Beyond the Local Impacts of Place-Based Policies: Spillovers through Latent Housing Markets

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Abstract

Place-based policies target geographic areas, aiming to generate localized investment for economic development. Do place-based policies create new economic activity or do they reallocate it? Empirically evaluating this question is challenging because of the difficulty in ascertaining areas that might experience spillovers. I develop a data-driven approach to characterize the areas most likely to be affected when others receive targeted investment. Tax Increment Financing in Chicago provides a setting to consider whether place-based policies revitalizing neighborhoods are zero-sum. I find that while the effect of Tax Increment Financing on property values in targeted areas is positive, the spillover effect on property values in non-targeted areas is negative. Business activity shifts in a manner consistent with Tax Increment Financing subsidizing development that would have occurred elsewhere. I combine the direct and spillover effects to calculate a back-of-the-envelope estimate of an overall effect close to zero. Due to the targeting of the policy, it results in a limited amount of redistribution towards relatively disadvantaged targeted areas.

JEL Codes: H71, R23, R58

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1 Introduction

Place-based polices are widespread vehicles to direct investments and economic development to targeted areas (P. Kline and Moretti, 2014b; Gaubert, P. M. Kline, and Yagan, 2021; A. Hanson, 2021; Gaubert, G. H. Hanson, and Neumark, 2024).[1] While they aim to revitalize specific locations, place-based policies may affect the broader region through the presence of market failures and the responses of households and firms (Coates and Humphreys, 2008; Glaeser and Gottlieb, 2008; Moretti, 2010; Fajgelbaum et al., 2019). The challenge in assessing whether these policies create new economic activity or simply reallocate it is identifying where spillovers occur. Without a clear understanding of how investment affects non-targeted areas, it is difficult to determine whether place-based policies achieve their intended goals or merely shift economic activity across space.

This paper develops a new, data-driven approach to identify and quantify the spillover effects of spatially targeted investments, allowing for a comprehensive understanding of place-based policies. I apply this framework to Tax Increment Financing (TIF) in Chicago, a neighborhood revitalization policy that directs investment into well-defined geographic areas. Using the staggered rollout of TIF districts, I first estimate its direct effect on property values and find that it is locally effective. However, measuring spillovers requires identifying which non-targeted areas are meaningfully affected. Prior work often assumes that spillovers are limited to geographically adjacent areas, but there may be effects in more distant locations. Because I study the effects of the policy on residential property values, I consider spillover effects propagated through housing markets and refer to them as market spillover effects.[2] By explicitly distinguishing market spillover effects from spatial spillover effects, this paper provides a framework for evaluating the broader impact of place-based policies and other

[1] See Bartik (1990), Bartik (1991), and Neumark and Simpson (2015) for overviews of place-based policies and their prevalence.

[2] Because the method is data-driven, I may be capturing non-spatial spillovers other than spillovers through housing markets. Using other data (e.g., commuting flows) would result in other types of non-spatial spillovers. I discuss this more below in Section 2.

policies that may induce non-spatial spillovers. This approach allows me to evaluate whether place-based policies reallocate economic activity or generate new growth, contributing to a long-standing discussion in the literature.

Because housing markets are unobserved, researchers often use existing geographic definitions. However, housing markets may not be contiguous due to housing supply, location of amenities and transit, or segregation patterns. To characterize housing markets, I construct a network of connected blocks using data on household moves, and define the underlying groupings of the network using a model of community detection, Stochastic Blockmodeling (SBM).[3] Under a revealed-preference framework, I interpret moves as informative about the households' choice sets. I use the moves to characterize latent housing markets and estimate market spillover effects. Instead of only relying on spatial proximity or observed characteristics (Goodman and Thibodeau, 2003; A. Hanson and Rohlin, 2013), SBM allows me to define housing markets based on unobserved characteristics as well. This approach can be applied to other empirical frameworks that already identify direct treatment effects, and thus bolster economic analysis by assessing effectiveness outside of targeted areas. Section 2 describes method and presents the estimated housing markets for Chicago.

I use TIF in Chicago to study market spillover effects because of its staggered implementation and large concentration of public investments into well-defined geographic areas. Municipalities create TIF districts in which a portion of property taxes are used for a wide variety of economic development activities. TIF districts are selected based on a combination of eligibility factors, potential for success in repayment of costs, and public-private mutual interest (Johnson and Kriz, 2001; Klacik and Nunn, 2001; Kriz and Johnson, 2019).

[3]Holland, Laskey, and Leinhardt (1983), Y. J. Wang and Wong (1987), T. A. Snijders and Nowicki (1997), and Nowicki and T. A. B. Snijders (2001) are foundational works introducing SBM. Jackson (2011) provides an introduction to community detection methods. While a growing literature uses SBM in the context of labor markets to classify types of jobs and workers (Costa Dias et al., 2021; Fogel and Modenesi, 2022; Jarosch, Nimczik, and Sorkin, 2023; Nimczik, 2023), SBM has not been applied to the problem of defining housing markets to my knowledge. Finkelstein, Gentzkow, and Williams (2021) also use residential mobility to control for unobservable characteristics following a similar logic to my revealed-preference framework.

The property taxes can be used directly for economic development activities like demolitions of vacant structures, or as leverage for debt mechanisms and private investment (Johnson, 1999; Johnson, 2001; Weber, 2010; Luby et al., 2019). TIF is a widespread policy that constitutes a large investment for municipalities in local economic development. Chicago's implementation of TIF is particularly widespread resulting in its recognition as emblematic of TIF (Healey and McCormick, 1999; Craft and Weber, 2019). My analysis includes TIF districts established between 2000 and 2022, corresponding to the height of its implementation. Section 3 details TIF in Chicago and Section 4 describes the data I use for the analysis.

I use variation in the timing of TIF districts to identify and estimate the effects of economic development. Areas may be targeted for place-based investment due to their potential to grow, challenging the identifying assumption of parallel trends when comparing targeted areas to non-targeted areas. Instead, I compare targeted areas to areas targeted in the future using stacked difference-in-differences (Guryan, 2004; Fadlon and Nielsen, 2015; Cengiz et al., 2019; Deshpande and Li, 2019). To consider the validity of the empirical design, I estimate heterogeneous treatment effects for TIF districts by monetary investment. I find that the estimated effect for TIF districts with below-median investment is zero. This supports that the empirical design is capturing the casual impact of TIF's economic development activities rather than unobservable determinants of the timing of TIF districts. Section 5 specifies the stacked difference-in-differences framework I use to estimate direct and spillover treatment effects.

Many economic development policies aim to increase property values (Foell and Pitzer, 2020) because property values dictate local property taxes that provide a revenue stream to fund public goods and services (Brülhart, Bucovetsky, and Schmidheiny, 2015). In the case of TIF and other policies of land-value capture, the increasing property taxes pay for the investment (Youngman, 2016). Within the targeted areas, I estimate an average treatment

effect across time periods on property values of 2.65%. Dynamic treatment effects demonstrate that the impact of TIF begins soon after the initiation of a TIF district and increases over time. I estimate weakly positive spatial spillover effects (0.8%). While informative, the spatial spillover effects do not include responses of households and firms outside of the immediate vicinity of the TIF districts. I estimate a market spillover effect of -1.56%. To consider mechanisms that may drive the negative market spillover effect, I use outcomes related to firms. I estimate an increase in the flow of business licenses within TIF districts and a decrease outside of TIF districts, supporting that TIF redirects investment away from non-targeted areas within housing markets.

I combine the direct effects on the targeted areas with the spillover effects to calculate a back-of-the-envelope, "overall" treatment effect that is close to zero. This illustrates that omitting market spillover effects may substantially alter the understanding of the effectiveness of place-based economic development. Because TIF areas tend to be negatively selected on property values, the policy may result in redistribution even if the overall effectiveness is small. I find that within housing markets, TIF districts are relatively disadvantaged, indicating the policy redistributes within housing markets. Section 6 presents the results and robustness checks of the empirical design and regression specifications.

1.1 Related Literature

Methodologically, this paper builds on the literature studying spillover effects, which tends to focus on spatial spillover effects (Bollinger and Ihlanfeldt, 1997; Bowes and Ihlanfeldt, 2001; Schwartz et al., 2006; Hudgens and Halloran, 2008; Diamond and McQuade, 2019; Lu, J. Wang, and Zhu, 2019; Hyman et al., 2022), with recent developments expanding design-based methods (Borusyak and Hull, 2021; Pollmann, 2023; Y. Wang et al., 2023). I build on this work by adding the consideration of market spillover effects, which are important for considering if a place-based policy is zero-sum.

Related work proposes approaches to decompose treatment effects explicitly accounting for spillovers and resorting due to place-based policies (Butts, 2021; Alves, Burton, and Fleitas, 2024) or using observed characteristics to determine areas that may experience spillover effects (A. Hanson and Rohlin, 2013). These approaches are complementary to my approach, which studies non-spatial spillover effects by using a data-driven classification of housing markets. Developed contemporaneously to this paper, Mast (2024) uses a different algorithm to define neighborhoods using migration data from the Census. Similar to my classification of housing markets, that classification incorporates observed and unobserved determinants of neighborhood. Unlike my approach, Mast limits the neighborhoods to be spatially contiguous, which is useful for other applications but would limit the geography of the market spillover effects I aim to estimate and defeat the purpose of separating spatial and non-spatial spillovers.

Empirically, this paper contributes to the literatures studying TIF and economic development more broadly by adding evidence of an example in which a place-based policy targeting neighborhoods is zero-sum. Greenbaum and Landers (2014) provide a recent review of the literature evaluating TIF, which generally finds positive impacts of TIF on property values (Weber, Bhatta, and D. Merriman, 2003; B. C. Smith, 2006; Carroll, 2008; B. C. Smith, 2009).[4] Instead of relying on observed characteristics for matching or control-function approaches, my empirical framework assumes parallel trends between treated and not-yet-treated areas and allows for dynamic treatment effects. I use fine-grained, time-varying fixed effects to account for unobserved heterogeneity that may otherwise threaten identification. I further extend this work by considering spillovers, especially by introducing

[4]There is a small literature that models the theory behind TIF (see Kriz, 2019, for a review). Most models specify the expected net present value of implementing TIF from the perspective of the local government (Lawrence and Stephenson, 1995; Dye and D. F. Merriman, 2000; Kriz, 2001). In these frameworks, the efficiency of TIF depends on the growth rates of the properties inside and outside the TIF district before and after TIF, and in the counterfactual scenario if TIF were not implemented. Brueckner (2001) presents a model with amenities and household preferences based on a hedonic framework (Brueckner, 1979; Brueckner, 1982). In this model, the efficiency of TIF depends on the extent public goods were under-provided prior to TIF.

the concept of market spillover effects.[5]

More generally, the consideration of market spillover effects relates to studies that impose structure to consider overall implications of spatially targeted economic development (e.g., P. Kline and Moretti, 2014a; Wheeler, 2022).[6] The structure allows for an investigation of the mechanisms of general equilibrium effects (e.g., Auerbach and Hassett, 1991; Gaubert, 2018). The approach in this paper to characterize markets allows for consideration of some general equilibrium responses within an empirical framework. It relies on assumptions on household behavior that allow for a revealed-preference framework instead of fully specifying structure on the market failures or firm and household decisions. I rely on estimating direct and spillover effects on other outcomes related to firm behavior to consider those mechanisms.

2 Characterization of Latent Housing Markets

Place-based policies may affect the housing markets of the targeted areas. Ideally, the analyst can observe housing markets, but they are unobservable. Rather than using other boundaries (e.g., historical neighborhood definitions) or matching on observed characteristics (A. Hanson and Rohlin, 2013), I use household moves between Census blocks to characterize housing markets in Chicago. I introduce the underlying revealed-preference framework that allows me to interpret household moves as informative on time-invariant housing markets. Households move to blocks that are in their choice sets and do not move to blocks that are not. I apply Stochastic Block Modeling (SBM) to group blocks into housing markets so that households are more likely to move within the estimated housing markets rather than between them.

[5]My findings on market spillover effects align with prior estimates of spatial spillover effects (Weber, Bhatta, and D. Merriman, 2007; Yadavalli and Delgado, 2019). A negative effect farther away from the targeted areas may indicate that the two areas are within the same housing market. My approach separates these two spillover mechanisms allowing for separate analyses.

[6]The overall effectiveness of TIF is explored in papers studying the municipal-level effect of adopting TIF in the the 1980s and 1990s when the policy was gaining traction (Anderson, 1990; Man and Rosentraub, 1998; Man, 1999; Dye and D. F. Merriman, 2000; D. F. Merriman, Skidmore, and Kashian, 2011). Because my approach uses smaller units of analysis and separates targeted and non-targeted areas within the municipality, it allows for more nuanced empirical results and interpretation.

2.1 Revealed-Preference Framework

My approach interprets household moves as informative on the latent housing markets. Several models of household decisions may be consistent with this interpretation. I introduce a revealed-preference framework, which obviates explicitly modeling the individual contributions of the observed and unobserved inputs to the households's decision problem.

I index I households, T time periods, and J blocks with i, t, and j. Let $B \subset J$ be a nonempty set of blocks. The choice set $C^{it}(B) \subset B$ are the blocks that household i would choose in time t. I assume that the underlying choice correspondence that defines $C^{it}(B)$ satisfies the Weak Axiom of Revealed Preferences (Samuelson, 1938). This means that if both blocks j and k are affordable to the household, and the household moves to k, then as long as both remain affordable, the household will always select k over j. In order to have time-invariant markets, I assume that the choice sets are structurally invariant to policy changes. That is, given B, $C^{it}(B) = C^{i}(B)$ for all t. Then, even if the set of feasible blocks changes due to changes in the household's income, home prices, or other shocks like changes to family structure, the household's residential decisions reflect its stable preferences.

2.2 Stochastic Blockmodeling for Estimating Markets

I observe the block in which household i resides in period t, whether the household moves in $t+1$, and to which block the household moves. I describe the movement of household i living in block j in period t with the indicators $\{S_{jk}^{it}\}_{k=1}^{J}$, where for all k,

$$S_{jk}^{it} = \begin{cases} 1 & \text{if household } i \text{ moves from block } j \text{ to block } k \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Each block is a member of an unobserved housing market M_j. I assume that there is a discrete set of markets so that $M_j \in \{1, 2, \ldots, M\}$, which are time-invariant assuming that

households's choice sets are constant over time. I denote the $J \times 1$ vector that maps blocks to markets as $\boldsymbol{M} := \{M_j\}_{j=1}^{J}$. The blocks within a market are substitutes, even if some characteristics differ (Pryce, 2013).

To uncover the number of markets, M, and the mapping from blocks to markets, $\boldsymbol{M}$, I use Stochastic Block Modeling (SBM; Breiger, Boorman, and Arabie, 1975; Holland, Laskey, and Leinhardt, 1983; T. A. Snijders and Nowicki, 1997; Nowicki and T. A. B. Snijders, 2001). See Appendix A.1 for more details on SBM and its estimation.

The only input for SBM is a $J \times J$ adjacency matrix, $\boldsymbol{A}^t$. Each element, $\boldsymbol{A}^t_{jk}$, indicates if at least one household moves from block j to block k in the sequential time periods t and $t+1$. Note that $\boldsymbol{A}^t$ need not be symmetric, meaning that just because households move from block j to k does not mean that households need to move from block k to j. I aggregate the matrices across all time periods into one adjacency matrix $\boldsymbol{A}$. For all blocks j and k,

$$\boldsymbol{A}_{jk} = \begin{cases} 1 & \sum_{t=1}^{T} \sum_{i=1}^{I} S_{jk}^{it} > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Given a proposed number of markets, the estimation procedure categorizes the blocks so that the probabilities of transitioning between markets maximize the likelihood function. In Appendix D.5, I evaluate the sensitivity of my empirical results to the specification of the SBM estimation by changing the number of housing markets. Across specifications, I find similar results. The likelihood function contains a penalty term allowing me to estimate of the number of markets M. The baseline specification results in a resolution limit in which the number of markets possible to estimate has an upper bound that is a function of the number of blocks. I use a nested model structure to increase this limit (Peixoto, 2014b). The nested model implements the estimation to categorize the blocks into markets. Then, it repeats the estimation to categorize those markets into larger markets. The algorithm

continues until there is one market encompassing all the smaller divisions. The output of this approach confers benefits for the empirical application as well. I interpret the coarser markets as "broader" housing markets, which are useful to control for broader market trends in the regression models.

I present an example using simulated data to illustrate the connection between SBM and the intuition of defining housing markets.[7] Suppose that there are 100 Census blocks (Figure 1a). While the latent market structure is unobserved, the household movement between each pair of blocks is observed. Figure 1b shows the matrix that summarizes the household movement information. This is the only input for SBM, which then estimates groupings based on the connections (Figure 1c). The output is a mapping between Census Blocks and estimated markets (Figure 1d).

2.3 Possible Endogeneity of Housing Markets

I estimate housing markets using observations on household movement between 2006 and 2020, which overlaps with the period of analysis when TIF districts are established. There may be a concern that TIF generates changes in amenities and property values, which in turn change the housing markets. An alternative approach is to only use years prior to the establishment of a TIF district to determine the housing markets for the spillovers of that district. However, this would severely limit the number of districts possible to analyze. More fundamentally, if TIF does impact housing markets, market spillover effects estimated with the pre-TIF housing markets would exclude effects from areas that I aim to characterize and study.

Thus, the estimated market spillover effects reflect both changes in housing markets and the spillover effect itself. I address this concern partially by using binary SBM, where the adjacency matrix elements are one if any movement occurs between the corresponding Census blocks and zero otherwise, independent of the number of households moving. This

[7] See Appendix A.5 for details of the simulation.

Figure 1: Illustration of SBM for Market Characterization

(a) Observed Census Blocks

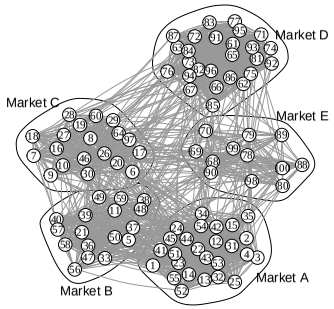
1	2	3	4	5	6	7	8	9	10
11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30
31	32	33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48	49	50
51	52	53	54	55	56	57	58	59	60
61	62	63	64	65	66	67	68	69	70
71	72	73	74	75	76	77	78	79	80
81	82	83	84	85	86	87	88	89	90
91	92	93	94	95	96	97	98	99	100

☐ Census Blocks

(b) Input for SBM: Observed Movement between Census Blocks



(c) SBM Algorithm



(d) Estimated Markets

A	A	A	A	B	C	C	C	C	C
B	A	A	A	A	C	C	C	C	C
B	A	A	A	A	C	C	C	C	C
A	A	B	A	A	B	B	B	B	B
A	A	A	A	A	C	B	B	B	B
A	A	A	A	A	B	B	B	B	C
D	D	D	C	D	D	D	E	E	E
D	D	D	D	D	D	D	E	E	E
D	D	D	D	D	D	D	E	E	E
D	D	D	D	D	D	C	E	E	E

Estimated Market ■ A ■ B ■ C ■ D ■ E

Note: Using simulated data, this figure illustrates the steps for the estimation of housing markets using Stochastic Block Modeling (SBM). Census blocks (panel a) are observed, but the latent housing markets are unobserved. The input for SBM is a matrix indicating if there is movement between Census blocks (panel b). The SBM algorithm groups the blocks to parsimoniously maximize movement within groupings (panel c). The output is a correspondence between blocks and housing markets (panel d). I arbitrarily name the markets A, B, C, D, and E.

classification allows TIF to influence the number of movers without altering the underlying market structure. Chicago's persistent neighborhood definitions and patterns of residential segregation help support this approach (Aaronson, Hartley, and Mazumder, 2021). In Appendix A.3, I show that the yearly adjacency matrices are similar across time and closely match the aggregated adjacency matrix that I use in the analysis, further supporting aggregating across years.

