Indiana Economic Development Association
FOUNDATION

ANALYSIS OF Tax Increment Financing IN INDIANA

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1. Executive Summary

Introduction

Tax increment finance (TIF) has witnessed widespread adoption and utilization in the past three decades. TIF involves the use of incremental tax revenues that arise from the development of properties within a designated TIF district, and the resulting increased taxable value, to finance projects designed to stimulate economic development activity or enhance quality of life.

TIF, as an economic development tool, was first implemented in California in 1952. Currently, 49 states in the U.S. use TIF.

Local governments use TIF to address a number of issues that include infrastructure development, to stimulate economic activity in under-performing areas within a community, to compete with other jurisdictions, or to develop quality of life assets. In 2015, there were 765 TIF districts and these accounted for nearly 9 percent of the gross assessed value of property in the State of Indiana.

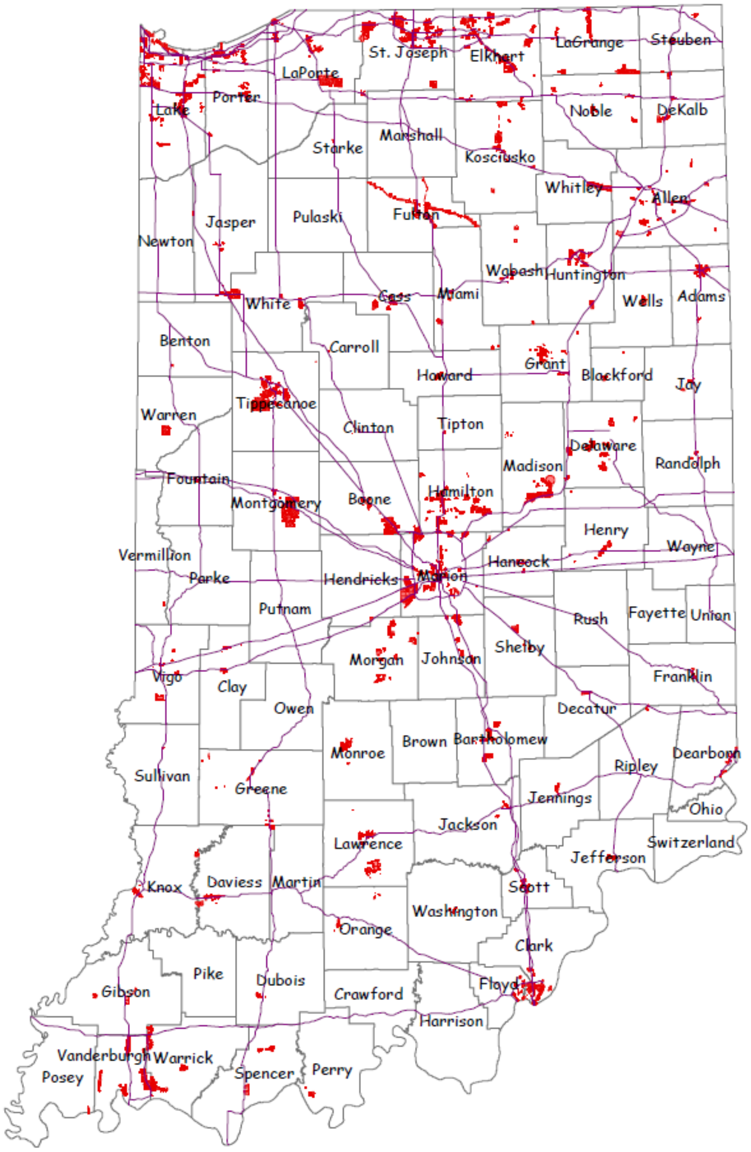
In its role as a 'platform mechanism' within a local economy, TIF has relatively high visibility compared to other economic development tools, such as tax abatements, training grants and other incentives. Understandably, with the widespread use of tax increment finance, there is greater awareness among stakeholders about this particular instrument. It is not surprising, then, to find that as the use of tax increment finance has grown, so has the scrutiny of the tool. There is an ongoing push to ensure that transparency and accountability are at the forefront of efforts to monitor and evaluate the impacts, intended and unintended, of the use of TIF.

This study was initiated to contribute to the ongoing need for transparency and accountability of tax increment finance in Indiana.

This study was able to include a broader range of TIF data than have been available to prior analysts and, as such, is able to present a more nuanced analysis of the impact of TIF throughout Indiana. For this study, the effects of the 'Great Recession' (2007 – 2009) have been more fully accounted for, thus providing a broader view of changes in TIF activity over time.

1. Data show that TIF districts comprise a minimal portion of taxable property throughout the state of Indiana.

- TIF districts represent approximately 3 percent of all parcels in the State of Indiana. In 2015, parcels in TIF districts with non-zero incremental assessed value represented only 1.98 percent of all parcels in the State of Indiana.


St. Joseph
Elkhart
LaGrange
Steuben
LaPorte
Porter
Lake
Noble
DeKalb
Starke
Marshall
Kosciusko
Whitley
Allen
Jasper
Pulaski
Fulton
Newton
Wabash
Huntington
Wells
Adams
White
Cass
Miami
Benton
Carroll
Grant
Howard
Blackford
Jay
Warren
Tippecanoe
Clinton
Tipton
Delaware
Randolph
Madison
Fountain
Montgomery
Boone
Hamilton
Henry
Wayne
Vermillion
Parke
Hendricks
Marion
Hancock
Putnam
Rush
Fayette
Union
Shelby
Morgan
Johnson
Vigo
Clay
Franklin
Owen
Decatur
Brown
Bartholomew
Monroe
Dearborn
Ripley
Sullivan
Greene
Jennings
Ohio
Jackson
Lawrence
Switzerland
Jefferson
Knox
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Martin
Scott
Washington
Orange
Clark
Pike
Dubois
Floyd
Gibson
Crawford
Harrison
Vanderburgh
Warrick
Spencer
Perry
Posey

1. **This study provides a rigorous analysis of the impact of the Great Recession on the effectiveness of TIF.**

   - The sharp fall in employment during the Great Recession – not caused by TIF – can swamp any positive employment effects of TIF in periods before, during, and after the Great Recession, producing the impression that TIF has an overall negative impact on employment.

Figure 1: Total Employment in Indiana (2003-2012) with Trend Line

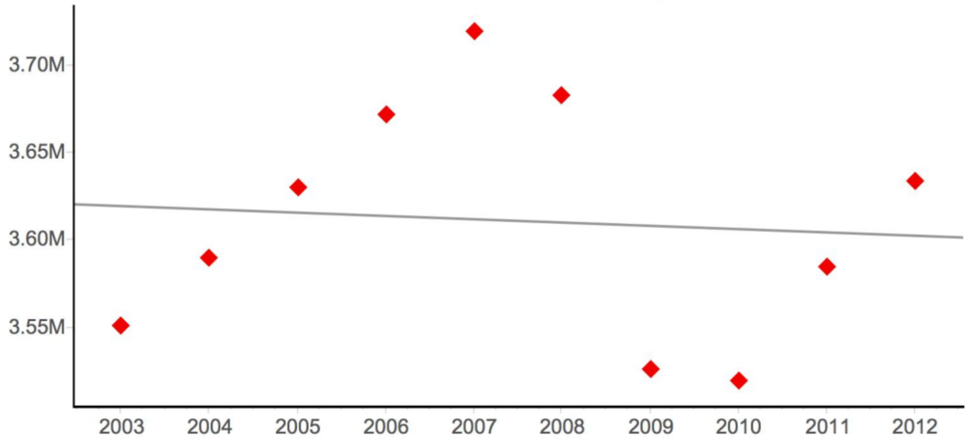
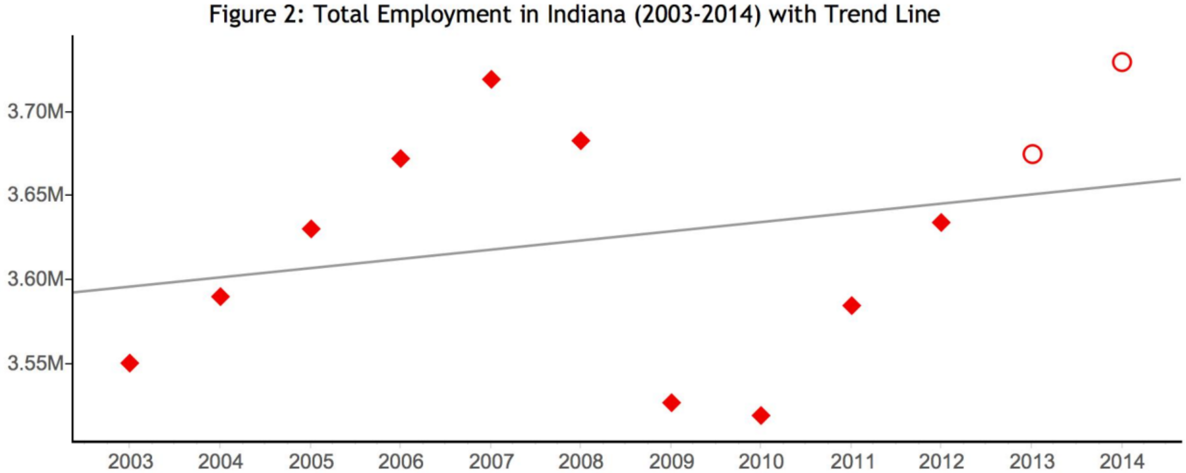


Figure 2: Total Employment in Indiana (2003-2014) with Trend Line



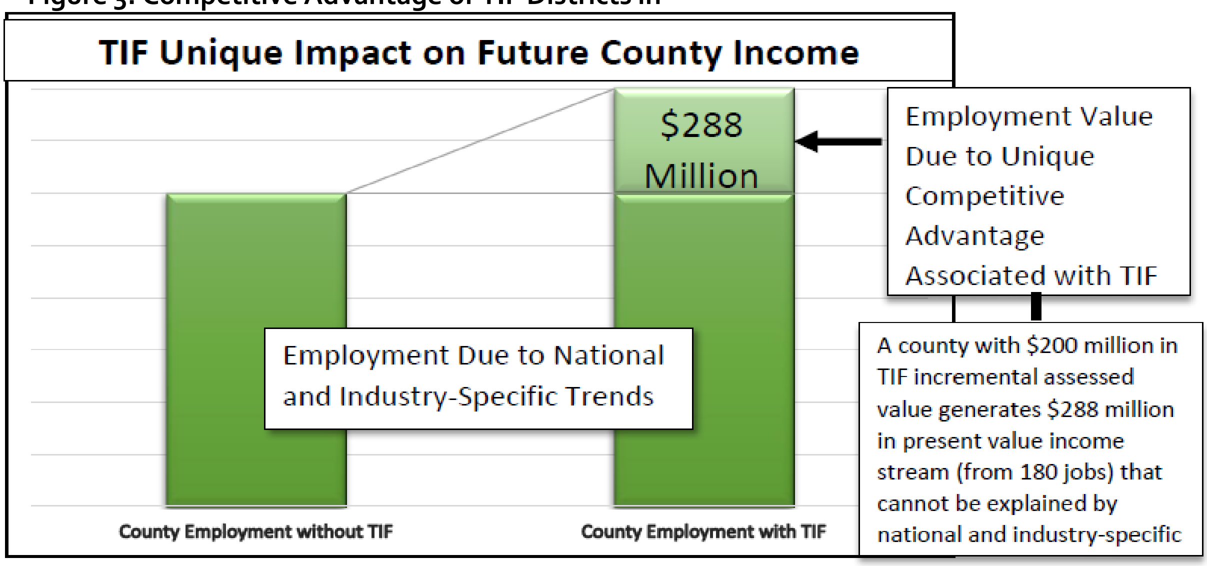
Source for Figures 1 and 2: Employment by 2-digit NAICS sectors, as well as proprietors, farm, and nonfarm data; http://www.stats.indiana.edu/bea/simple/naics/ee_n.html

   - Analyzing employment patterns from 2003-2012 by fitting a trend line indicates declining employment over this time period. <u>Adding two years of data (2013-2014) reverses this result.</u>
   - This study uses sophisticated econometric techniques that effectively account for the geographic connections and employment patterns over the 2003-2014 time-period and, consequently, deliver a more complete analysis of the effectiveness of TIF.

2. **TIF activity has a positive impact on employment and wages**.

   - Three alternative statistical approaches are employed to control for the effects of the Great Recession. All three approaches yield a positive effect of TIF on local employment. The first approach analyzes data for the Pre-recession and Post-Recession time periods separately. The second approach pools data from the two time periods. Results from this approach indicate that a $1 million increase in TIF assessed value leads to 5.3 additional jobs or $8.5 million in present value from the income flow in a county, in the Pre-recession period, and 4.4 additional jobs or $7 million in present value from the income flow in a county, in the Post-recession period. The third approach, in addition to controlling for the effects of the Great Recession, controls for the effects of some national and regional trends – to ensure that these trends are not driving the positive effect TIF on employment. This implies that the use of TIF does indeed impart a 'unique competitive advantage' to the area and that TIF is not 'piggy-backing' on these trends to generate a positive impact on employment.

Figure 3: Competitive Advantage of TIF Districts in



3. **The positive employment effects uncovered in this study, based on TIF incremental assessed value, echo similar findings of the recent Legislative Services Agency (LSA) study (2015), based on gross assessed value, which demonstrate that (on average) a parcel in TIF areas outperforms a parcel in non-TIF areas with similar characteristics in multiple economic development measures.**

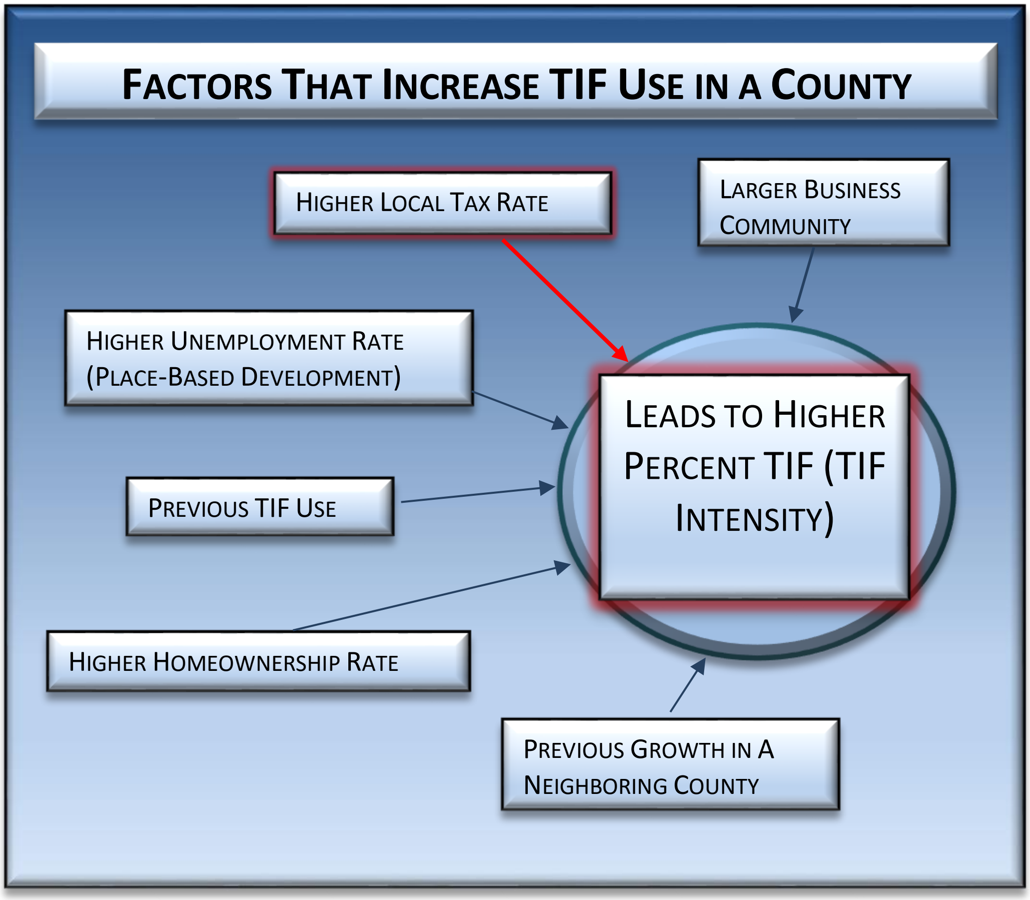
- "After controlling for characteristics that influence TIF adoption, we find the average TIF establishment tends to create 0.7 more jobs than its non-TIF counterpart." (LSA study; 2015, pg. 109). This positive employment effect is statistically significant (at the 5% level – see Table 54 in the LSA study; 2015, pg. 109).
- "After controlling for characteristics that influence TIF adoption in the first place, we find the average parcel in a TIF area may display gross assessed value (GAV) of approximately $4,500 more than the average parcel in a similarly situated non-TIF area." (LSA study; 2015, pg. 105). This positive GAV effect is statistically significant (at the 10% level – see Table 53 in the LSA study; 2015, pg. 108).

4. **TIF activity generates spillover benefits to neighboring counties and exhibits considerable potential as an instrument for place-based economic development (quality of place).**

    - Statistical results show that increasing TIF use in a county generates positive employment effects in neighboring counties.
    - Statistical results show that a high unemployment rate in a county is associated with greater TIF activity in the county, often as a means of generating employment opportunities for households that have limited relocation potential.

5. **Communities are sensitive to property tax rates in surrounding areas – hence areas with higher property tax rates rely more heavily on TIF activity**.

    - Statistical evidence indicates that there is greater TIF activity in response to higher local taxes rather than the intensity of TIF usage in neighboring counties.
    - Counties with higher tax rates are more likely to expand TIF activity as a method for financing improvements (i.e. infrastructure) without having to raise property tax rates.



- Larger Business Community: Employment density is used to proxy for the strength of the business community and this is shown to have a positive impact on TIF activity. A strong business community may lead policymakers to be more receptive of their infrastructure needs.
- Higher Local Tax Rate: The higher the local tax rate, the greater the use of TIF as a method for financing improvements (i.e. infrastructure) without having to raise property tax rates.
- Higher Home Ownership Rate: Higher percent of owner-occupied housing leads to greater TIF activity as these residents have a higher likelihood of voting in local elections.
- Higher Unemployment Rate: TIF may be used to generate greater employment opportunities for households with limited relocation potential.
- Previous TIF Use: Having previous experience with TIF encourages communities to adopt additional TIF districts.
- Previous Growth in a Neighboring County: Counties increase TIF activity to position themselves in a way so as to take advantage of positive economic spillovers from neighboring areas.

Foreword

This report covers the first phase of a study commissioned by the Indiana Economic Development Association (IEDA) in 2015. The request for proposal identified the primary focus as a comprehensive analysis of TIF in Indiana. Specific requirements include an examination of the impact of TIF on employment, wages, assessed property values, tax revenues, and indicators of economic dynamism; an assessment of the effectiveness of TIF; a review of data and methodological issues in previous research on TIF in Indiana; the development of representative case studies of best practices and non-performing TIF districts/projects, and providing recommendations that may strengthen TIF as an economic development tool.

Our approach to addressing the requirements for the study involves:

- an examination of the historical record on TIF utilization in Indiana
- an analysis of changes to Indiana's redevelopment commission legislation
- a review of the existing literature on TIF activity in Indiana as well as across the US with regard to key findings, theoretical models, and empirical methods
- an assessment of the availability and usability of TIF and related data to conduct a comprehensive analysis of TIF in Indiana
- the design of a process for selecting TIF areas /districts to be included in the case studies development of appropriate models and frameworks for the analysis of TIF activity in Indiana

Based on our approach the analysis of TIF in Indiana occurs in two phases. The first phase focuses on an aggregate analysis of TIF activity in Indiana based on relatively recent improvements in data collection and dissemination by the Department of Local Government Finance, the Legislative Services Agency, the Auditor of State's Settlements Department, and the Indiana Business Research Center. Our aggregate analysis is also influenced by conceptual and empirical developments in the analysis of local and regional economic developments such as the study of strategic behavior, for example, tax mimicking and recent advances in spatial econometrics.

A key insight from our aggregate analysis is the extent of the differentiation that exists among TIF districts in Indiana. There is considerable differentiation with regard to the underlying purpose for the establishment of TIF districts, the connectivity of a TIF district to other economic development initiatives, the growth path of incremental assessed value of property in TIF districts, and the scale of the impacts associated with different types of TIF districts and levels of outlays associated across TIF districts.

Phase 2 of the study addresses this differentiation in TIF districts. The framework for organizing and studying this differentiation is presented in this Report. This framework is built using the technique of cluster analysis, which helps to group counties that share TIF and socio-economic characteristics. These clusters provide a basis for identifying representative case studies which will be completed in a companion report.

Acknowledgments

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We also appreciate the suggestions and insights from members of the Indiana Economic Development Association (IEDA) and our colleagues at the University of Southern Indiana. Individuals who have made contributions at different stages of the study are: Heidi Amspaugh, Alexandra Busch, Rusty Carr, Linda Dillbeck, Bruce Donaldson, James Durbin, Carolyn Elliott, Brian Gerth, Joe Gries, Matthew Kimmick, Jim Landers, Lee Lewellen, Loren Matthes, Chad Milewicz, Todd Mosby, Darla Perigo, Curtis Price, Isaac Ray, Kenneth Rogers, Aaron Schibik, Timothy Schibik, William Sheldrake, Michelle Simmons, Michael Snyder, Mary Spahn, Greg Wathen, and Michael Williams.

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Columbus Economic Development Board
Daviess Co. Economic Development Corporation
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Wells County Economic Development
City of Whiting
Whitley County ED

The authors are solely responsible for any shortcomings of this report.

2. TIF and Economic Development

Economic Development: Overview and Challenges

The local government system in the U.S. is complex, resilient, and over time has demonstrated success in converting contemporary opportunities into the long run future. Briffault (2010) highlights four contemporary characteristics of the U.S. local government system, namely, decentralized decision-making, a high degree of fragmentation which tends to result in interlocal struggle for investment, increasing fiscalization of local economic development policy, and a growing emphasis on entrepreneurial thinking and initiatives in operational and strategic activities (e.g. public-private partnerships). These characteristics result in the ongoing interaction of diverse stakeholders (residents, elected officials, state agencies), growth in networks, the constant challenge to develop robust coordination mechanisms, and the distinctive value associated with each local government system.

Tax increment financing (TIF), which involves the use of incremental tax revenues arising from the development of property, and a resulting increase in the value of taxable property, has witnessed widespread adoption and utilization over the past three decades. In a number of ways, tax increment financing reflects certain 'ecosystem characteristics' of the local government system in the U.S. A diversity of stakeholders ranging from capital market participants to property owners, elected officials, real estate developers, businesses, and households are impacted by tax increment financing. Given the relatively long-term horizon associated with TIF property development, its integration with aspects of the property tax system, capital markets, and economic activity, TIF creates a web of complex and extensive networks. The ongoing interaction and range of participants involved with TIF also necessitate robust coordination mechanisms. Additionally, because of tax increment financing local investment is capitalized in property that is developed and the future property tax increment is captured over an extended period. As a result, tax increment financing embodies foundational aspects of a free enterprise system such as the time value of money, which in the local government context involves impacting the cost and benefit distribution between contemporary and future residents in a local community.

In its role as a 'platform mechanism' within a local economic economy, tax increment financing has relatively high visibility compared to alternative economic development policy tools such as tax abatements, and other tax incentives. Understandably with the widespread use of tax increment financing there is greater awareness among stakeholders and the public of this economic development policy instrument in comparison to other contemporary economic development policy instruments. Inevitably, as with any policy instrument, in spite of its actual and potential success, tax increment financing is susceptible to abuse. It is not surprising, therefore, to find that as the use of tax increment financing has grown, there has been a corresponding push to ensure that transparency and accountability are at the forefront of efforts aimed at improving this economic development tool.

Fiscally, local governments are facing crises. In the time period since the onset of the Great Recession (2008-2009), the condition of local government finances has deteriorated considerably.[1] In this context, maintaining resiliency and sustainability is an ongoing challenge for local governments, where resiliency refers to the capacity of local governments to recover from shocks such as the Great Recession and

[1] Fisher and Wassmer (2016) provide a brief overview of State and Local Government fiscal conditions after the Great Recession.

sustainability refers to a local government's success in converting current opportunities into the long run future. The extent to which a local government demonstrates resiliency and sustainability is influenced by the depth of the dip in performance and is exhibited by the speed of recovery from a shock.

