The Effectiveness of Tax Increment Financing (TIFs) in Ameliorating Blight and Promoting Economic Development for The City of Chicago

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1 Introduction

What are TIFs?: Tax Increment Financing is a special funding tool that is directed towards areas of diminished economic value and quality of life. Municipalities perform studies to determine if an area is eligble for a TIF if it is considered blighted or in danger of becoming blighted. If a TIF is determined as necessary a development project is created and a TIF budget is allocated to the region. TIFs have been a practice in Chicago since the 1970's. Usually, those who live outside of the TIF region pay more in Excessive Vacancies taxes that support the TIF budget. Much of the budget goes towards plan development, surveys, engineering, acquiring land, environmental clean up, demolition, infrastucture improvemnets, job training, building construction, consulting fees, etc. When a TIF ends, remaining money is then given back to the county.

Controversy around TIFs: There are several reasons why many consider TIFs to be controversial. Many believe that the term "blighted" is applied too loosely ,such as in the case of extending TIF funding to wealthier areas. TIFs also are subject to scrutiny in light of the fact that their funds are kept separate from other municipal revenue. Many also criticize TIFs for allowing corporate eligibility.

Research Question: "Do TIFs in Chicago ameliorate blight and promote economic development?"

2 Data Preparation

In this project I used five different data sets. One that held an index for all Chicago community areas, one that held extensive information on TIF spending in Chicago from the 90's to the 2020's, one that held information on every vacant building in Chicago communities from 2008 to 2018, one that held information on completed tree trimming service requests in Chicago communities from 2011 to 2018, and one that held information on new business licenses in Chicago communities from 2003 to 2023. Sources for these data sets can be found in the project file.

The data cleaning for these data sets was extensive and required a lot of meticulous work, so I will not into detail here about the process, that can be found in my project file. However, I will state that I created three data frames where the rows were organized as community area by year pairs. Each pair was associated with the accumulated TIF spending up until that year in that respective community. Each of the pairs was also associated with either the number of vacant buildings, the number of completed tree trimming service requests, or the number of business licenses issued that year in its respective community, depending on the data frame.

3 Model Building

I designed three key questions that if answered concretely, would help me answer some aspects of my research question.

- Does TIF spending have an overall effect on the occurrence of vacant buildings?
- Does TIF spending increase the number of completed tree trimming services and new business licenses issued?

To answer these questions I create several negative binomial mixed effects models where I allow blight indicators, and economic development indicators to be my response and log accumulated TIF spending over years as my dependent variable. This mixed effect model acts as an inference model because it attempts to quantify the relationship between indicators and accumulated TIF spending. For example:

$$\log(\mathbb{E}[I_{cy}|b_{0c}, b_{TIF,c}]) = \beta_0 + b_0c + (\beta_{TIF} + b_{TIF,c})\log(1 + x_{cy}) \tag{1}$$

c is the index for which community we are working in (c for community). y indexes which ε_{cy} represents the residualsobservation (year) in our data set we are looking at in our respective community (y for year). I denotes which blight indicator we are looking at. β_0 represents the intercept, and β_{TIF} represents the slope. These are the fixed effects across all communities. b_{0c} is the random intercept and $b_{TIF,c}$ represents the random slope. These are the random effects for each individual community. x_{cy} represents the rolling TIF balance for the community.

In addition to this, I do not use the traditional linear mixed effects model with the "lme4" package, instead I use the "glmmTMB" package. This is largely because each of my response variables, **vacant buildings, completed tree trimming services,** and **new business licenses** come as a count variable. For this reason a generalized mixed effects linear model makes more sense. Furthermore, when I was creating my model, I ran into issues with overdispersion. To treat this, I used a negative binomial distribution to model my data so that the overdispersion was incorporated into the model. This gave my model more explanatory power. I will also mention that the **vacant buildings** model is only valid between the years 2008 and 2018, the **completed tree trimming services** model is only valid between the years 2011 and 2018, and the **new business licenses** model is only valid between the years 2003 and 2023.

