The dynamic and persistent effects of tax increment financing as an example of place-based policy: Evidence from Cook County, Illinois

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Abstract

Using a staggered difference-in-differences design, this paper analyzes the effects of tax increment financing (TIF) in Cook County, Illinois. TIF is negatively correlated with the number of establishments in Chicago, likely due to unintended tax burdens and competition between TIF districts. In non-Chicago areas, TIF shows positive effects on employment for 6 to 20 years. Lastly, this study provides evidence of the persistent effects of TIF and its potential to move localities from low-density to high-density economic activity, calling for a re-evaluation of the argument against subsidizing economically lagging areas.

1. Introduction

Concentrated investments in designated areas are expected to help stimulate local economic activity, reduce spatial inequality, and improve local amenities. Accordingly, the U.S. has seen a significant increase in place-based policies since approximately the 1980s (Eisinger, 1998) and tax increment financing (TIF) is one of the leading examples. Since it was first adopted in 1952 in California, TIF has been implemented in 49 states and the District of Columbia (Merriman, 2018), playing a crucial role in local economies. For instance, in Chicago, more than $1 billion (38%) of Chicago's property tax revenue flowed into TIF districts in 2020 (Cherone, H., 2021). With the growing use of TIF and the subsequent increase in the amount of revenues and resources allocated to the program, TIF has drawn substantial interest from researchers. However, previous studies are far from conclusive on the effectiveness of TIF and have provided inconsistent empirical results.

This paper provides comprehensive and fine-grained empirical evidence on the effectiveness of TIF by analyzing the dynamic and persistent effects of TIF on employment and establishments in Cook County, Illinois, from 1990 to 2014. Understanding the dynamic and long-term effects of TIF is essential because the intensity of development activities is likely to vary in each phase of the program, and the effects may accumulate over its entire life span. Also, as Kline & Moretti (2014) point out, specific insights into such evolutionary and cumulative effects could help lessen the confusion and controversy over the effects of place-based policies (PBPs). However, the literature includes only a few, limited mentions of the dynamic effects of TIF and they either focus on the aggregated effect of TIF over its life span (Dye & Merriman, 2000; Lester, 2014; Byrne, 2010) or simply include a variable indicating the age of TIF (Weber et al., 2007; Kane & Weber, 2016), which is insufficient to demonstrate its dynamic effects.

Measuring persistent effects is also crucial for assessing the effectiveness of PBPs. When assisting in lagging areas, policymakers seek to achieve sustainable effects. If TIF districts successfully established a sustainable agglomeration economy during the designation period, we would expect to find a lasting positive impact, which would provide evidence in favor of PBPs. Alternatively, the effects of TIF could soon dissipate once the incentives or other governmental efforts are no longer concentrated on TIF districts. To date, no studies have explored whether the effects of TIF persist or dissipate after the program is terminated.

This research contributes to regional empirical studies and a growing literature on quantitative policy evaluations of the effects of PBPs in three ways. First, examining dynamic treatment effects at each stage of TIF can inform an optimal treatment regime or sequence, allowing policymakers to maximize policy effectiveness. Second, showing the long-lasting effects of PBPs may justify their continued use, as it suggests that investing in less productive areas may be an efficient use of resources, triggering another agglomeration economy or growth impetus. Lastly, the conceptualization and newly developed staggered difference-in-difference design adopted to measure TIF's dynamic and persistent effects could be applied to evaluate other PBPs.

2. A brief background of TIF

TIF is one of the most widely used economic development policies in the U.S. (Warner & Zheng, 2013), and has also been exported abroad to Australia and the United Kingdom. In the U.S., it takes different forms in different states. However, they share a commonly stated goal: to revitalize “blighted” neighborhoods through geographically concentrated investments.

In its most basic form, TIF works as follows: first, a municipality or county establishes a TIF district in a blighted area. Once the TIF district is established, property tax revenues in the area that initially flowed to the existing taxing bodies, such as park or school districts, are frozen for approximately 20 years. For example, in Illinois, the lifespan of a TIF district is 23 years, with the option of an additional 12-year extension. Any future increment in property tax revenues resulting from increased development activities and property values is earmarked for the TIF district and used to provide direct incentives to the areas that hold the potential to positively impact the local economy.

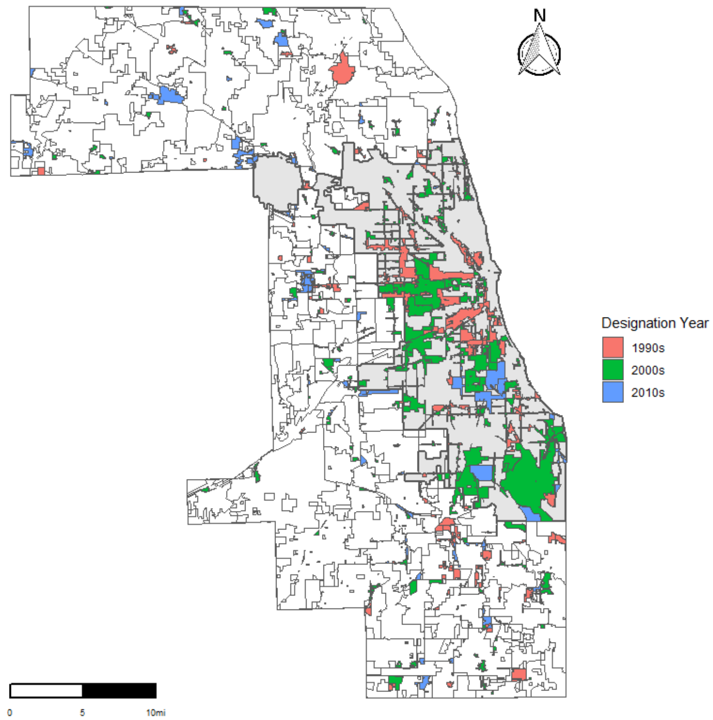
TIF funds are required to be expended on permitted uses. According to Lester’s (2014) examination of TIF in Chicago, 42% of TIF funds were disbursed directly toward economic development in the form of subsidies to developers for covering up-front expenses, relocation costs, and site acquisition and preparation. Another 38% of the funds were allocated toward enhancing public facilities, such as schools and transportation infrastructure, while approximately 16% was expended on infrastructure development, such as street beautification and lighting.

The applications mentioned above of TIF funds are expected to directly and indirectly impact the labor market. Investing in economic development activities has the potential to directly incentivize firms to establish operations in TIF districts by offering and enhancing office, housing, and commercial spaces, as well as facilitating the relocation of firms. In addition, providing public facilities and infrastructure improvements can contribute to employment growth by promoting better economic and physical conditions. Despite the government efforts and assistance, if a TIF district fails to attract (re)development activities, the city council then considers whether to continue or repeal the TIF. This process generally takes place several years after the initial designation, for example, seven years in the case of Chicago.[1] However, if substantial (re)development activities occur during its lifespan, the TIF is terminated when the life of the project has been fully expended unless the intended (re)development goals have been achieved or all planned projects are completed and associated projects costs have been paid before the initial termination date. After TIF is terminated, the overlapping taxing bodies can collect taxes from the increments in the assessed values that occurred over the lifespan of TIF.

Illinois began establishing TIF districts after the Tax Increment Redevelopment Act was passed in 1977. Since then, over 500 TIF districts have mushroomed in Cook County. As shown in Figure 1, TIF districts have been used more heavily in Chicago, while other municipalities have used TIF less intensively, resulting in a relatively scattered dispersion. However, the aggressive adoption of TIF has not been without its challenges and there has been a fierce pushback to adoption of TIF from other taxing districts that are forced to forgo their tax bases and are denied access to future increments in tax revenues, particularly in Chicago. An instance of such conflict is the legal action undertaken by school districts against TIF districts. Furthermore, skepticism about the effectiveness of TIF has also spurred debate. It argues that TIF either just captures revenues that would otherwise have flowed to already existing taxing bodies or have not been effective in stimulating development. So far, previous studies on this topic have yielded conflicting results.

[1] Chicago, which makes extensive use of TIF, reviews TIF districts annually and publishes the rules and conditions under which they can be terminated. However, in many other cases, termination decisions are made on a case-by-case basis, although the criteria outlined above apply similarly.

Figure 1. TIF districts in Cook County by designation year



Note: The City of Chicago is indicated by the shaded area. Data on boundaries and designation years are obtained from the Cook County Clerk's Office and the City of Chicago's data portal.

3. Related literature

To measure the effectiveness of the TIF program, most previous studies evaluate employment, the number of establishments, property values, or tax rates considering TIF's basic revenue flow structure and its goals. The analysis results vary, but many studies assessing the effects on employment find insignificant or even negative effects of the program in multiple states and cities (El-Khattabi & Lester, 2019; Funderburg, 2019; Lester, 2014) while others report evidence of positive effects of TIF (Man, 1999; Byrne, 2010). For instance, Byrne (2010) finds a positive relationship between industrial TIF and municipal employment growth in municipalities in Illinois; however, TIF districts show no significant effects or negative effects on retail employment in Chicago (Lester, 2014).

One possible reason for the diverse results found in previous studies on TIF is that they were conducted at different geographical levels. Earlier studies, such as Man (1999) and Dye & Merriman (2000) analyze the effects of TIF at the municipality level, providing relatively large-scale evidence of how TIF affects the economy. However, since TIF districts often cover only a small part of a municipality or even smaller locales, research that uses a more geographically precise unit of analysis at the intra-municipal level, such as this study, is likely to capture the effects of TIF more accurately. Thus, the next generation of TIF studies often have conducted more micro-level research. For instance, Funderburg (2019) shows that TIF decreases private employment in Polk County, Iowa, based on parcel-level analysis.

Another line of the related literature examines the implications of TIF on overlapping taxing bodies or neighboring areas. Once a new TIF district is formed, it captures tax revenues from growth in property values and utilizes the increment for its fund that might otherwise go to other overlapping taxing bodies. As a result, these overlapping taxing bodies are left with increasing costs due to the new and higher service demands associated with (re)development activities in the TIF districts that cannot be taxed from the increase in the tax base. This might compel an overlapping school district to raise its tax rates. In fact, findings from Skidmore & Kashian (2010) and Weber et al. (2008) suggest that adopting TIF districts leads to an increase in property tax rates in overlapping jurisdictions.

TIF can also generate spillovers to neighboring areas, either negative or positive. Positive spillovers can occur if TIF generates agglomeration and attracts businesses from other areas. This could result in a downward bias when estimating the effects of TIF on the targeted areas. However, if businesses from neighboring areas relocate to the targeted area, it may represent a transfer from the immediate areas and create an upward bias when estimating the effects of TIF in the targeted areas. Ham et al. (2011) and Hanson & Rohlin (2013) highlight the importance of considering spillover effects in evaluating the benefits of PBP and, on the same note, Weber et al. (2003) and Immergluck (2009) test the effects of TIF on nearby housing prices.

Despite these various efforts, some aspects of TIF remain to be explicated. Additionally, some difficulties have plagued previous studies that examine the effects of TIF and other PBPs. First, only a few studies have considered the dynamic and long-term effects by examining the entire PBP lifespan. The effects of PBPs may depend on how long the targeted areas have been exposed to the treatment. For instance, redevelopment activities in a TIF district could be concentrated in the early years of the policy per the city's willingness to redevelop certain underdeveloped areas (Kane & Weber, 2016). Several previous studies have explored TIF's dynamic and long-term effects but in fairly limited ways. Weber et al. (2007) and Kane & Weber (2016) show how the effects of TIF on property values differ by the age of the TIF district, while Dye & Merriman (2000), Lester (2014), and Byrne (2010)'s research covers almost the entire life span of the TIF districts. Nevertheless, these studies do not estimate the dynamic effects for each stage of the program but focused on the aggregated effects.

Second, little is known about the persistent effects of TIF after its termination. For example, if a TIF district has effectively nurtured a neighborhood's innovative capabilities during its life span, the area may no longer require continuous subsidies. Conversely, if a sustainable economic system has not been established, the subsidized areas may require a continuous input of additional subsidies to maintain the growth momentum. If so, this finding could support the efficiency argument about the need to provide direct public investment in already developed and more productive areas rather than in less productive areas. However, except for Skidmore & Kashian's (2010) study that demonstrates the relationship between TIF closure and tax rates, no studies have examined the effects of TIF termination, especially regarding the program's persistent effects on labor market outcomes.

4. Descriptions of data and empirical approach

4.1. Data

First, through their websites and Freedom of Information Act requests, I compile information on TIF from the Cook County Clerk's Office and the City of Chicago Data portal. The TIF data include designation and termination date and geographical information on boundaries. The boundaries of active and expired TIF districts are matched to the 2010 Census block boundaries, compiled from TIGER/Line shapefiles of the U.S. Census Bureau.

I consider a census block to be in a TIF district when a TIF district covers more than 30 percent of the area and it is the treatment variable of interest.[2] Employment and the number of establishments are obtained from the National Establishment Time Series (NETS). The NETS includes all private sector establishments and provides related information including employment, addresses, and North American industry code (NAICS) at the establishment level, from 1990 to 2014. Referring to previous studies (Drucker et al., 2019; Lester, 2014), the labor market indicators are further divided into three key industry categories: manufacturing (NAICS 33), office (NAICS 51-56), and retail (NAICS 42, 44, 45), and the analyses are conducted accordingly by industry.

The population and housing characteristics data are compiled from 1990 and 2000 Decennial Census data at the census block level and used as covariates when predicting TIF treatment. I also collect information on the date of designation and boundaries of state enterprise zones in Cook County from the

[2] Lester (2014) and Yadavalli & Landers (2017) use a 50% threshold when they estimate the effects of TIF at the block group level. Given the relatively smaller size of the census blocks and the effects, I use the smaller thresholds of 30%.

Illinois Department of Commerce and Economic Opportunity. It is also used in propensity score calculation procedures (see Table 1 for detailed variables used). A more detailed explanation of the data set construction procedure is included in Appendix A.

4.2. Empirical approach

4.2.1. Unit of analysis and Study Scope

Frequently, TIF only covers a small portion of a municipality, census tract, or block group, and the remaining areas have no direct relationship to TIF. Moreover, multiple TIF districts could be at work in some areas, with two or more different TIF designations overlapping within, for example, a block group. These issues could impede the accuracy of the intervention's impact, suggesting a need for a more precise geographical definition to capture the effect more closely. Considering this, this study analyzes the effects of TIF at the census block level, a finer level than that used by most previous studies.

To ensure accuracy, the analysis is restricted to TIF districts created after 1990 because, first, building a relationship between the block boundaries of 1980 and 2010 would be inaccurate without publicly available crosswalks; and approximately 90% of TIF districts in Cook County were established after 1990.[3] This left me with a total of 509 TIF districts (designated between 1990 and 2014) for all of Cook County, including 78 expired TIFs.

As for the spatial scope of this study, I first analyze the effects of TIF in Cook County and then delve into the two subregions of the City of Chicago and other municipalities (non-Chicago) because, as a major city, the City of Chicago enjoys significantly greater market power in attracting employees and establishments than other municipalities in Cook County. Also, Chicago has disparate economic and fiscal structures (e.g., Chicago generally has higher property tax rates (Funderburg et al., 2021)) and relies more heavily on TIF districts, which could have an impact on TIF outcomes through competition and "cannibalization" among TIF districts (Drucker et al., 2019).

[3] When applying the 30% threshold to define the treated group, years 1990 to 1993 exhibit no associated blocks and so they are excluded from the analysis. Additionally, the associated blocks for the years 1994 and 1995 in Chicago are smaller than 30 (26 and 8 respectively) and hence, they are also excluded from the analysis. I also estimate the effects TIF with all available years and the results are similar and are not changed substantially. These results are available upon request.