Economic development can be defined as the sustained capacity to produce goods and services and enhance quality of life within an economy. While the use of increased amounts of inputs such as labor and capital is a source of output expansion, studies of long-run economic growth (Solow, 1956; Gordon, 2014) have shown that sustained production capacity is driven by growth in total factor productivity (TFP). Total factor productivity[2] is the portion of output not explained by the amount of inputs used in production and its growth is associated with technological progress. In addition to direct technological change, such progress includes innovations in the use of accumulated knowledge, institutional arrangements (e.g. rule of law), and coordinating mechanisms (e.g. managerial and organizational practices).

Over the past one hundred and forty-five years, the U.S. economy has exhibited sustained growth of per capita real GDP of around 2 percent per year. This longer-term trend obscures variations over time such as the Great Depression, when real GDP per person fell by about 20 percent, the Great Moderation, when GDP per person grew by 48 percent, and the Great Recession, when real GDP per person fell by about 7.2 percent. In addition, the longer-term trend in output growth obscures variations across geographic areas reflected in regional patterns of convergence and divergence in output growth.

While incomes across states converged at a rate of 1.8 percent per year for over a century, the past quarter century has witnessed a dramatic weakening of this trend. The convergence rate from 1990 to 2015 was less than half the historical norm, and in the period leading up to the Great Recession there was almost no convergence. During the century-long era of strong convergence, population also flowed from relatively low income to relatively high-income states. Prior to 1980, people were moving, on net, from lower income places to higher income places. Like convergence, this historical pattern has declined over the last thirty-five years. Molloy et al., (2014) show that internal migration within the United States has fallen continuously since the 1980s, reversing the upward trend that occurred from the early 20th century.

Molloy et al., (2014) assess several explanations for the secular decline in migration, focusing on factors that may have played a role throughout the entire thirty-five year period. Considering the contributions of a number of demographic and socioeconomic factors to the change in migration from the 1980s to the 2000s using a decomposition framework, Molloy et al., find sharp differences across long-distance (inter-county or inter-state) migration and migration over shorter distances (within county). For intra-county migration, compositional changes in age, homeownership, and other observable characteristics explain a large portion (nearly 80 percent) of the decline since 1980. By contrast, changes in age and other demographics only explain a small part of the decline in long-distance migration. Consequently, there is a substantial drop in the probability of migration that is common among all of the demographic and socioeconomic groups in the model.

An investigation of alternative explanations for declining long-distance moves suggests that the labor

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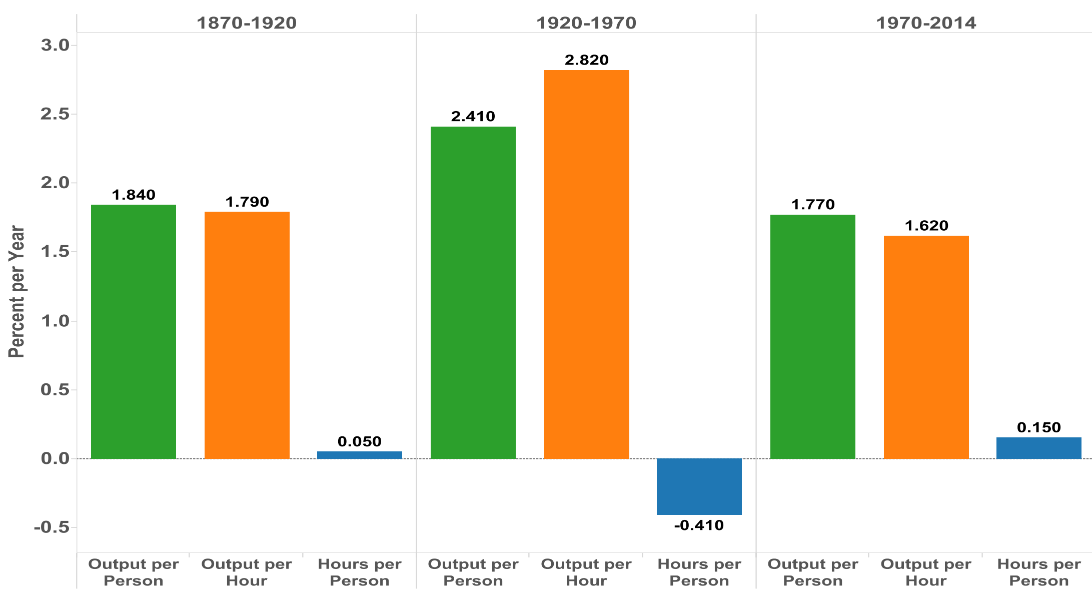
[2] Its level is determined by how efficiently and intensely the inputs are utilized in production. TFP growth is usually measured by the Solow residual. The Solow residual accurately measures TFP growth if (i) the production function is neoclassical, (ii) there is perfect competition in factor markets, and (iii) the growth rates of the inputs are measured accurately.

market has played a key role. First, the decline in migration was more pronounced for labor force participants. Second, it has also been sharper for longer distance moves (i.e. across states or metropolitan areas). Third, other measures of turnover in the labor market, such as quits have also trended down during this period. These findings suggest that the mechanism for the long-run decline is likely to be found in the labor market, as opposed to the housing market or in compositional changes within the population.

Figure 1 shows basic data for the standard of living, labor productivity, and hours worked per person between 1870 and 2014. An examination of the historical record reveals strong similarities in annualized growth of output per person, output per hour, and hours per person across two time intervals and quite different performance in the intervening time interval. Growth in output per person and labor productivity are substantially higher and annualized growth of hours worked per person is considerably lower in the 1920 -1970 period compared to the 1870 - 1920 and 1970 - 2014 time periods.

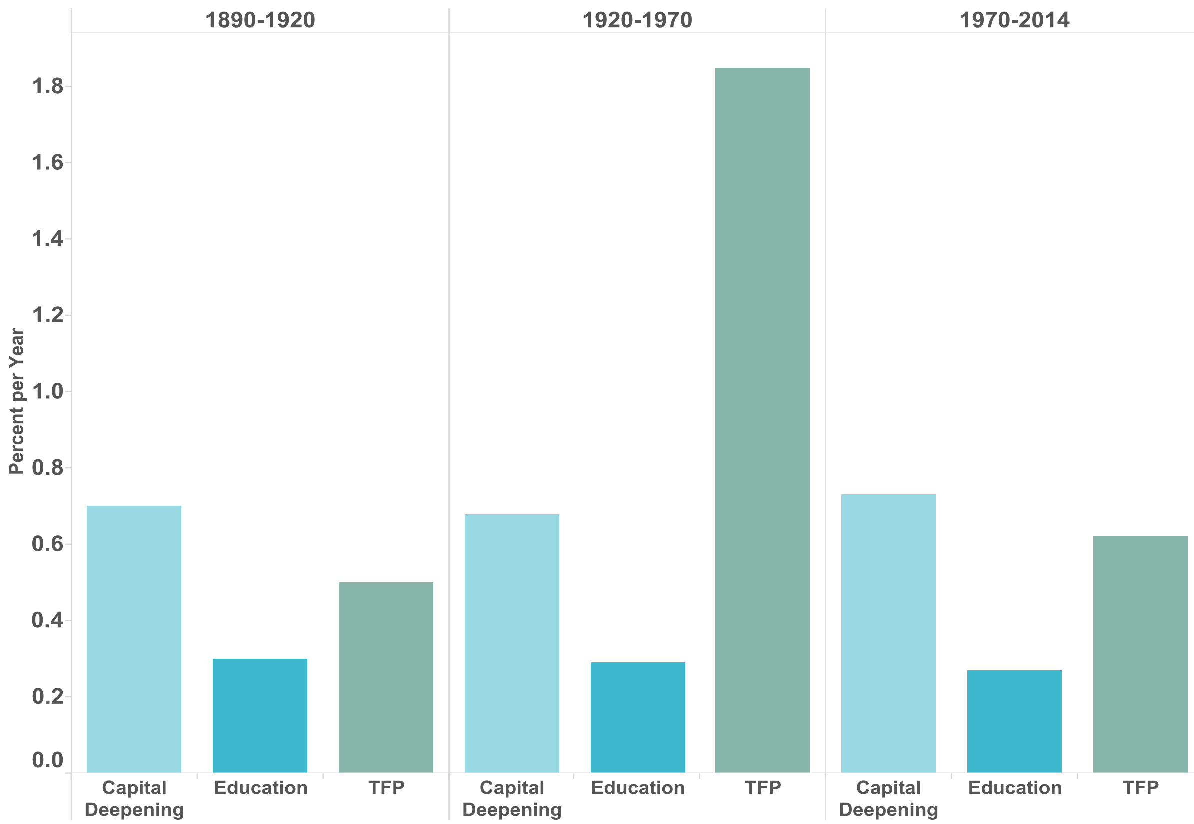
Figure 1: U.S. Annualized Growth Rate of Output per Person, Output per Hour, and Hours per Person,1870-2014



Source: Gordon, 2014.

Decomposition of the growth in labor productivity over much of the same period shows the relative contributions of educational attainment, capital deepening (a larger amount of capital per worker), and technological progress (reflected by the growth in total factor productivity). As figure 2 shows, because the contributions of capital deepening and education were roughly the same in each of the three intervals, the faster growth of labor productivity in the 1920 – 1970 period was the result of more rapid innovation and technological change.

Figure 2: U.S. Average Annual Growth Rates of the Components of Output per Hour, 1890–2014



Source: Gordon, 2014

The Great Moderation demonstrated a discernable shift toward low volatility for a range of macroeconomic aggregates such as output, inflation, and employment during most of the period from 1980 to 2007 compared to the period from 1950 to 1980. Low volatility combined with one of the longest periods of expansion in output, income, and employment in U.S. history led to the view that 'the business cycle was dead' due to structural changes in the economy.

The Great Recession revived a focus on business cycle fluctuations. However, in the slow recovery environment since the Great Recession, some have argued that the Great Recession is consistent with low volatility behavior. Other scholars contend that the Great Recession reflects another instance of structural change.[3] Each of these perspectives has important implications for economic development theory, policy and practice.

[3] See, for instance, Rissman (2009) for a discussion of these perspectives with regard to employment growth.

In the aftermath of the Great Recession, the effectiveness of instruments of economic development has come under greater scrutiny. This increased attention has, in turn, sparked a debate on whether certain economic phenomena (such as the labor-force participation rate) are a reflection of structural changes in the economy - that is, these are changes that are outside the influence of economic development instruments – or whose patterns can in fact be influenced by economic development instruments and consequently display responsiveness to policy changes. The two figures below provide an illustration of this debate in the context of a phenomenon that has recently received considerable attention - a declining labor force participation rate.

Figure 3: Civilian Labor Force Participation Rate: 1970 - 2015

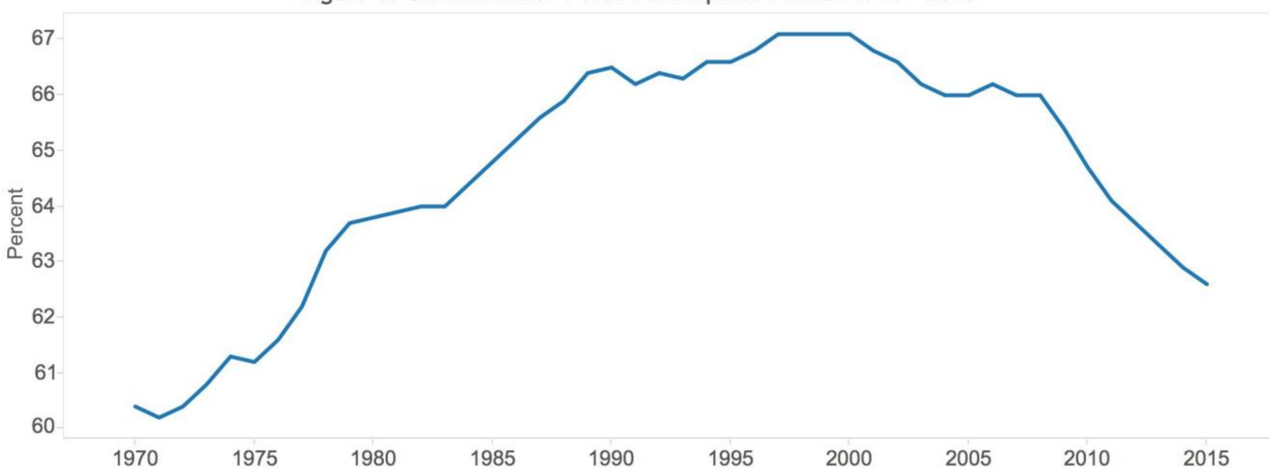
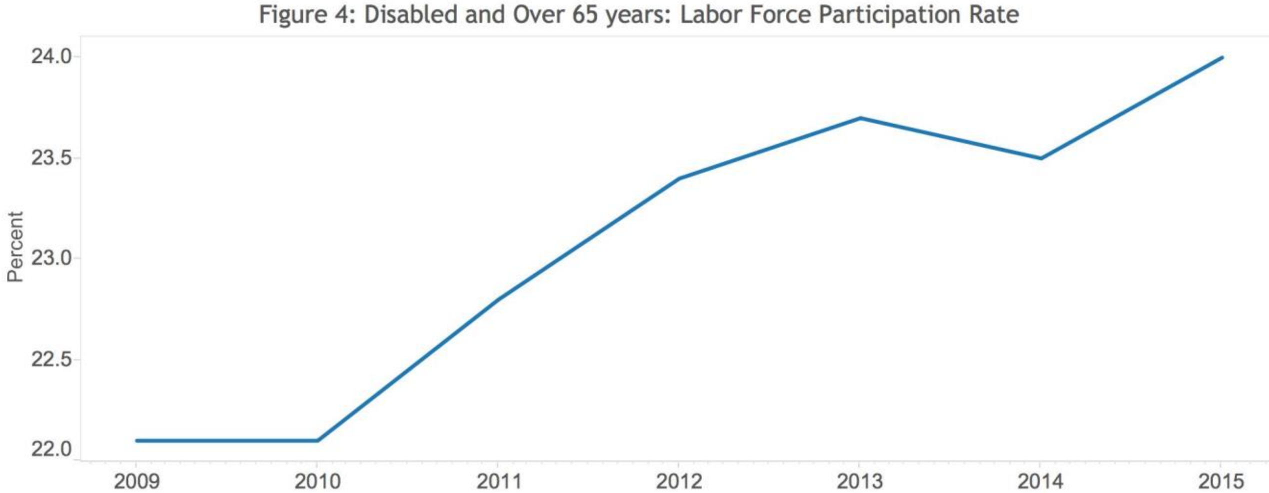


Figure 4: Disabled and Over 65 years: Labor Force Participation Rate



Source: St. Louis Federal Reserve, FRED Economic Data, see, https://fred.stlouisfed.org/

Figure 3 shows that the overall labor participation rate has been declining since the late nineties (reflecting the aging of the U.S. population and a peaking of women's participation rate in the 90s). This is often interpreted as a structural change in the U.S. economy. Figure 4 however, indicates that the labor participation rate of those 65 and over has been rising after the Great Recession. This contrast has prompted an ongoing debate as to whether observed changes in the labor force participation rate represent cyclical or structural changes in the US economy.[4]

Similar issues arise at the regional level. For example, at the state level in Indiana, there have been wider fluctuations in total employment in the period after 2000 compared with the 1990 to 2000 time period. The contrasting trajectories of a number of economic performance indicators in the pre-Great Recession and post-Great Recession time periods shown in Figures 5, 6, 7, and 8 below also raise questions about the relative roles of cyclical and structural forces in accounting for observed changes in Indiana's economy.

Figure 5: Indiana - Real Personal Income, Real Total Nonwage Personal Income and Real Wage Disbursements

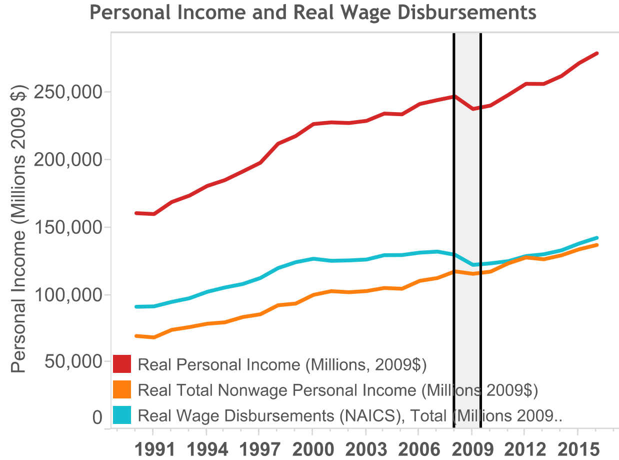


Figure 6: Indiana - Total Employment and Total Non-farm Employment

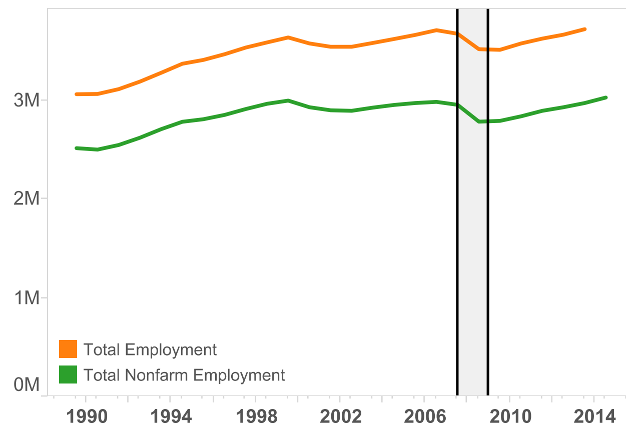


Figure 7: Indiana - Real Gross State Product

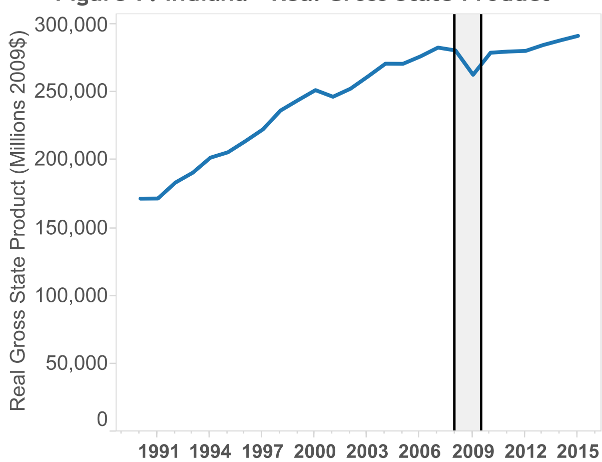
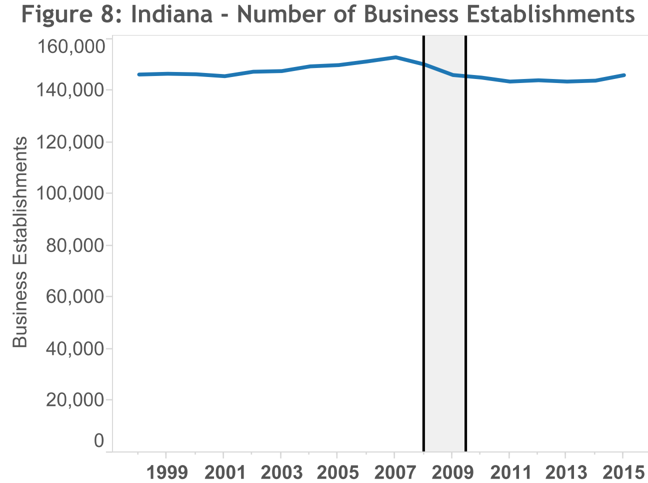


Figure 8: Indiana - Number of Business Establishments



At the county level in Indiana, figures 9, 10, 11, and 12 indicate similarities in the trajectories of economic performance indicators for a substantial number of counties. There is also some indication of a higher degree of divergence among counties with regard to growth paths of personal income. This is supported by preliminary estimates of convergence among Indiana counties that is greater for the 1975 to 2000 time period than for the 2000 to 2015 time period.[5]

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[4] For more discussion, see: https://fredblog.stlouisfed.org/2015/05/labor-force-participation-is-a-trend-or-a-cycle-at-work/.

[5] These results are preliminary and will be investigated more extensively as an outgrowth of this study.

Figure 9: County Real Wage Disbursements

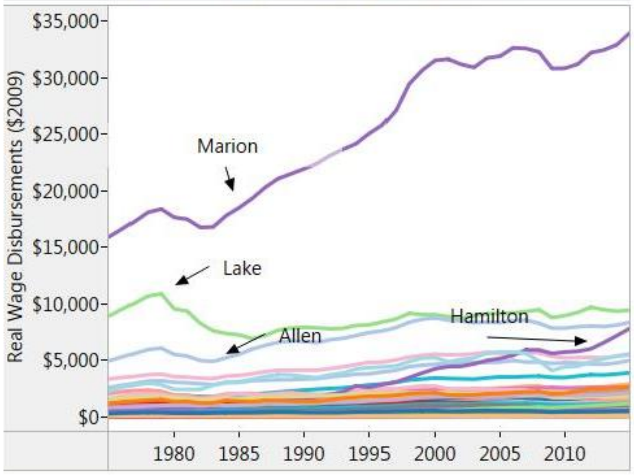


Figure 10: County Real Personal Income

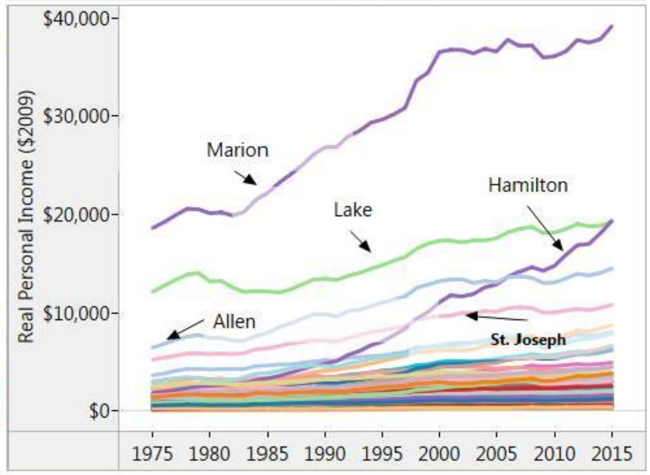


Figure 11: Real Gross County Product

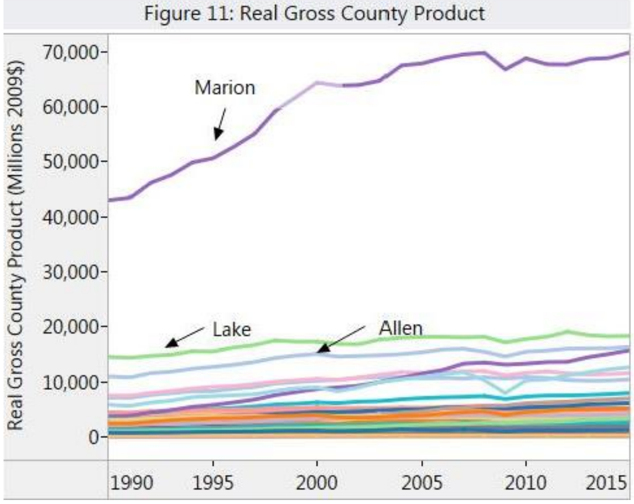
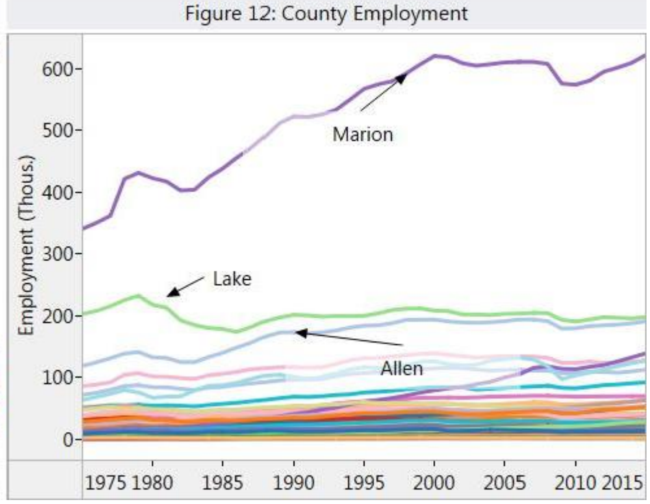


Figure 12: County Employment



Over the last decade or so, in matters of governance, there has been an intensive examination on the role of decentralization (see, e.g., Bardhan; 2002). For the U.S., certain dimensions of decentralization (at the county level) have been found to have a positive impact on various economic variables, such as employment (Hammond and Tosun; 2009). In this context, the design of economic development policy is more likely to be effective if it has a 'local' basis, since what may appear be to a structural phenomenon at, say, the state level may not be so at the county level. [6]

Concomitant with decentralization has been a greater preference for a place-based approach to economic development (Renn; 2016). The principal characteristics of a place-based approach to economic development are: a) long-view of economic development beyond immediate employment creation, b)

[6] On the issue of evaluating instruments of economic development, there is a growing movement away from examining their impact on employment or income, and towards analyzing how the 'capability set' of the stakeholders has changed, which, in turn, informs how their well-being or quality of life has altered – the ultimate dimension of concern for all economic development activity. For the capability approach to development, see Sen (1999), and for how it is being operationalized, see, for instance, Frediani (2010).

greater reliance on local capacity in terms of providing an understanding of the contextual environment within which development is to occur, and 3) decentralized decision-making in matters of governance (Markey 2010). With regard to funding such economic development, TIF has become one of the more utilized options at the local level and the next section provides a brief overview of some previous research findings.