2.4 Estimated Housing Markets for Chicago

2.4.1 Data on Household Moves

I match a cross-sectional dataset across consecutive years to observe household moves. InfoUSA is a commercial dataset that aims to include every household in the U.S. observed annually between 2006 and 2020 (Data Axle, 2020). I clean the cross-sections of the InfoUSA data, restricting the data to households in Cook County. I match the addresses's geographic coordinates with the 1990 definitions of Census blocks. I assign all Census blocks outside of the City of Chicago as one suburban block. I match households between consecutive years (2006-2007, 2007-2008, ..., 2019-2020) using a household ID.[8] In total, I observe 871,627 households and 108,061 moves (see Table 1).

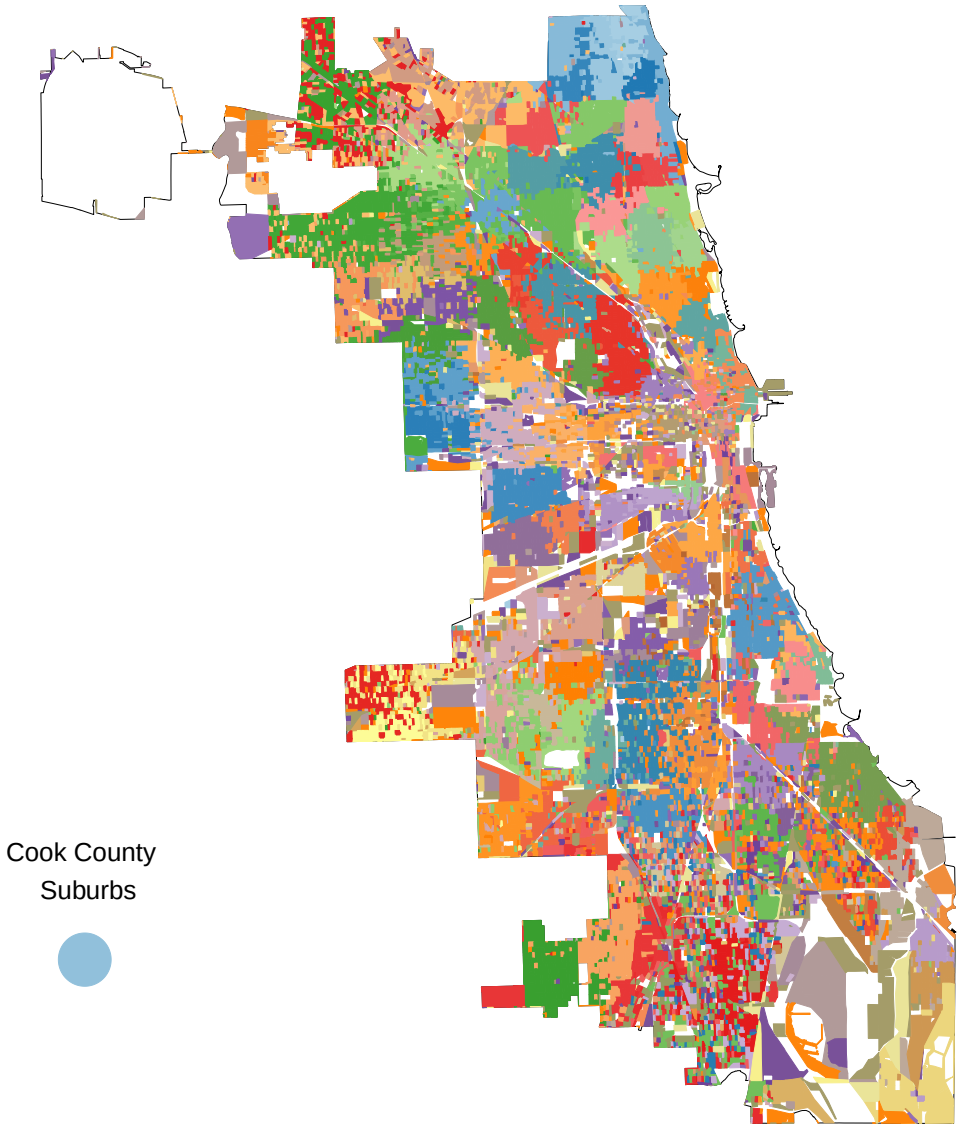
2.4.2 Estimated Housing Markets

I estimate 146 housing markets in Chicago as shown in Figure 2. See Appendix A.2 for maps of the broader markets estimated in the nested algorithm. None of the markets perfectly coincide with historical neighborhood definitions. While many of the markets contain blocks that are spatially clustered, many markets are disperse. For example, some some markets follow highways or public transportation routes.

The market characterization successfully distinguishes highly segregated neighborhoods

[8]The households that do not match may have some inconsistency in household ID, move outside of Cook County, or be absorbed in another household. This matching procedure results in matching approximately 75% of the households.

Figure 2: Estimated Markets in the City of Chicago



Note: This figure displays the 146 housing markets that the Stochastic Block Modeling (SBM) algorithm estimates.

that are adjacent, such as North Lawndale and Little Village (Figure 3a). Some markets seem related to observed amenities, such as proximity to Lake Michigan (Figure 3b). Even though race/ethnicity and amenities are not inputs into the algorithm, the estimated housing markets reflect these observed characteristics. While the markets are related to observed characteristics and amenities, they are also determined by unobservables.[9] In all of the cases in Figure 3, spatially adjacent areas are in separate housing markets and may not experience spillover effects through market channels, highlighting the need to distinguish between market and spatial spillover effects.

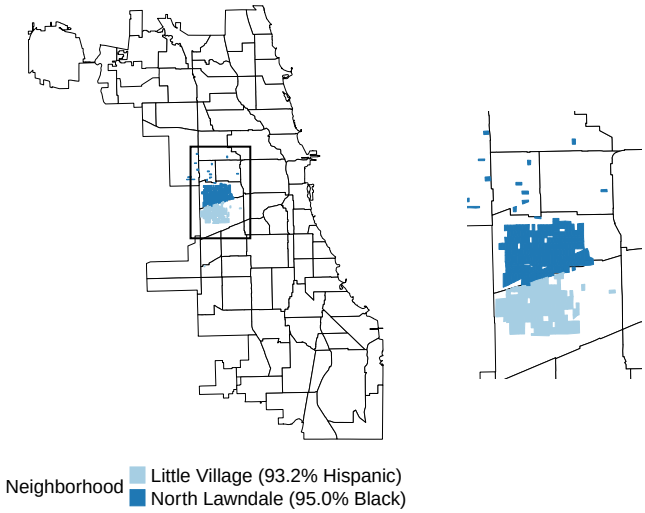
Given the reliance of the method on household movement, it is important to characterize the moves and movers. Table 1 displays the proportion of moves that are across rather than within estimated housing markets. Each year an average of 35.2% of moves are across markets and 64.8% of moves are within markets. The larger percentage of moves being within markets aligns with the intuition of the revealed-preference framework and the algorithm. This pattern holds across the income distribution, regardless of whether the household rents or owns, and across race/ethnicity of the household head.

Households may move across markets due to changes in income, employment, age, family size, or other shocks. This is still consistent with the revealed-preference framework. The choice sets for the households can depend on the state, such as having a child. The key assumption is that conditional on that state, the choice sets do not change over time. For this reason, it is logical to have at least some of the moves be across markets.

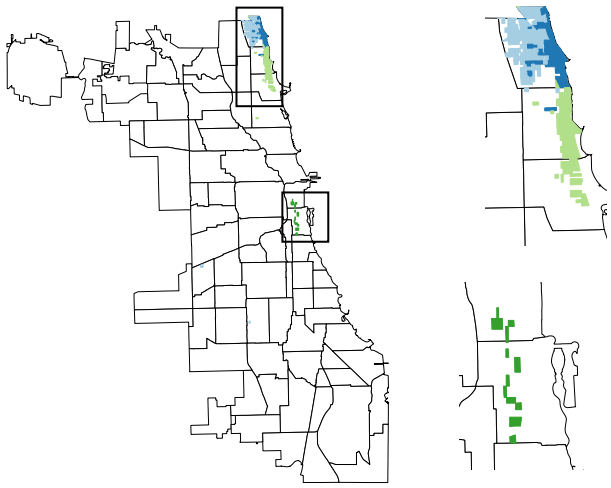
[9]See Appendix A.4 for a discussion of the relationship between the estimated housing markets and observed characteristics

Figure 3: Example Housing Markets

(a) Racial Segregation



(b) Proximity to Lake Michigan



Note: This figure demonstrates two examples in which the Stochastic Block Modeling (SBM) algorithm recovers housing markets that follow observed characteristics. Each shaded area is a separate housing market. The thin, black lines follow the historic definitions of community areas. Panel(a) shows an example of two areas that are adjacent but in separate housing markets due to racial segregation. Panel (b) shows an example of housing markets that may reflect proximity to Lake Michigan.

Table 1: Household Moves Across and Within Estimated Markets

	Proportion of Moves		Total	
	Across Markets	Within Markets	Households	Moves
All	0.352	0.648	871,627	108,061
Household Income				
1st Quartile	0.361	0.639	255,274	32,698
2nd Quartile	0.365	0.635	207,105	24,405
3rd Quartile	0.35	0.65	193,673	22,892
4th Quartile	0.302	0.698	215,575	28,066
Tenure				
Renter	0.317	0.683	446,523	42,329
Owner	0.363	0.637	188,191	27,751
Race/Ethnicity				
Black	0.379	0.621	285,654	32,842
Hispanic	0.345	0.655	175,803	20,457
White	0.359	0.641	367,948	49,479
Asian	0.344	0.656	36,555	4,921
Other	0.357	0.643	2,634	362

Note: All numbers are yearly averages for all moves in Cook County recorded in InfoUSA. I determine cutoffs for the quartiles using the distribution of household income in the base year (2006). InfoUSA predicts household income and tenure. I use Imai and Khanna (2016) to estimate race/ethnicity. For the calculation by tenure, I omit households with undetermined renter or owner status. I use household income and renter or owner status in the base year to classify households.

3 Tax Increment Financing

TIF is a widespread policy that provides an opportunity to study spillovers of place-based economic development targeting neighborhoods. It is used in almost all U.S. states (Klacik and Nunn, 2001; Kriz and Johnson, 2019) and increasingly outside the U.S. (Baker et al., 2016). TIF reduces the transaction costs of development by bypassing usual budgetary processes, reallocating city- or county-wide resources to more local entities, and fostering public-private commitments.

TIF facilitates a wide range of economic development activities within designated TIF districts. Once a municipality establishes a TIF district, any increase in the property taxes therein above the base-year amount goes towards economic development activities within the district. Other taxing bodies continue to collect property taxes on the base-year amount. After the TIF district expires (usually 23 years in Chicago), the taxing bodies collect property taxes on the total amount, which is ideally higher due to TIF-driven development (Department of Planning and Development, 2020).

Chicago's implementation of TIF is emblematic (Healey and McCormick, 1999; Craft and Weber, 2019). After the first district in 1986, its use expanded in the 1990s. In 2021, TIF revenues were over $1.2 billion (2020 USD), accounting for 14.5% of the total property taxes in Chicago (Cook County Clerk's Office, 2020). Figure 4 demonstrates the geographic spread of TIF districts throughout the city. I highlight the 106 TIF districts established between 2000 and 2022 that overlap with the data span for my analysis.[10]

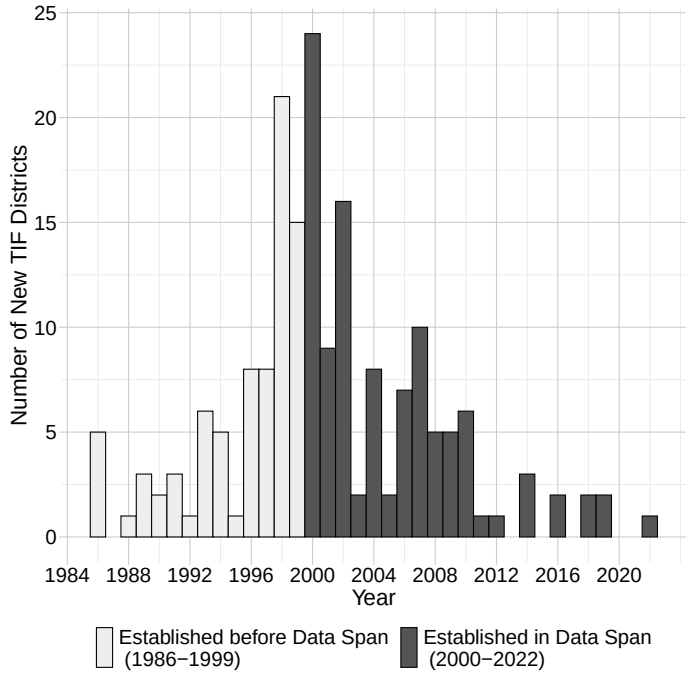
TIF districts must meet two criteria. First, the properties, infrastructure, and built environment of the TIF district must exhibit "blight,"[11] such as inadequate utilities or

[10] In practice, I use 90 TIF districts. I describe the sample selection in Section 4.

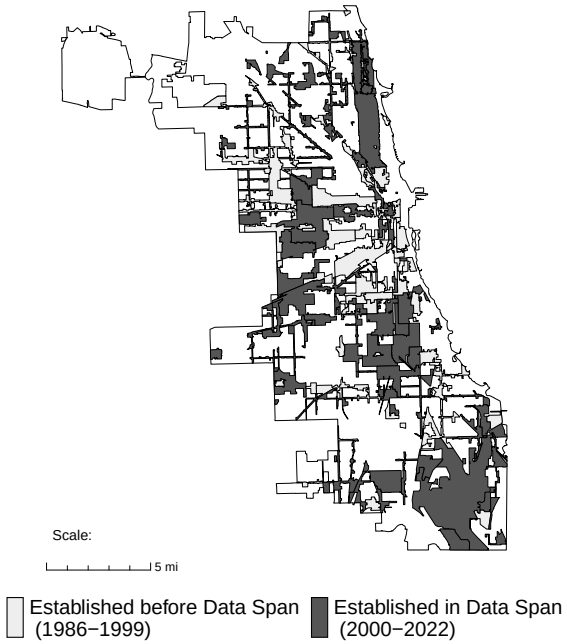
[11] I acknowledge the racial implications of the term "blight" (e.g., Pritchett, 2003; Weber, 2015; Mock, 2017). In this writing, I use the term referring to its historical and current use in TIF legislation and implementation. Weber and O'Neill-Kohl (2013) argue that the close relationship between federal urban renewal policies and TIF led to the same reliance on the concept of blight.

Figure 4: Tax Increment Financing Districts in Chicago

(a) Districts by Implementation Year



(b) Geographic Distribution



Note: Panel (a) plots the number of new TIF districts established by year. Panel (b) maps the TIF districts designated within Chicago. The data for the main analysis span 1999-2022, so I use districts established after 1999 in my analysis. In both panels, dark gray corresponds to districts with those in my period of analysis ($N = 106$). Light gray corresponds to districts established before my period of analysis ($N = 79$). Data from City of Chicago (2022).

dilapidation.[12] In addition to the presence of blight factors, there must be justification for the "but for" clause, i.e., the area would not develop "but for" the implementation of TIF. This requirement is often completed in an ad hoc manner with private interests pledging investment only to leverage TIF funding (Briffault, 2010).

A redevelopment plan outlines the planned activities, stakeholders, land use, budget, and projected revenues. Chicago's Department of Planning and Development (DPD), housed in the Office of the Mayor, coordinates with ward alderpersons, special tax districts, private developers, and community stakeholders to implement TIF, with final approval from the City Council (Department of Planning and Development, 2020). The process to initiate, design, and approve a TIF district lasts approximately one year.[13]

Once the city establishes a TIF district, the natural appreciation of property values may gradually accrue and fund the activities outlined in the redevelopment plan. Alternatively, the city can rely on private investments or borrow against the expected increase in property values as a result of the TIF-funded interventions (Luby et al., 2019).[14] TIF funds may be used within the district for a broad array of economic development activities such as property acquisition and demolition, environmental remediation, or construction of public works.[15] These activities may contribute to different types of development, including residential, commercial, industrial, institutional, or transportation. Most districts during my period of analysis are intended for mixed-use development, focusing on residential and

[12]See Appendix Table A.2 for a full list of the blight factors.

[13]See Appendix B for more details on the process of establishing a TIF district.

[14]For the 148 districts with information on project costs, the median total cost per project is $\$9,818,150$ with $\$2,843,244$ being the median subsidy amount from the TIF district. Cumulatively across projects with recorded costs, the median district involves $\$59,900,450$ of total investment, $\$13,945,775$ of which is subsidized with TIF funds. All values are in 2020 USD. The costs only include projects completed in partnership with private firms or other taxing bodies (e.g., the school district). They do not include costs from infrastructure projects or other types of TIF-funded investment. In Section 6, I perform heterogeneity analysis by the amount of costs and subsidies.

[15]In practice, there are two instances in which the funds raised within the TIF district are used outside of it. First, TIF funds can be used for an adjacent public space (Chen, 2013). Second, TIF funds can be "ported" between adjacent districts. I consider both of these instances to be valid in my empirical framework. The treatment that occurs inside the targeted area may include these implementation realities.

commercial development.

I use property values as my primary outcome of interest. Because TIF operates through capturing increases in property taxes to be reinvested into the TIF district, increasing property values is critical to TIF's success (Youngman, 2016). Furthermore, property values capitalize changes in amenities, allowing me to consider changes due to TIF's varied economic development activities (Rosen, 1974). I estimate treatment effects for firm outcomes to consider mechanisms through which TIF affects property values, both within TIF districts and in other areas through spillovers.

4 Data

I combine data on TIF's implementation in Chicago with data on properties, households, and Census Blocks. Appendix C provides additional information.

4.1 Property Values and Characteristics

The Cook County Assessor's Office (CCA) provides information on the universe of properties in Chicago between 1999 and 2022 (Cook County Government, 2023). I restrict the sample to single-family residential properties with observed geographic coordinates.

I focus on assessed values as my measure of choice for property values. Although sale prices are observed market prices, they provide a selected sample of properties that sell (Bishop et al., 2020). For empirical frameworks that rely on panel data, the issue of selection is even more severe (e.g., Gatzlaff and Haurin, 1994). Unlike sale prices, assessed values are observed annually for every property.[16] I present the main results of the paper using sale prices instead of assessed values in Appendix D.1. The results are noisy but qualitatively similar to the results using assessed values.

I perform the analysis at the Census block level to aggregate the individual properties

[16]The CCA officially recalculates assessed values for properties in the City of Chicago every three years. In the intervening years, there is additional variation in property values from appeals and inflation adjustments.

and reduce the impact of possible prediction error (Avenancio-León and Howard, 2020). I use the 1990 definitions of Census Blocks for analysis. This avoids concerns that the TIF districts established starting in 2000 would affect the boundaries of the blocks (Manson et al., 2022).

4.2 TIF Implementation

The City of Chicago and Cook County publish data on the implementation of TIF. I define treated Census blocks as those within 100 meters of TIF district boundaries.[17] This definition allows for TIF districts primarily covering commercial or industrial properties to directly treat residential properties within neighboring Census blocks. Figure 5 shows the targeted Census blocks for an example TIF district.

