Determinants of Property Value Growth for Tax Increment Financing Districts

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Abstract

Although the majority of empirical research on Tax Increment Financing (TIF) examines municipal-level effects, there is a dearth of research looking at TIF effects at a more localized level. This paper examines the characteristics of the areas in which TIF districts are located as well as the factors influencing property value growth within TIF districts. The findings of the paper show that TIF districts on average are located in areas that are more economically disadvantaged than the municipality as a whole. The results also show that the spatial size of a TIF district has a positive influence on property value growth. Furthermore, TIF districts located in areas that have a higher proportion of white residents, and lower population density than the city as a whole, have higher growth. Additionally, results suggest a positive relationship between blight and subsequent property value growth.

1 Introduction

A common characteristic of public spending is that its benefits are often spatially concentrated. While many spending decisions are made at the municipal level, the benefits may often be limited to a smaller geographical area within the city. This pattern can be a serious impediment to optimal provision of the public good. For while the marginal benefit of a project may be greater than the marginal cost, because the benefit is concentrated in a small portion of the municipality, citywide support may be lacking. Because Tax Increment Financing (TIF) circumvents this problem, it has become a popular tool for city managers in financing public spending for projects that may not benefit an entire municipality.

When a municipality creates a TIF district, part of the process is to specify the geographical area that encompasses the district. While property within the TIF district continues to be taxed at the same total rate as in the base year, the tax revenue passed on to the respective overlapping tax jurisdictions is capped at the level received in the base year. Any additional tax revenues generated by increases in property value within the TIF district are captured by the TIF administrator. This incremental revenue can then be used to finance public improvements within the TIF district, an outcome that is achieved without raising anyone's tax rate. Once the TIF has expired, all of the overlapping taxing jurisdictions experience increased tax revenue.

Although the majority of empirical research on TIF districts examines TIF effects at the municipal level, there is a dearth of research looking at TIF effects at a more localized level. This paper fills this significant hole in the current research by looking at the performance of TIF districts at the actual district level, using data from Illinois. The paper answers the following two questions. First, what does the typical TIF district look like? As with most controversial topics, most lay discussions of TIF districts are peppered with anecdotal evidence, purported to imply some sort of statistical relevance. This paper is the first to undertake a more substantial examination of the characteristics of the areas in which TIF districts are located. The second, and more important, question is: which district characteristics are important in influencing the success of TIF, as measured by the growth rate of property values in the TIF district?

Regarding the characteristics of areas containing TIF districts, the findings of the paper show that TIF districts on average are located in areas that are more economically disadvantaged than the municipality as a whole. TIF districts are located in areas with higher unemployment rates, lower incomes, higher vacancy rates and older structures than the rest of the municipality.

The results show that the spatial size of a TIF district and a dummy for recently created TIFs have a positive impact on property value growth within TIFs, relative to their respective municipalities. In addition, TIF districts located in areas that have a higher proportion of white residents, and lower population density than the city as a whole, have higher growth. The results also suggest a positive relationship between blight and subsequent property value growth. Furthermore, quantile regressions show that population density, recent creation and TIF size are significant across growth quantiles, while racial makeup only has a significant impact on growth in the highest quantile.

2 Prior Research

At the beginning of 2001, there were 707 TIF districts in the State of Illinois[1]. Legislation authorizing the creating of TIF districts in Illinois was first passed in 1977 with the Tax Increment Allocation Redevelopment Act. The popularity of TIF as a development tool started to grow in the 1980's. Prior to 1980, only two TIF districts had been created, but by

[1] Source of current statewide TIF statistics is the Illinois Tax Increment Association Web Site.

1986, 143 additional districts had been created statewide. This study focuses on TIF districts in the Chicago metropolitan area over 1990 to 1993, at which time there were 128 districts.

The nationwide proliferation of TIF as an economic development tool has motivated a number of empirical studies of TIF and property value growth. The primary question researchers have attempted to answer is whether TIF raises property values. Anderson (1990) compared aggregate property value growth of Michigan municipalities that employed TIF to growth in municipalities that did not use TIF. Controlling for selectivity bias, he found that cities adopting TIF experienced higher aggregate property value growth than those that did not. However, Anderson did not address the issue of causality because there was no data on growth prior to TIF creation. Dye and Merriman (2000) studied municipalities in the metropolitan Chicago area and controlled for prior property value growth. They found that TIF adoption had a negative impact on aggregate property value growth in a municipality. They too controlled for selectivity bias but unlike Anderson did not find significant evidence of selectivity bias in their sample. Man and Rosentraub (1998) used a slightly different approach, measuring TIF efficacy by looking at the growth in median housing value (rather than aggregate value) for Indiana municipalities. Unlike Dye and Merriman, they found that TIF adoption led to increases in property value growth. However, a drawback to using median housing values is that this variable may miss TIF effects on the non-residential real estate markets.