TIF as an Instrument of Economic Development

(TIF)[7] is distinctive from other economic development incentive programs because of its financing feature. Tax abatements, tax credits, and other tax incentives, enterprise zones, and direct subsidy programs either forego tax revenue or facilitate expenditures from current tax revenue to support or encourage development projects. In the case of TIF, future tax revenues based on increased assessed property values can be used to repay lenders who provide funding for development projects.

The appeal of TIF is evident from its widespread adoption across the country. Since 1952 when enabling legislation was introduced in California, TIF statutes have been enacted in all fifty states and the District of Columbia. Currently, forty-nine[8] states permit tax increment financing.[9] In comparison, thirty-seven states employ property tax abatements and forty-two states have adopted enterprise zones since their initiation in 1982 (Kenyon, Langley and Paquin, 2012).

Local governments use TIF to address spatial disparities (e.g., concentrated infrastructure decay) and equity concerns (e.g. concentrated poverty), to improve efficiency (e.g., attempting to foster agglomeration economies – concentrated economic activity), or to respond to incentives offered by other local governments in an effort to remain competitive (Greenbaum and Bondonio, 2004).

Like most policy initiatives, economic development agencies (including redevelopment commissions) are expected to assess the effectiveness of their development programs. Not surprisingly, the widespread use of TIF has precipitated many studies evaluating its effectiveness. Those studies have cumulatively identified some relatively consistent results. First, there is a time lag between the adoption of TIF legislation and its actual implementation by local governments (Calia, 1997; Cox, Mundell, and Johnson 2001; LaPlante, 2001). However, once adopted its use becomes pervasive, both in its use within a local government district and in neighboring districts (Man, 1999a). There is evidence that increasing populations, low residential tax share, and reduced state funding per capita encourage TIF adoption. In these circumstances, there is a greater need for expanded public services, as well as a need a greater

[7] Tax Increment Financing (TIF) involves the designation of a geographic area called an allocation area or district and the creation of an economic development plan. A base year is designated and the allocation area borrows (e.g. issues bonds) to fund projects pursuant to the plan. Moving forward, tax revenues generated in excess of the base year's levels (labeled incremental revenues) are disbursed to the district to repay lenders (e.g. bondholders). In general, any tax revenue can be used for TIF, but most often property tax and occasionally sales tax revenues are leveraged. TIF is most typically utilized as urban redevelopment tools for the following types of projects: redevelop brownfields (environmentally contaminated/hazardous properties); eliminate blighted areas; build affordable housing; finance public infrastructure.

[8] Tax Increment Finance State-By-State Report: An Analysis of Trends in State TIF Statutes, from the Council of Development Finance Agencies Online Resource Database at: https://www.cdfa.net/

[9] Arizona repealed its TIF legislation in 1999 and California ended its use of TIF in 2012. However, in 2014, California established Enhanced Infrastructure Financing Districts (EIFDs), which allows of the use of TIF.

need to use property taxes within the local district more effectively. Population growth and reduced state funding also increase local public tax burdens, whether directly (through higher property values and taxes based on that value) and indirectly (through local government budget reallocations driven by reductions in state funding). Hence, TIF becomes a politically attractive option because it funds redevelopment efforts without an explicit increase in tax rates (Man, 1999a).[10]

At the same time, the literature recognizes many idiosyncrasies in TIF use across districts. California presents perhaps the best example (Lefcoe and Swenson, 2014). The passage of Proposition 13 (which effectively froze assessed property values until such time as the owners sell their property) created a unique situation that dramatically increased the use of TIF. By freezing property tax assessments during a period of ownership, the property tax base is held artificially low, but is also made artificially stable. The stability of property tax bases makes TIF-backed bonds appealing to investors. The reduction in the property tax base created tax revenue shortfalls. To offset these shortfalls, the State of California began to siphon TIF-generated tax revenues back to the state. It essentially forced local governments in California to create redevelopment commissions and continually initiate new TIF projects to ensure adequate tax revenue streams. Because the vast majority of other states do not have legislation that is similar to Proposition 13, it is unlikely that evaluations of TIF in California can be generalizable to other states.

A related problem is the definition of "blight." In order to justify redevelopment in a particular area (and by extension, the use of TIF to fund the redevelopment), some states require that an area in question be deemed so distressed that it could not be addressed (whether by private or government intervention) without redevelopment (Lefcoe and Swenson, 2014). Unfortunately, the definition of "blight" is defined regionally and locally, rather than nationally. Moreover, some states, including Indiana, do not require a blight designation. This makes evaluations of TIF across states more challenging, since the lack of a blight-designation allows local governments much more flexibility in the types of redevelopment projects that are initiated, whether funded by TIF or an alternative means.

Further, there may be strategic considerations in the adoption of TIF - not directly tied to economic development purposes – for spatially competitive reasons (Mason and Thomas, 2010). For instance, one geographic area may adopt TIF following the adoption of TIF by an adjoining area, so as to preserve its tax base, which in turn then lowers the returns to the TIF-adoption by the 'leading' area, and both areas end up in a Prisoner's Dilemma-type equilibrium[11] (with regard to the return on tax dollars).

In terms of assessing the effectiveness of TIF in Indiana, Schaafsma (2014) points to the inherent challenges due to issues with reporting, compliance and variability in TIF characteristics across the state. These challenges notwithstanding, a number of studies have, over the years, attempted to examine the impact of TIF in Indiana and have found mixed results. For instance, Man (1999b) examined employment outcomes in Indiana cities between 1985 and 1992 and generally found positive associations between TIF adoption and local employment. Hicks, Faulk and Quirin (2015) found that, on average, there was a small, positive correlation between the size of a TIF district and capital accumulation (measured as assessed value). However, TIF activity was negatively correlated with other measures of economic

[10] In Indiana, the property tax reform (2008) prescribed property tax caps and circuit breaker tax credits which have raised fiscal pressures on many local governments (Stafford; 2015).
[11] Prisoner's Dilemma is a classic scenario in the discipline of Game Theory that is used to demonstrate how two individuals (prisoners) end up making choices that leave them both worse off compared to some other choices.

development such as employment, business establishments and sales tax revenue.[12]

Update on TIF Activity in Indiana

Since the General Assembly passed enabling legislation for the establishment of TIF allocation areas in 1975 it is estimated that between 700 and 800 tax increment-financing districts were established over time in Indiana (LSA, 2015). Data obtained for 2015 from the pay 2016 TIF neutralization forms identify 765 tax increment financing districts across 87 counties. Currently, there is no reported TIF activity for 5 counties (Harrison, Martin, Ohio, Pulaski, and Switzerland). As figure 13 shows, there has been sustained growth in the number of TIF establishments since 1990, with a surge in the number of TIF districts established in 2006 and more recently in 2014 and 2015. The counties without TIF districts have populations and number of business establishments that range between 5,938 and 39,578 and between 90 and 680 respectively.

The state of Indiana is 36,117 square miles in size and has a population of 6.6 million. Local government capital outlays have averaged $1.96 billion per year over the past three decades and currently the state has over 13,000 county bridges, over 65,310 miles of county roads, and over 18,989 miles of municipal streets.[13] The land area that represents taxable property in the state is comprised of over 4 million parcels of land. Residential property accounts for 63 percent of all taxable property parcels, while agricultural, industrial, and commercial property parcels account for 12, 1, and 4 percent of all taxable property parcels respectively. A comparison with TIF districts shows a different distribution. In the combined TIF districts parcels, residential property account for 46 percent of all taxable property parcels, while agricultural, industrial, and commercial property parcels account for 3, 7, and 27 percent of all taxable property parcels respectively.[14]

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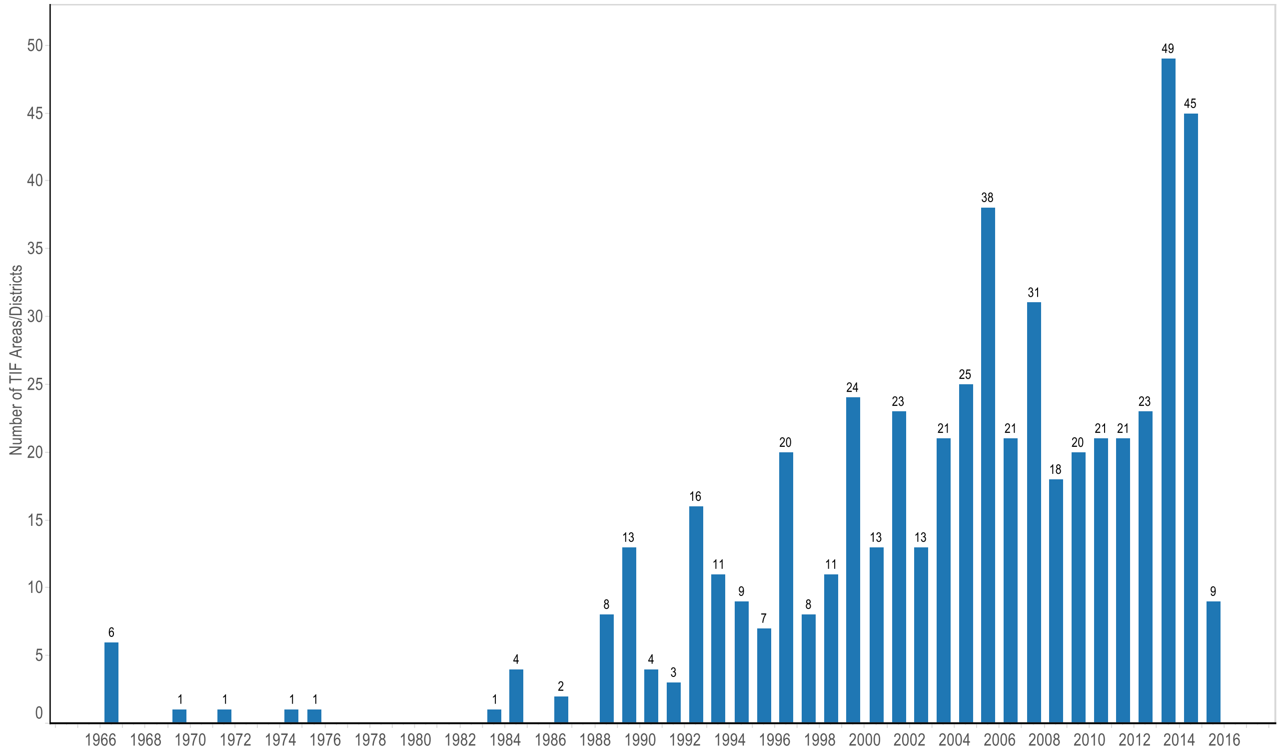
[12] In section 4.4.5, a detailed review of the results of various studies examining the effectiveness of TIF in Indiana is presented.

[13] Data extracted from various issues of the Comprehensive Annual Financial Report - Indiana Auditor of State - see: http://www.in.gov/auditor/2370.htm

[14] Based on data from County Data Submissions per 50 IAC 26.

Figure 13: Indiana - TIF Districts Established by Year



Tax increment financing districts account for 133,011 parcels which represent just over 3 percent of all parcels in the state. In 2015, there were approximately 71,401 parcels in Indiana that capture increment assessed value, which account for 1.72 percent of all parcels in the state. In 2012, there were approximately 71,053 parcels with increment in tax increment financing districts accounting for 1.74 percent of all parcels in the state. Between 2012 and 2015, assessed value of property in TIF districts as a percentage of total assessed value captured in the state increased from 6.69 percent to 7.25 percent.[15]

In 2014, gross assessed value of property in the state was about $471.3 billion and net assessed value was about $307.6 billion. Gross assessed value of property within TIF districts accounts for about 8.6 percent of the gross assessed value in the state. Net assessed value of property within TIF districts accounts for 11.5 percent of net assessed value of property within the state.[16]

The incremental assessed value associated with all the TIF districts in 2015 was about $24.2 billion.[17] This represents about 1.46 times the base assessed value of the properties within the different TIF districts. Circuit breaker credits for all jurisdictions in the state were $788 million in 2015. For all the TIF districts this amounted to $61.5 million, which represents 7.7 percent of all property tax cap credits in the state.[18]

[15] Based on data from County Data Submissions per 50 IAC 26.
[16] Based on data from County Data Submissions per 50 IAC 26.
[17] Data obtained from the Department of Local Government Finance.
[18] Data from Indiana Legislative Services Agency publications website: https://iga.in.gov/legislative/2016/publications/property_tax/ and Department of Local Government Finance Circuit Breaker Information & Reporting website: http://www.in.gov/dlgf/8225.htm.

Characteristics of Debt Instruments Issued by TIF Districts

We use data for 2013 from the Indiana Gateway for Government Units website to analyze the use of debt by TIF districts. Of the four hundred and twenty-eight debt instruments listed for five hundred and fifty-six TIF districts, there were three hundred and ninety-two debt instruments (ninety-two percent) for which incremental tax revenues were pledged as the primary or secondary security for debt payments. The revenue stream of a TIF district is dependent on the incremental portion of the tax base, which is derived from the increase in assessed value of real estate and business personal property and adjusted base assessed value in the district. Since both the tax base and tax rate are outside the direct control of redevelopment authorities, there is an inherent risk for buyers of bonds secured by incremental tax revenues. The extent of the perceived risk associated with lending to TIF districts is usually reflected in the interest rates of the bonds issued.

The average interest rate on TIF bonds is 4.16 percent and the median interest rate is 4.06 percent. Interest rates ranged from zero to twelve percent and the distribution of interest rates shown in figure 14 indicates that a majority of debt instruments issued by TIF districts have interest rates at four percent or below. The downward trajectory in interest rates for bonds issued by TIF districts between 1992 and 2015 is indicated in figure 15.

The median amount borrowed through the issued securities is $3 million and the average is $6.1 million. Figure 16 shows the distribution of the principal of the bonds issued by TIF districts, which is highly skewed to the right indicating that there is a concentration of bond issues at the lower end of the range of principal amounts. About 90 percent of bond issues have a principal amount below $14 million.

Based on figure 17, the average bond maturity is around 16 years and 75 percent of the bonds issued have a term-to-maturity more than 12 years. Twenty-five percent of the bonds issued have a term-to-maturity between 20 and 30 years. To the extent that bond maturity is a proxy for the expected useful life of the activities financed by bond proceeds, then most TIF bonds are long-term bonds sold to finance long-term projects. Further analysis of the bonds reveals a wide range of activities underlying the establishment of TIF districts. Figure 18 shows that while project-based and neighborhood revitalization are the major types of TIF activities.

Outstanding local government debt secured by tax increment revenues in TIF districts was $4.4 billion, which represents 13.37 percent of local government debt.[19]

Between 2003 and 2013, the cumulative amount borrowed by TIF districts was $2.245 billion.[20] The increase in incremental assessed value for TIF districts between 2003 and 2013 was $12.3 billion.[21] On average, for every dollar spent by TIF districts, there was an associated $5.5 in incremental assessed value.

[19] Based on debt data obtained from the Fiscal Health Indicators site at Indiana Gateway for Government Units: https://gateway.ifionline.org/default.aspx

[20] Based on bond data extracted from the TIF District Viewer site at Indiana Gateway for Government Units: http://gateway.ifionline.org/TIFviewer/

[21] Data obtained from the Department of Local Government Finance.

Figure 14: Distribution of Interest Rates for Debt Instruments Issued by TIF Districts