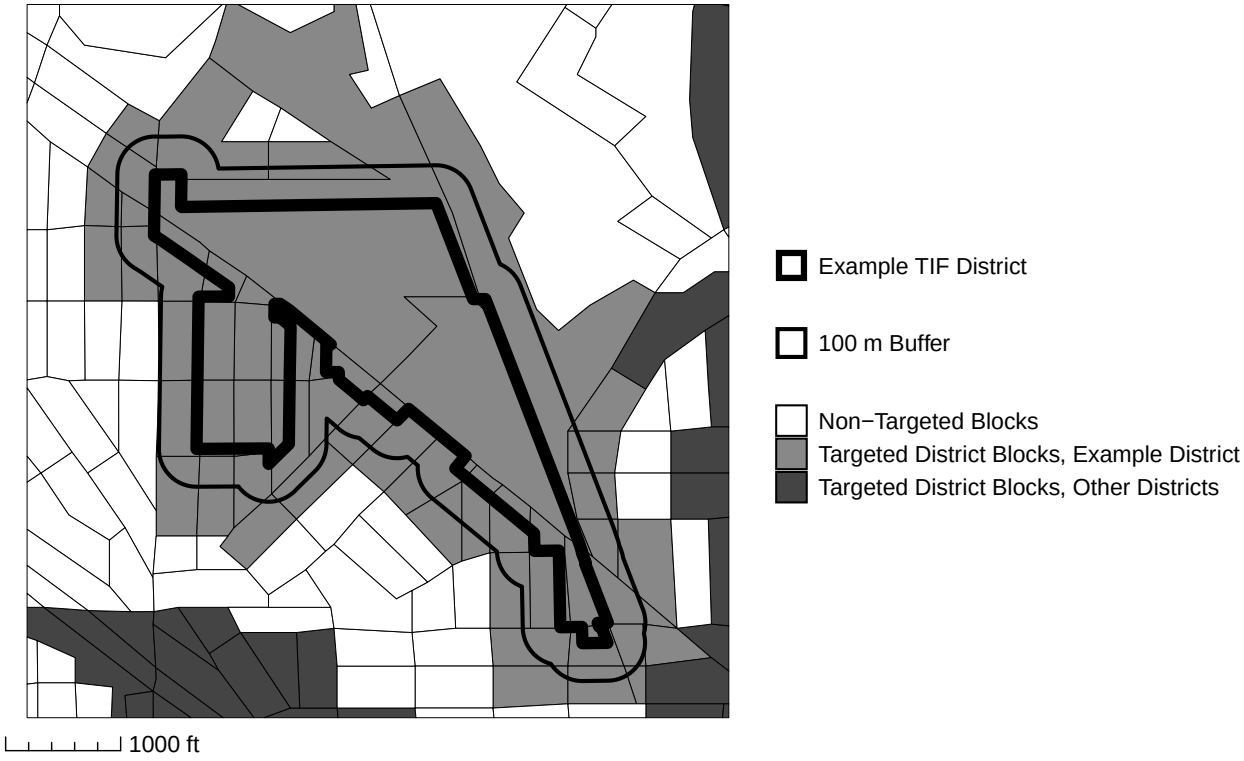
I define that treatment begins in the year that the TIF district is established. Even if there is a delay between the establishment of the TIF district and the actual development, there is a mutual agreement between stakeholders, and there may be signaling effects. If a block overlaps with more than one TIF district, I assign it to the district that was established earliest.

4.3 Sample

I construct a sample to align with the empirical design of stacked difference-in-differences, comparing treated blocks to blocks treated at least 5 years later. Given this and the CCA's data span (1999-2022), I study TIF districts established between 2000 and 2017. I exclude TIF districts that do not have any residential properties within a 100-meter buffer. This leaves me with 90 TIF districts that are considered in the treatment group. The not-yet-treated group must contain blocks within 100 meters of TIF districts established at least 5 years after the TIF districts in the treatment group (between 2005 and 2022). Note that TIF districts can appear in both the treated and not-yet-treated groups.

[17] In Appendix Figure A.6, I estimate similar direct effects for different definitions of treated Census blocks.

Figure 5: Treatment Definition for an Example TIF District and its Surrounding Area



Note: This map exemplifies the definition of treatment I use. I map Census blocks and an example TIF district (thick black line). The thin line surrounding the TIF district represents a 100-meter buffer. I define the light gray Census blocks to be targeted by the TIF district because they overlap with the buffer. The dark gray Census blocks are targeted by other TIF districts and the white Census blocks are non-targeted. Data from City of Chicago (2020) and Cook County Government (2023).

4.4 Summary Statistics

Table 2 describes the blocks in the analysis sample (columns 1 and 2) and the non-targeted blocks (column 3). Compared to the non-targeted blocks, the blocks in the analysis sample have higher rates of impoverished and renting households. The selection criteria of TIF relate to the built environment, but this is correlated with household characteristics that indicate disadvantage. In addition to observed differences between blocks in the analysis sample and non-targeted blocks, there may be unobserved differences in the trends in potential outcomes. Many papers evaluating TIF and other place-based policies rely on matching strategies to

compare treated to never-treated areas (e.g., Czurylo, 2023). Instead, my main empirical strategy relies on comparing treated blocks to not-yet-treated blocks.

Across characteristics, the treated and not-yet-treated blocks are similar. The not-yet-treated blocks correspond to TIF districts established later and suggestively exhibit less disadvantage in terms of household income and poverty. The large value of commercial assessed land values indicate that these are more commercial-focused areas. As I discuss in Section 5, the key assumption for the empirical design is that treated and not-yet-treated blocks would follow parallel trends in property values in the absence of treatment.

5 Empirical Design

TIF districts are designed to fund themselves as property values rise while also targeting areas with distressed built environments. This combination of feasibility and targeting results in TIF districts that are not randomly assigned. Hypothetically, randomizing TIF districts would remove the concern that changes in property values are correlated with unobserved neighborhood characteristics rather than due to the economic development activities of TIF. The empirical design of the direct treatment effects addresses this endogeneity concern by exploiting temporal and spatial variation in TIF's implementation, comparing Census blocks in TIF districts to those in TIF districts established later. The empirical design of the market spillover effects has a similar approach, but compares Census blocks within the same market as TIF districts to those in different markets.[18] This follows the logic of spatial spillover effects that compare geographically close areas to those that are geographically far.

5.1 Direct Effects

The direct estimates of TIF capture the intention to treat distressed areas with economic development activities. I exploit the variation from the staggered treatment in a stacked

[18] An alternative is to compare blocks with in the same markets as TIF districts to those that will be in the same markets as TIF districts in the future. This would better mirror the comparison of the direct effects, but is infeasible in this context due to the large geographic coverage of TIF districts.

Table 2: Baseline Property, Household, and Firm Census-Block Characteristics

	(1) Treated Est. 2000-2017	(2) Not-Yet-Treated Est. 2005-2022	(3) Non-Targeted
Number of TIF Districts	90	38	0
Number of Census Blocks	6,843	2,829	7,416
Number of Residential Properties (1999)	149,042	65,368	207,334
Residential Property Characteristics (1999)			
Assessed Value	170,924.61	199,862.39	195,059.42
	(150,187.08)	(191,147.12)	(251,718.96)
Sale Price	232,883.48	337,733.03	264,210.93
	(307,678.85)	(281,932.53)	(310,214.43)
Transactions	0.03	0.02	0.02
	(0.32)	(0.17)	(0.16)
Household Characteristics (2000)			
Median Income	53,032.76	60,342.98	61,549.21
	(24,655.68)	(28,778.00)	(20,454.69)
Poverty (proportion)	0.21	0.18	0.14
	(0.15)	(0.14)	(0.11)
Renter (proportion)	0.58	0.57	0.44
	(0.26)	(0.25)	(0.29)
Non-Hispanic Black (proportion)	0.38	0.38	0.28
	(0.43)	(0.44)	(0.40)
Non-Hispanic White (proportion)	0.29	0.35	0.39
	(0.31)	(0.36)	(0.35)
Hispanic (proportion)	0.27	0.22	0.28
	(0.31)	(0.31)	(0.31)
Firm Characteristics (2000)			
New Business Licenses	0.02	0.02	0.01
	(0.14)	(0.16)	(0.13)
Commercial Land Assessed Value	564,063.0	900,070.1	825,580.8
	(3,414,825.9)	(4,885,613.2)	(4,024,911.6)
Industrial Land Assessed Value	404,510.9	346,184.3	353,330.2
	(745,098.0)	(508,400.9)	(801,767.6)

Note: Treated Census blocks are within 100 meters of TIF districts established 2000-2017. Not-yet-treated blocks are treated by TIF districts established 2005-2022. For all variables except transactions and business licenses, I report weighted means (weighted standard deviations) weighing by the number of properties or households. All monetary values are in 2020 USD.

difference-in-differences approach to estimate the direct treatment effects comparing treated Census blocks to not-yet-treated Census blocks.

Let i index Census blocks and d index the districts. I use E_d to denote the period in which district d is established. I denote the set of blocks that district d targets as $\mathcal{N}_d$. Then, the definition of the indicator for district d targeting block i is

$$D_{id} = \begin{cases} 1 & \text{if } d = \arg\min_{d'}\{E_{d'} \mid i \in \mathcal{N}_{d'}\} \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

That is, if block i is targeted by many districts, it is assigned to the earliest one. I denote the time period in which block i begins treatment as E_i. If block i is never treated, then $E_i = \infty$.

I compare the treated blocks to the blocks that will be treated in the future, that is the not-yet-treated blocks. This comparison assumes that time-varying, unobservable characteristics correlated with the potential for growth are present in all targeted areas, regardless of particular treatment timing. Then, the identifying assumption is that in the absence of treatment, the potential outcomes of the treated areas would be parallel to those of the areas treated in the future. I specify that the comparison blocks must be treated at least $\Delta := 5$ periods after e.[19] While too large of a Δ may result in a comparison group that is too dissimilar (challenging parallel trends) or too thin of support in the data, too small of a Δ limits the capacity to estimate longer-run effects (Fadlon and Nielsen, 2015).

I combine blocks treated by the district ($D_{id} = 1$) and blocks treated at least 5 periods after district d. I append the districts's datasets into one stacked dataset. With those data,

[19]Restricting the comparison group this way avoids bias from including concurrently treated units in the comparison group (e.g., de Chaisemartin and D'Haultfœuille, 2020; Borusyak, Jaravel, and Spiess, 2021; Goodman-Bacon, 2021). See Guryan (2004), Callison and Kaestner (2014), Fadlon and Nielsen (2015), Cengiz et al. (2019), Deshpande and Li (2019), and Butters, Sacks, and Seo (2022) for empirical implementations of stacked difference-in-differences.

I estimate the direct treatment effect of TIF on outcome Y_{it} measured in time t with the following regression model:[20]

$$Y_{it} = f(i,t) + \beta D_{id} + \sum_{\ell \in \mathcal{L}} \beta_\ell \mathbf{1}\{t - \ell = E_d\} + \sum_{\ell \in \mathcal{L}} \gamma_\ell D_{id} \mathbf{1}\{t - \ell = E_d\} + \varepsilon_{it}. \tag{4}$$

I specify general fixed effects $f(i,t)$ to represent block and time fixed effects that control for hyper-local trends that could influence economic activity. In practice, I use Census block and Census tract $\times$ year fixed effects.[21] The error term is ε_{it}. I represent the number of periods until or since treatment with ℓ. The set of considered event times is $\mathcal{L}$. In practice, I omit $\ell = -2$ to avoid collinearity resulting from linear dependence with the fixed effects. Because units may appear both as treated and comparison units, it is possible to include the indicator D_{id}, with corresponding parameter β, and indicators for time until or since the beginning of treatment, with corresponding parameters $\{\beta_\ell\}_{\ell \in \mathcal{L}}$. I use Equation (4) to estimate the effects of TIF on property values, calculated as the log of the mean, real, assessed value of the Census block. The parameters $\{\gamma_\ell\}_{\ell \in \mathcal{L}}$ correspond to the parameters of interest.

To estimate a static intent-to-treat effect, I use the analogous model averaging over post-treatment periods:

$$Y_{it} = f(i,t) + \beta D_{id} + \sum_{\ell \in \mathcal{L}} \beta_\ell \mathbf{1}\{t - \ell = E_d\} + \gamma D_{id} \mathbf{1}\{t \geq E_d\} + \varepsilon_{it}. \tag{5}$$

[20] Wing, Freedman, and Hollingsworth (2024) discuss the formal properties of stacked difference-in-differences and propose an alternative regression model that reweighs the estimator to allow for differences in cohort size. In Appendix D.4, I show that that the estimates are similar to those from Equation 4.

[21] See Appendix Figure A.4 for an example of the overlap between Census tracts, blocks, and TIF districts.

5.2 Spillover Effects through Markets

I use the method described in Section 2 to estimate the housing markets for Chicago. If a Census block is in a market that also overlaps with a TIF district, I consider it to be within the same market as that district. Even though I do not impose that housing markets are spatially contiguous, I allow for spatial correlation and many of the estimated housing markets are spatially clustered to varying degrees. To separate the spillover effect that operates through market channels from the spillover effect that operates through geographic proximity, I omit Census blocks that are within a close geographic area of the TIF district (within 400 meters).

I define D_{id}^m to indicate if block i is within a housing market that also overlaps with district d. I define D_{id}^s to indicate if block i is geographically close. I use 400 meters, or approximately a quarter of a mile. For each district d, I include non-targeted units that are market-close to the district ($D_{id}^m = 1$) and not spatially close to the district ($D_{id}^s = 0$). The comparison units are those that are non-targeted and not market-close to any district established within 5 years of E_d. I assign the comparison units the event time of the treatment units. I stack the datasets of each TIF district to create the analysis dataset. For the spatial spillover effects, I follow the same logic as for the market spillover effects. The regression models for dynamic and static estimates are analogous to Equations (4) and (5), but replacing D_{id} with D_{id}^m or D_{id}^s.

Unlike in the case of the direct effect, the notation allows for blocks to be spatially or market-close to multiple districts. By definition, spillover effects are not the result of targeting but rather the result of proximity (either spatial or market). This proximity is a fact of the relevant space and cannot be fully characterized based on the first exposure, as is the case for the direct treatment effects (Abbring and James J. Heckman, 2007). In practice, I rely on fixed effects to account for the history of exposure.

6 Results

6.1 Effects on Property Values

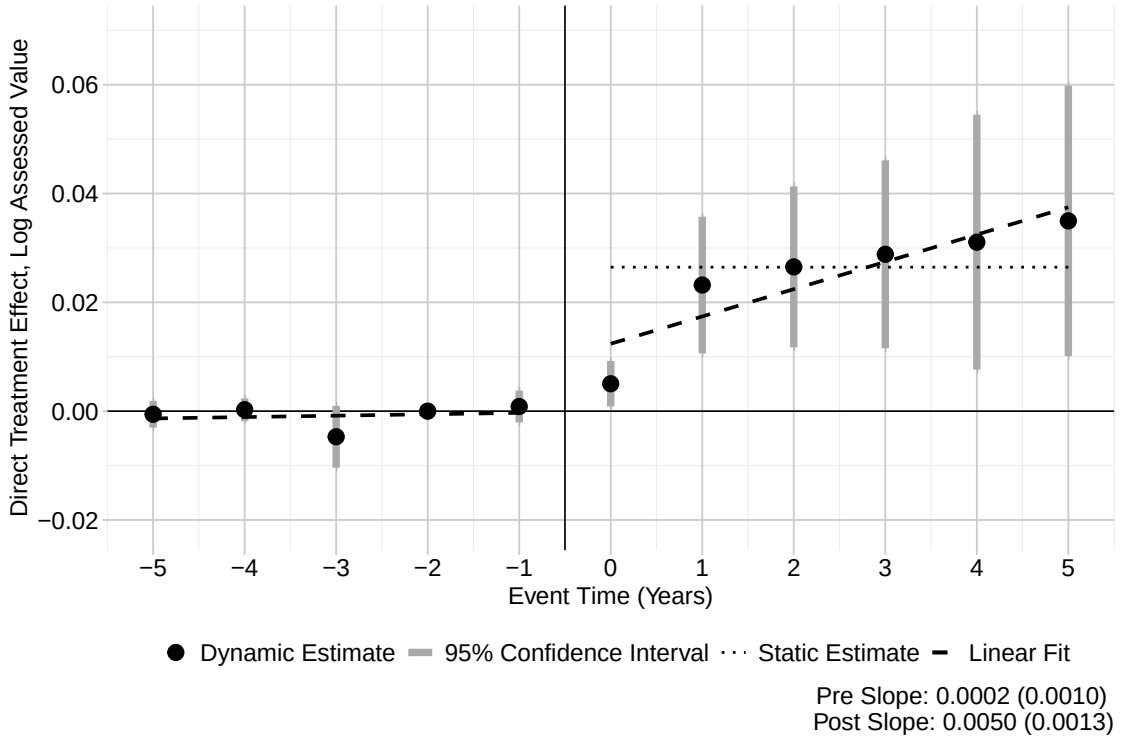
I implement the model of Equation (4) to estimate the dynamic effect of TIF on property values within the targeted areas. These estimates speak to the direct effectiveness of the policy.

Figure 6 plots the estimates of the dynamic treatment effects of TIF on property values, comparing treated properties to those treated at least 5 years later. There is no evidence of anticipation before 2 years prior to the establishment of the TIF district, supporting the empirical design. Once the TIF district is established, the treatment effects are significant, positive, and increasing over the ensuing 5 years. While the initial increase may be due to signaling or changes in expectations, the later increase may also include capitalization of the TIF-funded development. The corresponding static estimate from Equation (5) is 0.0265 (standard error 0.00785), meaning that property values increase by an average of 2.65% after the establishment of the TIF district.

The specifications allow for unobserved heterogeneity that varies across time within small geographic areas by including Census tract $\times$ year fixed effects. As I show in Appendix Figure A.4, due to the spatial clustering of the TIF districts, Census tracts contain blocks that are targeted by different districts. There is sufficient variation of treatment status within tract. Estimates with other fixed effects that do not allow for time-varying, within-tract heterogeneity (Figure 8) are not significant and the pre-trends deviate from zero. However, the point estimate is similar to that from my main specification. This supports that the tract $\times$ year fixed effects account for relevant unobserved heterogeneity to allow for identification without subsuming excessive variation.

I cluster standard errors at the level of the TIF district (Abadie et al., 2022) to account for the fact that Census blocks appear as both treated and control units within the regression

Figure 6: Dynamic Direct Treatment Effect, Log Assessed Property Value



Note: This plot displays estimates for $\{\gamma_\ell\}_{\ell \in \mathcal{L}}$ from Equation (4). The outcome is the log of the average assessed value in 2020 USD within 1990 Census blocks. The specification compares blocks that are treated to those that are not-yet-treated. All estimates are relative to event time -2. The error bars indicate 95% confidence intervals with TIF district-clustered standard errors.

(Wing, Freedman, and Hollingsworth, 2024). Figure 8 displays the sensitivity to different inference. Even with standard errors that allow for spatial correlation (Conley, 1999), the main estimates remain significant. This suggests that the district-clustered standard errors adequately account for spatial correlation while also allowing for correlation within TIF districts due to the provision of the policy.

I extend the analysis studying the direct impact of TIF to consider its spillover effects to non-targeted areas. In the baseline specification of the market spillover estimates, I include Census block, side (North, South, West) $\times$ year, use (residential, commercial, etc.) $\times$ year, and broad market (see Appendix Figure A.1b) $\times$ year. These fixed effects capture broad geographic, industry, and market trends. It is not possible to use Census tract $\times$ year fixed effects for the market spillover effects as the comparison is necessarily across areas of the city.