Michael Dardia's (1998) work stands alone as the only previous paper studying the effects of TIF at the disaggregate level. He used a matched-pair approach to measure TIF effectiveness. Dardia created a matched pair for each TIF district by looking for areas with similar values for a vector of census variables. Comparing the growth difference between TIF districts and their respective matches, he found that TIF designation increased property value growth but not by enough to justify the tax increment the TIF district received.

The attribute that differentiates this paper from previous studies is the empirical question it asks. Past research asks the question: Does TIF increase municipal property value growth? The question asked here is: What influences growth within TIF districts? As Dye and Merriman demonstrated, it is possible for property value to grow faster in a TIF district than in the municipality as a whole, yet for TIF to still have a negative impact on municipal growth. This happens when the TIF channels development and infrastructure improvements into non-optimal areas. This paper does not focus on the issue of TIF's effect on municipal growth, shedding light instead on what influences growth within TIF districts without considering whether the municipality benefits overall. From a public policy standpoint, previous papers ask whether TIF should be implemented. This paper, by contrast, takes TIF as given and asks what the TIF district should look like and where it should be put.

3 Data

This paper uses two primary sources of data. The first source is the same data set used by Dye and Merriman (2000), which contains the Equalized Assessed Values (EAV) of the properties within the TIF districts from the year of creation until 1993 for the Chicago metropolitan area. The data set also has aggregate EAVs for entire municipalities within the metropolitan area. The second main data set is census tract demographic characteristics taken from the US Census Bureau's 1990 census. Additional TIF data and TIF maps were obtained from the County Clerk's offices in the respective metropolitan Chicago counties.

The first step of this study was to link demographic characteristics with the various TIF districts. This was done by using paper maps and/or legal descriptions of the TIF districts, when available, to create digital maps of each district using GIS software. From these maps, variables such as TIF Area and Distance to CBD were created. For most TIFs in the sample (about 70%), the entire TIF district was contained completely within a single census tract. These districts were simply assigned the demographic characteristics of the census tract in which the district resides. For the remaining districts, which overlap two or more census tracts, demographic characteristics were assigned by creating a weighted average of characteristics based on the proportion of the district area lying within each census tract.

Out of the original 128 observations, the sample size for econometric analysis was limited by two factors. First, for some TIFs, maps were unavailable and the location of the TIF could not be accurately determined by the legal description. Second, given that the dependent variable is annualized TIF growth from 1990 to 1993, some districts were not included in the final sample because they were not in existence for the entire time period. The final size of the sample used for econometric analysis is 89 TIF districts spread over 67 municipalities. Table 1 contains summary statistics for the sample. The mean annualized property value growth rate is 35% (17.6% at the median), a substantial rate, but not surprising considering that a development plan is often a prerequisite for TIF district creation. The mean TIF encompasses 138 acres, and the median area is 67 acres. Furthermore, the typical TIF district is in a neighborhood that was 77% white, had a median income of $39,635 and had an unemployment rate of 6.2%.

Most TIF districts are classified with respect to the type of development (redevelopment) that is to take place. The six classifications are Central Business District, Mall/Commercial, Mixed-Use, Industrial, Housing and None/Multiple Classifications. Table 2 shows the mean annualized growth rates for TIF districts broken down by classification. Industrial TIF districts experienced the highest median annualized property value growth, at 31.6%, followed by Commercial TIF districts, with 25.6% median growth and CBD TIF districts, with 15.9% median growth. Mixed-Use TIF districts had the lowest median property value growth of the four major TIF classifications, with only 10.4% annualized growth. TIF districts of the Mixed-Use and Industrial classifications were most influenced by outliers, as can be seen by the large differences between their median and mean growth rates.

A simplistic way to evaluate TIF performance would be to run a regression with Annualized TIF growth as the dependent variable (Y_{TIF}) and TIF characteristics as independent variables (X_{TIF}). This approach, however, measures absolute, not relative performance. Yet, TIF is a development tool implemented by a municipality to spur growth, and as such, property value growth within a TIF is a less accurate measure of success than growth relative to the municipality's overall growth rate. For example, if we compare two TIF districts, the first with 3% annualized growth and another with 6% annualized growth, one might be inclined to pronounce the latter a bigger success. However, the municipality in which the former existed might have experienced 1% property value growth, while the second TIF's municipality might have had 9% growth citywide. Clearly, controlling for differences between the TIF districts and their respective municipalities, the first TIF was more successful at spurring growth. Therefore, the difference between TIF and municipal growth rates is a more appropriate dependent variable than the absolute TIF growth rate. For the same reason, it is important to express exogenous variables as differences between TIF and municipal values.