4.2.2. Staggered difference-in-difference framework

One of the most popular approaches for estimating the dynamic treatment effects of PBPs applied over multiple time periods is the two-way fixed effects (TWFE) model. The TWFE model allows researchers to go beyond canonical DID setup with two time periods and two groups; however, a recent development in the econometric literature points out possible pitfalls that could bias estimates from the TWFE (de Chaisemartin & D'Haultfœuille, 2020). That is, the TWFE model uses early-treated groups as controls for later-treated groups and this could lead to bias if there are heterogeneous effects across analysis units or time. As a remedy to this issue, I adopt a staggered DID design and estimate group-time average treatment effects, as proposed by Callaway & Sant'Anna (2021). Denoted $ATT(g,t)$, their estimation procedure identifies the average treatment effect on the treated at time t for the group of census blocks first treated at time g. The group-time average treatment effect of interest can be expressed as:

$$ATT(g,t) = \mathbb{E}[Y_t(g) - Y_t(0)|G_g = 1] \quad (1)$$

where G_g is a dummy variable that is equal to 1 if a census block is first treated in time g. $Y_t(g)$ denotes the potential outcomes for the treatment time group g at varying time t, and $Y_t(0)$ defines the potential outcome at time t without treatment. Then we can estimate, for example, the average treatment effects in the year 2007 for the group treated at the year 2006. Callaway and Santa'Anna's inference procedure allows one to either solely use never-treated observations (G_g = 0) or a combination of never-treated and not-yet-treated observations (i.e., census blocks that have not yet been treated by time period t) as a control group. I choose to include not-yet-treated census blocks because they are more likely to have similar (un)observable characteristics to treated groups given that they are eventually designated as TIF districts. The group-time average treatment effects are estimated using the following equation,

$$ATT_{(g,t)} = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{p_g(X)(1-D_t)(1-G_g)}{1-p_g(X)}}{\mathbb{E}\left[\frac{p_g(X)(1-D_t)(1-G_g)}{1-p_g(X)}\right]}\right)(Y_t - Y_{g-1} - m_{g,t}^{not-yet}(X))\right] \quad (2)$$

where $p_{g,t}(X)$ is a propensity score, the probability that a census block is first treated at time g is conditional on having covariates X and on either being a treatment time group g (i.e., $G_g = 1$) or a not-yet-treated group by time t (i.e. $(1 - D_t)(1 - G_g) = 1$). D_t is a binary variable equal to one if a census block is treated in period t or zero otherwise. And $m_{g,t}^{not-yet}(X)$ = $\mathbb{E}[Y_t - Y_{g-1}|X, D_t = 0, G_g$ = 0].

Essentially, the estimator is a weighted average of the differences in outcome. The weights in the first term depend on the propensity scores calculated from the values of covariates in the latest pre-treatment period. The second term is a regression that looks at the change in outcomes between time t and $g-1$. This estimator is considered doubly-robust since it is a consistent estimate of ATT if either term has a correct specification (Sant'Anna & Zhao, 2020). The propensity score weighting procedure is adopted to recalibrate the differences between the treated and control group so I can compare groups with the most similar characteristics. As Dye & Merriman (2000) and Gibson (2003) note, TIF districts are unlikely to be randomly selected. For instance, a municipality might designate TIF districts because those areas seem to have high economic potential that could bring a new revenue stream in a short time. Propensity score weighting helps address this selection bias. Moreover, to ameliorate the possible biases resulting from simultaneous economic development programs, I control for the possible influence of state enterprise zones given the large size and wide use of the program as well as data availability.

$ATT(g,t)$ provides several ways to aggregate treatment effects. I estimate average treatment effects for every length of exposure e including pre-treatment periods ($e < 0$), which is calculated by taking an average of ATT across treatment time groups. It is analogous to even-study parameters and reveals not only treatment effects by the length of exposure but also differential trends between the treated and control groups in the pre-treatment periods. I also report the *overall* average treatment effects. The estimate is a weighted average of $ATT(g,t)$ for $t \geq g$ over all treatment time groups and all time periods.

To account for autocorrelation, standard errors are clustered at the census block level, and all inference procedures are based on bootstrap algorithms.[4] Also, instead of conventional point-wise confidence intervals, simultaneous confidence intervals are adopted to control for dependence across the coefficients of event-times. This staggered DID framework is applied throughout the regression models.

4.2.3. Estimating the persistent effects

Next, to test whether formerly designated but now expired TIF areas have persistent and sustaining effects, I estimate the effects of TIF after its termination compared with currently active TIF districts (i.e., blocks associated with active TIF districts at each event-time and that are not-yet-expired). This is the reverse of standard DID conceptualization in that the treatment variable is the expiration of an existing policy, not the initiation of a new policy. Blocks that have never been treated are not included because they are more likely to display different pre-trends. The identification and estimation strategies operate according to the same rules. The focus is on immediate or short-term effects because the outcome of TIF termination may be

[4] Standard errors clustered at the census block group and place level are also tested. The findings are largely unaffected with identical coefficients and slight decreases in significance.

offset or affected by other factors after some years so those immediate periods are likely to capture the persistent effects more closely.

5. Summary statistics

Table 1 presents summary statistics for blocks in TIF districts and blocks not in TIF districts for Chicago and the non-Chicago areas, respectively. In both areas, blocks in TIF districts exhibit about a 1.5 times higher minority share and half the homeownership rate compared with blocks not in TIF districts. These characteristics are often associated with economically lagging areas. However, average values of employment and establishments for "TIFed" blocks are higher. This may indicate a spatial mismatch, given that the NETS comes from workplace-based information. Upon examining employment by industry, TIF districts exhibit a higher concentration of employment in the manufacturing and retail sectors than the office sector.

Table 1. Summary Statistics for TIF districts and non-TIF blocks in 1990

	Chicago				non-Chicago			
	TIF districts		Blocks not in TIF districts		TIF districts		Blocks not in TIF districts	
Variable	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Employment*	44.84	446.56	29.88	423.16	56.10	260.14	21.61	205.01
Office employment	14.44	261.90	10.82	233.62	9.66	76.89	4.86	92.08
Manufacturing employment	8.00	68.26	3.58	101.10	10.47	72.06	4.01	69.61
Retail employment	6.00	64.38	3.35	52.00	16.02	180.06	4.00	52.75
Establishments*	2.25	14.20	1.84	22.24	2.94	7.78	1.47	14.11
Office establishments	0.54	3.40	0.41	6.70	0.76	2.04	0.31	3.39
Manufacturing establishments	0.21	1.26	0.12	1.91	0.33	1.38	0.12	1.45
Retail establishments	0.60	7.03	0.54	6.11	0.64	2.13	0.40	4.06
Minority share*	0.53	0.46	0.35	0.38	0.19	0.34	0.11	0.22
Homeowner share*	0.27	0.30	0.53	0.34	0.29	0.35	0.66	0.40
Enterprise Zone*	0.46	0.50	0.11	0.31	0.00	0.02	0.00	0.03
Share of office employment*	0.06	0.19	0.06	0.22	0.09	0.23	0.07	0.24
Share of manufacturing employment*	0.10	0.26	0.05	0.19	0.13	0.28	0.05	0.19
Share of retail employment*	0.06	0.20	0.02	0.11	0.05	0.18	0.02	0.12

Notes: Employment and establishment data are from the NETS. Minority population includes all non-white residents. Population and residential information are from the 1990 Decennial Census. All information is for the year 1990. An asterisk indicates variables used to calculate the propensity score. Statistics for blocks not in TIF districts are calculated after excluding contiguous areas.

6. Empirical results

6.1. The effects of TIF in Cook County

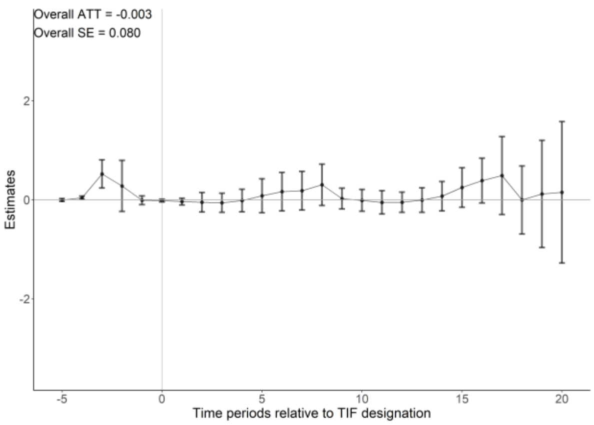
I first discuss the effects of TIF in Cook County. The control group comprises blocks that are not-yet-treated and do not border the TIF districts. I exclude areas contiguous to TIF districts to reduce possible biases from spillover effects to the estimates.[5] Going forward, preferred "post-spillover" models will serve as a foundation for discussing TIF effects as they are likely to capture the effects of TIF more closely and precisely. Figures 2 and 3 present the post-spillover results. The TIF effects are shown by years relative to TIF designation including pretreatment periods. e (i.e., the event-time coefficient) is the running variable on the x-axis. Each coefficient is calculated by averaging the effect of TIF for all treatment time groups that have been in TIF districts for exactly e time periods. For instance, e equal to 1 provides the average effects of year 1 after a TIF is designated. The figures also contain overall average treatment effects on the treated area (i.e., overall ATT), which are the estimates of a weighted average of group-time treatment effects over all treatment time groups and time periods.

First, insignificant pretreatment estimates found in all panels of Figures 2 and 3 indicate that there is no difference in pre-trends between the treated and the propensity-weighted not-yet-treated groups. After treatment, coefficients show fluctuations and sometimes reveal negative signs, which are not the expected outcome of an economic development policy (see Panels A and B of Figure 2). Despite this, almost all event-time coefficients are insignificant, and, overall, the ATTs do not achieve statistical significance. However, the mostly insignificant results in the Cook County models may be due to offsetting or varying effects by region, and I put this hypothesis to the test by dividing Cook County into two sub-geographical regions.

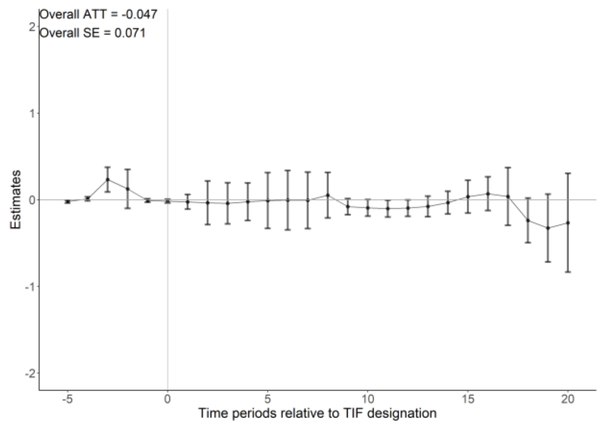
[5] I evaluate the spillover effects on the contiguous blocks around the TIF districts versus other blocks that are not treated (See Figures B1 and B2 in Appendix B). I find weak evidence of the spillover effects on contiguous areas to TIF districts (see Panels A and C in Figure B1 in Appendix B).

Figure 2. The dynamic effects of TIF designation on the number of establishments after excluding contiguous blocks in Cook County

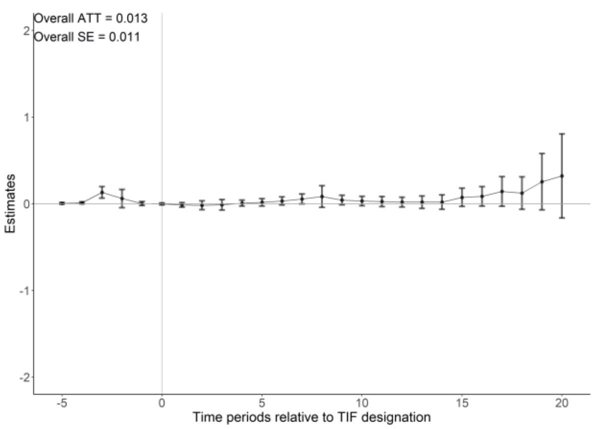
(A) Entire Establishments



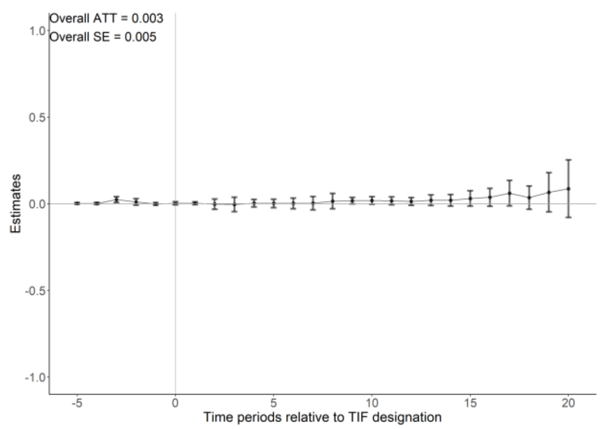
(B) Office Establishments



(C) Retail Establishments



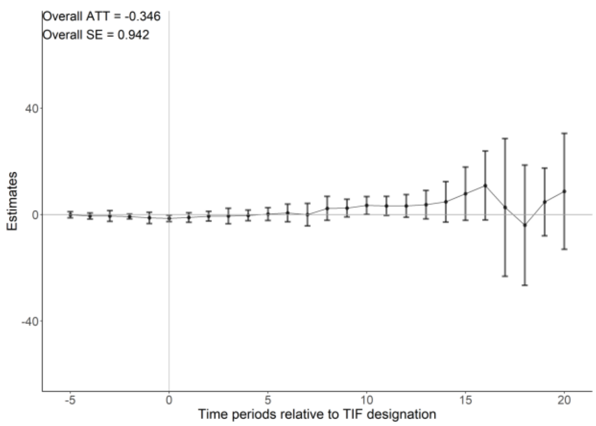
(D) Manufacturing Establishments



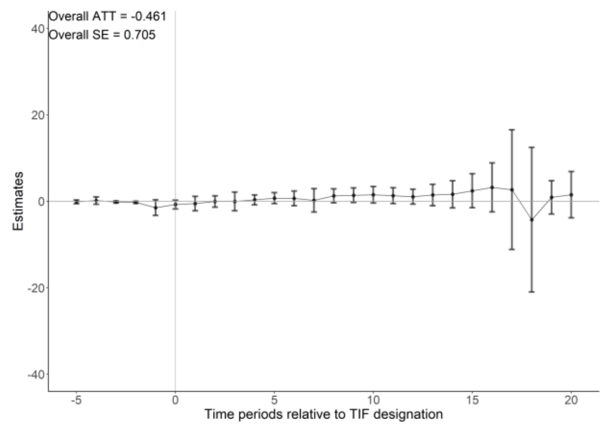
Notes: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure 3. The dynamic effects of TIF designation on employment after excluding contiguous blocks in Cook County

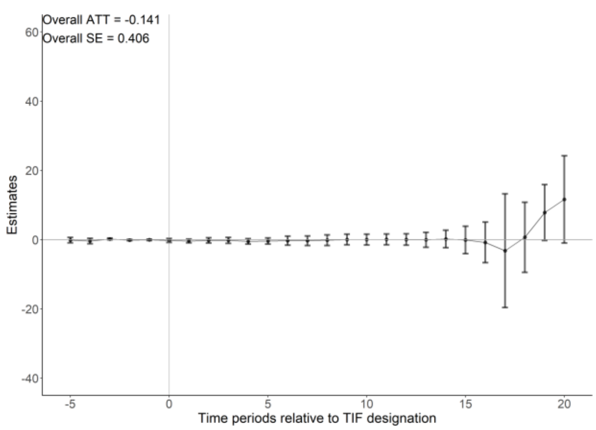
(A) Entire Employment



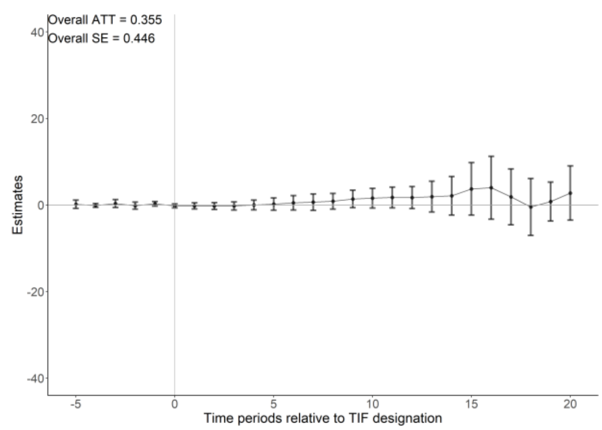
(B) Office Employment



(C) Retail Employment



(D) Manufactruing Employment



Note: See notes from Figure 2.

6.2. The effects of TIF in Chicago

I now turn to evaluate the two sub-geographical regions of Cook County separately. Figures 4 and 5 present the effects of being located in TIF districts in Chicago, and the results demonstrate some significant negative event-time coefficients about 9 years after TIF onset. Specifically, for the entire establishments and office establishments, the results show negative and significant effects between 9 years and 15 years after TIF designation. The event-time coefficients then start to pick up and become insignificant. Retail establishments also show negative coefficients, but they are insignificant. The dynamic effects depicted here are similar to those in the Cook County models, but with slightly more significant negative effects.[6] The employment effects also show overall negative ATTs and some negative coefficients around the same estimation window. However, for employment, none of the estimates are statistically significant.

These results are largely consistent with those of Lester (2014), who finds negative effects of TIF on the retail industry in Chicago from 1990 to 2008. Lester suggests that the general trend of shifting from small-sized retail stores to larger retail chains may account for decreases in the number of establishments. Thus, it is expected that other similar subsidy programs that aim to stimulate economic development in economically lagging areas such as federal EZ will cause similar effects in the retail industry. However, other studies do not necessarily show the same pattern (Freedman, 2013; Hanson & Rohlin, 2011) and the retail industry even sees higher growth than other industries (Hanson & Rohlin, 2011).

