and outside it.

These industry groupings and the industries they comprise include:

- **Retail, Leisure, and Hospitality Industries**
  - Retail trade (CNS07)
  - Arts, entertainment, and recreation (CNS17)
  - Accommodation and food services (CNS18)
- **Educational and Health Services Industries**
  - Educational services(CNS15)
  - Health care and social assistance (CNS16)
- **Goods Producing and Export Driven Industries**
  - Construction (CNS04)
  - Manufacturing (CNS05)
  - Utilities (CNS03)
  - Transportation and warehousing (CNS08)
  - Wholesale trade (CNS06)

4.3.2 Permit Activity Outcomes

Permit data are aggregated to the block group and census block, for the estimation of TIF designation effects and TIF spillover effects, respectively. The total number of permits is a count of permits at both the block group and census block geographic units. Likewise, total permit amount is the sum of permit values in a geographic unit for each year. From these broad categories we derive outcome measures indicating the amount for residential permits and commercial permits in each geographic unit.

4.3.3 Property Sale Outcomes

In the analysis of TIF designation effects at the block group level of geography, aggregated home sales data is used to measure the total count of all residential property sales and the total amount of property sales within a block group. For the spillover analysis of the impact of TIF designation on residential property sale appreciation, the unit of analysis is individual homes. Spillover effects are analyzed for all sales, sales of properties that sold more than once between 2002 and 2013, and repeat sales where the first sale occurred before designation and the last sale after TIF designation.

4.3.4 Other Variables and Covariates

Demographic, Socioeconomic, and Neighborhood Variables

The indicators used to derive the propensity score in the block group analysis include the following: population, households, percent vacant homes, median household income, median housing value, gross rent, percent owner-occupied units, unemployment rate, percent not in the labor force, percent of residents with incomes below poverty, the percent of residents who moved within the last five years, percent minority/non-white population, percent of residents who receive public assistance, and percent college graduates. Census 1990 variables for population and the number of households are used to calculate change over time variables between 1999 and 2000 for population and the number of households.

Land Use

Using ArcGIS, the proportion of the census geographies that represent the different land uses was calculated and expressed as percentages of the total land coverage of a block group or census block. These percentages, or land use indicators were included in the block group analysis as propensity score estimation criteria and in the census block analysis as controls.

Neighborhood Amenities

The proximity of TIF districts to various neighborhood amenities are used as control variables in the analysis of TIF spillover effects. ArcGIS was used to calculate the distance between the centroid of each census block or each home sale and the nearest bus stop, light rail station, commuter train station, subway stop, university, and location of the central business district (census tract 401).

Housing Market Typology

Since 2002 Baltimore City's Planning Department has produced a market value analysis or housing market typology of Baltimore City neighborhoods as a tool to inform public policy and resource allocation decisions about housing market intervention strategies. In partnership with The Reinvestment Fund this typology has been updated four times since then in 2005, 2008, 2011, and 2014.

While the methodology for this analysis has evolved with each update, essentially housing market indicators derived from administrative housing data are used in a cluster analysis. The cluster analysis groups block groups into clusters that are relatively similar to each other and dissimilar to block groups in other clusters. For the 2005 housing market typology (HMT) those housing market indicators are:

- Median home sales price
- Percent of homes in foreclosure
- Owner occupancy rates
- Percent of properties with code violations
- Percent of rental market that is subsidized
- Percent of commercial properties
- Percent of properties that are vacant
- Percent of properties that are vacant lots created through demolition

Block groups are classified into five categories: competitive, emerging, stable, transitional, and distressed. The HMT is used in the analysis of TIF spillover effects as appreciation is estimated across the five different typologies of the housing market.

4.4 Research Design

This dissertation uses the difference-in-difference quasi-experimental research design, propensity score estimation, and the repeat sales method, a variation of hedonic price regression, to estimate the causal impact of selected TIF districts in Baltimore City on employment and private investment outcomes. Chapter Three outlined previous TIF and STEDI research using these research designs.

This section will present the strengths and limitations of this strategy as well as the empirical models and a discussion of how to interpret the analyses. Additionally, the specifications for estimating TIF designation effects using economically close comparison units and TIF spillover using geographically close comparison units and repeat sales of residential properties will be outlined.

4.4.1 TIF Designation Effects Using DID and Propensity Scores

The pre-test post-test two-group design is the most common research design (PTTGD). In experiments using a PTTGD, the treatment and control groups are assumed to be equivalent due to randomization. For quasi-experiments, specific design elements attempt to minimize the threats to internal validity due to nonrandom assignment. The three identifying design elements for this research design include:

1) **Assignment to a treatment or non-treatment group.** In randomized experiments, assignment is random (R). In quasi-experimental research designs, assignment can be nonrandom (N), or determined by some cutoff score or measure indicating selection into treatment.
2) **The treatment or incentive (X in the design notation).**
3) **Pre-test and post-test measures.** Pre-test measures are used to determine the similarity between the treatment and non-treatment groups. Post-test measures represent the outcomes under study.

Figure 4.1. Pre-Test Post-Test Two-Group Design

Assignment	**Pre-Test**	**Treatment**	**Post-Test**
Assignment Type	O	X	O
Assignment Type	O		O

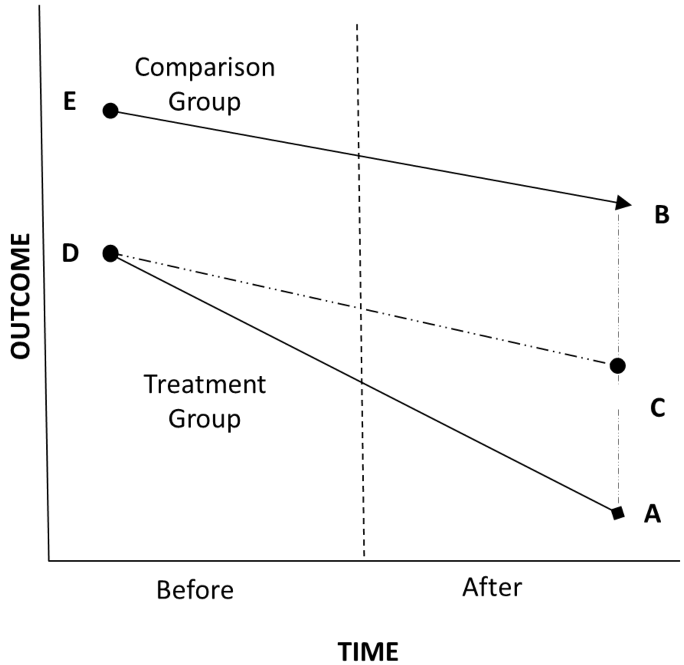
Difference-in-difference is one such PTTGD research design with nonrandom assignment of units into treatment and comparison groups that estimates the difference in outcomes between the pre-test and post-test measures for both groups. The design can be conceptualized as the combination of a before-and-after analysis and a cross-sectional analysis. Figure 4.2 below illustrates a comparison of DID to these other designs.

A simple before-and-after design (one-group pretest-posttest) observes changes in the pre-test and post-test measures of treated units, from point D to point A. There is no comparison group, therefore it cannot be determined that a change between periods did not occur everywhere due to secular, or long-term, trends and omitted time-invariant variables are not controlled for.

A cross-sectional design with two groups and no pre-intervention measure (posttest-only design with nonequivalent groups), estimates the impact of an intervention between points A and B which represent post-test measures for a treatment and comparison group. The design assumes the relationship between treatment and outcomes and that difference in post-test measures is solely due to the treatment.

While before-after designs can rule out historical threats to validity, the combination of this technique with the cross-sectional design using a comparison group produces a “double-difference” that can further rule out other threats to internal validity. This difference-in-difference approach essentially identifies the counterfactual with an assumption that any change over time in the comparison group is the same change that would have happened to the treatment group, if that group did not receive the treatment. Therefore the difference between the estimated outcomes of both groups (other than random sampling error) is interpreted as the impact of the intervention.

Figure 4.2. Difference-in-Difference



The difference-in-difference is represented as the dotted DC line with the same trend as the comparison group in figure 4.2. Therefore the actual effect of the treatment is the difference between points A and C (the endpoints of the treatment and counterfactual trend lines).

<u>General DID Model</u>

Equation 1 is a simple cross sectional model of TIF designation effects where T indicates whether a block group (i) is designated as a treated unit and valued as 1 or comparison unit valued as 0, as discussed in a later section.

$$\ln Y_i = \alpha_i + \beta T_i + \varepsilon_{it} \qquad (1)$$

The variable Y represents the natural log of the post-designation outcome measures. This simple model produces naïve ordinary least squares OLS estimates of the impact of TIF designation, represented as coefficient β. Here, TIF designation serves as an exogenous variable and is therefore not correlated with unobserved factors. However, isolating the impact of the treatment is difficult if there are omitted unobserved characteristics that are potentially correlated with both the outcomes and designation. This omitted variable bias may produce biased estimates of the treatment effect.

The basic DID model for estimating the impact of TIFs that compares treatment and comparison block groups before and after designation is as follows:

$$\ln Y_{it} = \alpha_i + \beta T_{it} + \gamma t_{it} + \delta T_{it} t_{it} + \varepsilon_{it} \qquad (2)$$

In equation 2 the coefficients α, β, γ, and δ, are unknown parameters. The model regresses the natural log of the outcomes of interest in this study (Y) on an indicator variable T that is coded 1 if a block group (i) is identified as treated in year t and is coded 0 otherwise. As such, β is the treatment group effect. This simple DID model uses two time periods and the time trend (γ) is the coefficient of the variable t denoting time periods before and after TIF designation for treatment and comparison groups.

The coefficient δ represents the estimator, or true effect which is interpreted as the average treatment effect of TIF designation, or the average difference of outcome measures Y for each geographic unit (i). Calculating the average difference in outcomes separately for treatment and comparison units before and after designation and then taking an additional difference between the mean changes in outcomes for these two groups estimates the DID impact. DID essentially differences or subtracts the pre-treatment difference in outcomes for designated and non-designated areas from the post-incentive difference. With this model and each following difference-in-difference equation, for each outcome of interest in this study, the associated null hypothesis to be tested in the analysis is that the coefficient δ of the product term signifying treatment is not equal to 0.

In both equations 1 and 2, the variable α is the constant term and is the average outcome for the comparison group. Lastly, ε_i is an unobserved error term which contains all determinants of the outcome variable that are likely omitted from the equation. While DID is an improvement over simpler methods, standard errors for a given observation might be serially correlated creating biased estimates, or autocorrelation. To adjust for this, standard errors will be clustered at the block group for estimated TIF designation effects and at the census block for spillover effects estimated in this dissertation.

<u>Panel Fixed Effects</u>

The panel fixed effects model generalizes the two-period model with multiple time periods. Introducing additional data for time periods before and after the treatment can determine whether year-to-year variation differs for changes other than TIF designation. More specifically, these additional pre-test and post-test observations test whether the outcome variable followed parallel trends over time and identify whether there are maturation threats to internal validity. This is of particular importance with the DID design since the main assumption is that the treatment group has the same trend as the comparison group.

Panel data with multiple observations of each geographic unit can control for factors that vary across geographic units, or individual differences within these geographies. There are two types of variation. This variation can be between geographic units as with a cross-section or within unit variation over time. This between-unit variation potentially produces omitted variable bias due to pre-designation differences between treatment and comparison units. With observations at multiple points in time, panel methods use an individual panel for each unit as its own comparison group. The fixed effects model assumes that the error component in the model is correlated with designation and unobserved or unmeasured characteristics (heterogeneity) are time invariant or do not change over time. Therefore focusing on within unit variation removes the effect of omitted variable bias as it can be "differenced" out of the time fixed-effects model and the internal validity can be improved.

In equation 3 the outcomes of interest Y_{it} are regressed on the interaction term $T_{it}t_{it}$. The error term has three components, including ω_i which is a place-specific fixed-effect component that varies across geographic unit (Baum-Snow and Ferreira, 2015).Similarly λ_t represents a time-dependent fixed-effect for each year of data considered, expressed as a set of year dummy variables. The classical error term ε varies across both time and space. This is often referred to as a two-way fixed effects model.

$$\ln Y_{it} = \beta T_{it} + \gamma t_{it} + \delta T_{it}t_{it} + \omega_i + \lambda_t + \varepsilon_{it} \qquad (3)$$

As a result of the inherent problems associated with using OLS to estimate panel data, researchers often use methods to address this variation in the data due to individual pre-existing differences in population and neighborhood characteristic trends between the non-equivalent treatment and comparison groups. This dissertation approaches this challenge by identifying economically close comparison block groups using propensity score analysis.

Identifying Treated Block Groups with Propensity Score Estimation

Based on Census 2000 geography, there are 710 block groups in Baltimore City. To identify treated block groups, a shapefile of block groups was overlaid onto the TIF shapefile of the seven Baltimore City TIF districts included in this study. The block groups that contain or intersect the TIF districts are identified as TIF block groups and, coded with a value of 1, and non-TIF block groups are coded 0. While block groups are generally large in comparison to the actual TIF district, this unit of analysis is necessary due to the fact that it is the lowest level of geography at which socioeconomic data are available for using propensity score estimation.

LODES jobs data are available at the Census 2010 census block geography and needed to be aggregated to the Census 2000 block group boundaries. To reconcile this, the census block and block group shapefiles are overlaid and 2010 census blocks are aggregated to the 2000 block groups within which its centroid lies.

It is important to note that each TIF was designated during a different year. For the purposes of this analysis, we identify the "post" period for TIF block groups beginning one year after the TIF development is completed. All TIF districts selected for this study were designated and the development completed by 2009. As such, the "post" period for the comparison block groups is identified as the years 2010-2013.

DID with Propensity Score Estimation

Per the introduction in Chapter Three, propensity score estimation can be combined with the DID research design. This technique strengthens the estimated difference between outcomes for treatment and comparison groups over time by ensuring comparison units are as similar as possible based on observed base year (pre-designation) characteristics.

To accomplish this, a set of demographic, socioeconomic, neighborhood, and land use covariates are selected. Propensity scores are derived from a probit regression equation that reduces each unit's covariate value to a single score ranging from 0 to 1. This essentially represents the probability of a block group being assigned to treatment, in this case TIF designation.

In equation 4, T is equal to 1 if a block group is ever a TIF block group in any year of the study and 0 otherwise. Every block group will have an estimated propensity score.

$$P(X) = \Pr(T = 1 | X) \quad (4)$$

The justification for this approach is that two units with the same propensity score will be balanced on all observed covariates, thereby reducing selection bias attributable to differences in initial pre-designation characteristics that could confound the estimated treatment effects. In Chapter Five, this covariate balance will be checked to determine whether the average propensity score and the average of the covariate are the same along the propensity score distribution.

There are two assumptions associated with propensity score estimation. The first is that the treatment is based only on observed characteristics (Rosenbaum and Rubin, 1983). The second assumption is the presence of a relatively large common support, where the distributions of propensities is the same for treated and comparisons or at least overlaps, ensuring there are similar comparison units for all treated units (Heckman, Ichimura, and Todd, 1997).

Propensity scores can be used for matching treatment and comparison units and also for weighting strategies such inverse probability of treatment weighting (IPTW) (Lunceford and Davidian, 2004). There are different types of matching techniques for matching treated and untreated units, including nearest-neighbor matching, caliper or radius matching, stratification or interval matching, and kernel and local linear matching. Each method has different criteria such as matching with or without replacement and the allowable distance between propensity scores that determines whether an untreated unit can be matched to a treated unit.

With a one-to-one nearest neighbor match, each treated unit is matched to only one untreated unit with the closest propensity score. Due to the limitation in possible matches, there could be no untreated units matched to treated units. Nearest neighbor matching allows the selection of the number of matches possible for each treated unit. Caliper and radius matching selects untreated units only within some pre-determined propensity score range, or radius. Stratification matching groups observations into strata or blocks based on the propensity score and then estimating the relationship between treatment and outcomes for each strata. Kernel and local linear matching create a weight based on the distance between each comparison unit and the treated units based on an optimal value of a bandwidth parameter to estimate the average effect on the treated (Heckman, Ichimura, and Todd, 1997).

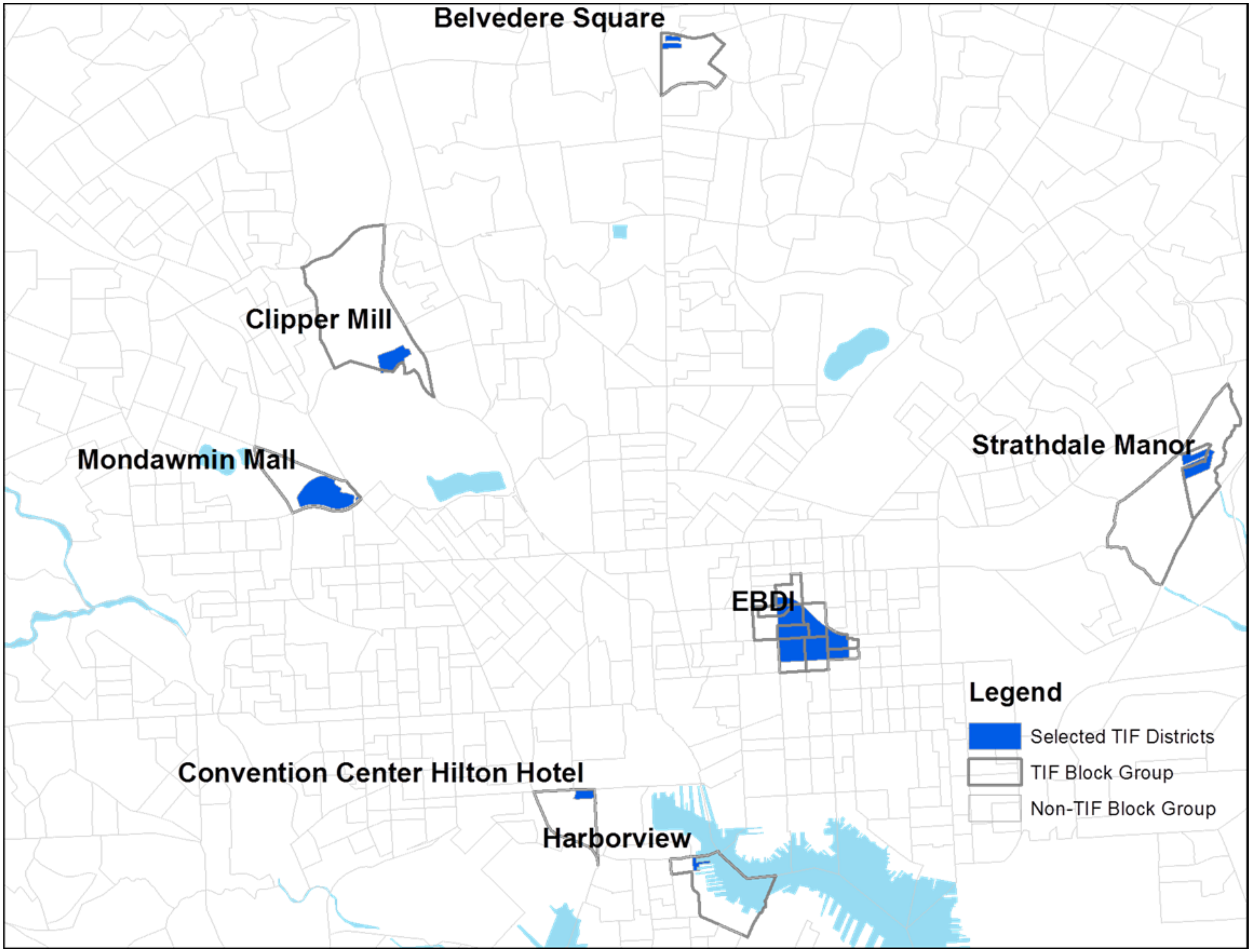
As an alternative to these matching techniques, Hirano, Imbens, and Ridder (2003) suggest using the inverse nonparametric estimate of the propensity score, or the inverse probability of treatment weight (IPTW), an approach similar to Greenbaum and Engberg (2004) whereby treated units receive a weight equal to the inverse of the estimated propensity score (1/Pr), and untreated units receive weights of (1/1–Pr). Weights are then normalized to one, mimicking randomized assignment in that all units are considered conditionally interchangeable and therefore the selection bias of estimates due to pre-designation characteristics of block groups is reduced. These weights are included in the panel fixed effects model in equation 5:

$$\ln Y_{it} = \beta T_{it} + \gamma t_{it} + \delta T_{it} t_{it} + \phi Pr_i + \omega_i + \lambda_t + \varepsilon_{it} \qquad (5)$$

There are tradeoffs for using matching techniques compared to weighting. Matching usually results in fewer observations included in the analysis depending on the matching strategy. This ultimately increases the variance of treatment effect estimates. With weighting, observations are not dropped from the analysis; rather the contribution that each unit makes to the average outcome of interest is determined. In addition, it is intuitive to assign a greater weight to comparison units with higher propensity scores, or higher probabilities of treatment (Handouyahia, Haddad & Eaton, 2013).

This dissertation is also interested in the heterogeneous impacts of TIFs across different TIF types using the difference-in-difference design. As such, in equations 2, 3, and 5, the variable T distinguishes between non-TIF block groups coded 0 and multiple treatment categories where TIF block groups are coded 1 for mixed TIFs and coded 2 for residential TIFs. Further, as a test of sensitivity, the dissertation also estimates TIF designation effects using DID with one-to-one, nearest neighbor, radius, and kernel matching.

Figure 4.3. Selected Baltimore City TIF Districts and TIF Block Groups



4.4.2 TIF Spillover Effects Using Geographically Close Comparisons and Difference-in-Difference Analysis

Positive and Negative Spillover

Identifying economically similar block groups using propensity score estimation to observe unbiased TIF designation effects is a methodological improvement over TIF studies conducted at the municipal level of geography or using larger geographic units such as the census tract or zip code. However, Baltimore City TIF districts mostly consist of one project or multiple parcels and are still relatively small and cover only a portion of a block group.

Therefore, it is difficult to estimate the net impact of TIFs. TIF designation effects could be biased by economic activity around the district as surrounding areas experience what is called spillover. Spillovers of effects can be positive or negative. A positive spillover implies that the effects of an incentive are observed not only within the designated area but in the surrounding area. It follows that even where there are significant TIF designation impacts, if TIF designation effects spillover to adjacent areas beyond the TIF district, for example, there could be overall job loss in the block group that contains the TIF district resulting in a negative net impact of TIF designation on employment. This ultimately leads to a downwardly biased designation effect estimate at the block group level of geography.

In contrast, if businesses leave surrounding areas and relocate to a designated TIF district or property owners elect to make improvements or purchase homes in or closer to TIF districts despite the adjacent area presumably being similar except for the designation status, this negative spillover inflates estimated effects. This simply shifts rather than induces economic activity, leading to estimates that could be upwardly biased.

The potential bias associated with the inability to observe net TIF designation effects at the block group level of geography illustrates the main limitation for the DID analysis with propensity score estimation and provides the basis for the analysis of TIF spillover effects. In the following section this dissertation estimates the spillover effects of TIF designation on overall employment, building permit activity, and residential sales appreciation using geographically determined spillover and comparison areas.

Identifying Spillover and Comparison Areas within Distance of TIF Districts

As outlined in chapter 3, previous TIF and STEDI studies have estimated spillover with proximate comparison groups as geographically close units are expected to be similar to designated areas with the exception of designation. Where spillover prone areas are significantly different than adjacent comparison areas, spillover potentially exists. Much of this research is conducted at the census tract or block group level of geography.

As an example, Ham et. al. (2011) estimate spillover effects by comparing the census tracts nearest and surrounding an Empowerment Zone to the next nearest adjacent census tracts. If the next nearest geographic units are statistically different than the nearest, they are dropped from the analysis and the third nearest are included in the analysis and then on to the next set of geographic units until the difference between the nearest and comparison census tract is insignificant and there is no spillover effect. The approach used in this analysis of spillover is similar but differs in important ways.

This dissertation uses three spillover proximity specifications whereby the spillover areas and adjacent geographically close comparison units or observations are determined by proximity to the TIF district. Using ArcGIS, buffers around the TIF districts are created to identify TIF spillover areas .125, .25, and .5 mile from the TIF district and equidistant comparison areas .126-.25, .26-.5, and .51-1 mile from the TIF district.

Table 4.1. Spillover Proximity Specifications

	Eighth to Quarter (EQ)	Quarter to Half (QH)	Half to Mile (HM)
Spillover Area	0-.125	0-.25	0-.5
Comparison Area	.126-.25	.26-.5	.51-1

As demonstrated in table 4.1 this dissertation focuses on the following specifications:

1. EQ-units of analysis within an eighth of a mile from the TIF district are the spillover area and units between an eighth of a mile and a quarter mile from the TIF district are the comparison area.
2. QH- units of analysis within a quarter of a mile from the TIF district are the spillover area and units between a quarter mile and a half mile from the TIF district are the comparison area.
3. HM- units of analysis within a half mile from the TIF district are the spillover area and units between a half mile and a mile from the TIF district are the comparison area.

Identifying and then comparing spillover and comparison areas in this way addresses the data and geographic limitations of previous studies that looked at employment and private investment outcomes across an entire municipality or for geographic areas much larger than the designated TIF district. The next section explains how comparing geographically close comparison units using DID can estimate spillover effects of TIF designation and ultimately determine whether estimates of TIF designation effects are biased.

DID and TIF Spillover Estimation

Since job measures are available at the census block, spillover areas are identified as census blocks immediately surrounding the TIF district where spillover effects are likely to exist. Comparison census blocks are adjacent or geographically close census blocks. Pooled permit data is also aggregated to the census block for the analysis of TIF spillover effects.