4 What Do TIF Districts Look Like?

Table 3 summarizes the difference variables, showing both the difference in growth rates and demographic characteristics between the TIF districts and the corresponding municipalities. Note that since the variables Distance to CBD, TIF Area and Years Since Created are not measured relative to the enacting municipality, they are not included in Table 3.

Not surprisingly, the annualized growth of TIF districts was higher than municipality-wide growth. Districts within the sample experience annualized growth between 1990 and 1993 that was 29.1 percentage points greater than city growth. While this is an exceptionally high difference, it is not unexpected. As mentioned earlier, because the existence of a development plan is a prerequisite for TIF district creation, one would expect property values in these districts to experience strong growth that outpaces municipal growth.

The summary statistics for the independent variables in Table 3 are in and of themselves a valuable contribution to the study of TIF districts. There has been a dearth of information in the literature, beyond anecdotal evidence, on the characteristics of TIF districts. These data represent essentially a first glimpse into the characteristics of areas where TIF districts are being used[2], and as such, they are quite relevant to policy issues, especially for the State of Illinois.

One frequently asked question is whether TIF is used in the legislatively intended manner. That is, is TIF truly being used in economically depressed areas? On average, the answer is yes. Table 3 shows that Illinois TIF districts are generally located in areas with higher unemployment rates, higher vacancy rates, older buildings and poorer residents in comparison to the municipality as a whole. Yet perhaps just as telling is the fact that this is not universally the case. From column five, we see that 25% of the TIF districts were in areas that had median

[2] Dardia had the mean values for vacancy rates, poverty rate, median income and median rent for both the TIF sample as well as the same mean characteristics for the non-TIF portions of the cities. However, he did not construct any variables showing how each individual TIF district compared to its respective municipality.

incomes at least $3,113 greater than the municipality as a whole. In fact, 5% of the TIF districts are in areas whose median incomes were at least $13,278 greater than the city wide median income. Additionally, the twenty-fifth percentile for vacancy rate and unemployment rate difference is -0.87% and -0.66% respectively, indicating some TIFs are located in areas with stronger housing demand and lower unemployment than the municipality as a whole. Therefore, while TIF districts tend to be used in areas that are experiencing some sort of economic difficulties relative to the municipality as a whole, there does appear to be evidence of possible misuse.

Table 4 shows the correlation matrix for the exogenous variables in the sample. Some of the highest correlation values are between the blight variables: Unemployment, Median Income and Vacancy Rate. As a result, these variables are not included in any regressions simultaneously. As one would expect, Distance to CBD is positively correlated with TIF Area. Furthermore, the correlation between the difference in Percent White and the differences in Unemployment and Median Income are negative and positive respectively. Yet, none of these correlations is so high as to suggest that multicollinearity should be a major concern. The Variance Inflation Factor (VIF) for the correlation table below is only 1.42. For the specifications regressed in the remainder of the paper, the VIF varies from 1.63 to 1.90, making multicollinearity a minor concern.

5 Empirical Analysis of TIF Success

5.1 Empirical Model

Table 5 shows the results from rudimentary regressions based on the model

$$Y_{TIF} = a + bX_{TIF} + gD_{CLASS} + h, \qquad (1)$$

where both the dependent and independent variables consist only of TIF characteristics, and not TIF-municipal differences, and where D_{CLASS} is a matrix of dummy variables for TIF Classification[3]. Column one shows the results of a regression using only the dummy variables for classification of the TIF district, while column two shows results when Population Density, TIF Area, Distance to CBD, Years Since Created, Percent White, Median Age of Structures and Vacancy Rate are included. For the first regression, Industrial TIF is the only independent variable whose coefficient is significantly different from zero. In the second specification, with the complete set of exogenous variables, the coefficient of Industrial TIF is no longer significant. As for the rest of the variables, only TIF Area has a significant impact on TIF district growth. These results highlight the fact that a model based upon the absolute level of TIF district growth may not be useful.

As discussed earlier, a better approach to examining TIF success is to measure the variables as TIF-municipal differences. Although TIF districts experience growth that is on average 29.1% greater than their municipalities, clearly there is a large variation in the success of TIF districts. The primary question this paper tries to address is which characteristics of TIF districts account for this variation in TIF success. Table 6 shows results from OLS regressions based on the following model:

$$Y_{DIFF} = a + bX^1_{DIFF} + lX^2_{TIF} + gD_{CLASS} + h\ . \qquad (2)$$

Y_{DIFF} is annualized TIF growth less annualized municipal growth. X^1_{DIFF} is the vector of exogenous variables measured as the difference between the TIF district and municipal measure. These include Population Density, Vacancy Rate, Median Age of Structures and Percent White. X^2_{TIF} is the vector of exogenous variable for which differences are not taken: TIF Area, Distance

[3] Housing & No Classification is the omitted category.

to CBD and Years Since Created. Finally, D_{CLASS} is the matrix of dummy variables of TIF classification and η is the error term.