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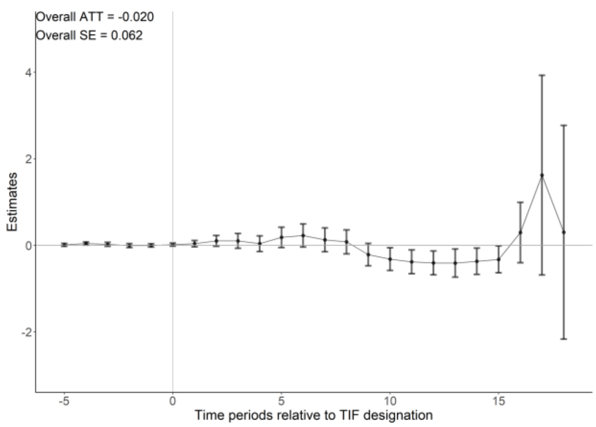
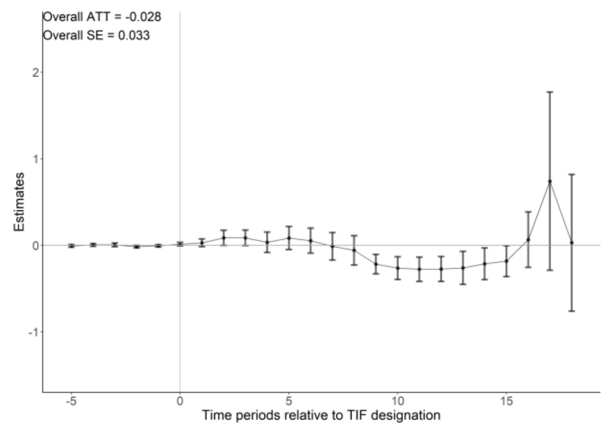
[6] This is perhaps due to the offsetting positive effects from the non-Chicago area as shown in Section 6.3.

Figure 4. The dynamic effects of TIF designation on the number of establishments after excluding contiguous blocks in Chicago.

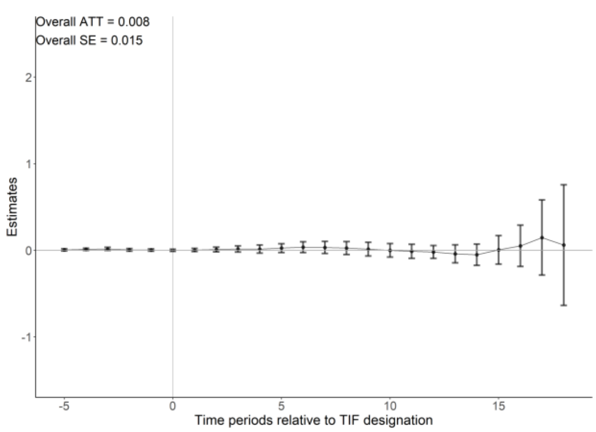
(A) Entire Establishments



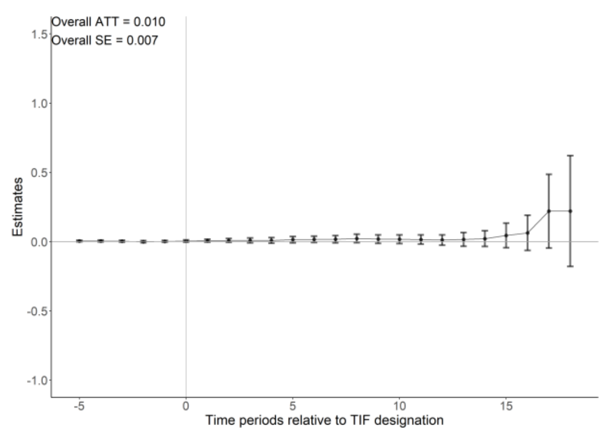
(B) Office Establishments



(C) Retail Establishments



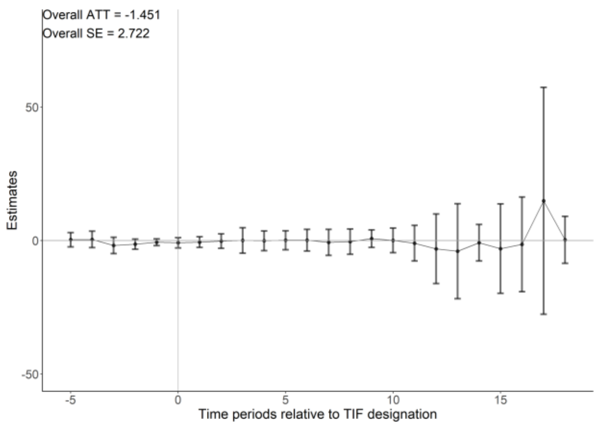
(D) Manufacturing Establishments



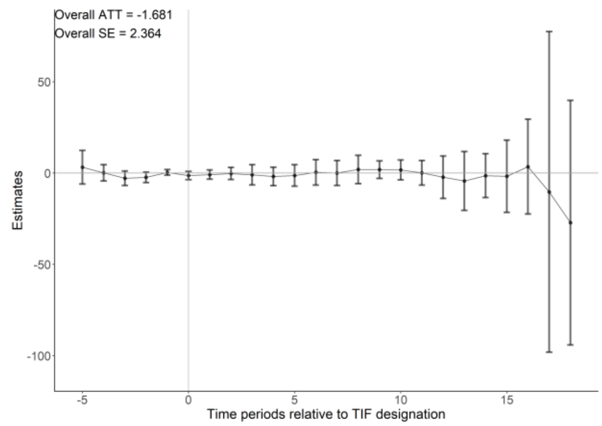
Notes: See notes from Figure 2.

Figure 5. The dynamic effects of TIF designation on employment after excluding contiguous blocks in Chicago

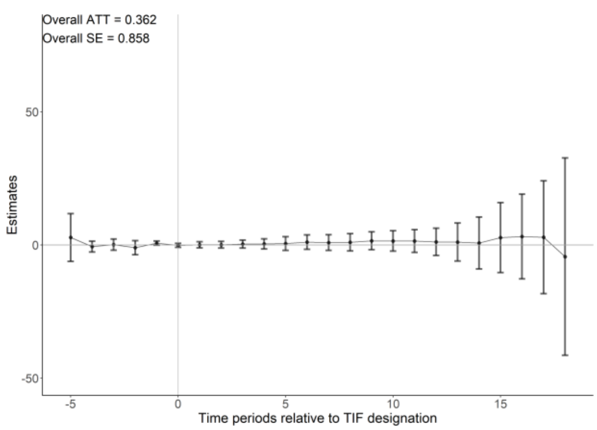
(A) Entire Employment



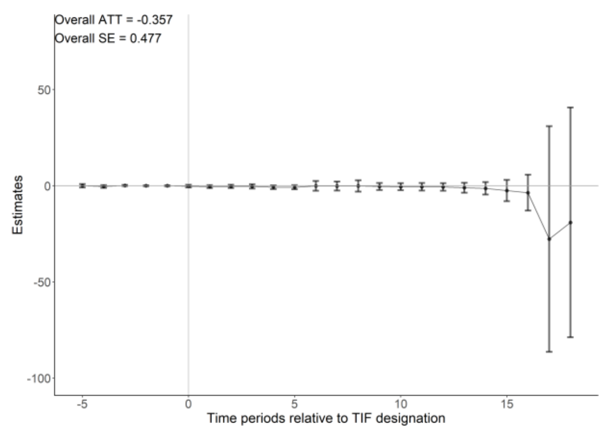
(B) Office Employment



(C) Retail Employment



(D) Manufacturing Employment



Notes: See notes from Figure 2.

What could be the possible explanations for the negative effects of TIF designation? First, it could be due to unexpected and unintended consequences on overlapping taxing bodies. Empirical evidence suggests that the introduction of TIF led to increases in tax rates for the overlapping taxing districts, such as park and school districts, because TIF captures the increased revenues from property tax and shifts costs associated with development to these other jurisdictions (Skidmore & Kashian, 2010; Weber et al., 2008).

To see if the same relationship holds true in Chicago, I examine the association between TIF and the tax rates of the overlapping taxing districts[7] using property tax codes. A tax code consists of a group of parcels, identifies the taxing authorities, and sets a consolidated property tax rate, which is the sum of the tax rates imposed by each local taxing body.[8] The results, as shown in Appendix D, support previous studies' findings that TIF is likely to be associated with a higher consolidated tax rate. These findings imply that the negative influence resulting from hikes in tax rates may outweigh the symbolic effects of TIF designations and incentives, repelling existing businesses and discouraging potential new businesses from moving into the area.

Second, the growth and expansion of businesses may also be hampered by heightened competition or geographical proximity to other TIF districts (Drucker et al, 2019). This may be especially relevant for Chicago, where TIFs cover approximately 30% of taxable land (Kerth & Meiffren, 2012). Businesses in existing TIF districts may be tempted to relocate to a newer one when and if the new one offers a more favorable business climate, such as improved facilities and a larger consumer market. This phenomenon is often referred to as "cannibalization." Moreover, TIF districts could crowd out other PBPs and subsidies that provide, for instance, property tax relief due to concerns about the spatially uneven and regressive allocation of public resources and associated public sentiment.

6.3. The effects of TIF in the non-Chicago area

Unlike Chicago, overall ATTs of all outcomes show positive effects in the non-Chicago area, as would be expected for place-based economic development programs (see Figures 6 and 7). The results examining establishments demonstrate gradual increases in the estimates until about 15 years across all the sectors. Then, after 15 years, retail and manufacturing present constant positive trends whereas the estimates for the entire and office establishments drop to the point where some event times show negative but insignificant coefficients. In contrast, I find positive effects on employment. On average, TIF increases entire employment by 4.384 while it raises retail employment by 1.873, with significant effects emerging between approximately 6 and 20 years after TIF designation.

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[7] I recognize that possible selection bias where places with lower tax rates could have been deliberately designated as TIF districts to attract firms. Also, due to unavailability of census data at the tax codes level, the regression only measures the association between variables, rather than establishing a causal relationship.

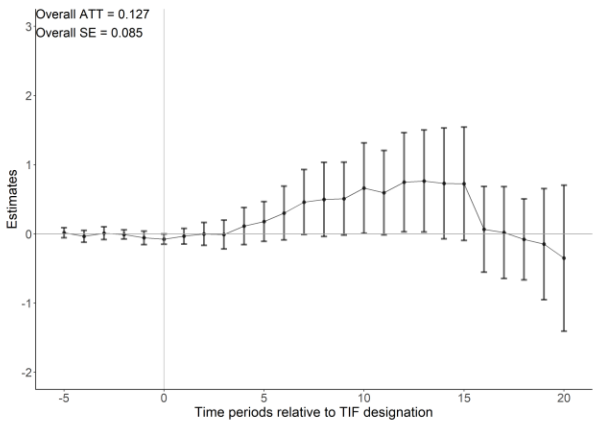
[8] The local taxing bodies include, for instance, the Chicago Park District, the Metropolitan Water Reclamation District of Greater Chicago, the Board of Education, and the Chicago of Chicago. See more detailed description on tax codes in Illinois in Drucker et al., (2020).

One possibility behind these contrasting and positive results in the non-Chicago area is that municipalities in the non-Chicago area have been able to make more concerted efforts and concentrate on their relatively fewer TIF districts than in Chicago, providing a compilation of economic benefits and incentives to establishments seeking relocations or expansion. In contrast, Chicago's heavier reliance on TIF and the sheer number of TIF districts constrain the city from making an intense investment in each TIF district it has. Relatedly, the competition and "cannibalization" that drive the negative effects are less likely to occur in the non-Chicago areas. As shown in Figure 1, compared with Chicago, TIF districts in the non-Chicago areas are distributed with much lower density and are more sparsely located, lowering the possibility that newer TIF may poach businesses or induce existing establishments from nearby TIF districts.

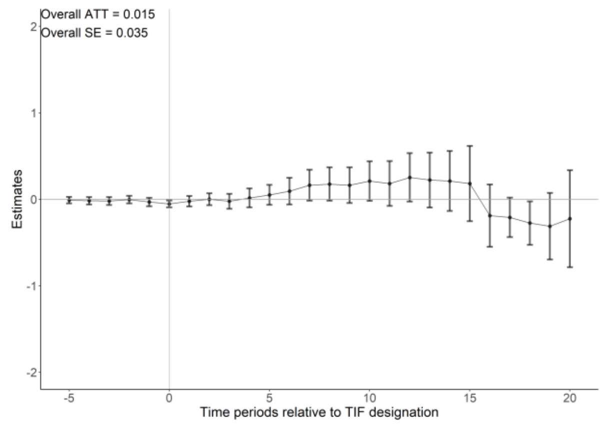
Second, overlapping taxing districts are still likely to increase tax rates in non-Chicago municipalities; however, according to Skidmore & Kashian's (2010) empirical study, their municipal property tax rates tend to move in the opposite direction. Municipal services such as police and fire can benefit from economies of scale as a result of increased development activities, which may translate into reductions in tax rates. However, as a single municipality, it is hardly a viable option for Chicago to match or adjust its municipal tax rates in accordance with the establishment of each TIF district and the increases in non-municipal tax rates.

Figure 6. The dynamic effects of TIF designation on the number of establishments after excluding contiguous blocks in the non-Chicago area

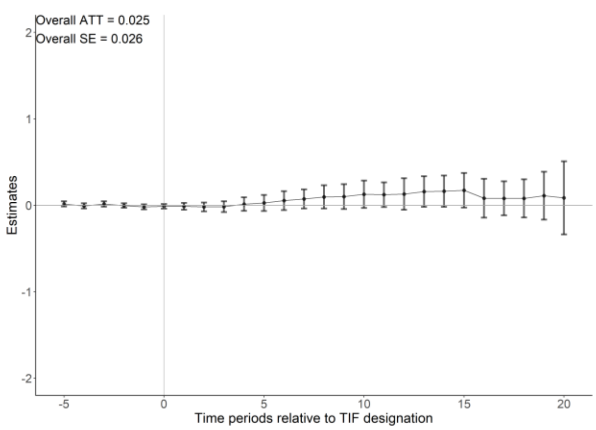
(A) Entire Establishments



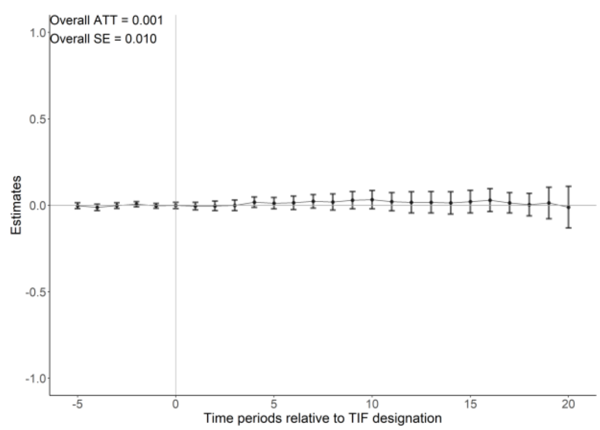
(B) Office Establishments



(C) Retail Establishments



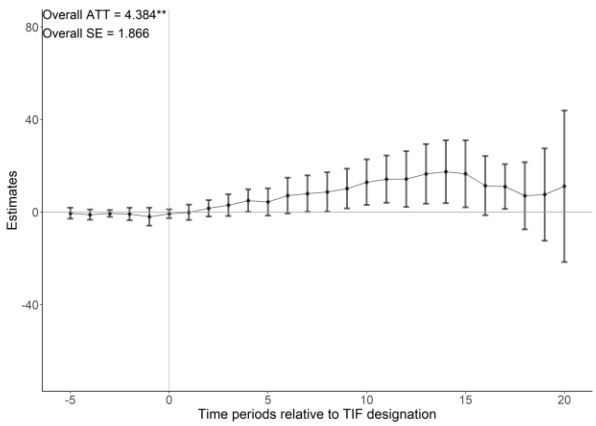
(D) Manufacturing Establishments



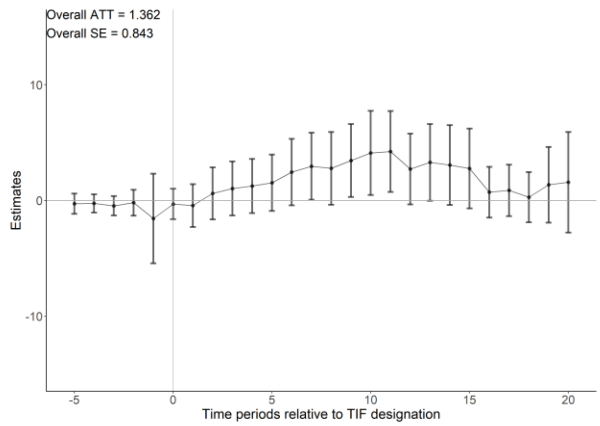
Notes: See notes from Figure 2.