4 Interpretation of Results

For each of the indicator variables I created three separate models:

(a) **A Null Model**

(b) **A Fixed Slope Model**

(c) **A Random Slope Model**

The null model was created as a way to test partial significance for the fixed slope model. The fixed slope model is also used to test partial significance for the random slope model. To actually perform the hypothesis tests, I used an ANOVA table with a likelihood ratio test to determine the χ^2 test statistic and p-value for each partial significance test. The next subsections will be dedicated to displaying the results of these tests for each indicator variable.

4.1 Vacant Buildings Hypothesis Testing

Null Model:

$$\log(\mathbb{E}[VacantBuildings_{cy}|b_{0c}]) = \beta_0 + b_{0c} \tag{2}$$

Fixed Slope Model:

$$\log(\mathbb{E}[VacantBuildings_{cy}|b_{0c}]) = \beta_0 + b_{0c} + \beta_{TIF}\log(1 + x_{cy}) \tag{3}$$

Random Slope Model:

$$\log(\mathbb{E}[VacantBuildings_{cy}|b_{0c}, b_{TIF,c}]) = \beta_0 + b_0c + (\beta_{TIF} + b_{TIF,c})\log(1 + x_{cy}) \tag{4}$$

Null Model v.s. Fixed Slope Model

Null Hypothesis: $H_0 : \beta_{TIF} = 0$
Alternative Hypothesis; $H_a : \beta_{TIF} \neq 0$
$\chi^2 = 5.0158$, $p = 0.02512$, degrees of freedom $= 1$, $\alpha = 0.05$
Interpretation: We reject H_0 and conclude that adding log accumulated TIF spending to a negative binomial mixed effects model associating the log expected number of vacant buildings in Chicago communities with just random intercepts and the mean is statistically significant.

Fixed Slope Model v.s. Random Slope Model
Null Hypothesis: $H_0 : \text{Var}(b_{TIF,c}) = 0$
Alternative Hypothesis: $H_a : \text{Var}(b_{TIF,c}) > 0$
$\chi^2 = 2.3973$, $p = 0.3016$, degrees of freedom = 2, $\alpha = 0.05$
Interpretation: We fail to reject H_0 and conclude that adding log accumulated TIF spending with random slope to a negative binomial distribution model associating the log expected number of vacant buildings in Chicago communities with just random intercepts and the mean is not statistically significant.

4.2 Tree Trimming Service Request Completion Hypothesis Testing

Null Model:

$$\log(\mathbb{E}[NumberTreesTrimmed_{cy}|b_{0c}]) = \beta_0 + b_{0c} \tag{5}$$

Fixed Slope Model:

$$\log(\mathbb{E}[NumberTreesTrimmed_{cy}|b_{0c}]) = \beta_0 + b_{0c} + \beta_{TIF}\log(1 + x_{cy}) \tag{6}$$

Random Slope Model:

$$\log(\mathbb{E}[NumberTreesTrimmed_{cy}|b_{0c}, b_{TIF,c}]) = \beta_0 + b_0c + (\beta_{TIF} + b_{TIF,c})\log(1 + x_{cy}) \tag{7}$$

Null Model v.s. Fixed Slope Model
Null Hypothesis: $H_0 : \beta_{TIF} = 0$
Alternative Hypothesis; $H_a : \beta_{TIF} \neq 0$
$\chi^2 = 4.9813$, $p = 0.02562$, degrees of freedom = 1, $\alpha = 0.05$
Interpretation: We reject H_0 and conclude that adding log accumulated TIF spending to a negative binomial mixed effects model associating the log expected number of completed tree trimming service requests in Chicago communities with just random intercepts and the mean is statistically significant.

Fixed Slope Model v.s. Random Slope Model
Null Hypothesis: $H_0 : \text{Var}(b_{TIF,c}) = 0$
Alternative Hypothesis: $H_a : \text{Var}(b_{TIF,c}) > 0$
$\chi^2 = 58.15$, $p = 2.359 \times 10^{-13}$, degrees of freedom = 2, $\alpha = 0.001$
Interpretation: We reject H_0 and conclude that adding random slopes for log accumulated TIF spending to a negative binomial mixed effects model associating the log expected number of completed tree trimming service requests in Chicago communities with just fixed slope and random intercepts is statistically significant.