5.2 Results

The first specification of Table 6 regresses growth difference on the dummy variables of TIF Classification. The results show that the Industrial TIF designation is the only classification having a significant impact on TIF success. The second specification goes one step further and includes the vector X^2_{TIF} in the regression. Once Distance to CBD, TIF Area and Years Since Created are included, none of the TIF Classification coefficients are significant. Furthermore, none of the coefficients of the added variables are significant either.

Specifications three through five add the difference variables to the regression, with the alternative models reflecting different ways of modeling years since TIF creation. Specification three uses the variable Years Since Created, which assumes a smoothly diminishing effect of TIF age on growth over the 1990-1993 period. In specification three, the sign of the coefficient of Years Since Created is negative as expected, but the coefficient is not significantly different from zero. However, one might contend that instead of there being a smooth decline in TIF growth over time, there is an initial development period where TIF districts experience stronger growth before falling to lower growth for the remaining time period. Column four includes a dummy variable indicating whether the TIF was created between 1988 and 1990 (Recent TIF) along with the linear component, while the fifth column has only the Recent TIF dummy. Note that Recent TIF indicates TIF districts that have been in existence for no more than two years. In specification four, diminished TIF growth over time is again rejected, while the specification of column five shows the presence of a Recent TIF effect. The highly significant positive sign on the dummy variable's coefficient indicates that a period of particularly strong growth occurs early in a TIF district's life. For TIF districts created between 1988 and 1990, the annualized property value growth difference from 1990 to 1993 is 30 percentage points greater than that for older TIFs.

As for the remaining variables, TIF districts located in areas with a higher percentage of white residents relative to the municipality as a whole tend to be more successful in terms of property value growth. Each percentage point difference in racial makeup raises the TIF growth difference by 1.05 percentage points. This finding could be interpreted as a sign of discrimination in the housing market. A lower willingness of businesses and residential buyers/renters to move into a minority or racially mixed TIF area would temper the effect of increased public good provision on property value growth[4].

Population Density has a negative impact on TIF growth, with an estimated coefficient of –0.0377. This coefficient indicates that an additional 4.7 people per acre (one standard deviation) leads to a decrease in the TIF growth difference of 17.7 percentage points. This pattern could result from TIFs capturing the property value increases accompanying the natural rapid pattern of development in the least dense areas of a city. Yet, it could just as well be a sign of less dense areas having a strong underprovision of public goods and infrastructure, leading to higher returns on improvements. The effect of TIF Area on growth is fairly constant across specifications, with a 10-acre increase leading to a 0.9 percentage point larger growth difference in the final specification, implying increasing returns to scale.

Differences in vacancy rates do not have a significant impact on growth rates at even the 10% level. Nonetheless, it is interesting to note that the sign of the coefficient is the opposite of

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[4] When Income is included in the regression, either as an alternative measure of blight or along with Vacancy Rate, the coefficient for Percent White is unchanged in both magnitude and significance. This dismisses the possibility that the coefficient is measuring an income effect and not a racial effect.

what we would expect. Assuming a high vacancy rate is an indication of deficient infrastructure, suggesting an area where the productivity of TIF should be high, we would expect a positive coefficient. Regressions were also run using the unemployment rate and income in place of the vacancy rate. Coefficients for both of these variables predict the same weakly significant relationship between blight and growth, with no major impact on the remaining results. Another possible blight variable, the difference in the median age of structures, is included in all the specifications, but it has no significant impact on TIF growth. Finally, the TIF Classification also has no significant impact on TIF growth.

Despite the lack of significance of the classification coefficients, Table 7 shows the growth difference predicted by specification five for TIF Classification. The first column has predicted growth based on the assumption that both X_{TIF}^{2} and X_{DIFF}^{1} are set to the sample median. Commercial and Industrial TIF districts have the highest predicted growth difference at close to twenty percentage points. The model predicts Mixed-Use TIF districts to have a growth difference of 12.8 percentage points and predicts CBD TIF districts to outgrow their municipalities by 1.7 percentage points. The second column gives the predicted growth difference when X_{DIFF}^{1} is set to zero, i.e. the TIF district is in a typical area of the municipality. Under this assumption, the model predicts a lower growth difference, while predicting a slightly negative growth difference for CBD TIF districts. Note, however, that all these results are based on point estimates that are not significantly different from zero.