Figure 7. The effects of TIF designation on employment after excluding contiguous blocks in the non-Chicago area

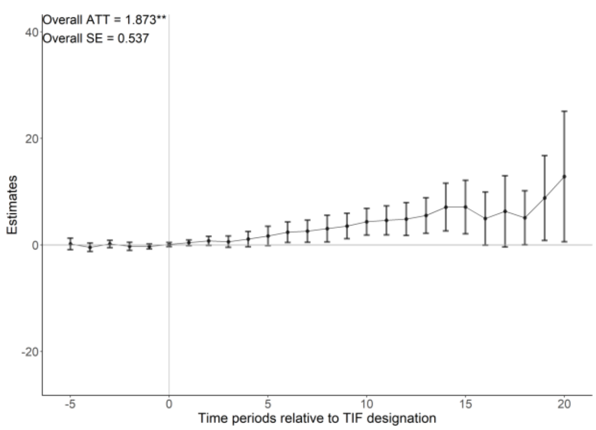
(A) Entire Employment



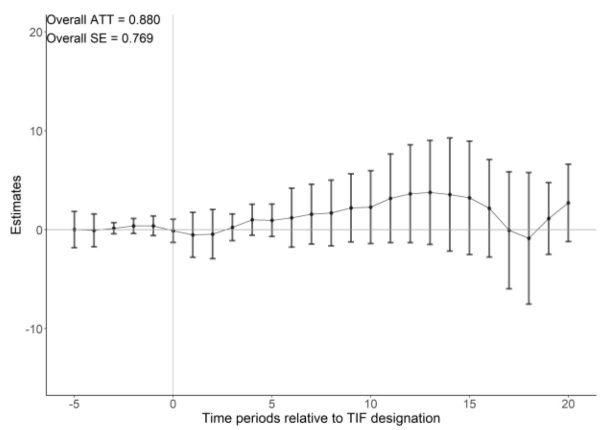
(B) Office Employment



(C) Retail Employment



(D) Manufacturing Employment



Notes: See notes from Figure 2.

6.4. The persistent effects of TIF after its termination

To measure the persistent effects of TIF, the treated group needs to be newly defined. It now includes TIF districts that expired between 2006 and 2014. The year 2006 marks the first instance of TIF district termination, and, as with the analyses presented above, the years with insufficient observations are excluded.[9] Also, only TIF districts that had been in operation at least 15 years prior to termination are included because some TIF districts dissolve early if they fail to attract development proposals and do not complete their life cycle.[10]

Figures 8 and 9 show estimates for the persistent effects on establishment and employment. [11] First, as for the pre-treatment periods, the coefficients are very close to zero and insignificant for both establishments and employment. It suggests that there is no difference between the expired TIF and not-yet-expired TIF before the TIF districts expire. When measuring the effects for the post-termination period, immediate and short-term effects, in addition to the pre-treatment period, hold special importance and are more informative than the aggregated effects, which include relatively long-term effects. This is because the effects of the TIF termination may be offset or affected by other factors after some years.

The analysis results of the post-treatment period could go in two contrasting directions. First, if the positive effects of TIF identified in both event-time coefficients and overall ATTs of Figure 7 dissipate after TIF is terminated, (retail) employment is expected to decrease. Conversely, if these positive effects persist, then no difference is likely to be observed between the expired TIF districts and the not-yet-expired TIF districts. In other words, in this particular case, "failing" to distinguish the expired group from the not-yet-expired group (i.e., no significant overall ATTs and insignificant event-time estimates for both establishment and employment) indicates that the expired group may still remain more appealing locations with greater concentrations of business activities and productive advantages. In fact, during the post-termination periods, the expired group is not statistically distinguishable from the not-yet-expired group. This finding is further corroborated by the observation that the overall ATTs derived from both the overall

[9] The termination years included are 2006, 2009, 2010, 2011, and 2014.

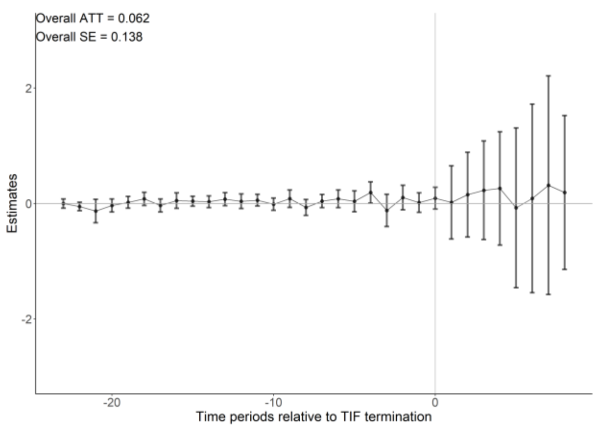
[10] A concern that expired TIF districts and active TIF districts may be significantly different can be arisen. In particular, cases where TIFs have been terminated early due to inactivity may be considered different from active TIF districts. However, municipalities typically decide at city council meetings whether to continue a TIF if there is no redevelopment activity a few or several years after its creation, as discussed in Section 2. Therefore, this study, which considers only TIFs that lasted 15 years or more as expired TIFs, is unlikely to include cases that were repealed early due to a lack of activity. Moreover, the results measured with TIFs that lasted 23 years or more (Figures 13 and 14 in Appendix C) and the finding that the pre-trend is not different between active and expired TIFs (Figures 8 and 9) provide corroborative evidence.

[11] For instance, to determine the coefficients for year 0, I compute the change in the outcome variable between 2006 and 2005 for TIF districts at work in 2006, the change in the outcome variable between 2007 and 2006 for TIF districts at work in 2007, the change in the outcome variable of the then-active TIF districts between 2008 and 2007, and so forth, as the control group. The same computation method is applied to the treatment group to calculate differences between the control group and treatment group. Then, I compute the average effect of treatment across treatment time groups.

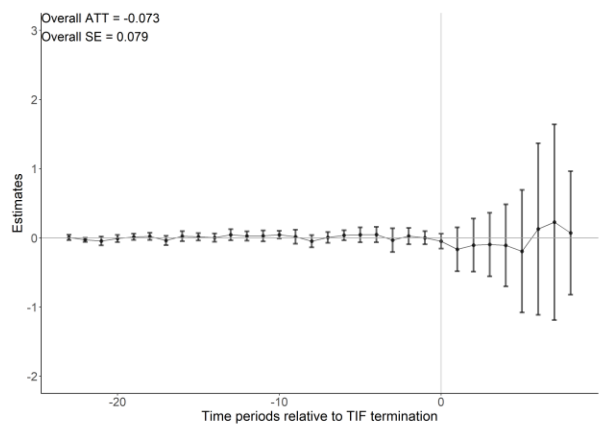
and retail employment models exhibit a statistically significant positive sign initially but lose significance in Figure 9.[12]

Figure 8. The persistent effects of TIF designation on the number of establishments in the non-Chicago area

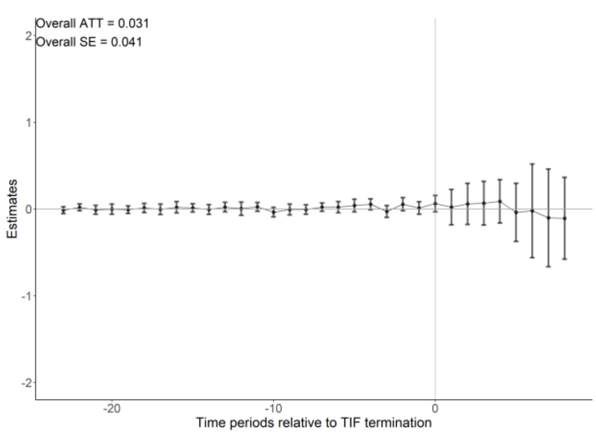
(A) Entire Establishments



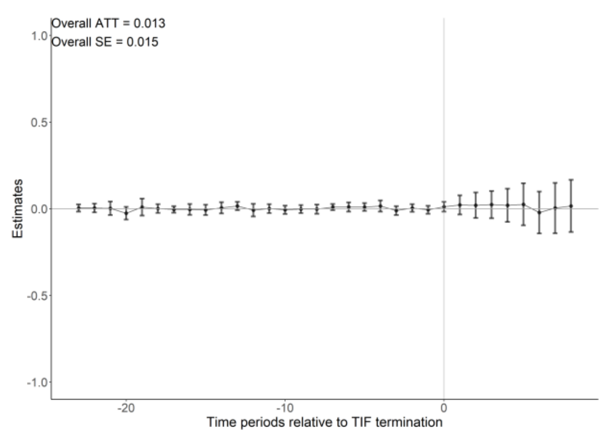
(B) Office Establishments



(C) Retail Establishments



(D) Manufacturing Establishments

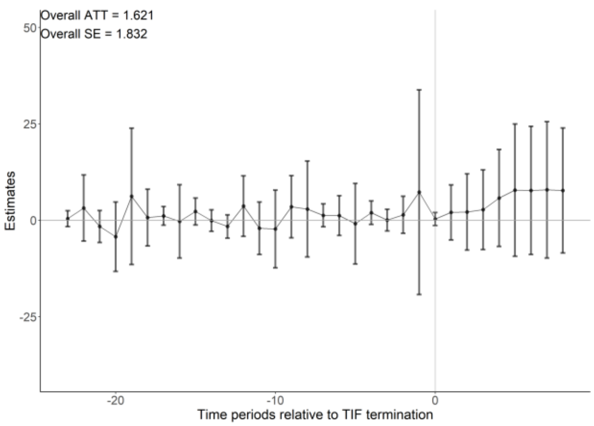


Notes: Overall ATT shows the average effect of the TIF *termination* across all treatment time groups that participate in the treatment all time periods.

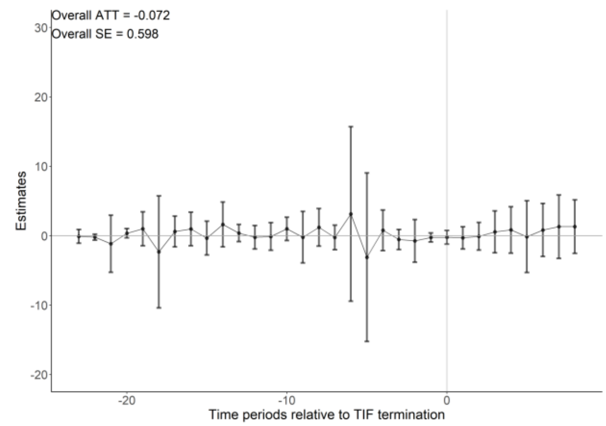
[12] Some results in Figures 8 and 9 have relatively larger confidence intervals in the later years and thus they are less informative. This is partly due to the rarity of observations five years after TIF termination compared with the earlier period.

Figure 9. The persistent effects of TIF designation on employment in the non-Chicago area

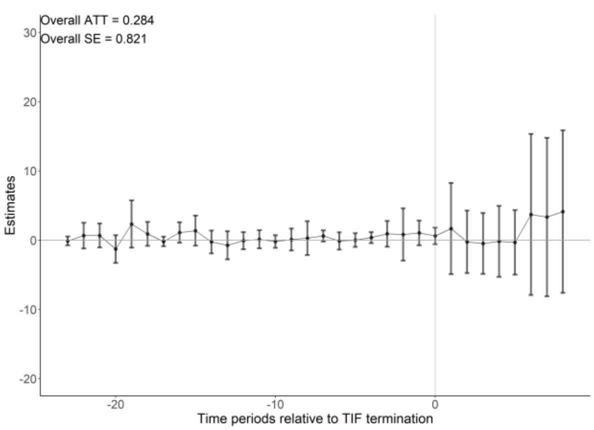
(A) Entire Employment



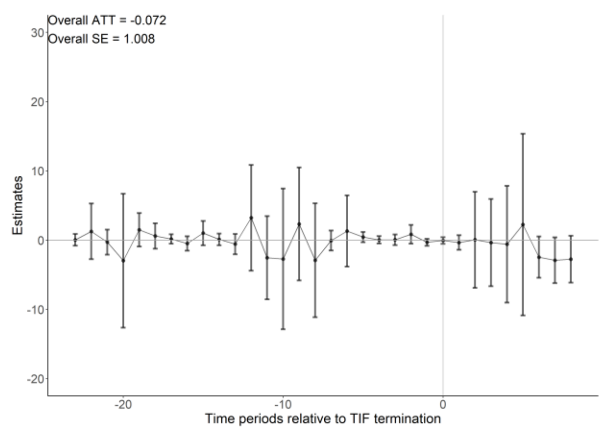
(B) Office Employment



(C) Retail Employment



(D) Manufacturing Employment



Notes: Overall ATT shows the average effect of the TIF *termination* across all treatment time groups that participate in the treatment all time periods.

7. Robustness of main results

There are multiple requirements for municipalities to create a TIF district in Illinois. Applying municipal districts must devise a redevelopment plan, hold public meetings or hearings, and get approval from a Joint

Review Board of affected taxing agencies. Consequently, there is a possibility that some establishments may relocate to the area expected to be designated or hire more employees in anticipation of infrastructure improvements before the actual TIF designation. So, as a first further robustness check, I incorporate this possible anticipatory behavior in the estimation process. In the main estimates, the comparison period is the period immediately before treatment occurs. Here, the comparison period is adjusted to two years before TIF designation (e.g., if a TIF district is designated in 2006, then the comparison period is 2004). The results are available in Figures C1 to C6 in Appendix C. The overall ATT for office employment flips its sign from statistically significant positive to insignificantly negative in the non-Chicago area. Other than that, allowing for treatment anticipation does not substantively alter any other estimates.

Next, I change the threshold used in defining TIFed blocks to confirm that key findings are robust to an alternative threshold. In the main estimates, a block is considered TIFed when a TIF district covers 30 percent or more of a block. Figures C7 to C12 in Appendix C contain the estimates with a threshold of 20 percent. The results are very similar to the main estimates. The effects of the TIF designation on the entire and office establishments in Chicago point to negative relationships around 10 years after the designation, while the estimates for employment yield negative overall ATTs and some negative but insignificant coefficients again around 10 years after the TIF onset. In the non-Chicago area, the results confirm the significant positive effects on employment and show the same positive but insignificant estimates for establishments. There are no coefficients that flip their signs, and the magnitudes are also nearly identical. One notable result is that overall ATT for office employment shows even stronger effects and is now significant.

8. Policy implications

The findings of this study provide several important implications for policymakers and researchers of spatial disciplines. First, examining the dynamic and long-term treatment effects over the entire life span of the policy could inform an optimal treatment regime or sequence that would allow policymakers to maximize the policy effectiveness. The results of the analysis show that TIF effects start to appear approximately 8 years after their initial designations and that they either maintain or ramp up for the majority of outcomes for approximately 15 to 20 years. These dynamic effects of TIF are unlikely to be unique to Cook County, as TIFs in other places also focus primarily on redevelopment projects that typically involve a lengthy process of stakeholder coordination with existing merchants, property owners, and other stakeholders. Consequently, it is more probable to observe the effects of TIF after several years have elapsed, rather than in the early stages of implementation and therefore worth considering that the timing of TIF effects may be heterogeneous over the course of the policy.

However, it should be noted that because temporal dynamics vary depending on the outcomes, the results do not necessarily imply a tipping point or critical juncture at exactly 8, 15, or 20 years. Instead, the key takeaway from this research, as Beer et al. (2020, p.75) also point out, is that it is critical to acknowledge that the success of PBP should be assessed by the "performance of place over a long time frame."

In Illinois, several TIF districts were dissolved after only a few years of operation. Several serious issues were raised for those districts, including the appropriateness of the uses of TIF assistance and funds, a lack of transparency and accountability, and a lack or absence of "immediate" effects. The dissolution decisions may have been sufficiently justified without the evaluation of the lack of immediate effects, but given the findings of this study and the nature of redevelopment activities that require more time-consuming processes, a longer-term and more patient approach may be required when it comes to evaluating the TIF effects. In addition, a better understanding of optimal treatment sequences may help to ensure the most effective use of TIFs in Australia, the UK, and elsewhere in the U.S., where TIFs are being introduced primarily to stimulate redevelopment and are likely to experience temporal sequences.

The next main policy implication pertains to the persistent effects of TIF. Advocates of place-neutral approaches claim that dispersing economic activities is detrimental to taking full advantage of the optimal level of established agglomeration economy and it slows economic growth of regional and/or national growth (Feldman & Storper, 2018). That is, assisting economically lagging areas through PBP is not a more efficient use of public resources than investing in areas with already existing strong economic activities and productivity.