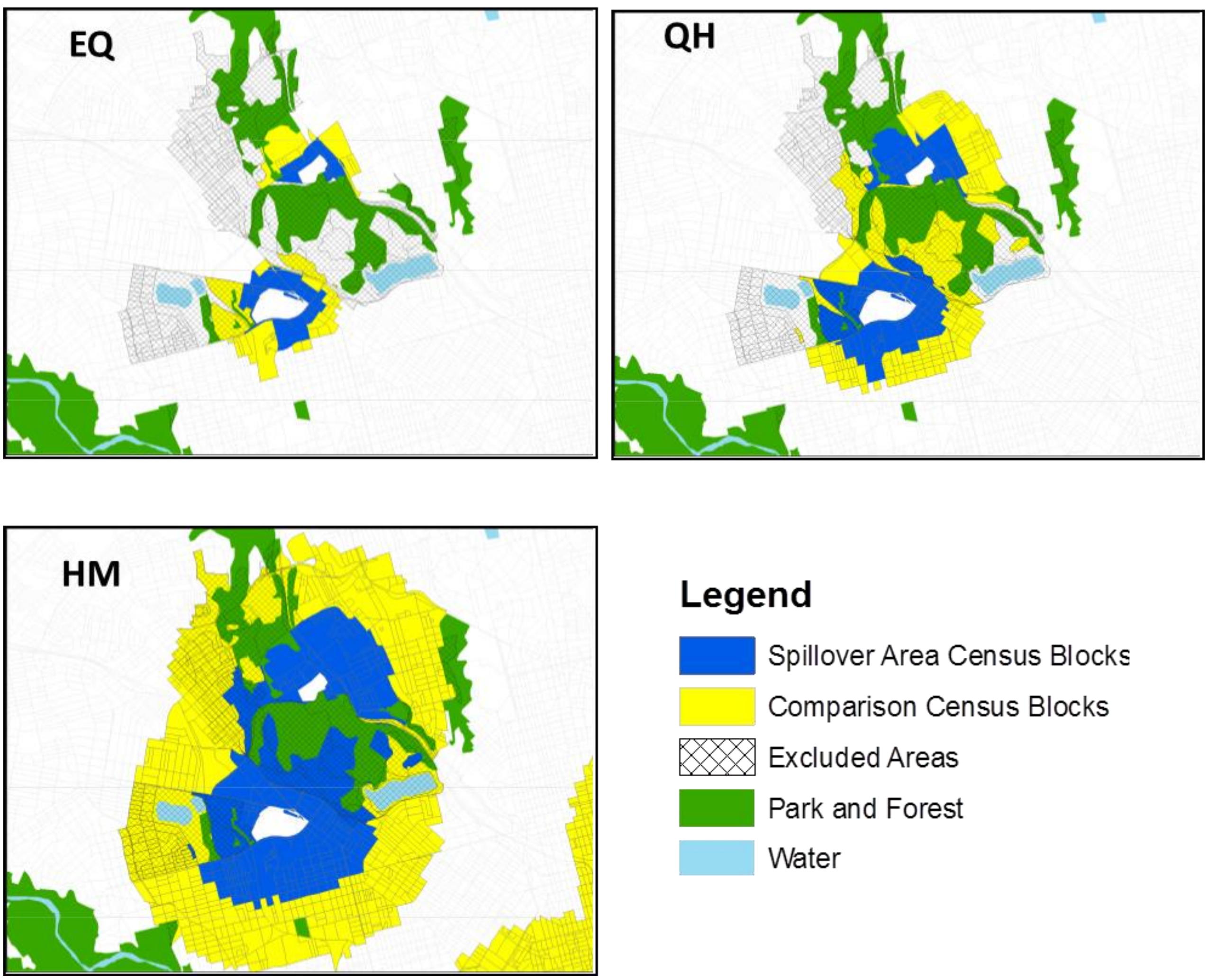
The DID fixed effects model in equation 3 is also used to analyze spillover effects. Here, variable T is equal to 1 where the census block's centroid is within the spillover area (.125, .25, or .5 mile from the boundary of the TIF district) and 0 for the comparison census blocks in the next ring of census blocks (.25, .5, or 1 mile from the boundary of the TIF district). Comparison census blocks will have the same "post" period of the TIF district it surrounds after its designation. The variable t equals 1 for those census blocks within distance of a TIF district after designation. Otherwise t equals 0. For census blocks that are within the comparison area for more than one TIF, the earlier TIF will determine the "post" period.

There are 13,598 census blocks in Baltimore City using Census 2010 geography, which is used since LODES data are only available at the Census 2010 spatial geography. There have been drastic changes to census blocks in Baltimore City between 2000 and 2010 where many census blocks have been split into multiple census blocks and some have been merged into a single census block. Attempting to apportion and allocate the LODES data to the 2000 geography with 9,010 census blocks would likely skew the analysis.

At the time of this dissertation, there has been no study of the spillover effect of spatially targeted economic development incentives on outcomes using the census block as the unit of analysis. These small geographic units improve the estimation of spillover effects since census blocks are the smallest census geographic unit, small enough that they closely reflect TIF district boundaries and spillover of effects can be observed. This addresses the data and geographic limitations of previous studies that looked at outcomes for an entire municipality or for geographic areas much larger than the designated area.

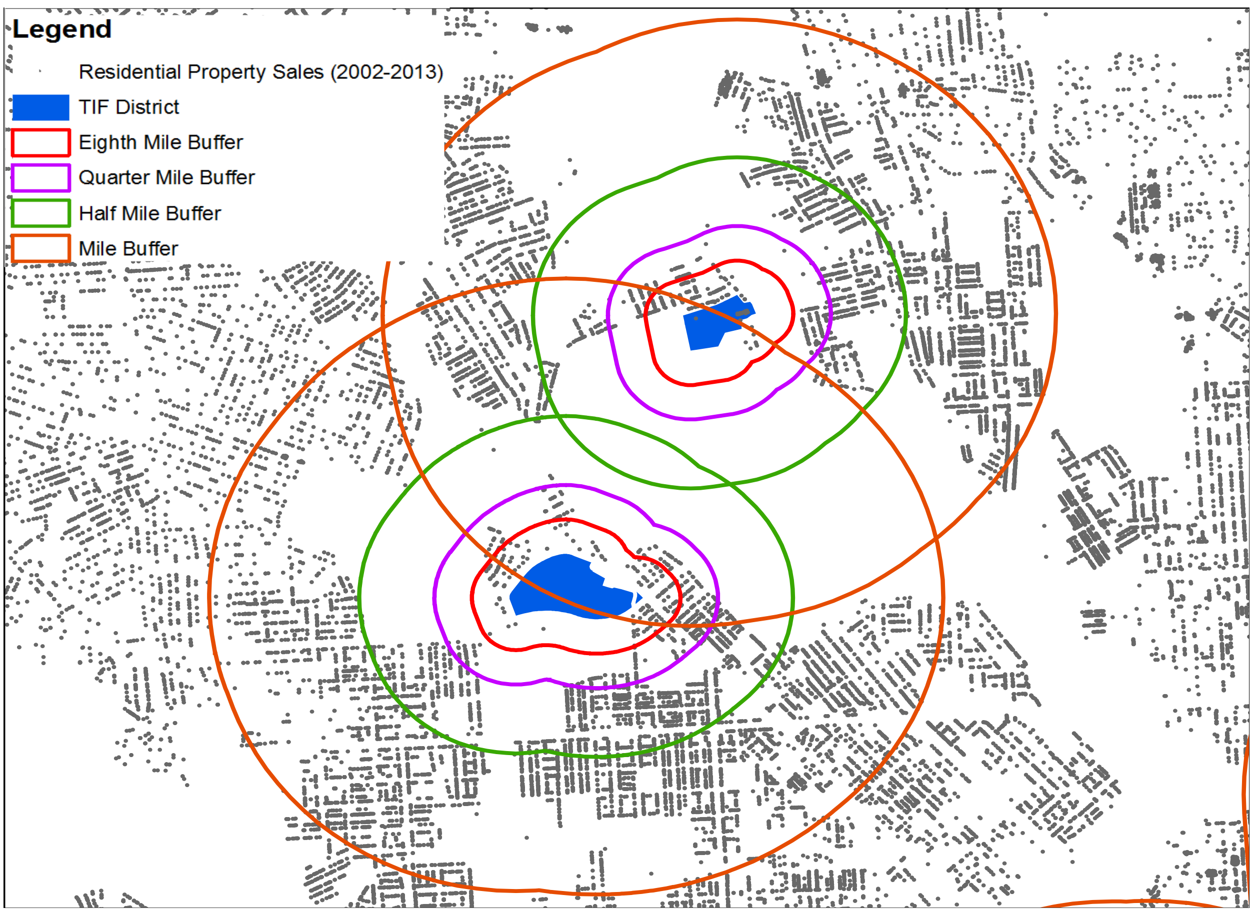
There are 83 TIF census blocks in total. For the purpose of estimating spillover they are excluded from the analysis. Census blocks that either contain or geographically extend beyond geographic barriers such as parks, green space/forest, barren land, highways, and water bodies are also excluded from the analysis. These exclusions are identified for every proximity specification of the analysis. For instance, figure 4.4 visualizes the spillover (blue) and geographically close census blocks (yellow) associated with the Mondawmin and Clipper Mill TIF districts. The crosshatch represents the excluded census blocks in and extending beyond the park, greenspace, and lakes.

Figure 4.4. TIF District Spillover and Comparison Area Census Block Specifications



In order to utilize the individual characteristics of each home, estimation of the spillover effects of TIF designation on residential property sales uses the sales transaction as the unit of analysis. For the difference-in-difference design, sales are identified as being within the spillover area or the adjacent comparison area based on the distance from the nearest designated TIF district for each proximity specification. Figure 4.5 illustrates the distance buffers used to construct the spillover and comparison areas for each spillover proximity specification.

Figure 4.5. TIF District Spillover and Comparison Area Buffers and Residential Property Sales



Homes that fall within the previously defined excluded areas are not included in the analysis. In addition, the study is limited to arm's length transactions in which buyers and sellers have no relationship to each other and the selling price reflects demand. Other restrictions used to exclude property sales records are outlined in section 4.2.3. For this analysis, sales within the TIF district are excluded as spillover effects are estimated.

Using the difference-in-difference fixed effects model expressed in equation 3, T equals 1 for sales transaction within the spillover area of a TIF that has been designated at the time of the transaction and is 0 otherwise. The variable t represents the time trend, where t equals 1 if the sale occurred after the nearest TIF's year of designation and is valued as 0 if it occurred before designation. For the property sales outcomes, the place-specific fixed-effect component ω_i varies across the census block just as with the model for the job and permit outcomes, however, the time-dependent fixed-effect ($\lambda_{t,}$) relates to the quarter during which the house was sold, rather than year.

Ultimately spillover is identified where the coefficient δ is significant, indicating that the null hypothesis that there is no relationship between spillover areas and comparison areas can be rejected. A negative coefficient suggests that there is less appreciation observed in proximity to the TIF district. It follows then that TIF designation effects are likely positively biased. A positive coefficient implies a negative bias.

4.4.3 Spillover and Residential Property Sale Appreciation with Repeated Sales Models

Housing is a basic need, a necessity. According to Galster (1996), it is also a special type of commodity, one that is spatially immobile, highly durable, highly expensive, multi-dimensionally heterogeneous, and physically modifiable. Its condition and location often determines one's access to transportation, quality education, services, economic opportunity, and a healthy environment.

Previous studies of the spillover effects of TIF designation on residential property sales have used hedonic price regression and a cross-section of sales transactions within varying distances from TIF districtss to estimate price appreciation (Smith, 2009). These models determine sales price appreciation using the structural characteristic of the property, neighborhood characteristics, and the home's location in proximity to neighborhood amenities and resources.

As an example, equation 6 represents a cross sectional model of sales price appreciation:

$$\ln P_{it} = \delta T_{it} + \beta S_i + \gamma L_i + \lambda_t + v_i + \varepsilon_i \qquad (6)$$

In this model, the natural log of the sales price of a home is a function of its proximity to the nearest TIF and the characteristics of that TIF district (T), the structural characteristics of the property (S), and proximity to neighborhood amenities and resources (L). The coefficients of these independent variables are interpreted as the percentage change in housing price appreciation resulting from a one-unit change in the independent variable corresponding to the coefficient.

The structural characteristics of each parcel indicating housing condition and quality include age and square footage of the building, and presence of a basement, deck, enclosed porch or a garage. These indicators of property condition are derived from the 2013 release of MdProperty View. To measure each property's proximity to neighborhood amenities and resources, ArcGIS was used to calculate the distance between each property sold and the nearest bus stop, light rail station, commuter train station, subway stop, university, and location of the central business district (census tract 401). These measures indicate a property's access to transportation modes, anchor institutions that act as the economic drivers in Baltimore neighborhoods, and proximity to the most concentrated area of market activity in the city.

Most importantly, the study identifies the nearest TIF and the characteristics of that TIF, including the number of years after it was designated that the sale occurs, measuring the duration of a home's exposure to TIF, and finally the actual distance to the TIF expressed as indicator values of 1 for sales located in the spillover area. Buffers are created to identify property sales within .125, .25, and .5 mile from TIF districts.

Using this kind of cross sectional hedonic price model does not account for time invariant observables that may be correlated with proximity to TIFs. However, panel methods that remove these unobservable factors are increasingly used to estimate sales price appreciation in other policy areas and in the study of TIFs. The spillover analysis in the preceding section using a difference-in-difference fixed effects model is one such panel methodology. The repeat sales methodology is another.

Taking advantage of homes that have sold more than once during the study period, following previous studies investigating the relationship between TIF designation and the associated effect on property values this study uses a repeat sales methodology to estimate spillover that further eliminates time invariant observables and selection bias as most homes are unlikely to have changed significantly between sales (Weber, Bhatta, & Merriman, 2007). The analysis is restricted to the first and last sales transaction for a parcel between 2002 and 2013. Additionally, using property sales beginning in 2002, it is possible to distinguish between repeat sales in relation to the designation year of the nearest TIF. To further test the impact of TIF designation on property sales prices, a specification with only observations where the first sale occurred prior to designation and the last sales after designation is included in the analysis.

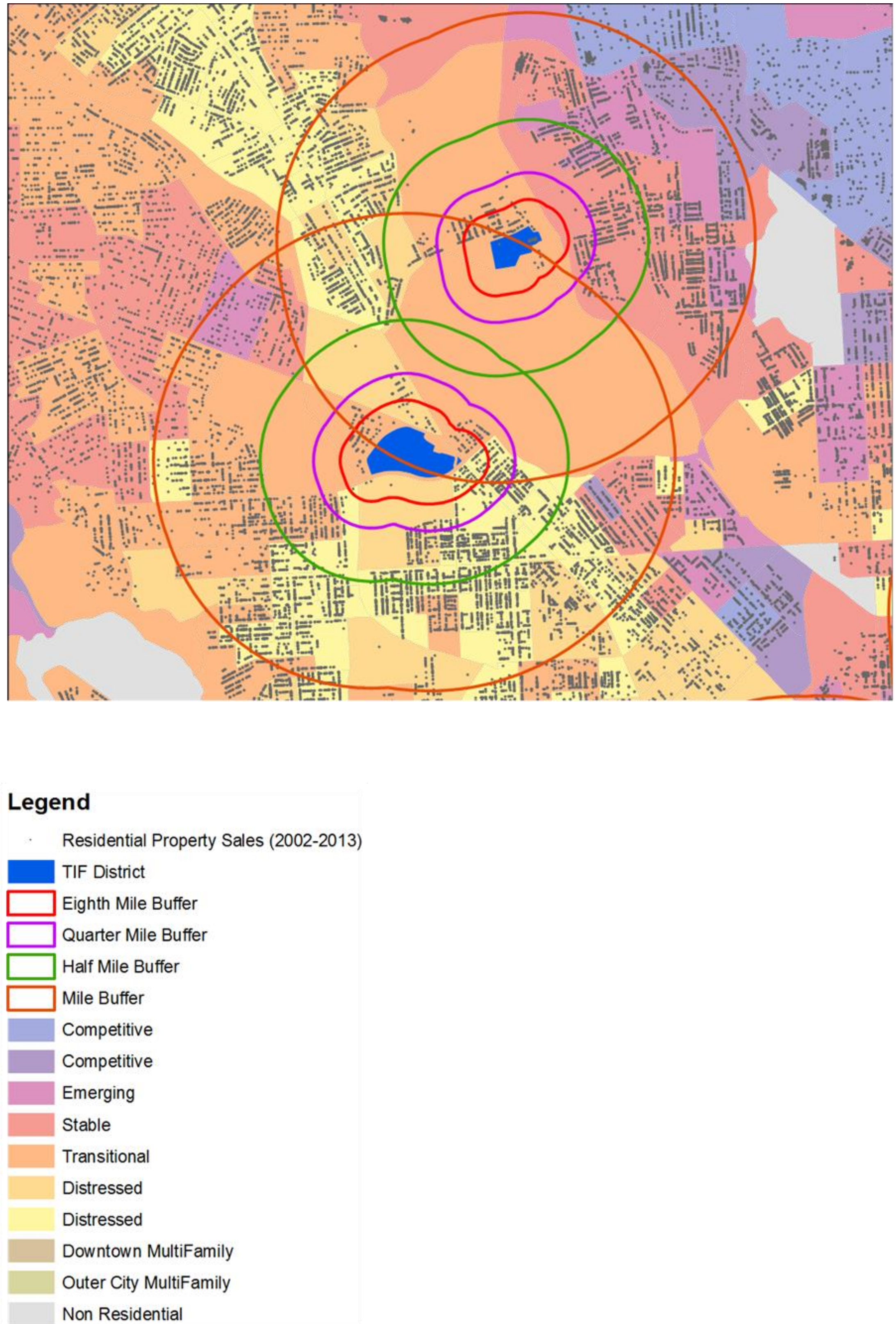
Equation 7 expresses the repeat sales model:

$$\Delta \ln P_i = \alpha_i + \delta T_i + \gamma t_{it} + \lambda_t + \omega_i + \varepsilon_i \qquad (7)$$

Here, the unit of analysis (i) is the individual residential sales transaction in Baltimore City. The dependent variable (P_i) is the natural log of the price difference between the first and last sale of a residential property. The variable T is an indicator of distance that equals 1 if the home falls within an eighth, quarter, or half mile distance from a TIF district. The t variable is equal to 0 for the first sale occurrence and 1 for the last sale. Without a comparison group, the model is essentially a before-after estimator. The time invariant controls are not included in this panel model due to the inclusion of geographic fixed effects at the census block level of geography, represented by ω_i in the model. A set of dummy variables, $\lambda_{t,}$ represent the quarter in which a sale occurred. Lastly, εit is the random error term.

The study also distinguishes heterogeneous effects across housing market typology categories for both the DID and repeat sales methodologies: competitive, emerging, stable, transitional, and distressed. It is hypothesized that Baltimore City's housing market typology serves as an indication to prospective homebuyers the willingness of the public sector to make investments in a neighborhood. Those expectations are capitalized into homebuyers' willingness to pay a higher sales price. Therefore the spillover effects of TIFs will likely differ by typology as competitive, stable, or emerging housing markets experience sales price increases, a hypothesis that can be tested with separate models of sales appreciation for each typology. Limiting observations to those where a home sold more than once can also be a shortcoming of the repeat sales methods as some homes are more likely to sell multiple times. Estimating the spillover effects by housing market typology attempts to account for this shortcoming as the robustness of the repeat sales model is tested across homes in different housing markets. Figure 4.6 illustrates Baltimore City's 2005 Housing Market Typology together with property sales and distance buffers.

Figure 4.6. 2005 Housing Market Typology and Residential Property Sales with Distance Buffers



5 RESULTS AND DISCUSSION: TIF DESIGNATION EFFECTS WITH PROPENSITY SCORE ESTIMATION

In this chapter, TIF designation effects are estimated to address this study's first five research questions. For employment, building permit activity, and residential property sale outcomes, the difference-in-difference research design is used to compare TIF and non-TIF block groups before and after TIF designation. To address the selection bias inherent in this kind of analysis due to pre-designation characteristics of block groups, the propensity score analysis identifies non-TIF designated block groups that are economically similar to TIF designated block groups. The dissertation contributes to the gap in the literature by using these advanced econometric research designs together with data available at small levels of geography to determine the extent to which TIF districts impact the outcomes of interest in this study.

The first section presents the propensity score analysis and the result of the probit regression and the propensity scores derived from demographic, socioeconomic, neighborhood, and land use indicators. These propensity scores are used to weight observations in the difference-in-difference analysis.

Next, the effects of TIF designation on job outcomes are explored using the Census Bureau's LODES data. Specifically, the analysis focuses on the growth of total jobs and local jobs as well as the distribution of jobs by industry and wage categories. In the final section, the relationship between TIF designation and private investment is explored with building permit activity and residential property sales data aggregated to the block group. The count and value of permits and residential sales are the outcomes of interest, along with permit values across residential and commercial investments and residential properties by the home type. Effects for all outcomes are observed for mixed TIF districts and residential TIF districts. For both employment and private investment outcomes, sensitivity analysis involves observing TIF designation effects using propensity score matching techniques instead of propensity score weighting.

5.1 Propensity Score Estimation Results

TIF block groups are identified as those containing or intersecting the seven Baltimore City TIF districts of interest in this study. In the interest of unbiased DID estimates non-TIF block groups used for comparison should be similar to those TIF block groups.

Table 5.1 presents the mean values of demographic, socioeconomic, housing, and neighborhood indicators from the 1990 and 2000 Census and land use indicators from administrative shapefiles for the 16 TIF block groups and the 694 non-TIF block groups. While Baltimore City doesn't have explicit criteria that determine TIF district designation eligibility based on these characteristics, they represent the factors that are likely taken into consideration for siting a project and selection for designation. A t-test is used to compare the mean values of the indicator variables for the treatment and comparison groups.

As the asterisks in column 5 indicate, TIF block groups have significantly higher vacant property rates, poverty rates, and a decrease in population between 1990 and 2000 compared to all non-TIF block groups. The poverty and vacancy rates lend themselves to the theory that TIF districts are designated in blighted areas or areas where the cost of redevelopment or the return on investment would be unfavorable to developers, thus requiring public subsidies.

Although not significant it is important to note that the minority population is nearly 13 percentage points higher in TIF block groups and while the median housing value is $20,000 less than non-TIF block groups, the rent is slightly higher. Disaggregating the mean values for all TIF block groups into the means for mixed and residential TIF block groups provides some insight for these trends as residential TIFs have an average median rent nearly $300 higher than both

Table 5.1. Mean Values of Block Group Characteristics by TIF Designation and TIF Type

	All TIF Block Groups	Mixed TIF Block Groups	Residential TIF Block Groups	Non-TIF Block Groups	All TIF vs. Non-TIF Difference	All TIF vs. Non-TIF Weighted Difference
Population (2000)	745	674	1056	921	-176	-172
Population Change (1990-2000)	-283	-279	-298	-116	-167*	-160
Households (2000)	298	251	501	365	-67	-71
Household Change(1990-2000)	-65	-75	-24	-25	-40	-40
Percent Vacant (2000)	0.224	0.253	0.100	0.150	0.075*	0.074
Median Household Income (2000)	$27,193	$23,497	$43,208	$31,551	-$4,358	-$4,602
Median Housing Value (2000)	$49,019	$41,900	$79,867	$69,851	-$20,832	-$21,221
Gross Rent (2000)	$578	$513	$857	$510	$68	$62
Percent Movers within Last 5 Years (2000)	0.488	0.444	0.680	0.440	0.048	0.047
Percent Owner-Occupied (2000)	0.453	0.470	0.378	0.528	-0.075	-0.073
Unemployment Rate (2000)	0.170	0.189	0.089	0.124	0.046	0.046
Percent Not in Labor Force (2000)	0.469	0.508	0.300	0.432	0.037	0.037
Percent Poverty (2000)	0.363	0.399	0.207	0.234	0.129**	0.127
Percent Minority Population (2000)	0.821	0.859	0.657	0.693	0.129	0.123
Percent Public Assistance (2000)	0.110	0.118	0.072	0.084	0.025	0.026
Percent College Graduates (2000)	0.150	0.132	0.225	0.173	-0.023	-0.023
Percent Commercial Land Use (2002)	0.098	0.083	0.160	0.077	0.020	0.020
Observations	16	13	3	694		

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

mixed TIF block groups and non-TIF block groups. Additionally, the average median housing value is $79,867 for residential TIF block groups, $41,900 for mixed TIF block groups and $69,851 for non-TIF block groups.

In this study, it is necessary to identify non-TIF block groups that are demonstrably similar to or only randomly different from TIF block groups to reduce selection bias of estimated TIF designation effects attributable to differences in initial pre-designation characteristics. Therefore, TIF designation is expressed as a function of relevant demographic, housing, socioeconomic, and land use indicators prior to designation. The results of the probit regression expressed in equation 4 are in table 5.2.

Table 5.2. Probit Estimates Indicating TIF District Designation

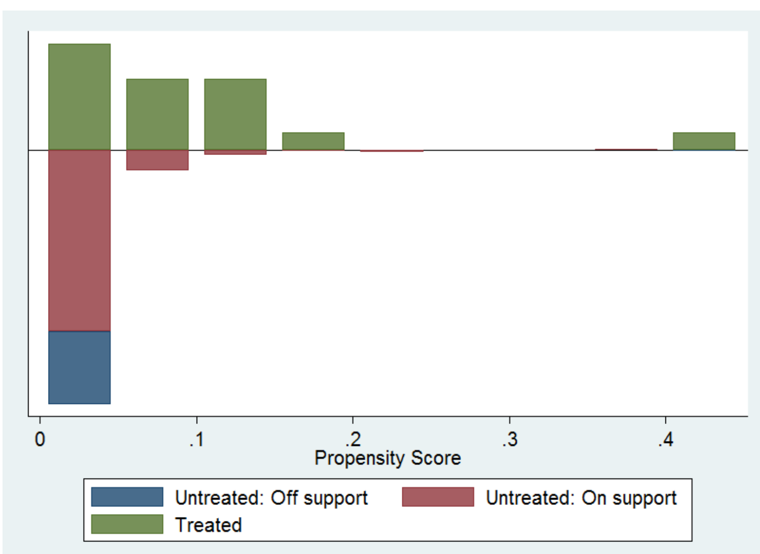
	Probability	Std. Error
Population (2000)	-0.0009	0.001
Population Change (1990-2000)	-0.0007	0.001
Households (2000)	0.0018	0.002
Household Change(1990-2000)	-0.0001	0.002
Percent Vacant (2000)	-0.3892	0.936
Median Household Income (2000)	0.0000	0.000
Median Housing Value (2000)	-0.0000**	0.000
Gross Rent (2000)	0.0021*	0.001
Percent Movers within Last 5 Years (2000)	0.4860	0.756
Percent Owner-Occupied (2000)	0.8630	0.952
Unemployment Rate (2000)	0.1076	1.606
Percent Not in Labor Force (2000)	-0.6018	1.289
Percent Poverty (2000)	3.3754**	1.066
Percent Minority Population (2000)	0.9216	0.686
Percent Public Assistance (2000)	-0.8608	1.506
Percent College Graduates (2000)	0.6687	1.457
Percent Commercial Land Use (2002)	0.3019	0.817
Constant	-4.8600**	1.530
Log likelihood	-61.3191	
Pseudo R^2	0.1960	
Observations	700	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In this model there are three significant indicators. Among them, the percentage of residents with incomes below the poverty threshold and the gross rent are both positively related to TIF designation while the median value of owner-occupied homes is negatively related to TIF designation. These results suggest that the probability of a block group being designated as a TIF district is determined by a neighborhood's economic distress as determined by high poverty and low-home values, but also the neighborhood's stage of transition as higher rents indicate increased demand relative to non-TIF block groups. The results of the probit regression are primarily used to calculate a propensity score for each block group by reducing indicator values to a single score that represents the probability of a block group receiving TIF designation.