5.3 Implication of Results for Years Since Created

The fact that a TIF district's age has no significant effect on the difference in TIF growth, beyond the initial creation period, can offer some insight into characterizing how TIF works. We can think of the theoretical modeling of TIF districts in two ways. In the traditional approach, TIF increases the public good level within the district, which in turn increases property values. This public good can be thought of as infrastructure improvement, which, for the sake of argument, does not depreciate or depreciates at a negligible rate. Another modeling approach is to assume that TIF simply subsidizes businesses located within the TIF district. This view is prompted by critics of TIF who charge that TIF expenditures are used to finance what are essentially normal business expenditures. If TIF districts offered nothing more than an operating subsidy for developers, the subsidy would expire with the TIF. Consequently, one would expect property value growth to decrease as the expiration date of the TIF approaches. However, in none of the specifications is this the case, supporting the idea that TIF districts provide durable public improvements rather than offering temporary subsidies for businesses within the district.

5.4 Potential Endogeneity

A potential problem with the results so far is that the variables taken from the 1990 census could be endogenous. To understand this issue, consider Figure 1, which shows a histogram of the Year of TIF Creation for the sample. The key observation is that a number of TIF districts in the sample were created more than a few years before the 1990 census was taken. Given the small sizes of census tracts, it is possible that the creation of a TIF district within the tract could alter the demographic characteristics of that tract, which are measured in 1990. An ideal solution for dealing with this potential endogeneity would be to limit the sample to TIFs created in 1990. Yet, as can be seen from Figure 1, this would give us only 22 observations, too small a sample to yield reliable results.

Two alternative approaches are examined for dealing with this problem. The first is to use census tract characteristics from the 1980 census instead of the 1990 census. Since none of the TIF districts in the sample were created before 1980, the possibility of endogeneity is eliminated. The drawback to using the 1980 census, however, is that many of the TIFs were created well after 1980 (only 10 TIFs existed before 1986). One could argue that if neighborhoods are changing over time, the characteristics from the 1980 census are only shadows of the true characteristics of an area whose growth we are measuring from 1990 to 1993. A second approach is to rerun the regressions using only TIF districts created just prior to 1990. Limiting the sample to the 45 TIF districts created between 1988 and 1990 could make the impact of endogeneity negligible if we believed that TIF effects take longer than two years to materialize. The drawback of this approach is that if TIF impact on the census tract characteristics happens quickly, limiting the sample to TIF districts created just before the census was taken would still yield biased results.

Columns six and seven show the results from these two approaches. Column six uses the same model but with 1980 Census data. As would be expected, changes in the coefficients of the non-census variables are minor. The coefficients for TIF Area, Recent TIF, Distance to CBD, and TIF Classification are all within a standard error of the coefficients from the original regression. The Percent White coefficient is similar whether using 1980 or 1990 census tract data. The coefficient for Population Density becomes considerably smaller under this approach and is no longer significant, suggesting a negative bias. Meanwhile, the coefficient for Median Age of Structures is now significantly positive, suggesting a negative bias in the previous results. Switching to 1980 census data also changes the sign of the Vacancy Rate coefficient, which is now positive and marginally significant. In the original regression using 1990 data, a one-percentage point greater vacancy rate difference resulted in 3.48 percentage points lower growth. Using 1980 data, however, a one-percentage point greater vacancy rate difference results in 2.1 percentage points *higher* growth.

The changes in the coefficients for these blight variables suggest that endogeneity may indeed bias the results that rely on the 1990 census data. A successful TIF district would lead to increased housing demand, resulting in a lower vacancy rate in the district and creating a negative bias in the measured effect of the vacancy rate on growth. Similarly, development spurred by successful TIFs can also lead to newer buildings, creating a negative bias in the coefficient for Median Age of Structures. The results in column six are consistent with this view.

The second approach to examining the prevalence of bias is limiting the sample to recently created TIF districts. Column seven gives the results from the regression using these 45 TIFs. The coefficient for Percent White is the only significant coefficient, which is not surprising given the much smaller sample size. The coefficients for the rest of the variables are insignificant, but their signs are the same as with the full sample.

5.5 Quantile Regression

Ordinary least squares results estimate the effect TIF characteristics have on the conditional mean of property value growth. However, it may be beneficial to go beyond OLS's mean regression by using quantile regression. This methodology, first introduced by Koenker and Bassett (1978), can provide further insight into the role TIF characteristics play in TIF property value growth. An advantage of using quantile regression is that it measures the relationship between TIF characteristics and growth across the growth distribution. Though the

OLS approach assumes that the covariate effects are constant throughout the distribution, there is no theoretical reason to expect this condition to hold. As such, quantile regression gives us a more complete picture of what influences TIF property value growth. Furthermore, under the quantile regression framework, outliers impact the results much less than with OLS. Since the influence of outliers on the results was somewhat of a concern, quantile regression is an attractive empirical tool.