The skepticism on PBP from an efficiency perspective has been widely recognized. Nonetheless, the persistent effects of PBP and the possibility of developing a new agglomeration economy provide a different viewpoint. The findings of this study suggest that the recipient neighborhoods do not appear to be regressing toward their original socioeconomic state and needing further intervention(s), although the revenue earmarked for the designated area has now been allocated to serve broader needs such as school districts and county government. The sustained positive effects may be attributable to the formation and anchoring of new or expanded locally-based enterprises as well as the transformation from a low-density economic activity area to a high-density economic activity area, which could jumpstart a new agglomeration economy. Then, the short-run efficiency cost invested as location-based subsidies could be compensated for or dwarfed by the potential long-term benefits of an agglomeration economy, implying that the argument advanced by advocates of place-neutral approaches that subsidizing areas with slim chances of growth and survival leads to inefficient use of resources and increased tax burden may need to be reconsidered. Moreover, this strengthens the justification for the uses of not just TIF but the entire range of PBPs.

Finally, the empirical approach of this study also has the potential to aid in conducting a more comprehensive evaluation of policies. Evaluating policies “during the program” period, which is the area most previous PBP studies have focused on, is important because it directly indicates the effectiveness of government efforts and assistance. Furthermore, if it is possible to determine whether the effects persist after the government intervention has ended and in the absence of further intervention, this would provide a fuller picture of the effectiveness of the policy and a stronger case for supporting its adoption.

9. Further discussion and conclusion

This paper offers empirical evidence of the effectiveness of TIF in Cook County, Illinois from 1990 to 2014. First, I find that a TIF designation is inversely correlated with the number of establishments in Chicago, especially around 9 years after TIF districts are established. The observed negative relationship may be the result of an unintended shift of tax burdens from TIF districts to overlapping taxing bodies, which would lead to higher tax rates that deter businesses. Growth could also be impeded by competition or proximity to other (perhaps newer) TIF districts (Drucker et al, 2019). It is particularly possible in Chicago given its heavy reliance on TIF.

In the non-Chicago area, I find evidence of beneficial effects, especially on employment after around 6 years and that they either maintain or ramp up for the majority of outcomes for about 15 to 20 years. This may have been possible because the relatively less intense use of TIF allows municipalities in the non-Chicago area to make more spatially concentrated investments compared with TIF districts in Chicago. Moreover, the occurrence of “cannibalization” caused by competition from nearby TIF districts is less likely to occur in non-Chicago areas with relatively dispersed TIF districts. Third, unanticipated consequences (i.e., increases in tax rates) on overlapping taxing districts are more likely to be counterbalanced by municipal tax rate reductions in non-Chicago municipalities.

This paper also calls attention to the persistent effects of PBP. After all, the ultimate goal of TIF (and other PBPs) is to achieve lasting economic improvements in struggling areas, even after the subsidies are withdrawn. Despite that, little is known about the persistent effects of TIF. This research finds that the effects of TIF last and are persistent even after the program’s expiration. Specifically, the expired TIF districts in non-Chicago municipalities remain more appealing locations for establishments with higher employment levels than the non-TIF block control locations. Moreover, the results reveal that the identified positive effects of TIF persist and do not dissipate in the short term.

This study has some limitations. First, due to data availability, the persistent effects of TIF cannot be explored and verified in Chicago. Also, it is hard to claim that the results from this research are completely generalizable to other TIF districts in other states since each state has different criteria for how and where TIF funds are spent and varying life spans. Despite these limitations, examining the under- and unexplored dynamic and persistent effects of TIF using a recently developed econometric method could serve as a reference for future research to achieve a more comprehensive assessment of the effects of TIF.

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Appendix A

A. Data Appendix

A.1 TIF data

Each year CCCO provides a Tax Increment Agency Distribution Summary and I obtain information on the first and termination year of each TIF from this report. The boundaries data are from Cook County open data portal. However, the data only include TIF districts that were active as of 2018 and it does not show the boundaries of expired TIF districts. So, I obtained the boundaries for the expired TIF districts through FOIA request. This mapping projects 509 TIF districts to 98,941 census blocks in Cook County.

A.2 NETS data

I match the complete set of private sector establishments based on the provided longitude and latitude information to their corresponding census block. Each establishment is assigned a census block. Then the number of establishments and employment are aggregated to a census block level. For establishments that relocated during the 1990-2014 period, I geocode their destination addresses using the provided longitude and latitude information to identify the census block where the establishment was located in each year. The destination addresses, rather than origin addresses, are used because the NETS data looks at January data so business dynamics occurring from January to December each year would be captured better in the destination address.

The NETS data are useful in that they contain information at a finer level (i.e., address level) that are often not publicly available in government datasets (Barnatchez et al., 2017). However**,** some researchers are concerned with the accuracy of geographical location information (Neumark and Kolko, 2010) because the NETS uses the centroid of zip code rather than exact address coordinates in some cases. Kaufman et al., (2015)'s research addresses this concern and provides a specific discussion on the geocoding accuracy of the NETS. They analyze how precisely the address coordinates are geocoded by comparing the NETS data with three different private geocoder programs. The results show that approximately 70%, 84%, and 98% of the addresses are geocoded with precision at the block level in 1990, 2000, and 2010 respectively. Also, up to 94% of the address coordinates in the NETS are within 100 meters of the coordinates geocoded by private geocoder programs. Furthermore, the block-level aggregation, which this paper adopts, ensures a minimal impact of the possible inaccuracy in geocoding.

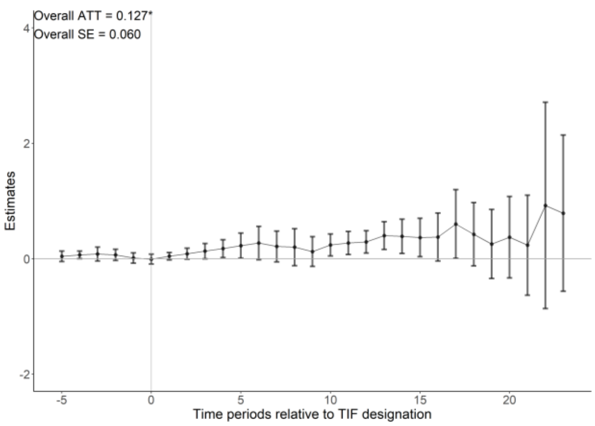
A.3. Census Data

In this paper, census block level data from 1990 and 2000 Decennial Census, and 2010 Census boundaries are used. Census Bureau boundaries change over time to accommodate changes resulting from, for instance, annexation or detachment. And, since this study spans from 1990s to 2010s, it is necessary to correspond geographic units from one census year to the other year. I use a crosswalk provided National Historic Geographic Information System (NHGIS) to identify the intersections between 1990, 2000, and 2010 Censuses. NHGIS' block level crosswalk provides interpolation weights calculated using population and housing units data at the census block level. To correspond Censuses with 2010 census blocks, I multiply the 1990 and 2000 counts data respectively by their corresponding crosswalk's interpolation weights for 2010 Census blocks. Then these estimated counts are added together for each 2010 census block.

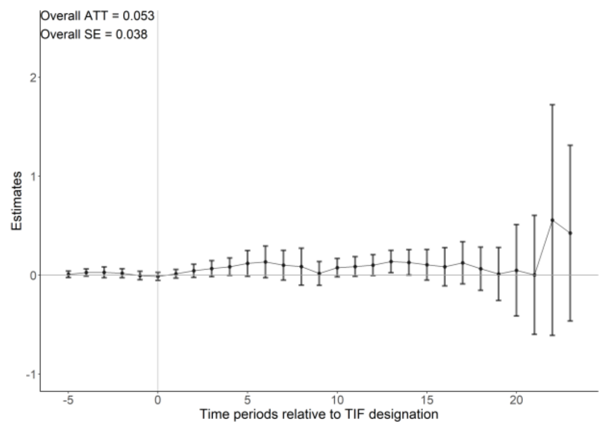
Appendix B

Figure B1. The spillover effects of TIF designation on the number of establishments in Cook County[1]

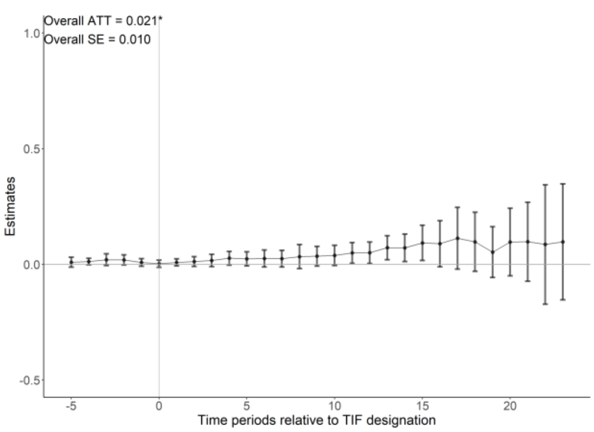
(A) Entire Establishments



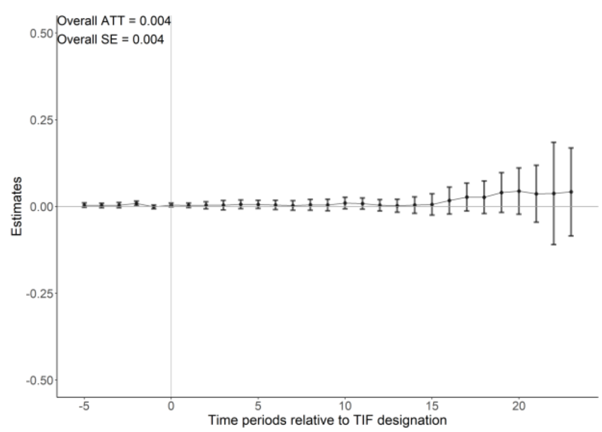
(B) Office Establishments



(C) Retail Establishments



(D) Manufacturing Establishments



Notes: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

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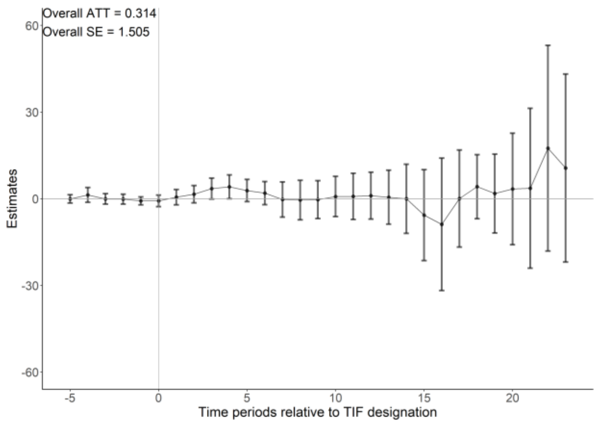
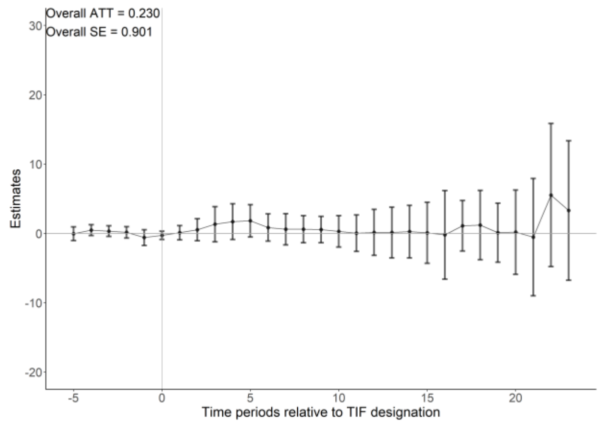
[1] I also investigate the spillover effects on the 2nd-level contiguous blocks around TIF districts, and find that the spillover effects become insignificant.

Figure B2. The spillover effects of TIF designation on employment in Cook County

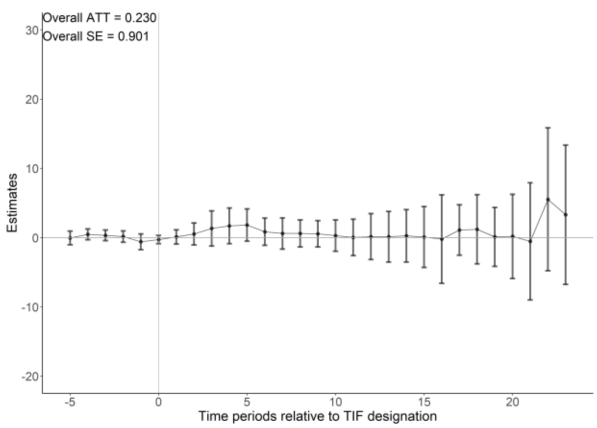
(A) Entire Employment



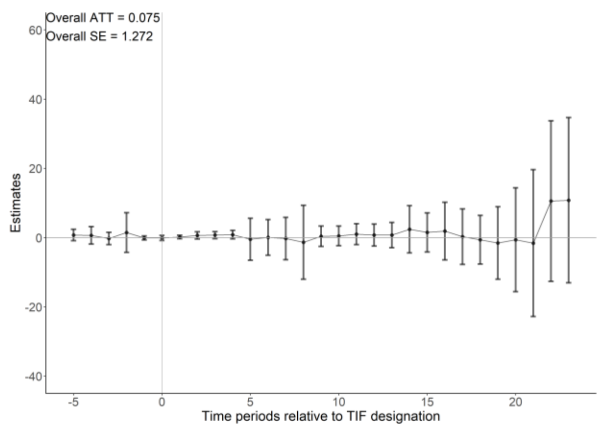
(B) Office Employment



(C) Retail Employment



(D) Manufactruing Employment

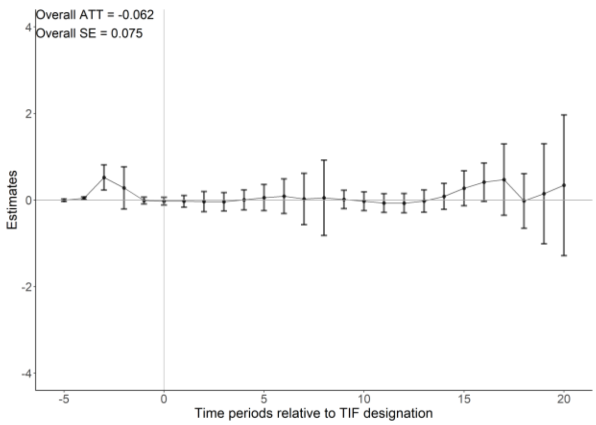


Notes: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

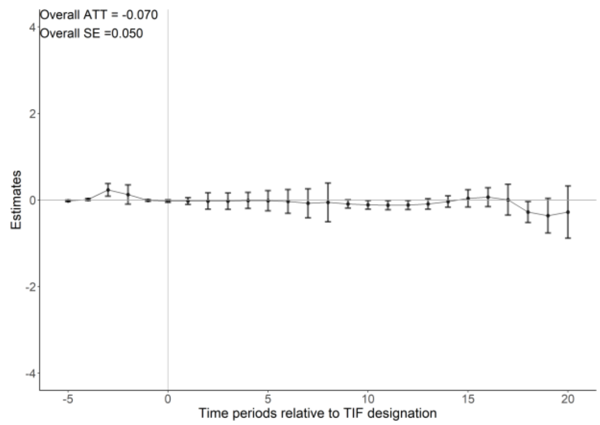
Appendix C. Robustness check results

Figure C1. The effects of TIF designation on establishment with treatment anticipation in Cook County