One of the main assumptions of propensity score estimation is that there is a relatively large common support, where the distributions of propensity scores for TIF and non-TIF block groups overlaps (Heckman, Ichimura, and Todd, 1997). Whether this assumption holds is first tested with a graphical representation of propensity scores. Figure 5.1 illustrates the distribution of propensity scores, probabilities valued between 0 and 1, and the overlap of propensity scores for treated (green) and untreated (blue and red) block groups.

Figure 5.1. Distribution of Propensity Scores of TIF and Non-TIF Block Groups by Common Support



The region of common support where the distribution of propensity scores for the treatment and comparison group overlap is between .00252528 and .40107386. In this analysis these values represent the lowest and highest calculated propensity scores for all 16 treated block groups. Of the 694 untreated block groups in Baltimore City that do not intersect the subset of TIF districts in this analysis, 510 are "on-support", meaning they fall within this range of propensity scores. The untreated units that are "off-support" include the 10 non-TIF block groups with no population or housing and thus were dropped from the propensity score estimation as well as the remaining 175 off-support block groups with propensity scores that are not within the region of common support. This demonstrates support for the assumption of a large region of common support and subsequent estimation of treatment effects only includes observations within this range of propensity scores. For those block groups within the common support region, the overall average probability to be designated is 2.9 percent, and is 9.2 percent for TIF block groups and 2.7 percent for non-TIF block groups.

As discussed in Chapter Four, as an alternative to using propensity scores to match treated and untreated units that results in reduced observations, the propensity scores are used to derive the normalized inverse nonparametric estimate of the propensity scores, or the inverse probability of treatment weights (IPTW). Treated units receive a weight equal to the inverse of the estimated propensity score (1/Pr), and untreated units receive weights of (1/1–Pr). Weights are then normalized to one, mimicking randomized assignment in that all units are considered conditionally interchangeable and therefore the selection bias of estimates due to pre-designation characteristics of block groups is reduced. These weights are included in the panel fixed effects model in the difference-in-difference estimation.

In table 5.1 above, the sixth column represents the difference in the means for TIF and non-TIF block groups within the common support region after weighting. The results of the comparison of mean values indicate that vacancy rate, population change between 1990 and 2000, and the poverty rate indicators are no longer significantly different and that treatment and comparison groups are now balanced.

5.2 TIF Designation Effects using DID with Propensity Score Estimation

5.2.1 TIF Designation Effects on Job Outcomes

The rationale proffered by municipalities and private developers is that using TIF to finance the infrastructure of development projects that otherwise would not be completed ultimately attracts businesses and creates or retains jobs in the TIF district. As previously discussed, there are only a few empirical studies estimating the impact of tax increment financing on employment outcomes (Man, 1999; Byrne, 2010; Lester, 2014).

To contribute to this body of research, this study investigates the relationship between TIF designation and employment for select TIF districts in Baltimore City. Using LODES data with job counts aggregated to the block group level of geography, the analysis below addresses the first four research questions: (1) Does TIF designation facilitate job growth in TIF districts? (2) Does TIF designation increase the employment of local residents? (3) What is the relationship between TIF designation and the distribution of low, moderate, or high-wage jobs? and (4) What is the relationship between TIF designation and the distribution of jobs by industry for retail, leisure, and hospitality industries, goods-producing and export driven industries, and educational and health services industries?

Descriptive Analysis of Job Outcomes

For the entire city between 2002 and 2013 the highest number of private jobs was 248,287 in 2002, the lowest was 235,711 in 2010. In 2013, the last year of available data, the number of total jobs was 245,434 and the number of local jobs, or jobs where city workers also live in Baltimore, was 102,936 (41.9 percent)

Examining overall trends of total jobs across TIF block groups and non-TIF block groups, figure 5.2 illustrates mean jobs for years 2002-2013 for total jobs and local jobs in the first graph, jobs by industry in the second graph and jobs by wage category in the third graph. While the official period for the most recent U.S. recession is between December 2007 and June 2009, the red lines in each graph approximate this time frame.

The graphs show that the trend for jobs is relatively consistent over time for TIF and non-TIF block groups. The average number of jobs for all years in all block groups is 674, 326 for non-TIF block groups, and 1,022 for TIF block groups. In addition, for TIF block groups there is more variation across the years. As many as 95 and as few as 42 block groups have a count of 0 jobs, in 2003 and 2013, respectively. Most of these are non-TIF block groups.

For local jobs, there is an overall average of 117 workers in a block group who also live in Baltimore City. Over time, the average decreased from 141 in 2002 to 109 in 2013. Across TIF designated block groups, there is a larger gap between total and local jobs for TIF block groups as the average of local jobs is 112 for non-TIF block groups and 360 for TIF block groups.

Although the average number of jobs decreases over time from 701 jobs to 647 jobs during the study period, educational and health services jobs are far and away the industry category with the greatest number of jobs in TIF block groups. For non-TIF block groups, the average slightly increases from 94 to 114 within this industry. Retail, leisure, and hospitality jobs increased from 124 in 2002 for TIF block groups to 186 in 2013 while the average for non-TIF block groups is consistent across time with an average of 50 jobs in this industry. With respect to wages, TIF Block groups experienced an increase in the average high wage jobs from 414 to 609 and a decrease in moderate wage jobs from 497 to 307. The pattern is the same for non-TIF block groups but with a smaller magnitude—an increase from 112 to 160 for high wage jobs and a decrease from 144 to 116 for moderate jobs. The highest number of low wage jobs was 182 in 2002 and the lowest number was 111 in 2010 for TIF block groups. By 2013 the average number of jobs in this wage category was 151. For non-TIF block groups low wage jobs increased steadily from 112 to 160.

Of course, more than average annual trends are needed to estimate the relationship between TIF designation and the growth of total and local jobs and jobs by industry and earnings. This analysis uses a difference-in-difference research design to that end. DID estimates TIF impact by taking the post-designation mean difference in job counts for designated and non-designated block groups and subtracts the pre-designation mean difference.

Rather than total job counts, the outcome of interest is the log of jobs for each outcome of interest. The histograms in figure 5.3 visualize the distribution of jobs and the natural log of jobs for total jobs and all other job segments. These graphs demonstrate the need to use the natural log of outcomes to obtain a normal distribution of observations.

DID Estimation of Job Outcomes

The following analysis of the effect of TIF designation on job outcomes uses a DID fixed effects weighted model described in equation 5.

$$\ln Y_{it} = \beta T_{it} + \gamma t_{it} + \delta T_{it} t_{it} + \phi Pr_i + \omega_i + \lambda_t + \varepsilon_{it} \qquad (5)$$

For this model, the natural log of each job outcome is regressed on an indicator of TIF designation, TIF designation in year t, an interaction of both those terms, and a set of year indicator variables. The coefficient of the interaction terms for each job outcome is reported in table 5.3 (year indicator variables not shown). This coefficient is interpreted as the average

Figure 5.2. Mean Jobs by Block Group TIF Designation

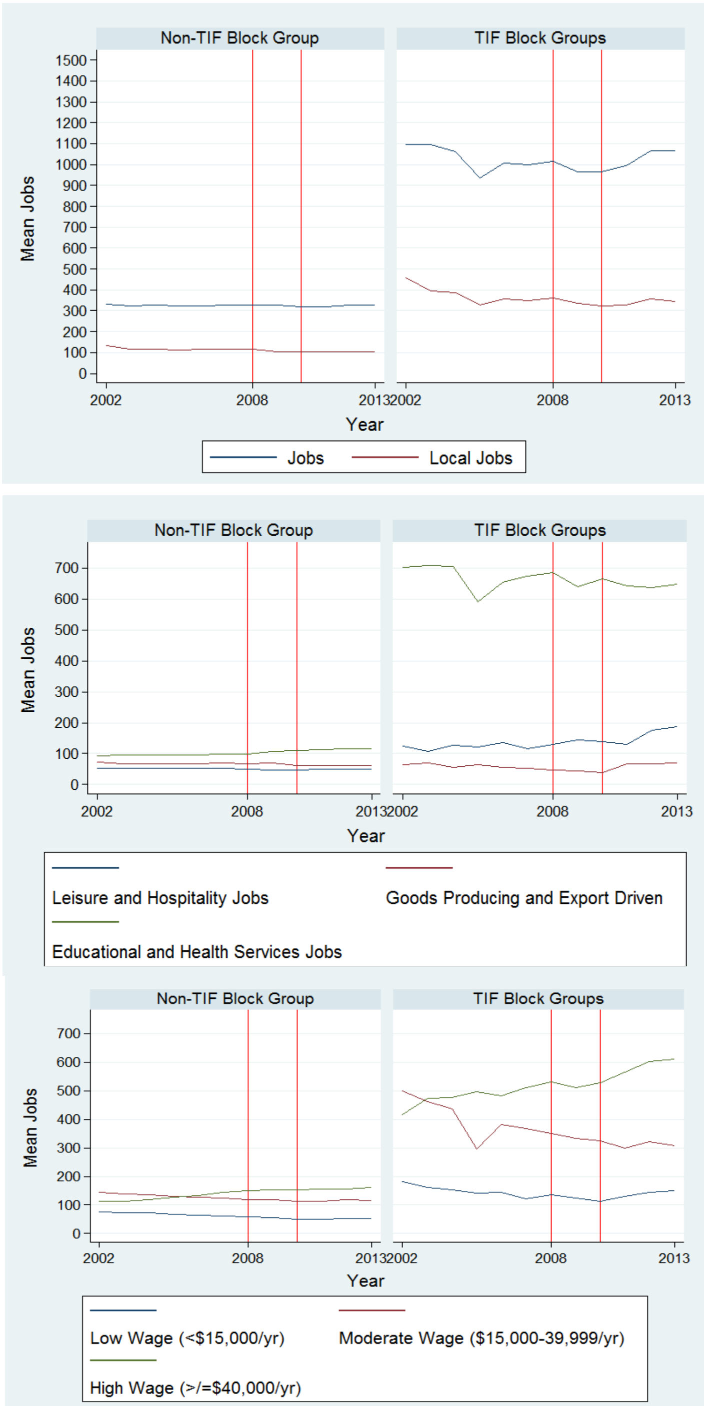
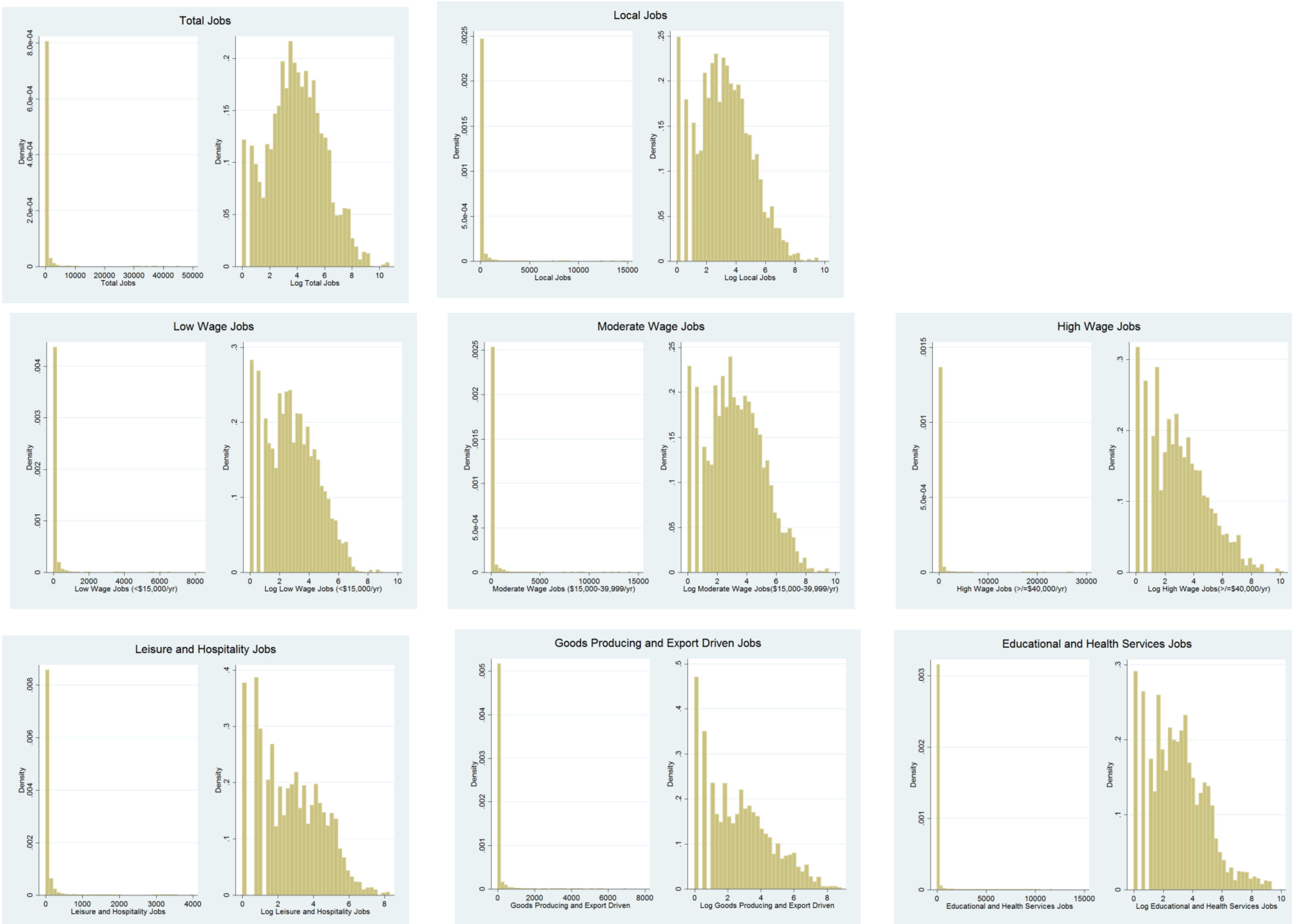


Figure 5.3. Distribution of Job Counts and Natural Log of Jobs (2002-2013)



percentage point change in the number of jobs in treated TIF block groups compared to non-TIF block groups post-designation.

The results of a naïve OLS model and a fixed effects model with no weighting (equation 1 and 3) are presented in columns 1 and 2 of table 5.3. Estimates in column 3 incorporate fixed effects across time and geographic units along with propensity score estimation, weighting both TIF and non-TIF block groups with the inverse propensity score derived from the probit of demographic, socioeconomic, and land use indicators. All models exclude observations that are not within the common support region. Standard errors are clustered by block group across this panel dataset. These standard errors are below the difference-in-difference estimates in table 5.3.

The cross sectional naïve OLS estimates of TIF designation effects are upwardly biased and are quite large. The results suggest that there is near or over a significant 100 percentage point increase in jobs in TIF block groups compared to non-TIF block groups for local jobs, goods producing and export driven jobs, and both moderate and high wage jobs. These results illustrate the need to address omitted variable bias, specifically selection bias.

Using fixed effects reduces these biased cross-sectional estimates such that time invariant unobservable factors that vary within a block group over time are eliminated. Not only are the fixed effects estimates in column 2 smaller in magnitude compared to OLS estimates, many of the coefficients are now negative for all job outcomes except for the retail, leisure, and hospitality industry jobs and low wage jobs. Of these job outcomes, only the coefficient for the moderate wage category is statistically significant indicating a -39.3 percentage point decrease in the natural log of jobs in TIF block groups compared to non-TIF block groups.

Across the findings for the DID fixed effects weighted model in column 3, the job outcome estimates are also largely insignificant. Taking into account the sign and magnitude of these insignificant estimates, for total jobs the model yields a negative coefficient. While these results conflict with the expected sign based on theory about the relationship between TIF designation and employment, it mirrors the estimated insignificant effects observed in other studies. Local job estimates are also negative and slightly larger than total jobs indicating that there was a larger decrease in jobs held by Baltimore City residents in TIF block groups than for total jobs overall. The moderate wage job estimate is the only significant job outcome, suggesting a -25.7 percentage point decrease in jobs at the 5 percent level of significance. The estimate for high wage jobs above $40,000 is insignificant yet has relatively smaller negative estimates than the moderate earnings category. For these total, local, moderate, and high wage jobs these estimates are all negative for the non-weighted fixed effects model and smaller yet still negative for the weighted fixed effects model.

While insignificant, low wage job estimates are all positive, indicating a 8.8 percentage point increase in jobs below $15,000 annually. While both insignificant and positive, the coefficient for those industries that comprise the retail, leisure, and hospitality category of jobs indicates an increase of 26.3 percentage points. For both these positive estimates, the fixed effects coefficients are consistent and larger after propensity score weighting but are still insignificant.

For goods-producing and export driven job estimates, the estimate is negative and the magnitude is larger with weighted observations. This -43.6 percentage point decrease is the largest estimate in magnitude among all job outcomes. The educational and health services coefficient nears zero in the weighted model. This is the only job outcome where the fixed effects coefficient changes sign after weighting.

Table 5.3. TIF Designation Effects on Job Outcomes

	OLS	Fixed Effects	Fixed Effects Weighted
Log Total Jobs	1.547*	-0.168	-0.067
	(0.604)	(0.115)	(0.102)
	n=2,670	n=7,688	n=5,529
Log Local Jobs	1.240*	-0.301	-0.092
	(0.587)	(0.173)	(0.114)
	n=2,508	n=7,297	n=5,167
Log Retail, Leisure, and Hospitality Jobs	1.586**	0.194	0.263
	(0.527)	(0.176)	(0.140)
	n=2,040	n=5,868	n=4,177
Log Ed. and Health Services Jobs	0.559	-0.273	0.020
	(0.768)	(0.382)	(0.187)
	n=1,750	n=4,874	n=3,279
Log Goods Prod. and Export Driven Jobs	0.848	-0.244	-0.436
	(0.491)	(0.314)	(0.263)
	n=1,598	n=4,775	n=3,152
Log Low Earnings Jobs	1.278*	0.064	0.088
	(0.521)	(0.152)	(0.104)
	n=2,450	n=7,191	n=5,100
Log Mod Earnings Jobs	1.449**	-0.393**	-0.257*
	(0.551)	(0.151)	(0.106)
	n=2,527	n=7,262	n=5,154
Log High Earnings Jobs	1.511*	-0.132	-0.117
	(0.664)	(0.158)	(0.100)
	n=2,297	n=6,549	n=4,516

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2.2 TIF Designation Effects on Permit Outcomes

<u>Descriptive Analysis of Permit Outcomes</u>

In this section, the fifth research question examining the effect of TIF designation on private investment is also analyzed. This dissertation ultimately seeks to determine whether this theorized impact of TIFs on private investment exists by estimating the effect of TIF designation on the number and amount of permits for TIF block groups after designation using propensity score-weighted DID estimation.

Property owners and developers are required to obtain permits from Baltimore City's Department of Housing's Office of Permits & Building Inspections for the construction, alteration, and improvement of residential, commercial, and institutional structures. Between 2000 and 2013 there were a total of 16,242 permits issued above $50,000 in Baltimore City, varying in size and scope. The largest permit issued during the study period was a $460 million permit related to construction of Johns Hopkins Hospital near the EBDI TIF. The largest residential permit issued was in the amount of $82.5 million for a multi-family condo development near the Harbor View TIF. Most permits are much smaller in value, with 92% below $1 million and two-thirds below $200k. Overall the average permit value is $729,513 for all permits.

To estimate the effects of TIF designation in this study by comparing economically similar units, permits are aggregated to the block group level of geography. As there are many more non-TIF block groups than those that contain or intersect TIF districts, obviously the majority of permit activity occurs in non-TIF block groups, totaling 15,277 permits. Of the 694 non-TIF block groups, 47 have no permit activity at all during the study period, about 10 percent only have one permit, and about half have fewer than 10 permits. The maximum number of permits concentrated in a non-TIF block group is 1,187. Within TIF block groups, there were a total of 965 permits issued, with between an aggregated count of 1 and 169 permits issued.

The top panel of figure 5.4 graphs the mean count and value of permits across years by designation status. There is considerable variation across TIF block groups compared to non-TIF block groups, again, likely due to the disparate number of geographic units in each group. Between 2000 and 2013 the average aggregate number permits issued for non-TIF block groups alternated between 1 and 2. However, for TIF block groups, the average sum of permits in TIF block groups was always slightly higher and reaching a number of 7 in 2004 and 2005. The average aggregated permit value non-TIF block groups was $2.3 million in 2008, the highest average between 2000 and 2013. Following that year, the average aggregate permit value ofr non-TIF block groups considerably decreased for years 2009 through 2011 under to under $1 million. For TIF block groups, aggregated permits averaged nearly $16.5 million in in 2006. The average continued to steadily decrease through 2009. In 2010 the rend reversed and aggregate values reached a second highest peak of $9.3 million in 2011. In 2013, the average of aggregate for non-TIF block groups was $1.4 million and $1.1 million for TIF block groups.

This dissertation is interested in the heterogeneous impacts of TIF designation by permit type. Across all individual permits, the average residential and commercial permit values are $263,494 and $921,963, respectively. The bottom panel of figure 5.4 shows trends of the average aggregate of permit values for residential and commercial permits by block group TIF designation status. In the first two years of the study period, the average aggregate for non-TIF block groups was less than $50,000 as the majority of block groups did not have any residential permit activity. By 2006 the average aggregate value increased to slightly above half a million dollars and then decreasing through 2010 before increasing through 2011 and 2013.

The average aggregate value of residential permits for TIF block groups also experienced initial low values between 2000 and 2003 before increasing to $1.1 million in 2004 and reaching a peak of $3 million in 2005. In the subsequent years, the sum of permits decreased but following no specific pattern. By 2013, the average aggregate for non-TIF block groups was $137,284 and $120,291 for TIF block groups. Aggregate commercial permits issued averaged between about $200,000 and $400,000 for non-TIF block groups between 2000 and 2007 before reaching a peak of $1.4 million in 2008. In the following years, the average sum of these kinds of

Figure 5.4. Mean Number of Permits and Permit Amounts by Block Group TIF Designation

