Tax Increment Financing and Spatial Spillovers in Oklahoma City: Estimating the Localized Marginal Effects of Proximity to TIF Districts

Jacob Dearmon, Ph.D.
Director, Center for Data Analytics
Associate Professor of Economics, Meinders School of Business
Oklahoma City University

Russell R. Evans, Ph.D.
Executive Director, Steven C. Agee Economic Research and Policy Institute
Assistant Professor of Economics, Meinders School of Business
Oklahoma City University

Mary N. Gade, Ph.D.
Associate Professor of Economics
Oklahoma State University

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Executive Summary

Tax Increment Finance has emerged as a prominent form of financing local economic development initiatives. The widespread use of TIF is not an indication of the universal acceptance of its virtues. Rather, TIF strategies receive mixed reviews in the literature. We contribute to the findings on TIF effectiveness by examining as a case study the effect of Oklahoma City's TIF 2 district on the growth rate of property parcels in and around the TIF district. Among the key takeaways from this report are the following.

- Evidence of the effectiveness of TIF programs is mixed with findings that TIF programs are associated with faster growth in property values countered by findings that cities that employ TIF programs grow more slowly than their counterparts that forego TIF strategies
- Persistent questions remain unresolved; specifically, what is the impact of TIF programs on property valuations both within and adjacent to TIF districts
- A focus on property values is particularly relevant as increased property valuations may be a reflection of the value of the increases amenity packaged financed through the TIF program and capitalized into individual property valuations
- The TIF impact question is fundamentally a spatial question – how does the presence of a TIF district effect the geographic distribution of property values and patterns of economic growth
- We employ a Gaussian Process Regression (GPR) approach to estimate the functional form of the parcel valuation growth rates across space controlling for parcel location, initial assessed value, parcel size, and distance to the TIF 2 district
- We examine 4,236 individual parcels within 20,000 feet (approximately 3.8 miles) of TIF 2; an initial linear regression suggests positive spillovers that decay over space

- GPR estimates reinforce these findings (see figure 3)
    - As expected a priori, nearly all of the parcels located with the TIF 2 district benefit from the development investment financed through the TIF program
    - Parcels outside but proximate to the TIF 2 district enjoy positive spillover effects on property value growth rates; parcels nearest the TIF 2 district disproportionately benefit from proximity to the district, with the localized marginal effect decaying over a distance of about 2.65 miles (see figure 4)
- The parcel-specific approach reveals a handful of properties that are proximate to the TIF 2 district but experience negative spillover effects on growth rates
    - This handful of properties tend to be characterized by intermediate size, low value commercial and industrial parcels; this finding both reinforces the success of the TIF in targeting redevelopment funds inside the district where public infrastructure investment compliments private development projects and highlights the importance of carefully drawing TIF district boundaries to minimize the number of potential redevelopment parcels that get left behind
- To give some idea of the magnitude of the impact we use the GPR parcel-specific estimates to create a hypothetical counterfactual in which all parcels are moved to the outer limit of our analysis (20,000 feet or 3.8 miles) but otherwise retain their parcel-specific characteristics; under this counterfactual we find an average parcel growth rate change of -4.75%, or a 22% reduction from the mean growth rate of the sample.

I. Background

Tax increment finance (TIF) has become a critical component of local economic development policy over the past six decades. TIF moves the incremental portion of the local property tax or and/or sales tax base from the general tax rolls and reallocates the revenue stream to the targeted district to subsidize development. The goals of TIF are to create economic incentives that encourage local growth within the targeted district, spill over to surrounding areas, stimulate new business, create jobs, reform blighted areas, and stabilize the region. The growth triggered by the TIF will create an incremental increase in total tax revenue generated within the district, without increasing tax rates. The incremental tax revenue is then used to pay for the improvements made within the TIF, which are often financed upfront with a bond issue.

The existing economic literature on the empirical effects of TIF districts as a tool of economic development policy began in earnest in the 1990's. Much of that research focused on the jurisdiction's reasons for using TIF and its resulting effects, primarily the impact on property values. Anderson (1990) focused on the relationship between TIF adoption among cities and municipalities in Michigan and concluded that faster growing regions were more likely to adopt a TIF, but stopped short of suggesting that TIF adoption was the cause of faster growth.

There is a steady stream of empirical research that follows the initial work and broadens the issues to examine the effects of TIF on employment growth, sales, production, and tax revenues. However, the basic questions continue to be relevant, including: estimation of the difference between growth realized under the TIF regime and what would have been realized in the absence of the TIF regime, spillover growth effects (positive and negative) on surrounding areas, and budget implications to overlapping layers of local government.