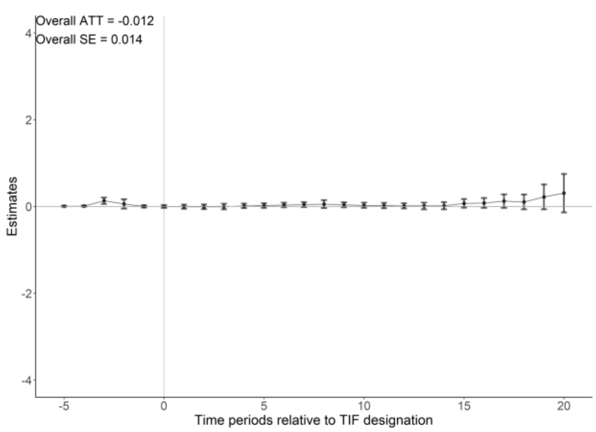
(A) Entire Establishments



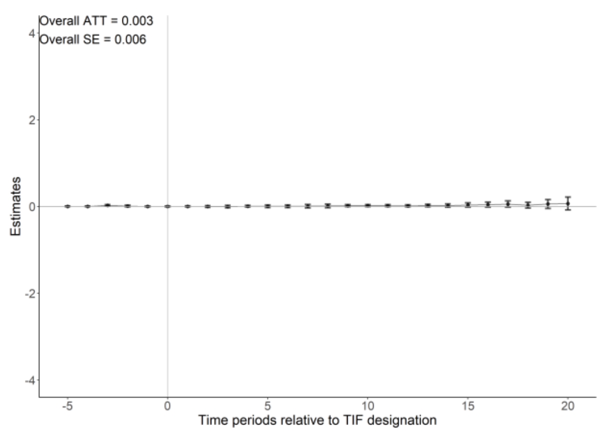
(B) Office Establishments



(C) Retail Establishments



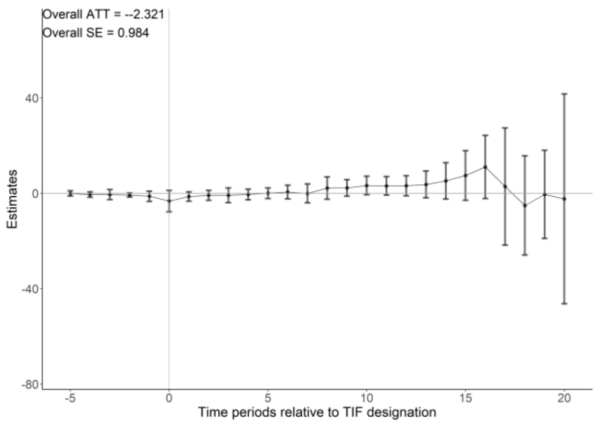
(D) Manufacturing Establishments



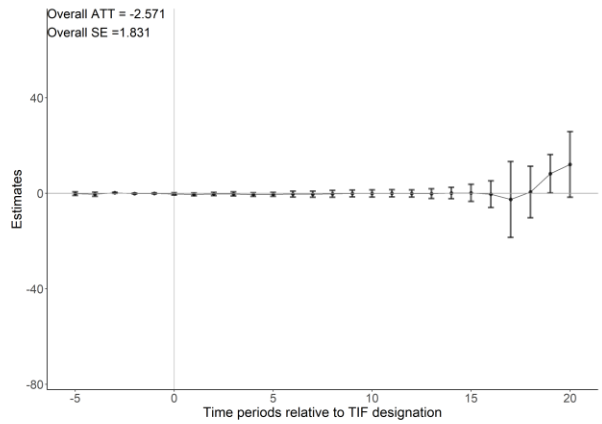
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C2. The effects of TIF designation on employment with treatment anticipation in Cook County

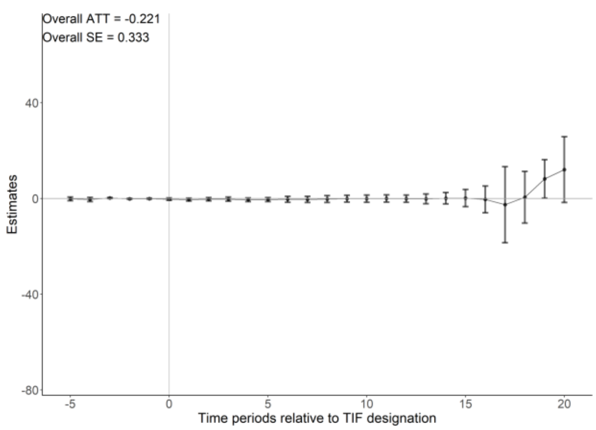
(A) Entire Employment



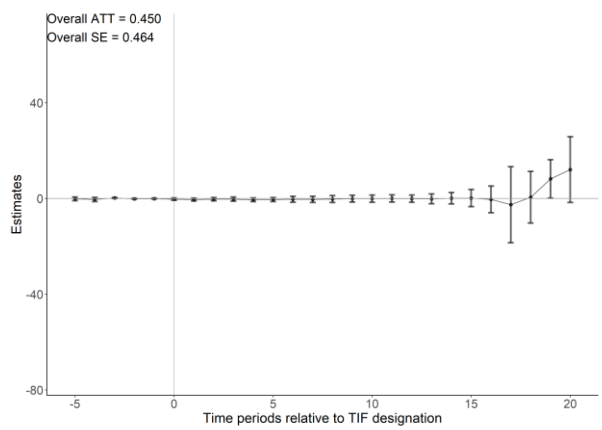
(B) Office Employment



(C) Retail Employment



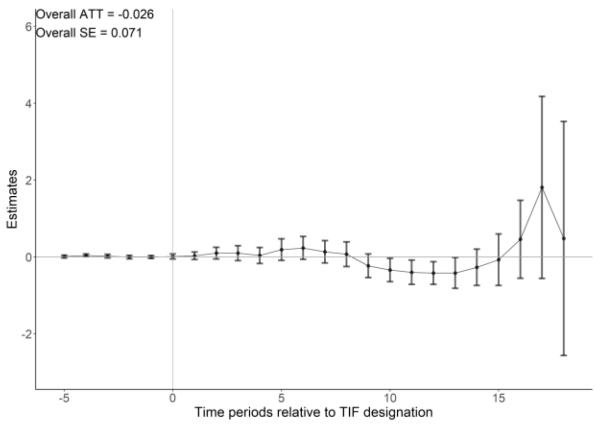
(D) Manufacturing Employment



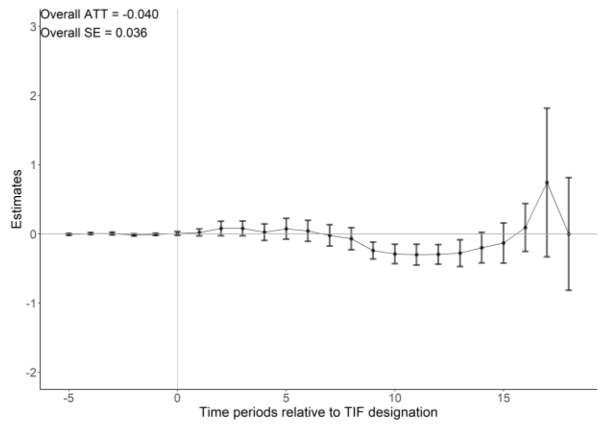
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C3. The effects of TIF designation on establishment with treatment anticipation in Chicago

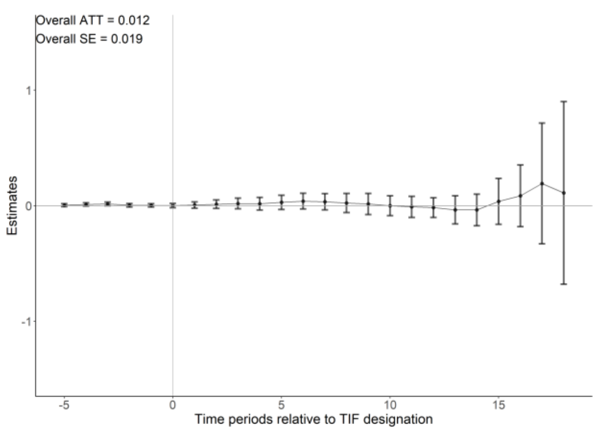
(A) Entire Establishments



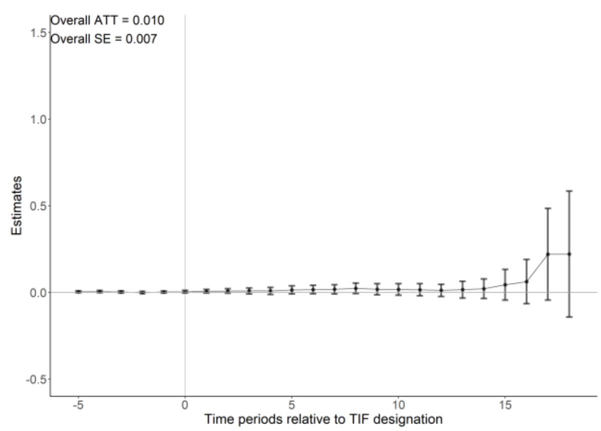
(B) Office Establishments



(C) Retail Establishments



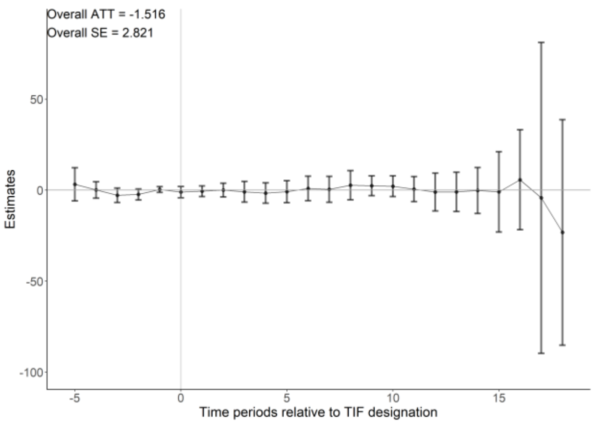
(D) Manufacturing Establishments



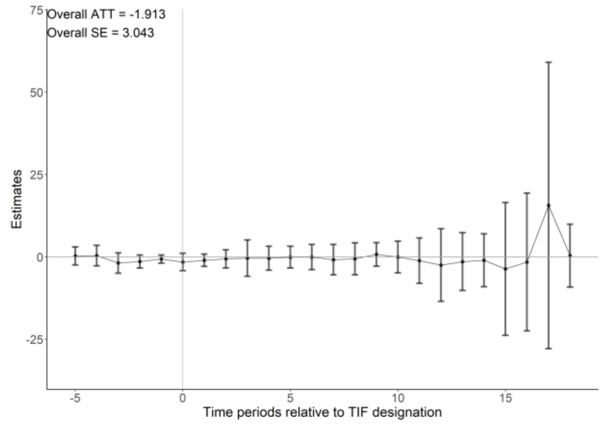
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C4. The effects of TIF designation on employment with treatment anticipation in Chicago

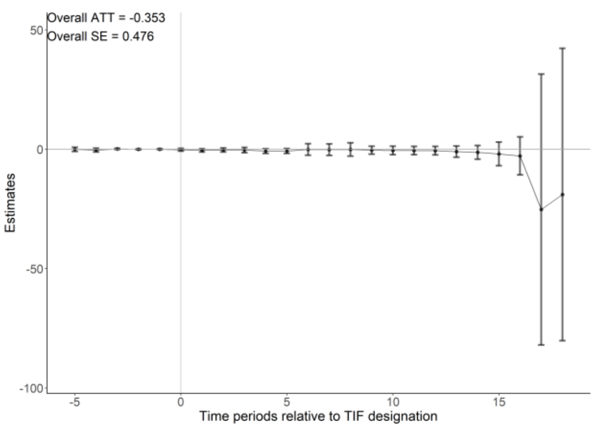
(A) Entire Employment



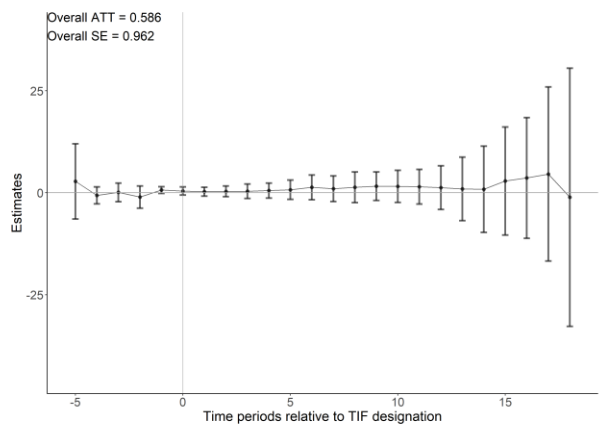
(B) Office Employment



(C) Retail Employment



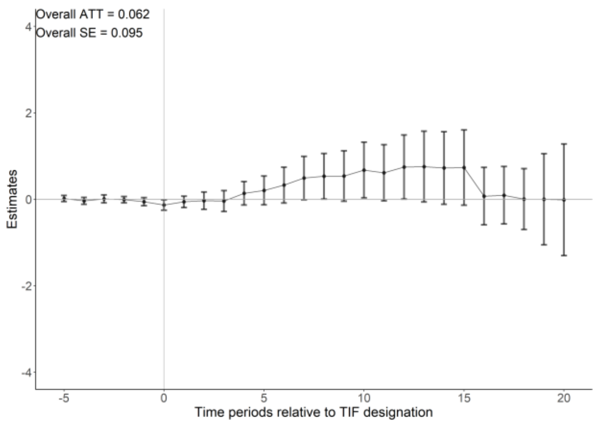
(D) Manufacturing Employment



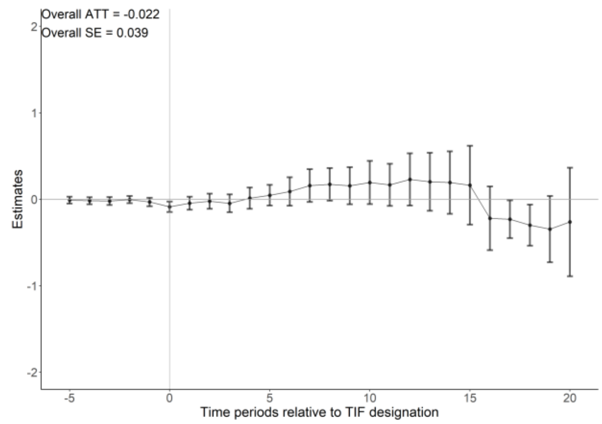
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C5. The effects of TIF designation on the number of establishments with treatment anticipation in the non-Chicago area

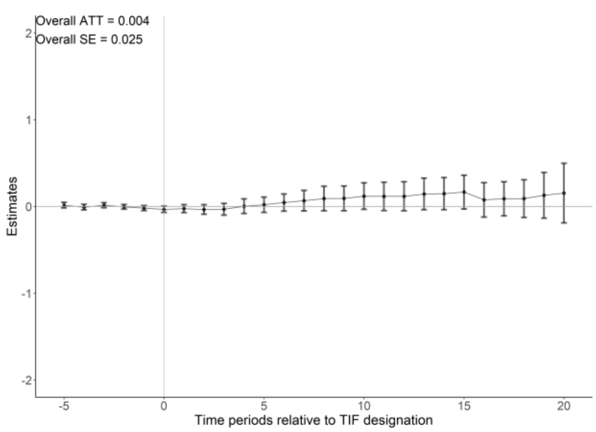
(A) Entire Establishments



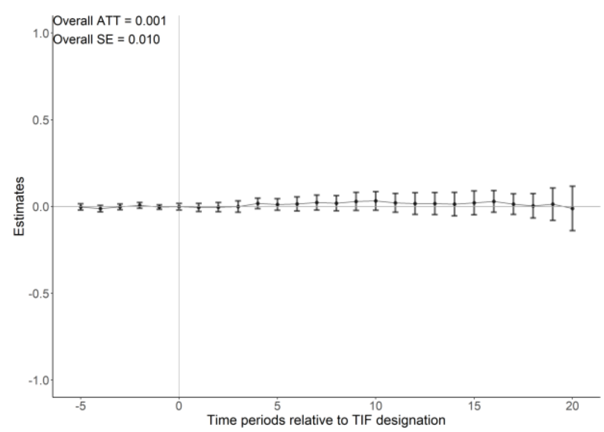
(B) Office Establishments



(C) Retail Establishments



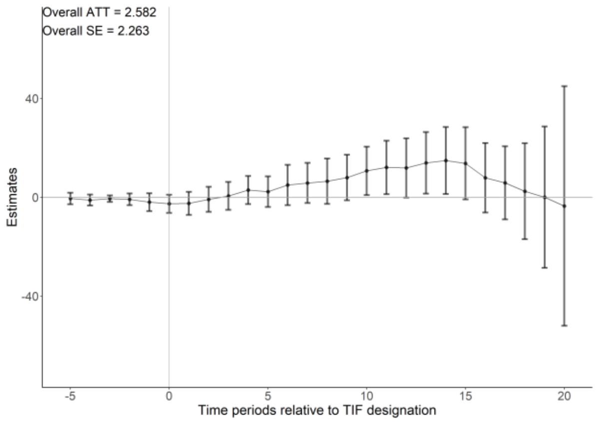
(D) Manufacturing Establishments



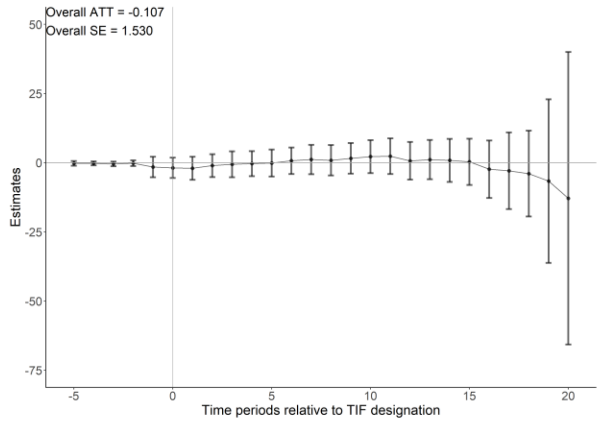
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C6. The effects of TIF designation on employment with treatment anticipation in the non-Chicago area