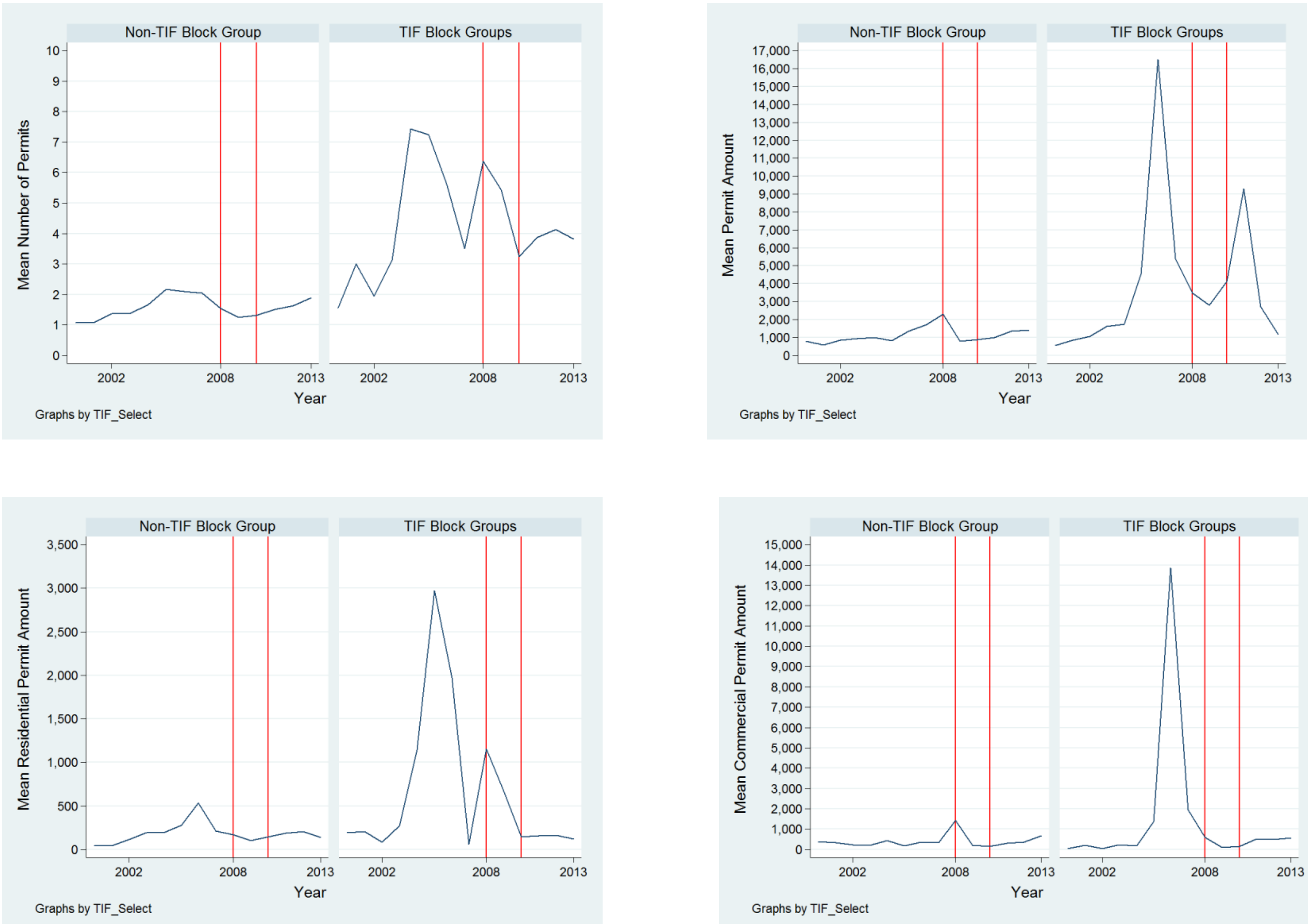
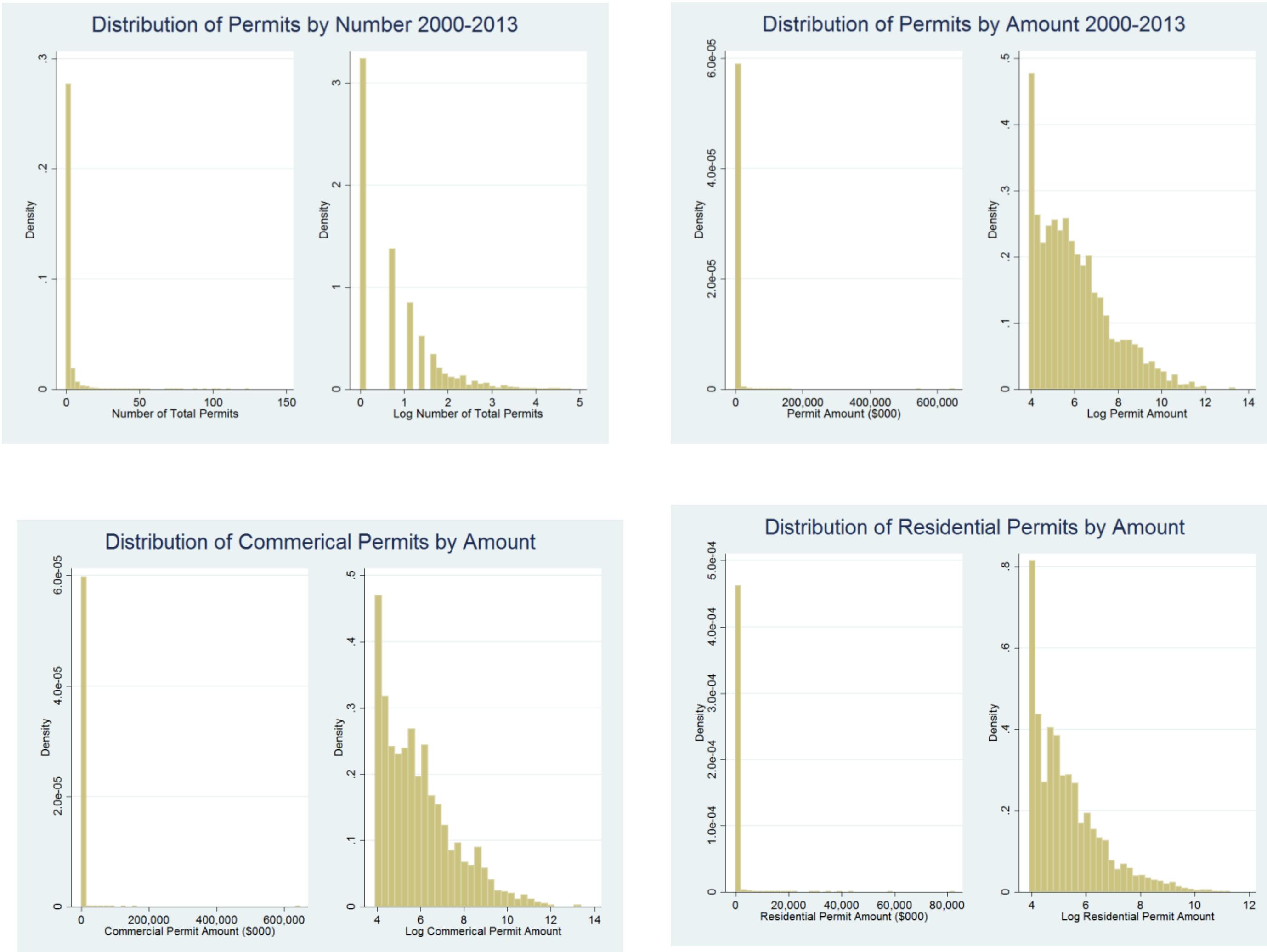


Figure 5.5. Distribution of Permits by Number and Amount (2000-2013)



permits for non-TIF block groups returned to values in previous range before increasing up to $667,488 in 2013. For TIF block groups there is no clear pattern of aggregate commercial permit activity except the peak of $13.8 million in 2006 with averages over $1 million in the year immediately prior and after in 2005 and 2007.

The graphs of average aggregates of permit activity for non-TIF and TIF block groups in figure 5.4 show us that both the mean number and amount of permits trend downward for total permits during the most recent recession period. In addition, disaggregating aggregate permit amounts by permit type demonstrates that permit activity substantially varies for residential and commercial permits.

The histograms in figure 5.5 illustrate the distribution of the count and value of permits aggregated to the block group. The distribution of the natural log of the permit outcome measures is still not quite a normal distribution but is improved compared to the raw values and are used to analyze the percentage change in permit activity with the difference-in-difference methodology, with and without weighting observations based on the propensity score. The results of this analysis are reported in the next section.

DID Estimation of Permit Activity

In the first column of table 5.4, estimates of the naïve cross-sectional OLS model indicate significant increases in overall permit activity in TIF block groups compared to non-TIF block groups. More specifically, there is a 46 percentage point increase in the log number of permits and a 70.7 percentage point increase in the log of the aggregated permit value at the 1 and 5 percent level of significance, respectively. These large and biased coefficients demonstrate the need to use a more advanced econometric methodology such as the difference-in-difference strategy.

In the fixed effects model the log of the aggregated count of permits and their values are dependent variables regressed on an indicator of TIF designation, year, an interaction of designation and year, along with a set of year indictor variables. The results in column two correspond to equation 3 while the estimates in the third column represent the results using equation 5 that includes IPTW inverse probability of treatment propensity score weighting.

Based on the results of the DID fixed effects weighted model, the insignificant coefficients suggest that there was no difference in the number of permits issued and the total permit values in TIF block groups after designation compared to non-TIF block groups.

Table 5.4. TIF Designation Effects on Permit Activity Outcomes

	OLS	**Fixed Effect**	**Fixed Effect Weighted**
Log Number of Total Permits	0.460**	0.044	0.006
	(0.172)	(0.212)	(0.141)
	n=1,282	n=4,027	n=2,757
Log Amount Total Permits	0.707*	-0.354	-0.389
	(0.300)	(0.348)	(0.239)
	n=1,282	n=4,027	n=2,757
Log Amount Residential Permits	0.183	-1.226*	-0.421
	(0.272)	(0.563)	(0.349)
	n=792	n=2,475	n=1,536
Log Amount Commercial Permits	0.352	-0.166	-0.590*
	(0.346)	(0.335)	(0.282)
	n=450	n=1,464	n=945

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Propensity score weighting appears to make the most difference when examining permit values by permit type. The significant coefficient of the interaction terms in column 3indicates that there is an average -59 percentage point decrease in the amount of commercial improvements over $50,000 for establishments that include for offices, industrial sites, auto repair shops, and hotels.

5.2.3 TIF Designation Effects on Residential Property Sales

Descriptive Analysis of Residential Property Sales Outcomes

Based on transaction data made available from Maryland Department of Planning's Md PropertyView, after data cleaning, there were 93,275 residential property sales in Baltimore City between 2002 and 2013. Each property sale record in the dataset includes the date of the sales transaction and the amount of consideration for the sale.

The overall average residential property sale price is $158,753 and the maximum sale amount is $3,200,000. Sales prices vary considerably by the housing unit type. Table 5.5 presents the total number of sales, the average sales price and the maximum sales price for condominiums, apartments, single-family homes, and townhouses. There is no housing unit type coded in 8,404 sales records.

Table 5.5. Residential Sales Price by Housing Unit Type (2002-2013)

	Condominium	Apartment	Single-Family	Townhouse	Total
Number of Sales	5,283	7,248	16,050	56,290	93,275
Average Sale Amount	$255,689	$66,004	$213,683	$159,532	$158,753
Maximum Sale Amount	$3,240,000	$475,000	$2,520,000	$2,150,000	$3,240,000

Sales prices follow a pattern across time that show home sales were affected by the 2008 recession. Between 2002 and 2007 the average sales price increase each year from $112,149 to $185,073, and decreases until 2009. In 2010 the average then rebounds to $203,497, the highest annual average during the study time period. Then there is a sharp decline in 2011 to the lowest annual average of $142,569 and then subsequently increases.

In this chapter, property sales are aggregated to the block group level of geography. With so few block groups intersecting or containing TIF districts in this study, 91,142 of sales are within non-TIF block groups (97 percent) with the remaining 2,133 in TIF block groups. In TIF block groups, the number of property sales range between 4 and 937. Of the 694 non-TIF block groups

22 have no property sales and the number ranges from 1 to 920 for those containing sales. The maximum number of property sales by TIF designation was 16,007 for non-TIF blocks in 2005 and 395 in 2005 for TIF block groups.

The average annual number and price of aggregated residential property sales are graphed in the top panel of figure 5.6. There is a similar pattern within each category of block groups as the average number of permits issued increases to an average of 20 sales in 2005 and 2006 for both non-TIF block groups and TIF block groups. Similarly, the average aggregate permit value steadily increases between 2002 and 2005, peaking in 2006 at $3.4 million and $6.5 million for non-TIF and TIF block groups, respectively. Sales activity for both TIF and non-TIF block groups follow the overall trend with declines and indicating recovery of demand.

Disaggregation by the type of housing reveals a similar trend of bubble and bust for townhomes, single-family homes, and condominium sales. For townhomes, average annual aggregate sales prices reached a peak of $2 million in 2005 for non-TIF block groups and $3.4 million in 2006 for TIF block groups. These values decreased to lows of $484,741 in 2011 for non-TIF block groups and $689,091 in 2012 for TIF block groups, followed by slight subsequent increases. Single family sales prices follow a similar trend as average aggregate prices increase up to 2005 to $794,972 in non-TIF block groups and $699,798 in 2006 for TIF block groups. This measure is $301,348 and $78,263 in 2013. Condominiums, more variation in TIF block groups, up to $3.2 million in 2005, lowest annual average in 2011 at $267,192. Annual averages are never above $225,000 for non-TIF block groups. There are no apartment sales in TIF block groups between 2002 and 2009 and therefore can't be compared to non-TIF block groups over time.

Per figure 5.7 the natural log of residential sales prices nearly approximate a normal distribution while the distribution for the count of prices improves compared to the distribution of raw counts. The sales price distribution for all housing types follows the same pattern, therefore there is no graph for those outcome measures.

DID Estimation of Residential Property Sales

With regard to residential property sales, TIFs are designated based on the assumption that the assessed value of property in the district will increase as demand for homes in and near TIF districts increases, ultimately increasing the sales prices of homes. The DID estimation of TIF designation effects on residential property sale price appreciation supports this theory.

The naïve OLS model using a cross-section of block groups post-designation from equation 2 yields a statistically insignificant near zero coefficient as the estimate of the impact of TIF designation on the total number of residential sales, indicating no difference of property sales in block groups designated non-TIF and TIF block groups. These results are in the first column of table 5.6 along with this model's positive coefficients of TIF designation effects for all the sales price outcome measures, none of which are significant.

Using the DID fixed effects weighted model, the coefficient for the log number of home sales increased by 40.8 percentage points and by over 121 percentage points for the total sales amount. Both estimates are significant within a tenth of a percentage point. Furthermore, both townhomes and single-family homes experienced significant price increase in TIF block groups, however decreased by 126 percentage points compared to non-TIF block groups after designation.

Figure 5.6. Mean Number and Amount of Residential Property Sales by Block Group TIF Designation

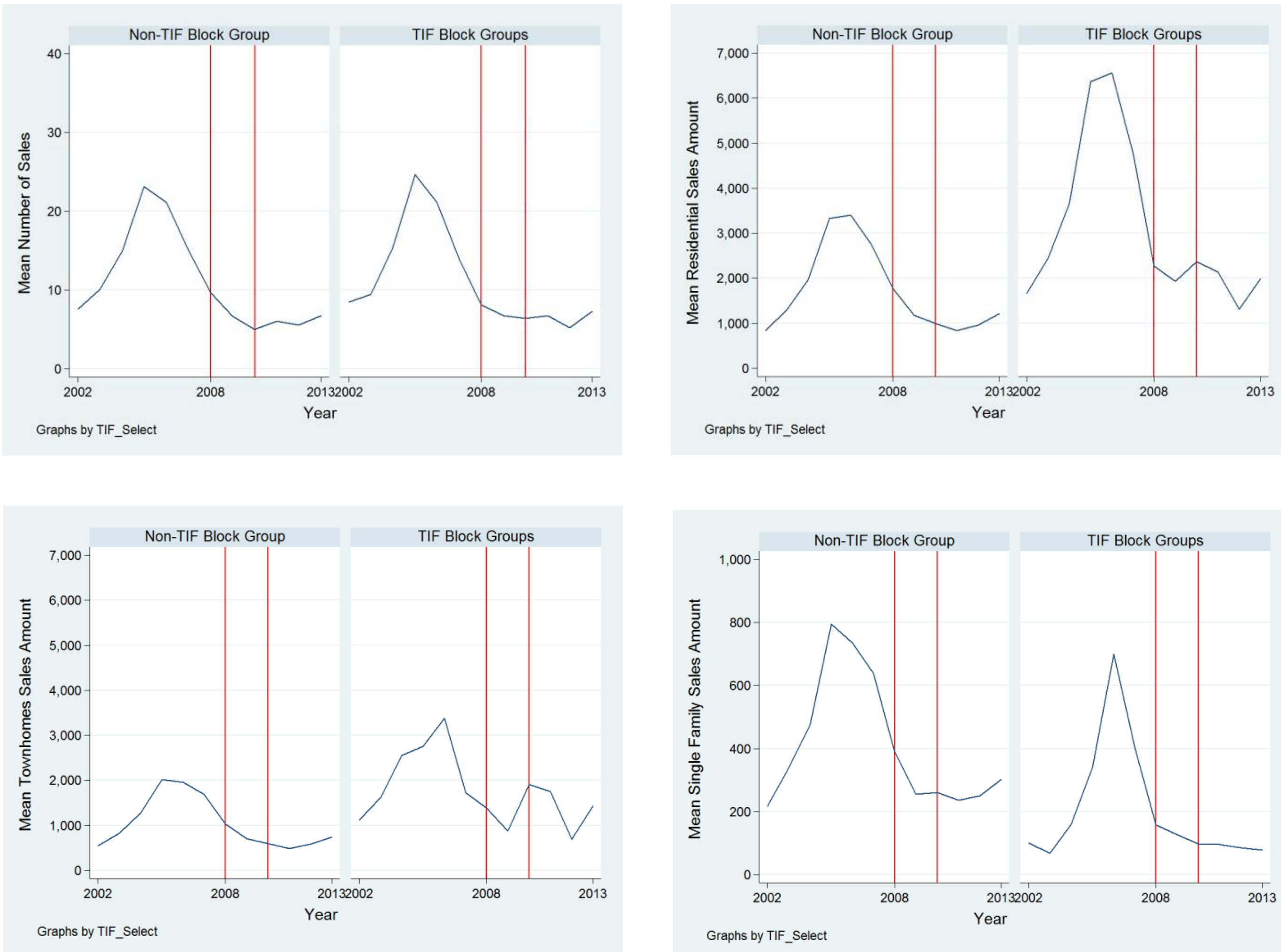
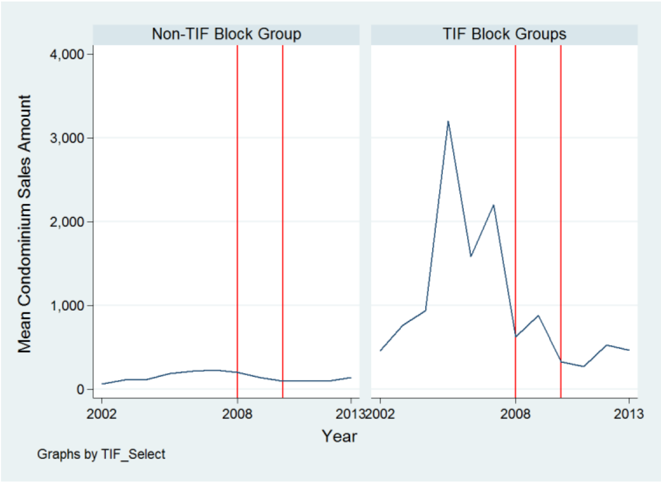


Figure 5.6. Mean Number and Amount of Residential Property Sales by Block Group TIF Designation (cont'd)



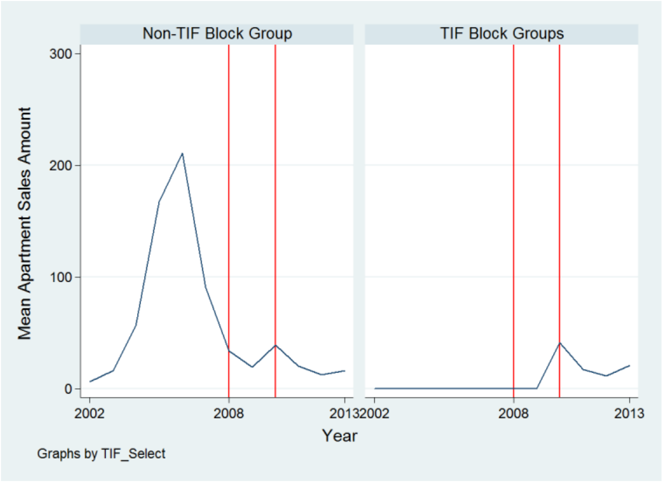
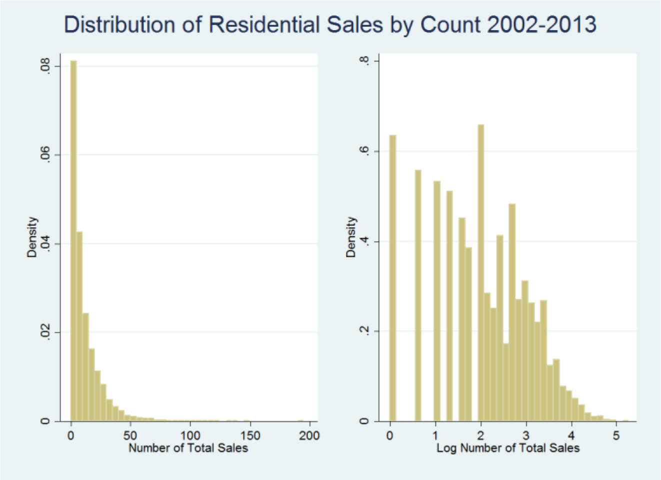


Figure 5.7. Distribution of the Number and Amount of Residential Sales (2002-2013)



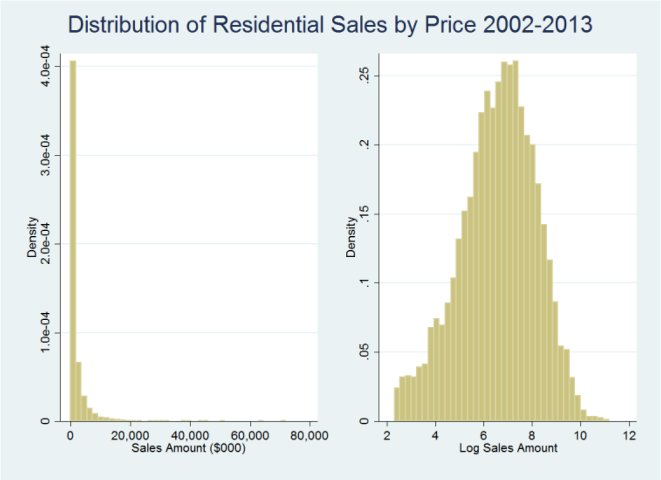


Table 5.6. TIF Designation Effects on Property Sale Outcomes

	Naive	Fixed Effect	Fixed Effect Weighted
Log Total Number Sales	-0.006	0.289*	0.404***
	(0.354)	(0.139)	(0.095)
	n=2,455	n=7,344	n=5,343
Log Amount Total Sales	0.325	0.756**	1.211***
	(0.545)	(0.268)	(0.169)
	n=2,455	n=7,344	n=5,343
Log Amount Townhome Sales	0.755	0.343	1.281***
	(0.624)	(0.289)	(0.263)
	n=1,583	n=5,009	n=3,490
Log Amount Single Family Sales	0.068	0.269	0.178*
	(0.574)	(0.140)	(0.074)
	n=875	n=2,761	n=1,556
Log Amount Condo Sales	0.655	-0.462	-1.261**
	(1.050)	(0.368)	(0.455)
	n=197	n=611	n=305

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3 Subgroup Analysis

Following Byrne's (2010) and Lester's (2014) estimation of TIF designation effects across TIFs based on the type of project financed with the incentive, this subgroup analysis similarly investigates TIF impacts based on the characteristics of the project financed by the TIF included in this study. As discussed in section 2.5, the dissertation includes Baltimore City's mixed and residential TIF districts. Mixed TIF districts include commercial, retail, hotel, industrial, and office development alone or together in the same development with residential development. Multi-family housing developments and developments with single-family homes, townhomes, or condominiums comprise residential TIF districts. In the interest of observing heterogeneous impacts for employment, building permit activity, and residential property sales, in the weighted DID fixed effects model used to estimate TIF designation effects TIF block groups are considered as having multiple treatment categories based on whether the TIF development it contains is a mixed or residential development project.

Subgroup Analysis: Job Outcomes

The second and third columns of table 5.7 report fixed effects difference-in-difference estimates of job outcomes for mixed and residential TIFs. Estimates across mixed and residential TIFs are the same sign for the majority of job outcomes. For the natural log of total, local, goods-producing, moderate and high wage jobs, the estimates are all negative and the magnitude of the coefficients are larger for residential TIFs, as well as statistically significant. The goods producing and export driven jobs estimate is again quite large, indicating a -108.3 percentage point decrease for residential TIF block groups, over three times the magnitude of the estimate for mixed TIFs. In addition, the weighted estimates for high wage jobs for residential TIF block groups are significant and larger in magnitude compared to mixed TIFs, indicating a -36.8 percentage point decrease. Just as with overall TIF designation effects, moderate wage jobs are also significantly different than non-TIF block groups with a -56.1 percentage point decrease. These results indicate that residential TIF block groups are significantly different from non-TIF block groups. The exception is goods-producing jobs whereby the mixed TIF -34.9 percentage point estimate is significant instead of the residential TIF. In addition, the coefficients for the moderate wage job category are significant for both mixed and residential TIFs.

The TIF designation effects associated with retail, leisure, and hospitality jobs are all positive and similar in magnitude and sign but remain insignificant. In relation to non-TIF block groups, these kinds of jobs increased in mixed and residential TIF block groups, but not significantly. For educational and health services jobs and low wage jobs, the estimates are positive for mixed TIFs and negative for residential TIFs.

Table 5.7. DID Fixed Effects IPTW Weighted Estimates for Job Outcomes by TIF Type

	All TIFs	Mixed TIFs	Residential TIFs
Log Total Jobs (n=5,529)	-0.067 (0.102)	-0.036 (0.087)	-0.349*** (0.092)
Log Local Jobs (n=5,167)	-0.092 (0.114)	-0.078 (0.115)	-0.216** (0.073)
Log Retail, Leisure, and Hospitality Jobs (n=4,177)	0.263 (0.140)	0.268 (0.141)	0.222 (0.136)
Log Ed. and Health Services Jobs (n=3,279)	0.020 (0.187)	0.028 (0.188)	-0.046 (0.506)
Log Goods Prod. and Export Driven Jobs (n=3,152)	-0.436 (0.263)	-0.349* (0.157)	-1.083 (0.597)
Log Low Earnings Jobs (n=5,100)	0.088 (0.104)	0.108 (0.105)	-0.089 (0.111)
Log Mod Earnings Jobs (n=5,154)	-0.257* (0.106)	-0.222* (0.094)	-0.561*** (0.083)
Log High Earnings Jobs(n=4,516)	-0.117 (0.100)	-0.089 (0.098)	-0.368* (0.164)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Subgroup Analysis: Permit Outcomes

While the DID fixed effects weighted estimate for the number of total permits is near zero and insignificant, observing TIF designation effects for mixed and residential TIFs in this dissertation demonstrates that TIF designation effects differentiate by the type of project financed. The DID fixed effects weighted model yields a positive but small insignificant estimate of the impact of TIF designation on the number of total permits, reported in column 1 of table 5.8. The coefficient for mixed TIFs is also positive and insignificant. However, for residential TIFs, the coefficient of the interaction term in the model is quite large and negative. The

Similarly, the negative estimate for total permit amounts is slightly larger in magnitude but insignificant while the coefficient for residential TIFs is the largest estimate, indicating a significant decrease of permit values by -275 percentage points after designation for TIF block groups. For residential permits, the pattern is similar with the mixed TIF estimate slightly larger with the same sign that is close in magnitude to the overall estimate for all TIFs and a large coefficient indicating a -178 percentage point decrease.

Table 5.8. DID Fixed Effects IPTW Weighted Estimates for Permit Outcomes by TIF Type

	All TIFs	Mixed TIFs	Residential TIFs
Log Number of Total Permits (n=2,757)	0.006 (0.141)	0.142 (0.177)	-1.682*** (0.393)
Log Amount Total Permits (n=2,757)	-0.389 (0.239)	-0.198 (0.191)	-2.751*** (0.383)
Log Amount Residential Permits (n=1,536)	-0.421 (0.349)	-0.238 (0.330)	-1.782*** (0.156)
Log Amount Commercial Permits (n=945)	-0.590* (0.282)	-0.581* (0.282)	-1.801*** (0.277)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The interaction term coefficient for commercial permits was the only significant permit activity outcome derived from the DID fixed effects weighted model. Across the two different types of TIF districts defined in this study, the coefficient for the mixed TIFs for this measure is both significant and nearly the same as the coefficient for overall TIFs, indicating that after designation TIF block groups experienced a decrease of -58.1 percentage points compared to non-TIF block groups. As with the other permit activity outcomes, the coefficient for residential TIFs is quite large with a -180 percentage point decrease in commercial permit values.

Subgroup Analysis: Residential Property Sale Outcomes

The results of the DID analysis of the impact of TIF designation on residential property sales prices were significant for each property sales outcome where non-TIF block groups are weighted by inverse propensity scores. Observing effects across mixed and residential TIFs yields coefficients of the interaction term included in table 5.9, the sign and significance of the estimates for all TIFs hold for the estimation of effects across TIF types.