Table 8 shows the results of the previous OLS regression using 1990 census data[5] along with quantile regression results for the .25, .75 and median quantiles. TIF Area and Recent TIF continue to have positive effects on growth, with a more pronounced effect in the upper tail of the distribution. Population Density, meanwhile, has an impact that is most significant at the tails of the distribution. Each additional person per acre depresses growth by 1.5 percentage points at the 0.25 quantile and by 2.3 percentage points at the 0.75 quantile. Perhaps the most unsettling result from the OLS regressions is the impact of racial differences on TIF success. However, quantile regression shows that this covariate has a significant positive influence on growth only at the highest growth quantile. Additionally, while TIF Classification has no significant effect on growth in the OLS regression, Industrial TIF and Mall/Commercial TIF designations strongly influence growth in the upper tail of the distribution. Finally, for the 0.25 quantile, the growth difference falls by 0.6 percentage points with each additional mile from downtown Chicago.

Conclusion

This paper answers two questions regarding TIF: what are the characteristics of TIF districts, and which TIF characteristics influence growth? With new TIFs being enacted each

[5] Tables containing quantile regression results using 1980 census tract data is available upon request.

year, this paper gives us a better idea of what kind of growth we can expect. Characteristics influencing TIF growth are TIF Area, Population Density, Percent White and whether a TIF is recently created. Furthermore, results using 1980 Census data suggest that Vacancy Rate and Median Age of Structures have a positive effect on TIF growth. Thus, the results suggest a positive relationship between blight and property value growth in TIF districts. Quantile regression shows that some covariates have different effects across the growth distribution.

This paper also sheds light on some of the criticism of TIF. Although TIF districts typically exist in the more economically depressed areas of cities, TIF is sometimes used in well-to-do areas, buttressing a claim of critics. Finally, the lack of diminishing TIF district property value growth over time suggests that TIF provides durable public good improvements as opposed to subsidizing normal business expenditures, as critics sometimes claim.

Table 1: Summary Statistics

Variable	Obs	Mean	Median	St. Dev.	Min	Max
Annualized TIF Growth	89	0.350	0.176	0.683	-0.391	4.279
Annualized Municipal Growth	67	0.060	0.0555	0.029	-0.110	0.151
Years Since Created	89	2.48	2	2.03	0	9
Distance to CBD (Miles)	89	19.107	18.8	9.886	0	49.3
TIF Area (Acres)	89	138.3	66.8	209.9	1.3	1270.7
Percent White	89	0.766	0.886	0.267	0	1
Vacancy Rate	89	0.049	0.039	0.031	0	0.203
Population Density	89	5.96	4.57	6.11	0.16	38.93
Median Age of Structures	89	27.2	27	11.1	4	50
Median Income	89	39,635	37,053	16,723	10,644	113,426
Unemployment Rate	89	0.062	0.048	0.052	0	0.306

Table 2: Mean TIF Growth by Classification

TIF District	Observations	Mean Annualized Growth Rate	Median Annualized Growth Rate
CBD	23	0.1690	0.1588
Mall/Commercial	15	0.2909	0.2556
Mixed-Use	29	0.3446	0.1037
Industrial	12	0.8393	0.3156
Housing	1	0.3283	-
None/Multiple	13	0.2480	0.1622
Entire Sample	89	0.3502	0.1755

Table 3: Difference Variables

Variable	Mean Difference	Median Difference	25th %-tile	75th %-tile
$Y_{TIF} - Y_{MUNI}$				
Annualized Growth[a]	0.2906	0.1132	-0.0071	0.2969
$X^1_{TIF} - X^1_{MUNI}$				
Percent White	-0.0134	-0.0021	-0.0299	0.0544
Vacancy Rate	0.0040	0.0035	-0.0087	0.0136
Population Density	-1.0811	-0.9011	-2.5883	1.0582
Median Age of Structures	0.5695	0.1624	-3	4
Median Income	-1,134.3	-1,592	-7,268	3,113.4
Unemployment Rate	0.0057	0.0005	-0.0066	0.0154

a: Annualized Growth is for 1990 to 1993

Table 4: Correlation Matrix

	DIF % White	DIF Vac.Rate	DIF Pop Den.	DIF Med Age	DIF Med Inc	DIF % Un.	Distance to CBD	TIF Area
$X^1_{TIF} - X^1_{MUNI}$								
DIF (% White)	1							
DIF (Vacancy Rate)	-0.1054	1						
DIF (Pop. Dens.)	0.0359	0.2404	1					
DIF (Median Age)	0.1057	-0.1051	0.0222	1				
DIF (Med Income)	0.2757	-0.3252	-0.1836	-0.1302	1			
DIF (% Unempl.)	-0.5618	0.3148	0.1894	0.0331	-0.5222	1		
X^2_{TIF}								
Distance to CBD	0.1676	0.1938	0.2159	0.1522	0.1099	0.0241	1	
TIF Area (Acres)	0.0520	0.0360	-0.0796	-0.0540	0.2023	0.0172	0.4101	1
Years Since Created	0.1173	0.1299	0.1090	0.0371	-0.0726	-0.1015	0.0125	-0.1027