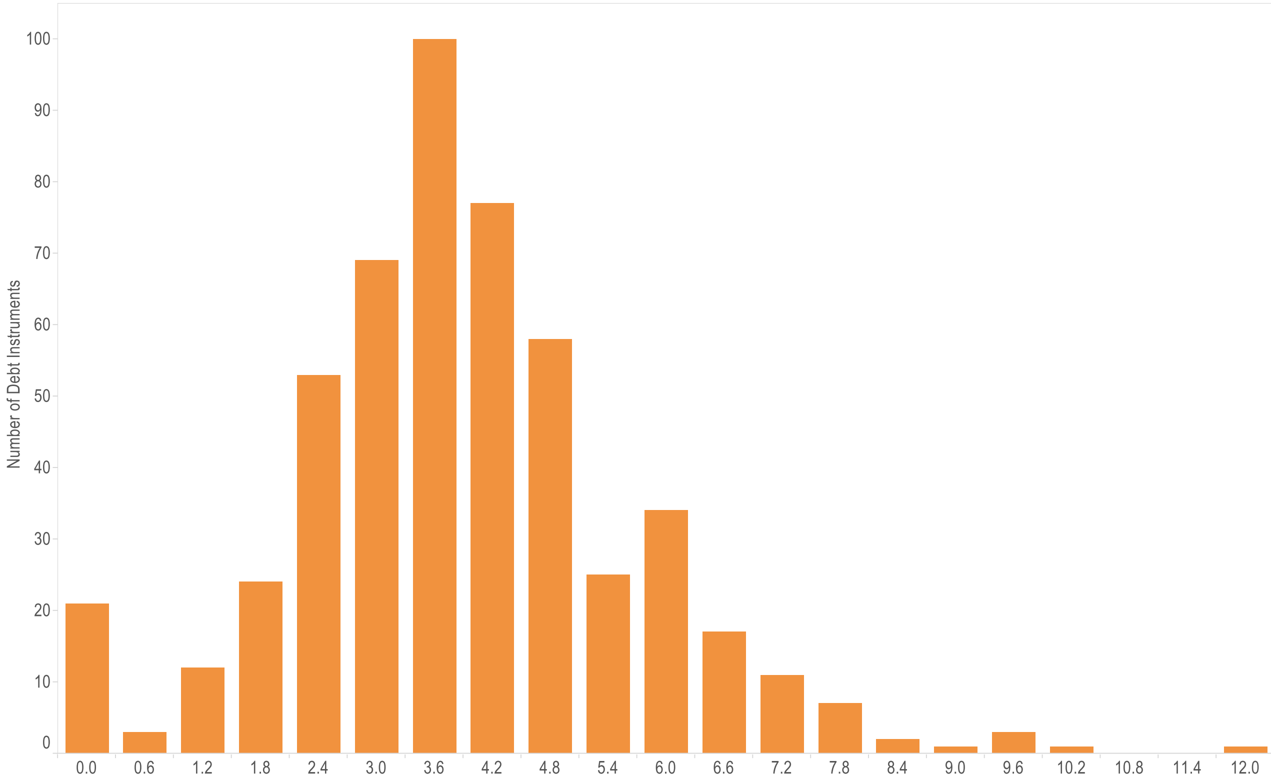


Figure 15: Interest Rates of Debt Instruments - Average by Year

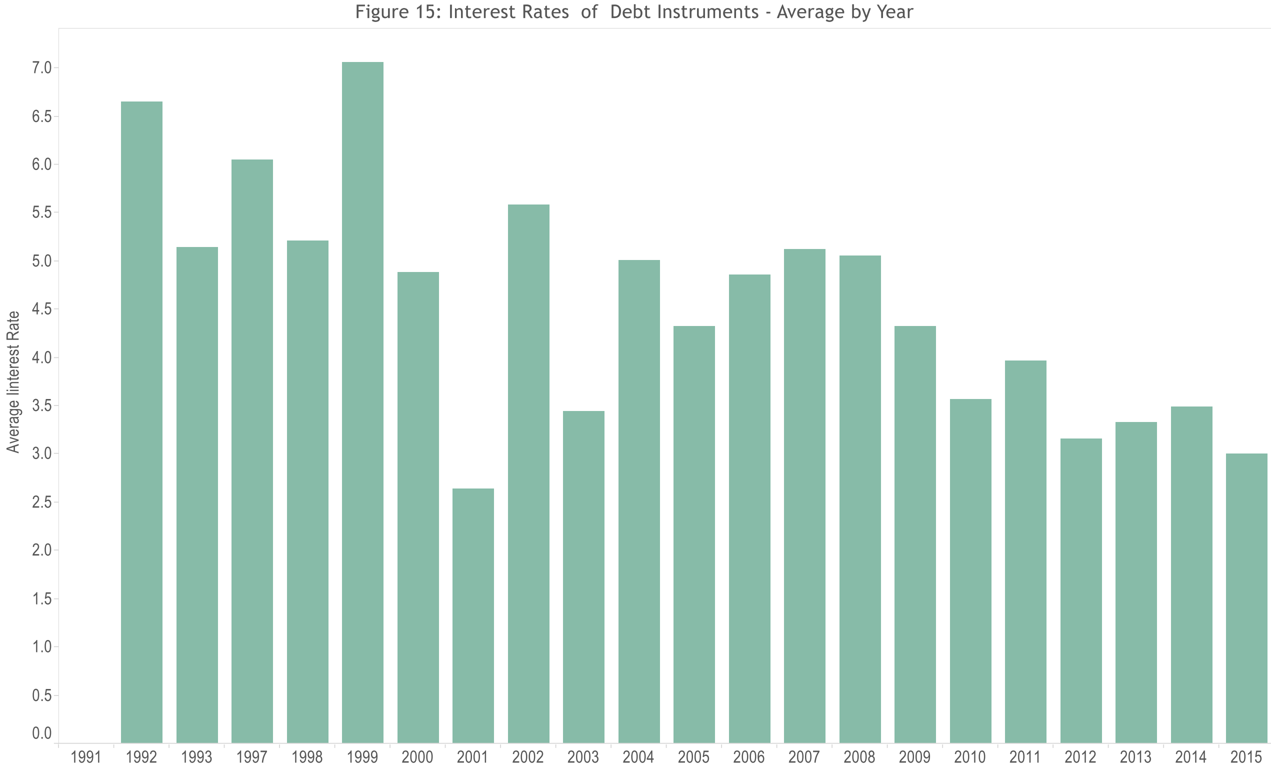


Figure 16: Distribution of Amounts Borrowed by TIF Districts

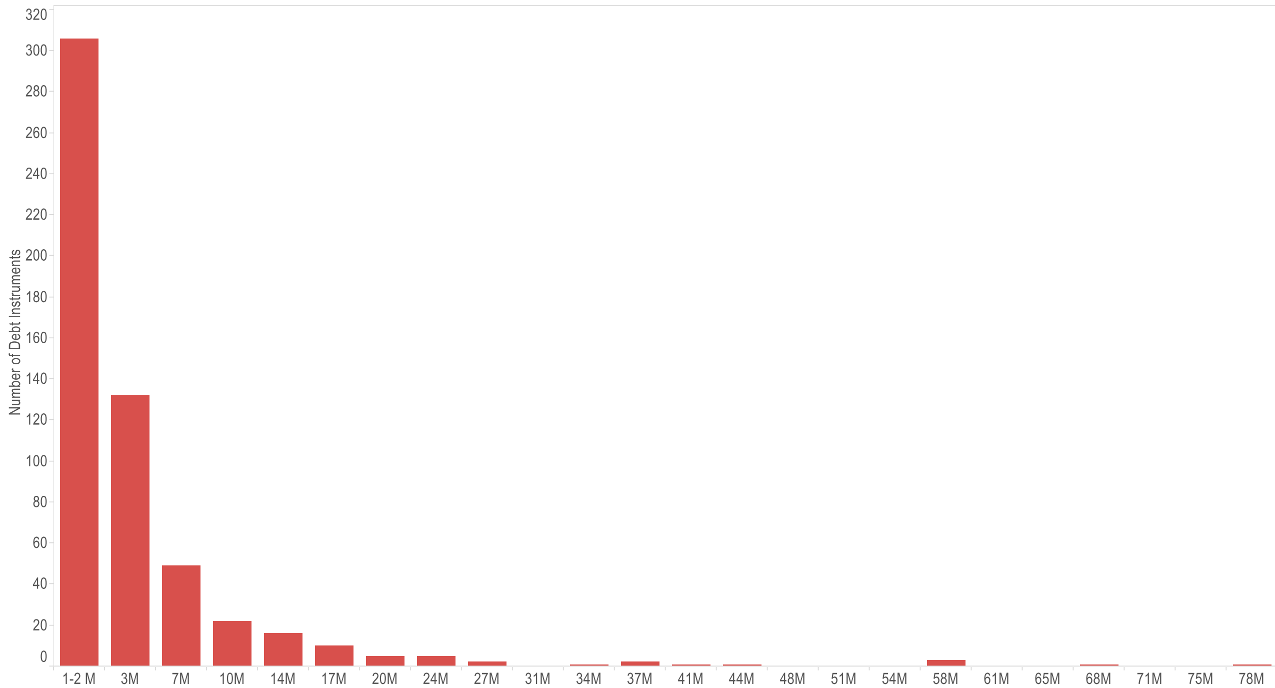


Figure 17: Time to Maturity of TIF Districts Debt Instruments

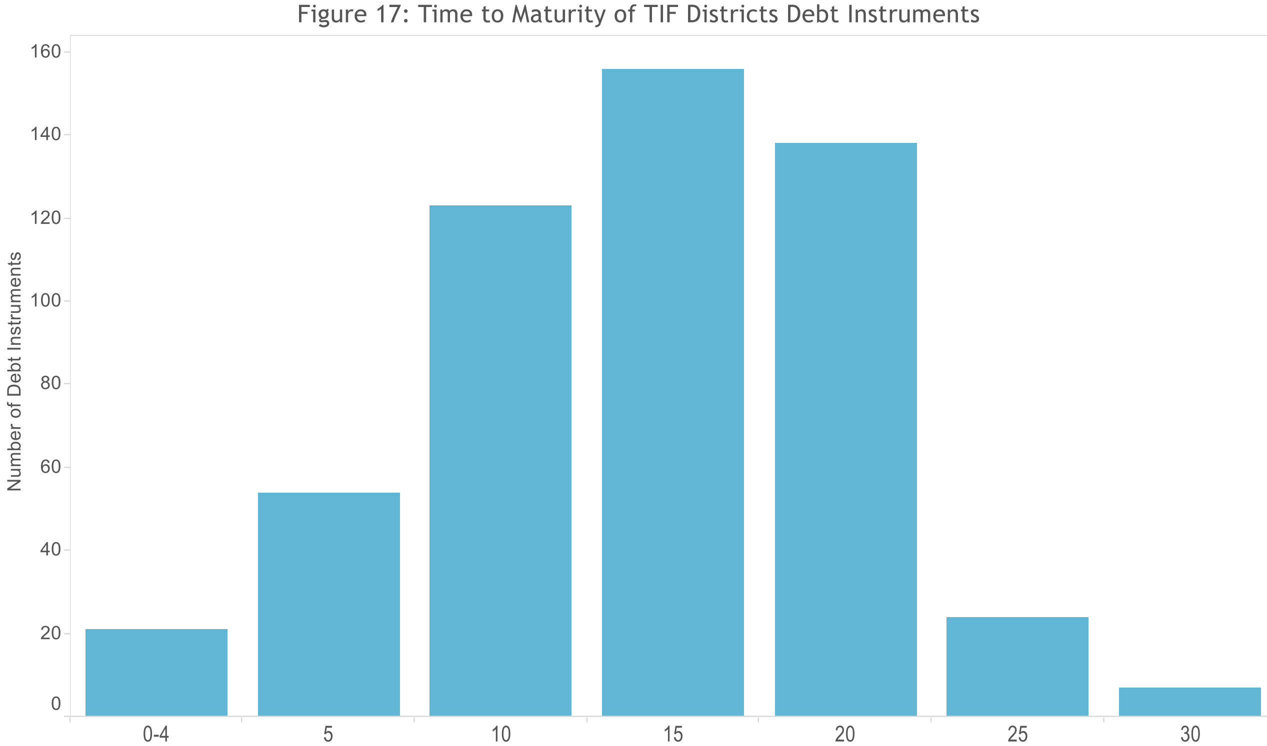
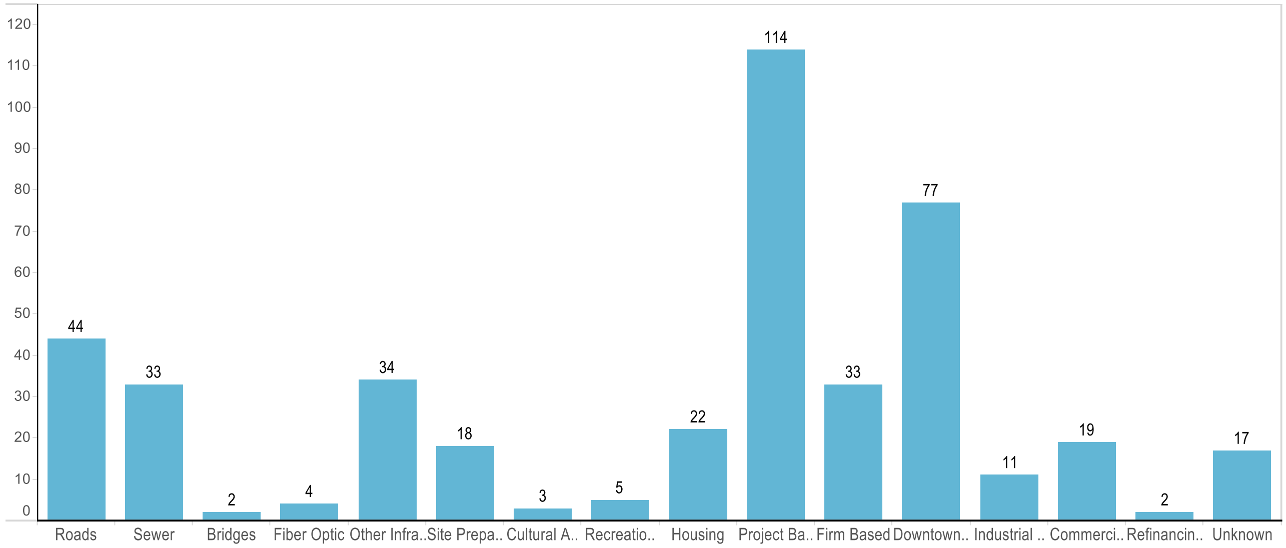


Figure 18: Type of TIF Activity Based on Bond Information



TIF Legislation in Indiana: Ongoing Refinement and Redesign

The enabling redevelopment commission legislation was passed in 1975.[22] In 1981, the Indiana Code was overhauled and IC 36-7-14 became the governing statute for redevelopment commissions in all counties except Marion County. IC 36-7-15.1 governs TIF activity in Marion County. This section provides an overview of legislative changes in the redevelopment commission statute IC 36-7-14 between 1981 and 2015. There were over three hundred new provisions and amendments made to IC 36-7-14 between 1981 and 2015.[23] These changes occurred in twenty-seven of the thirty-five years between 1981 and 2015. Major changes in the redevelopment commission law occurred in 1995, 2008, 2011, and 2014. To a large extent, those legislative changes reflect responses to concerns about transparency, accountability, efficiency, equity, and impacts associated with tax increment financing.

An analysis of the legislative changes show that about twenty-seven percent represent new provisions and seventy-three percent represent amendments. Of the eighty-four sections in IC 36-7-14, fifteen witnessed the most changes (sections 8, 13, 15, 16, 17, 19, 20, 22, 27, 27.5, and 39) accounting for forty percent of the new provisions and amendments. Table 2.1 indicates the sections in the redevelopment commission statute that had the most legislative changes between 1981 and 2015.

[22] However, the 2015 Tax Incentive Review conducted by the Legislative Services Agency notes that the earliest TIF areas were initiated in 1967 by the Gary Redevelopment Commission.
[23] This was based on counts of the changes indicated in a document obtained from: http://iga.in.gov/static-documents/9/2/b/5/92b5e9dc/TITLE36_AR7_ch14.pdf

Table 2.1: Sections of the Redevelopment Commission Statute with the most legislative changes between 1981 and 2015

IC 36-7-14 Section	Section Heading	Count of New Provisions and Amendments
39	Distribution and allocation of taxes; allocation area; base assessed value determinations	30
25.1	Issuance of bonds; procedure; tax exemption; limitations; indebtedness of taxing district; legislative body approval	14
39.3	Allocation Provisions – Depreciable Personal Property	9
27	Certain bonds or leases; special tax levy; legislative body approval; disposition of accumulated revenues; review of sufficiency of levies	8
8	Commission meetings; reporting; disbursements of funds; officers; treasurer; rules; quorum; approval of actions	7
13	Annual reports; contents; subject to laws of general nature	7
15	Data concerning areas in need of redevelopment; declaratory resolution; amendment to resolution or plan; approval	7
22	Public sale or lease of real property; procedure	7
48	Allocation of property taxes; fund; use; credit calculation; limitation on distribution of fund; excess assessed valuation calculation [Housing TIF]	7
15.5	Redevelopment project areas in certain counties; inclusion of additional areas outside boundaries	6
17	Notice and hearing	6
27.5	Tax anticipation warrants; authorization; procedure; legislative body approval	6
16	Approval of resolutions and plans by unit	5
19	Acquisition of real property; procedure; approval	5
20	Eminent domain; procedure; legislative body resolution	5

Between 1981 and 2015, the legislative changes related to redevelopment commissions and tax increment financing generally have been designed to address one or more policy concerns related to a lack of oversight, accountability, and transparency; scope of activities beyond the intended purpose of TIF, and the adverse impact of redevelopment commissions and TIF related activities on other taxing units. A review of public discussion over the years highlights the following major concerns with tax increment financing in Indiana.

- Concern that TIF is taking money away from other taxing units
- Perception of too much power in unelected redevelopment commissions resulting in a lack of transparency and lack of elected official oversight
- "Stockpiling" of TIF by redevelopment commissions instead of releasing excess (unneeded) AV back to the base
- Use of TIF beyond its intended purposes: (a) geographically, (b) substantively, and (c) in terms of duration
- Capturing AV growth that would have occurred anyway without the use of TIF

An examination of the changes in IC 36-7-14 in the context of these major concerns revealed a high degree of responsiveness by the General Assembly. In particular, the major concerns were addressed progressively in 1995, 2008, 2011, and 2014. Table 2.2 provides a synopsis of the key changes in IC 36-7-14 that occurred in those years.

Table 2.2: Major Legislative Changes in Response to Citizens' Concerns

Prior to 1995	1995 Legislative Change	Concern addressed by legislative changes
No expiration date for a TIF allocation	30-year limit to a TIF allocation area	Adverse Impact on Other Units
Residential property value (including single-family homes) was captured in the tax increment	Residential property value excluded from tax increment	Adverse Impact on Other Units
Prior to 2008	**2008 Legislative Change**	**Concern addressed by legislative changes**
50 years was the maximum term allowed for TIF bonds	25-year term allowed for TIF bonds	Scope beyond intended purpose of TIF
Membership of Redevelopment Commission Board did not include a representative from schools	A non-voting adviser representing school corporations was added to the Redevelopment Commission Board	Lack of oversight and transparency
A Redevelopment Commission could amend its plan or the size of an allocation area through a public hearing unless the area expanded by more than 20 percent in which case	Any change in the size of the TIF area or any amendment to its plan required going through the entire process as if a new TIF area was being established	Lack of oversight and transparency

the full process of legislative body approval was required		
Redevelopment Commissions had eminent domain power in blighted areas but not in EDAs	Redevelopment Commissions need local legislative body/fiscal body approval for eminent domain	Lack of oversight and transparency
Lease financing could go up to 50 years	25-year limit for lease financing	Scope beyond intended purpose of TIF
Redevelopment Commissions were permitted to make improvements within, or in areas directly servicing or benefitting, the TIF area	Certain types of improvements are required to be physically located in or physically connected to a TIF area.	Scope beyond intended purpose of TIF
Redevelopment Commissions could make determination about excess value and just needed to notify the county auditor	Redevelopment Commissions are required to notify the county auditor, the fiscal body, and all taxing units of its determination about the use excess value	Lack of oversight and transparency; Stockpiling of excess AV
Redevelopment Commissions could issue bonds below $3 million without legislative body approval	All Redevelopment Commission bonds regardless of amount required to be approved by the legislative body	Lack of oversight and transparency
30-year limit to life of a TIF area	25-year limit to life of a TIF area. In 2010, 25-year limit is from the first day of a bond or lease obligation rather than the date of establishment	Adverse impact on other units; Stockpiling of excess AV
Prior to 2011	**2011 Legislative Change**	**Concern addressed by legislative change**
Referendum authorized in 2008 allowed taxes associated with all referendum levies, including school operating levies and debt levies for capital projects, to be captured in TIF areas	All referendum levies excluded from being captured in TIF area	Stockpiling of excess AV
Prior to 2014	**2014 Legislative Changes**	**Concern addressed by legislative changes**
No expiration for TIF areas established before 1995	TIF areas established before 1995 will expire on the later of July 1, 2015 or the final maturity date of any bond	Scope beyond intended purpose of TIF

	issues outstanding on July 1, 2105. As a result, the latest possible expiration year for pre-1995 TIF area is 2040	
No specific requirements on pass through of excess value	If the excess value is more than 200 percent of debt service and other anticipated redevelopment commission obligations, the excess amount has to be indicated to the elected body and the elected body can modify the redevelopment commission's decision about the use of excess amounts	Stockpiling of excess AV
"But For" was implicit in legislation	Whenever a TIF area is created or expanded there needs to be a finding supported by evidence that the creation or expansion of the TIF area will result in new property tax revenues that would not have been generated but for the TIF related activity	Capturing AV growth that would have occurred anyway
Acquisition of property by Redevelopment Commissions via long-term installment purchase financing methods didn't need legislative body approval	Some acquisitions of property by redevelopment commissions need local legislative body approval. For instance, a redevelopment commission that purchases property with payments for more than 3 years or that cost $5 million or more requires legislative body approval.	Lack of oversight and transparency
Redevelopment Commissions had certain reporting requirements related to their budgets.	Added requirements – (i) redevelopment commissions are required to submit detailed budgets to elected legislative bodies for review; (ii) annual reporting; (iii) more streamlined reporting process	Lack of oversight and transparency
Redevelopment Commission with approval from elected body had eminent domain power in redevelopment areas	Eminent domain power removed from Redevelopment Commissions	Lack of oversight and transparency
Redevelopment Commissions had the option to hire treasurer or utilize elected fiscal officers	Redevelopment Commissions are required to use elected fiscal officers	Lack of oversight and transparency

The changes outlined in Table 2.2 are indicative of a process of refinement and redesign of the primary statute governing TIF related activities in Indiana. Section 39 which deals specifically with tax increment financing had the most legislative focus. In addition to being the section with the most legislative changes, there were thirteen other sections that had legislative changes with a connection to section 39.

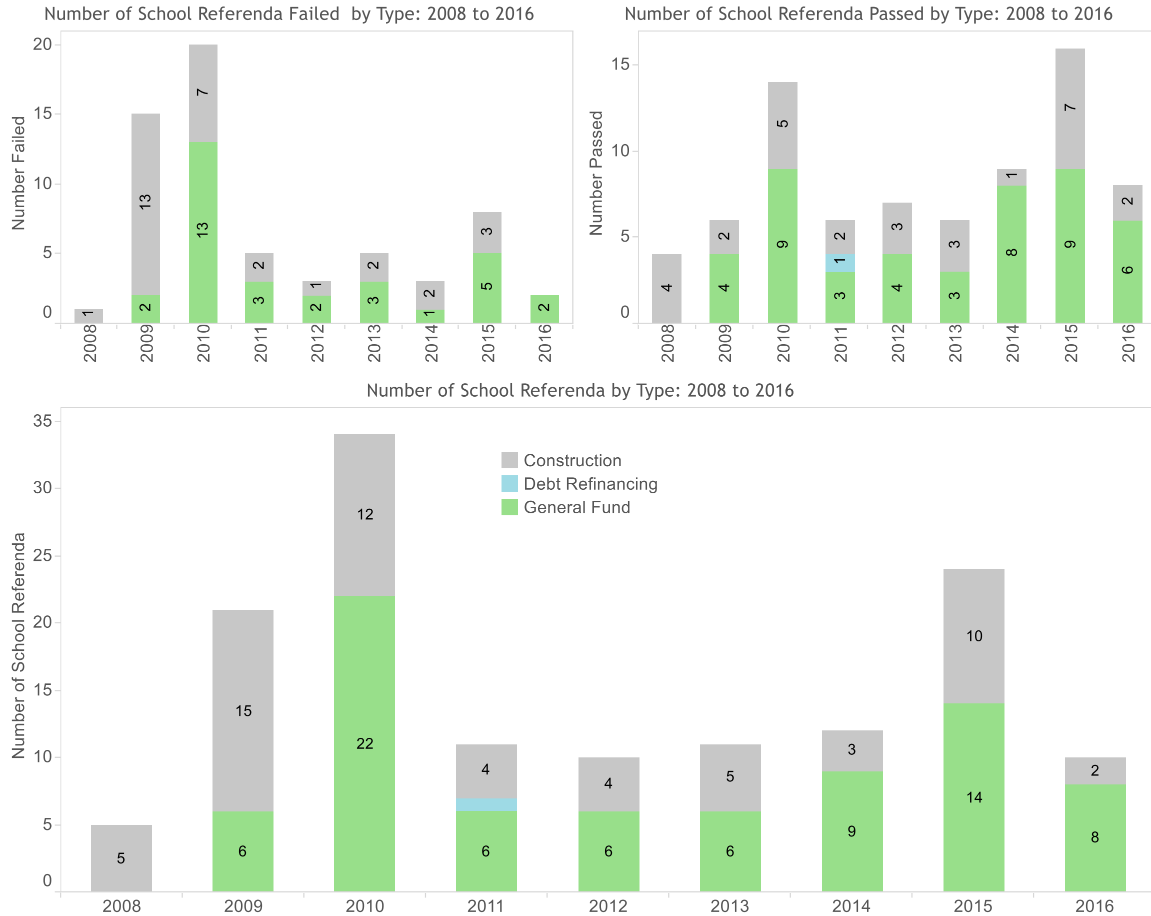
Table 2.3 provides the results of an analysis of major changes to the law governing redevelopment commissions and tax increment financing in 1995, 2008, 2011, and 2014 with regard to the major concerns identified above.

Table 2.3: Response to Concerns via Legislative Action

Concerns	Percent
Legislative changes that address concern that TIF districts take money away from other taxing units	14%
Legislative changes addressing lack of transparency and lack of elected official oversight	43%
Legislative changes addressing the concern that redevelopment commissions "stockpile" excess incremental assessed value instead of releasing unneeded amounts to the base	19%
Legislative changes that address concern that TIF is used beyond its intended purposes (a) geographically, (b) substantively, (c) duration	19%
Legislative changes that address concern that TIF districts capture assessed value that would have occurred anyway without the use of tax increment financing.	5%

Based on our analysis of challenges facing TIF districts, there are some emerging issues that will likely require legislative consideration. One in particular, is the impact of school referenda on debt coverage ratios, in particular, referenda involving capital projects. Since 2008, there have been 138 school referenda and 92 have involved school corporations that intersect with TIF districts. Figure 19 shows that there was a substantial increase in the number of school referenda in 2009 and 2010 and another surge in 2015. While more school referenda failed than passed in 2009 and 2010, since 2011 the number of school referenda passed has exceeded the number failed. General fund school referenda represent 56 percent of all referenda and 61 percent of the referenda that have passed over the 2008 to 2016 time period.

Figure 19: Number and Type of School Referenda: 2008 to 2016



While general fund school referenda have not posed long-term challenges for TIF districts there is emerging evidence that the 2011 legislation that excluded capital projects debt levies from being captured in TIF areas is creating serious debt service challenges for a number of TIF areas.

Figures 20 and 21 below illustrate the impact of the legislative change that excludes school capital projects debt referenda taxes from being captured by TIF areas. In each instance, the long-term impact on projected tax increments in TIF areas as a result of the exclusion of debt levies for capital projects have sharply reduced projected debt coverage ratios.

As Figure 20 shows, with the assumed tax increment projected based on a stable projected net tax rate of 1.7232 per $100 of assessed value, debt coverage ratios fall within the range of 1.4 and 1.2 over the repayment years. With the capital project school referendum and the exclusion of those levies from the TIF area, the projected tax increments are adjusted downwards and as a result the debt coverage ratios are now in the range of 0.88 to 1.15.

Figure 20: Impact of School Referndum on Debt Coverage Ratio of TIF District

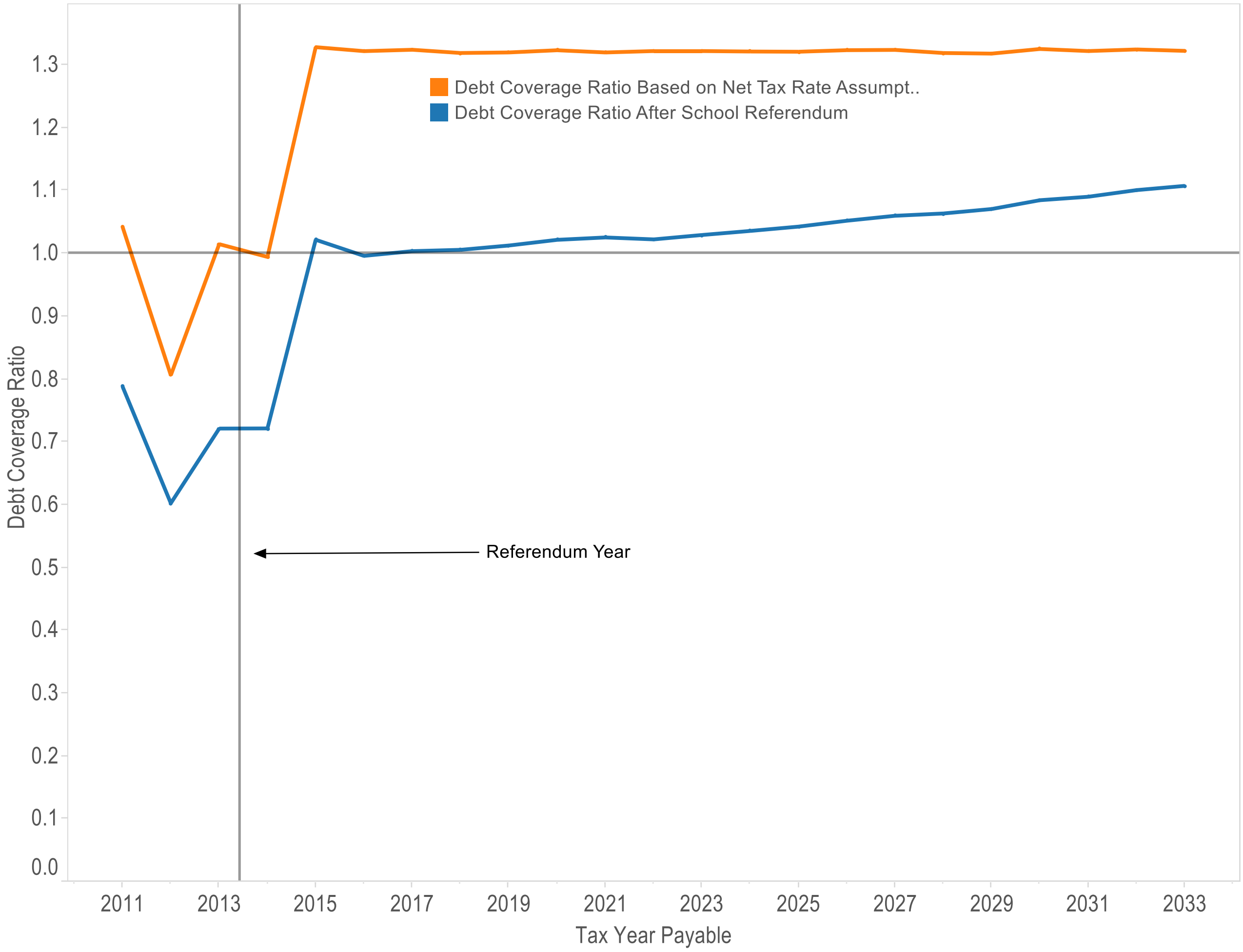
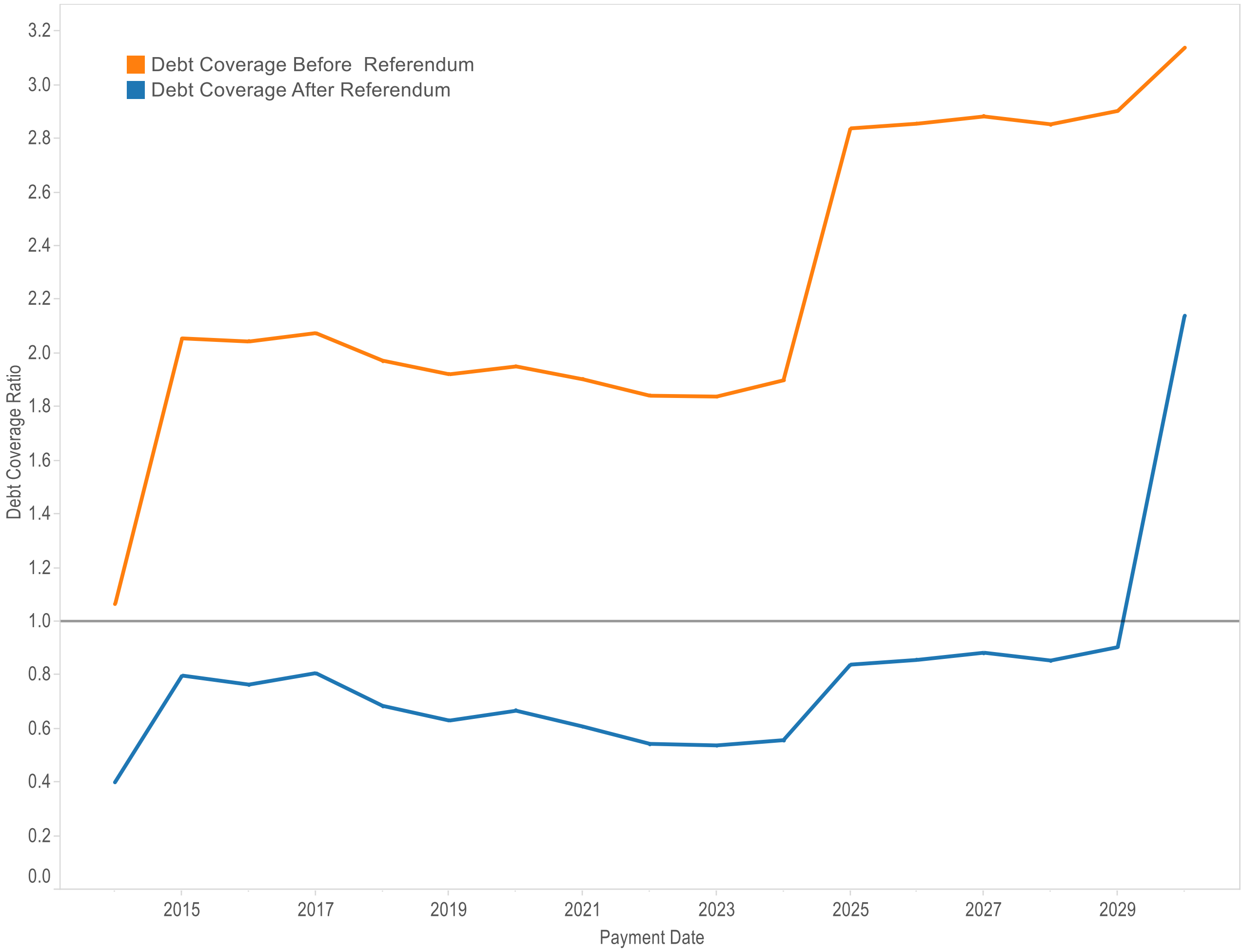


Figure 21 provides another illustration with a shorter-term bond and a recent school construction referendum. In this case the projected impact is catastrophic. As an emerging issue there is an opportunity to design a framework to detect the likely incidence of similar occurrences. This also represents an opportunity to re-calibrate the policy related to non-capture of taxes in TIF areas associated with school referenda on debt refinancing and capital projects.