I present estimates with different configurations of these fixed effects in Figure 8 and find they only go to 0 when only controlling for side × year fixed effects alone. This highlights the importance of allowing for more fine-grained trends.

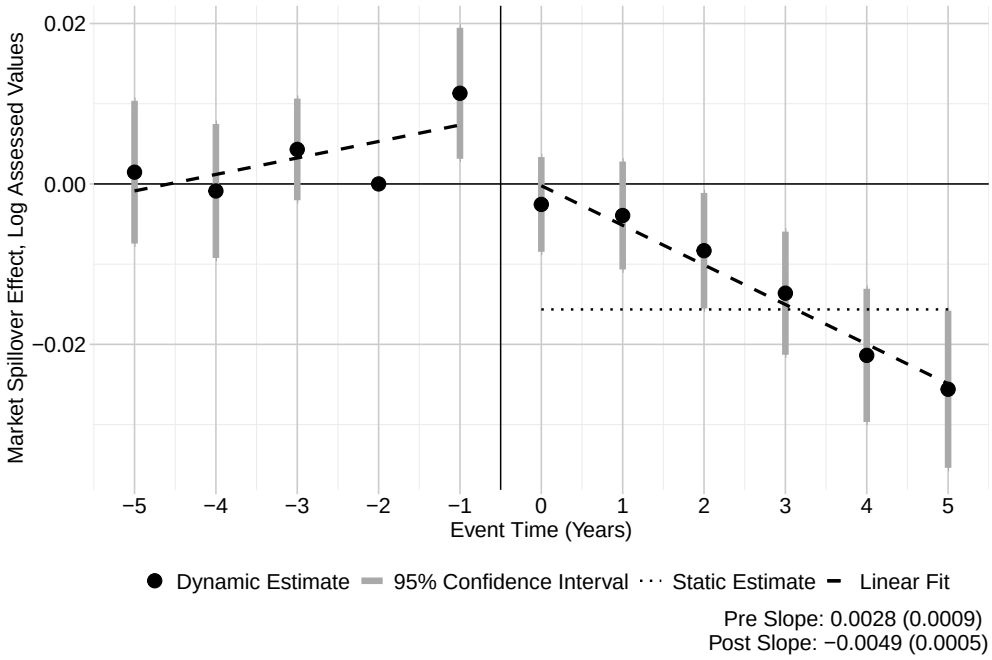
Figure 7 displays the dynamic market spillover effects. The estimates before two years prior to TIF do no vary significantly from zero, supporting the validity of comparing blocks within the same housing markets as TIF districts to those that are in different housing markets. The market spillover effects are negative and decreasing beginning two years after the start of TIF, with a static estimate of -0.0156 (standard error 0.0022). The spatial spillover effects exhibit large standard errors due to a small number of blocks that are spatially close but not in the same housing market as the TIF districts. The estimates are not significant and the static effect is 0.0085 (standard error 0.0127). Without separating spatial and market proximity, these two effects would be conflated.

In Appendix Table A.4, I present estimates of the spillover effects for different distances. The spatial spillover effects remain small in magnitude and statistically insignificant. The corresponding market spillover effects increase in magnitude. This pattern illustrates robustness of the opposite directions of the two types of spillover effects. *Given the small magnitude and imprecision of the spatial spillover effect estimates, I focus on the direct treatment effects and market spillover effects henceforth.*

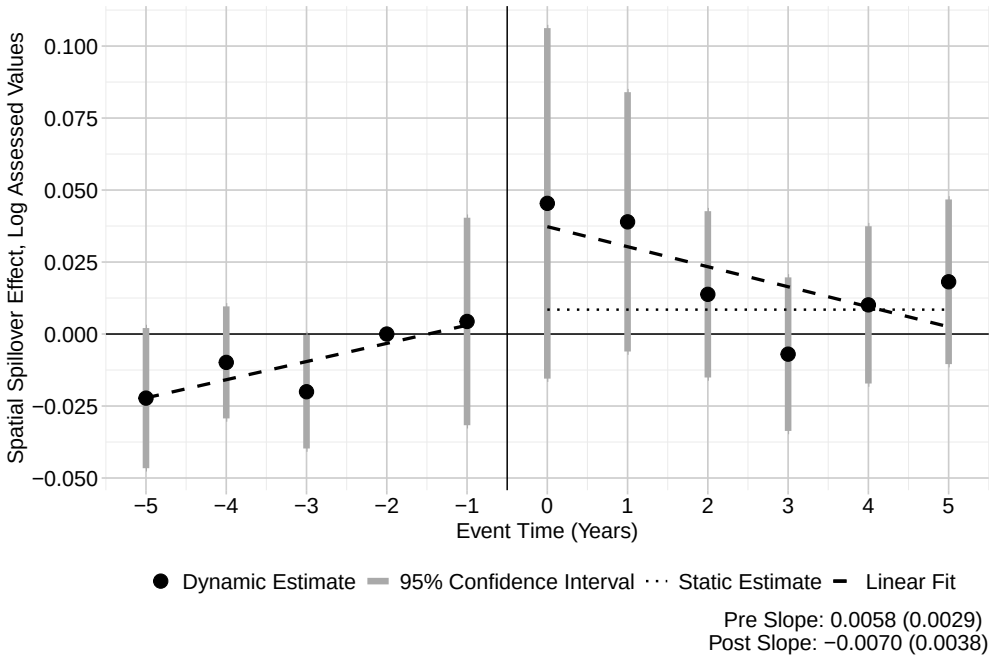
The positive direct effect of 2.65% and the negative market spillover effect of -1.56% suggest several interpretations. One is that with the investment of the TIF district, the relative values of the targeted properties increase relative to the non-targeted properties within the same housing market. This aligns with the interpretation that the housing markets represent substitutable units. Under this interpretation, TIF investments could be novel to the city, in that they otherwise would not have occurred in the absence of TIF. Alternatively, TIF could incentivize business activity to move from other areas. To consider these interpretations, I explore other outcomes.

Figure 7: Dynamic Spillover Effects, Log Assessed Property Value

(a) Market (Non-Spatial)



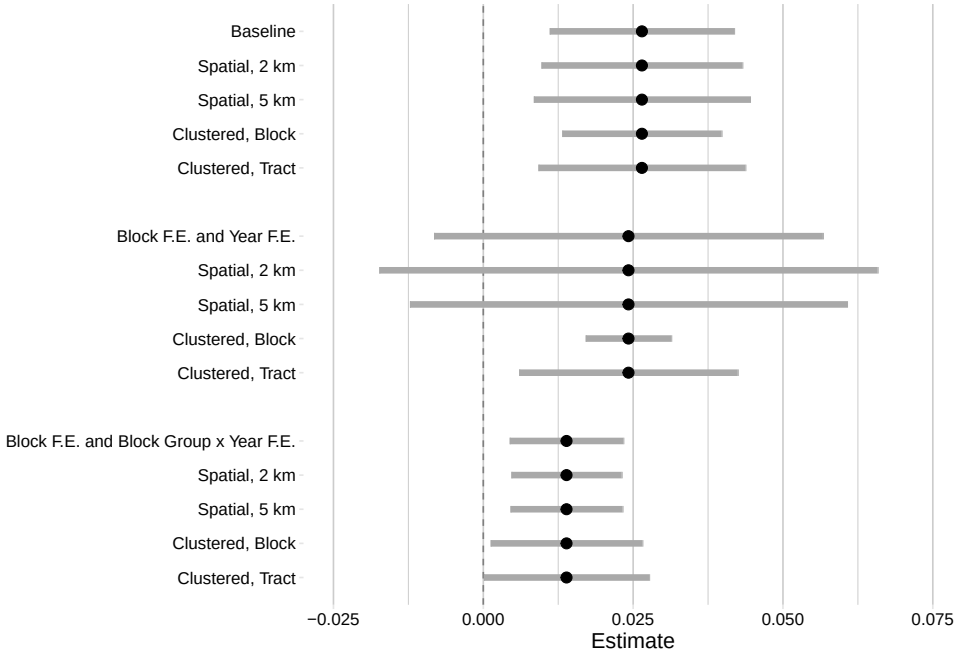
(b) Spatial



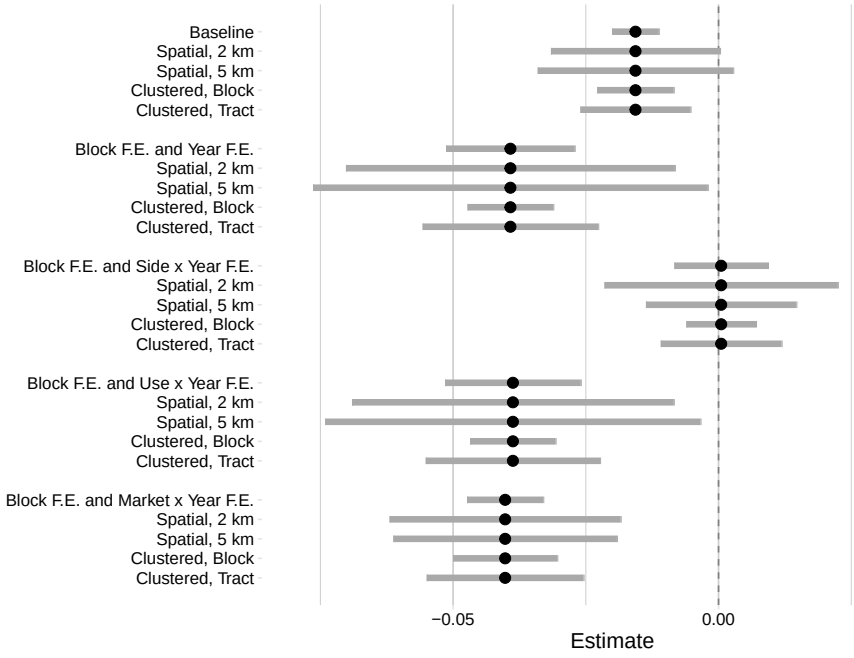
Note: This plot displays estimated $\{\gamma_\ell\}_{\ell \in \mathcal{L}}$ from Equation (4) using D_{id}^m or D_{id}^s for market and spatial spillover effects. The outcome is the log of the average assessed value in 2020 USD within 1990 Census blocks. All estimates are relative to event time -2. The error bars indicate 95% confidence intervals with TIF district-clustered standard errors.

Figure 8: Direct Treatment Effect on Log Assessed Property Value, Sensitivity Analysis

(a) Direct Estimates



(b) Market (Non-Spatial)



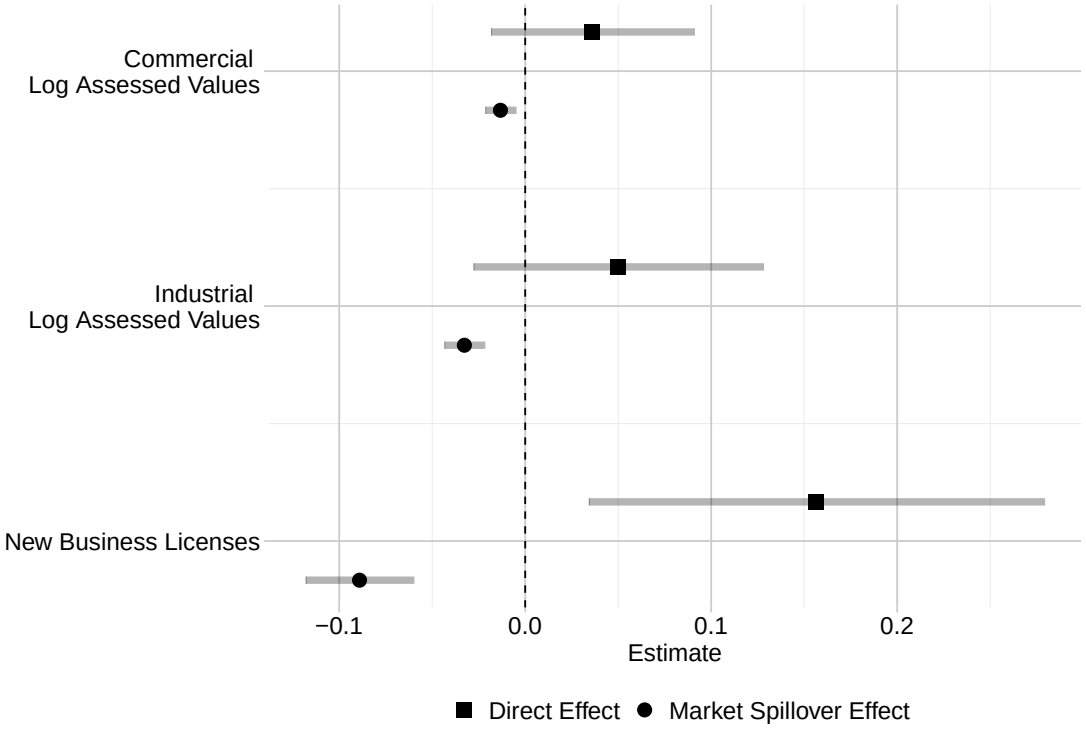
Note: These figures plot the static estimates of the direct treatment effects and market spillover effects on log assessed property value for the labeled specifications and inference. The error bars indicate 95% confidence intervals.

6.2 Effects on Firm Outcomes

I consider firm outcomes to contextualize the estimates on property values. I follow the same strategy as in Section 5 to estimate direct and market spillover effects.

Figure 9 displays the static estimates of the direct treatment effects and market spillover effects for outcomes related to firms. Because the data on new business licenses begin in 2000, I restrict the sample to TIF districts established in 2001 or later. The assessed values for both commercial and industrial properties suggestively increase locally and significantly decrease in market-close areas. The estimates on new business licenses are more decisive. TIF increases new business licenses locally by 0.157 licenses per year and decreases new business licenses by −0.0891 business licenses per year in market-close areas. These results align with the estimates on property values and support a relocation mechanism.

Figure 9: Direct and Market Spillover Effects, Firm Outcomes



Note: This plot displays the static estimates for the direct treatment effects and market spillover effects for the listed outcomes. The error bars indicate 95% confidence intervals with TIF district-clustered standard errors.

6.3 Heterogeneous Effects

In Figure 10, I display heterogeneous effects by characteristics of the TIF districts and targeted areas. To calculate the heterogeneous effects, I limit the stacked dataset to blocks that belong to each subsample. Across the subsamples, the direct effects remain positive and the market spillover effects remain negative even if some of the subsamples produce imprecise estimates.

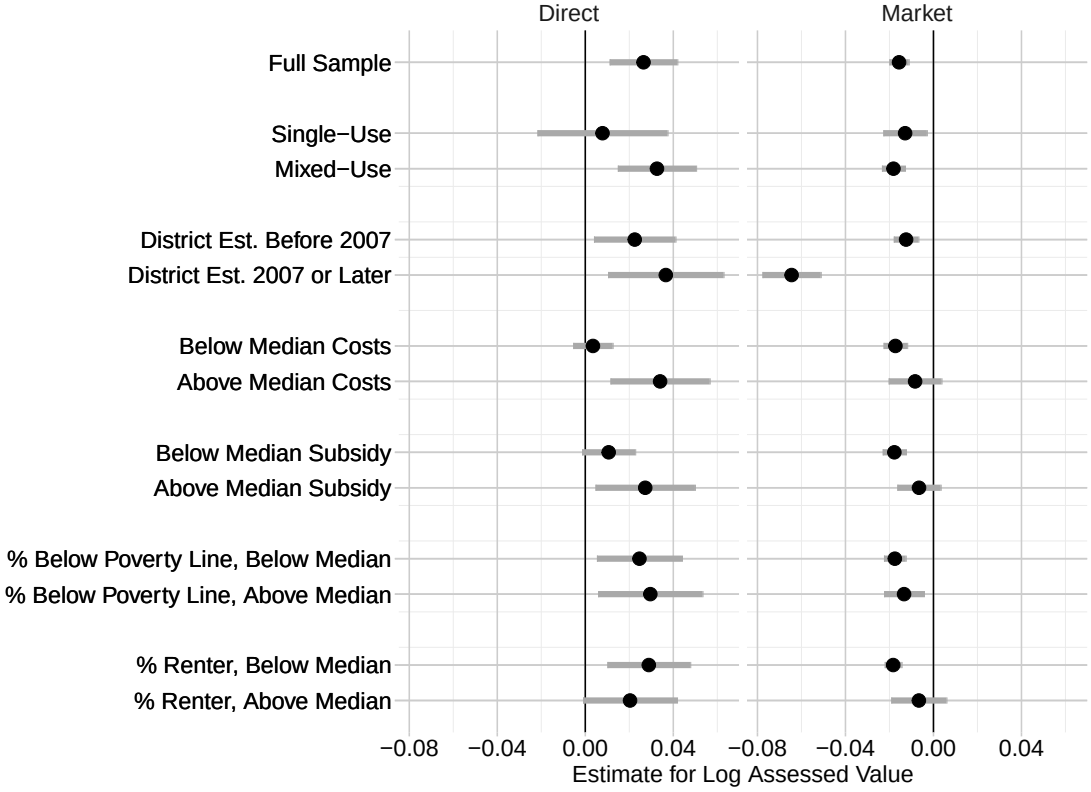
The majority of the TIF districts I study are used for mixed-use purposes. These developments may include any combination of types of development, with most including both residential and commercial investments. While single-use TIF districts have an insignificant treatment effect, the mixed-use TIF districts have a large and significant direct effect. Because the sample overlaps with the Great Recession, I split the districts into those established before 2007, the majority of the sample, and those established in 2007 or later. While the direct and spillover estimates for the districts established before 2007 are similar to those for the full sample, the spillover estimate is much larger in magnitude for the districts established in 2007 or later. Those later districts may include more activities that draw economic activity away from similarly situated areas within the same market. It is also possible that the later districts are in areas that experienced substantial growth relative to the non-targeted areas.

I calculate heterogeneous treatment effects by the amount of TIF-funded investment that occurs within the district. The data on project costs are limited to only projects completed in partnership with private developers or other public entities. I use these data as a proxy for the full amount of investment. I calculate the median total amount of costs of the TIF-funded projects and the median amount of the subsidy. I categorize the districts as being larger than the median ("Above Median") or smaller than or equal to the median ("Below Median"). The direct effect is much smaller for the districts with lower costs and subsidy amounts. This indicates that larger investment results in larger direct treatment effects, and

helps support the empirical design.

The above subsamples relate to characteristics of the TIF district. It is possible that characteristics of the households in the targeted areas correlate with the effect of the TIF districts. I focus on the percent of households below the poverty line and the percent of households that rent (both measures are from the 1990 Decennial Census to capture the pre-period).[22] I separate the sample by districts that have below or above median percentages of these households. The results are similar regardless of the amount of households in poverty. However, the estimates are insignificant for the districts with a greater share of renting households. This suggests that the main effects are driven by areas with greater rates of home ownership.

Figure 10: Heterogeneous Direct and Market Spillover Effects, Log Assessed Property Value



Note: This plot displays the static estimates for the direct treatment effects and market spillover effects, dividing the sample by characteristics of the TIF districts or Census blocks. The error bars indicate 95% confidence intervals with TIF district-clustered standard errors.

[22]Results split by racial or ethnic make-up of the blocks do not reveal any heterogeneity.