4.3 Business Licenses Issued Hypothesis Testing

Null Model:

$$\log(\mathbb{E}[LicensesIssued_{cy}|b_{0c}]) = \beta_0 + b_{0c} \tag{8}$$

Fixed Slope Model:

$$\log(\mathbb{E}[LicensesIssued_{cy}|b_{0c}]) = \beta_0 + b_{0c} + \beta_{TIF}\log(1 + x_{cy}) \tag{9}$$

Random Slope Model:

$$\log(\mathbb{E}[LicensesIssued_{cy}|b_{0c}, b_{TIF,c}]) = \beta_0 + b_0c + (\beta_{TIF} + b_{TIF,c})\log(1 + x_{cy}) \tag{10}$$

Null Model v.s. Fixed Slope Model
Null Hypothesis: $H_0 : \beta_{TIF} = 0$
Alternative Hypothesis; $H_a : \beta_{TIF} \neq 0$
$\chi^2 = 323.04$, $p < 2.2 \times 10^{-16}$, degrees of freedom = 1, $\alpha = 0.001$
Interpretation: We reject H_0 and conclude that adding log accumulated TIF spending to a negative binomial

mixed effects model associating the log expected number of business licenses issued in Chicago communities with just random intercepts and the mean is statistically significant.

Fixed Slope Model v.s. Random Slope Model
Null Hypothesis: $H_0 : \mathrm{Var}(b_{TIF,c}) = 0$
Alternative Hypothesis: $H_a : \mathrm{Var}(b_{TIF,c}) > 0$
$\chi^2 = 22.987$, $p < 1.02 \times 10^{-5}$, degrees of freedom = 2, $\alpha = 0.001$
Interpretation: We reject H_0 and conclude that adding random slopes for log accumulated TIF spending to a negative binomial mixed effects model associating the log expected number of business licenses issued in Chicago communities with just fixed slope and random intercepts is statistically significant.

5 Evaluation and Discussion

5.1 Discussion Points for Accumulated TIF Spending v.s. Vacant Buildings

Conclusion: We found that the random slope model was insignificant in associating the log expected number for vacant buildings in Chicago communities. However, we did find that the fixed slope model was statistically significant.

Here I lay out the full specification of the fixed effects for the fixed sloped model:

$$\log(\mathbb{E}[VacantBuildings_{cy}|b_{0c}]) = 3.01595 + b_{0c} + 0.03232 \log(1 + x_{cy}) \tag{11}$$

$$\mathbb{E}[VacantBuildings_{cy}|b_{0c}] = e^{3.01595+b_{0,c}}(1 + x_{cy})^{0.03232} \tag{12}$$

From our data we also know that

$$-4.483449 \leq b_{0,c} \leq 2.67039 \tag{13}$$

So I concluded that accumulated TIF spending between the years of 2008 and 2018 does have any statistically significant impact on the frequency of the expected value of vacant buildings in Chicago communities, with a fixed slope. On top of this we can see that an increase in $x_{c,y}$ (accumulated TIF spending) will only increase the expected number of vacant buildings. But, this will only slowly. Hence, from our model **we can conclude that an increase in accumulated TIF spending does not help ameliorate the number of vacant buildings in the communities of Chicago**. It is also true that not every community starts off with the same amount of vacant buildings when the spending is at 0.

5.2 Discussion Points for Accumulated TIF Spending v.s. Tree Trimming Service Request Completions

Conclusion: It was found via partial significance tests that both the fixed slope model and the random slope model were statistically significant. However, for the fixed slope model it was only significant if $\alpha = 0.05$; whereas the random slope model was far more significant than the fixed slope model, even with $\alpha = 0.001$. Hence, we can say that there is significant fixed slope associating the number of completed tree trimming service request completions across all communities. We can see the random slope model with a full specification

$$\log(\mathbb{E}[NumberTreesTrimmed_{cy}|b_{0c}, b_{TIF,c}]) = 5.11668 + b_{0c} + (0.05866 + b_{TIF,c}) \log(1 + x_{cy}) \tag{14}$$

$$\mathbb{E}[NumberTreesTrimmed_{cy}|b_{0c}, b_{TIF,c}] = e^{5.11668+b_{0c}}(1 + x_{cy})^{0.05866+b_{TIF,c}} \tag{15}$$