Table 5: Rudimentary Regression

($Y_{TIF} = a + bX_{TIF} + gD_{CLASS} + h$)

(t-statistics in parentheses)

Variable	(1)	(2)
CBD TIF	-0.0847 (-0.384)	0.1569 (0.665)
Mall/Commercial TIF	0.0372 (0.154)	0.3557 (1.246)
Mixed-Use TIF	0.0909 (0.429)	0.1809 (0.788)
Industrial TIF	**0.5856** **(2.285)****	0.4350 (1.631)
Population per Acre		-0.0277 (-1.963)*
Distance to CBD		-0.0152 (-1.599)
TIF Area (Acres)		**0.0007** **(2.028)****
Years Since Created		-0.0507 (-1.525)
Percent White		0.2848 (0.847)
Median Age of Structures		0.0033 (0.432)
Vacancy Rate		-1.8148 (-0.722)
Constant	0.2537 (1.457)	0.3875 (0.741)
R^2	0.0925	0.2089
Adjusted R^2	0.0512	0.1014

*: Significant at 10% Level **: Significant at 5% Level ***: Significant at 1% Level

Table 6: Modeling with Difference Variables

$$Y_{DIFF} = a + bX^{1}_{DIFF} + lX^{2}_{TIF} + gD_{CLASS} + h$$

(t-stats in parentheses)

Variable	(1)	(2)	(3)	(4)	(5)	1980 Census (6)	Recent TIFs (7)
CBD TIF	-0.1029 (-0.445)	0.0636 (0.265)	0.1896 (0.855)	0.1823 (0.831)	0.1873 (0.858)	0.0262 (0.119)	0.1050 (0.225)
Mall/Commercial TIF	0.0359 (0.140)	0.0925 (0.340)	0.3988 (1.575)	0.3820 (1.523)	0.3759 (1.507)	0.2407 (0.954)	0.4511 (0.942)
Mixed-Use TIF	0.0992 (0.440)	0.1302 (0.555)	0.2768 (1.292)	0.3110 (1.458)	0.2984 (1.416)	0.2821 (1.273)	0.4265 (0.975)
Industrial TIF	**0.5969** **(2.236)****	0.4829 (1.783)*	0.3410 (1.383)	0.3886 (1.580)	0.3624 (1.515)	0.4914 (1.971)*	0.1432 (0.326)
Distance to CBD		-0.0109 (-1.368)	-0.0074 (-0.960)	-0.0095 (1.220)	-0.0091 (-1.179)	**-0.0187** **(-2.37)****	-0.0101 (-0.623)
TIF Area (Acres)		0.0007 (1.830)*	**0.0008** **(2.247)****	**0.0009** **(2.543)****	**0.0009** **(2.505)****	**0.0011** **(2.789)*****	0.0009 (1.022)
Years Since Created		-0.0568 (-1.552)	-0.0543 (-1.632)	0.0317 (0.502)			
Recent TIF				0.4099 (1.596)	**0.2998** **(2.250)****	**0.3827** **(2.776)*****	
DIF: Population per Acre			**-0.0444** **(-3.016)****	**-0.0356** **(-2.286)****	**-0.0377** **(-2.528)****	-0.0019 (-0.785)	-0.0614 (-1.556)
DIF: Percent White			**1.0148** **(2.691)****	**1.0527** **(2.814)*****	**1.0543** **(2.832)*****	**1.3612** **(2.927)*****	**1.8097** **(2.627)****
DIF: Median Age of Structures			0.0104 (1.088)	0.0117 (1.230)	0.0114 (1.203)	**0.0265** **(2.765)*****	0.0090 (0.462)
DIF: Vacancy Rate			-3.4574 (-1.382)	-3.5514 (-1.434)	-3.4751 (-1.413)	2.1384 (1.645)	-1.6970 (-0.287)
Constant	0.2010 (1.087)	0.3886 (1.383)	0.1839 (0.700)	-0.2162 (-0.559)	-0.0802 (-0.337)	0.0313 (0.130)	0.2199 (0.404)
R^2	0.0986	0.1645	0.3602	0.3810	0.3789	0.3428	0.3931
Adjusted R^2	0.0557	0.0923	0.2688	0.2832	0.2902	0.2477	0.2146
N	89	89	89	89	89	88	45

*: Significant at 10% Level **: Significant at 5% Level ***: Significant at 1% Level