Figure 21: Debt Coverage Ratio Before and After School Referendum



3. Strategic (Dynamic, Game-Theoretic) Considerations in the Adoption of TIF[24]

The Strategic Context

The stated purposes behind the adoption of TIF are either spurring the economic development of an area (TIF with Economic Development Area or EDA-designation) or jumpstarting the redevelopment of a 'blighted area' (TIF with Redevelopment Area or RDA-designation). While these are the primary stated purposes behind the adoption of TIF, empirical evidence has been uncovered for other 'drivers' of TIF adoption. One such driver is strategic – where TIF is adopted by one geographic area in response to (or in anticipation of) TIF adoption by an adjoining geographic area. There are two possible reasons behind this strategic behavior: competitive or complementary. The competitive perspective states that TIF adoption in one county makes that county more appealing for business location (or relocation) and therefore adjacent counties must also adopt TIF to protect and preserve their private business-investment. The complementary perspective states that as one county adopts or expands TIF, that county experiences economic growth and adjacent counties can take advantage of this growth (owing to positive spillovers or agglomeration economies) by adopting or expanding their own TIF usage.

Previous studies such as Man (1999) and Byrne (2006) found evidence of strategic TIF-related behavior for some Indiana municipalities and municipalities in the Chicago metropolitan area, respectively. More recently, Mason and Thomas (2010) also found evidence for strategic TIF adoption in Missouri. These studies examine the timing of initial TIF adoptions in surrounding municipalities to infer strategic behavior, although Mason and Thomas (2010) also analyze the number of TIF districts. Our study seeks to expand this research in two areas. First, previous studies rely on cross-sectional data (across geographic areas), whereas we collect panel data (across both geographic areas and across time periods) in order to analyze the issue from a dynamic perspective. Second, instead of interpreting strategic behavior as simply the timing and number of TIF adoptions, we look at 'TIF intensity' which we define as the incremental assessed value of TIF districts as a proportion of the total net assessed value of property in a county. This variable allows us to more precisely capture the extent of TIF usage than the number of TIF districts or TIF adoptions – since a county may set up a number of TIF districts but not actively invest in them.

TIF Intensity - the degree to which a county uses TIF as a development tool measured by the ratio of TIF incremental assessed value to total net assessed value in a county

[24] The data used in this and subsequent sections are all in nominal and not real terms. This is done for two reasons: a) Price-level indices for each county in Indiana are not readily available for the time period considered, and b) Deflating the nominal variables by a state-level price-index, while not quite appropriate, does not qualitatively affect our results.

Strategic Behavior – Simple Correlation Approach

We examine the strategic TIF behavior of counties through two lenses. First, we superficially examine strategic TIF-related behaviors from an 'imperfect information' or simple correlation perspective. This gives us a base-level analysis that we can then subject to more sophisticated scrutiny. For example, a county redevelopment commission may not use advanced statistical techniques in making decisions about TIF usage and instead may rely on 'eyeball estimates'. That is, commissions may simply assess what neighboring counties are doing in relation to economic development, and make imperfect inferences about the connections between the two. If they observe a positive correlation between a neighboring county's TIF intensity and its economic growth measures, they may infer a causal relationship and increase their own TIF intensity. Thus a positive correlation between the two provides a rationale to further explore the issue.

To perform this base-level analysis, we use a core-periphery framework. First we define core counties. A core county is a county which has sent a strong signal to its adjacent or periphery counties that it has used and intends to use TIF at high levels of intensity. A high TIF-intensity, or core county is defined as a county that attained 10percent or more of its incremental assessed value (IAV) to net assessed value (NAV) at some point between 2003-2014. While other thresholds above or below 10 percent can certainly be employed, we posit that a 10 percent threshold strikes a reasonable balance between a county's commitment to TIF use, and a need to have a reasonable number of core counties with which to conduct the empirical analysis. Given that the analysis focuses primarily on observed correlations (with more detailed causal analyses conducted later in the report) the use of a 10percent threshold (while admittedly ad hoc) is not of substantial concern. Based on our definition, Table 3.1 lists the counties that emerge as CORE counties and their corresponding 'signal year'. Figures 3.1 and 3.2 show the core-periphery counties under different timeframes.

Table 3.1 Core Counties

County Name	Signal Year
Perry County	2003
Gibson County	2005
Clark County	2006
Saint Joseph County	2007
Hamilton County	2008
Hendricks County	2008
Tippecanoe County	2008
Spencer County	2010
Whitley County	2010
Orange	2011
Scott County	2011
Decatur County	2012
Grant County	2012
Bartholomew	2013
Jennings	2013

Marion	2013
Shelby	2013
Boone	2014
Madison	2014

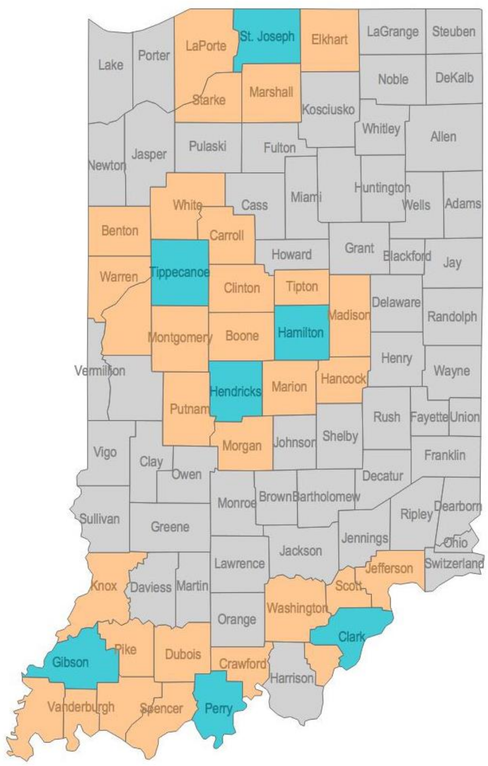


Figure 3.1 Core (blue) and periphery (orange) Counties: 2003-2008

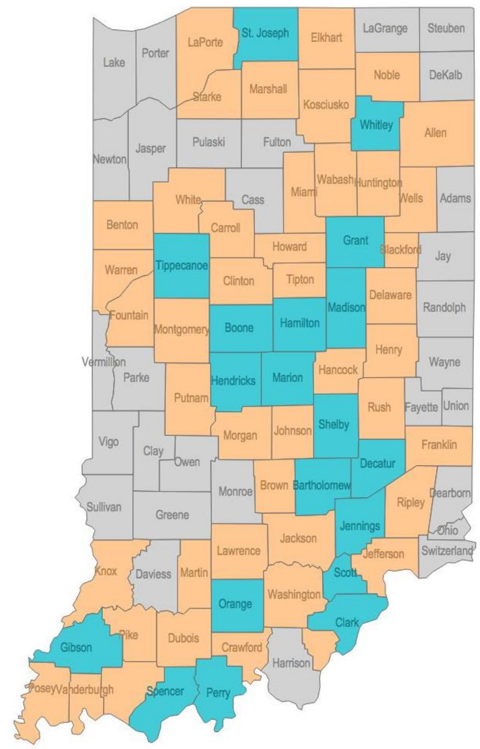


Figure 3.2 Core (blue) and periphery (orange) Counties: 2003-2014

After identifying core counties, we calculate a simple correlation coefficient for each adjacent county's TIF intensity and its employment growth rate over the study period since the initiation of the core county. These correlations are subsequently averaged for each core county. The results from Table 3.2 show a small but positive correlation between the adjacent county's average TIF intensity and its average employment growth rate over the time period. The positive correlation is interpreted as follows: the higher the adjacent county's TIF intensity, the higher the average employment growth rate in that adjacent county that year. It should be noted that though these two variables are positively correlated, it does not necessarily follow that TIF intensity *causes* higher employment growth rates in the core-adjacent counties. The results do suggest, however, that the strategic response of an adjacent county to a county that has signaled itself as a high TIF-intensity user is to increase its own TIF-intensity. Thus, there appears to be preliminary evidence of strategic behavior.

Table 3.2: Correlation Coefficient of Adjacent Counties to a Core County
(Percent of IAV in TIF in Adjacent County and the Adjacent County's Employment Growth Rate)

Core County Signal Year	Number of Core Counties	Average Correlation Coefficient for Adjacent Counties (2003-2014)	Average Correlation Coefficient for Adjacent Counties (2010-2014)
2003-2005	2	0.048	0.254
2003-2008	7	0.044	0.063
2003-2010	9	0.024	0.053
2003-2012	13	0.035	0.037
2003-2014	19	0.040	-0.009

It should also be noted that while the coefficient is positive, the magnitude is small, meaning that the relationship is weak. However, it is important to note that the magnitude of the relationship increases as the signal year of the county is earlier in time. This is logical as many of these core counties did not 'signal' their core status until later in the time period meaning that there may be a significant lag period for TIF activity. For example, as described in Table 3.1, many of the core counties did not signal their status until at least 2008 with many counties not signaling until 2012 and later. This may be why the correlation coefficient is negative only for the time period 2010-2014, when core counties with a signal year of 2013 and 2014 are included.

Strategic Behavior – Statistical Analysis

After establishing the possibility of strategic behavior with TIF intensity, we move on to a more formal statistical analysis. The first step is to choose the appropriate econometric model. Given that we are analyzing strategic behavior across geographic space, we must take spatial considerations into account. Anselin (1988) popularized a series of multiple spatial models with minor variations attempting to distinguish each model for specific cases; however, LeSage (2014) argues that only two spatial models need to be considered: the spatial Durbin error model (SDEM) and the spatial Durbin model (SDM).[25] The benefit of these models is that they allow for parameter estimation of both direct (own-region) effects and indirect (other-region or spillover) effects (Lesage and Pave; 2009). Regarding the modeling of strategic behavior and TIF intensity, it is expected that, if strategic behavior exists, an increase in TIF intensity in County A for example, should lead to an increase in TIF intensity in bordering County B which

[25] The SDEM model should be used in cases of local spillovers meaning that there are no endogenous feedback loops whereas the SDM should be used when these endogenous feedback loops may be present, also known as global spillovers.

then feeds back to affect County A's behavior, but also should affect County C which borders County B. The basic (linear in parameters, reduced form) SDM model with spatial panel data is represented in Equation (1):

$$Y_{i,t} = \rho WY_{j,t} + X_{i,t}\beta + WX_{j,t}\theta + \mu + \alpha_t \iota_N + u_t \qquad (1)$$

where county i's TIF intensity, or Y, in year t is a function of the $\mathrm{TIF\ Intensity}$ of other counties j at time t weighted by the spatial lag matrix, W, which in this case is the first order contiguity matrix for each county (i.e. the adjacent or "neighboring" counties), a matrix of own region determinants or independent variables, a matrix of these independent variables in neighboring counties at time t, a vector of spatial fixed effects, μ, time period fixed effects, α_t, and an error term, u_t.

Elhorst (2014) surveys existing econometric models on spatial panel data including the static model shown above as well as a dynamic spatial Durbin model represented in Equation (2), where $\tau Y_{i,t-1}$ is the lagged value of TIF intensity in the last period for county i and $\eta WY_{j,t-1}$ is the time-lagged value in surrounding counties. He demonstrates the benefit of analyzing the change in a dependent variable over space and time. Elhorst and Fréret (2009) illustrate techniques to determine the appropriate model - which will also be used in our analysis.

$$Y_{i,t} = \tau Y_{i,t-1} + \rho WY_{j,t} + \eta WY_{j,t-1} + \beta X_{i,t} + WX_{j,t}\theta + \mu + \alpha_t \iota_N + u_t \qquad (2)$$

Model Specification

The next step is to determine the appropriate matrix of own and other region determinants on TIF intensity. Here we utilize the empirical models from the previous studies on TIF adoption cited above. The basic empirical model specification derived from the work of Man (1999), Dye and Merriman (2000) Byrne (2006) and Mason and Thomas (2010) is that TIF adoption is a function of the following with the expected sign though we substitute TIF Intensity for TIF adoption.

TIF Intensity = F (Political Cost (+), Fiscal Stress/Market Failures (+), Blight/Current Infrastructure (+), Ability to Pay Taxes (-), Strength of Business Community (+), Path Dependency (+) and possibly Strategic/Neighbors (+) and Revenue Capture (+)) (3)

As mentioned, we can improve on this model by using panel data, using a dynamic SDM and examining the intensity of TIF use as opposed to just TIF adoption. As a result, we have estimated the above model using many of the same variables found in the previously cited studies:

<u>*Political Cost*</u>

-*Local Tax Rate:* It has been argued by Anderson (1990), Man (1999) and Byrne (2006) that higher local tax rates should have a positive impact on TIF adoption as local officials pay a higher political cost for raising taxes and, therefore, look to alternative sources of funding for infrastructure projects.

-*Homeownership Rate*: Byrne (2006) also argues that the percent of owner-occupied housing should lead to a higher likelihood of TIF adoption as these residents pay the property taxes and are more likely to vote since they are less transient. Higher homeowner participation in the local election process is also supported by Glaser and Hildreth (1999); however, residents that are more involved politically are also less likely to be satisfied with local public services (Scott and Vitartas 2008).

Fiscal Stress/Market Failures

-*Population:* As argued by Byrne (2006), growing cities may face added stress on local public services and seek to find alternative funding sources for larger infrastructure projects. Dye and Merriman (2000) also argue that larger cities may be able to devote more resources to economic development initiatives.

-*Unemployment Rate*: The local unemployment rate could function in a couple of ways. First, it could signal fiscal stress as less residents have the ability to pay taxes - as argued by Byrne (2006) or as argued by Man (1999), it could signal private market failure in the area, leading to local government intervention to restructure the area's economy based on more suitable industries. The latter type of local government intervention is also known as place-based economic development in which factors of production (in this case labor) are not perfectly mobile due to many reasons including poverty, relational networks or other constraints leading to local policies aimed at increasing the efficiency of these factors (Partridge, Rickman, Olfert and Tan; 2015).

Blight/Current Infrastructure:

-*Poverty Rate:* Local blight and redevelopment is often given as an official reason in the adoption of TIF with the RDA (Redevelopment Area) designation. It may also be a proxy for the current quality of local infrastructure.

Ability to Pay Taxes:

-*Personal Income*: The greater the local area's ability to pay taxes, the less likely the need to seek alternative funding sources. Personal income was chosen over per capita personal income as population is already included in the model.

Strength of Business Community*:*

-*Employment Density*: Dye and Merriman (2000) and Byrne (2006) argue that a stronger business community may lead local policymakers to be more receptive to their infrastructure needs. Dye and Merriman (2000) use the non-residential share of equalized assessed value (EAV) and Byrne (2006) uses the percentage of non-residential property. We use employment/acre to proxy for the strength of the local business community as residents may commute in from neighboring counties for employment.

Previous Use*:*

-*Lagged TIF Intensity*: Reese (2006) finds that cities in Michigan that used tax abatements previously were more likely to use them over time. Our dynamic framework naturally allows us to examine this issue with TIF intensity. Does prior investment in TIF lead to a greater use of TIF over time? There may be two reasons for this: first the county could simply be more familiar with the tool and second, they could have experienced positive results in the past with it.

Strategic/Neighbors*:*

-*Spatially Lagged TIF Intensity*: As mentioned earlier, multiple studies have found evidence of strategic behavior in TIF adoption. We analyze whether there is strategic behavior in relation to the magnitude or intensity of a county's use of TIF - as measured by the proportion of the incremental assessed value in a county to total incremental assessed value of surrounding counties.

Revenue Capture:

-Prior Growth of Incremental Assessed Value (IAV): Byrne (2006) uses the prior growth of property value to test whether TIF is used to capture future expected growth or revenue. An increase in the previous IAV in the county would signal future expected growth thereby leading cities to expand their use of TIF in order to capture this anticipated revenue. This is calculated as the difference between the current county IAV and the previous year's county IAV.

A Note on Fixed Effects: As shown in equation (2), the model used here includes spatial fixed effects and time fixed effects. While other studies include a set of other variables to control for various differences across space and time, such as demographics, this study, through the use of county and time fixed effects controls for all time-invariant and time-specific shocks, greatly reducing the possibility of omitted variable bias. A drawback to this approach is specificity. We know little about what factors specifically drive the significance of these effects, should significant fixed effects occur. Given the nature of the analysis, we contend that the need to prevent omitted variable bias trumps the specificity concern.

Data: The data used in this analysis are for all Indiana counties (except LaPorte) from 2009-2014. These years were chosen as homeownership rates were not available prior to 2009 and focusing only on the post-recession timeframe allows us to avoid the modeling difficulties posed by the Great Recession. These difficulties will be discussed later in the report.

Regression Analysis

The technique of regression helps in isolating the effect of a particular (independent) variable – the independent variable of interest - say, TIF intensity of surrounding counties on another variable (the dependent variable), say, TIF intensity of the 'surrounded county', by accounting for the influences of other major variables that might impact the dependent variable. Without accounting for these influences of the other variables, one would not able to determine whether changes in the dependent variable are being driven the independent variable of interest or by some other variable that is correlated with this variable (say, population).

The regression results from implementing (3) above are presented in Table 3.4. Model 1 includes all of the above variables except for Prior Growth of Incremental Assessed Value (IAV) which will be included later. To ensure that the appropriate model is used, the methodology in Elhorst and Fréret (2009) will be employed. Their methodology essentially utilizes a likelihood ratio (LR) test, applied under different model specifications. The first goal of the test is to justify the use of a dynamic model (Equation 2) over a static model (Equation 1). Here, we test whether the time-lagged variables of the dependent variable, $\tau Y_{i,t-1}$ and $\eta WY_{j,t-1}$, are jointly significant. The LR test results indicate a value of 111.72 ($p < 0.001$), strongly rejecting the static model.

Specification tests can also be conducted to determine appropriate use of county fixed effects. The Hausman test results indicate a value of 291.40 ($p < 0.001$), strongly rejecting the random effects model. Another test can be conducted to determine the validity of using time fixed effects. The LR test results indicate a value of 33.85 ($p < 0.001$), strongly rejecting a model without time fixed effects. Cumulatively, the results suggest that dynamic SDM with both county and time fixed effects is the most appropriate model (Equation 2).

The regression results show that there is no statistical support for strategic interaction among counties with regard to TIF intensity, as shown by the Spatial - Percent TIF results at the top of the table. This result is in contrast to previous literature regarding the strategic behavior of TIF adoption, though as noted this is the first study that we know of, to analyze strategic behavior based on TIF intensity. In other words, while geographic areas may engage in strategic behavior in the timing of initial TIF adoption, they do not appear to engage in strategic behavior when it comes to the magnitude or the intensity of their level of investment in TIF areas. There may be strategic behavior in starting TIFs, but counties do not continue to strategically escalate their TIF intensity. While the simple correlation approach appeared to give evidence for strategic interaction, the more formal statistical analysis based on an empirical model did not. In other words, other covariates in the model are responsible for the simple bivariate correlations identified in the previous section of this report.-

While the results do not support strategic behavior with regard to TIF intensity, the other variables in the model do have significant explanatory power in determining increases in TIF intensity in a county. Here as with several other studies, the higher the local tax rate the more likely a county increases its TIF intensity suggesting that political cost is a significant factor in counties increasingly investing in TIF districts. This is reinforced by the homeownership rate which also proxies for political cost.

As an explanatory variable, personal income is negative and statistically significant, as expected. As county constituents have a greater ability to pay, the less reliant a county has to be on alternative sources of revenue. The unemployment rate is positive, indicating the influence of either fiscal stress or market failure and the use of TIF as a place-based instrument.