Much of the empirical work on the effect of TIF on property value outcomes found positive results in the TIF districts. Man and Rosentraub (1998) examined the experience of Indiana and concluded that the TIF program was associated with positive growth in median housing values in municipalities from 1980-1990. Smith (2006) found positive effects of TIF designation and residential property value growth in Chicago from 1992-2000. In a follow-up study, Smith (2009) found positive associations between TIF districts and commercial property values in Chicago over the same time period. Weber, Bhatta, and Merriman (2003) examined the effect of TIF on industrial property values in Chicago over a similar time period and found positive but insignificant effects. Hall and Bartels (2014) found that better managed TIF districts in Dallas-Fort Worth had a more positive effect. Carroll (2008) looked at the TIF in Milwaukee between 1980 and 1999 and found an increase in business property values with TIF adoption.

However, there are some studies that are consistently critical of the TIF program in their particular area of focus. Dye and Merriman (2000), using data from Chicago from 1980-1995, found that cities using TIF grew more slowly than those that did not use TIF. Dye and Merriman (2003) supported this result. Dardia (1998) suggested that growth in property values within TIF districts in California from 1983-1996 does not imply the policy was a success.

Others studies have been more neutral in their findings. Merriman, Skidmore, and Kashian (2011) used data from Wisconsin and found evidence that the use of TIF does increase commercial property values, but not residential or manufacturing. Byrne (2006) also found mixed results, with the specific location of industrial property in downtown Chicago playing a role in the outcome. Even though Weber, Bhatta, and Merriman (2003) found insignificant positive results on property values inside mixed use TIF districts, they found negative effects with respect to commercial or manufacturing districts. They also found mixed results on single family homes in Weber, Bhatta, and Merriman (2007).

Common to nearly all of these research efforts is an attempt to isolate the growth effects of TIF adoption. An examination of the economic influence of TIF adoption is fundamentally a spatial question – how does the presence of the TIF effect the geographic distribution of property values and patterns of economic growth. While the evidence is somewhat mixed, it is clear that the use of more disaggregated data is important in order to identify the effectiveness of using TIF and to quantify the impact it might have on the district and its surrounding region.

Similar to previous research, we are interested in the spillover effects of a TIF regime. In contrast to previous research, we recognize the limitation of a linear spatial specification. Instead, we adopt a Gaussian-process regression specification that instead of estimating the parameter coefficients of linear explanatory variables (traditional linear regression) estimates the functional form that defines the relationship between a dependent variable and its functional arguments.

II. Spatial Econometrics and Gaussian Process Regression

This section provides a brief technical review of Gaussian Process Regression (GPR) and its spatial applications. It is a variant of kriging, a commonly used spatial mapping technique found in the oil and gas industry. Readers not inclined to delve into technical details can skip this section without loss.

Theory

Let y_i denote the response variable at location i which depends on a vector of explanatory variables $x_i = (x_1, .., x_k)$. If $x_i \in \mathcal{X}$ and $\mathcal{X} \subseteq \mathbb{R}^k$, the relationship between y_i and $x_i = (x_1, .., x_k)$ can be modeled as a stochastic process, $y(x_i)$. In modeling this stochastic process, a Gaussian Process prior is usually assumed. This implies that any finite subset of random variables, $y(x_i)$, is multinormally distributed with a mean ($\mu(x)$) and covariance function ($K(x, x')$) such that

$$y(x) \sim GP(m(x), K(x, x'))$$

A typical modeling approach is to set $m(x) = 0$ which forces the covariance function to do all the work. However, in our current project, long range correlations appear to be important. Consequently, we specify both constant and linear mean functions.

While many covariance functions can be employed, one of the most popular is the anisotropic squared exponential kernel:

$$K_\omega(x, x') = v \exp\left(\frac{1}{-2}\sum_{j=1}^{k}\frac{\left(x_j - x_j'\right)^2}{\tau_j^2}\right)$$

where $\omega = [\mathrm{v}, \tau_1, .., \tau_k]$ are non-negative hyperparameters that consist of (v) and a length scale per dimension (τ_j). If the points x and x' are the same, the covariance function collapses to v (the variance). As x and x' begin to deviate, however, the distance between them gets larger reducing the correlation to something less than v by making the exponential term smaller. Within the exponential term, the length scale's role is to weight each dimension of x differently providing a weighted squared distance measure. The presence of the negative in the exponential function implies that as the squared distance grows larger, the exponential term gets closer to zero.

For standardized values of x where x has been demeaned and scaled by the standard deviation, the length scales serve to determine the relevance of individual explanatory variables. Higher length scales indicate that further distances must be traveled along that scaled dimension to elicit a similar response in y. Thus, smaller length scales for standardized variables suggest relatively more important explanatory variables. This process is called Automatic Relevance Determination.