6.4 Back-of-the-Envelope Aggregation

I perform a back-of-the-envelope calculation to consider the long-term overall effect of the policy on property values. I combine the direct and spillover effects into one coarse estimate of an "overall" effect. I consider a weighted sum of the long-term direct treatment effect (γ_5), the market spillover effect (γ_5^s), the spatial spillover effect (γ_5^m), and a spillover effect that compares non-targeted areas that are both market and spatially close to those that are far ($\gamma_5^{s\cap m}$). For all of these estimates, I consider the long-run effect at five years after the beginning of the policy. I calculate the weighted sum,

$$\frac{W\gamma_5 + W^s\gamma_5^s + W^m\gamma_5^m + W^{s\cap m}\gamma_5^{s\cap m}}{W + W^s + W^m + W^{s\cap m}}, \tag{6}$$

with different population-based weights that correspond to the areas that are directly affect (W), spatially close (W^s), market-close (W^m), or both spatially and market-close ($W^{s\cap m}$).

I weigh by the number of affected blocks and estimate an overall effect of 0.0111. I bootstrap to calculate a TIF district-clustered standard error to calculate a 95% confidence interval of $[-0.0051, 0.0273]$. I perform the same exercise weighing by the number of properties to calculate an overall effect of -0.0015 $[-0.0126, 0.0097]$. Finally, I weigh by the average property value in each of the areas and calculate an overall effect of -0.0020 $[-0.0107, 0.0148]$. All of these estimates are statistically indistinguishable from zero. Suggestively, this indicates that TIF does not introduce net new development from the perspective of the central planner despite achieving moderate redistribution within housing markets.

Although informative, there are caveats to this back-of-the-envelope analysis. First, it does not include the Census blocks that are in TIF districts established before 2000. These blocks may also receive spatial or market spillover effects as a result of the TIF districts in my sample. However, I cannot distinguish these effects from long-term complementarities between the TIF districts. My empirical framework and data span limit me to only consider

non-targeted areas and areas targeted by TIF districts established in 2000 or later. Second, the calculation does not include non-targeted areas that are neither market-close nor spatially close and I do not extrapolate the spillover effects to these areas. My approach considers these areas to be unaffected. Controls outside the City of Chicago are needed to estimate spillover effects on these areas, but this design may introduce concerns of internal validity.

This exercise does not include a level change as a result of the policy. The empirical approach only identifies the parameters to a constant. In the presence of a level change, the overall estimate is biased (James J Heckman, Urzua, and Vytlacil, 2006). This is plausible under the scenario in which the city-wide TIF program results in an overall increase in the property values of the city separate from the direct and spillover effects.

The market spillover effects provide insight into some of the broader regional impacts of TIF. While targeted areas experience benefits as a result of the policy, non-targeted areas incur costs. Without additional context, it is unclear how a central planner can interpret these findings. It is possible that the policy, instead of addressing observed inequality in the built environment, further consolidates resources to relatively advantaged areas. However, if the targeted areas are relatively disadvantaged compared to the market-close areas, then the policy redistributes resources throughout the city. To consider these two possibilities, I compare the observed characteristics of the targeted and market-close areas.

I display these in Table 3 using Census characteristics from the 2000 Decennial Census. The median household income is larger in the market-close areas than in the targeted areas and households are more likely to be renters in the targeted areas. Still, the differences are not as large when comparing targeted areas to all non-targeted areas (Table 2). The market-close areas are more advantaged than the targeted areas, despite being in the same housing markets, suggesting that the policy results in a redistribution of resources. However, the redistribution is within housing market. If redistribution is a goal of the planner, then policies that transfer across housing markets may be more efficient.

Table 3: Targeted and Market-Close Areas, Comparison

	Treated Est. 2000-2017	Market-Close
Number of Census Blocks	6,747	6,741
Assessed Value	170,966.6	164,246.0
	(150,242.5)	(174,965.3)
Median Income	53,103.19	61,066.94*
	(24,550.17)	(18,068.82)
Renter (proportion)	0.58	0.35***
	(0.26)	(0.27)
Non-Hispanic Black (proportion)	0.38	0.41
	(0.43)	(0.45)
Non-Hispanic White (proportion)	0.29	0.31
	(0.31)	(0.34)
Hispanic (proportion)	0.27	0.24
	(0.31)	(0.30)

Note: This table presents descriptive statistics of the targeted areas and the areas that are in the same market ("Market-Close"). For each characteristic, I report means and standard errors in parentheses. I report the significance of the comparison between the market-close and targeted means. Significance levels are indicated as *: $\alpha = 0.1$, **: $\alpha = 0.05$, ***: $\alpha = 0.01$.

7 Conclusion

Analysis of the overall effects and redistribution of policies that target geographic regions, such as place-based policies, requires considering spillover effects that propagate to areas that are not necessarily geographically close. The methodological approach in this paper allows for the consideration of spillover effects due to non-spatial mechanisms. I exemplify the approach with a particular place-based, economic development policy, Tax Increment Financing (TIF) in Chicago. In that context, spillovers may operate through housing markets in response to the decisions of households and firms. I apply Stochastic Blockmodeling (SBM) to data on household moves to characterize the latent housing markets and categorize which areas are in the same housing markets as TIF districts. This approach informs a policy analysis that

considers overall effects without a fully specified structural model of general equilibrium, providing a bridge between structural modeling and "reduced-form" empirical frameworks. The approach of defining underlying network structure to characterize non-targeted units that are market-close to targeted ones and consider non-spatial spillovers can be applied to other empirical frameworks. While housing markets may be relevant to study spillovers in place-based, economic development policies, the same approach may be applicable to consider spillover effects in other contexts (Huber and Steinmayr, 2021), such as research on gentrification (e.g., Ding, Hwang, and Divringi, 2016; Asquith, Mast, and Reed, 2023; Ferreira, Kenney, and B. Smith, 2023).

Despite being a locally effective policy, the market spillover effects of TIF are negative, implying that TIF relocates development away from similarly situated areas. This may result in further consolidation of resources within an inequitable environment, or it may redistribute investment to areas that otherwise would not receive it. Although my findings point to negative market spillover effects for TIF in Chicago, other contexts of place-based economic development may result in positive market spillover effects if overall investment and population are increasing or in the presence of other complementarities.

TEXAS A&M UNIVERSITY

Appendix

Beyond the Local Impacts of Place-Based Policies: Spillovers through Latent Housing Markets

A Details of Stochastic Block Modeling for Estimating Markets

A.1 Estimation Details

Stochastic Block Modeling (SBM) is a method of community detection (Breiger, Boorman, and Arabie, 1975; Holland, Laskey, and Leinhardt, 1983; T. A. Snijders and Nowicki, 1997; Nowicki and T. A. B. Snijders, 2001). I draw from Peixoto (2019) to explain the details behind SBM and its estimation.

The adjacency matrix describing the movement of households between blocks is $\boldsymbol{A}_{J\times J}$. Each block is a member of an unobserved housing market $M_j \in \{1, 2, \ldots, M\}$. I denote the $J \times 1$ vector that maps blocks to markets as $\boldsymbol{M} := \{M_j\}_{j=1}^{J}$. I use $\boldsymbol{p}_{M\times M}$ to denote the transition matrix with probabilities of households moving between markets. For a binary SBM, the likelihood is

$$P(\boldsymbol{A} \mid \boldsymbol{p}, \boldsymbol{M}) = \prod_{j=1}^{J}\prod_{k=1}^{J} \quad \boldsymbol{p}_{\boldsymbol{M}_j,\boldsymbol{M}_k}^{\boldsymbol{A}_{jk}} \quad (1 - \boldsymbol{p}_{\boldsymbol{M}_j,\boldsymbol{M}_k})^{1-\boldsymbol{A}_{jk}}. \tag{A.1}$$

In practice, I use the Minimum Description Length (MDL), which clarifies the penalization of additional groupings,

$$-\ln P(\boldsymbol{A} \mid \boldsymbol{p}, \boldsymbol{M}) - \ln P(\boldsymbol{p}, \boldsymbol{M}). \tag{A.2}$$

The first term contains the information needed to characterize the data and the second term contains the information needed to characterize the parameters of the model. The second term prevents the model from producing too many groupings, in the most extreme case categorizing each neighborhood into its own grouping.

I use the `graph-tool` library in Python to implement the estimation (Peixoto, 2014c). The function `minimize_nested_blockmodel_dl` relies on a Markov Chain Monte Carlo (MCMC)

approach for efficiency (Peixoto, 2014a). The idea is to first randomly perturb the grouping of each block and then accept the change based on a function of the change in the MDL. This algorithm increases efficiency over alternatives by reducing the number of possible groupings over which to compute the MDL.

There are two complications that I incorporate into the estimation procedure. First, I use a nested model structure (Peixoto, 2014b). While the MDL ensures that the algorithm does not estimate groupings that are too fine, there is a "resolution limit" that is a function of the number of blocks. The nested model structure increases this limit, resulting in a larger number of groupings possible to characterize. Second, I correct for the number of degrees (Karrer and Newman, 2011). This avoids grouping blocks together just because they are connected to the same number of blocks.

A.2 Estimated Housing Markets

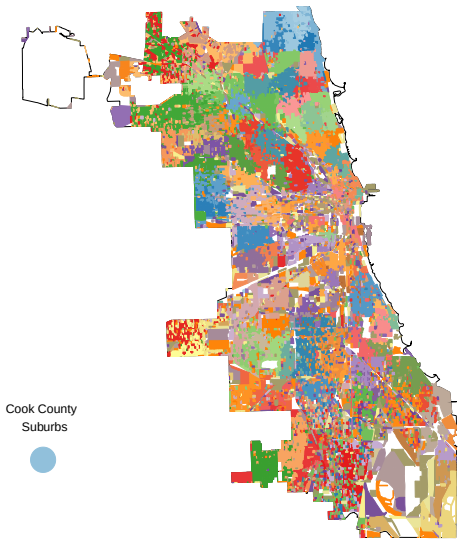
Figure A.1 plots the groupings estimated at the different levels of the estimation. I use the 146 estimated groupings estimated in level 0 in my baseline analysis. I consider these to be the latent housing markets. Following the same approach as in level 0, the algorithm groups these 146 groupings into 28 broader groupings. I consider these to be the broader latent housing markets and use them in fixed effects to control for broader market trends. The algorithm continues to estimate broader groupings until it reaches one grouping in level 5.

A.3 Evaluating the Change in Markets Over Time

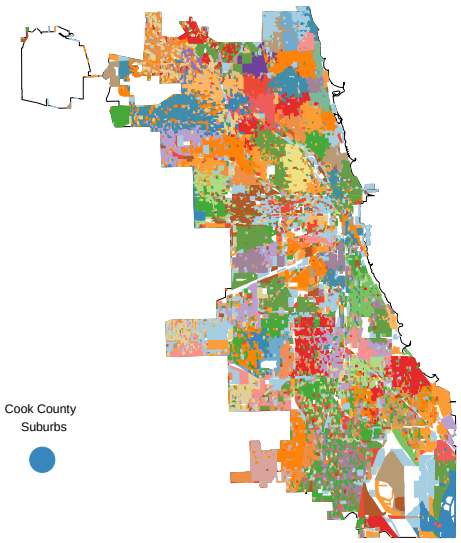
I further interrogate the decision to use all observations between 2006 and 2020 to classify housing markets. I quantify the degree to which the pattern of movements between Census blocks changes over time. I calculate the binary adjacency matrices for each year, $\boldsymbol{A}^t$, using the moves that occur between t and $t+1$. I calculate the Jaccard distance between these matrices and the adjacency matrix I calculate using the full panel, $\boldsymbol{A}$ (Jaccard, 1901; Kosub, 2019). The Jaccard distance represents the proportion of elements between the two matrices

Figure A.1: Estimated Markets, City of Chicago

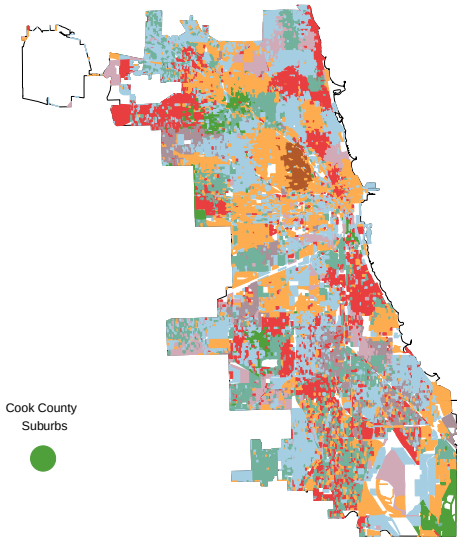
(a) Level 0: 146 Estimated Groupings



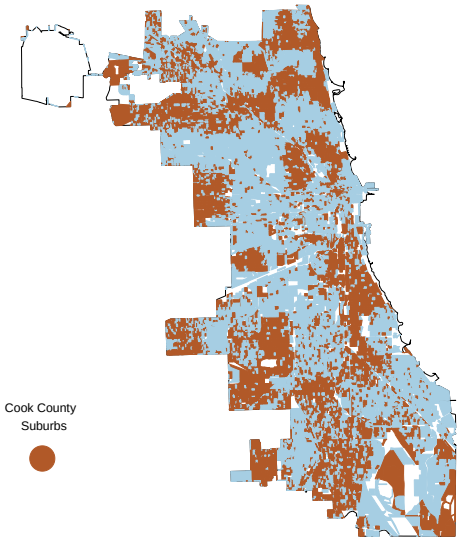
(b) Level 1: 28 Estimated Groupings



(c) Level 2: 8 Estimated Groupings



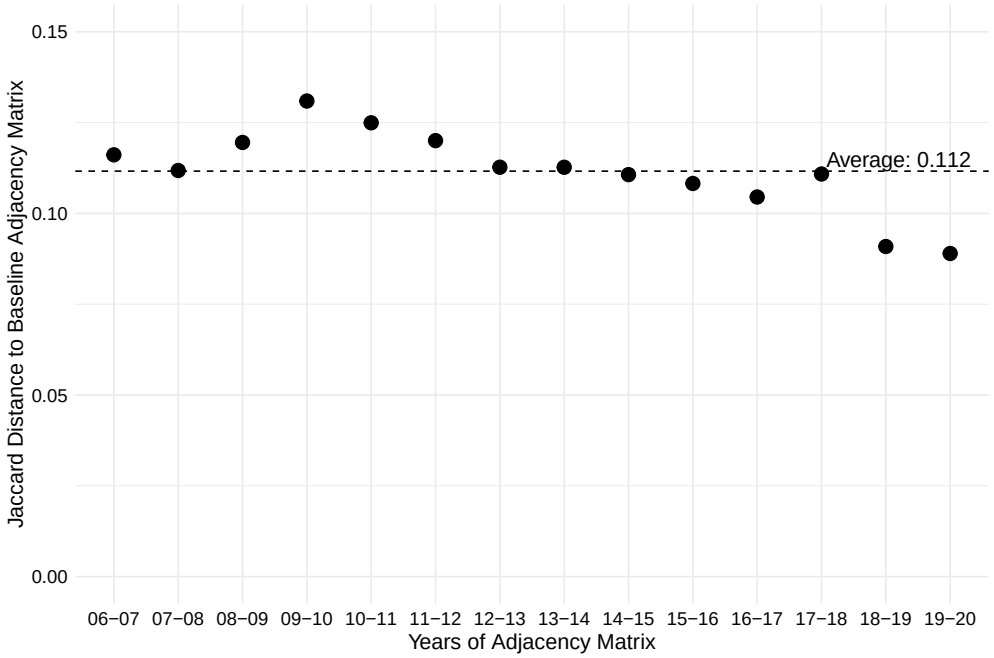
(d) Level 4: 2 Estimated Groupings



Note: This figure maps the estimated groupings for the different levels of the nested approach.

that are equal:

Figure A.2: Jaccard Distance of Adjacency Matrices



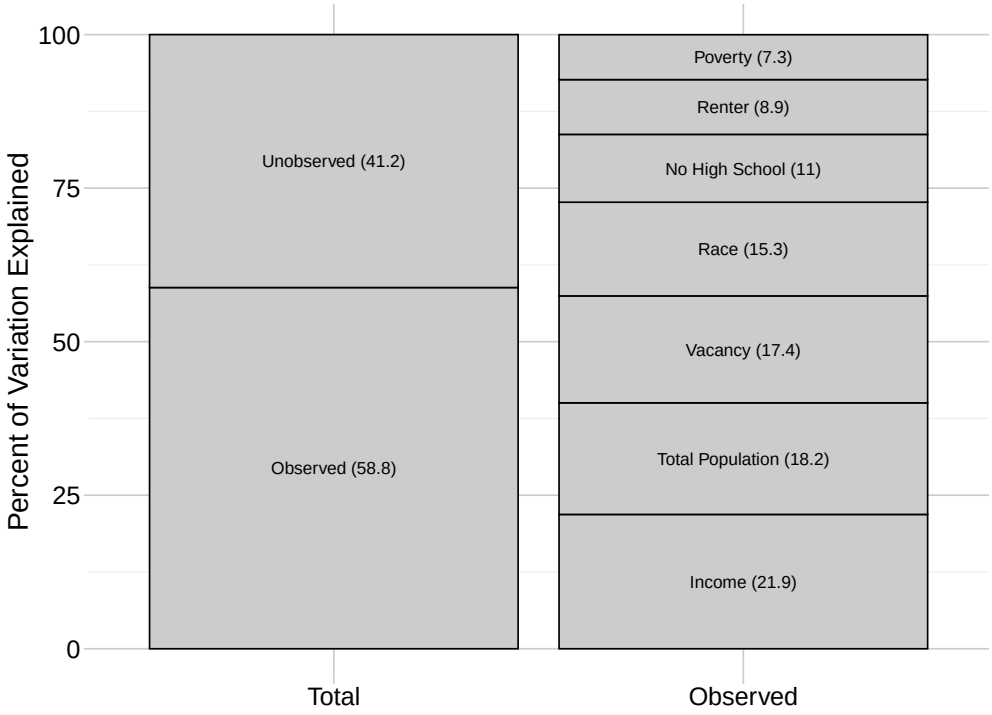
Note: This figure plots the Jaccard distances between adjacency matrices based on movement during different years and the adjacency matrix based on movement across 2006-2020. The Jaccard distance is a measure of similarity between matrices that ranges from 0 (identical elements) to 1 (no elements in common) (Jaccard, 1901).

$$\begin{aligned}\delta(\boldsymbol{A}^t, \boldsymbol{A}) &= 1 - \frac{\mid \boldsymbol{A}^t \cap \boldsymbol{A} \mid}{\mid \boldsymbol{A}^t \cup \boldsymbol{A} \mid} \\ &= 1 - \frac{\mid \boldsymbol{A}^t \cap \boldsymbol{A} \mid}{\mid \boldsymbol{A}^t \mid + \mid \boldsymbol{A} \mid - \mid \boldsymbol{A}^t \cap \boldsymbol{A} \mid}. \end{aligned} \tag{A.3}$$

A Jaccard distance of zero indicates that the matrices are identical while a distance of one indicates that no elements of the matrices are the same.

Figure A.2 plots the distances between the yearly adjacency matrices and $\boldsymbol{A}$. They are all small indicating a large amount of similarity. On average, 11.2% of the yearly adjacency matrices differ from the adjacency matrix I use for my main estimates.

Figure A.3: Decomposing Average Housing Values of Housing Markets



Note: This figure displays a decomposition of the average housing value of the estimated markets. The first bar of the figure displays the percent of the R^2 that is due to observed and unobserved factors using the observed factors in the right bar. All factors come from the 2000 Decennial Census. The second bar decomposes the amount of observed variation due to each factor accounting for the correlation between the factors (Israeli, 2007).

A.4 Evaluating Determinants of Markets

Estimating housing markets using household moves does not require specifying household preferences over neighborhood characteristics, avoiding biases from misspecification, measurement error, and omitted variables. It is still informative to evaluate the extent to which unobserved factors contribute to the estimated housing markets. I regress the market-level average residential property value on characteristics from the 2000 Decennial Census. I display the results in Figure A.3. As the first bar indicates, 41.2% of the variation is due to factors other than those listed in the second bar. Estimating housing markets using household moves allows for households to move based on unobservable neighborhood characteristics.