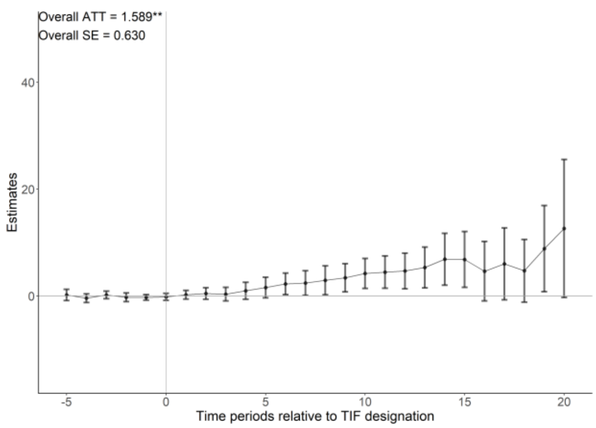
(A) Entire Employment



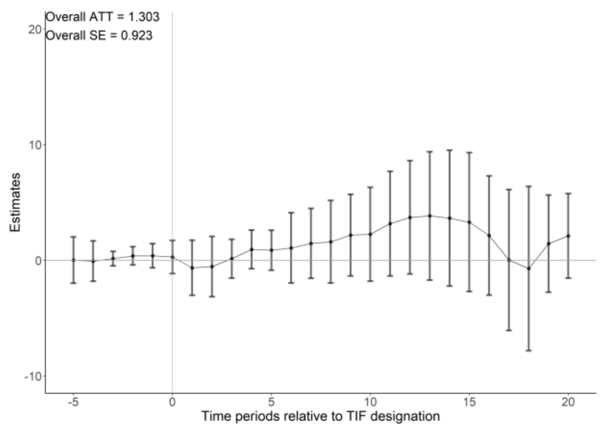
(B) Office Employment



(C) Retail Employment



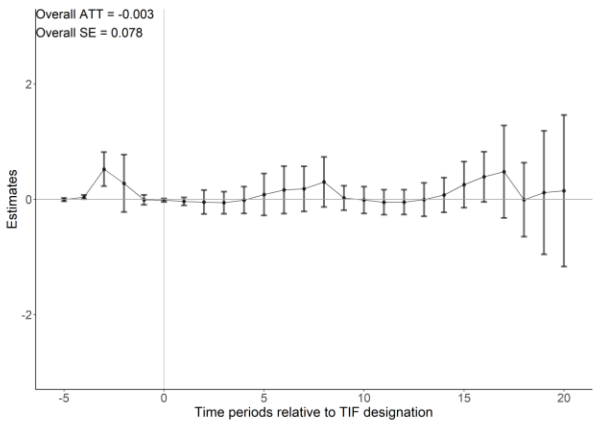
(D) Manufacturing Employment



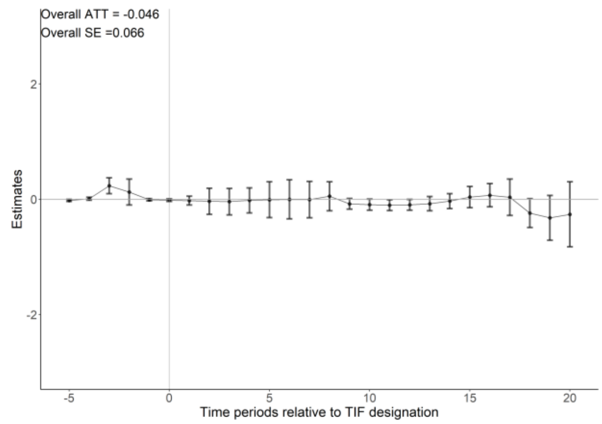
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C7. The effects of TIF designation on the number of establishments with 20% threshold in Cook County

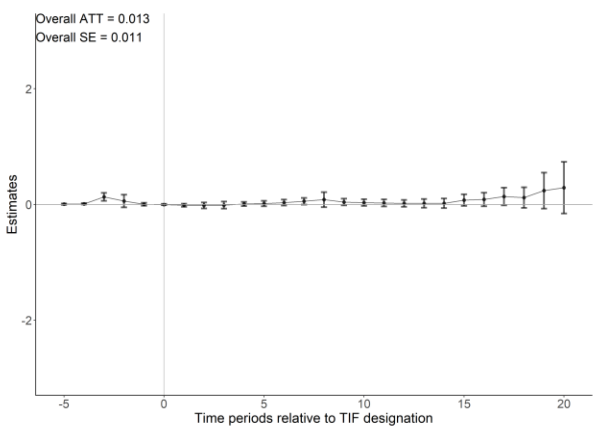
(A) Entire Establishments



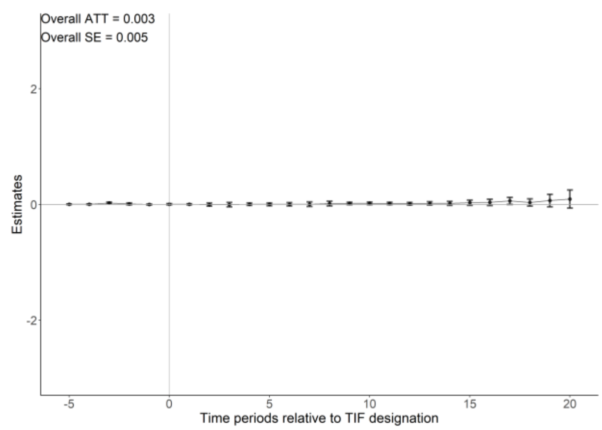
(B) Office Establishments



(C) Retail Establishments



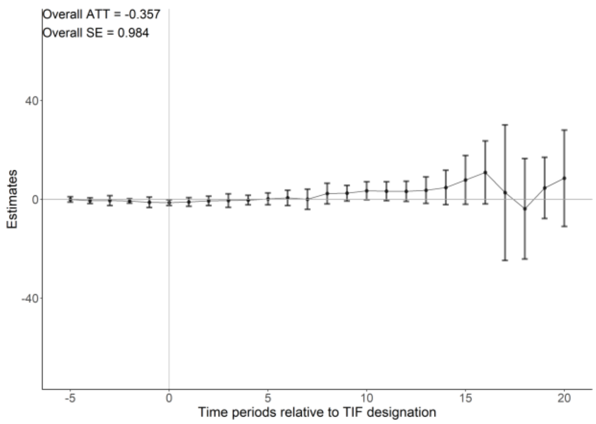
(D) Manufacturing Establishments



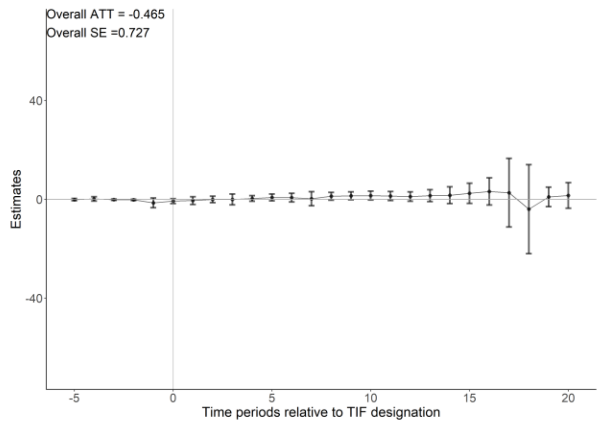
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C8. The effects of TIF designation on employment with 20% threshold in Cook County

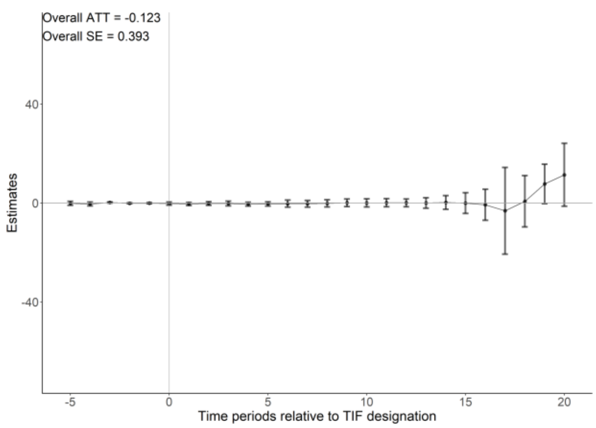
(A) Entire Employment



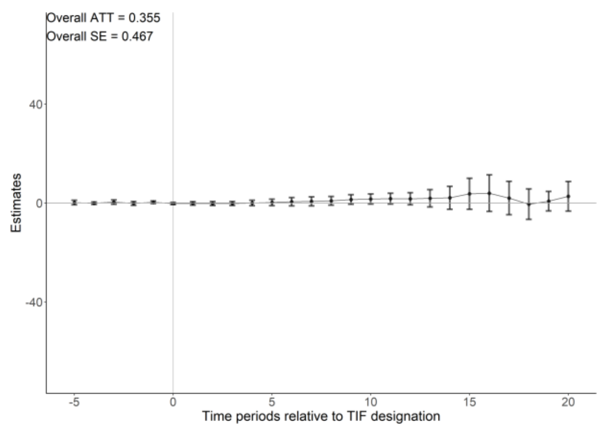
(B) Office Employment



(C) Retail Employment



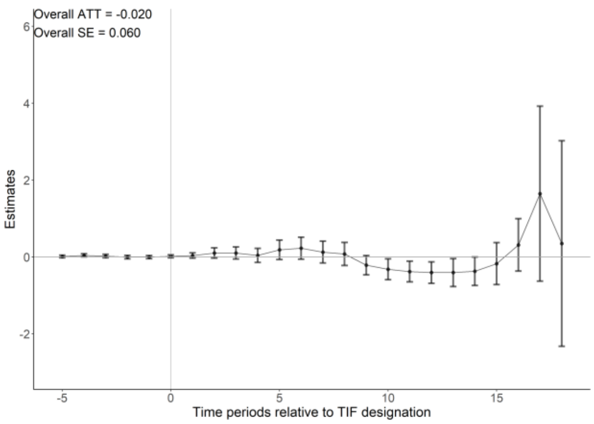
(D) Manufacturing Employment



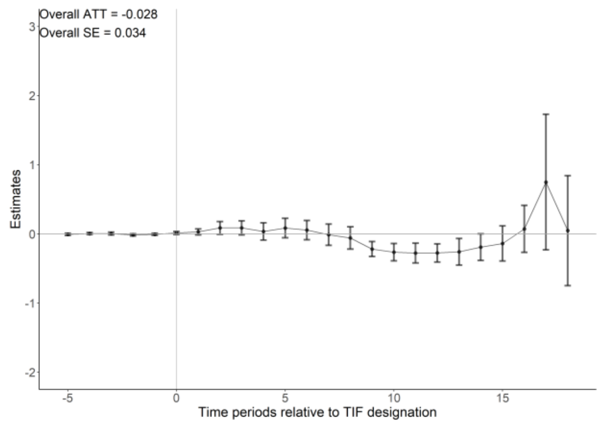
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C9. The effects of TIF designation on the number of with 20% threshold in Chicago

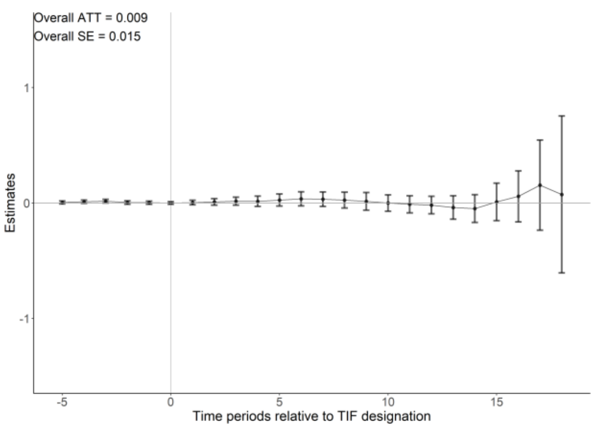
(A) Entire Establishments



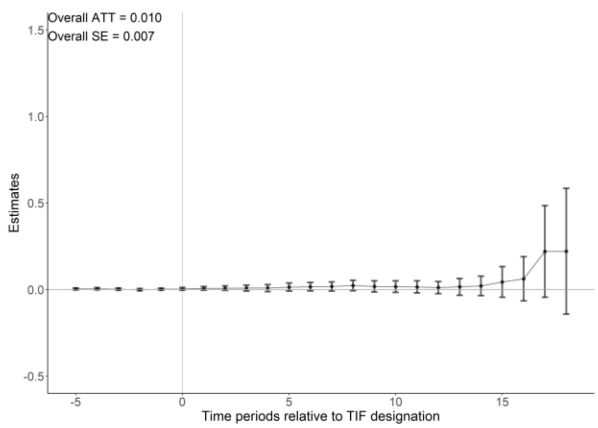
(B) Office Establishments



(C) Retail Establishments



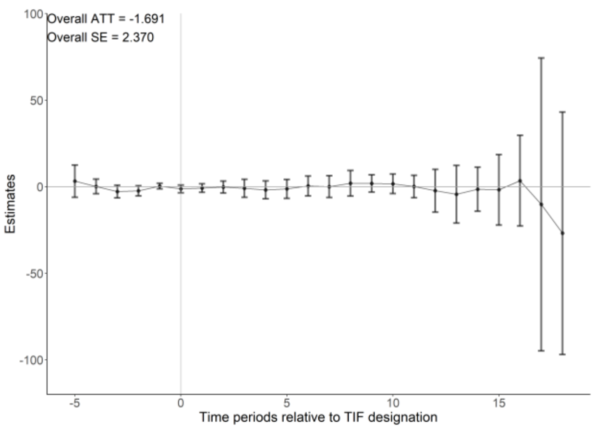
(D) Manufacturing Establishments



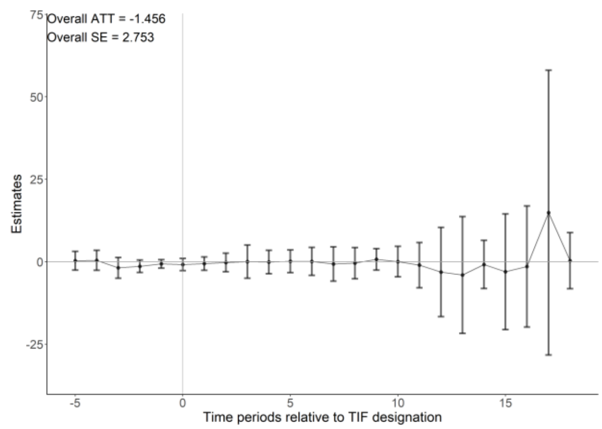
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C10. The effects of TIF designation on employment with 20% threshold in Chicago

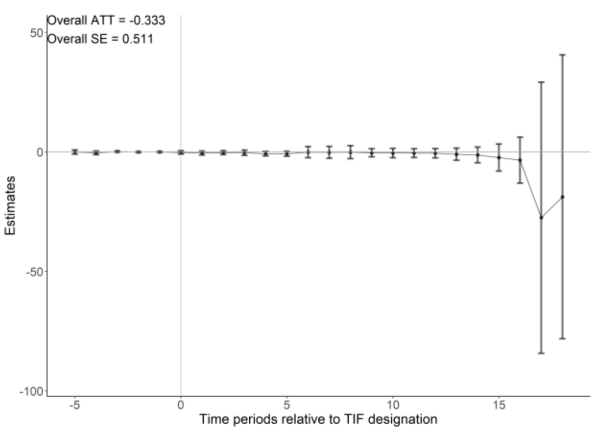
(A) Entire Employment



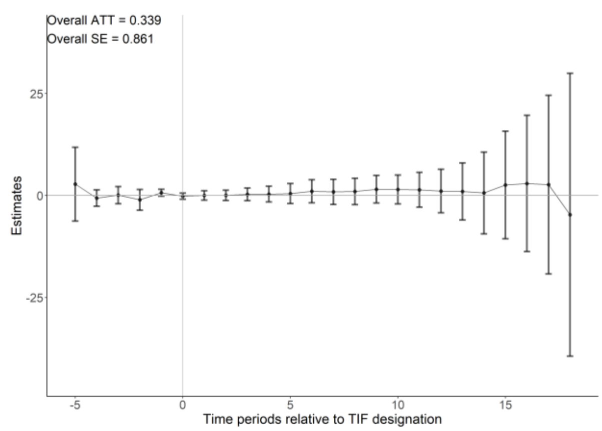
(B) Office Employment



(C) Retail Employment



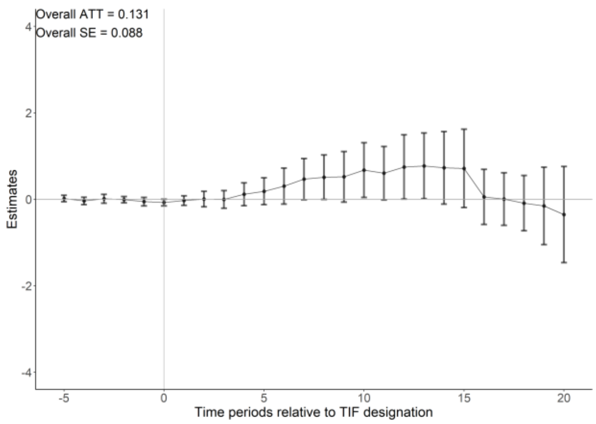
(D) Manufacturing Employment



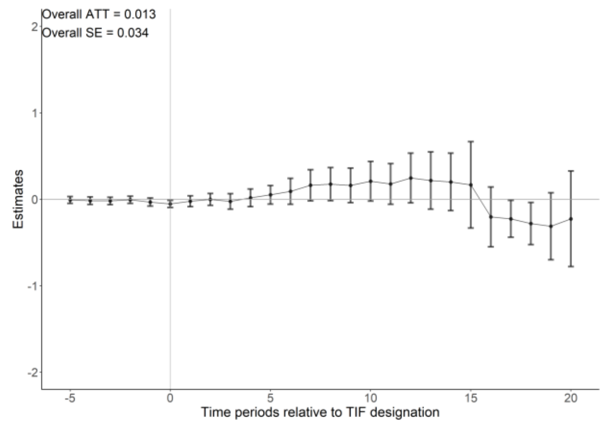
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C11. The effects of TIF designation on the number of establishments with 20% threshold in the non-Chicago area