Gaussian Process Regression

Given n observed values with $\widetilde{\mathrm{X}} = (\tilde{\mathrm{x}}_i: i = 1 \ldots n)$ and $\tilde{\mathrm{y}} = (\tilde{\mathrm{y}}_i: i = 1 \ldots n)$, we assume that this stochastic process has been corrupted by measurement noise, namely

$$\tilde{y}\left(\widetilde{X}\right) = y\left(\widetilde{X}\right) + \epsilon, \qquad \epsilon \sim N(0, \sigma^2)$$

where $\tilde{y}(\widetilde{X})$ is multinormally distributed as $\tilde{y}\left(\widetilde{X}\right) \sim N\left(0_n, K_\omega\left(\widetilde{X}, \widetilde{X}'\right) + \sigma^2 I\right)$. Given a new point, x, we can calculate the predictive distribution by applying the definition of a multivariate normal:

$$\begin{pmatrix} y \\ \tilde{y} \end{pmatrix} \sim \left(\begin{bmatrix} 0 \\ 0_n \end{bmatrix}, \begin{bmatrix} K_\omega(x,x) & K_\omega(x,\tilde{X}) \\ K_\omega(\tilde{X},x) & K_\omega(\tilde{X},\tilde{X}) + \sigma^2 I \end{bmatrix} \right)$$

where the predictive conditional distribution for the new point y is given by:

$$y|\tilde{X},\tilde{y},x \sim N(E(y|\tilde{X},\tilde{y},x), Var(y|\tilde{X},\tilde{y},x))$$

with

$$E(y|\tilde{X},\tilde{y},x) = K_\omega(x,\tilde{X})\left(K_\omega(\tilde{X},\tilde{X}') + \sigma^2 I\right)^{-1}\tilde{y}$$

and

$$Var(y|\tilde{X},\tilde{y},x) = K_\omega(x,\tilde{X}) - K_\omega(x,\tilde{X})\left(K_\omega(\tilde{X},\tilde{X}') + \sigma^2 I\right)^{-1}K_\omega(\tilde{X},x)$$

Hyperparameter Optimization

The full set of hyperparameters, $\theta = [\omega, \sigma^2]$, can be calculated by maximizing the marginal likelihood ($\hat{\theta}$) or by obtaining the Maximum-a-Posteriori (MAP) estimate, $\tilde{\theta}$, within a Bayesian framework,

$$p(\theta|\tilde{y},\tilde{X}) \propto p(\tilde{y}|\tilde{X},\theta)p(\theta)$$

where $p(\theta)$ is the prior on θ. For this project, we use the Bayesian approach with standard priors as implemented in Vanhatalo et. al.'s (2013) GPStuff version 4.6.

Localized Marginal Effect

Let $x_{k,i}$ denote the k^{th} explanatory variable associated with observation i. One may write the change in x_k at some location i as $\Delta x_{k,i} = x_{k,i,2} - x_{k,i,1}$. Further, let x_2^* be x where the k,i element has been replaced by $x_{k,i,2}$; similarly let x_1^* be x where the k,i^{th} element has been replaced by $x_{k,i,1}$. The localized marginal effect, or the effect of a change in variable *k* at location *i* upon growth, while holding all other variables constant at their localized value, is given by

$$ME_{x_{k,i}} \approx \frac{\left(E(y|\tilde{X},\tilde{y},x_2^*) - E(y|\tilde{X},\tilde{y},x_1^*)\right)}{\Delta x_{k,i}}$$

In less technical terms, our goal is to understand how a change in an explanatory variable, such as distance to TIF, influences assessed value growth while holding all other attributes, such as square feet or location, constant. The use of the word "localized" implies that the marginal effect of a given variable can look very different across parcels.

III. Empirical Analysis of Oklahoma City's TIF 2

The dataset used in the following empirical analysis is based on County Assessor files provided to City Planning for the City of Oklahoma City.[1] This dataset contains parcel level data for two distinct years[2]; for each parcel, many different attributes have been included. Of particular interest for this project are the Assessed Value, latitude, longitude, and square feet.

To examine the existence of and spatial decay of TIF 2's spillover effect, we first begin by defining a model whose level of observation occurs at the individual parcel level and whose dependent variable is given as growth in Assessed Value (AV),

$$g_{AV} = \frac{AV_{2015}}{AV_{2011}} - 1$$

where the subscripts denote the year.[3] In setting up our specification, we anticipate that growth might be related in some unknown way to latitude (lat), longitude (lon), initial assessed value (AV_{2011}), square feet in 2015 ($SQFT_{2015}$) and distance (D) to the nearest TIF 2 parcel. In other words, we are controlling for location, the initial value of the parcel, the size of the property and its proximity to TIF 2. We can write this relationship as:

$$g_{AV} = f(lat, lon, AV_{2011}, SF_{2015}, D)$$

Our objective is to first estimate this relationship.

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[1] A special thanks to Phillip Walters of City Planning for assistance in assembling our dataset.
[2] In nearly all sampled cases, parcel values were found to be for 2011 to 2015; a single sampled parcel had values that corresponded to years 2010 and 2014.
[3] See Footnote 2.

$$g_{AV} = \hat{f}(\text{lat}, \text{lon}, AV_{2010}, SF_{2014}, D)$$

with $\hat{f}(\cdot)$ being our estimate of $f(\cdot)$. We are particularly interested in how distance to TIF 2 influences the growth rate of the parcel. Put another way, how would this parcel's growth rate be affected if we took TIF 2 and moved it further away while holding all other parcel attributes constant? If the growth rate decreases as distance increases, we would observe a negative localized marginal effect (that is, $ME_{x_{D,i}} < 0$), which is suggestive of a positive spillover effect. In this case, parcels that are closer (with smaller distances) would have higher growth rates, everything else held constant.