A.5 Data Simulation for Illustration of SBM

I simulate data to illustrate SBM. I impose that there are 100 Census Blocks. I define the latent markets. In reality, these are unobserved, but I need to define them to simulate data that show similar patterns to Chicago's estimated markets.

I impose that there are five unobserved markets. I define the transition matrix for the markets as

$$S = \begin{pmatrix} 0.8 & 0.1 & 0.01 & 0.05 & 0.04 \\ 0.2 & 0.7 & 0.02 & 0.03 & 0.05 \\ 0.01 & 0.03 & 0.9 & 0.03 & 0.03 \\ 0.04 & 0.09 & 0.05 & 0.75 & 0.07 \\ 0.04 & 0.05 & 0.03 & 0.07 & 0.81 \end{pmatrix}. \tag{A.4}$$

I determine the groupings of the blocks using the rules specified in Table A.1. This design mimics the estimated housing markets in the data. While the markets are relatively condensed spatially, there is still some dispersion.

Using these groupings, I define the adjacency matrix. Let M_i and M_j be the markets for blocks i and j using the rule in Table A.1. Then the (i, j) element of the adjacency matrix is one with probability T_{M_i,M_j}. For all random decisions, I set a seed.

Table A.1: Rules for Determining Latent Markets

Census Blocks	Market Designation	
	90% Probability	10% Probability
1, 2, 3, 4, 5, 11, 12, 13, 14, 15, 21, 22, 23, 24, 25, 31, 32, 33, 34, 35, 41, 42, 43, 44, 45, 51, 52, 53, 54, 55	A	B
61, 62, 63, 64, 65, 66, 67, 71, 72, 73, 74, 75, 76, 77, 81, 82, 83, 84, 85, 86, 87, 91, 92, 93, 94, 95, 96, 97	C	D
6, 7, 8, 9, 10, 16, 17, 18, 19, 20, 26, 27, 28, 29, 30, 36, 37, 38, 39, 40	D	E
36, 37, 38, 39, 40, 46, 47, 48, 49, 50, 56, 57, 58, 59, 60, 66, 67, 68, 69, 70	B	D
68, 69, 70, 78, 79, 80, 88, 89, 90, 98, 99, 100	E	C

Note: This table describes the rules I follow to simulate the data used for Figure 1.

B Additional Institutional Background

In this Appendix, I provide additional details on TIF. In the U.S., states pass legislation that allows municipalities to implement TIF and defines the parameters of the specific TIF policy (see Kriz and Johnson, 2019, for a recent review of each state's TIF policy). Even though Illinois passed the TIF-enabling legislation in 1977, TIF began in Chicago in 1984, and the first district was established in 1986.

The Chicago Department of Planning and Development (DPD), housed in the Office of the Mayor, coordinates with ward aldermen, special tax districts, private developers, and community stakeholders to implement TIF. The idea to implement a particular TIF district may come from any stakeholder or coalition. The DPD hires consultants to complete an eligibility study and a redevelopment plan. The eligibility study describes the built environment of the proposed district. Table A.2 lists the factors and the number required

for different designations of districts. There must also be justification of the "but for" clause, i.e., the area would not develop "but for" the implementation of TIF. After the DPD incorporates feedback from public hearings into the redevelopment plan, there are two committees that vote on whether the City Council should consider the district for approval: a committee comprised of representatives of the other taxing bodies and a committee comprised of mayor-appointed members. The City Council's Committee on Finance must vote to approve the district before it goes to vote in the full City Council (Department of Planning and Development, 2020).

Once the city establishes a TIF district, the natural appreciation of property values may gradually accrue and fund the activities outlined in the redevelopment plan. However, this accrual may take many years or the district may be in an area with declining property values. The city can rely on private investments early in the TIF district's existence or borrow against the expected increase in property values as a result of the TIF-funded interventions. TIF-backed debt instruments are not general obligation bonds and so must be paid back using the revenues from the TIF districts (Luby et al., 2019). Private and public actors apply for TIF funding for projects to be completed within the boundaries of the district. While the process to initiate TIF districts and implement projects requires several rounds of voting, there is little evidence that TIF districts and projects are frequently denied (Craft and Weber, 2019). For example, starting in 2019, Chicago established a committee to formalize the review of these proposed projects. Since then, almost 90% of them have been accepted without further review (City of Chicago, 2022).

The TIF legislation lists the specific economic development activities for which TIF funds can be used. These include administrative costs; property acquisition and demolition, site preparation, environmental remediation; rehabilitation, repair, and remodeling of existing structures; construction and improvements of public works; job training; financing; capital costs of the other taxing bodies; relocation; payment in lieu of taxes; reimbursing school

Table A.2: Eligibility Criteria for TIF Districts

Panel (a): Types of TIF Districts

Blight

Improved: At least 2 acres, at least 5 factors from Panel (b)

Vacant: Vacant land, at least 2 factors from Panel (c) or previous structures had at least 5 factors from Panel (b)

Conservation

At least 2 acres, 50% or more of the structures are at least 35 years old, at least 3 factors from Panel (b)

Transit

No size or blight requirements

Panel (b): Factors for Improved Blight Areas

Age
Dilapidation
Obsolescence
Deterioration
Illegal use of individual structures
Presence of structures below minimum code standards
Excessive vacancies
Overcrowding of structures and community facilities
Lack of ventilation, light, or sanitary facilities
Inadequate utilities
Excessive land coverage
Deleterious land use or layout
Depreciation or lack of physical maintenance
Lack of community planning

Panel (c): Factors for Vacant Blight Areas

Obsolete platting of the vacant land
Diversity of ownership of vacant land
Tax and special assessment delinquencies on vacant land
Deterioration of structures or site improvements in neighboring areas to the vacant land

Note: 65 ILCS 5 (1977, §11-74) lists and explains these criteria.

districts to cover increases in enrollment due to TIF-funded housing; construction of affordable housing (65 ILCS 5, 1977). These activities may contribute to different types of

development including residential, commercial, industrial, institutional, transportation, or mixed-use which may combine any of the above.

Table A.3 presents the percentage of TIF districts falling into these categories. Most districts during my period of analysis are intended for mixed-use development and most districts fulfill the conservation eligibility criteria.

Table A.3: Characteristics of TIF Districts

	Established before Data Span (1986-1999)	Established in Data Span (2000-2022)
Number of Districts	79	106
Eligibility Factors (%)		
Blight Alone	50.63	22.64
Conservation Alone	34.18	60.38
Blight & Conservation	15.19	16.04
Transit	0	0.94
Purpose (%)		
Residential Alone	5.06	12.26
Commercial Alone	10.13	3.77
Industrial Alone	32.91	12.26
Transportation Alone	0	0.94
Mixed-Use	51.9	70.75

Note: This table describes all 185 TIF districts. I use districts established between 2000 and 2022 in my analysis in the main paper. Percentages add to 100% without rounding error. Data from City of Chicago (2022).

C Data

C.1 Property Values and Characteristics

The Cook County Assessor's Office (CCA) publishes historic assessed values, sale transactions, and property characteristics for the universe of parcels in the county for the years 1999-2022 (Cook County Government, 2023). I inflate all monetary values to 2020 USD using the CPI for all urban consumers in Chicago-Naperville-Elgin (Federal Reserve Bank of St. Louis, 2022). I combine four datasets into one panel with each row corresponding to a property $\times$ year observation. I average within 2000 Census blocks to create an analogous block $\times$ year panel.

C.1.1 Assessed Values

I restrict the properties to those that are residential, commercial, or industrial. I drop very few observations that are missing assessments or those with other missing information. These missing values arise due to inconsistencies in the sampling frame of the Cook County Assessor's Office. I use assessed values (land, building, and total) defined as the initial assessed value mailed to property owners. I calculate the values by multiplying assessed values by 10. I inflate assessed values to 2020 USD.

C.1.2 Sale Transactions

I follow the recommendations in Nolte et al. (2021) to identify non-arms-length sales. First, I remove transactions with sale prices of \$0 or \$1. Second, I remove transactions with a buyer or seller with an institutional name (e.g., containing the word "veteran" or "city"). Third, I remove transactions at risk of being done within family. To do so, I calculate a string distance between the buyer and seller names and remove transactions for which the string distance is 0. The second and third steps rely on observing the buyer and seller names. At least one name is missing for %16 of transactions. I assume that these are arms-length transactions. Together, I remove $26,458$ transactions that are not considered arms-length

according to this process. This leaves $2,123,297$ transactions that are credibly arms-length and thus assumed to reflect the true market price.

C.1.3 Universe of Parcels

The above datasets do not have geographic information. The universe of parcels contains property-level coordinates. I drop properties with missing geographic coordinates ($N = 81,050$, approximately 8.2% of properties) and with coordinates outside the boundaries of the City of Chicago ($N = 2$). I merge the remaining properties with the 1990 definitions of Census tracts ($N = 929$), block groups ($N = 2,614$), and blocks ($N = 21,578$).

I merge these four datasets together using a property-level identifier (PIN) that is unique within years and stable across years. I only create this dataset for properties in the City of Chicago.

C.2 Household Characteristics

This description complements that in Section 2. InfoUSA (Data Axle, 2020) is a consumer database that compiles address lists and other public sources to predict characteristics of all households in the U.S. between 2006 and 2020. These data contain (predicted) information on the household. Relevant for my analysis, it includes household income, incumbency, owner or renter status, and race and ethnicity and name of the household head. There are three steps that I follow to prepare these data for analysis. First, I construct and clean the cross-sectional data. Second, I match households between pairwise years. Third, I calculate the in- and out-migration between Census blocks.

C.2.1 Cross-Sectional Data Construction

I restrict the data to addresses in Cook County and variables of interest for my analysis. The household information includes household income, home value, renter or owner status, incumbency, and age, name, and race and ethnicity of the household head. Except for the

head's age, most observations of these variables contain predicted values.

I inflate household income and home value to 2020 USD. InfoUSA provides a 9-level scale for renter or owner status to reflect the certainty of the prediction. I assign households with 1-3 to be renters, those with 7-9 to be owners, and those with 4-6 to be of unknown tenure. The models that predict these variables are proprietary, but Data Axle benchmarks the estimates to align with public data sources, including the Census. Due to the large number of missing values in race and ethnicity variables, I calculate race and ethnicity based on name and geography (Census tract for the years 2006-2019 and county for the years 2020). I use the `wru` package in `R`, which implements the method in Imai and Khanna (2016).

C.2.2 Longitudinal Match

In addition to variables describing household characteristics, Data Axle assigns a household ID intended to be stable over time and uniquely identify families in the InfoUSA sample.

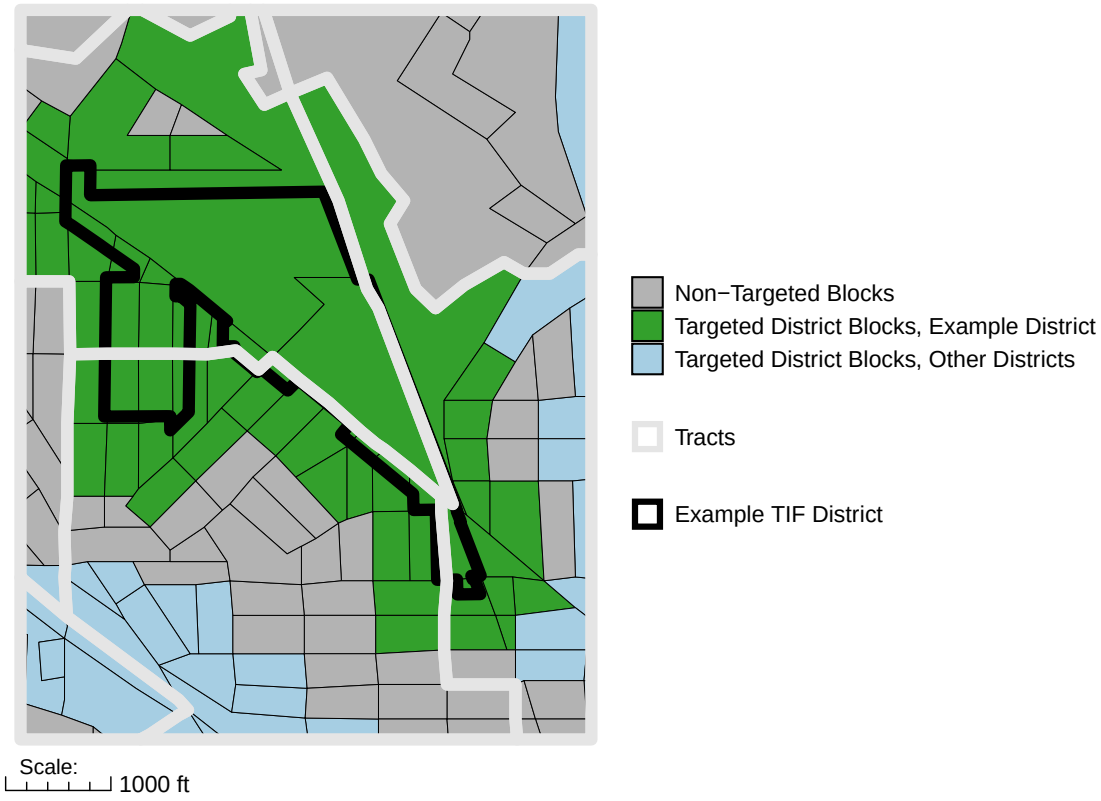
C.2.3 Block-to-Block Flows

For each year 2006-2020, I clean the cross section of the InfoUSA data, restricting the data to households in the City of Chicago. I match the addresses' geographic coordinates with the 1990 definitions of Census tracts and blocks. I match households between consecutive years (2006-2007, 2007-2008, ..., 2019-2020) using a household ID. The households that do not match may have some inconsistency in household ID, move outside the City of Chicago, or be absorbed in another household. This matching procedure results in matching approximately 75% of the households.

C.3 Overlap of TIF Districts, Census Blocks, and Census Tracts

Figure A.4 maps the overlap between an example TIF district, Census blocks, and Census tracts. The map illustrates that within tract, there can be blocks targeted by multiple TIF districts as well as non-targeted blocks. Generally, TIF districts overlap with Census tracts

Figure A.4: Overlap between Census Geographies and an Example TIF District



Note: This figure maps an example TIF district and the corresponding Census tracts and Census blocks. All Census geographies are from the 1990 Decennial Census.

in this way as the districts do not follow Census geographies and instead follow streets, commercial or industrial corridors, landmarks, or residential areas.

D Additional Results and Sensitivity

D.1 Sensitivity of Estimates Using Sale Prices

Figure A.5 shows the analogous plots as Figures 6 and 7a but using sale prices. Because sales are infrequent, the sale specification is noisier: the static estimate is noisier However, there is still evidence that the pre-trends are indistinguishable from 0 and that the sale prices increase after treatment begins in targeted areas and decrease in market-close areas. The main difference with the baseline direct estimate is that there is a (non-significant) decrease in the sale price in period 1, which brings down the estimated static treatment effect.

D.2 Sensitivity of Estimates to Different Definitions of Treatment

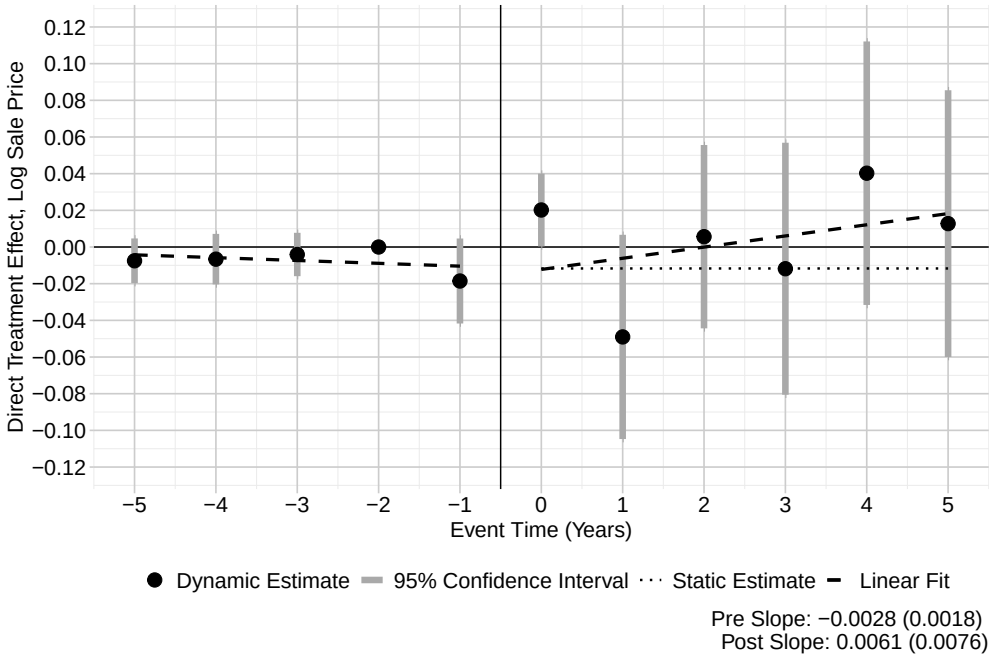
As described in Section 3, I define Census blocks as treated if they are within 100 meters of a TIF district. Figure A.6 shows how the estimates vary when the definition changes. Across the definitions, the estimates are significantly different than 0 and within the confidence interval of the baseline estimate (blocks 0-100 meters from TIF districts). Increasing the size suggestively reduces the estimated effect, consistent with results decaying farther from the TIF district.