Table 3.4 Strategic Behavior and TIF Intensity

	Model 1		Model 2		Model 3		Model 4	
Dependent Variable	Percent TIF		Percent TIF		Percent TIF		Percent TIF	
	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
Spatial - Percent TIF	0.0134	0.19	0.0192	0.27	0.0148	0.21	0.0096	0.13
Direct	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
Local Tax Rate	0.8830	1.89*	0.9074	1.94*	0.9047	1.92*	0.9518	2.03**
Homeownership Rate	0.0733	1.71*	0.0707	1.64*	0.0669	1.53	0.0696	1.63
Personal Income	-1.27E-06	-5.13***	-1.29E-06	-5.12***	-3.33E-07	-2.29***	-1.20E-06	-4.80***
Unemployment Rate	0.2402	3.08***	0.2372	3.07***	0.1396	1.99**	0.2151	2.70***
Poverty Rate	-0.0414	-1.01	-0.0447	-1.09	-0.0474	-1.19	-0.0410	-1.0
Population	0.0001	0.80	0.0001	1.02	-	-	0.0001	0.99
Employment Density	0.0564	3.16***	-	-	-	-	0.0502	2.76**
Total Employment	-	-	1.30E-04	3.03***	-	-	-	-
Prior Growth IAV	-	-	-	-	-	-	7.24E-12	0.51
Lag Percent TIF	0.4051	11.19***	0.4094	11.31***	0.4486	12.09***	0.4014	11.12***
Indirect	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
Local Tax Rate	-1.856	-1.62*	-1.786	-1.55	-1.905	-1.47	-1.416	-1.14
Homeownership Rate	0.0327	0.35	0.0356	0.38	0.0026	0.03	0.0270	0.31
Personal Income	5.23E-07	0.92	6.06E-07	1.04	7.06E-07	2.68***	8.42E-07	1.30
Unemployment Rate	-0.2557	-2.37**	-0.2572	-2.35**	-0.1908	-1.98**	-0.0021	-1.92*

Poverty Rate	0.0470	0.57	0.04818	0.58	0.04487	0.52	0.2326	1.03
Population	-0.0001	-0.64	-0.0001	-0.20	-	-	-0.0001	-0.22
Employment Density	0.0192	0.64	-	-	-	-	-0.0046	-0.12
Total Employment	-	-	1.57E-05	0.17	-	-	-	-
Prior Growth IAV	-	-	-	-	-	-	6.67E-11	2.05**
Lag Percent TIF	0.0348	0.31	0.0372	0.35	0.05568	0.62	0.0569	0.55
Fixed Effects	Yes		Yes		Yes		Yes	
Time Period Effects	Yes		Yes		Yes		Yes	
N	546		546		546		546	

The county poverty rate is a not significant factor, suggesting that TIF activity has focused less on blight correction and more on economic development, with most of the TIF districts possessing an EDA as opposed to an RDA designation. These results, however, do not indicate that TIF is not used for or not successful in blighted areas, but that changes to a county's poverty rate do not drive a change in TIF intensity. Employment density is a positive factor and significant indicating that local business strength may lead to more investment in TIF districts. This could also mean that growing counties are more likely to invest in TIF as it is highly correlated with population. There could also be endogeneity issues[26] in the model as more investment in TIF could lead to more employment. Also, the lagged percent TIF is positive and significant suggesting previous use effects exist in TIF as they did in tax abatements found by Reese (2006); therefore, suggesting that once a county increases its TIF intensity, it is more likely to use this economic development tool to a greater degree in the future.

The indirect or spillover effects in Model 1 show some statistically significant indirect effects. The unemployment rate is negative and significant. This is an intuitive result meaning that the higher a county's unemployment rate, the less likely it is that the surrounding counties will invest in TIF districts. The other statistically significant indirect effect is the local tax rate which is positive and significant meaning that the higher a county's local tax rate, the less likely it is that surrounding counties invest in TIF. This may imply that surrounding counties do not need to use TIF as much for business attraction given their lower relative tax rates or that surrounding counties act strategically with regard to tax rates and thus an increase in a neighboring county's tax rate may lead to an increase in the local tax rate and

[26] Endogeneity arises when an 'independent variable', say employment density, is influenced, in turn, by the dependent variable, investment in TIF.

decreased use of TIF investment.[27]

Models 2-4 test for robustness of the results under different model specifications. Model 2 substitutes total employment for employment density with no major changes in the results. Model 3 removes both total employment and population as these variables are highly correlated with each other and also with personal income. Model 4 takes the natural log of both personal income and total employment. There is little change in the results under these different specifications, demonstrating that the results are relatively robust to these adjustments.

Further, Model 4 takes the original variables in Model 1 and adds Prior Growth of Incremental Assessed Value (IAV) to test whether or not TIF is simply a tool for revenue capture. In other words, an increase in the previous IAV in the county would signal future expected growth thereby leading counties to expand their use of TIF in order to capture this anticipated revenue. The direct results for prior growth are statistically insignificant; however, the indirect results are positive and highly statistically significant, implying that an increase in the prior growth of IAV in a county leads to an increase in surrounding counties' TIF intensity - suggesting that the neighboring counties may be trying to best position themselves to take advantage of any positive spillovers. This result does furnish some evidence of strategic behavior with regard to TIF intensity. As mentioned above, there are two possible reasons behind this strategic behavior: competitive or complementary - and this result is not able to identify whether the underlying motive is to compete to attract business away from the growing county or whether it is to assume an advantageous position with regard to capitalizing on potential positive spillovers.

Main Insight

This section analyzed the various reasons behind a county's decision to increase its TIF intensity. The simple correlation approach attempted to model this decision through the lens of casual observations - in that a county may not use sophisticated statistical techniques in making decisions about TIF usage and instead may rely on 'eyeball estimates', by observing what neighboring counties are doing in relation to how they are growing, and make imperfect inferences about the connection between the two. The simple correlations appeared to give evidence for strategic behavior. However, the more formal statistical analysis based on an empirical model did not. The statistical analysis based on an empirical model revealed that there is no statistical support for strategic interaction among counties with regards to TIF intensity; however, there appears to be a statistically significant positive indirect effect of the prior growth of a county's TIF intensity on surrounding counties.

The rest of the statistical results reflect significant explanatory power with regard to TIF intensity in a county and are consistent with other academic studies. Higher local tax rates and homeownership rates lead to higher TIF intensity due to higher political costs. Higher unemployment rates and greater employment density also lead to more TIF investment, while higher personal income leads to less TIF investment as the county does not need to rely on alternative funding sources for investment projects. Also, TIF does not appear to be used as a revenue capture tool. The next section will attempt to analyze the impacts of TIF on a county's economic development metrics.

[27] This strategic behavior of a county is further investigated in the next section.

4. Spatial Modeling of TIF: Impact of TIF on Tax Rate and Employment

Overview of Issues

One of the suggested impacts of TIF expansion from previous studies is that an increase in TIF intensity leads to higher local tax rates. While the results in the previous section and in other studies find evidence that the higher local tax rates lead to higher TIF intensity by way of political costs, others argue that the direction of causation should be reversed – higher TIF intensity leads to higher local tax rates. The direction of causation is difficult to sort out (as causality may actually be bilateral/endogenous) because many, if not all the variables that affect TIF intensity also affect local tax rates. The reason is that both are funding sources for the county – taxes are a direct funding source and TIF is an alternative funding source. To help provide some clarity, however, we will draw from the large amount of literature on the strategic behavior based on tax rates between geographic areas. This is termed Tax Mimicking. If we are able to determine the primary strategic interaction between counties, this will allow us to better infer the direction of causation.

The other topic of interest in this section is the impact of TIF on traditional economic development measures such as employment. As with the above, the relationship between TIF and employment is not as straightforward as it may appear. One of the primary reasons is that in the middle of the timeframe used by recent studies looms one of the largest recessions in US history. If this is not accounted for appropriately, it can bias the results. Other issues that will be discussed are the lack of sufficient appropriate data regarding TIF in Indiana and the lack of a theoretical and/or an empirical model that explains the long-term economic performance of local areas in Indiana.

An Analysis of TIF Intensity and Tax Rates

As mentioned above, one of the suggested impacts is that an increase in TIF intensity leads to higher local tax rates. To help with this issue we will draw from the tax mimicking literature on strategic behavior between areas. If we are able to determine the primary strategic interaction between counties, this will allow us to better infer the direction of causation.

The study of tax mimicking has become a recent focus of the academic literature on local and regional economic development in the past decade alongside advances in spatial econometrics. While the causes of tax mimicking are still in dispute ranging from local expenditure spillovers to factor attraction to yardstick competition (Allers and Elhorst 2005), the econometric models are relatively similar. This section does not attempt to distinguish the exact cause of tax mimicking, but rather to determine whether or not it exists among Indiana counties. If it can be determined that that counties primarily interact around tax rates instead of TIF intensity, this gives support for the results in the previous section that the primary direction of causation is that higher local tax rates cause increases in TIF intensity and not vice versa.

The econometric model to be used in analyzing tax mimicking is the same as that employed for analyzing

TIF intensity - as we are testing for spatial interaction across space and time, the dynamic SDM (equation 2). Again, the timeframe considered will be from 2009-2014 for the reasons stated earlier. Not surprisingly, many of the explanatory variables associated with TIF intensity are also relevant in modeling tax mimicking since they represent sources of revenue for counties. A brief literature review and justification for the empirical model used are provided below.

Political Cost

-*Homeownership Rate*: As Byrne (2006) argued for TIF intensity, the percent of owner-occupied housing should lead to relatively lower local tax rates as these residents pay the property tax directly and are more likely to vote in local elections, thus any increase in local tax rates is likely to face the ire of local voters.

Fiscal Stress

-*Population/Population Density*: Ladd (1992a) established a link between higher population density and local public sector spending due to the increases complexity of public services. As such recent studies on tax mimicking include population density (see Ladd 1992b and Gérard, Jayet and Paty 2010). Heyndels and Vuchelen (1998) include the region's geographic size. Other studies include population only (Brueckner and Saavedra 2001 and Revelli 2002a).

Ability to Pay Taxes:

- *Personal Income*: Personal income should positively impact the local tax rate. Greater ability to pay taxes should lead to higher local tax rates. This variable is also included in multiple tax mimicking analyses, including Ladd (1992b), Heyndels and Vuchelen (1998), and Gérard, Jayet and Paty (2010).

- *Unemployment Rate*: Another control for ability to pay in the literature is the local unemployment rate (see Revelli 2002b and Gérard, Jayet and Paty 2010). A higher unemployment rate could lead to less ability to pay and thus a lower local tax rate.

Fixed Effects: As with TIF intensity, the use of fixed county effects and time period effects allows us to control for many potential omitted variables including demographics. The same caveat regarding the tradeoff between omitted variable bias and specificity applies here.

While one reason to analyze tax mimicking across Indiana counties is to determine the primary source of interaction and strategic behavior, another is to analyze whether there is a significant impact of TIF intensity on the local tax rate. Given that many of the variables are the same across the two strands of literature, we will begin with the same model used with TIF intensity, but exchange the local tax rate for TIF intensity. After this we will move to a more appropriate tax mimicking model.

The regression results are presented in Table 3.1. As in the previous section, all models use a linear in parameters, reduced form specification. Model 1 shows a very strong spatial interaction effect. The value of the coefficient (0.28) is similar to other studies on property taxes including Revelli (2001) and Revelli (2002b) who estimated ranges of 0.4-0.5 and 0.3-0.6 respectively and Bordignon, Cerniglia and

Revelli (2003) and Solé Ollé (2003) with estimates of 0.3 and 0.39 respectively. Feld, Josselin and Rocaboy (2003) estimated a range between 0.3-0.6. Alongside the TIF intensity results, which gave no statistical support for county strategic behavior, it appears that counties primarily interact around their local tax rate. This means that counties are conscious and sensitive to the neighboring counties' tax rate and act/react relative to it.

Table 4.1 TIF Intensity and Local Tax Rates

	Model 1		Model 2		Model 3	
Dependent Variable	Local Tax Rate		Local Tax Rate		Local Tax Rate	
	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
Spatial – Local Tax Rate	0.2788	4.53***	0.2762	4.48***	0.2718	4.40***
Direct	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
Percent TIF	0.0040	1.50	0.0036	1.38	0.0039	1.52
Homeownership Rate	0.0034	1.19	0.0038	1.15	0.0040	1.15
Personal Income	5.38E-08	2.44**	3.94E-08	2.00**	4.00E-08	2.04**
Unemployment Rate	-0.0028	-0.52	-0.0016	-0.31	-0.0026	-0.51
Poverty Rate	-0.0021	-0.75	-0.0023	-0.74	-	-
Population	6.56E-06	1.69*	-	-	-	-
Employment Density	-0.0009	-0.50	-	-	-	-
Population Density	-	-	0.0028	2.20**	0.0028	2.04**
Lag Local Tax Rate	-4.07E-06	-2.00**	-4.46E-06	-2.29**	-4.12E-06	-2.28**
Indirect	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
Percent TIF	-0.0009	-0.14	0.0001	0.01	0.0005	0.04
Homeownership Rate	-0.0040	-0.69	-0.0040	-0.46	-0.0034	-0.36
Personal Income	4.45E-08	0.89	3.96E-08	0.71	3.62E-08	0.68
Unemployment Rate	-0.0141	-1.30	-0.0197	-2.33**	-0.0188	-2.23**
Poverty Rate	0.0072	1.24	0.0074	0.82	-	-
Population	-0.0001	-1.60	-	-	-	-
Employment Density	0.0046	0.98	-	-	-	-
Population Density	-	-	-0.0015	-0.43	-0.0012	-0.33
Lag Local Tax Rate	-4.89E-06	-0.66	-3.96E-06	-0.77	4.30E-06	-0.88
Fixed Effects	Yes		Yes		Yes	
Time Period Effects	Yes		Yes		Yes	
N	546		546		546	

While many variables affect the local tax rate, Jonas (2012) examines the post-recession impacts at the sub-national level and finds that the Great Recession had severe adverse effects on state and local finances, while simultaneously increasing demand for local public services - leading to a decrease in reserves, spending cuts and increasing tax rates. As income and housing values fell, local governments faced significant declines in local tax revenue over time. In Indiana, this was further exacerbated by property tax caps, which went into effect in 2009 and were formally put into the state constitution in 2010. This budget shortfall may have put pressure on local governments to increase local tax rates; however, this strained their political capital possibly leading some of them to try and mitigate or eliminate this effect by looking for alternative funding sources such as TIF.

TIF Intensity is positive but not statistically significant at conventional levels suggesting that TIF intensity does not have a statistically significant effect on the local tax rate. The reason that this result differs from previous studies using the same data is that previous studies only tested for simple correlation between two variables without taking into account a literature-supported empirical model to explain local tax rates such as we have done here with tax mimicking.

Model 1, however, is not the preferred model in the tax mimicking literature. Model 2 replaces population and employment density with the preferred population density variable. Personal income and population density are positive and significant as expected. Model 3 removes the poverty rate. The results do not change drastically suggesting robustness of the coefficient estimates.

While the results for TIF intensity on local tax rates are not statistically significant at conventional levels, this does not mean that we can conclude that it definitely has no impact on local tax rates. The standard tests for statistical significance do not allow for such a definitive statement. It is more preferable for policy implementation to use confidence intervals as they allow for a range of possibilities. This gives policymakers more information for assessing the risks and potential consequences of various decisions. In other words, we argue that it should be the policymaker who makes the decisions using data and reasoned-discretion instead of data determining the decisions for policymakers.

Table 4.2 provides the 90 percent confidence interval for TIF intensity on local tax rates using Model 3. The interval below can be interpreted as follows: we are 90 percent confident that a one percentage point increase in TIF Intensity leads to a Local Tax Rate change between -0.0003 and 0.0081 percentage points. The reason that it is not considered statistically significant is because we cannot rule out a value of zero or no impact, but the true value may be anywhere within this range or even outside it, though we are 90 percent confident it is within this range given the specification of the model. The true value may in fact be negative. One reason may be that TIF could increase economic activity leading to a larger tax base allowing the same amount of tax revenue with a lower tax rate. On the other hand, the true value may, in fact, be positive suggesting higher burdens on local residents due to revenue capture.

Table 4.2: 90 Percent Confidence Interval for TIF Intensity and Local Tax Rate

	90 Percent Confidence Interval	
Impact of TIF Intensity on Local Tax Rates	-0.0003	0.0081

Estimation Results of the Spatial Models

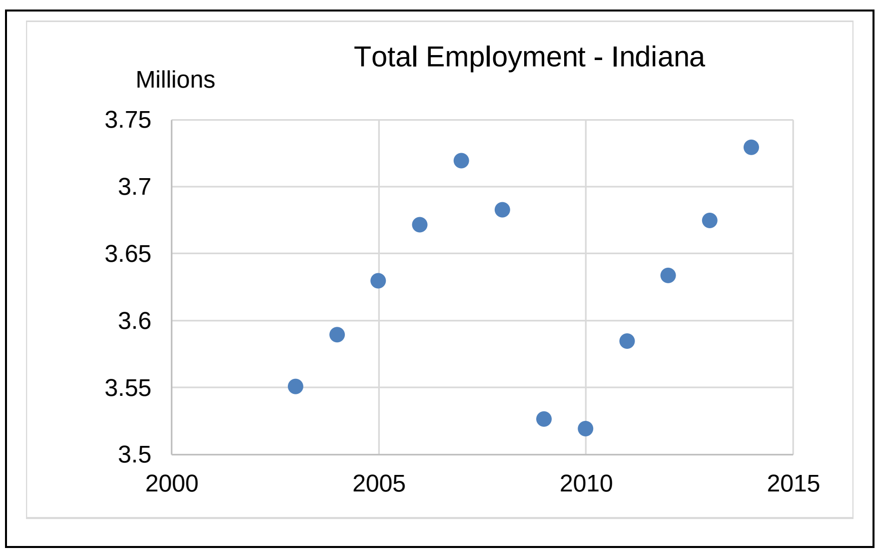
There are two main objectives of this section. The first is to analyze the direct impact of TIF usage on economic development measures in a county. The second is to analyze the indirect impacts of TIF usage on surrounding counties to help determine if TIF functions as a competitive economic development tool (meaning that surrounding counties are disadvantaged though negative 'spillovers' when an adjoining county increases its use of TIF) or a complementary economic development tool (meaning that surrounding counties are advantaged through positive spillovers such as agglomeration effects or lower transportation costs). Evidence for TIF functioning as a competitive tool would imply that the strategic adoption of TIF by a county is a defensive strategy to protect it from the poaching of economic development by neighboring counties. Evidence for TIF functioning as a complementary tool would imply that the strategic adoption of TIF by a county is an offensive strategy aimed at taking advantage of a neighboring county's actions.

In attempting to analyze the first objective, it is important to first consider the broader economic context of the years in which the data were collected as this can affect the results. The data for the economic development measures consist of the years 2003 to 2014 and the total employment numbers for the State of Indiana are shown in Table 4.3 and Figure 4.1 below. What is clear from the data is that the Great Recession of 2008-2009 had a significant impact on total employment during the timeframe considered. Given the structural break created by the Great Recession, it is incorrect to model the effects of TIF on economic development variables without correcting for it. One way around this difficulty is to analyze the time periods separately. This is the tactic used below where the pre-recession period and the post-recession period will be analyzed. Next, the entire time period will be analyzed to demonstrate the inherent problems of this approach. The final section considers two different model specifications that allow for the entire time period to be modeled in one equation.

Table 4.3

Year	Employment
2003	3,550,537
2004	3,589,378
2005	3,629,742
2006	3,671,528
2007	3,719,240
2008	3,682,729
2009	3,526,276
2010	3,519,340
2011	3,584,521
2012	3,633,616
2013	3,674,547
2014	3,729,352

Figure 4.1



Prerecession Estimation Results of the Spatial Models

Starting with the pre-recession (2003-2007) results, Table 4.4 analyzes the relationship between TIF assessed value in a county and three economic development measures: total employment, average wage and poverty rate. In the specification of the dynamic Spatial Durbin Model, the impacts are a function of the own county factor and the behavior of neighboring counties, therefore the Direct and Indirect impacts are the relevant results (LeSage and Pace 2009). This specification also allows us to analyze spillovers.

Looking at the direct results from Table 4.4 suggest that for the average county, a $1 million increase in TIF incremental assessed value leads to 2.20 more jobs. To put in perspective the impact of TIF on employment, it is important to calculate the value of a job. The average total compensation per worker in Indiana in 2015 was $50,954 according to EMSI[28]. Each job is actually an income stream of not only the current year, but all future years as well. To measure the value an average job in Indiana, the present value of this income flow must be calculated. To calculate present value, a 'risk-free' investment that earns interest, is needed (also called the discount rate). The rate on the 10-year US Treasury bill is considered a safe investment, which currently has an interest rate of 1.87 percent. To be conservative, a 2 percent discount rate is used here (the higher the discount rate the smaller the present value). A job is considered an on-going or permanent income flow without a definitive timeframe, but again to be conservative, a 40-year timeframe will be used. 40 years was chosen as this represents a typical work span of one individual from age 25 to 65, corresponding to one "job". Given the assumptions, the value of an average job in Indiana created today has a present value of $1.60 million.

The prerecession results in Table 3.4 shows, a $1 million increase in TIF incremental assessed value leads to 2.20 more jobs in a county. Given that each job has a present value of $1.60 million, a $1 million increase in TIF incremental assessed value creates $3.52 million in present value associated with employment income flows.

It also increases the average wage in a county by a small but statistically significant amount, though it does not seem to have a statistically significant impact on the county's poverty rate. Turning to the indirect results, none of the economic development measures show a statistically significant impact at conventional levels; however, the indirect employment result is positive with a relative high t-statistic suggesting that there is weak evidence that TIF activity functions as a complementary economic development tool with positive spillover effects. This is somewhat offset by the indirect average wage effect which is negative. The relatively high t-statistic suggests that TIF activity may spur economic activity that spills over to neighboring counties, but may be competitive in terms of providing higher wage jobs.

Table 4.4 Prerecession (2003-2007) Regressions

Dependent Variable	Employment		Average Wage		Poverty Rate	
	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
Spatial Autocorrelation	-0.04	-0.47	0.08	1.06	0.03	0.37
Direct						
TIF incremental assessed	2.20	5.98***	0.43	2.24**	-.001	-0.12

[28] www.economicmodeling.com defined as QCEW reported earnings plus supplements.

value ($ million)						
Lagged Dependent Variable	0.92	30.93***	0.48	10.28***	0.29	5.15***
Indirect						
TIF incremental assessed value ($ million)	1.08	1.14	-0.78	-1.37	0.01	0.44
Lagged Dependent Variable	-0.02	-0.35	0.19	2.43***	0.04	0.38
Fixed Effects	Yes		Yes		Yes	
Time Period Effects	Yes		Yes		Yes	
N	346		346		346	

*** p-value < 0.001; **p-value < 0.05; *p-value <0.1

Post-Recession Estimation Results of the Spatial Models

Analyzing the post-recession (2010-2014) results in Table 4.5 shows similar results. The direct results suggest that a $1 million increase in TIF incremental assessed value leads to 4.26 more jobs or $6.82 million in present value from the income flow in a county. As with the pre-recession results, it also increases the average wage in a county by a small but statistically significant amount, and does not seem to have a statistically significant impact on the county's poverty rate. The post-recession results, however, do show a statistically significant impact on employment in surrounding counties and the average wage coefficient is positive but statistically insignificant at conventional levels.

Table 4.5 Post-Recession (2010-2014) Regressions

Dependent Variable	Employment		Average Wages		Poverty Rate	
	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
Spatial Autocorrelation	0.28	14.98***	0.33	5.40***	0.06	0.88
Direct						
TIF incremental assessed value ($ million)	4.26	11.61***	0.25	1.86*	-0.01	-0.37
Lagged Dependent Variable	0.02	3.66***	0.02	3.06***	-0.02	-1.03
Indirect					-	
TIF incremental assessed value ($ million)	6.09	5.05***	0.70	1.39	0.01	0.23
Lagged Dependent Variable	0.01	1.42	0.01	0.28	0.04	0.38
Fixed Effects	Yes		Yes		Yes	
Time Period Effects	Yes		Yes		Yes	
N	455		455		455	

Full Period Estimation Results of the Spatial Models

The results from the regression analyses considering the pre-recession and post-recession periods separately show a positive correlation between TIF incremental assessed value and employment as well as average wages. Next we turn to the difficulties imposed by the Great Recession of 2008-2009 and demonstrate the inherent problems of the full period approach. A recent study that analyzes the impact of Indiana TIF activity at the county level (Hicks, Faulk and Quirin; 2015) used the period 2003-2012 for model estimation and found a negative correlation between TIF assessed value and employment. The results found in Table 4.6 are based on a semi-dynamic spatial model. The model is similar to the fully dynamic spatial Durbin model used throughout this report. However, it does not include a spatially-weighted lagged dependent variable – and hence, it is spatially semi-dynamic. The 2003-2012 timeframe was also analyzed with the fully dynamic spatial Durbin model and the results are reported in Table 4.7.