We only consider parcels that are either in TIF 2 or are outside of a TIF. We narrow our focus to a sub-sample of observations where the parcel centroid is within a Euclidean distance of 20,000 feet from the nearest TIF 2 parcel, whose assessed value is greater than or equal to 20,000, and whose size is at least 500 square feet. By applying these criteria we are able to reduce the parcel population to a more manageable sample size of 4,236 parcels. Summary statistics for these 4,236 observations are provided below:

	g_{AV}	AV_{2011}	SF_{2015}	LON	LAT	D
Mean	0.214	79456	17556	2107775	179534	11275
Std. Dev.	2.6	249092	48944	8146	11797	6165
Min	-0.9	20001	598	2088690	149070	0
Max	143.6	6136427	819976	2132955	195681	19995

Table 1 Summary Statistics for Dataset (n=4236)

Before turning to GPR, we begin with a simple linear regression model on a much larger dataset consisting of 115,566 observations using the following specification:

$$g_{SA} = b_0 + b_1 \cdot AV_{2011} + b_2 \cdot SF_{2015} + b_3 \cdot LON + b_4 \cdot LAT + b_5 \cdot D + b_6 \cdot D^2 + \epsilon$$

with $\epsilon \sim N(0, \sigma^2 I)$. Here we introduce a quadratic term for D which suggests that the marginal effect of a change in Distance may depend on the proximity to TIF 2.

A 100 ft increase from TIF 2 at 1 ft from the TIF 2 boundary may have a larger impact than a 100 ft increase from a parcel located 5 miles away. The implied marginal effect for distance is given by :

$$\frac{\partial g_{SA}}{\partial D} = b_5 + 2 \cdot b_6 \cdot D$$

Estimation results for this full sample, including individual coefficient estimates, are provided below in Table 2.

Variable	Coefficient	t-statistic	P-value
Intercept	1.11E+01	1.62E+00	0.11
AV2011	-5.00E-06	-4.27E+00	0.00
SF2015	3.10E-05	4.70E+00	0.00
LON	-5.00E-06	-1.63E+00	0.10
LAT	2.00E-06	6.96E-01	0.49
D	-4.50E-05	-3.61E+00	0.00
D^2	8.05E-10	4.26E+00	0.00

Table 2 OLS Regression Results (Full Sample)

While many of these coefficient estimates are statistically significant, the coefficient estimates for D and its quadratic term, D^2, are of particular interest. Here we can see that both the coefficients associated with the linear and quadratic terms are significant. Consequently, this suggests a nonlinear marginal effect of Distance upon growth where the effect depends on the current distance away from TIF 2:

$$\frac{\partial \text{growth}}{\partial D} = (-4.50E^{-05}) + 2 * (8.05E^{-10}) * D$$

The numerical values come from the appropriate coefficient estimates. As shown in Figure 1 below, at low values for D the first term dominates; here the marginal effect is negative suggesting increasing distance from TIF 2 has a negative effect on growth; this may also be interpreted as a positive spillover effect. However, as distance increases, the second term becomes dominant turning the marginal effect positive suggesting that this spillover effect decays over distance.

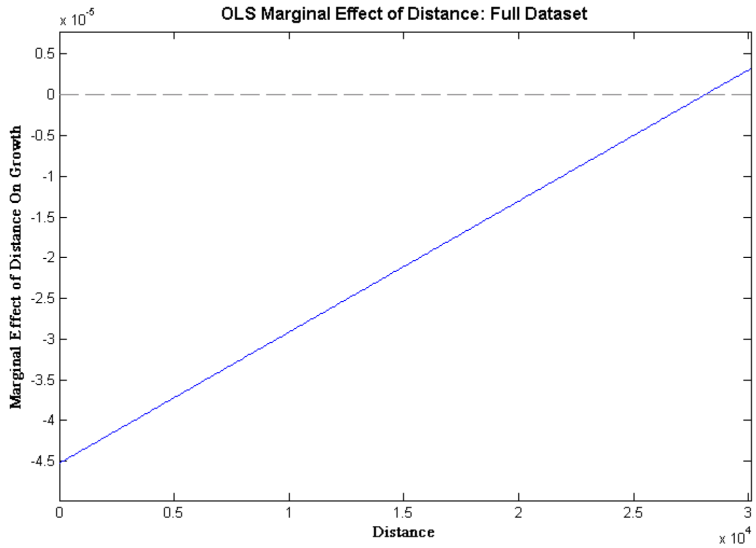

Figure 1 Marginal Effect of Distance (Full Sample Regression Results)

Re-doing the exercise on the restricted sub-sample consisting of 4,236 observations, we notice qualitatively similar results. Statistical significance remains relatively unchanged for this smaller sample.