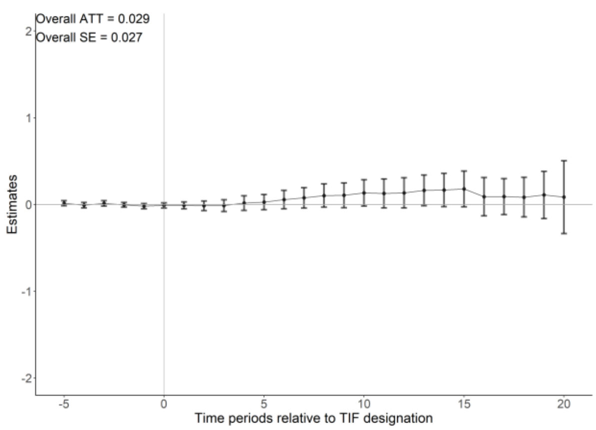
(A) Entire Establishments



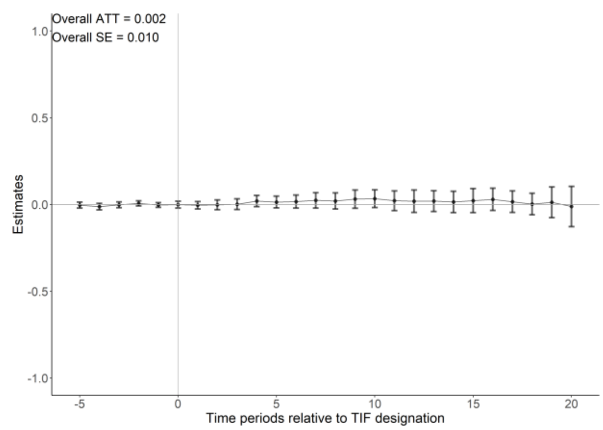
(B) Office Establishments



(C) Retail Establishments



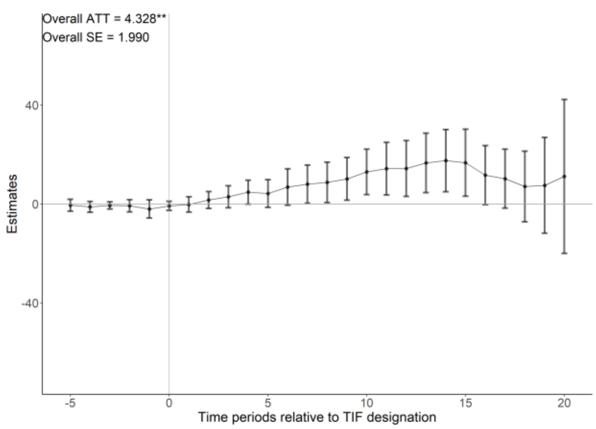
(D) Manufacturing Establishments



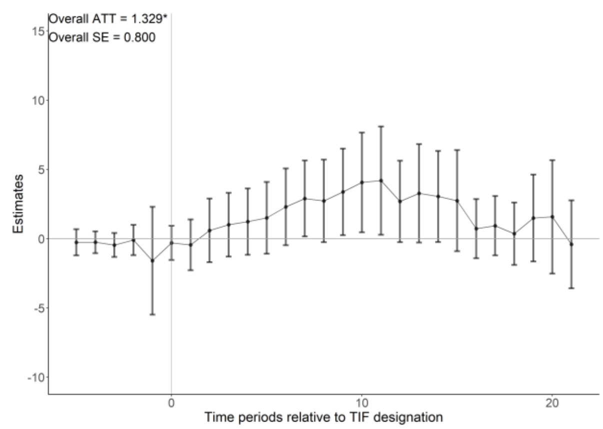
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C12. The effects of TIF designation on employment with 20% threshold in non-Chicago area

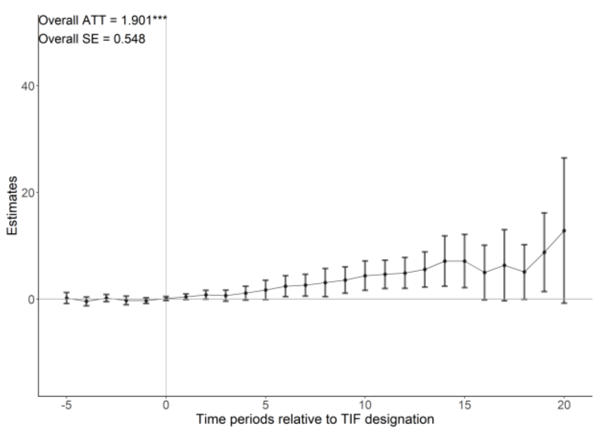
(A) Entire Employment



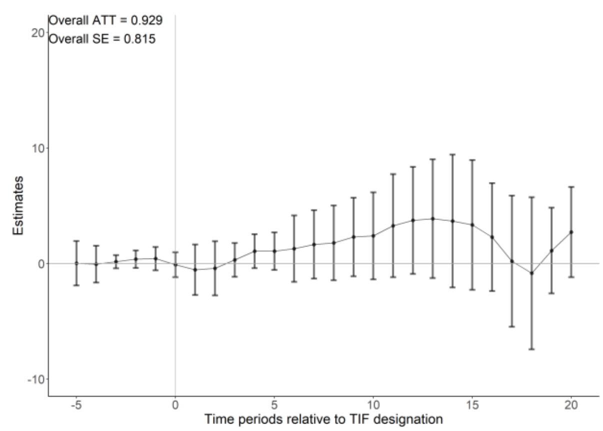
(B) Office Employment



(C) Retail Employment



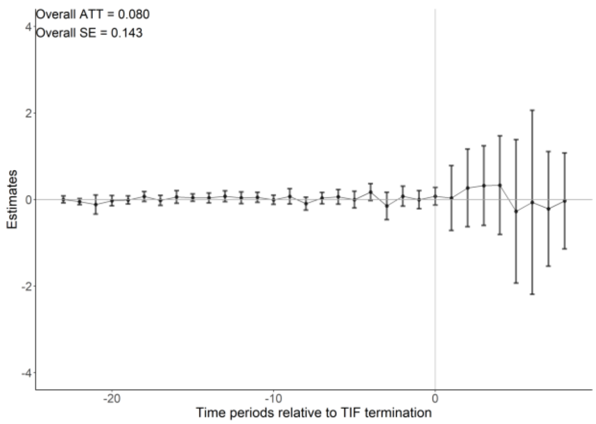
(D) Manufacturing Employment



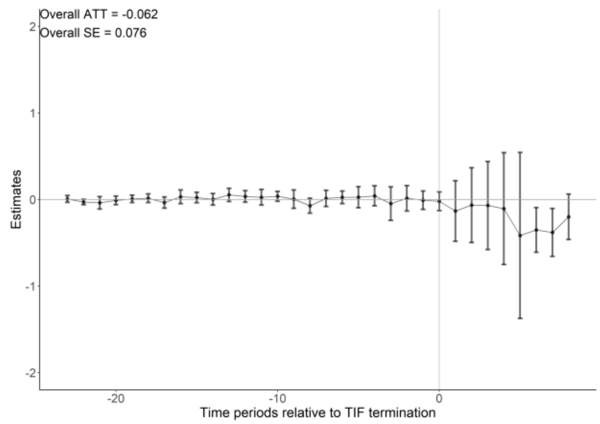
Note: Overall ATT shows the average effect of being in a TIF district across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C13. The persistent effects of TIF designation on establishments in the non-Chicago area, including TIF districts that last 23 or more years

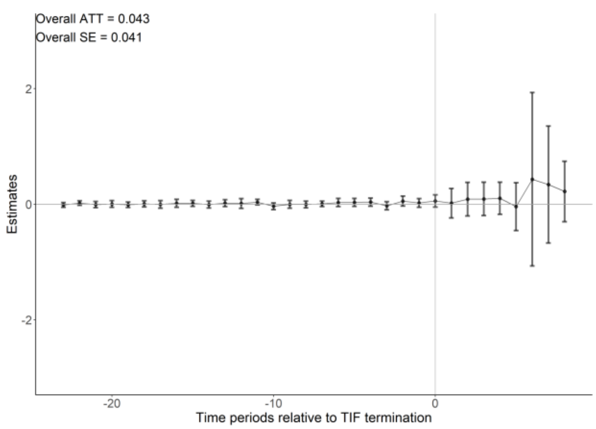
(A) Entire Establishments



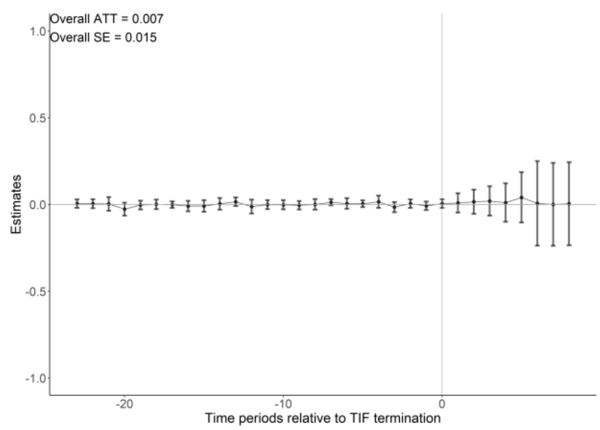
(B) Office Establishments



(C) Retail Establishments



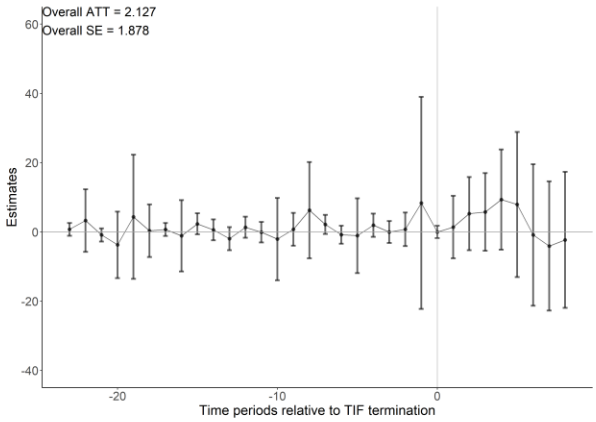
(D) Manufacturing Establishments



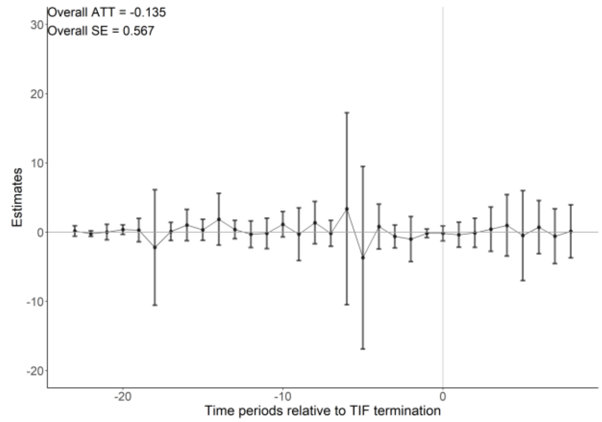
Note: Overall ATT shows the average effect of the TIF termination across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Figure C14. The persistent effects of TIF designation on employment in the non-Chicago area, including TIF districts that last 23 or more years

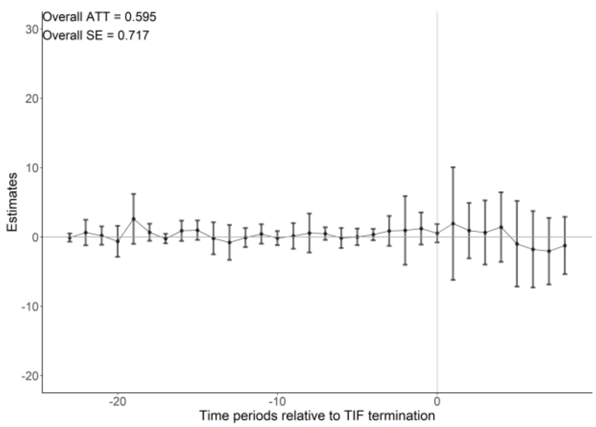
(A) Entire Employment



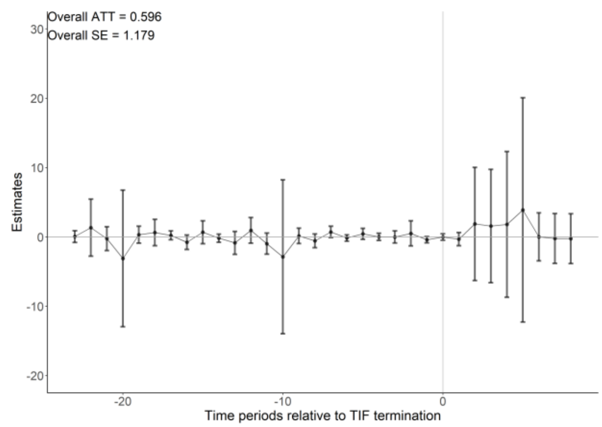
(B) Office Employment



(C) Retail Employment



(D) Manufacturing Employment



Note: Overall ATT shows the average effect of the TIF termination across all treatment time groups that participate in the treatment all time periods. Overall SE presents standard errors and are clustered at the census block level. The shaded areas represent bootstrapped 90% simultaneous confidence intervals and event-time coefficients for years relative to TIF designation are included.

Appendix D

To show the association between TIF and the consolidated tax rates of overlapping taxing bodies in Chicago, I compare the tax codes with TIF and those without TIF.[2] This analysis focuses on Chicago and the time period of 2012 to 2014, which are the specific region and duration for which I was able to obtain the relevant data from the Cook County Assessor's office.[3]

I run a two-way fixed regression using a balanced panel of 508 tax codes in Chicago and the specification employed in the regression is:

$$Y_{it} = \alpha_i + \gamma_t + \beta hasTIF_{it} + \epsilon_{it}$$

The dependent variable (Y) is composite tax rates in tax code i at year t and a dummy variable ($hasTIF$) is included where it is coded as 1 when a tax code has a TIF, and 0 otherwise. α_i and γ_t are unit and time fixed effects. ϵ_{it} is the error term. The results show that TIF is, in fact, positively associated with the tax rates imposed by overlapping taxing bodies, supporting the possible unexpected consequences of TIF on overlapping taxing bodies.

Table D1. The association between TIF and consolidated tax rates in Chicago, 2012-2014

Dependent variable – Consolidated tax rates	
hastif	0.274***
	(0.050)
2013	0.388***
	(0.004)
2014	0.384***
	(0.004)
constant	5.279***
	(0.042)
Tax code fixed effects	Yes
Observations	1,524

Notes: Asterisks denote significance at the 1% (***) level.

[2] Because of two factors, namely 1) unavailability of historical data on the boundaries of tax codes back to 1990, and 2) inevitable inaccuracies in matching tax codes to census blocks (i.e., some blocks have more than one tax code), I examine the relationship based on tax codes, rather than incorporating tax rates by tax code as a control variable into the main results.

[3] Due to this limitation, the examination of the correlation between TIF and consolidated tax rates of overlapping taxing bodies is constrained. However, it still provides supportive evidence for the main argument of this analysis.

References

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Kaufman TK, Sheehan DM, Rundle A, et al. (2015) Measuring health-relevant businesses over 21 years: Refining the National Establishment Time-Series (NETS), a dynamic longitudinal data set. *BMC Research Notes* 8(1). BioMed Central: 1–13. DOI: 10.1186/s13104-015-1482-4.

Neumark D and Kolko J (2010) Do enterprise zones create jobs? Evidence from California's enterprise zone program. *Journal of Urban Economics* 68(1): 1–19. DOI: 10.1016/j.jue.2010.01.002.