For the total number of property sales, the total amount of sales, and sales amounts for townhomes, and condominiums, all coefficients indicate appreciation in sales prices in TIF block groups after designation. The coefficients for mixed TIF block groups are slightly smaller in magnitude than the overall estimate for all TIFs.

Table 5.9. DID Fixed Effects IPTW Weighted Estimates for Residential Property Sales Outcomes by TIF Type

	All TIFs	Mixed TIFs	Residential TIFs
Log Total Number Sales (n=5,343)	0.404^{***}	0.348^{***}	0.930^{***}
	(0.095)	(0.100)	(0.057)
Log Amount Total Sales (n=5,343)	1.211^{***}	1.175^{***}	1.552^{***}
	(0.169)	(0.197)	(0.120)
Log Amount Townhome Sales (n=3,490)	1.281***	1.258^{***}	1.436^{***}
	(0.263)	(0.302)	(0.186)
Log Amount Condo Sales (n=305)	-1.261^{**}	-1.852^{***}	-0.404^{***}
	(0.455)	(0.147)	(0.112)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The sale of residential properties in block groups containing residential developments financed by TIF are larger than mixed TIFs, with a 93 percentage point increase in the number total sales, a 155 percentage point increase in sales prices for all residential sales, and a 143 percentage point increase for townhomes. Estimates of condo sales prices are also consistently negative and follow the same pattern of smaller estimates for mixed TIFs and larger for residential TIFs. There were no single-family sales in residential TIF block groups therefore subgroup analysis could not be conducted for sales prices outcomes for that housing type.

5.4 Sensitivity Analysis

Using propensity score estimation together with the difference-in-difference research design, the premise for understanding the preceding results estimating TIF designation effects is that weighting observations by the inverse probability of treatment improves DID estimation. Comparison non-TIF block groups that are economically similar to TIF block groups and more likely to be treated are more heavily weighted. Therefore, outcome estimates that account for the pre-designation socioeconomic and demographic characteristics of comparison block groups ultimately reduces selection bias.

The choice to use the inverse probability of treatment weighting derived by propensity scores instead of a propensity score matching technique in this dissertation is also an important one. As discussed in Chapter Four, propensity scores can be used for the inverse probability of treatment weighting (IPTW) strategy used in this chapter whereby treated units are weighted by the normalized inverse of the estimated propensity score (1/Pr), and untreated units receive weights of (1/1–Pr), simulating random assignment. The panel fixed effects model is then estimated with these weighted observations. The use of propensity score estimation is better known across research and evaluation fields of study as a quasi-experimental research design that matches treatment and comparison units based on the propensity score. This smaller sample of observations is then used to estimate effects.

The dissertation further explores the sensitivity of the findings from the fixed effects weighted model used in this study's analysis by estimating impacts using these different types of matching techniques for matching treated and untreated units and comparing the estimated TIF designation effects. To that end, the goal of this sensitivity analysis in this dissertation is to determine whether the effects estimated herein vary based on the use of propensity score matching or the propensity score weighting technique.

The matching techniques explored include one-to-one matching, nearest neighbor matching, radius matching, and kernel matching. With a one-to-one nearest neighbor match, each TIF block group is matched to only one TIF block group with the closest propensity score. All the other non-TIF block groups are dropped from the analysis. Nearest neighbor matching is similar, with the exception that the number of non-TIF block group matches can be selected. In the analyses that follow, 20 matches for each TIF block group are selected. These matches are selected with replacement, meaning that a non-TIF block group can be matched to more than one TIF block group if it has a close propensity score. For radius matching, non-TIF block groups selected as matches fall within a propensity score range of 0.1. Lastly, kernel matching creates a weight based on the distance between each non-TIF and TIF block group based on an optimal value of a bandwidth parameter to estimate the average effect on the treated. The default bandwidth of 0.06 is used here. In this section, the impact of TIF designation on employment, permit, and property sales outcomes are estimated with each of these matching techniques and the difference-in-difference fixed effects model.

Sensitivity Analysis: Job Outcomes

In the weighted fixed effects model estimating the effect of TIF designation on total jobs, the coefficient of the interaction term is small and negative, indicating an insignificant -6.7 percentage point decrease in TIF block groups after designation compared to non-TIF block groups. For one-to-one matching where a comparison non-TIF block group for each TIF block group is included in the sample, the coefficient is a different sign than the weighted estimate and the coefficients from the DID fixed effects models estimated with the other matching techniques which range between -0.186 and -0.216 in columns 3, 4, and 5 of table 5.10.

Several other job measures have one-to-one matching coefficients in column 2 that are a different sign than the weighted estimate and estimates from other matching models, including retail leisure and hospitality jobs, as well as all job wage categories. This is likely due to the small sample size as each TIF block group is matched with only one other non-TIF block group. Otherwise, for these measures estimates the weighted and matching models are close in magnitude. For example, the moderate wage job estimate was the only significant coefficient for job measures using propensity score weighting, indicating a -25.7 percentage point decrease after designation for TIF block groups. For all matching models except one-to-one matching, there are similarly significant negative findings for moderate wage jobs, between -39.4 and -45.9 percentage point decreases for TIF block groups.

Only the educational and health services jobs fixed effects weighted estimate was a different sign than all the DID with matching estimates. The results suggest an insignificant 2 percentage point increase in educational and health services jobs using the weighted model compared to coefficients between -.382 and -.571 for the DID matching estimates. One explanation could be that the majority of Baltimore City jobs are within the education and health services industry, therefore it follows that the largest decrease in jobs would be observed for these jobs.

Table 5.10. DID Matching Estimator Sensitivity Analysis for Job Outcomes

Dependent Variable	(1) Weighted	(2) One to One	(3) Nearest Neighbor	(4) Radius	(5) Kernel
Log Total Jobs	-0.067 n=5,529	0.232 n=315	-0.216 n=1,959	-0.186 n=5,517	-0.191 n=5,505
Log Local Jobs	-0.092 n=5,167	-0.27 n=296)	-0.349 n=1,833	-0.32 n=5,155	-0.334 n=5,143
Log Retail, Leisure, and Hospitality Jobs	0.263 n=4,177	-0.043 n=224	0.1 n=1,548	0.158 n=4,165	0.126 n=4,162
Log Ed. and Health Services Jobs	0.02 n=3,279	-0.382 n=194	-0.571 n=1,128	-0.383 n=3,267	-0.494 n=3,266
Log Goods Prod. and Export Driven Jobs	-0.436 n=3,152	0.014 n=196	-0.251 n=1,064	-0.163 n=3,147	-0.226 n=3,147
Log Low Wage Jobs	0.088 n=5,100	-0.122 n=288	0.002 n=1,826	0.021 n=5,088	-0.007 n=5,076
Log Moderate Wage Jobs	-0.257* n=5,154	-0.195 n=287	-0.459** n=1,816	-0.394** n=5,142	-0.409* n=5,130
Log High Wage Jobs	-0.117 n=4,516	0.406 n=271	-0.194 n=1,596	-0.084 n=4,504	-0.109 n=4,492

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In contrast, propensity score matching can be very sensitive to outliers that could be excluded from the matching estimates but are still included in the fixed effect weighted model. The education and health services estimate with an insignificant coefficient close to zero is a more likely outcome than estimates suggesting that upwards of a -57 percentage point drop for the jobs in that industry in TIF block groups after designation. The other job outcome estimates in this sensitivity analysis were not markedly different in direction or magnitude, indicating that the results were not particularly sensitive to using the IPTW weighting technique compared to matching methods when there are sufficient observations and similar sample sizes.

It is important to note that standard errors are not reported in table 5.10 or for the other DID models using matching techniques for other outcomes in subsequent sections. The discussion about the standard errors in a two-stage estimation that includes propensity score matching suggests that the steps necessary to estimate propensity scores adds more variation than the normal sampling variation and should be incorporated into the treatment effect model (Heckman, Ichimura, and Todd, 1998). To that end, within the literature researchers have used bootstrapping standard errors as a solution however Abadie and Imbens (2008) argue that this is still insufficient. Following Morgan and Harding's (2006) example, the standard errors derived from the estimation of TIF designation effects using propensity matching techniques in this sensitivity analysis are thus excluded.

<u>Sensitivity Analysis: Permit Outcomes</u>

According to the results in table 5.11, the estimates derived from one-to-one, nearest neighbor, radius, and kernel matching are consistent in direction and insignificance compared to the weighted DID estimates for the number of permits, total permit amount, residential permit amount, and commercial permit amount outcome measures. Comparatively, the fixed effects weighted estimate for the number of permits and the total amount of all permits are smaller than the coefficients for the DID models using the four propensity score matching techniques. However, both weighted estimates are more precise with slightly smaller standard errors. The weighted fixed effects model yields a slightly larger or less negative coefficient for residential permit amounts.

The only fixed effects weighted estimate that differs from the findings of the matching models is the only significant fixed effects weighted coefficient in the estimation of the impact of TIF designation on permit activity. Commercial permits above $50,000 decreased in TIF block groups after TIF designation by a -59 percentage point decrease. This opposes the positive coefficients of 16.4, 7.8, and 17.5 for this outcome using the nearest neighbor, radius, and kernel matching methods, respectively. In this analysis, permit amounts are aggregated to the block group level of geography and there are many non-TIF and TIF block groups that did not have any commercial permits issued during the study period. Propensity score matching further limits the size of the sample of block groups included in the analysis. This may have influenced the sensitivity of the estimation of these results based on whether a weighting or propensity score matching technique was used with DID fixed effects estimation.

Table 5.11. DID Matching Estimator Sensitivity Analysis for Permit Outcomes

Dependent Variable	**(1) Weighted**	**(2) One to One**	**(3) Nearest Neighbor**	**(4) Radius**	**(5) Kernel**
Log Total Permit Number	0.006 n=2,757	0.097 n=227	0.206 n=1,037	0.204 n=2,743	0.272 n=2,737
Log Total Permit Amount	-0.389 n=2,757	-0.271 n=227	-0.079 n=1,037	-0.227 n=2,743	-0.007 n=2,737
Log Residential Permit Amount	-0.421 n=1,536	-1.421 n=130	-0.948 n=560	-0.769 n=1534	-0.687 n=1,528
Log Commercial Permit Amount	-0.590* n=945	-0.251 n=106	0.164 n=397	0.078 n=940	0.175 n=940

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Sensitivity Analysis: Residential Property Sales Outcomes

Coefficients for the number of home sales are consistent for both matching and weighted model results in table 5.12. Compared to the estimation of a 40.4 percentage point increase derived from the weighted DID model, all the propensity score matching estimates ae also positive and the coefficients range between .255 and .39. The coefficient for the radius matching estimate is also significant at the 5 percent level of significance, indicating a 28 percentage point increase for the TIF block groups compared to non-TIF block groups. Similarly, the estimate of condo sales prices using radius matching is also a significant coefficient of the same sign, in this case negative, and smaller in magnitude than the weighted model estimate.

For overall sales prices, the positive effect of TIF designation holds across all models as they are all significant. However, it is important to note, the coefficients for the matched DID models are more conservative, estimating between an 79.2 and 86.6 percentage point increase after designation for TIF block groups compared to the 121 percentage point increase estimated using the weighted model. In addition, it is important to note that townhome and single-family sales price appreciation are not significant for any matching technique and the coefficients are much smaller for townhome sales and only slightly so for single-family homes. There is no estimate of effects using kernel matching for single-family sales prices.

Table 5.12. DID Matching Estimator Sensitivity Analysis for Property Sales Outcomes

Outcomes	(1) Weighted	(2) One to One	(3) Nearest Neighbor	(4) Radius	(5) Kernel
Log Total Sales Number	0.404^{***} n=5,343	0.390 n=289	0.255 n=1,796	0.280^{*} (n=5,331	0.269 n=5,326
Log Total Sales Amount	1.211^{***} n=5,343	0.834^{*} n=289	0.866^{**} n=1,796	0.792^{**} n=5,331	0.809^{**} n=5,326
Log Amount Townhome Sales	1.281^{***} n=3,490	0.191 n=169	0.381 n=997	0.384 n=3,479	0.343 n=3,479
Log Amount Single Family Sales	0.178^{*} n=1,556	0.082 n=64	0.034 n=372	0.151 n=1,556	
Log Amount Condo Sales	-1.261^{**} n=305	-0.308 n=39	-0.631 n=122	-0.707^{*} n=293	-0.629 n=293

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter Discussion

Overall, the empirical findings in this study did not indicate that TIF designation has a significant impact on employment or building permit activity. However, TIF block groups did yield significant and considerable residential sales price appreciation. The results are similar to other studies of the impact of TIF designation.

The clearest indication of the impact of TIF designation on job outcomes is the apparent shift of jobs by wage category, whereby jobs with annualized wages between $15,000 and $40,000 decreased significantly for TIF block groups. This outcome along with the sign and magnitude of other insignificant job outcomes offer important insight about TIF designation impacts. Essentially, this outcome suggests that TIF designation was not a firewall against the shift to low-wage jobs during the Great Recession which took place during the study period.

In addition, the type of project financed by TIF is important. Residential projects did not generate economic activity to positively impact employment. This might suggest that the increased demand for goods and services for residents living in and near these TIF-financed residential developments are satisfied by businesses in other neighborhoods.

At the time of this writing, Lester (2014) is the only empirical study of the impact of TIF designation on permit activity. At the block group level of geography that study similarly reports insignificant, negative or near zero TIF designation impact estimates. Ultimately the results of this difference-in-difference analysis of permit activity associated with TIF designation indicate there is no difference in the number of permits issued and permit values in non-TIF and TIF block groups after designation. Commercial permit values is the only measure where the decrease in permit value is significant using the model that weights non-TIF and TIF block groups based on the economic similarity between these groups. However, the estimates of commercial permit amounts are sensitive to the methodology used for addressing selection bias with propensity score weighting or propensity score matching techniques.

The findings for increased home sales and sales price appreciation confirm the results of previous studies of the effects of TIF designation on home sales, although the magnitudes of the significant estimates are comparatively large (Smith, 2009; Dardia, 1998; Anderson, 1990). This extreme growth in prices might be due to increased demand in previously low-valued homes in the areas surrounding TIF districts. Inflation is less of a factor since homes in both TIF and non-TIF designated block groups would be affected. However, timing of home sales in relation to TIF designation and the 2008 recession likely have several important implications.

For example, five of the seven TIF districts included in this study were designated between 2003 and 2005 and the remaining two were designated in 2008. Therefore the years determined to be post-designation (beginning with the year after designation) for TIF block groups vary while the post-designation period for all non-TIF block groups is after all TIF designations have occurred. In other words, some of the hyper-sales activity leading up to the recession period would be captured as "post-designation" for TIF block groups but "pre-designation" for non-TIF block groups. However, due to the limitations of this methodology and the absence of this effect in the estimation of other outcomes in this study, there is no real way to determine whether that is indeed the reason for such large estimates of sales price appreciation for TIF block groups after designation.

In summary, there are likely other factors that likely contribute to the empirical findings for employment, building permit activity, and residential property sales outcomes derived from the propensity score weighted difference-in-difference fixed effects model. While observing TIF designation effects at the block group level of geography is an improvement over previous TIF studies conducted at the municipal level and other geographic units such as the census tract, block groups are still large in comparison to the TIF districts in Baltimore that mostly consist of one project or multiple parcels. Therefore, for example, even where there is job growth in a TIF district, there could be overall job loss in the block group that contains the TIF district resulting in a negative net impact of TIF designation on job growth. Similarly, residential property sales could be positively biased as the estimates capture growth in neighborhoods beyond the TIF district.

Propensity score estimation addresses selection bias by weighting observations dependent on whether they are economically similar comparison block groups. However, the potential bias associated with the inability to observe net TIF designation effects illustrates the main limitation for the analysis presented in this chapter and provides the basis for the analysis of TIF spillover effects in Chapter Six. Estimating TIF spillover effects will aid in the determination of whether the TIF designation effects are biased by economic activity in the areas surrounding TIF districts.

6 RESULTS AND DISCUSSION: TIF SPILLOVER EFFECTS

This chapter explores the sixth research question in this study seeking to determine the extent of spillover effects of TIF designation on employment, permit activity, and residential property sales outcomes in areas adjacent to TIF districts. As discussed in Chapter 5, the estimation of TIF designation effects using propensity score estimation addresses inherent selection bias associated with TIF districts whose designation is often influenced by the conditions of the neighborhood. The results of the difference-in-difference fixed effects analysis using propensity scores to identify economically similar geographic units in Chapter Five indicate that there is no increase in overall employment and permit activity associated with TIF designation. However, residential property sale appreciation is significantly large for TIF blocks after designation compared to non-TIF block groups. These estimates could be influenced by TIF designation spillover effects that bias these estimates. However, the net effect of TIF designation is obscured at the block group level of geography as estimated effects could be biased by economic activity around the district as surrounding areas experience spillover.

Spillover areas are those immediately adjacent to and determined by proximity to the TIF district. Comparison areas are equidistant geographically close comparison units. Where outcomes for spillover areas are significantly different than adjacent comparison areas, spillover potentially exists. The various distances used to identify spillover and comparison areas measure the sensitivity of these spillover effect estimates.

For job outcomes, the unit of analysis is the census block, the smallest geographic unit at which jobs data are available. Permit data are also aggregated to the census block. Spillover and comparison areas are identified by the distance of the census block centroid to the TIF district boundary. The unit of analysis in the study of residential sales price appreciation is the sales transaction within distance of a TIF district that has been designated at the time of the transaction. Sales transactions are identified as being within the spillover area or the adjacent comparison area.

In the following section this dissertation presents a descriptive analysis and comparison of means for various neighborhood indicators, including proximity to centers of economic activity, transportation access, and land use coverage for spillover and comparison areas. In addition, the analysis includes annual trends for the three spillover proximity specifications of interest in the study—comparison of units within an eighth mile and a quarter mile, a quarter mile and a half mile, and a half mile and a mile from the TIF district. The study then estimates the spillover effects of TIF designation on the job and private investment outcomes using the difference-in-difference fixed effects approach.

In addition to difference-in-difference analysis, following Weber, Bhatta, and Merriman (2007) a repeat sales model is used to exploit the balanced panel nature of homes that have sold more than once during the study period using the first and last sales transaction for a parcel between 2002 and 2013. To further test the spillover impact of TIF designation on property sale values, a repeat sales model with only observations where the first sale occurred prior to designation of the nearest TIF district and the last sales after designation is included in the analysis. In addition, the impact of TIF designation spillover effects on home sales prices for both the DID and repeat sales methodologies distinguishes heterogeneous effects across housing market typology categories. Subgroup analysis for TIF spillover effects includes previously used estimation of effects by the characteristic of projects financed by the TIF, mixed or residential developments.

6.1 Descriptive Analysis of Spillover and Comparison Areas

In this dissertation, the estimation of the impact of TIF designation spillover on job and permit activity outcomes are estimated at the census block level of geography. This section serves as a descriptive analysis of spillover and comparison area census blocks.

There a total of 13,598 census blocks in Baltimore City. As defined for this analysis, spillover census blocks have centroids within .125, .25, and .5 mile from TIF districts. TIF spillover effects are estimated with the difference-in-difference methodology, therefore spillover areas are compared to census blocks in the next equidistant ring created with distance buffers in GIS that have centroids between .126 and .25 mile, .26 and .5 mile, and .51 and 1 mile from the TIF districts. These spillover and comparison areas create three specifications of the DID model that compare census blocks within an eighth and quarter mile (EQ), within a quarter mile and a half mile (QH), and a half mile and a mile (HM). Figure 6.1 visualizes the census blocks in these three specifications. There are 219 census blocks within .125 mile of TIF districts, 515 within .25 mile, and 1,522 within a half mile. There are 296 comparison census blocks between .126 and .25 mile from the TIF, 1,007 between .26 and .5, and 2,332 between .51 and 1 mile.

Table 6.1 includes descriptive statistics for spillover and comparison census blocks, including the average, minimum, maximum, and standard deviation for indicators of proximity to centers of economic activity, proximity to transportation access, and land use indicators. Proximity to centers of economic activity is measured as each census block’s proximity to the central business district where economic activity is concentrated and proximity to university anchor institutions in Baltimore City that act as the economic drivers in Baltimore neighborhoods. Proximity to transportation access indicates the distance between a census block’s centroid and various transportation modes including the nearest bus stop, lightrail stop, commuter train stop, and subway stop in miles. Additionally, land use indicators include the percentage of residential, commercial, industrial, and institutional land use coverage in a census block determined using a 2002 GIS land use layer.

In the first, fifth, and ninth column of table 6.1, the means of the indicators show that spillover census blocks within an eighth mile of TIF districts are further away from the central business district, a 2.5 mile average distance. There is no clear pattern in the relationship between TIF districts and universities as spillover census blocks within a quarter mile are farthest away from these institutions. Lightrail stops and commuter train stops are closest to spillover census blocks a half mile from TIF districts, on average 1.3 and 1.7 miles, respectively. Subway stops are on average 1.2 miles away from census blocks within an eighth of a mile from the TIF district while census blocks within a quarter mile and half mile are further away. In contrast, census blocks within an eighth mile are .065 mile away from the nearest bus stops, closer than census blocks further away from TIF districts. With regard to land use, commercial and industrial land use is more concentrated in census blocks closer to TIF districts. However, the concentration of residential land use increases with the distance from TIFs as census blocks within a half mile from TIF districts have the greatest residential land use coverage, approximately 66.9 percent.

Table 6.2 presents a comparison of the mean of these centers of economic activity, transportation access, and land use indicators for spillover and comparison areas using a t-test to determine whether the difference between spillover and comparison areas is significant. Overall, comparing spillover census blocks within .125 mile to the census blocks between .126 and .25, or the EQ specification, indicates these groups are similar with the exception of their mean distances from the central business district as spillover census blocks are significantly further away from this neighborhood resource compared to the adjacent equidistant comparison census blocks. For the nearest bus stops, spillover areas are significantly closer to access points to this transportation mode. Per columns 3-6 in table 6.2, for the QH specification, the distance from the CBD is significantly different for spillover and comparison areas. This is also true s the nearest commuter train stop. A half mile from the TIF district, census blocks are significantly different than census blocks in the next ring between .51 and 1 mile from the TIF district across a number of indicators including the nearest bus stop and university and every type of land use except for institutional land uses.

Ultimately, the preceding section provides context about the spillover and comparison areas that are used in the following difference-in-difference analysis estimating TIF designation spillover effects for job and permit outcomes. Figure 6.1 is a map of the spillover areas (blue) and geographically close comparison areas (yellow) for all the TIF districts included in the study.