Variable	Coefficient	t-statistic	P-value
Intercept	-18.847973	-1.70	0.09
AV_{2011}	-3.24E-06	-12.44	0
SF_{2015}	2.01E-05	15.11	0
LON	8.62E-06	1.65	0.1
LAT	6.95E-06	1.96	0.05
D	-0.0001023	-4.53	0.00
D^2	4.22E-09	3.90	0.00

Table 3 OLS Regression Results (Restricted Sample)

The marginal effect of distance follows a qualitatively similar pattern as that from the full sample (see Figure 2):

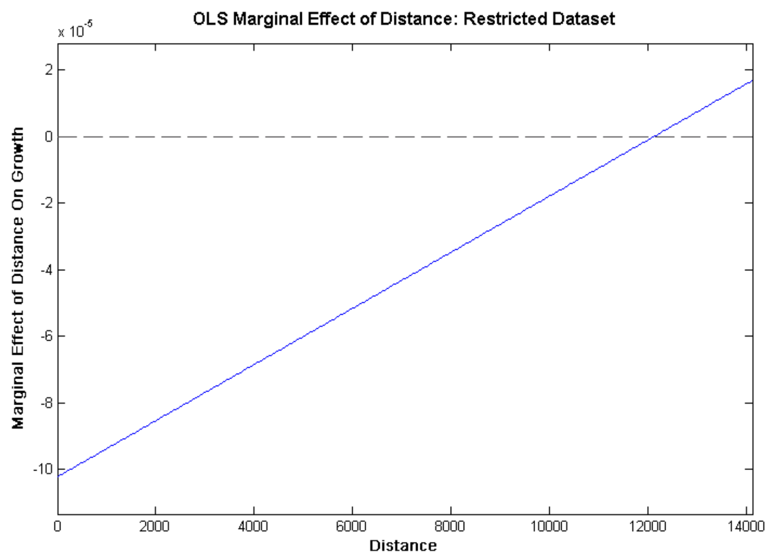

Figure 2 Marginal Effect of Distance (Restricted Sample)

According to the least squares estimates, the marginal effect of proximity to the TIF becomes positive at a distance from the TIF of just over 12,000. However, linear regression models are inflexible and this limits their predictive power, especially in contexts such as this, where rapidly changing values that vary in a highly nonlinear manner are to be expected. For example, we may observe high property values until we move "across the tracks" where property values drop precipitously before rising again after a certain distance. This nonlinearity, unless specifically *known* a priori and specifically incorporated into the linear specification, would be missed by a standard linear regression model.

In an effort to identify a more flexible nonlinear relationship, we now turn to GPR with its superior performance on both in-sample and out-of-sample data. GPR can capture a much more nuanced view of these rapidly changing patterns and can also provide individual marginal effects for each location. [4]

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[4] From a more technical perspective, a linear regression model selects either a line or a plane (think a flat sheet of paper) that best fits the data; this process may be inadequate in situations where the underlying data generating process is complex. GPR, however, is more agnostic regarding functional form, capturing more complex surfaces (e.g., the surface could be bent, bumpy or flat).

IV. Results

We assess the impact of an approximate two foot change (centered at its current location) in the distance from the parcel's location to TIF 2. For each of the 4,236 parcels, we plot a single orange dot whose location on the plot is determined by the distance from the TIF (the x-axis) and the estimated localized marginal effect of increasing distance on the parcel growth rate (the y-axis). This scatter plot is shown in Figure 3 below. The orange dots below the dashed grey zero line represent parcels with negative marginal effects indicating the marginal effect of moving away from the TIF has a negative impact on growth rates.