Where we have our random intercept and random slope go between these bounds

$$-7.968488 \leq b_{0,c} \leq 7.609632 \tag{16}$$

$$-0.4884086 \leq b_{TIF,c} \leq 0.4490269 \tag{17}$$

So we can see there is a large variation in the value for $e^{5.11668+b_{0c}}$, meaning that when the accumulated TIF spending value is zero, the expected value for the number of tree trimming service requests completed varies a lot by community. Hence, the starting conditions are different for each community. In addition to this, we can see the $(1 + x_{cy})^{0.05866+b_{TIF,c}}$ term is at least

$$(1 + x_{cy})^{0.05866-0.4884086} = (1 + x_{cy})^{-0.4297486} \tag{18}$$

and is at most

$$(1 + x_{cy})^{0.05866+0.4490269} = (1 + x_{cy})^{0.5076869} \tag{19}$$

So for some communities the expected value for the number of tree trimming service requests completed decreases as a function of accumulated TIF spending and for others it increases. Hence, **accumulated TIF spending is only associated with ameliorating blight by increasing these service request completions for some communities.**

5.3 Discussion Points for Accumulated TIF Spending v.s. Business Licenses Issued

Conclusion: It was found via partial significance tests that both the fixed slope model and the random slope model were statistically significant. For both the fixed slope model and random slope model, we see they were significant if $\alpha = 0.001$. Since we can say that there are both significant fixed slope and random slope models associating the number of completed tree trimming service request completions across all communities, we can choose to interpret random slope as it is the more nuanced model. We can see the random slope model with a full specification

$$\log(\mathbb{E}[LicensesIssued_{cy}|b_{0c}, b_{TIF,c}]) = 10.3820 + b_{0c} + (-0.2505 + b_{TIF,c}) \log(1 + x_{cy}) \tag{20}$$

$$\mathbb{E}[LicensesIssued_{cy}|b_{0c}, b_{TIF,c}] = e^{10.3820+b_{0c}}(1 + x_{cy})^{-0.2505+b_{TIF,c}} \tag{21}$$

Where we have our random intercept and random slope go between these bounds

$$-5.733632 \leq b_{0,c} \leq 8.47845 \tag{22}$$

$$-0.4172714 \leq b_{TIF,c} \leq 0.2245065 \tag{23}$$

Once again we can see there is a large variation in the value for $e^{10.3820+b_{0c}}$, meaning that when the accumulated spending value is zero, the expected value for the number of business licenses issued varies a lot by community. Hence, the starting conditions are different for each community. In addition to this, we can see the $(1 + x_{cy})^{-0.2505+b_{TIF,c}}$ is at least

$$(1 + x_{cy})^{-0.2505-0.4172714} = (1 + x_{cy})^{-0.6677714} \tag{24}$$

and is at most

$$(1 + x_{cy})^{-0.2505+0.2245065} = (1 + x_{cy})^{-0.0259935} \tag{25}$$

We can see for both of these cases, the expected value for the number of business licenses issued decreases as a function of accumulated TIF spending. Hence, **accumulated TIF spending does not increase the expected value for the number of business licenses issued in Chicago communities, rather it decreases it.**

5.4 Overall Conclusions:

In this project, I found many instances where either accumulated TIF spending did not associate with, or associated weakly with the indicators, or economic development was seen to decrease with accumulated TIF spending or blight increased with accumulated TIF spending. So in this way, **I did not see a strong argument, for my indicators, that accumulated TIF spending had an association with helping reduce blight and increase economic development in Chicago communities.**

Doing this project I noticed that there were major limitations in obtaining data in the correct form (for each community area over years). This project may have had more significant results if the data had been more robust. If I had to take a different approach I would look at each community more closely, and use something that isn't a mixed effects model. I say this since TIFs are a complex issue that requires less general analysis. The results of this project don't tell a great deal about the nature of TIF spending, which either means the effects of TIFs spending are minimal, or there is a deeper structure I am missing. If I were to do this project differently I would use methods in econometrics. I say this since the relevance of money in this project goes without explanation.