Figure 6.1. TIF Spillover and Comparison Area Census Block Proximity Specifications

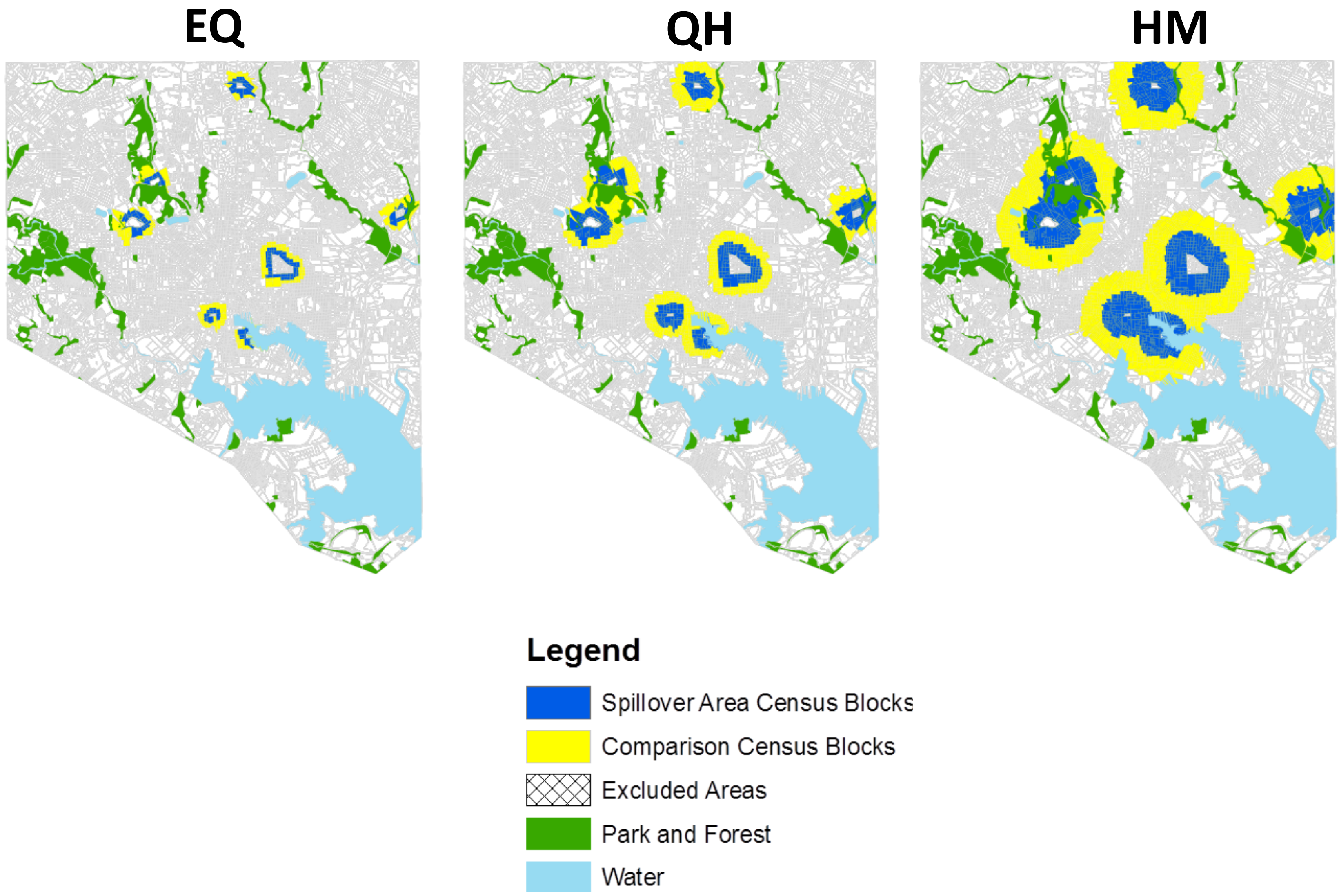


Table 6.1. Descriptive Statistics of Neighborhood Resource Proximity, Transportation Access, and Land Use Indicators for Spillover Census Blocks

	Eighth Mile				Quarter Mile				Half Mile			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Distance to CBD (Miles)	2.513	1.483	0.305	5.253	2.357	1.482	0.146	5.383	2.157	1.480	0.022	5.634
Nearest University (Miles)	0.863	0.707	0.038	3.190	0.870	0.689	0.036	3.257	0.849	0.643	0.036	3.285
Nearest Bus Stop (Miles)	0.065	0.045	0.003	0.256	0.072	0.046	0.003	0.256	0.070	0.048	0.003	0.355
Nearest Lightrail Stop (Miles)	1.418	1.058	0.010	4.399	1.402	1.049	0.010	4.516	1.339	0.992	0.010	4.550
Nearest Commuter Train Stop (Miles)	1.925	1.218	0.111	4.399	1.810	1.228	0.018	4.516	1.677	1.193	0.018	4.550
Nearest Subway Stop (Miles)	1.178	1.344	0.019	4.104	1.168	1.283	0.019	4.256	1.175	1.189	0.010	4.484
% Residential Land Use	0.615	0.438	0.000	1.000	0.642	0.437	0.000	1.000	0.669	0.430	0.000	1.000
% Commercial Land Use	0.149	0.308	0.000	1.000	0.125	0.286	0.000	1.000	0.140	0.309	0.000	1.000
% Institutional Land Use	0.100	0.267	0.000	1.000	0.114	0.290	0.000	1.000	0.102	0.269	0.000	1.000
% Industrial Land Use	0.033	0.144	0.000	0.949	0.023	0.123	0.000	0.998	0.022	0.126	0.000	1.000
Observations	219				515				1,522			

Table 6.2. Means of Neighborhood Resource Proximity, Transportation Access, and Land Use Indicators for Spillover and Comparison Census Blocks

	EQ			QH			HM		
	Spillover	**Comparison**	**Diff**	**Spillover**	**Comparison**	**Diff**	**Spillover**	**Comparison**	**Diff**
Distance to CBD (Miles)	2.513	2.242	0.271*	2.357	2.055	0.302***	2.128	2.128	0.000
Nearest University (Miles)	0.863	0.875	-0.012	0.870	0.838	0.032	0.838	0.881	-0.043*
Nearest Bus Stop (Miles)	0.065	0.077	-0.012**	0.072	0.069	0.003	0.071	0.085	-0.014***
Nearest Lightrail Stop (Miles)	1.418	1.390	0.028	1.402	1.307	0.095	1.330	1.343	-0.013
Nearest Commuter Train Stop (Miles)	1.925	1.725	0.200	1.810	1.609	0.201**	1.662	1.629	0.032
Nearest Subway Stop (Miles)	1.178	1.161	0.016	1.168	1.178	-0.010	1.159	1.223	-0.064
% Residential Land Use	0.615	0.662	-0.046	0.642	0.683	-0.041	0.663	0.592	0.070***
% Commercial Land Use	0.149	0.106	0.043	0.125	0.148	-0.024	0.140	0.136	0.004
% Institutional Land Use	0.100	0.124	-0.024	0.114	0.097	0.017	0.102	0.072	0.030***
% Industrial Land Use	0.033	0.015	0.018	0.023	0.022	0.001	0.024	0.077	-0.053***
Observations	219	296		515	1,007		1,555	2,332	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2 TIF Spillover Effects

6.2.1 TIF Spillover Effect on Job Outcomes

Descriptive Analysis: Job Outcomes

LODES jobs data are available at the census block level of geography. There are 13,598 census blocks, with many of them having a count of zero jobs. These are residential and other areas where no businesses or commercial activities. In 2013, 73 percent of census blocks have a count of zero jobs. Across census blocks for years 2002 through 2013, there is an average of 17 jobs in a census block and a maximum of 10,706 jobs in this geographic unit.

Spillover effects of TIF designation are herein estimated comparing spillover and comparison areas identified by the distance of the census block from the boundary of the TIF districts. Figure 6.2 illustrates the mean count of total jobs between 2002 and 2013 for each spillover and comparison area specification. Per the upper left graphs, for the EQ specification, the mean number of total jobs in the spillover area within an eighth mile from the TIF district is roughly the same as the mean jobs in the census blocks of the comparison area, both experiencing dips to the lowest annual average of 67 jobs in 2009, the same year the comparison area decreased to 60 jobs.

In the QH specification, the mean jobs in the spillover area census blocks are demonstrably higher. The highest annual average number of jobs for census blocks within a quarter mile is 87 jobs in 2013 and the lowest annual average is 61 in 2009. In contrast, the annual averages for QH comparison areas range between 32 in 2012 and 41 in 2007. The spillover areas within a half mile from the TIF district are also on average higher than the comparison area although the range of mean jobs for both groups is relatively steady across the study period.

Figure 6.2 Mean Jobs for Spillover and Comparison Areas by Year

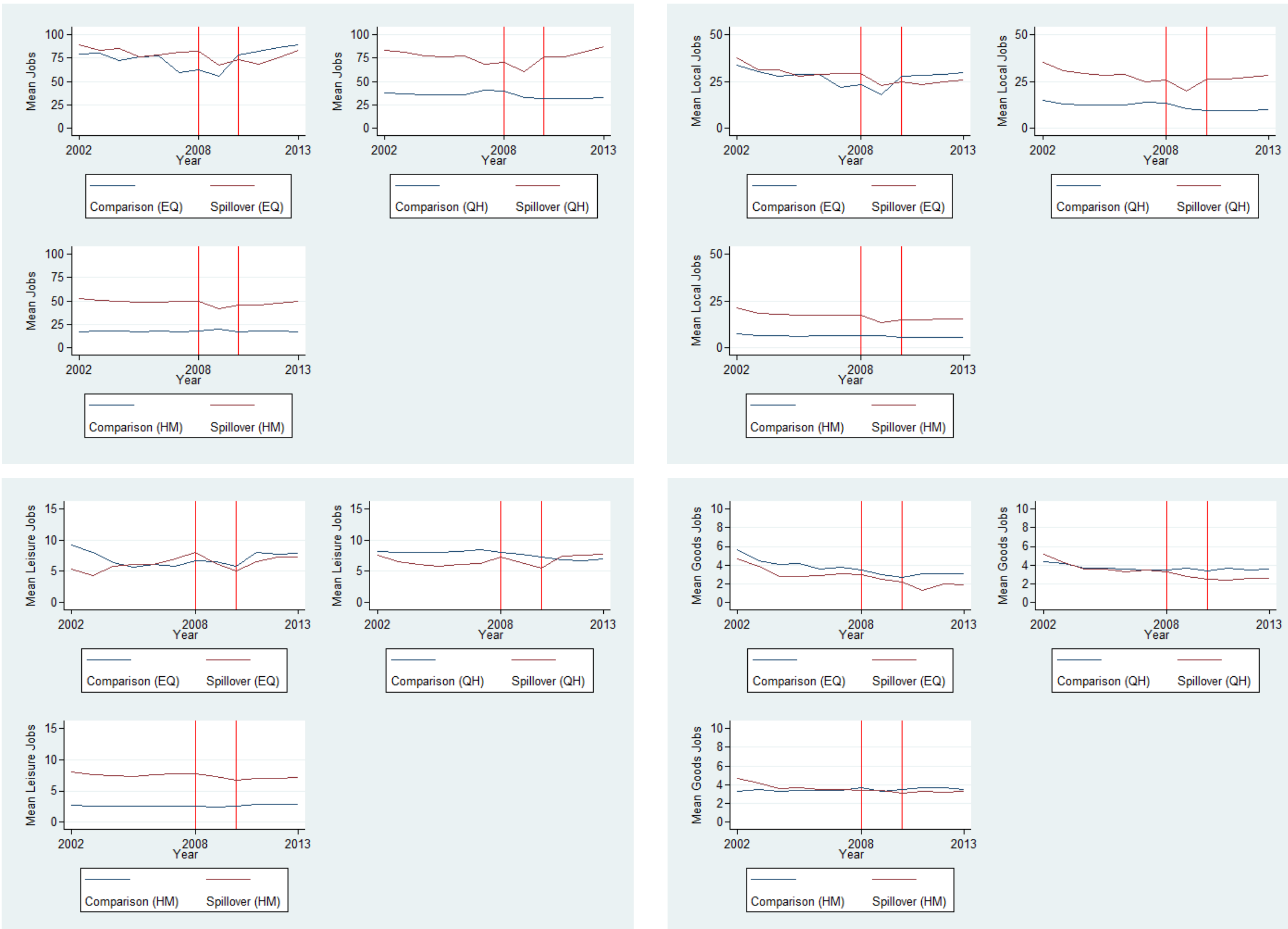
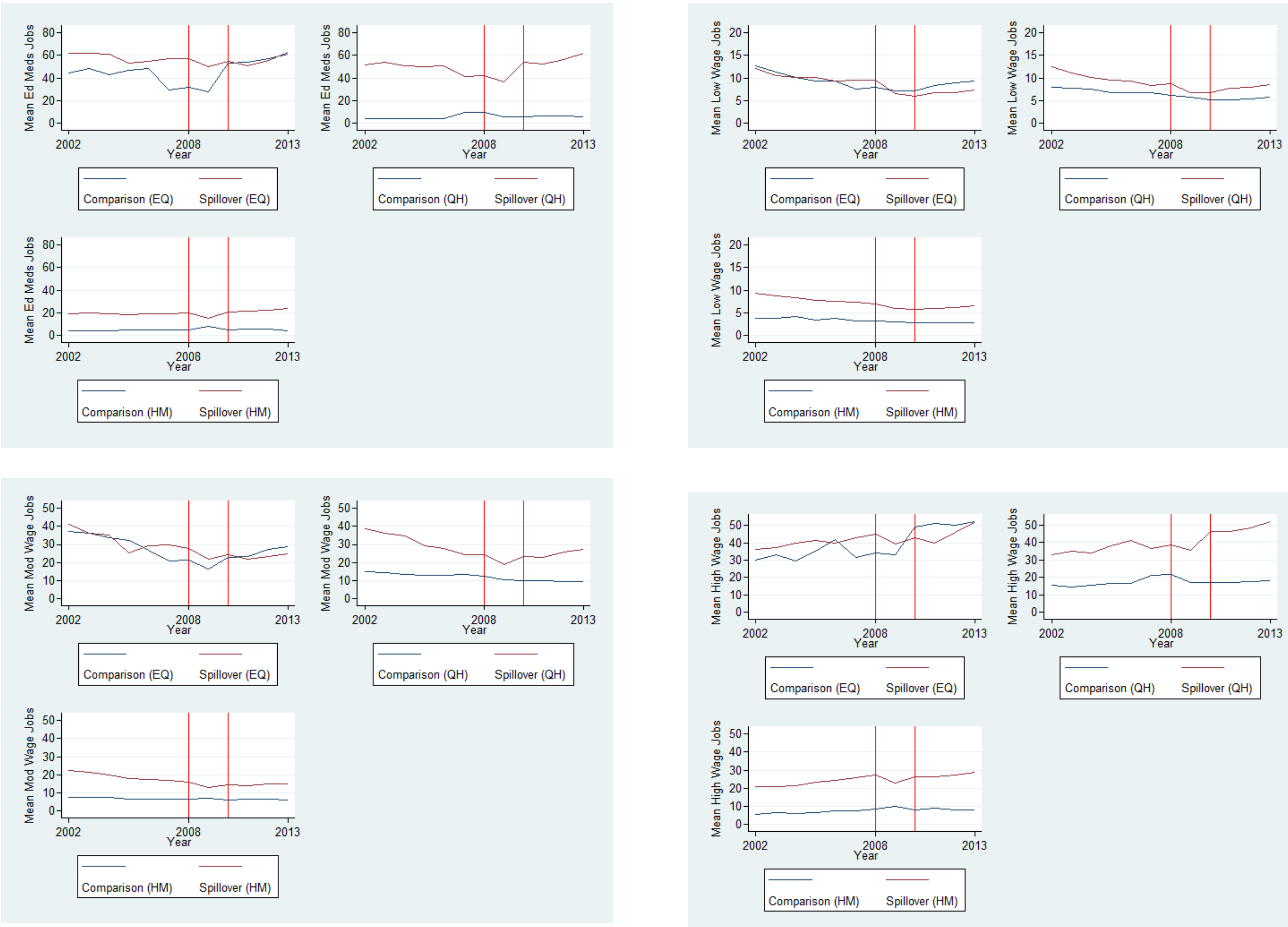


Figure 6.1. Mean Jobs for Spillover and Comparison Areas by Year (cont'd)



The trend is similar for local jobs in the upper right set of graphs, except as expected the annual mean numbers of these jobs held by Baltimore City residents is smaller than total jobs. Likewise, the remaining graphs show the mean jobs for different types of jobs by industry and wage category and generally show the same patterns between spillover and comparison areas. Of course, these average job counts offer a view of employment trends across years in spillover and comparison census blocks however the spillovers effects that are attributable to proximity to TIF districts is estimated using the DID fixed effects model in the next section.

DID Estimation: Job Outcomes

With respect to employment this dissertation seeks to determine whether there are spillover effects associated with TIF designation at the census block level of geography. As previously discussed in Chapter Four, spillover effects are potentially present where outcome values for spillover areas are significantly different than adjacent comparison areas. Spillover effects could bias the TIF designation effects estimated at the block group level of geography that compares block groups that contain or intersect TIF districts to economically similar non-TIF block group comparisons.

To that end, a difference-in-difference fixed effects model as outlined in equation 3 is used to determine whether employment in spillover areas is significantly different than comparison areas after the designation of the nearest TIF district. In equation 3 the natural log of total jobs are regressed on indicators of TIF designation, time, an interaction of the two indicators, and time and geographic fixed effects.

$$\ln Y_{it} = \beta T_{it} + \gamma t_{it} + \delta T_{it} t_{it} + \omega_i + \lambda_t + \varepsilon_{it} \qquad (3)$$

In table 6.3 below, for the EQ, QH, and HM spillover proximity specifications the results of a naïve OLS model, an OLS model with covariates, and the difference-in-difference fixed effects model are reported. The naïve OLS model uses a cross-section of spillover area census blocks and the explanatory variable in the regression is proximity of the closest TIF district after designation in year t. The estimates in columns 1, 4, and 7 of table 6.3 represent the percentage point change in the natural log of jobs in spillover census blocks for each specification. At an eighth mile, quarter mile, and half mile the coefficients for total log jobs are 19.9, 21.8, and 30.0, respectively.

The estimate for the half mile spillover census blocks are the only statistically significant estimate of the three proximity specifications. As is the nature of cross-sectional models with two groups and no measures prior to designation, all naïve OLS are likely positively biased as there are likely other factors that determine the relationship between proximity to TIF districts and employment.

The OLS regression model with covariates takes into account these other factors with covariates indicating spillover census blocks' proximity to neighborhood resources and transportation access as well as the concentration of various land uses that comprise the census blocks. This model yields the estimates in columns 2, 5, and 8 of table 6.3. According to these results, the proximity of spillover census blocks to the central business district and light rail stops is significantly and negatively related to job growth while the distance to commuter train stops is positively related across all proximity specifications. Likewise, higher concentration of residential land uses is associated with job decreases across all specifications.

The estimates of employment in the first two proximity specifications, EQ and QH, are insignificant. Within an eighth of a mile from TIF districts, these explanatory variables reduce the effect of the relationship between proximity to TIF districts after designation to a negative and near zero estimate, -.007. At a quarter mile, the estimate is negative with covariates, indicating a 3.1 percentage point decrease for spillover census blocks. At a half mile where more of the covariates are significantly different for spillover census blocks, the change in log jobs is relatively large at 21.1 percentage points and significant at the 1 percent level of significance.

The DID fixed effects estimates in columns 3, 6, and 9 represent the coefficient of the interaction between proximity to designated TIFs at any time and designation in a particular year as outlined in equation 3. Unlike the naïve OLS model and OLS model with covariates previously discussed, this model compares not only spillover and comparison areas, but also incorporates observations of the number of jobs in census blocks for these two groups before designation of the closest TIF in an attempt to identify the job change that would have happened to the spillover census blocks with no designated TIF district in proximity.

The results of this model indicate that across each spillover proximity specification, none of the DID fixed effect estimates are significant. Within a quarter mile and half mile, estimates are near zero. Within an eighth mile, the coefficient in column 3 is slightly negative with a -2.8 percentage point decrease. Although insignificant, the implication of the sign of this coefficient is that there is less job growth in census blocks closer in proximity. In all, there is no difference between spillover and comparison areas, and thus, no spillover effects associated with TIF designation for job outcomes.

Table 6.3. TIF Designation Spillover Effects on Total Jobs

	Eighth Mile			Quarter Mile			Half Mile		
	Naive	**Covariates**	**DID FE**	**Naive**	**Covariates**	**DID FE**	**Naive**	**Covariates**	**DID FE**
Log Total Jobs	0.199	-0.007	-0.028	0.218	0.298*	-0.007	0.300***	0.340***	0.001
	(0.264)	(0.232)	(0.128)	(0.159)	(0.135)	(0.080)	(0.089)	(0.076)	(0.048)
Distance to Central Business District (Miles)		-1.433***			-0.355*			-0.250***	
		(0.392)			(0.165)			(0.075)	
Nearest Bus Stop (Miles)		2.228			0.836			0.655	
		(2.605)			(1.454)			(0.793)	
Nearest Lightrail Stop (Miles)		-1.052***			-0.450***			-0.272***	
		(0.239)			(0.134)			(0.080)	
Nearest Commuter Train Stop (Miles)		2.812***			0.601*			0.368***	
		(0.648)			(0.242)			(0.102)	
Nearest Subway Stop (Miles)		-0.214			0.023			0.021	
		(0.197)			(0.113)			(0.078)	
Nearest University (Miles)		-0.617*			-0.191			-0.265**	
		(0.311)			(0.152)			(0.102)	
% Residential Land Use		-2.005**			-0.988*			-0.548*	
		(0.647)			(0.425)			(0.217)	
% Commercial Land Use		-0.579			0.931*			1.141***	
		(0.738)			(0.459)			(0.241)	
% Institutional Land Use		0.308			0.589			0.710**	
		(0.731)			(0.482)			(0.269)	
% Industrial Land Use		0.139			1.225*			1.386***	
		(0.790)			(0.552)			(0.253)	
Constant	2.571***	3.939***	2.775***	2.420***	2.857***	2.684***	2.214***	2.344***	2.478***
	(0.195)	(0.698)	(0.054)	(0.090)	(0.448)	(0.034)	(0.055)	(0.240)	(0.023)
Controls	No	Yes	No	No	Yes	No	No	Yes	No
Census Block Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Comparison Units	No	No	Yes	No	No	Yes	No	No	Yes
Observations	726	726	2,397	2,196	2,196	7,011	5,339	5,339	17,013

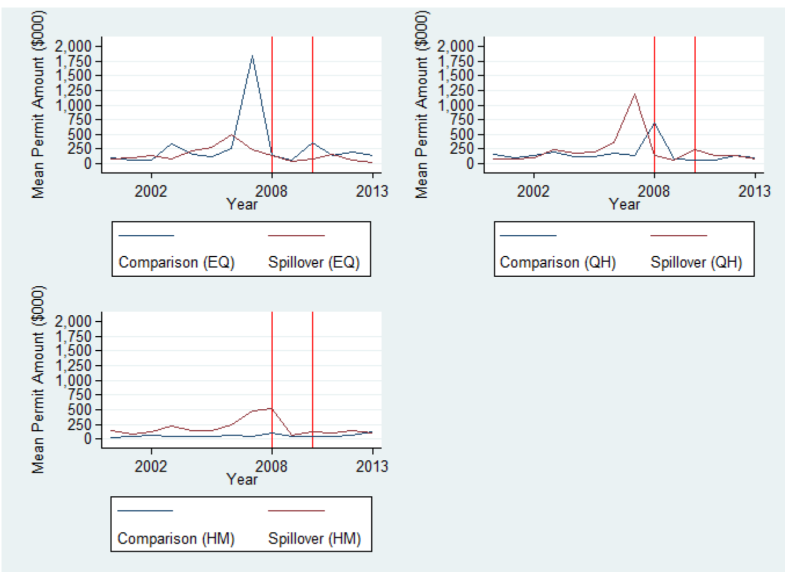
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2.2 TIF Spillover Effects on Permit Outcomes

Descriptive Analysis: Permit Outcomes

In the analysis of the relationship between TIF designation and permit activity in Chapter Five the permit amounts were aggregated to the block group level of geography and compared with economically similar block groups. The results of that analysis indicate no statistically significant difference in the number of permits issued and permit amounts due to TIF designation. In this section, permits are aggregated to the census blocks within which they were issued and the spillover effect of TIF designation on permit value is estimated by comparing spillover and comparison areas before and after designation of the nearest TIF district.

Figure 6.3. Mean Permit Amounts for Spillover and Comparison Areas by Year



Observing spillover census block trends over the study period, there is a large spike in the amount of permit amounts in the comparison area of the EQ specification in census blocks between .126 and .25 mile from TIF districts with an average of $1.85 million in 2007. In the QH specification, these census blocks are in the spillover area, which leads to the $1.18 million spike observed in 2007 in this proximity specification. Despite these spikes and with some exceptions the mean values of permits appears to be relatively consistent for the comparison and spillover areas in each proximity specification.

<u>DID Estimation: Permit Outcomes</u>

Estimates for the naïve OLS, OLS with covariates, and the DID fixed effects model are presented in table 6.4. For the naïve model the coefficients reported in columns 1, 4, and 7are insignificant. However, the sign of the estimate of the effect of proximity to TIF districts on permit value provide some insight as the coefficients are negative within an eighth mile, indicating an insignificant -13.2 percentage point decrease in the log of permit amount, while for the quarter mile and half mile specifications, the estimates are insignificant and positive, 21.5 and 19.2 percentage points, respectively. The results of the OLS model with land use and neighborhood proximity covariates (columns 2, 5, and 8) follow a similar pattern as the estimates have the same sign as the naïve model but are smaller in magnitude.

For the EQ and QH proximity specifications of the DID fixed effects model, the coefficients have the opposite sign compared to the naïve OLS and OLS models with covariates. Where permit amounts are negatively related to TIF district proximity at an eighth mile with the cross-sectional models that don't consider permit values in census blocks prior to TIF designation, the estimate in column 3 suggests an insignificant 3.4 percentage point increase in spillover areas compared to the adjacent comparison census blocks. Similarly, for the QH specification the insignificant -15.7 percentage point decrease (column 6) diverges from the estimated increases derived from the OLS models in column 4 and 5.

Only the HM specification is consistent in the sign of the coefficient across all three models but the magnitude of the coefficient in column 9 is small at 1.6 compared to the 19.2 and 2.4 percentage point increases estimated with the naïve OLS and OLS with covariate models reported in columns 7 and 8 of table 6.4. These results have several implications. First, the fixed effects estimates are smaller than coefficients of the OLS models, indicating that the OLS models indeed produce upwardly biased estimates. But most importantly, none of the coefficients for any of the models are statistically significant therefore there is no difference between the outcomes of permit value for census blocks in spillover and comparison areas.

Ultimately, there are no TIF spillover effects on permit amounts for areas immediately surrounding TIF districts regardless of the spillover census block's proximity to TIF districts. Thus, the insignificant permit amount for TIF designation effects in Chapter Five estimated at the block group level of geography are not downwardly biased as a result of spillover.

Table 6.4. TIF Spillover Effects on the Amount of Permits

	Eighth Mile			Quarter Mile			Half Mile		
	Naive	Covariates	DID FE	Naive	Covariates	DID FE	Naive	Covariates	DID FE
Log Permit Amount	-0.132	-0.123	0.034	0.215	0.106	-0.157	0.192	0.024	0.016
	(0.26)	(0.20)	(0.35)	(0.18)	(0.15)	(0.22)	(0.11)	(0.09)	(0.14)
Distance to Central Business District (Miles)		-0.392			-0.015			0.070	
		(0.49)			(0.29)			(0.12)	
Nearest Bus Stop (Miles)		1.354			1.220			0.646	
		(2.78)			(1.56)			(0.92)	
Nearest Lightrail Stop (Miles)		0.021			0.203			-0.000	
		(0.28)			(0.21)			(0.10)	
Nearest Commuter Train Stop (Miles)		0.928			0.188			0.003	
		(0.67)			(0.37)			(0.14)	
Nearest Subway Stop (Miles)		-0.253			-0.143			-0.019	
		(0.24)			(0.17)			(0.10)	
Nearest University (Miles)		-0.809^{*}			-0.768^{***}			-0.390^{**}	
		(0.31)			(0.19)			(0.13)	
% Residential Land Use		-0.913			-2.194^{*}			-1.368^{***}	
		(1.15)			(0.95)			(0.39)	
% Commercial Land Use		0.004			-1.124			-0.232	
		(1.15)			(0.99)			(0.45)	
% Institutional Land Use		0.751			-0.801			0.265	
		(1.23)			(1.05)			(0.46)	
% Industrial Land Use		0.960			-1.064			-0.025	
		(1.35)			(1.08)			(0.44)	
Constant	5.557^{***}	5.776^{***}	5.937^{***}	5.253^{***}	6.989^{***}	5.553^{***}	5.220^{***}	6.216^{***}	5.453^{***}
	(0.29)	(1.19)	(0.31)	(0.14)	(1.01)	(0.17)	(0.09)	(0.43)	(0.12)
Controls	No	Yes	No	No	Yes	No	No	Yes	No
Census Block Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Comparison Units	No	No	Yes	No	No	Yes	No	No	Yes
Observations	204	204	651	508	508	1,720	1,181	1,181	4,012

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2.3 TIF Spillover Effects on Residential Property Sales Outcomes

Descriptive Analysis: Residential Property Sales Outcomes

Based on sales transaction data made available from Maryland Department of Planning's Md PropertyView between 2002 through 2013 there were 93,275 residential property sales in Baltimore City. In this analysis of spillover effects, sales within TIF districts are excluded therefore there are 92,905 sales included here. Each property sales record in the dataset includes the date of the transaction, the amount of consideration for the sale, and other characteristics of the home. These characteristics include the age and size of the home, the number of times the home sold during the study period, as well as the structural characteristics of the home, including the presence of a basement, garage, deck, patio, or enclosed porch.