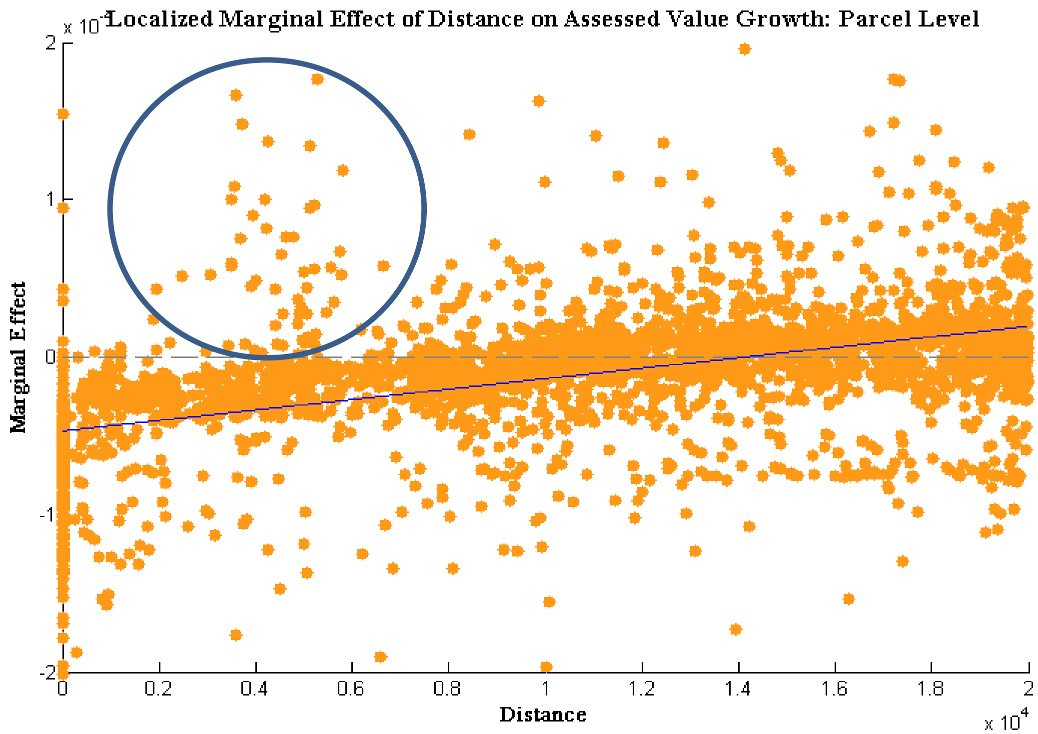

Figure 3 Localized Marginal Effects

The orange dots on the y-axis (distance from TIF is zero) represent parcels in the TIF district. As expected, nearly all of these parcels exhibit negative marginal effects suggesting that the direct impact of the TIF is to increase the growth rates of parcels in the district above the rate that those parcel attributes would otherwise predict. More importantly, those positive returns to growth spillover onto the parcels outside but proximate to the TIF. These positive returns to growth are seen as the balance of orange dots moving down the x-axis (greater distance from the TIF) initially lay below the grey-dashed zero line. However, as the distance from the TIF increases, the balance of orange dots shifts from below to above the zero line.

In other words, we find that spatially proximate parcels do enjoy positive spillovers and benefit from being closer to TIF 2. Further, we find that these localized marginal effects exhibit an upward trend suggesting that spillover effects slowly die out. A simple linear regression on these results (represented by the solid blue line in the graph) suggests that the average localized marginal effect for this sample changes sign at a distance of approximately 14,000 feet away (2.65 miles) from the nearest TIF 2 parcel. To give some idea of the magnitude of the impact we use the GPR parcel-specific estimates to create a hypothetical counterfactual in which all parcels are moved to the outer limit of our analysis (20,000 feet or 3.8 miles) but otherwise retain their parcel-specific characteristics. Under this counterfactual we observe an average parcel change in growth rate of -4.75%, or a 22% reduction from the mean growth rate of the sample.

To better appreciate the rate of decay in the positive spillover effects as parcels are moved further from the TIF boundary, we graph the distribution of marginal effects for various distance ranges estimated using a kernel density plot - effectively a smoothed histogram. Here the shaded area is the section of the distribution where the marginal effect is negative. The larger the shaded area, the larger the fraction of negative marginal effects, or put another way, the greater the number of parcels with positive spillovers. For parcels immediately proximate to the TIF (distance of less than 2,500 feet) 97% of the parcels experience positive spillover effects on property growth rates (see the first panel in figure 4). In contrast, only 37% of the parcels greater than 12,500 feet from the TIF enjoy positive spillover effects on assessed value growth rates (see the last panel in figure 4). The positive spillover effects appear decay over space and are concentrated within 2.5 miles of the TIF district.