Table 4.6 Full Period (2003-2012) Regressions –Semi-Dynamic Spatial Model

Dependent Variable	Employment		Employment	
	Coefficient	T-Stat	Coefficient	T-Stat
TIF incremental assessed value ($ million)	-1.77	-3.12***	-1.47	-2.75***
Average TIF incremental assessed value in adjacent county ($ million)	-0.04	-0.03	1.98	1.79*
Temporal Autocorrelation	0.01	2.93**	0.75	33.85***
Spatial Autocorrelation	0.30	7.60***	0.01	0.13
Time Trend	9.35	0.30	-	-
Fixed Effects	Yes		Yes	
Time Period Effects	No		Yes	
N	819		819	

Table 4.7 Full Period (2003-2012) Regressions – Fully Dynamic Spatial Durbin Model

Dependent Variable	Employment		Average Wages		Poverty Rate	
	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
Spatial Autocorrelation	0.02	1.18	0.06	1.05	0.15	2.96**
Direct						
TIF incremental assessed value ($ million)	-1.35	-2.98**	0.14	0.97	0.01	0.64
Lagged Dependent Variable	0.75	29.91***	0.82	36.45***	0.23	6.17***
Indirect						
TIF incremental assessed value ($ million)	2.87	2.18**	-0.36	-0.93	-0.01	-1.15
Lagged Dependent Variable	-0.07	-1.26	-0.03	-0.73	0.24	3.58***
Fixed Effects	Yes		Yes		Yes	
Time Period Effects	Yes		Yes		Yes	
N	819		819		819	

The results from Table 4.6 and 4.7 show a negative correlation between TIF incremental assessed value and employment during the 2003-2012-time period. Recall that these models do not account for the impact of the 2008-2009 Great Recession. The problem can be visualized by Figure 4.2 that plots the employment data with a trend line. Here the trend line does not match up well with the data and displays a negative employment trend in Indiana during this period whereas the actual employment data is much more complex. The limitation of the above model can also be demonstrated by adding more data. This is done in Table 4.8 which uses the same fully dynamic spatial Durbin model above, but adds two more years of data (2003-2014). Adding two more years of data causes the sign of TIF incremental assessed value to become positive. The full period results now suggest that a $1 million increase in TIF incremental assessed value leads to 0.89 more jobs on average. These results show that if the full period is to be analyzed, the effects of the Great Recession must be taken into account. The final section will argue for two different model specifications that allow for the entire time period to be modeled in one equation.

Figure 4.2 Total Employment (2003-2012) with Trend Line

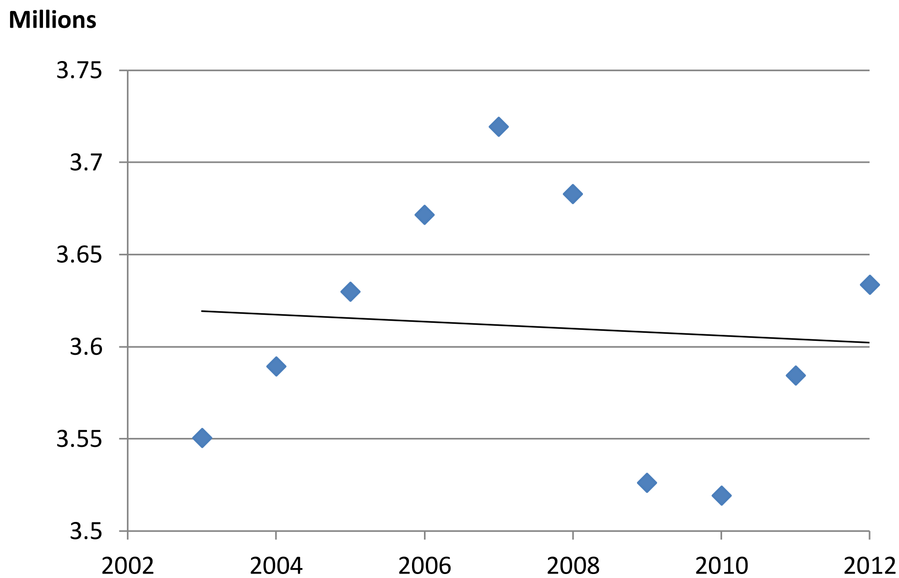


Figure 4.3 Total Employment (2003-2014) with Trend Line

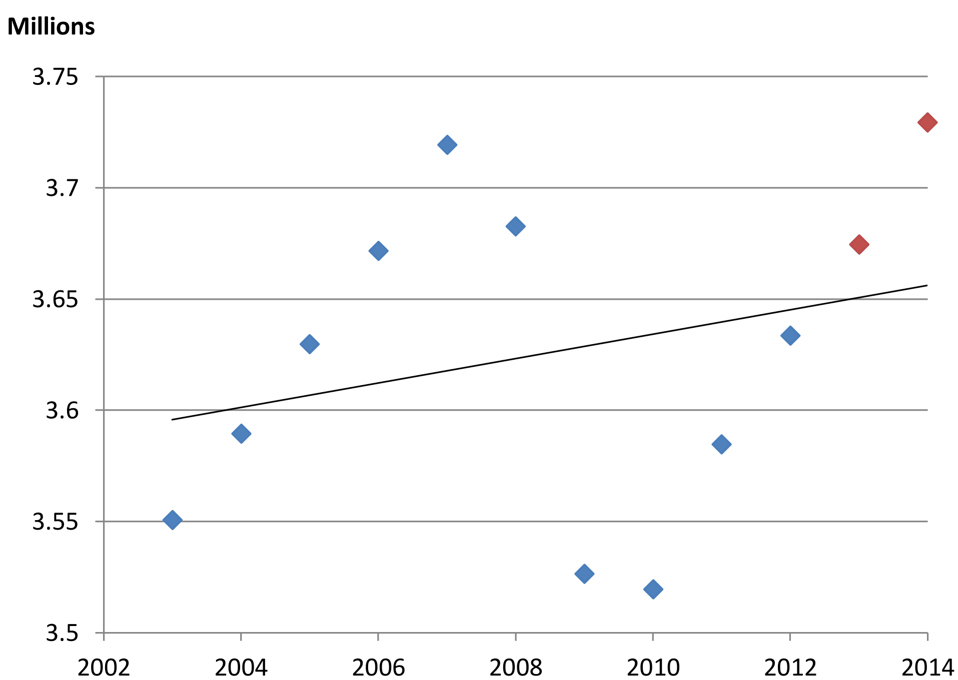


Table 4.8 Full Period (2003-2014) Regressions

Dependent Variable	Employment		Average Wages		Poverty Rate	
	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
Spatial Autocorrelation	0.08	1.74*	0.10	2.15**	0.16	3.65***
Direct						
TIF assessed value ($ million)	0.89	3.68***	0.001	0.02	0.01	1.24
Lagged Dependent Variable	0.78	36.56***	0.85	45.07***	0.24	7.11***
Indirect						
TIF assessed value ($ million)	2.43	3.35***	0.14	0.63	-0.01	-0.16
Lagged Dependent Variable	-0.05	-1.02	0.01	0.32	0.23	3.70***
Fixed Effects	Yes		Yes		Yes	
Time Period Effects	Yes		Yes		Yes	
N	1001		1001		1001	

Full Period Estimation Results of the Spatial Models with Structural Correction

One method for dealing with the structural shifts is to break the time period up using dummy variables and slope dummy variables. This technique was used by Dye, Merriman and Goulde (2014) to account for the Great Recession on TIF activity. Using the Semi-Dynamic Spatial Model, we analyze three time periods (pre-recession, recession and post-recession). Table 4.9 now shows similar results for the pre- and post-recession periods using 2003-2012 and 2003-2014 timeframes.

Table 4.9 Full Period Regressions – Semi-Dynamic Spatial Model

	2003-2012		2003-2014	
	Employment		Employment	
	Coefficient	T-Stat	Coefficient	T-Stat
Pre – TIF assessed value ($ million)	4.35	11.00***	5.30	15.05***
Recession – TIF assessed value ($ million)	-2.18	-3.28***	-3.69	-8.24***
Post – TIF assessed value ($ million)	3.04	9.21***	4.35	15.56***
Pre – Average TIF assessed value in adjacent county ($ million)	9.04	11.15***	2.13	2.97**
Recession – Average TIF assessed value in adjacent county ($ million)	-7.83	-6.64***	-1.24	-1.47
Post – Average TIF assessed value in adjacent county ($ million)	8.06	13.01**	1.68	3.07**
Pre – Dummy	1434.8	8.11***	856.8	5.16***
Post – Dummy	1567.6	8.44***	924.7	5.82***
Temporal Autocorrelation	0.78	34.87***	0.89	50.67***

Spatial Autocorrelation	2.27	62.51***	0.58	10.05***
Fixed Effects	Yes		Yes	
Time Period Effects	Yes		Yes	
N	819		1001	

Another way to control for the effects of the Great Recession is to correct relevant dependent variables prior to statistical analyses. Using total employment as a dependent variable does not control for the differences in the regional industrial mix. In other words, counties may differ in the types of industries that exist and these industries may differ over the time period. For example, one county could be an industrial county with a declining manufacturing base whereas another county may be more concentrated in emerging high-tech sectors. One way to control for this is through shift-share analysis. A brief explanation of shift-share analysis is provided below by Economic Modeling Specialist Inc. or EMSI. The data used in this section was obtained from EMSI.

Shift share is a standard regional analysis method that attempts to determine how much of regional job growth can be attributed to national trends and how much is due to unique regional factors. Shift share helps answer why employment is growing or declining in a regional industry, cluster, or occupation.

To conduct shift share analysis, we split regional job growth into three components: (1) industrial mix effect, (2) national growth effect, and (3) regional competitive effect. In addition, a time frame (start year and end year) is required to perform shift share analysis, since shift share deals with job growth over time.

The Industrial Mix Effect
The industrial mix effect represents the share of regional industry growth explained by the growth of the specific industry at the national level. To arrive at this number, the national growth rate of the total economy is subtracted from the national growth rate of the specific industry, and this growth percentage is applied to the regional jobs in that industry.

The National Growth Effect
The national growth effect explains how much of the regional industry's growth is explained by the overall growth of the national economy: if the nation's whole economy is growing, you would generally expect to see some positive change in each industry in your local region (the proverbial "rising tide that lifts all boats" analogy).

The Expected Change
This is simply the rate of growth of the particular industry at the national level. Algebraically, the expected change is the sum of the industrial mix and the national growth effects.

The Regional Competitive Effect
The regional competitive effect is the most interesting of the three indicators. It explains how much of the change in a given industry is due to some unique competitive advantage that the region possesses, because the growth cannot be explained by national trends in that industry or the economy as whole. This effect is calculated by taking the total regional growth of the given industry and subtracting the national growth for that same industry. Note that this effect can be positive even as regional employment in the industry declines. This would indicate that regional decline is less than the national decline.

As described above, after correcting the total employment dependent variable using shift-share analysis, we compute the competitive effect. This is described as the amount of change in the county's total employment that is due to some unique competitive advantage. Tables 4.10 and 4.11 display the results for the competitive effect using the semi-dynamic spatial model and the static and fully dynamic spatial Durbin model respectively over the 2003-2012 period. The results from the semi-dynamic spatial model suggest that a $1 million increase in TIF assessed value leads to 0.90 more local jobs or $1.44 million more present value income stream than can be explained by national and industrial trends. This result is consistent across model specifications as shown in Table 4.11 suggesting that the use of TIF in a county provides the county with "a unique competitive advantage".

Table 4.10 Full Period (2003-2012) Regressions – Semi-Dynamic Spatial Model

Dependent Variable	Competitive Effect		Competitive Effect	
	Coefficient	T-Stat	Coefficient	T-Stat
TIF incremental assessed value ($ million)	0.90	3.60***	0.93	3.70***
Average TIF incremental assessed value in adjacent county ($ million)	0.24	0.47	0.52	1.02
Temporal Autocorrelation	0.07	1.92*	0.07	1.87*
Spatial Autocorrelation	0.12	2.25**	0.05	0.96
Time Trend	-	-	-4.69	-0.35
Fixed Effects	Yes		Yes	
Time Period Effects	Yes		No	
N	819		819	

Table 4.11 Full Period (2003-2012) Regressions –Static and Fully Dynamic Spatial Durbin Model

Dependent Variable	Competitive Effect		Competitive Effect	
	Coefficient	T-Stat	Coefficient	T-Stat
Spatial Autocorrelation	-0.12	-2.23**	0.10	2.15**
Direct				
TIF incremental assessed value ($ million)	0.85	4.56***	0.89	4.13***
Lagged Dependent Variable	-	-	0.71	1.79*
Indirect				
TIF incremental assessed value ($ million)	0.15	0.03	0.17	0.33
Lagged Dependent Variable	-	-	-0.02	-0.24
Fixed Effects	Yes		Yes	
Time Period Effects	Yes		Yes	
N	910		819	

Comparison with Other Studies

The results above are aligned with many studies of TIF in Indiana from the 1990s. Man (1998, 1999a, 1999b) found that TIF increased the value of owner-occupied housing, created more jobs in cities which had TIF districts and that this could not be attributed to selection bias (growing cities were not more likely to have TIF districts). Further, an important[29] recent study of TIF activity in Indiana, the 2015 Indiana Legislative Services Agency (LSA) report on tax incentives, also found that, on average, a parcel (of property) in a TIF district has a higher amount of gross assessed value, higher growth of gross assessed value and a higher employment level compared to a parcel (of property) with similar characteristics in a non-TIF district. These findings are statistically significant at conventional levels.[30]

The LSA study, however, found that the difference between employment growth in a TIF parcel compared to that in a similar non-TIF parcel was not statistically significant at conventional levels. Two points are worth nothing here: a) while a TIF parcel actually experienced positive employment growth over the time period under consideration (2004 – 2013), a similar non-TIF parcel actually experienced a decline in employment over the same time period. b) If the employment growth result is interpreted in light of the recent exhortation by the American Statistical Association on appropriately interpreting statistical significance, then the result is of statistical importance. This is further discussed below.

The American Statistical Association (ASA) issued a report by Wasserstein and Lazar (2016) to educate researchers and the public on the proper interpretation and use of 'p-values', the statistical measure that researchers use to interpret the results of their models. Among the principles they state in the report, three are useful to paraphrase:

1. P-values do not determine if a studied hypothesis is true or false. In other words, in statistics, there is not a bright line called "statistical significance," that can be drawn to confirm or refute a hypothesis.

2. Business and/or policy decisions should not be based on whether a p-value passes a specific threshold (such as $p < 0.1$ or $p < 0.05$). They caution that to do so "can lead to erroneous beliefs and poor decision-making" and that the use of p-values or "statistical significance" as a "license for making a claim of a statistical finding (or implied truth) leads to considerable distortion of the scientific process."

3. Some statisticians prefer to use other approaches to analyze results such as confidence intervals as "they may more directly address the size of an effect (and its associated uncertainty) or whether the hypothesis is correct."

The above suggestion regarding confidence intervals will be drawn upon to analyze the results of the LSA

[29] The LSA study (2015) is the first study of TIF in Indiana that uses parcel-level data to isolate the effect of TIF on various economic development measures. It attempts to do this by matching TIF and non-TIF parcels that share similar economic, fiscal, structural and Census characteristics.

[30] Another recent study, Hicks, Faulk and Quirin (2015), finds negative and statistically significant impacts of TIF in Indiana on various economic development measures, such as employment. An important reason for the differences in findings may lie in the fact that our study more fully accounts for the effects of the Great Recession and uses more recent data.

(2015) study. Table 4.11 shows the results using confidence intervals regarding the impact of TIF on gross assessed value, employment levels and employment growth rates from the LSA study. The results show that on average, a property parcel in areas with TIF-designations outperforms a property parcel with similar characteristics in non-TIF areas on multiple economic development measures.

The research question in Table 4.11 is: whether TIF designation and activity cause an area to be significantly different in economic development measures compared to a non-TIF area in either direction: positive or negative. In other words the null hypothesis is: $H_0 = 0$. This is what we refer to as a 2-sided test. The 90 percent confidence intervals are interpreted as follows: if we were able to resample (and match) TIF and non-TIF parcels 100 times, then the average (from all TIF parcels) gross assessed value in a TIF parcel would be between 0.3% and 8.5% higher than the average (from all non-TIF parcels) gross assessed value in a non-TIF parcel in 90 out of the 100 samples.

A more relevant research question is: whether a TIF parcel performs at a significantly higher level in economic development measures compared to a non-TIF parcel? In other words, the null hypothesis is: $H_0 \leq 0$. This is usually referred to as a 1-sided test. For this research question, the results are presented in Table 4.12. In this case, the confidence intervals are narrower and all positive. The interpretation here, for example, is as follows: if we were able to resample (and match) TIF and non-TIF parcels 100 times, then the average (from all TIF parcels) employment growth in a TIF parcel would be between 0.6% and 9.9% higher than the average (from all non-TIF parcels) employment growth in a non-TIF parcel in 90 out of the 100 samples

Table 4.11: 90 Percent Confidence Intervals on Economic Development Measures for TIF Areas compared to Non-TIF Areas from the LSA Study (2-sided test)
Question: How much are TIF-designated areas "significantly different" than similar non-TIF areas in the following economic development measures?

Economic Development Measure	90 percent Confidence Interval	
Gross Assessed Value (GAV), 2013	[0.3%	8.5%]
Change in GAV, 2004-2013	[4.3%	8.9%]
Employment, 2013	[5.6%	20.4%]
Change in Employment, 2004-2013	[-0.7%	11.3%]

Table 4.12: 90 percent Confidence Intervals on Economic Development Measures for TIF Areas compared to Non-TIF Areas from the LSA Study (1-sided test)
Question: How much are TIF-designated areas "significantly greater" than similar non-TIF areas in the following economic development measures?

Economic Development Measure	90 percent Confidence Interval	
Gross Assessed Value (GAV), 2013	[1.1%	7.5%]
Change in GAV, 2004-2013	[4.8%	8.4%]
Employment, 2013	[7.1%	18.7%]
Change in Employment, 2004-2013	[0.6%	9.9%]

It may also be observed that the confidence intervals are far larger for the employment measures than the measures for assessed value. This has to do with the larger variance of the coefficients and it is this larger variance that leads to greater uncertainty and thus the larger intervals.

The analyses we conducted so far in examining the effectiveness of TIF was at the aggregate level where all types of TIF districts were lumped together and evaluated essentially on the two metrics of employment and wages. The drawback of this approach is that the metrics for evaluating the effectiveness of TIF districts may not necessarily be aligned with the rationales for creating them. For instance, a TIF district may be formed for building a road that links two communities. While there may be no visible business activity in the areas that border the road, this road may be saving both communities considerable commuting time that enhances their quality of life or expands the productive capacity of the State of Indiana, as the time that is saved may be used directly for work-purposes or for leisure activities that boost future work-productivity. Evaluating this TIF district on the number of direct jobs that have been created would produce the impression that it has 'underperformed'. Hence, the future directions of this Study – Phase 2 – consist of:

a) Developing an approach for broadly addressing the issue of differentiation in TIF districts and evaluating their respective effectiveness.

b) Implementing this approach for a few TIF districts

Part a) of Phase 2 has been completed and is described in the next two sections.

PHASE 2 – FUTURE DIRECTIONS OF THE STUDY

5. Foundations for Case Studies: County Clusters and Differentiation of TIF Districts

Cluster Analysis: Background and Assumptions

One limitation of both the literature and our analyses conducted so far is that they ignore project- specific details of TIF-related projects. While larger economic forces such as employment and existing industry mixes are certainly important drivers of TIF adoption and use, they are not exhaustive determinants of what allows a TIF-financed redevelopment project to be successful. Examples of these project-specific factors include (but are not limited to): land use restrictions, environmental concerns (noise pollution), the existence of specific infrastructure to support a project (i.e., proximity to natural resources used in the production process; available sanitation and waste disposal), the productive uses (both within an industry and within a multiproduct, multiplant firm) for which that redevelopment will be employed (i.e., an auto manufacturer may use a TIF-financed project to produce individual automobile parts or assemble automobiles), or simply community preferences for specific types of redevelopment initiatives. When identifying and prioritizing possible redevelopment projects, these factors must also align with economic fundamentals for the project to be successful. Many of these factors are not easily captured with a single variable or metric, nor are these variables measured consistently across local governmental units. Hence, including them in regression analyses is often infeasible.

How does one deal with the diversity of economic and social contexts within which TIF districts are established, and the variety of rationales for establishing a TIF district (even among infrastructure TIF districts, there may be those that are linked to one specific project – say, a convention center- and others that are anticipatory, such a 'connecting road' that is intended to attract more business with time)? Cluster analysis is a technique that brings organization to this diversity by helping form groups – each of which share common characteristics. This, in turn, makes the identification of representative case studies easier (see Hair, et al. 2006).

In the context of this study, cluster analysis uses general economic information and TIF-related data to identify counties that have relatively similar economic bases and TIF-related outcomes. Counties with similar economic trajectories and TIF outcomes are likely to share attributes with regard to many project specific factors, as mentioned above.

Cluster analysis requires few statistical or parametric assumptions. However, cluster analysis does require that sufficient theoretical bases exist to justify the inclusion of specific variables and specific observations in the data set. That is, there must be an economic rationale for selecting the variables used in the analysis, and there must be a plausible reason for selecting the observations in the data. Focusing on the entirety of counties in Indiana clearly meets the latter criterion. Focusing on the key economic indicators (using variables similar to those used in previous sections of this report, e.g. unemployment rate) also meets the former criterion. Cluster analysis further requires that the number of variables (and for non-hierarchical methods, the number of clusters) be selected relative to the number of observations available for analysis. Practically speaking, the number of variables and clusters should also be chosen to facilitate a clear and reasonable interpretation of the results. Too many variables, and too many clusters, lead to results that are difficult to interpret meaningfully.

Cluster analyses rely on two iterative processes to group i) variables (across a series of observations/counties) or ii) a series of observations/counties (across a series of variables). The first of these cluster analyses looks at the degree of similarity with which variables are related. Variables that are closely related, and contain similar informative content, are clustered together, while variables that convey more distinct information are grouped into other clusters. This information is typically presented pictorially using a Dendrogram, which is capable of conveying both the groupings of variable clusters as well as the relative relationships or 'distance' between clusters of variables. To generate these variable clusters, we employ Ward's method - a standard clustering technique (Hair, et al. 2006). Ward's method is well suited for our purpose as it generates clusters in a way that maximizes within-cluster homogeneity or minimizes within-cluster sums of squares. We note in passing that other commonly used methods to create the clusters, including the complete linkage method, were also used, and yielded similar results.

The second approach is to utilize a set of pre-defined variables and cluster observations/counties into groups. Known as non-hierarchical clustering, this method involves randomly assigning observations to a pre-defined set of clusters, and subsequently reassigning observations to different clusters to improve the 'distance' (usually, Euclidean distance) between the cluster centers, or improve the distinctiveness of each cluster (Hair, et al. 2006). This process iterates until an optimum distance between the clusters is reached (or the algorithm cannot further improve the distinctiveness of the clusters). Given that the number of clusters must be pre-specified, it is common practice to start with a defensible cluster number (based on a combination of parsimony and the complexity of the data being utilized), and conduct several sensitivity analyses using different numbers of clusters. A stable cluster analysis should not yield substantial differences in cluster membership across a variety of different cluster choices.

Data and Empirical Approach

Given the availability of data on economic variables of interest at the county-level rather than the parcel-level, a decision was made to conduct the analysis at the level of the county. This creates several tradeoffs. Using county-level data allows us to examine interrelationships between economic variables (for the hierarchical analysis) that can only be observed at the county level. Examining county data also at least partially abstracts from strategic behaviors between adjacent TIF districts while still examining the impact of TIF at the local level. The effectiveness of TIF projects is also crucially dependent upon county-level policies, precedents and ordinances. Hence, examining the clustering of TIF districts by county creates a straightforward and consistent means to compare TIF activity. However, the primary drawback to a county-level analysis is aggregation bias. Counties whose TIF districts are fundamentally different may lead to clusters that mask the underlying fundamentals driving TIF-related decisions. Since cluster analyses require subsequent county-level case study analyses to understand why clustering occurs, these limitations will be addressed in future case study analyses.

The economic variables used to generate clusters are given in Table 5.1 below, and are chosen based on relevant discussions in the TIF literature and the preceding regression analyses in this study. Variable names are provided in parentheses after each variable definition. Data are drawn from the Bureau of Economic Analysis website and other such federal websites.