Table 7: Growth Rates Predicted by OLS

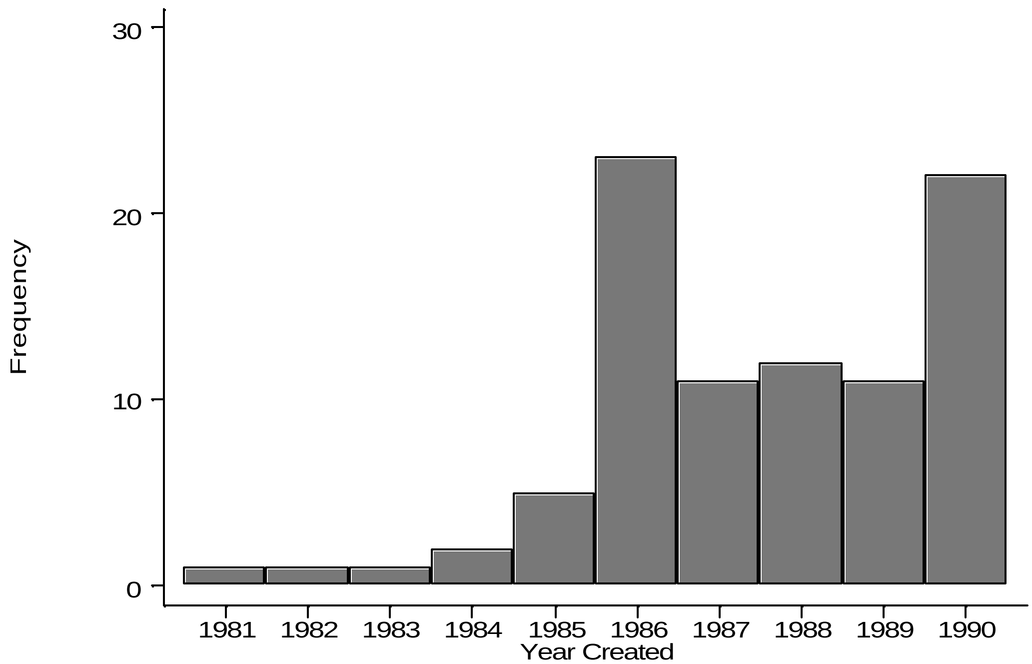
TIF Classification	X^2_{TIF}=Median X^1_{DIF}=Median Predicted Growth Difference	X^2_{TIF}=Median X^1_{DIF}=0 Predicted Growth Difference
CBD TIF	0.0173	-0.0031
Commercial TIF	0.2059	0.1855
Mixed-Use TIF	0.1283	0.1080
Industrial TIF	0.1923	0.1720

Table 8: Quantile Regression using 1990 Data
(t-stats in parentheses)

Variable	OLS	Quantile 0.25	Median	Quantile 0.75
CBD TIF	0.1873	0.0294	0.1084	0.2165
	(0.858)	(0.434)	(0.870)	(1.405)
Mall/Commercial TIF	0.3759	0.0002	0.1489	**0.4040**
	(1.507)	(0.003)	(1.056)	**(2.312)****
Mixed-Use TIF	0.2984	-0.1019	0.0277	0.2684
	(1.416)	(-1.546)	(0.231)	(1.702)*
Industrial TIF	0.3624	-0.0500	0.1664	**0.6570**
	(1.515)	(-0.718)	(1.245)	**(3.979)*****
Distance to CBD	-0.0091	**-0.0064**	-0.0061	-0.0087
	(-1.179)	**(-3.195)*****	(-1.471)	(-1.653)
TIF Area (Acres)	**0.0009**	**0.0005**	**0.0004**	**0.0008**
	(2.505)**	**(5.325)*****	**(2.370)****	**(2.664)*****
Created Between 1988 and 1990	**0.2998**	**0.1474**	**0.1809**	**0.2645**
	(2.250)**	**(3.517)*****	**(2.424)****	**(2.941)*****
DIF: Population per Acre	**-0.0377**	**-0.0148**	-0.0159	**-0.0229**
	(-2.528)**	**(-3.486)*****	(1.885)*	**(-2.223)****
DIF: Percent White	**1.0543**	0.1021	0.2400	**0.8483**
	(2.832)***	(0.379)	(1.172)	**(2.825)*****
DIF: Median Age of Structures	0.0114	0.0056	0.0044	0.0113
	(1.203)	(1.863)*	(0.859)	(1.687)*
DIF: Vacancy Rate	-3.4751	-0.3824	-2.1330	-1.6319
	(-1.413)	(-0.645)	(-1.677)	(-1.005)
Constant	-0.0802	0.0247	0.0523	0.0432
	(-0.337)	(0.397)	(0.395)	(0.243)

*: Significant at 10% Level **: Significant at 5% Level ***: Significant at 1% Level

Figure 1: Year of TIF Creation



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