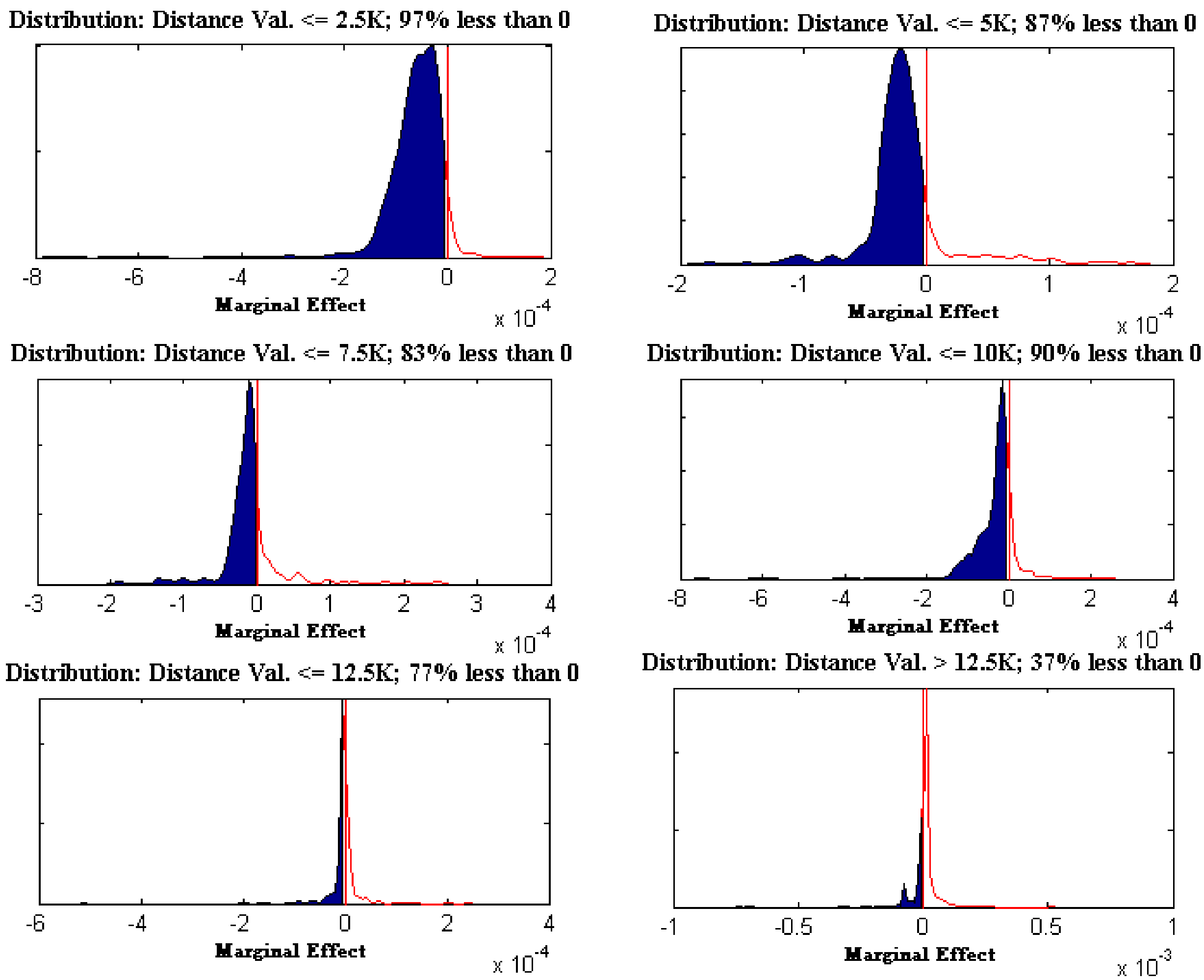

Figure 4 Distribution of Spillover Benefits by Distance from TIF

The dot scatterplot above (Figure 3) not only shows a positive growth rate spillover, but also substantial variation in the localized marginal effects with both localized positive and negative marginal effects existing at all distances. Of particular interests are the relatively few parcels contained in the blue circle in Figure 3. These parcels are proximate to the TIF, yet have a positive marginal effect which suggests that moving these properties closer TIF 2 may actually diminish growth rates.

To investigate these proximate positive marginal effects further, we segregate the parcels from figure 3 first into six subgroups by assessed values (Figure 5) and then by square feet (Figure 6).

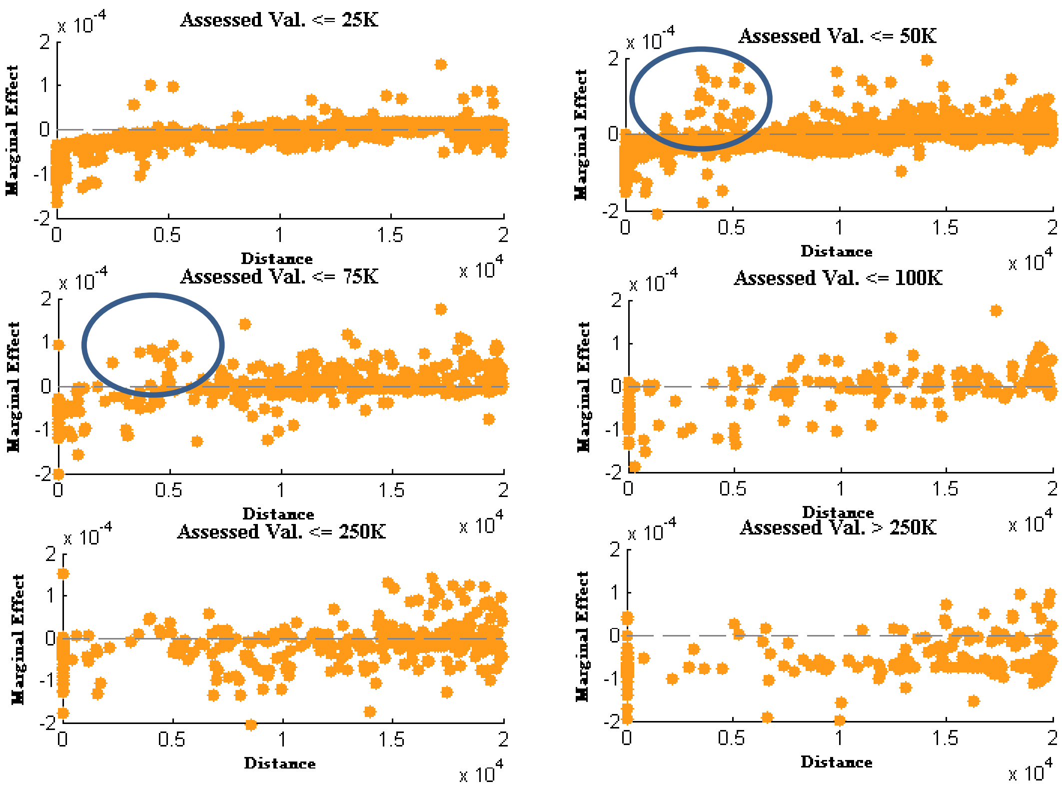

Figure 5 Localized Marginal Effects Broken Down by Assessed Value.