D.3 Sensitivity of Spillover Effects to Different Distances

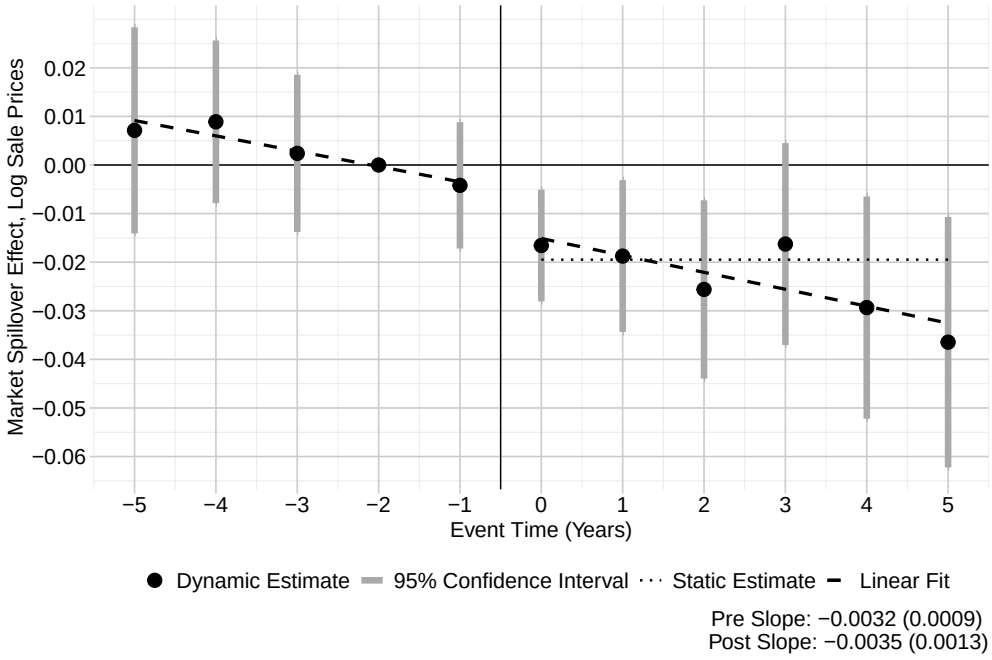
I present an exercise to contextualize the decision of the distance for the spatial spillover effects. Table A.4 shows the estimates of the spatial and market spillover effects for different distances. In the main paper, I use 400 meters to designate areas that are spatially close. I present the static estimates of the spatial spillover effects without removing the blocks that are also market-close ("All") and after removing these blocks ("Net of Market"). The latter is the estimate I use for my baseline estimate. I present analogous estimates for the market spillover effects. Across distances, the spatial spillover effects are not statistically significant. The market spillover effects increase in magnitude as the number of blocks that are considered spatially near increase. This speaks to an opposition between the spatial and

Figure A.5: Dynamic Treatment Effect, Sale Prices

(a) Direct Estimates

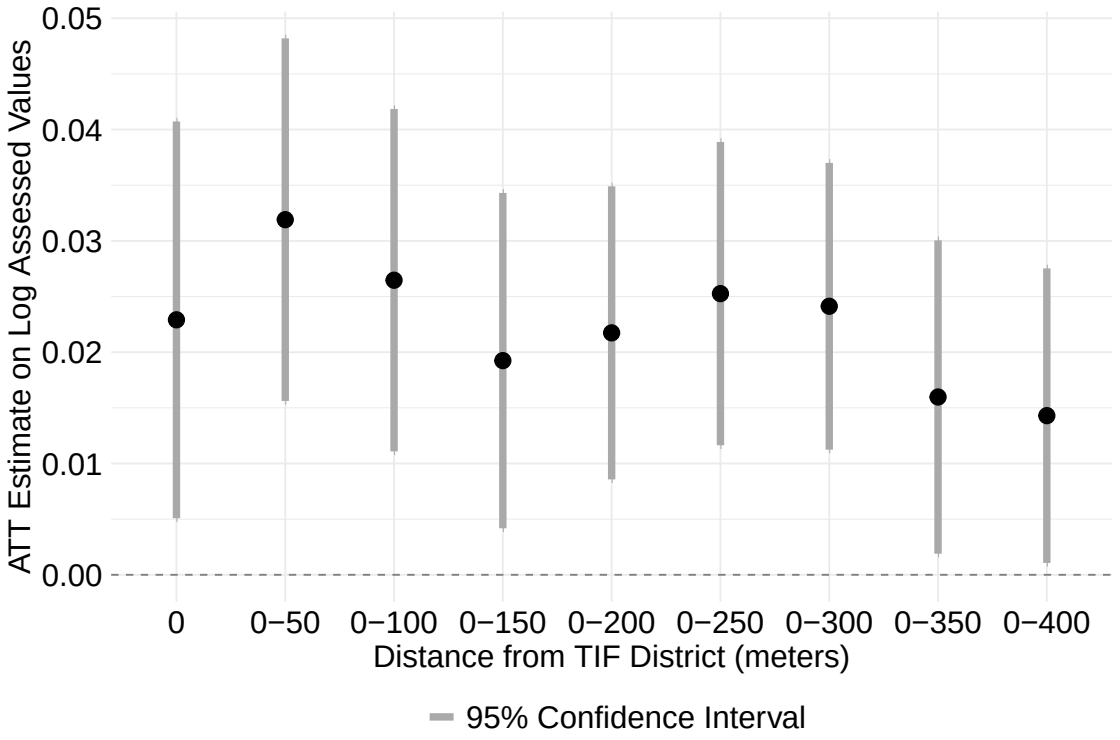


(b) Market Spillovers



Note: These plots display estimates for $\{\gamma_\ell\}_{\ell \in \mathcal{L}}$ from Equation (4) for the direct treatment effects and the market spillover effects. The outcome is the log of the average sale price in 2020 USD within 1990 Census blocks. All estimates are relative to event time −2. The error bars indicate 95% confidence intervals with TIF district-clustered standard errors.

Figure A.6: Different Treatment Definitions, Static Treatment Effect, Log Assessed Value



Note: This plot displays estimates for $\{\gamma_\ell\}_{\ell \in \mathcal{L}}$ from Equation (4) for different treatment definitions. The baseline estimates are for blocks 0-100 meters from TIF districts. The outcome is the log of the average sale price in 2020 USD within 1990 Census blocks. The specification compares blocks that are treated to those that are not yet treated. All estimates are relative to event time -2. The error bars indicate 95% confidence intervals with TIF district-clustered standard errors.

market spillover effects that is robust to the definition of spatially near.

D.4 Sensitivity of Direct Estimates to Weighted Regressions

Based on Wing, Freedman, and Hollingsworth (2024), I use the following weights for the regression model in Equation (4):

$$Q_{ie} = \begin{cases} 1 & E_i = e \\ \frac{N_e^T / N_{\mathcal{E}}^T}{N_e^C / N_{\mathcal{E}}^C} & E_i \neq e. \end{cases} \tag{A.5}$$

The weights depend on the number of Census blocks that are treated by a district

Table A.4: Spatial Spillover Estimates: Spatially Near Definition, Sensitivity Analysis

	Spatial		Market	
Distance (m)	All	Net of Market	All	Net of Spatial
	(s.e.)	(s.e.)	(s.e.)	(s.e.)
100-200	0.0113	0.0066	-0.0134^{***}	-0.0143^{***}
	(0.0091)	(0.0164)	(0.0025)	(0.0024)
100-400	0.0085	0.0085	-0.0134^{***}	-0.0156^{***}
	(0.0084)	(0.0127)	(0.0025)	(0.0022)
100-600	0.0042	0.013	-0.0134^{***}	-0.0165^{***}
	(0.0077)	(0.0116)	(0.0025)	(0.0021)
100-800	-0.0009	0.0107	-0.0134^{***}	-0.0172^{***}
	(0.0068)	(0.0109)	(0.0025)	(0.002)
100-1000	-0.0024	-0.004	-0.0134^{***}	-0.0184^{***}
	(0.006)	(0.0137)	(0.0025)	(0.0019)

Note: This table displays the corresponding static estimates for different definitions of spatially near. The baseline specification I present in the main paper is 100-400 meters. In all cases, the spatially far blocks must be at least 5 kilometers. The columns labelled All contain estimates using all blocks that are spatially or market close compared to those that are spatially or market far. The column labelled Net of Market contains estimates using blocks that are spatially close but not market close compared to those that are spatially far. The column labelled Net of Spatial contains estimates using blocks that are market close but not spatially close compared to those that are market far. In all cases, far blocks cannot be close to other districts established less than 5 years from the TIF district of interest. I report standard errors clustered by TIF district of interest in parentheses. Significance levels are indicated as *: $\alpha = 0.1$, **: $\alpha = 0.05$, ***: $\alpha = 0.01$.

established in period e, N_e^T, the number of Census blocks that are used as comparison units, N_e^C, and the total number of treated and control Census blocks across all treatment periods $\mathcal{E}$, $N_{\mathcal{E}}^T$ and $N_{\mathcal{E}}^C$.

The static specification is

$$\begin{aligned} Y_{it} = f(i,t) + \alpha_0 D_{id} + \alpha_1 \mathbf{1}\{t \geq E_d\} + \delta D_{id} \mathbf{1}\{t \geq E_d\} \\ + \sum_{\ell \in \mathcal{L}_{\text{pre}}} [\beta_\ell \mathbf{1}\{t - \ell = E_d\} + \gamma_\ell D_{id} \mathbf{1}\{t - \ell = E_d\}] + \epsilon_{it}. \end{aligned} \tag{A.6}$$

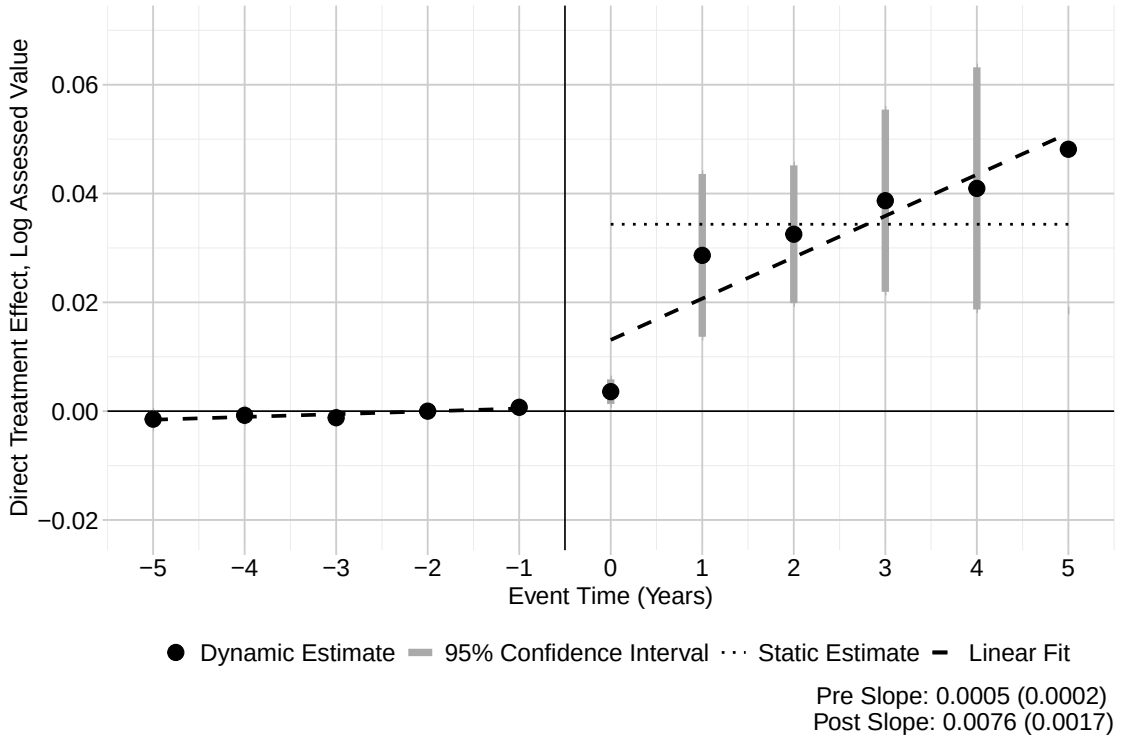
This specification differs from Equation 4 by grouping the post-treatment trend into one term, with corresponding parameter α_1. The parameter of interest is δ. The pre-treatment trend is controlled for individually, with corresponding parameters β_ℓ for $\ell \in \mathcal{L}_{\text{pre}}$. In practice, $\mathcal{L}_{\text{pre}} = \{-8, -7, -6, -5, -4, -3\}$. Unlike in Wing, Freedman, and Hollingsworth (2024), I add fixed effects $f(i,t)$ to align with the identifying assumption of my baseline results. That is, parallel trends hold conditional on fixed effects. As in the dynamic case, I weigh this specification the weights specified in Equation (A.5).

The estimates from these specifications are similar to those presented in the main paper. Figure A.7 shows the dynamic estimates. The corresponding static estimate is 0.0327 with a standard error of 0.0063.

D.5 Sensitivity of Market Spillover Effects to Estimated Housing Markets

The results presented in the main paper depend on the estimated housing markets. I estimate housing markets using different approaches to evaluate how much the main estimates change. Instead of allowing the algorithm to estimate the number of markets, I impose different amount of markets. The SBM algorithm groups the blocks to maximize the likelihood in Equation (A.1) given the imposed number of markets. Figure A.8 plots the static estimates

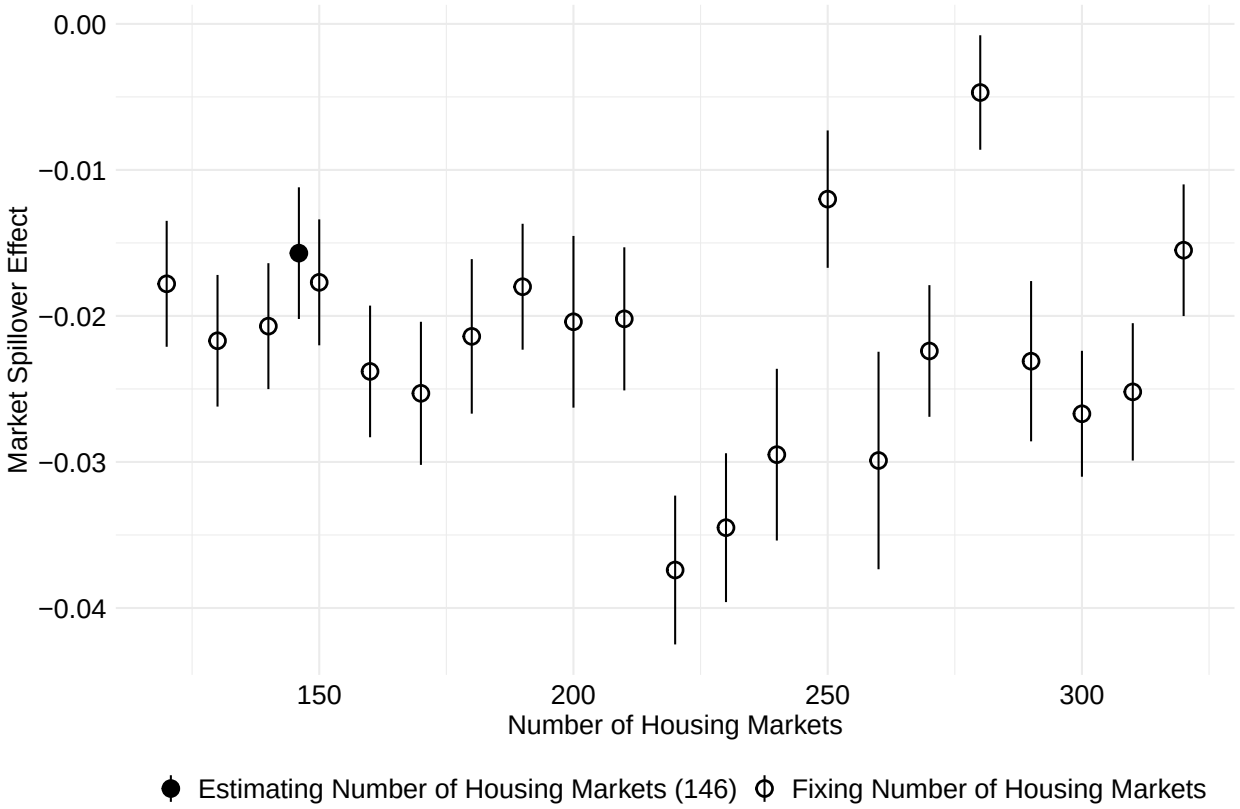
Figure A.7: Reweighted Dynamic Direct Treatment Effect, Log Assessed Property Value



Note: This plot displays estimates for $\{\gamma_\ell\}_{\ell \in \mathcal{L}}$ from Equation (4) wight weights as in Equation (A.5). The outcome is the log of the average assessed value in 2020 USD within 1990 Census blocks. The specification compares blocks that are treated to those that are not yet treated. All estimates are relative to event time -2. The error bars indicate 95% confidence intervals with TIF district-clustered standard errors.

of the market spillover effects. The estimates are all negative, consistent with the baseline estimate reported in the main paper. For 100 through 210 housing markets, the estimate is similar in magnitude as well. As the number of markets increase further, the estimates oscillate more. Note that except for $M = 146$, all the other estimates achieve optimality **conditional on** the number of markets. When $M = 146$, the estimate is optimal with the optimal number of markets.

Figure A.8: Market Spillover Effects, Imposing Number of Markets M



Note: This figure plots the static estimates of the market spillover effects imposing the number of housing markets. The solid point is the estimated market spillover effect when the number of housing markets is estimated. The error bars indicate 95% confidence intervals with TIF district-clustered standard errors.

References

Jaccard, Paul (1901). "Etude Comparative de La Distribution Florale Dans Une Portion Des Alpes et Des Jura". In: *Bull Soc Vaudoise Sci Nat* 37, pp. 547–579.

Samuelson, P. A. (Feb. 1938). "A Note on the Pure Theory of Consumer's Behaviour". In: *Economica* 5.17, p. 61.

Rosen, Sherwin (1974). "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition". In: *Journal of Political Economy* 82.1, pp. 34–55.

Breiger, Ronald L., Scott A. Boorman, and Phipps Arabie (1975). "An Algorithm for Clustering Relational Data with Applications to Social Network Analysis and Comparison with Multidimensional Scaling". In: *Journal of Mathematical Psychology* 12, pp. 328–383.

65 ILCS 5 (1977). *Illinois Municipal Code*.

Brueckner, Jan K. (Mar. 1979). "Property Values, Local Public Expenditure and Economic Efficiency". In: *Journal of Public Economics* 11.2, pp. 223–245. ISSN: 00472727. DOI: 10.1016/0047-2727(79)90006-9. URL: https://linkinghub.elsevier.com/retrieve/pii/0047272779900069 (visited on 04/13/2023).

— (Dec. 1982). "A Test for Allocative Efficiency in the Local Public Sector". In: *Journal of Public Economics* 19.3, pp. 311–331. ISSN: 00472727. DOI: 10.1016/0047-2727(82)90059-7. URL: https://linkinghub.elsevier.com/retrieve/pii/0047272782900597 (visited on 04/13/2023).

Holland, Paul W., Kathryn Blackmond Laskey, and Samuel Leinhardt (June 1983). "Stochastic Blockmodels: First Steps". In: *Social Networks* 5.2, pp. 109–137.

Wang, Yuchung J and George Y Wong (1987). "Stochastic Blockmodels for Directed Graphs". In: *Journal of the American Statistical Association* 82.397, pp. 8–19.

Anderson, John E. (June 1, 1990). "Tax Increment Financing: Municipal Adoption and Growth". In: *National Tax Journal* 43.2, pp. 155–163.

Bartik, Timothy J. (1990). "The Market Failure Approach to Regional Economic Development Policy". In: *Economic Development Quarterly* 4.4, pp. 361–370.

Auerbach, Alan J. and Kevin Hassett (1991). "Recent U.S. Investment Behavior and the Tax Reform Act of 1986: A Disaggregate View". In: *Carnegie-Rochester Conference Series on Public Policy* 35, pp. 185–216.

Bartik, Timothy J. (1991). *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, Michigan: W.E. Upjohn Institute for Employment Research.

Gatzlaff, D. and D. Haurin (1994). "Sample Selection and Biases in Local House Value Indices". In: *Unpublished Manuscript*.

Lawrence, David B. and Susan C. Stephenson (Win. 1995). "The Economics and Politics of Tax Increment Financing". In: *Growth and Change* 26, pp. 105–137.

Bollinger, Christopher R. and Keith R. Ihlanfeldt (Sept. 1997). "The Impact of Rapid Rail Transit on Economic Development: The Case of Atlanta's MARTA". In: *Journal of Urban Economics* 42.2, pp. 179–204. DOI: 10.1006/juec.1996.2020.

Snijders, Tom A.B. and Krzysztof Nowicki (1997). "Estimation and Prediction for Stochastic Blockmodels for Graphs with Latent Block Structure". In: *Journal of Classification* 14, pp. 75–100.

Man, Joyce Y. and Mark S. Rosentraub (Nov. 1998). "Tax Increment Financing: Municipal Adoption and Effects On Property Value Growth". In: *Public Finance Review* 26.6, pp. 523–547.

Conley, T.G. (Sept. 1999). "GMM Estimation with Cross Sectional Dependence". In: *Journal of Econometrics* 92.1, pp. 1–45.