In this dissertation, the spillover effect on home sale price appreciation in proximity to TIF districts is first estimated using the difference-in-difference fixed effects method. The analysis is conducted at the individual sale unit of analysis in order to incorporate the characteristics of each home into the analysis, such as the duration of a home's exposure to TIF designation at the time of sale as determined by the year the closest TIF was designated.

In the interest of identifying whether a home is in a spillover or comparison area for the various spillover proximity specifications of the DID estimation used in this study, buffers are created in GIS to identify the distance from the property sales and the nearest TIF district. As such, the study first identifies the TIF district nearest to each home. The average distance is 1.3 miles and the maximum is 4.3 miles. Table 6.5 provides descriptive statistics for home sales in the spillover areas. There are 1,251 sales within an eighth mile of a TIF, 3,463 within a quarter mile, and 12,443 within a half mile.

The average home sale prices are higher within closer proximity to TIF districts, approximately $311,000 within an eighth mile, $238,000 within a quarter mile and $195,000 within a half mile. At an eighth mile, homes are on average over 1,400 sq. ft. and were built 48 years ago. The maximum age and size are 213 years and 140,000 sq. ft. Compared to homes that have been sold that are within a quarter mile and half mile from TIF districts, those closer are also larger, built more recently, and sold approximately two years after designation of that closest TIF.

Fewer homes in closer proximity to TIF districts have basements, decks, and patios than those further away. The presence of basements range between 46 and 72 percent, decks between 13 and 26 percent, and patios .1 and 1.5 percent. However, more homes within an eighth mile have garages (7 percent) and enclosed porches (4.8 percent). Sold homes closer to TIF districts were on average farther from all neighborhood resources and transportation access points except lightrail and subway stops.

The means of the nearest TIF characteristics, structural characteristics, neighborhood resources, and transportation access are compared with a t-test across spillover and comparison areas in table 6.6. The indicators are revealed to be significantly different for homes sold during the study period that are within spillover and comparison areas for the EQ, QH, and HM proximity specifications.

Table 6.5. Descriptive Statistics of Property Sales, Nearest TIF Characteristics, Structural Characteristics, and Proximate Neighborhood Resource and Transportation Access in Spillover Areas

	Eighth Mile				Quarter Mile				Half Mile			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Home Sales Price (2002-2013) ($000)	311	376	10	3,240	238	268	10	3,240	194	188	10	3,240
Size of Building (sq. ft.)	1423	4136	0	140,000	1,299	2,590	0	140,000	1233	1,479	0	140,000
Age of Building (Years)	48	43	0	213	78	44	0	213	86	37	0	213
Distance to Nearest TIF (Miles)	0.062	0.037	0.001	0.125	0.148	0.074	0.001	0.250	0.317	0.1260	0.001	0.500
Age of Nearest TIF at Time of Sale	2.243	2.815	0	9	1.862	2.6585	0	9	1.702	2.549	0	9
Number of Times Sold	1.556	0.754	1	4	1.595	0.765	1	5	1.69083	0.811	1	7
Basement	0.458	0.498	0	1	0.626	0.484	0	1	0.721	0.449	0	1
Garage	0.071	0.257	0	1	0.060	0.237	0	1	0.047	0.212	0	1
Deck	0.130	0.337	0	1	0.226	0.418	0	1	0.261	0.439	0	1
Patio	0.010	0.097	0	1	0.011	0.105	0	1	0.0148	0.121	0	1
Enclosed Porch	0.048	0.214	0	1	0.046	0.209	0	1	0.035	0.184	0	1
University (Miles)	0.922	0.656	0.176	3.117	0.826	0.516	0.158	3.117	.874	0.415	0.060	3.117
Commuter Train (Miles)	1.688	1.149	0.238	4.386	1.560	1.165	0.146	4.386	1.616	1.109	0.146	4.546
Subway (Miles)	1.172	1.085	0.063	4.090	1.161	1.111	0.063	4.256	1.244	1.072	0.063	4.501
Central Business District (Miles)	2.109	1.430	0.599	5.262	2.020	1.441	0.296	5.377	2.087	1.372	0.241	5.632
Bus Stop (Miles)	0.092	0.052	0.001	0.216	0.088	0.047	0.001	0.237	0.076	0.048	0.001	0.320
Lightrail Stop (Miles)	1.286	1.012	0.030	4.386	1.196	0.896	0.030	4.386	1.288	0.826	0.030	4.546
Observations	1,251				3,463				12,443			

Table 6.6. Descriptive Statistics of Property Sales, Nearest TIF Characteristics, Structural Characteristics, and Proximate Neighborhood Resources and Transportation Access in Spillover Areas

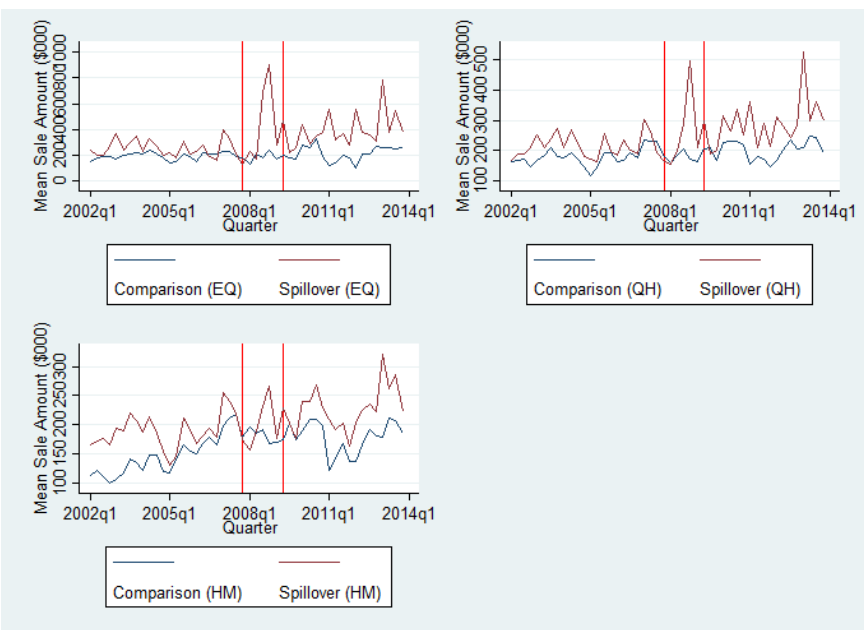
	EQ			QH			HM		
	Spillover	**Comparison**	**Diff.**	**Spillover**	**Comparison**	**Diff.**	**Spillover**	**Comparison**	**Diff.**
Home Sales Price ($000)	311	196	115***	238	178	60***	195	165	30***
Size of Building (Sq. Ft.)	1,423	1,227	196*	1,299	1,207	92**	1234	1313	-80***
Age of Building	48	95	-47***	78	89	-11***	86	89	-3***
Distance to Nearest TIF (Miles)	0.062	0.197	-0.136***	0.148	0.382	-0.234***	0.317	0.737	-0.420***
Age of Closest TIF at Time of Sale	2.243	1.647	0.596***	1.862	1.641	0.222***	1.710	1.431	0.279***
Number of Times Sold	1.556	1.617	0.060*	1.595	1.728	-0.133***	1.690	1.771	-0.081***
Basement	0.458	0.721	-0.263***	0.626	0.758	-0.132***	0.720	0.813	-0.093***
Garage	0.071	0.053	0.018*	0.060	0.042	0.017***	0.047	0.042	0.005*
Deck	0.130	0.280	-0.149***	0.226	0.274	-0.048***	0.260	0.214	0.046***
Patio	0.010	0.012	-0.003	0.011	0.016	-0.005*	0.015	0.012	0.003*
Enclosed Porch	0.048	0.045	0.003	0.046	0.031	0.015***	0.035	0.036	-0.001
University (Miles)	0.922	0.772	0.150***	0.826	0.892	-0.066***	0.871	0.950	-0.078***
Commuter Train (Miles)	1.688	1.488	0.199***	1.561	1.637	-0.076***	1.612	1.760	-0.148***
Subway (Miles)	1.172	1.154	0.017	1.161	1.276	-0.116***	1.240	1.319	-0.079***
Central Business District (Miles)	2.109	1.969	0.140**	2.020	2.113	-0.093***	2.080	2.231	-0.151***
Bus Stop (Miles)	0.092	0.085	0.007***	0.088	0.071	0.017***	0.076	0.080	-0.005***
Lightrail Stop (Miles)	1.286	1.146	0.140***	1.196	1.323	-0.127***	1.286	1.502	-0.216***
Observations	1,251	2,212		3,463	8,980		12,508	20,528	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 6.4 illustrates the quarterly trends for mean home sale prices in spillover and comparison areas across the three spillover proximity specifications. The red lines in the graphs indicate the period of the Great Recession between the fourth quarter of 2007 and the second quarter of 2009. The average sales price in the spillover area of the EQ specification reaches a zenith of $898,296 and there is a similar spike of $498,634 in the spillover areas of the QH specification, both in the fourth quarter of 2008. Otherwise, average sales prices of homes in the spillover area are generally higher than the comparison area and values for both groups visibly increase over time.

The next sections estimate whether there are statistically significant differences in these residential sales prices between the spillover and comparison areas after designation of the nearest TIF using two panel data methodologies—difference-in-difference and repeat sales.

Figure 6.4. Mean Sales Price Amount for Spillover and Comparison Areas by Year



DID Estimation: Residential Property Sales Outcomes

This section estimates the spillover effect of TIF designation on the appreciation in sales price for residential properties near TIF districts using a difference-in-difference fixed effects analysis. Since residential property sales outcomes are estimated using the individual property sales transaction as the unit of analysis, for the DID model expressed in equation 3 the subscript i represents a sales transactions and t represents the quarter in which the sale occurs. The interaction term representing the intersection of designation (T) and quarter (t) remains the coefficient of interest that estimates the impact of proximity to TIF districts on property sales appreciation.

Limiting observations to those where a home sold more than once can also be a shortcoming of the repeat sales methods as some homes are more likely to sell multiple times. Estimating the spillover effects by housing market typology attempts to account for this shortcoming as the robustness of the repeat sales model is tested across homes in different housing markets.

As with the other outcomes of interest in this study, a naïve OLS model and an OLS model with time invariant controls are estimated to illustrate whether the DID fixed effects model estimates reduce bias compared to the cross-sectional models. The results are reported in table 6.7 below.

The naïve model yields significant coefficients for all proximity specifications. The log of property sales prices within the spillover areas increased by between 14.7 and 24.5 percentage points at the 5 percent level of significance. In the OLS model with covariates, the presence of a garage and an enclosed porch along with distance to the nearest bus stop are significantly and positively related to sales prices for all proximity specifications. In contrast, the distance to the nearest university is negatively related to sales price.

The inclusion of each home's structural characteristics and other covariates result in estimates of sales price appreciation smaller in magnitude than the naïve OLS estimates. More specifically, home sales within an eighth mile increase in price by 15.4 percentage points compared to homes in the comparison area between .126 and .25 mile from TIF districts. The estimate is statistically significant. The estimate for the HM specification is also smaller yet insignificant. For the QH specification, the sign of the estimate of home sales price appreciation is negative as a result of the inclusion of covariates.

Similarly, the coefficient of the natural log of sales price estimated using the DID fixed effects model also changes to a negative sign for both the QH and HM specifications, -6.2 and -19.4 percentage point decreases, respectively. Only the HM specification is statistically significant and the coefficient is quite large compared to the other specifications. Thus, sales prices in spillover areas are significantly different than the comparison area between .51 and 1 mile from the TIF district. Based on the conception of spillover presented in this study, this suggests that there is spillover of TIF designation effects observed in this proximity specification. In this instance, the negative coefficient suggests that there is negative spillover whereby homebuyers pay less for homes closer to TIF districts compared to the comparison area. This negative spillover upwardly biases the 121 percentage point increase in residential sales prices estimated at the block level of geography using a propensity score weighted DID fixed effects model. However based on these and other results, it is possible the HM specification is too far a distance away from TIF districts to actually measure spillover effects.

Table 6.7. TIF Designation Spillover Effects on Residential Property Sales

	EQ			QH			HM		
	Naive	Covariates	DID FE	Naive	Covariates	DID FE	Naive	Covariates	DID FE
Log Sales Price Appreciation	0.245***	0.154*	0.062	0.147***	-0.050	-0.062	0.230***	0.092	-0.194***
	(0.048)	(0.066)	(0.108)	(0.026)	(0.053)	(0.055)	(0.014)	(0.057)	(0.046)
Age of Closest TIF at Time of Sale		0.360***			0.360***			0.221***	
		(0.069)			(0.057)			(0.028)	
Number of Times Sold		-0.051*			-0.010			0.024*	
		(0.019)			(0.011)			(0.010)	
Garage		0.614***			0.493***			0.525***	
		(0.123)			(0.053)			(0.056)	
Deck		0.030			0.171***			0.248***	
		(0.042)			(0.032)			(0.030)	
Patio		0.028			0.343**			0.374***	
		(0.138)			(0.121)			(0.065)	
Enclosed Porch		0.210**			0.184**			0.218***	
		(0.062)			(0.057)			(0.049)	
Basement		0.169			0.096			0.363***	
		(0.099)			(0.105)			(0.097)	
University (Miles)		-0.612**			-0.638***			-0.446***	
		(0.197)			(0.172)			(0.092)	
Commuter Train (Miles)		0.220			1.066***			0.938***	
		(0.268)			(0.218)			(0.091)	
Subway (Miles)		0.042			-0.110			-0.020	
		(0.188)			(0.185)			(0.098)	
Central Business District (Miles)		-0.300			-0.778***			-0.687***	
		(0.168)			(0.167)			(0.069)	
Bus Stop (Miles)		3.440*			1.914**			0.927*	
		(1.710)			(0.700)			(0.465)	
Lightrail Stop (Miles)		0.010			-0.189			-0.250***	
		(0.148)			(0.152)			(0.066)	
Constant	5.325***	5.637***	4.301***	5.212***	5.943***	4.262***	4.906***	5.160***	4.077***
	(0.091)	(0.196)	(0.111)	(0.049)	(0.137)	(0.046)	(0.037)	(0.134)	(0.036)
Observations	2,066	2,066	3,463	6,939	6,939	12,443	17,470	17,470	33,036

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Repeat Sales Estimation

The difference-in-difference fixed effects empirical strategy is used throughout this dissertation to estimate TIF designation effects and TIF spillover effects associated with proximity to TIF districts. In the preceding section, this panel methodology estimates the spillover effects of TIF designation on the sales prices of homes by comparing spillover and comparison areas before and after designation of the TIF district nearest the home sold.

In addition to difference-in-difference, a repeat sales model is also used in this analysis to estimate spillover effects. As discussed in Chapter Four, the repeat sales model estimates the residential sales price appreciation for homes that have sold more than once during the study period using the first and last sales transaction. Multiple sales of a property create a balanced panel of residential property sales and in this dissertation without a comparison group the repeat sales model is essentially a before and after estimator of TIF spillover effects.

The repeat sales method is essentially a variation of hedonic price regression that further eliminates time invariant observables by comparing sales prices for the same property that likely hasn't changed significantly between sales. Therefore characteristics of individual homes are not needed for the analysis. This advantage of this methodology is weighed against the disadvantage of a smaller sample of property sales transactions that sold more than once. An even smaller sample of sales transactions that includes only observations where the first sale occurred prior to designation of the nearest TIF district and the last sales after designation is included in the analysis to further isolate the spillover impact of TIF designation on residential property sales prices.

Table 6.8 summarizes the average sales prices of those homes that have sold more than once between 2002 and 2013 that are within the spillover areas defined in this study within an eighth, quarter, and half mile from TIF districts. Sales prices are higher for homes closer to TIF districts with an average sales price of $282,695 for all repeat sales and $266,486 for repeat sales before and after designation of the TIF district closest to the residential property. The small sample sizes are also shown in this table. As an example, there are a total of 1,251 sales within an eighth mile of a TIF districts, 464 repeat sales, and 134 repeat sales before and after TIF designation of the nearest district.

Table 6.8. Mean Sales Prices for Repeat Sales by Proximity Specification

		Eighth Mile	**Quarter Mile**	**Half Mile**
All Repeat Sales 2002-2013	Mean Sales Price	$282,695	$239.007	$198,044
	Observations	464	1,376	5,560
Repeat Sales Before and After Designation 2002-2013	Mean Sales Price	$257.069	$235,521	$200,967
	Observations	134	590	2,352

In the repeat sales model outlined in equation 7 below, the natural log of the price difference between the first and last sale of a residential property is regressed on an indicator that equals 1 if the home falls within an eighth, quarter, or half mile distance from a TIF district. The t variable is equal to 0 for the first sale occurrence and 1 for the last sale. Just as with the DID model using panel fixed effects for residential property sales a set of dummy variables represent the quarter in which a sale occurred. Lastly, in this model block groups are used for geographic fixed effects.

$$\Delta \ln P_i = \alpha_i + \delta T_i + \gamma t_{it} + \lambda_t + \omega_i + \varepsilon_i \qquad (7)$$

Table 6.9 reports the coefficients of the repeat sales model. Limiting the sample to the first and last sale for any home that sold more than once produces results disparate from the DID estimates for all sales depending on the spillover proximity specification. In column 2, at an eighth mile, the increase of log sales prices is similarly positive but the coefficient is much larger and significant, indicating a 105 percentage point increase for the most recent sale. For repeat sales within a quarter mile the model also yields a positive and significant coefficient, but slightly smaller in magnitude, an 84.4 percentage point increase. This outcome conflicts with the negative coefficient estimated for all sales using DID. At a half mile (column 5), the repeat sales coefficient is negative indicating a -3.2 percentage point depreciation of sales prices. However, this difference is not significant compared to the DID estimate for the same proximity specification and is also smaller in magnitude.

This dissertation is also interested in the impact of TIF designation on the change in sales prices for repeat home sales. To that end, the sample of repeat sales is further restricted to the residential property sales where the first sale occurred prior to designation of the nearest TIF and the last sale occurred post-designation. Among the findings for this specification reported in columns 3, 6, and 9 there is a pattern of significantly increased sales prices with every spillover proximity specification. At an eighth mile the coefficient for the pre-post TIF designation repeat sales estimation indicates a 35.5 percentage point sales price appreciation. The coefficient of interest decreases with distance from the nearest designated TIF however the 28.8 and 20.9 percentage point increases for the quarter mile and half mile proximity specifications, respectively, are also statistically significant.

The half mile specification for the repeat sales model using sales before and after TIF designation is of particular interest since the coefficient derived from the model is positive. This is in contrast to the negative DID estimate for the QH specification, the only statistically significant DID estimate. The estimate for all repeat sales is also negative. As such, while the before-after repeat sales model produces the most consistent estimates, this smaller sample of sales might lead to biased spillover effect estimates. Overall, these estimations of the sales price appreciation for repeat sales provide insight about impact of homes being located within proximity to TIF districts. According to the findings here, sales price appreciation is significant for homes immediately surrounding TIF districts within an eighth mile and quarter mile. This finding holds for all proximity specifications of the before-after repeat sales model.

One caveat of the repeat sales methodology is that homes that sell more than once might be systematically different than those that do not. Beyond the individual characteristics of a residential property, the home could be located in a housing market where other factors may account for why these homes sell more frequently. The next section explores the heterogeneous spillover impacts of proximity to designated TIF districts taking into account the type of housing market within which the sale occurs.

Residential Property Sales by HMT

Baltimore City's Housing Market Typology (HMT) is a snapshot of the housing market derived from a range of housing market indicators including median home sales price, homes in foreclosure, owner occupancy rates, properties with code violations, subsidized rentals, commercial properties, vacant properties, and vacant lots created through demolition. Cluster analysis of these indicators groups block groups into clusters that are relatively similar to each other and dissimilar to block groups in other clusters.

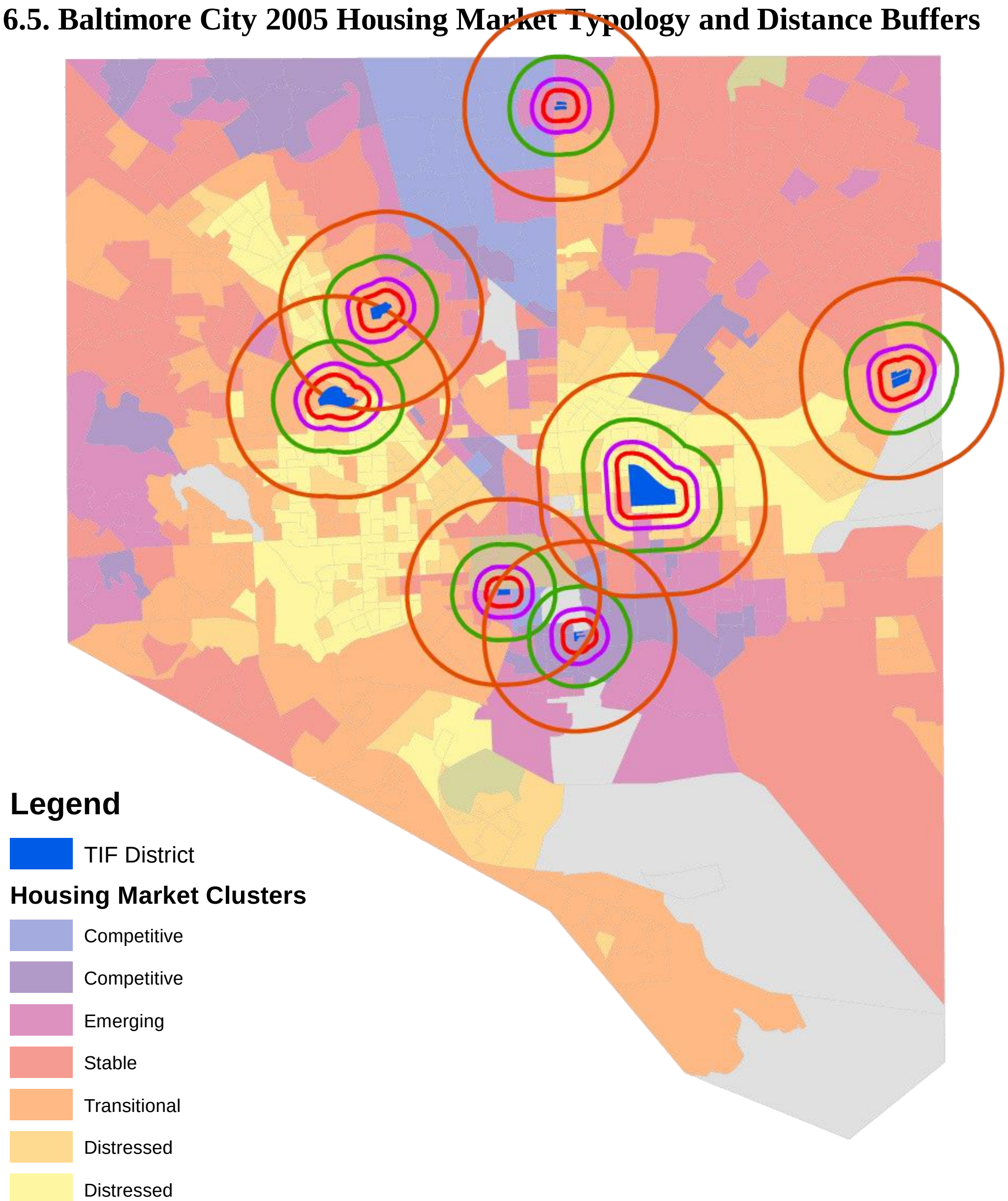
The HMT is used by various stakeholders as a guide for neighborhood planning and investment. Planners apply housing market intervention tools and strategies based on the market clusters as defined by the typology. Likewise, individuals purchasing homes are influenced by the typology as it signals the desirability of neighborhoods which often translates into a willingness to pay higher prices for homes.In figure 6.5, a map of Baltimore City illustrates the HMT for 2005 along with distance buffers at an eight, quarter, half and one mile.

Table 6.9. TIF Spillover Effects on Repeat Property Sales

	Eighth Mile		Quarter Mile		Half Mile	
	All Repeat Sales	Pre-Post Designation Sales	All Repeat Sales	Pre-Post Designation Sales	All Repeat Sales	Pre-Post Designation Sales
Log Sales Price	1.052***	0.355*	0.843***	0.288***	-0.032	0.209**
Appreciation	(0.129)	(0.136)	(0.061)	(0.078)	(0.053)	(0.065)
Constant	4.791***	4.594***	4.712***	4.531***	4.380***	4.574***
	(0.095)	(0.096)	(0.110)	(0.165)	(0.046)	(0.046)
N	464	134	1,376	590	5,560	2,352

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 6.5. Baltimore City 2005 Housing Market Typology and Distance Buffers



The competitive typology includes neighborhoods with robust housing markets, high owner-occupancy rates, high property values, a well maintained housing stock, a majority of single family detached homes, and low rates of vacancy and abandonment rates. Emerging neighborhoods with varied housing types and a mix of commercial land uses have homeownership rates slightly higher than average, lower foreclosure rates, and few vacant homes. Located in the outer edge of the city, stable neighborhoods have a relatively newer housing stock, lower median sales prices, and slightly higher average foreclosure rates but the homeownership rate is still significant. Transitional neighborhoods are ripe for reinvestment as they have high foreclosure rates and code violations but are on inner edge of the stable neighborhoods and have moderate real estate values and substantial homeownership rates. Lastly, distressed neighborhoods have predominately townhomes and have very high levels of vacant homes, high rates of code violations and lower homeownership rates. Table 6.10 demonstrates that average sales price decreases in each descending typology from competitive ($346,650) to distressed ($67,678). In addition, the majority of sales between 2002 and 2013 occurred in stable Baltimore City neighborhoods.

In the previous sections, spillover effects of TIF designation were estimated using the difference-in-difference and repeat sales panel methodologies. The first of these empirical strategies compared sales prices in spillover areas and adjacent comparison areas. The second analysis compared sales prices of repeat sales or homes that sold more than once during the study period. Here the HMT is used to determine the heterogeneous impacts of spillover effects of proximity to designated TIF districts on sales price appreciation across the five different housing market typology categories for both the DID and repeat sales methodologies. This analysis uses separate models of sales appreciation to test the hypothesis that spillover effects of TIFs differ by the typology clusters.