The decomposition into assessed value groupings (above) reveals that the positive proximate parcels generally have assessed values of between \$25,000 and \$50,000 and to a lesser extent between \$50,000 and \$75,000[5].

The decomposition into size groupings (below) reveals that the positive proximate parcels are generally of an intermediate size between 10,000 ft^2 and 40,000 ft^2. Combined, figures 4 and 5 suggest that the positive proximate parcels generally have relatively low valuations per square foot suggesting that many of these properties may be in a state of disrepair and moving towards blight.

[5] The assessed value ranges correspond to estimated market values between \$227,000 and \$682,000.

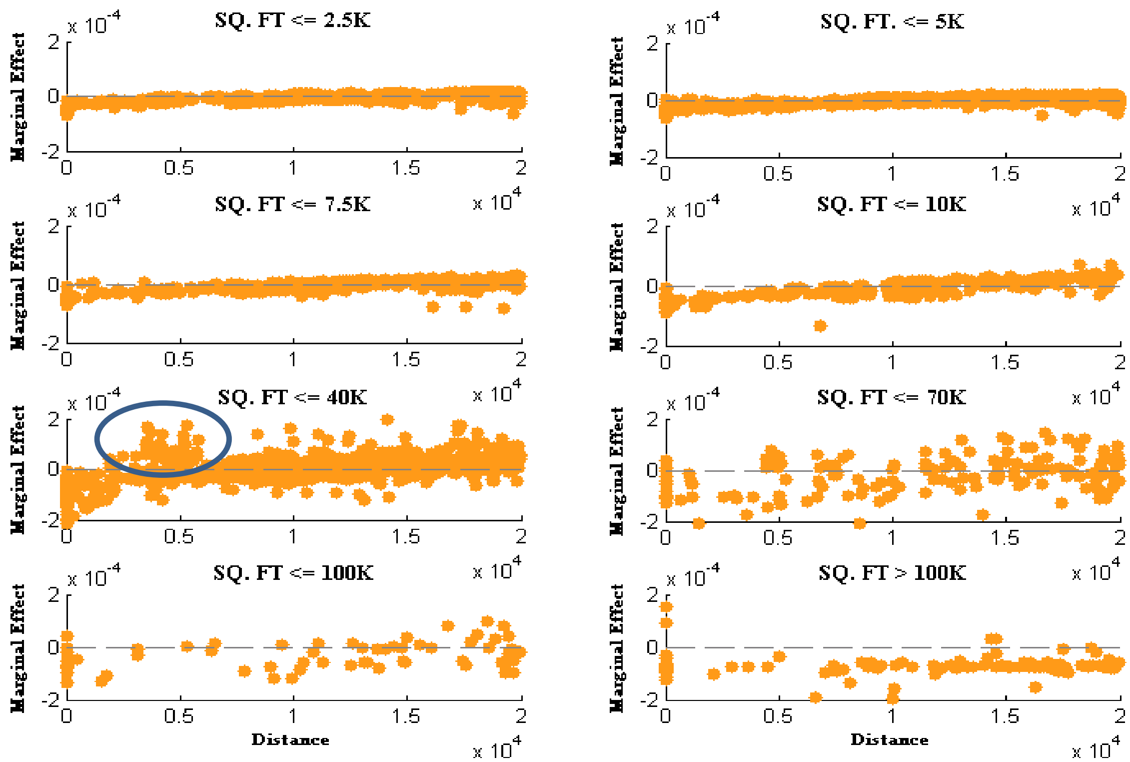

Figure 6 Localized Marginal Effects Broken Down by Square Feet.

Being proximate to but not inside the TIF may leave these parcels without the investment funds necessary for improvements as they require a targeted economic development strategy or a public-private partnership to be economically viable. The development challenges facing this small subset of parcels are an indicator that the TIF is functioning as designed, drawing private development funds to the district as a complement to public fund expenditures. However, the findings suggest that much care should be taken when drawing TIF boundaries, recognizing that a small but potentially important subset of parcels could be relegated to the outside of the development zone and left without access to the public support that similar parcels inside the TIF are afforded.

V. Conclusion

We examine the attributes and growth rates in assessed property values for 4,236 parcels in and around Oklahoma City's TIF 2 district for evidence that the TIF program imposes spillover growth benefits on surrounding parcels. Employing a GPR approach to model the spatial distribution of parcel growth, we find strong evidence that the TIF 2 district exerts a significant influence on parcel growth rates concentrated within 2.65 miles from the TIF. Property value appreciation is likely a reflection of the development of a local amenity package via TIF financing that is then capitalized into property values.

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