Table 5.1 Economic Variables for Generating Clusters of Counties

1. Ratio of TIF Incremental AV to Non-TIF NAV for a county (RatioTnT)
2. Ratio of County GDP to Mean State GDP (GDPratio)
3. Herfindahl-based measure of the distribution of employment by industry for a county (Hemp)
4. Herfindahl-based measure of the distribution of population by age for a county (Hpop)
5. Ratio of total employment in a county to the mean state-level employment (Empratio)
6. Ratio of personal per capita Income in a county to the mean state-level personal per capita income (PCIratio)
7. Ratio of TIF debt of a county for the year in question to the mean state-level TIF debt for that year (Debtrat)
8. Ratio of TIF debt maturing in the year in question to the mean state-level debt maturing for that year (Debtmatrat)
9. Ratio of nominal value of assets of a county to the mean state-level value of assets (Tassetsrat)

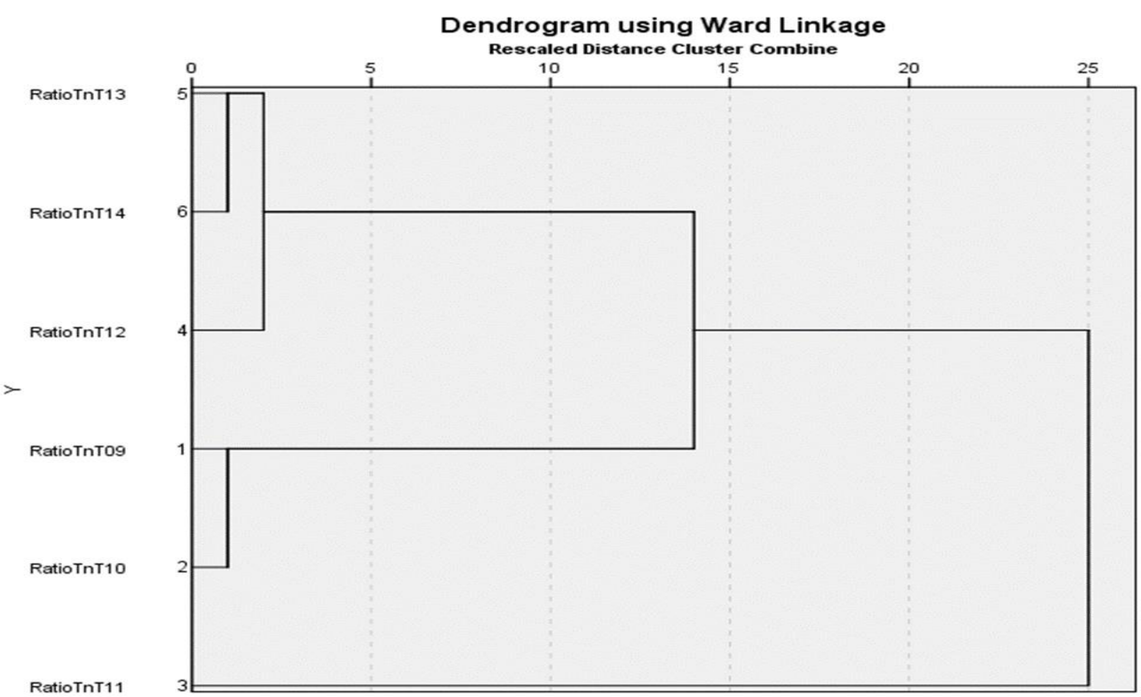
This analysis contains two separate applications of cluster analysis. First, we seek to understand the clustering of counties and variables using only TIF-specific information. To that end, a dataset was constructed that contains the ratio of TIF incremental assessed value to non-TIF net assessed value for a county (RatioTnT) in a given year. Data were collected over the years 2009-2014 (the most recent data available), where the TIF to non-TIF ratio in each year was recorded as a separate variable. This facilitates a hierarchical cluster analysis to examine clustering relationships in TIF activity over time. Similarly, non-hierarchical methods can be used to cluster counties over each of the variables. That is, counties can be clustered based on TIF incremental assessed values (relative to non-TIF net assessed values) over this six year period.

Second, we utilized a panel of all Indiana counties over the period 2013-2014 measuring each of the variables described in Table 5.1. We note in passing that at the time of this study, data were not available for the years 2009-2012 over all of the variables in Table 5.1. Hierarchical methods allow for the creation of a Dendrogram to measure the clustering of each of these variables, while non-hierarchical clustering techniques were used to cluster counties across each of these variables. The latter is important, as the clustering is now based on TIF-related activity in the county as well as the underlying socio-economic fundamentals.

Cluster Analysis of Counties Based on TIF to Non-TIF Values, 2009-2014

The first analysis examines clustering across counties based on changes in the RatioTnT variable over time. Hierarchical clustering with Ward's method yields the Dendrogram presented below. We note in passing that alternative methods (including using the complete linkage method in place of Ward's method, or standardizing the variable prior to clustering) yield similar results (Hair, et al. 2006). Note that at the base of the Dendrogram, the TIF to Non-TIF ratios for the years 2013-2014 - and to a slightly lesser extent 2012 - cluster tightly together. Similarly, the 2009 and 2010 years cluster together, while TIF incremental assessed values in 2011 remain distinct. These results support our earlier regression analyses, as they align closely with the change in TIF incremental assessed values during and after the most recent recession. The interpretation of the Dendrogram is straightforward. There appears to be a fundamental change in TIF to Non-TIF values around 2011, as local economies begin to recover from the recession. By 2013, local economies (and TIF incremental assessed values resulting from those conditions) appear to have moved onto another (presumably stable) trajectory.

Figure 5.1. Dendrogram Depicting Hierarchical Cluster Analysis of RatioTnT by Year



Of additional interest is the non-hierarchical clustering of counties based on these TIF to Non-TIF values. The table below shows the clusters of counties generated using six clusters. We also conducted sensitivity analysis using a variety of different clusters and obtained qualitatively similar results. When interpreting the clusters, it is also important to note that the cluster number should not be interpreted as a ranking or a more (or less) important cluster. Rather, it is the groupings of counties, and not the number attached to the cluster, that is of import.

Table 5.2 County Clusters Based on TIF to Non-TIF Values

1	Allen, Bartholomew, Boone, Carroll, Daviess, DeKalb, Delaware, Elkhart, Floyd, Fountain, Hancock, Henry, Jasper, Jefferson, Johnson, Knox, Kosciusko, LaGrange, Lake, LaPorte, Madison, Marshall, Monroe, Morgan, Noble, Porter, Putnam, Randolph, Tipton, Vigo, Wabash, Warrick, Wayne
2	Clark, Gibson, Perry, St. Joseph
3	Spencer
4	Adams, Benton, Blackford, Brown, Cass, Clay, Clinton, Crawford, Dearborn, Dubois, Fayette, Franklin, Fulton, Harrison, Howard, Jackson, Lawrence, Martin, Miami, Newton, Ohio, Owen, Parke, Pike, Posey, Pulaski, Ripley, Rush, Starke, Steuben, Sullivan, Switzerland, Union, Vermillion, Warren, Washington, Wells, White
5	Decatur, Grant, Hamilton, Hendricks, Jennings, Marion, Orange, Scott, Shelby, Tippecanoe, Vanderburgh, Whitley
6	Greene, Huntington, Jay, Montgomery

Examining the clusters of counties reveals some commonalities - around which one can base subsequent case study investigations. Clusters 4 and 6 appear to be comprised of rural counties with limited economic (usually agricultural) industrial bases. Cluster 5 includes much of the greater Indianapolis metropolitan area, as well as a corridor of counties connecting Indianapolis to Louisville. This cluster also contains Tippecanoe County, which is home to Purdue University, as well as Vanderburgh County. Cluster 1 consists of a mix of more populous counties with well-diversified economic bases. Many counties in this group are also in counties that include (i.e., Allen County, Bartholomew County), or are adjacent to larger communities (i.e., Lake County, Warrick County, Madison County). These factors likely imply similar redevelopment needs, and by extension similar TIF use (and net asset values associated with that use) over time. Clusters 2 and 3 consist, with the exception of Saint Joseph County, of a small number of counties primarily in the southern part of the state.

It is also possible to express the TIF to Non-TIF ratio mean values for each year of the panel, disaggregated by cluster. This allows for a characterization of those salient features that lead to cluster formation. We note in passing that some clusters may contain only one county, making the standard deviation inappropriate to consider. Hence, only mean values are reported. Results for the six group cluster analysis are illustrated below.

Table 5.3 County Cluster Means Based on TIF to Non-TIF Net Asset Values

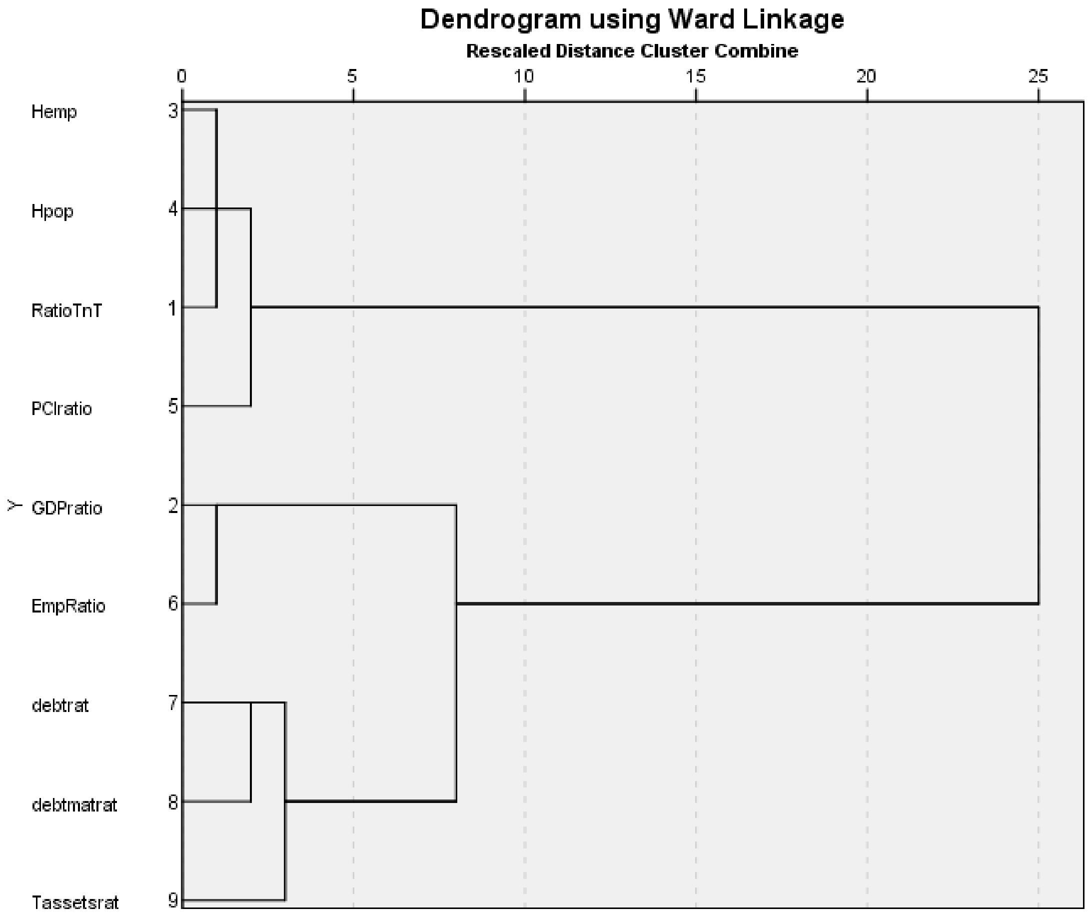
	Cluster					
Variable	**1**	**2**	**3**	**4**	**5**	**6**
RatioTnT09	0.0423	0.1547	0.0880	0.0059	0.0925	0.0398
RatioTnT10	0.0471	0.1729	0.1042	0.0064	0.1001	0.0435
RatioTnT11	0.0543	0.1760	0.1470	0.0092	0.1014	0.2281
RatioTnT12	0.0547	0.1709	0.2820	0.0084	0.1073	0.0409
RatioTnT13	0.0567	0.1763	0.2760	0.0093	0.1170	0.0448
RatioTnT14	0.0558	0.1874	0.2697	0.0099	0.1201	0.0462

Cluster 1 (consisting of more populated, economically diversified counties) is characterized by relatively low TIF use (relative to Non-TIF use). While mean values for the ratio grow over time, they do so relatively slowly. Cluster 2 (Clark, Gibson, Perry, and St. Joseph counties) exhibit much higher TIF to Non-TIF values over time, at between 15-20%, compared to counties in the first cluster. These counties also experienced a noticeable increase in TIF incremental assessed values (relative to Non-TIF net assessed values) in 2009 and 2014, but otherwise experienced relatively slow, positive growth. Spencer County (Cluster 3) is unique because it experienced very large, rapid increases in TIF incremental assessed value over the 6-year time window. Cluster 4, which consists primarily of rural counties, exhibits the lowest levels of TIF incremental assessed values (relative to Non-TIF net assessed values), at less than one percent. As with Cluster 1, TIF incremental assessed values rise steadily over the six-year window, from approximately 0.5 percent to 1 percent. Cluster 5, the more urban and urban-corridor counties, exhibits moderate TIF use, with TIF incremental assessed values of approximately 10 percent of Non-TIF values. This number also increases steadily over the panel, from about 9 percent to 12 percent. Counties in Cluster 6 are comparable to those from Cluster 1, except that the counties in Cluster 6 saw a very large spike in TIF incremental net assessed values in 2011. This suggests a one-time adjustment of either TIF or Non-TIF values in these counties.

Cluster Analysis Based on TIF to Non-TIF Values and Socio-Economic Characteristics, 2013-2014

As noted in the previous sections of this report, there is a fundamental shift in the use (and ramifications arising from the use) of TIF after the most recent recession. To that end, a second cluster analysis was conducted using county-level data from 2013-2014. These years were selected both due to data availability considerations, as well as the fact that (based on our previous analyses) data culled from these two years are comparable. In addition to the RatioTnT variable, a number of other variables as reported in Table 4.1 were included in a cluster analysis. As in the previous analysis, hierarchical methods were used to identify relationships between the variables. This allows us to identify those county-specific factors most (or least) closely aligned with changes in TIF incremental assessed values. Ward's method was used to identify the hierarchy, although other methods (complete linkage method, with and without standardized variables) provided similar results. The results of that analysis are depicted in Figure 5.2 below.

Figure 5.2 Dendrogram Depicting Hierarchical Cluster Analysis, 2013-2014



Examining the Dendrogram yields several interesting inferences. First, the ratio of TIF to Non-TIF values is most closely related to the Herfindahl indices measuring the age distribution of the county's population, as well as the distribution of employment by industry. To a lesser extent, these three variables are also closely related to the per capita income in the county (relative to the state). Similarly, county total employment and GDP (both measured relative to the state mean) are two closely related measures. While it is intuitive to suggest that local employment correlates with local GDP, the fact that these two indicators of community vitality are not as closely associated with relative TIF incremental assessed value is a new inference. Lastly, the measures of TIF-related debt and maturing TIF-related debt (again, relative to state mean values) are closely related, both to themselves and to the total county net assessed values. This last result is intuitive, since debt must be secured by collateral, and greater total net assessed value would facilitative both greater TIF debt and repayment of that debt. However, total TIF debt and debt maturity appear to be less strongly connected to overall economic output, as well as the relative reliance on TIF as a source of redevelopment. Relative reliance on TIF is more strongly associated with distributional considerations within the county.

The non-hierarchical clustering of counties based on these same nine variables is provided in Table 5.4 below. As before, we assumed a six cluster solution. However, we conducted sensitivity analysis using a variety of different clusters and obtained qualitatively similar results. Again, when interpreting the clusters, it is also important to note that it is the groupings of counties, and not the number attached to the cluster, that is of importance.

Table 5.4 County-Clusters Based on TIF Use and Socio-Economic Characteristics (Year of Observation)

1	Marion (2014)
2	Allen (2013, 2014), Elkhart (2013, 2014), Hendricks (2013, 2014), Johnson (2013, 2014), La Porte (2013, 2014), Porter (2013, 2014), St. Joseph (2013, 2014), Tippecanoe (2013, 2014), Vanderburgh (2013, 2014)
3	Marion (2013)
4	Hamilton (2013, 2014), Lake (2013, 2014)
5	All other counties (2013, 2014)
6	Delaware (2013), Lawrence (2014)

Note that Marion County is a unique cluster in each year of the panel. Hamilton and Lake counties consistently comprise another unique panel, as do Delaware and Lawrence counties for select years of the panel. Several of the more populous counties (including Vanderburgh, Allen, and Elkhart counties) consistently comprise yet another distinct cluster. All other county-year combinations, which largely represent rural counties in the state, are placed in one cluster.

Table 5.5 provides the mean values for each of the variables used in the analysis, disaggregated by cluster. This allows for a characterization of those salient features that lead to cluster formation.

Table 5.5 County Cluster Means Based on TIF Use and Socio-Economic Characteristics (Year of Observation)

	Cluster					
Variable	**1**	**2**	**3**	**4**	**5**	**6**
RatioTnT	0.1100	0.0962	0.0997	0.1031	0.0455	0.0551
GDPratio	21.8907	3.3195	21.9075	2.5535	0.4355	0.7143
Hemp	0.1331	0.1631	0.1321	0.1962	0.1809	0.1518
Hpop	0.1493	0.1510	0.1495	0.1627	0.1489	0.1512
PCIratio	1.0529	1.0473	1.0749	1.1405	0.9917	0.8860
EmpRatio	18.8044	3.4487	18.8492	2.2155	0.4647	0.9943
debtrat	11.7514	2.5443	16.8549	6.9415	0.4252	7.3208
debtmatrat	11.5447	2.4812	14.0160	7.8646	0.5120	0.7096
Tassetsrat	2.2034	3.1347	12.3712	5.3871	0.5727	0.4851

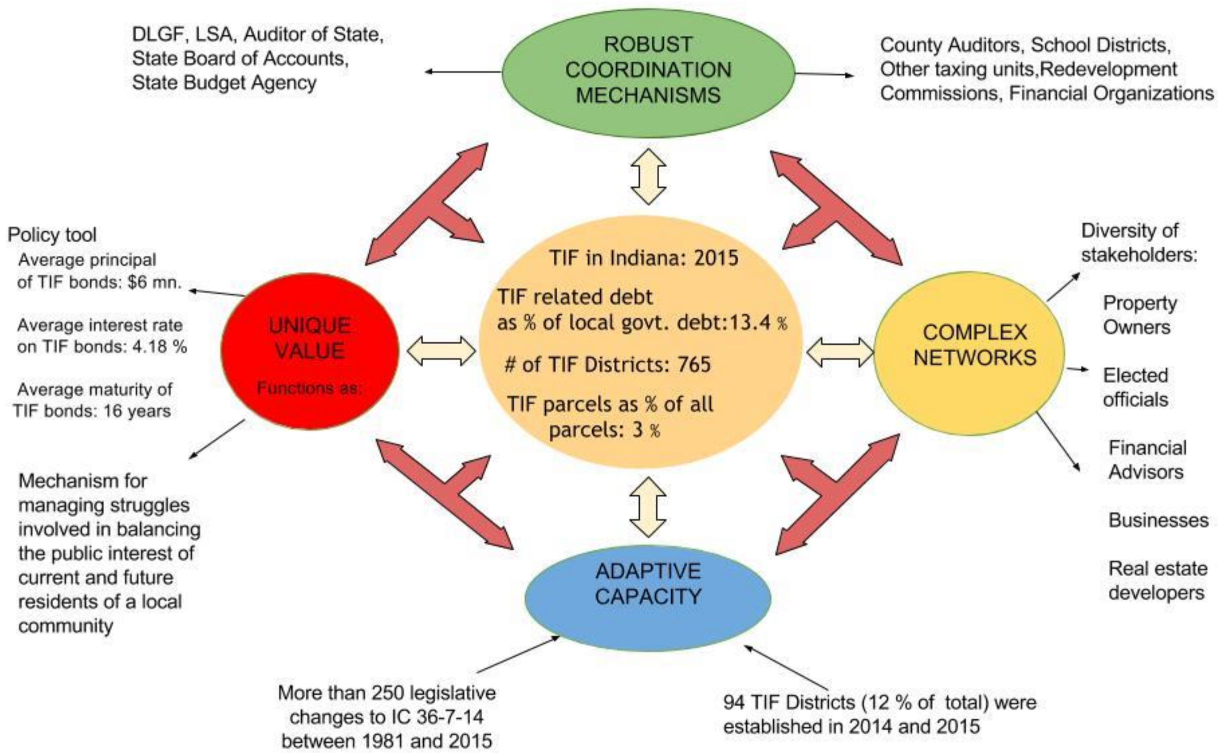
Clusters 1 and 3 represent Marion County in 2014 and 2013, respectively. As the home to the most populous city in the state, Marion County has much higher GDP and employment ratios, as well as above average per capita incomes relative to the rest of the state. TIF to Non-TIF values for Marion County are comparable to other clusters, especially Cluster 2 and Cluster 4, at approximately 10 percent. However, compared to other counties in the state, Marion County has much higher TIF debt and TIF debt maturation ratios compared to the rest of the state. The primary difference between Cluster 1 and Cluster 3 is that in 2013, there is a very large increase in the County's net assessed values relative to the rest of the state, relative to 2014. This suggests a likely change in the County's assessment and/or taxation practices in 2013. Counties 2 and 4 are also relatively similar in socio-economic characteristics, with Lake and Hamilton counties exhibiting much higher TIF debt rates, TIF debt maturation and total assets than other populous, economically diversified counties. Delaware and Lawrence counties (Cluster 6) exhibit lower TIF to Non-TIF values, lower total assets, lower TIF debt maturation, and slightly higher TIF debt relative to counties in Cluster 4. Cluster 6 also exhibits lower GDP and per capita income values than the counties in Cluster 4. These statistics indicate that counties in Cluster 6 are in a much worse financial position with regard to TIF debt than the counties in Cluster 4. Lastly, counties in Cluster 5 are largely rural, with less diversified distributions of employment, lower GDP, less per capita income and fewer assets compared to most of the other counties in the state. These counties also rely much less on TIF to finance redevelopment and, as a result, have less TIF debt.

6. A Methodological Framework for Case Studies

The cluster analyses presented above narrowed the task of identifying counties to be used for conducting detailed case study-analyses. These case study analyses will examine the utility of TIF-based financing strategies within an ecosystem perspective, as each cluster of county-years exhibits similar sociological, economic and environmental ecologies. The goal of each case study would be to comprehensively assess, using an array of qualitative and quantitative techniques, the expected role and utility of a specific TIF strategy. The value of clustering lies in the identification of comparison groups. Local policy makers often have a specific county or local area that is of primary importance – the one whose constituents they serve. Each county of primary importance has a specific set of characteristics. To assess the effectiveness of a TIF policy, one must identify at least one benchmark. A benchmark may be another local area whose socio-economic characteristics are similar (i.e., a 'peer' or cluster group member county) in which case the comparison is rooted in the differences in the projects supported by TIF funding. Alternatively, one can identify comparisons outside of one's peer (or cluster membership) group that implemented a similar TIF-funded project and assess how those cluster differences impact the success of the similar project.

There are several ways to conceptualize an ecological analysis, depending on whether one focuses primarily on the perspectives and priorities of the analyst. For example, from a local level-policy-making perspective, one might conceptualize the use of TIF based on building productive capacity, as illustrated in the figure below.

Tax Increment Financing in Indiana: Ecosystem Attributes



As this study continues with Phase 2, this eco-system framework will be utilized to conduct case analyses which help identify TIF areas and activities that reflect thriving and non-thriving TIF-related ecosystems. The cases analyses will also be guided by the following principles outlined in Underwood and Friesner (2016).

1) TIF-related projects necessarily rely on public-private partnerships. Hence, the first component would be to conduct a comprehensive business plan for the project (from the perspective of the major project investors), inclusive of a five forces (external) market analysis, a SWOT analysis, an environmental scan of the project, and financial projects over the first five years of the project. This will include financial and qualitative information. It would also highlight information addressing (from the perspective of the venture itself) the four components on the outer edge of the previous figure.

2) The ultimate goal of the project is to build capacity for community vitality. Hence, it is also vital to conduct community asset mapping (CAM) before, and after the project to demonstrate possible changes in the capacity of the community itself, and not just from the perspective of the businesses involved in the initiation and management of the TIF-funded projects (Mathie and Cunningham 2003). Similarly, CAM would address the four components on the outer edge of the previous figure, but do so from the perspective of consumer and residents in the county, not the interests of the venture itself.

3) Economic impact modeling will also be conducted to assess pre and post TIF changes on the structure of the economy. Emphasis should be paid to the direct, indirect and induced effects of the TIF project across multiple sectors of the local economy. Economic Impact analysis informs the previous ecosystem diagram from the perspective of the local economic structure and its participants, broadly defined.

4) It is important to assess, from an evolutionary perspective, the dynamic changes in the social/cultural, economic, and environmental features of the community created by TIF funding. Perhaps the most appropriate tool is Hayden's (2006) social fabric matrix approach. This approach used diagraphs and Boolean logic to map flows of resources and power across each of the players in the community, and over time. Thus, the social fabric matric connects the pre and post TIF CAMs, economic impact analyses, and business plans identified in 1) – 3).

5) Holistic criteria should be established to iteratively measure the impact of the TIF-financed project using ecologically sound, iterative criteria. One such set of criteria include the five-fold test for sustainability posited by Underwood, Friesner and Cross (2014) and Underwood, Hackney and Friesner (2015). It is also important to emphasize the need to evaluate these criteria with a perspective that includes the distributional impacts of the TIF-financed project. That is, previous sections of this report show that TIF intensity is closely related to the distributions of population and employment in the local community (and periphery communities). Thus any assessments using these criteria should give equal weight to both measures of central tendency as well as measures of variation.

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