Table 6.10. Summary of Residential Property Sales by Housing Market Typology

Typology	Average Sales Price	Number of Sales
Competitive	$346,650	13,243
Emerging	$212,259	16,091
Stable	$138,439	24,844
Transitional	$93,294	23,109
Distressed	$67,678	15,618

Below, table 6.11 reports the findings of the DID analysis estimating the spillover effects of TIF designation on home sales prices by housing typology. The coefficient of the interaction term are derived from equation 3 where the unit of analysis is the individual sales transaction and signifies the average change in the log of sales prices for the spillover area after designation. The results can be interpreted in two ways—looking at the different typology outcomes for each proximity specification (EQ, QH, HM) and within each typology across spillover proximity specifications.

Table 6.11. TIF Spillover Effects by Housing Market Typology

Log Amount Total Sales	EQ	QH	HM
All Sales	0.062	-0.062	-0.194***
	(0.108)	(0.055)	(0.046)
	n=3,463	n=12,443	n=33,036
Competitive	-0.027	-0.056	-0.132
	(0.027)	(0.042)	(0.067)
	n=1,263	n=4,263	n=6,393
Emerging	0.095	-0.029	-0.181***
	(0.142)	(0.042)	(0.048)
	n=485	n=1,191	n=7,317
Stable	-0.099	-0.151	0.029
	(0.097)	(0.095)	(0.062)
	n=218	n=1,727	n=5,921
Transitional	0.270	-0.163	0.011
	(0.125)	(0.093)	(0.108)
	n=425	n=1,608	n=5,582
Distressed	-0.252	0.208	0.094
	(0.388)	(0.141)	(0.106)
	n=962	n=3,526	n=7,445

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For the EQ specification, there are no statistically significant coefficients for any of the typologies, however, it is important to note that only homes in the emerging and transitional neighborhoods have sales prices increases after designation in the spillover area that are positively related to the designation of the nearest TIF, 9.5 and 27 percentage points, respectively. There are similarly no significant differences between the spillover area a quarter mile from TIF districts and comparison area between .26 and .5 mile from the TIF district. The negative coefficient for all sales transactions in the QH specification is driven by the decreases in sales prices in the spillover area for every typology except distressed neighborhoods where there is an insignificant increase in sales prices by 20.8 percentage points.

The competitive typology has a negative coefficient for the HM specification. This is the only typology where sales price coefficient is consistent for each proximity specification. Sales prices for homes in emerging neighborhoods within the half mile spillover area are the only other negative coefficient, indicating a decrease in sales prices by -18.1 percentage points. This is the only statistically significant estimate across all proximity specifications, just as the coefficient for all sales in the HM specification is significantly negative. If the spillover effect observed is valid at this distance from TIF districts, the potential downward bias of the TIF designation effect estimated in Chapter Five is driven by homes in the emerging market cluster. Comparing this outcome with the other specifications for this typology, it is likely that a half mile distance from TIF districts is too large of an area to estimate spillover of TIF designation effects.

The advantages of estimating heterogeneous impacts of spillover are obvious with the repeat sales estimation. Per table 6.12 sales in the emerging and stable market clusters within an eighth mile from TIF districts increase significantly by 44.6 and 99 percentage points and contribute to the overall large and statistically significant estimation of spillover effects for all repeat sales. Within a quarter mile, sales prices in distressed neighborhoods decreased by 147 percentage points, at the tenth of a percentage point level of significance.

This finding in such a weak housing market is not unexpected but conflicts with the large positive coefficient for overall repeat sales. Again, estimates for the half mile specification don’t follow a specific pattern and may not be valid as homes in stable neighborhoods experienced a decrease of -17.8 percentage points for the most recent sale while homes with the same typology but closer to TIF districts is large and positive. Again, the results of the repeat sales estimation alone suggest growth in sales prices for spillover areas in emerging and stable neighborhoods. However, it is not immediately clear that limited observations used in the repeat sales methodology are varied enough to make any conclusions about how designation effects estimated at the block group geography using the propensity score weighted model are biased compared to the spillover effects also estimated with the difference-in-difference analysis.

Table 6.12. TIF Spillover Effects for Repeat Sales by Housing Market Typology

Log Amount Total Sales	Eighth Mile	Quarter Mile	Half Mile
All Repeat Sales	1.052***	0.843***	-0.032
	(0.129)	(0.061)	(0.053)
	n=464	n=1,376	n=5,560
Competitive	0.064	0.106	-0.026
	(0.094)	(0.081)	(0.044)
	n=220	n=614	n=2,196
Emerging	0.446***	-0.027	-0.057
	(0.000)	(0.126)	(0.064)
	n=28	n=214	n=544
Stable	0.990***	-0.016	-0.178*
	(0.000)	(0.156)	(0.089)
	n=8	n=70	n=762
Transitional	-0.007	0.078	0.098
	(0.370)	(0.274)	(0.099)
	n=106	n=152	(n=678
Distressed	0.836	-1.470***	-0.354
	(0.600)	(0.234)	(0.666)
	n=86	n=306	n=1,350

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.3 Subgroup Analysis

In Chapter Five, estimates of TIF designation effects by TIF type for TIF block groups follow a pattern whereby total jobs and permit amount coefficients were insignificantly negative and near zero, respectively. Residential TIF block groups were significantly different than non-TIF block groups, with large negative estimates suggesting jobs and permits decreased after designation in and around the two residential TIF districts included in this study. For property sales, the estimates were consistently large and significant across all TIFs and each type of TIF.

In this section, spillover effects are also estimated by the type of project financed by the TIF for the main effects of total jobs, permit amount, and sales price outcomes. The coefficients of the difference-in-difference fixed effects model are included in table 6.13. Estimates for the natural log of jobs and permit amounts for census blocks in spillover areas are not significantly different than comparison areas for residential TIFs.

More specifically, at an eighth mile and a half mile, the total jobs coefficient for residential TIFs is negative although insignificant, indicating that while jobs in spillover area census blocks are negatively related to proximity to designated TIF districts, the estimate is not significantly different than the comparison area. At a quarter mile, the sign of the residential coefficient could indicate negative spillover for overall TIF designation effects at this distance from TIF districts however it follows that the insignificant results indicate the significantly negative TIF designation effect estimate at the block group level of geography using economically similar comparisons is not negatively biased due to spillover effects.

For permit activity, within an eighth mile in distance from TIF districts, the log amount of permits issued has a large negative coefficient comparing the spillover and adjacent comparison area. The QH proximity specification in columns 4, 5, and 6 is the only one where coefficients for mixed and residential TIFs are the same sign, both negative, and with residential TIF having the larger coefficient. For the HM proximity specification, the residential TIF coefficient for permit value is positive while the mixed TIF coefficient is negative. None of these estimates are significant.

Among the results for the natural log amount of sales prices, the mixed TIF coefficient for the EQ specification is positive, as is the coefficient for all outcomes for this kind of TIF. Across the three proximity specifications the coefficients for property sales outcomes are negative and increase in magnitude with greater distance from the residential TIF district. The estimates for the QH specification indicate that average sales price in the spillover area around TIF districts is 10 percentage points lower than the comparison area at the 5 percent level of significance. Likewise, sales prices within the half mile spillover area around residential TIFs also significantly decreased after designation by 36.7 percentage points.

Table 6.13. Spillover Effects by TIF Type

	EQ			QH			HM		
	All TIFs	**Mixed TIFs**	**Residential TIFs**	**All TIFs**	**Mixed TIFs**	**Residential TIFs**	**All TIFs**	**Mixed TIFs**	**Residential TIFs**
Log Total Jobs	-0.028	0.017	-0.319	-0.007	-0.014	0.140	0.001	0.007	-0.078
	(0.128)	(0.139)	(0.299)	(0.080)	(0.088)	(0.141)	(0.048)	(0.061)	(0.083)
	n=2,397	n=2,397	n=2,397	n=7,011	n=7,011	n=7,011	n=17,013	n=17,013	n=17,013
Log Amount Total Permits	0.034	0.108	-1.105	-0.157	-0.162	-0.623	0.016	-0.093	0.238
	(0.35)	(0.36)	(0.89)	(0.22)	(0.24)	(0.46)	(0.14)	(0.18)	(0.25)
	n=651	n=651	n=651	n=1,720	n=1,720	n=1,720	n=4,012)	n=4,012)	n=4,012
Log Amount Total Sales	0.062	0.134	-0.014	-0.062	-0.023	-0.102*	-0.194***	-0.092	-0.367***
	(0.108)	(0.144)	(0.045)	(0.055)	(0.076)	(0.047)	(0.046)	(0.057)	(0.052)
	n=3,463	n=3,463	n=3,463	n=12,443	n=12,443	n=12,443	n=33,036	n=33,036	n=33,036

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter Discussion

The primary purpose of this chapter is to determine whether there are spillover effects associated with TIF designation. Spillover implies that the benefits of an incentive such as TIF could either spillover to adjacent areas beyond the TIF district (positive spillover) or TIF districts could be the impetus for businesses to relocate or economic activity to shift inside or closer to the TIF district (negative spillover). It is important to estimate these spillover effects and the net impact of TIF designation to avoid biased estimates of TIF designation effects estimated at levels of geography larger than the TIF district, such as the block group analysis in Chapter Five.

To that end, in this chapter first the spillover effects were estimated using DID fixed effects. For job and permit outcomes, census blocks within an eighth, quarter, and half mile distance from TIF districts were compared to adjacent equidistant census blocks. Spillover estimates of residential property sales are estimated with individual sales transaction. Statistically significant differences between observations in the spillover area and the geographically close comparisons would indicate that there are indeed spillover effects that potentially bias the propensity score weighted TIF designation effects.

Overall, employment, permit activity, and home sales prices in spillover areas are not significantly different than the surrounding comparison areas and the lack of spillover effects is not sensitive to proximity to the TIF district. All the estimates of spillover derived from the DID fixed effects model are statistically insignificant across proximity specifications with the exception of the residential sales price depreciation observed a half mile from the TIF district.

However, this is a somewhat large distance at which to observe spillover estimates. For several of the TIF districts in this study, at this distance the spillover area covers areas even larger than the TIF block group. Therefore it is unlikely that the already large estimates of sales price appreciation as a result of TIF designation is downwardly biased by spillover. This determination is also supported by spillover effects subgroup analysis whereby the negative spillover of the impact of proximity TIF designation on sales prices is twice as large in areas half mile from residential TIF districts. Likewise, estimating spillover effects based on the housing market typology indicates that the estimated spillover effects for the HM specification is largely driven by changes in sales prices in emerging neighborhoods.

Spillover effects on price sales are also estimated using the repeat sales methodology. In this analysis the sample of sales transactions are restricted to homes that have sold at least twice during the study period. The repeat sales methodology doesn't require detailed individual characteristics of homes as does traditional hedonic price regressions. In addition the empirical strategy controls for selection bias more accurately than the hedonic model.

This panel methodology estimates the relationship between sales price changes and proximity to TIF districts, a technique used by Weber, Bhatta, and Merriman (2007). Within an eighth mile and quarter mile, sales prices for the most recent sale appreciate significantly and the magnitude decreases with distance from TIF districts. Of course, these repeat sales may not be representative of homes in markets where there is little mobility and housing turnover. As an example, only homes in emerging and stable neighborhoods on average experience significant growth for the eighth mile proximity specification and for the quarter mile specification, homes in distressed housing markets depreciated quite significantly while overall repeat sales appreciated.

The half mile specification once again deviates from the findings as the coefficient is both negative and insignificant, further supporting the invalidity of estimating spillover effects at this distance. In addition, this depreciation in prices for all repeat sales is driven by the estimated decrease in prices in stable neighborhoods that don't exhibit this kind of impact within spillover areas closer to TIF districts.

The effects of spillover on repeat sales prices are also estimated for homes where the first sale occurred before designation of the nearest TIF district and the last sale occurred after designation. This reduced sample results in spillover effects that are all statistically significant but smaller in magnitude for homes within an eighth and quarter mile compared with the full sample of repeat sales in those same spillover areas. This finding demonstrates that estimates of spillover effects that do not consider the timing of the designation of the nearest TIF in relation to when a home was sold, such as the simple repeat sales method, are likely upwardly biased.

7 CONCLUSIONS AND POLICY IMPLICATIONS

7.1 Conclusions

This dissertation estimates the impact of tax increment financing in Baltimore City on employment, permit activity, and residential property sales outcomes. There are few existing empirical studies evaluating TIFs due to methodological and data limitations. Previous studies focus on the political implications for adopting tax increment financing and the impact on the assessed value of property in the TIF district. However, conducting empirical evaluations using quasi-experimental research designs and other econometric methods is supported by researchers in the field and is ultimately necessary to determine whether designating TIFs accomplishes the broader goals of creating jobs and facilitating private investment in and around TIF districts.

The major contributions of this study that address the gap in the literature include evaluating this spatially targeted economic development incentive using advanced econometric research designs including difference-in-difference analysis, propensity score estimation, and repeat sales methodology along with data available at small levels of geography. This dissertation is intended to overcome the methodological shortcomings of previous studies that led to the overall inconclusiveness of estimations of the impact of TIF designation.

Previous TIF studies (Smith, 2009; Carroll, 2008; Lester, 2014) and studies of other spatially targeted economic development incentives including state enterprise zones and federal Empowerment Zones (Bondonio and Engberg, 2000; Greenbaum and Engberg, 2004; Bondonio and Greenbaum, 2007; Elvery, 2009; O'Keefe, 2004; U.S. Department of HUD, 2001; Oakley and Tsao, 2006; Busso and Kline, 2008; and Ham et. al., 2011) use a combination of a panel-data fixed effects difference-in-difference approach and propensity score estimation to estimate TIF designation effects. In this study the DID strategy addresses the main source of selection bias, unobservable pre-designation differences specific to each block group that do not change over time and may be correlated with designation. In addition, propensity score estimation is used to address the observable pre-designation demographic, housing, socioeconomic, and land use differences between TIF and non-TIF block groups. Using the inverse probability of weighting technique, a greater weight is assigned to economically similar block groups with higher probabilities of designation.

The findings of this study indicate that the impact of TIF designation on employment is insignificant. Ultimately, there is no evidence that the number of jobs increased in TIF designated block groups beyond what would have occurred without TIF designation. This confirms the estimated effects observed in the only other study of the relationship between TIF designation and employment at a similar level of geography and using a similar methodology (Lester, 2014). The moderate wage job estimate is the only significant job outcome, indicating a decrease in jobs with annualized wages between $15,000 and $40,000. This outcome suggests that TIF designation was not a firewall against the shift to low-wage jobs during the Great Recession which took place during the study period.

The results of this dissertation also support the findings of the only existing study of building permit activity and TIF designation that indicates there is no relationship between the incentive and this measure of private investment (Lester, 2014). The insignificant coefficients suggest that there was no difference in the number of permits issued and the total permit values in TIF block groups after designation compared to non-TIF block groups. Commercial permit values significantly decreased for TIF block groups, yet this outcome is sensitive to the propensity score estimation strategy and does not hold where propensity scores are used to match economically similar block groups instead of weighting TIF blocks by the inverse of their estimated propensity scores.

The increase in the number of home sales and sales prices estimated in this dissertation reflect the findings in other studies evaluating the impact of TIF designation on sales prices and the assessed value of property (Smith, 2009; Dardia, 1998; Anderson, 1990). However, the appreciation estimated in this dissertation is quite large, driven by the sale of townhomes and likely also increased demand in previously low-valued homes in the areas surrounding TIF districts. It is also important to note that these positive effects are observed for both mixed and residential TIF districts included in the study while the subgroup analysis conducted also indicates large decreases in job and permit outcomes for residential TIF block groups.

TIF spillover effects are estimated in this study to determine whether estimated TIF designation effects are biased by economic activity surrounding TIF districts. Spillover implies that the benefits of TIF designation could either spillover to adjacent areas beyond the TIF district (positive spillover) or TIF districts could be the impetus for businesses to relocate or economic activity to shift inside or closer to the TIF district (negative spillover). Using job and permit data aggregated to the census block along with individual residential property sales transactions, the spillover effects of TIF designation were estimated using the DID methodology and geographically close comparison areas within various distances from TIF districts. Spillover effects were not observed for total jobs or permit value outcomes and this finding is not sensitive to proximity to TIF districts. Therefore the insignificant TIF designation effects for those outcomes are not biased by spillover effects.

Several empirical strategies are used to estimate the spillover associated with TIF designation on residential property sales. Using the difference-in-difference methodology there is evidence of negative spillover a half mile from TIF districts however subgroup analysis and analysis of heterogeneous impacts across housing market typologies indicate that estimating spillover at this distance produces invalid results. Following Weber, Bhatta, and Merriman (2007) this dissertation also analyzes the TIF spillover effect associated with residential property sales prices using the repeat sales methodology. The findings conclude that sales price appreciation was greater for homes in emerging and stable neighborhoods in the areas immediately adjacent to TIF districts. The estimates are smaller in magnitude where TIF designation occurred during the period between the repeat sales transactions, signifying that this smaller sample of homes sold more than once during the study period is not representative of all repeat sales.

7.2 Limitations

As the contributions of this study are largely methodological, so are the limitations. First, while this study estimates the TIF designation effects on employment, building permit activity and residential property sales, these are indirect outcomes of TIF designation. While there may be many expectations about the impact of TIF districts in the municipalities that designated them, tax increment financing only directly diverts increased property tax revenue to pay off the bonds used to fund infrastructure and site preparation in the designated TIF area. This distinction is important to remember when considering the lack of findings in this dissertation.

While this study demonstrates how data available at small levels of geography and advanced econometric analyses can be used to improve empirical studies of TIF designation, there still exist methodological challenges. Of the three existing empirical TIF studies estimating job outcomes, two are conducted at the municipal level (Man, 1999; Byrne, 2010) and one at the block group level of geography (Lester, 2014). The LODES dataset enables estimation of TIF designation effects and TIF spillover effects using smaller geographic units, however the data are derived from synthetic data. For the purposes of confidentiality, noise infusion is applied to employment data so that individual firms and workers cannot be identified but the amount of noise is small enough not to distort the data.

It is also likely that the total number of jobs in TIF districts and the surrounding areas are not reflected in the data due to a number of reasons. For instance, for businesses with more than one establishment a worker's job location may not reflect the actual worksite. This may also be an issue specifically for construction jobs, however it is important to remember this study focuses on permanent jobs after the projects financed by TIFs have been completed. In addition, the dataset doesn't distinguish between permanent and temporary jobs. Contractual workers' job location may be assigned to a headquarter location and the self-employed are not included at all in the dataset. One other shortcoming of LODES data is that the wage categories don't change over time and are not normalized or adjusted for inflation between 2002 and 2013. Lastly, firm-level jobs data might provide more information about job change in individual businesses however the interest of this study is employment outcomes in geographic units that contain or intersect TIF districts and the time series LODES data serves this purpose. In addition, the tradeoff for more detailed data is the ease of access to LODES data compared to other proprietary data sources.

With regard to the propensity score estimation used in this dissertation, the factors identified that contribute to TIF designation are limited by the fact that they are not definitive as they are selected by the researcher and that not all factors are observable. In addition, the DID fixed effects analysis accounts for unobservable influences, however this methodology is complicated in that the post-designation period for non-TIF block groups in this study is determined as the year after all TIF districts were designated while the post-designation for TIF block groups vary by the year the TIF financed project was completed. However, it is not immediately clear whether or to what extent this impacts estimated TIF designation effects. It is also important to note that phases of the EBDI redevelopment, one of the largest TIF district in this study, are still under construction.

7.3 Policy Implications and Future Research

Tax increment financing is a spatially targeted economic development incentive. Its prevalence as an economic development strategy for localities across the country reinforces that "place matters" and that redevelopment often requires location-specific incentives. More specifically, TIFs decrease redevelopment costs, thereby reducing the risks associated with financing these kinds of projects in TIF districts, ultimately making the projects feasible. In addition, there are likely various intangible benefits experienced across an entire neighborhood when a rundown building is finally demolished and redeveloped or a parcel is simply renovated to its highest and best use.

However, based on the findings of this study it is not immediately clear that tax increment financing is an incentive that addresses market failures by improving the allocation of resources as, with few exceptions in Baltimore, TIF developments aren't primarily located in disadvantaged areas with limited spatial access to opportunities and resources. As a result, in some ways TIF designation, where investment is concentrated in TIF districts and not in other areas with perhaps more severe neighborhood conditions, contributes to rather than addresses uneven development (Smith, 2008).

Perhaps this is only a shortcoming of tax increment financing if policymakers and other stakeholders ascribe to a normative view of the role of TIFs, that this incentive should be used to eradicate blight or provide some social benefit for local residents. But TIFs are a widely used financing mechanism for which the goals are varied and the incentive is implemented in different ways in different municipalities. The success of TIFs is often viewed through the lens of the physical redevelopment of a place as the incentive really only directly diverts increased property tax revenue in TIF districts to pay off bonds that fund infrastructure improvements within them.

At the same time, state and local governments spend billions of dollars on this spatially targeted economic development incentive that influences other budgetary policies and expenditures. In Baltimore City, TIFs represent a significant outlay of initial public investment through issuance of municipal bonds as well as subsequent bond repayment obligations. Recent TIF awards for the Harbor Point, Poppleton, and the University of Maryland BioPark developments have sparked considerable interest in TIFs as city officials, residents, and developers attempt to understand and articulate the impact on local employment and private investment as well as the contribution of this spatially targeted economic development incentive to the overall prosperity of surrounding neighborhoods and the residents within them. Therefore, evaluating the employment and private investment outcomes associated with these TIF developments is necessary.

A Baltimore Development Corporation task force made up of various city stakeholders convened in January 2011 reviewed the processes and policies for designating Baltimore City TIFs and produced a report with recommendations that focused on transparency such as consistency in the “but for” argument for TIFs as well as monitoring of TIF activities and evaluation of TIF benefits (Baltimore City Council, 2011). The job counts, income tax, and real estate tax outcomes included in the report tell one part of the story about the impact of TIF designation. For example, if there is interest in the number of construction jobs created related to

TIF developments, rigorous performance management as part of process or outcome evaluations can create greater accountability for examining these kinds of short term outcomes.

However, empirical evidence is also necessary to determine the effectiveness of the incentive. To that end, methodological advancements demonstrated in this study have a myriad of implications for the evaluation of TIFs locally and beyond. Looking broadly, stakeholders across the country can use this study as a framework to conduct similar evaluations of the impact of TIF designation beyond program outputs within the TIF district, especially if job counts reported by businesses located in TIF districts represent an employment shift from other areas of the city or from other local businesses that can't be observed only with performance management and monitoring. In addition, the findings of this kind of evaluation can potentially be used as inputs into ex-ante studies and cost-benefit analyses investigating the long-term impacts on local budgets. Lastly, the study demonstrates how secondary data such as the LODES dataset and existing administrative data, including permit activity and residential property sales transaction data can be used to estimate the effects of TIF designation as well as spillover effects in surrounding neighborhoods. This addresses concerns about the costs of empirical evaluations with advanced research designs (Storey, 1990). At the same time, while this dissertation is a methodological improvement over previous studies, this study recognizes the continued limitations as advanced research designs and data still may not lead to better implementation of TIFs or improved employment and private investment outcomes.

Furthermore, the findings this dissertation estimated with this improved empirical strategy may not necessarily lead to changes in the support for tax increment financing or politicians' willingness to continue to subsidize private development in this way. Besides cost, the lack of evidence supporting the growth of jobs as a result of TIF designation in Baltimore City as observed in this dissertation might contribute to reluctance to evaluating the employment impact of local economic development with more sophisticated research designs (Storey, 1990). The political consequences for these results remain to be seen.

However, the results could provide an opportunity for proponents to reconsider the theoretical underpinnings of tax increment findings and perhaps the expectations and rhetoric about the incentive. More specifically, the findings have theoretical implications that suggest politicians' and local economic development officials' reliance on TIFs as a job creation strategy needs to better reflect the limitations of the incentive. If TIFs are not creating significant numbers of jobs in a municipality compared to what would have occurred otherwise, this has obvious implications for the expectation of a growing local workforce resulting from tax increment financing.

It also implies that alternative job creation strategies should be as vigorously pursued and supported as TIFs. The quality of jobs is also an important consideration. Many of Baltimore City residents are low-skill workers and a great number more face challenges and barriers to employment. If TIFs create the kinds of middle and high-skill jobs that are attractive to the local economy, local workers are less likely to be able to access them due to low educational attainment. Ultimately, if TIFs are not increasing employment nor providing employment opportunities for local workers, there should be an intentional effort to promote employment growth directly rather than expecting that these outcomes manifest as a result of TIFs. This might include a parallel focus on workforce development strategies and facilitating pathways between residents and jobs in TIF districts and jobs induced by TIF investments. This could require creating and supporting community-based workforce pipelines, financing mixed development projects near transit, connecting with anchor institutions and other major employers to identify employment and advancement opportunities for workers, and instituting local hiring goals for economic development initiatives such as those recently passed in Baltimore City. With respect to private investment, the findings of this dissertation indicate residential property sales prices in TIF districts and in surrounding spillover areas increase significantly after designation. A direct strategy of interest to policymakers could be ensuring the preservation and development of affordable housing in these areas. Among the existing TIF districts included in this study, EBDI is one of the more comprehensive redevelopments and is probably the best example of addressing these issues directly in creating a workforce pipeline, affordable housing, along with minority contracting and local hiring goals.

To capture the benefits of economic development projects and investments financed with public funds or supported by local government, some municipalities are requiring community benefit agreements (CBA). CBAs are legally enforceable contracts that require developers to commit various kinds of resources to the community where they are siting their projects (Wolf-Powers, 2010; Bartik, 2011; Weber and Santacroce, 2007). CBAs can take many different forms. As recently as February 2016 Baltimore's City Council President vowed that the community benefit fund established between the developer Wexford Science & Technology and community leaders in exchange for supporting the $17.5 million TIF to expand the University of Maryland's BioPark and projected to create 1,400 permanent jobs would become the standard for awarding TIFs in Baltimore City (Broadwater, 2016). According to members of the city council, the initial $1 million CBA that is expected to expand to $4 million would be funded by University of Maryland and the developer for various community development projects and initiatives.

Ultimately, private development funded with tax increment financing, even with these kinds of agreements is not a panacea. But policymakers and evaluators of policy still have a responsibility to estimate the relevant outcomes and to determine whether tax increment financing as a place-based strategy is creating local employment opportunities and catalyzing private investment rather than reinforcing disparities.

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