Healey, Lori and John F. McCormick (Dec. 1999). "Urban Revitalization and Tax Increment Financing in Chicago". In: *Government Finance Review* 15.6, pp. 27–30.

Johnson, Craig L. (Mar. 1999). "Tax Increment Debt Finance: An Analysis of the Mainstreaming of a Fringe Sector". In: *Public Budgeting & Finance* 19.1, pp. 47–67.

Man, Joyce Y. (Mar. 1, 1999). "The Impact of Tax Increment Financing Programs on Local Economic Development". In: *Journal of Public Budgeting, Accounting & Financial Management* 11.3, pp. 417–430.

Dye, Richard F. and David F. Merriman (Mar. 2000). "The Effects of Tax Increment Financing on Economic Development". In: *Journal of Urban Economics* 47.2, pp. 306–328.

Bowes, David R. and Keith R. Ihlanfeldt (July 2001). "Identifying the Impacts of Rail Transit Stations on Residential Property Values". In: *Journal of Urban Economics* 50.1, pp. 1–25.

Brueckner, Jan K. (Aug. 2001). "Tax Increment Financing: A Theoretical Inquiry". In: *Journal of Public Economics* 81.2, pp. 321–343.

Johnson, Craig L. (2001). "The Use of Debt in Tax Increment Financing". In: *Tax Increment Financing: Uses, Structures, and Impact*. Ed. by Craig L. Johnson and Joyce Y. Man. 1st ed. SUNY Press.

Johnson, Craig L. and Kenneth A. Kriz (2001). "A Review of State Tax Increment Financing Laws". In: *Tax Increment Financing and Economic Development: Uses, Structures, and Impacts*. Ed. by Craig L. Johnson and Joyce Y. Man. Vol. 1. Albany, NY: State University of New York Press.

Klacik, J. Drew and Samuel Nunn (2001). "A Primer on Tax Increment Financing". In: *Tax Increment Financing and Economic Development: Uses, Structures, and Impact*. Ed. by Craig L. Johnson and Joyce Y. Man. Vol. 1. Albany, NY: State University of New York Press.

Kriz, Kenneth A. (2001). "The Effect of Tax Increment Finance on Local Government Financial Condition". In: *Municipal Finance Journal* 22.1, pp. 41–64.

Nowicki, Krzysztof and Tom A. B Snijders (Sept. 2001). "Estimation and Prediction for Stochastic Blockstructures". In: *Journal of the American Statistical Association* 96.455, pp. 1077–1087.

Goodman, Allen C. and Thomas G. Thibodeau (Sept. 2003). "Housing Market Segmentation and Hedonic Prediction Accuracy". In: *Journal of Housing Economics* 12.3, pp. 181–201.

Pritchett, Wendell E. (2003). "The Public Menace of Blight: Urban Renewal and Private Uses of Eminent Domain". In: *Yale Law and Policy Review* 1.

Weber, Rachel, Saurav Dev Bhatta, and David Merriman (Sept. 2003). "Does Tax Increment Financing Raise Urban Industrial Property Values?" In: *Urban Studies* 40.10, pp. 2001–2021.

Guryan, Jonathan (2004). "Desegregation and Black Dropout Rates". In: *American Economic Review* 94.4, pp. 919–943.

Heckman, James J, Sergio Urzua, and Edward Vytlacil (2006). "Understanding Instrumental Variables in Models with Essential Heterogeneity". In: *The Review of Economics and Statistics* 88.3, pp. 389–432.

Schwartz, Amy Ellen et al. (Nov. 2006). "The External Effects of Place-Based Subsidized Housing". In: *Regional Science and Urban Economics* 36.6, pp. 679–707.

Smith, Brent C. (Mar. 2006). "The Impact of Tax Increment Finance Districts on Localized Real Estate: Evidence from Chicago's Multifamily Markets". In: *Journal of Housing Economics* 15.1, pp. 21–37.

Abbring, Jaap H. and James J. Heckman (2007). "Econometric Evaluation of Social Programs, Part III: Distributional Treatment Effects, Dynamic Treatment Effects, Dynamic Discrete Choice, and General Equilibrium Policy Evaluation". In: *Handbook of Econometrics*. Ed. by James J. Heckman and Edward E. Leamer. Vol. 6B. Elsevier B.V., pp. 5144–5294.

Israeli, Osnat (Mar. 14, 2007). "A Shapley-Based Decomposition of the R-Square of a Linear Regression". In: *The Journal of Economic Inequality* 5.2, pp. 199–212.

Weber, Rachel, Saurav Dev Bhatta, and David Merriman (Mar. 2007). "Spillovers from Tax Increment Financing Districts: Implications for Housing Price Apprecitation". In: *Regional Science and Urban Economics* 37.2, pp. 259–281.

Carroll, Deborah A. (Mar. 2008). "Tax Increment Financing and Property Value: An Examination of Business Property Using Panel Data". In: *Urban Affairs Review* 43.4, pp. 520–552.

Coates, Dennis and Brad R. Humphreys (2008). "Do Economists Reach a Conclusion on Sbusidies for Sport Franchises, Stadiums, and Mega-Events?" In: *Econ Journal Watch* 5.3, pp. 294–315.

Glaeser, Edward and Joshua Gottlieb (Spr. 2008). *The Economics of Place-Making Policies*. Brookings. DOI: 10.3386/w14373.

Hudgens, Michael G and M. Elizabeth Halloran (June 1, 2008). "Toward Causal Inference with Interference". In: *Journal of the American Statistical Association* 103.482, pp. 832–842.

Smith, Brent C. (June 2009). "If You Promise to Build It, Will They Come? The Interaction between Local Economic Development Policy and the Real Estate Market: Evidence from Tax Increment Finance Districts". In: *Real Estate Economics* 37.2, pp. 209–234. ISSN: 10808620, 15406229. DOI: 10.1111/j.1540-6229.2009.00240.x.

Briffault, Richard (2010). "The Most Popular Tool: Tax Increment Financing and the Political Economy of Local Government". In: *The University of Chicago Law Review* 77.65, pp. 65–95.

Moretti, Enrico (May 1, 2010). "Local Multipliers". In: *American Economic Review* 100.2, pp. 373–377.

Weber, Rachel (July 2010). "Selling City Futures: The Financialization of Urban Redevelopment Policy". In: *Economic Geography* 86.3, pp. 251–274.

Jackson, Matthew O. (2011). *Social and Economic Networks*. Princeton, N.J. Woodstock: Princeton University Press. 504 pp. ISBN: 978-0-691-14820-5.

Karrer, Brian and M. E. J. Newman (Jan. 21, 2011). "Stochastic Blockmodels and Community Structure in Networks". In: *Physical Review E* 83.1, p. 016107.

Merriman, David F., Mark L. Skidmore, and Russ D. Kashian (June 2011). "Do Tax Increment Finance Districts Stimulate Growth in Real Estate Values?: Do TIF Districts Stimulate Growth in Real Estate Values?" In: *Real Estate Economics* 39.2, pp. 221–250.

Chen, Feixue (2013). "Grant Park vs. Millennium Park: Evolution of Urban Park Development". Urbana, Illinois: University of Illinois at Urbana-Champaign.

Hanson, Andrew and Shawn Rohlin (Jan. 2013). "Do Spatially Targeted Redevelopment Programs Spillover?" In: *Regional Science and Urban Economics* 43.1, pp. 86–100. ISSN: 01660462. DOI: 10.1016/j.regsciurbeco.2012.05.002. URL: https://linkinghub.elsevier.com/retrieve/pii/S0166046212000385 (visited on 02/11/2025).

Pryce, Gwilym (Oct. 2013). "Housing Submarkets and the Lattice of Substitution". In: *Urban Studies* 50.13, pp. 2682–2699. ISSN: 0042-0980, 1360-063X. DOI: 10.1177/0042098013482502.

Weber, Rachel and Sara O'Neill-Kohl (Aug. 2013). "The Historical Roots of Tax Increment Financing, or How Real Estate Consultants Kept Urban Renewal Alive". In: *Economic Development Quarterly* 27.3, pp. 193–207.

Callison, Kevin and Robert Kaestner (Jan. 2014). "Do Higher Tobacco Taxes Reduce Adult Smoking? New Evidence of the Effect of Recent Cigarette Tax Increases on Adult Smoking". In: *Economic Inquiry* 52.1, pp. 155–172.

Greenbaum, Robert T. and Jim Landers (Sept. 1, 2014). "The Tiff over TIF: A Review of the Literature Examining the Effectiveness of the Tax Increment Financing". In: *National Tax Journal* 67.3, pp. 655–674.

Kline, Patrick and Enrico Moretti (Feb. 1, 2014a). "Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority". In: *The Quarterly Journal of Economics* 129.1, pp. 275–331.

— (Aug. 1, 2014b). "People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs". In: *Annual Review of Economics* 6.1, pp. 629–662.

Peixoto, Tiago P. (Jan. 13, 2014a). "Efficient Monte Carlo and Greedy Heuristic for the Inference of Stochastic Block Models". In: *Physical Review E* 89.1, p. 012804. arXiv: 1310.4378 [cond-mat, physics:physics, stat].

— (Mar. 24, 2014b). "Hierarchical Block Structures and High-Resolution Model Selection in Large Networks". In: *Physical Review X* 4.1, p. 011047.

— (2014c). "The Graph-Tool Python Library". In: *figshare*. DOI: 10.6084/m9.figshare.1164194.

Brülhart, Marius, Sam Bucovetsky, and Kurt Schmidheiny (2015). "Taxes in Cities". In: *Handbook of Regional and Urban Economics*. Ed. by Gilles Duranton, J. Vernon Henderson, and William C. Strange. Vol. 5. Elsevier, pp. 1123–1196. DOI: 10.1016/B978-0-444-59531-7.00017-X.

Fadlon, Itzik and Torben Heien Nielsen (July 2015). "Family Labor Supply Responses to Severe Health Shocks". In: *NBER Working Paper* 21352. DOI: 10.3386/w21352. URL: http://www.nber.org/papers/w21352.pdf (visited on 09/02/2023).

Neumark, David and Helen Simpson (2015). "Place-Based Policies". In: *Handbook of Regional and Urban Economics*. Ed. by Giles Duranton, J. Vernon Henderson, and William C. Strange. Vol. 5B. Elsevier, pp. 1197–1287.

Weber, Rachel (2015). *From Boom to Bubble: How Finance Built the New Chicago*. Chicago and London: The University of Chicago Press.

Baker, Tom et al. (Jan. 12, 2016). "Policies on the Move: The Transatlantic Travels of Tax Increment Financing". In: *Annals of the American Association of Geographers* 106.2, pp. 459–469.

Ding, Lei, Jackelyn Hwang, and Eileen Divringi (Nov. 2016). "Gentrification and Residential Mobility in Philadelphia". In: *Regional Science and Urban Economics* 61, pp. 38–51.

Imai, Kosuke and Kabir Khanna (2016). "Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Records". In: *Political Analysis* 24.2, pp. 263–272.

Youngman, Joan M. (2016). *A Good Tax: Legal and Policy Issues for the Property Tax in the United States*. Cambridge, MA: Lincoln Institute of Land Policy. ISBN: 978-1-55844-342-6 978-1-55844-343-3 978-1-55844-345-7 978-1-55844-346-4 978-1-55844-344-0.

Mock, Brentin (Feb. 16, 2017). "The Meaning of Blight". In: *Bloomberg*. URL: https://www.bloomberg.com/news/articles/2017-02-16/why-we-talk-about-urban-blight?utm_source=website&utm_medium=share&utm_campaign=copy (visited on 12/20/2022).

Gaubert, Cecile (Nov. 1, 2018). "Firm Sorting and Agglomeration". In: *American Economic Review* 108.11, pp. 3117–3153.

Cengiz, Doruk et al. (Aug. 1, 2019). "The Effect of Minimum Wages on Low-Wage Jobs". In: *The Quarterly Journal of Economics* 134.3, pp. 1405–1454.

Craft, Andrea and Rachel Weber (2019). "An Incentive Program Grows Up: The Evolution of TIF in Chicago". In: *Tax Increment Financing and Economic Development: Uses, Structures, and Impact*. Ed. by Craig L. Johnson and Kenneth A. Kriz. Vol. 2. Albany: SUNY Press.

Deshpande, Manasi and Yue Li (Nov. 1, 2019). "Who Is Screened Out? Application Costs and the Targeting of Disability Programs". In: *American Economic Journal: Economic Policy* 11.4, pp. 213–248.

Diamond, Rebecca and Tim McQuade (2019). "Who Wants Affordable Housing in Their Backyard? An Equilibrium Analysis of Low-Income Property Development". In: *Journal of Political Economy* 127.3, pp. 1063–1117.

Fajgelbaum, Pablo D et al. (Jan. 2019). "State Taxes and Spatial Misallocation". In: *The Review of Economic Studies* 86.1.

Kosub, Sven (Apr. 2019). "A Note on the Triangle Inequality for the Jaccard Distance". In: *Pattern Recognition Letters* 120, pp. 36–38.

Kriz, Kenneth A. (2019). "The Theory and Economic Impact of Tax Increment Financing". In: *Tax Increment Financing and Economic Development: Uses, Structures, and Impact*. Ed. by Kenneth A. Kriz and Craig L. Johnson. Vol. 2. SUNY Press.

Kriz, Kenneth A. and Craig L. Johnson (2019). "A Review of State Tax Increment Financing Laws". In: *Tax Increment Financing and Economic Development: Uses, Structures, and Impact*. Ed. by Craig L. Johnson and Kenneth A. Kriz. Vol. 2. Albany, NY: State University of New York Press.

Lu, Yi, Jin Wang, and Lianming Zhu (2019). "Place-Based Policies, Creation, and Agglomeration Economies". In: *American Economic Journal: Economic Policy* 11.3, pp. 325–360.

Luby, Martin J. et al. (2019). "The Use of Debt in Tax Increment Financing". In: *Tax Increment Financing and Economic Development: Uses, Structures, and Impact*. Ed. by Craig L. Johnson and Kenneth A. Kriz. Vol. 2. SUNY Press.

Peixoto, Tiago P. (Nov. 23, 2019). "Bayesian Stochastic Blockmodeling". In: *Advances in Network Clustering and Blockmodeling*. Ed. by Patrick Doreian, Vladimir Batagelj, and Anuška Ferligoj. Wiley, pp. 289–332.

Yadavalli, Anita and Michjael Delgado (2019). "Tax Increment Financing and Spatial Spillovers". In: *Tax Increment Financing and Economic Development: Uses, Structures, and Impact*. Ed. by Craig L. Johnson and Kenneth A. Kriz. Vol. 2. SUNY Press.

Avenancio-León, Carlos and Troup Howard (June 2020). "The Assessment Gap: Racial Inequalities in Property Taxation". In: *Washington Center for Equitable Growth Working Paper Series*.

Bishop, Kelly C. et al. (June 1, 2020). "Best Practices for Using Hedonic Property Value Models to Measure Willingness to Pay for Environmental Quality". In: *Review of Environmental Economics and Policy* 14.2, pp. 260–281.

City of Chicago (2020). "Annual Comprehensive Financial Reports Financial Statements Overview". URL: https://www.chicago.gov/city/en/depts/fin/supp_info/comprehensive_annualfinancialstatements.html.

Cook County Clerk's Office (2020). *City of Chicago TIF Revenue Totals by Year*. URL: https://www.cookcountyclerkil.gov/property-taxes/tifs-tax-increment-financing/tif-reports.

Data Axle (2020). "Infogroup Consumer Data 2006-2020". In.

De Chaisemartin, Clément and Xavier D'Haultfœuille (2020). "Two-Way Fixed Effects and Differences-in-Differences with Heterogeneous Treatment Effects: A Survey". In: *Unpublished Manuscript*.

Department of Planning and Development (2020). *Tax Increment Financing Program Guide*. City of Chicago.

Foell, A. and K. A. Pitzer (Sept. 2, 2020). "Geographically Targeted Place-Based Community Development Interventions: A Systematic Review and Examination of Studies' Methodological Rigor". In: *Housing Policy Debate* 30.5, pp. 741–765.

Aaronson, Daniel, Daniel Hartley, and Bhashkar Mazumder (Nov. 1, 2021). "The Effects of the 1930s HOLC "Redlining" Maps". In: *American Economic Journal: Economic Policy* 13.4, pp. 355–392.

Borusyak, Kirill and Peter Hull (Dec. 2021). "Non-Random Exposure to Exogenous Shocks: Theory and Applications". In: *NBER Working Paper* 27845. URL: http://www.nber.org/papers/w27845.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess (Aug. 27, 2021). "Revisiting Event Study Designs: Robust and Efficient Estimation". arXiv: 2108.12419 [econ]. URL: http://arxiv.org/abs/2108.12419 (visited on 03/22/2022).

Butts, Kyle (Nov. 11, 2021). "Difference-in-Difference with Spatial Spillovers". arXiv: 2015.03737v2 [econ.EM].

Costa Dias, Monica et al. (2021). "Worker Mobility and Labour Market Opportunities". In: *Unpublished Manuscript*.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams (Aug. 1, 2021). "Place-Based Drivers of Mortality: Evidence from Migration". In: *American Economic Review* 111.8, pp. 2697–2735. ISSN: 0002-8282. DOI: 10.1257/aer.20190825. URL: https://pubs.aeaweb.org/doi/10.1257/aer.20190825 (visited on 03/02/2025).

Gaubert, Cecile, Patrick M. Kline, and Danny Yagan (Jan. 2021). "Place-Based Redistribution". In: *NBER Working Paper* 28337. URL: https://www.nber.org/papers/w28337.

Goodman-Bacon, Andrew (Dec. 2021). "Difference-in-Differences with Variation in Treatment Timing". In: *Journal of Econometrics* 225.2, pp. 254–277.

Hanson, Andrew (Aug. 2021). "Taxes and Economic Development: An Update on the State of the Economics Literature". In: *Economic Development Quarterly* 35.3, pp. 232–253. ISSN: 0891-2424, 1552-3543. DOI: 10.1177/08912424211022832. URL: http://journals.sagepub.com/doi/10.1177/08912424211022832 (visited on 03/29/2022).

Huber, Martin and Andreas Steinmayr (Apr. 3, 2021). "A Framework for Separating Individual-Level Treatment Effects From Spillover Effects". In: *Journal of Business & Economic Statistics* 39.2, pp. 422–436.

Nolte, Christoph et al. (Sept. 4, 2021). "Studying the Impacts of Environmental Amenities and Hazards with Nationwide Property Data: Best Data Practices for Interpretable and Reproducible Analyses". In: *WVU College of Law Research Paper No.* 2021–013.

Abadie, Alberto et al. (Dec. 15, 2022). "When Should You Adjust Standard Errors for Clustering?" In: *The Quarterly Journal of Economics* 138.1, pp. 1–35.

Butters, R. Andrew, Daniel W. Sacks, and Boyoung Seo (May 1, 2022). "How Do National Firms Respond to Local Cost Shocks?" In: *American Economic Review* 112.5, pp. 1737–1772. ISSN: 0002-8282. DOI: 10.1257/aer.20201524. URL: https://pubs.aeaweb.org/doi/10.1257/aer.20201524 (visited on 06/19/2024).

City of Chicago (2022). "Chicago Data Portal". In: URL: https://data.cityofchicago.org.

Federal Reserve Bank of St. Louis (2022). "Consumer Price Index for All Urban Consumers: All Items in Chicago-Naperville-Elgin, IL-IN-WI (CBSA), Index 1982-1984=100, Annual, Not Seasonally Adjusted". In: URL: https://fred.stlouisfed.org.

Fogel, Jamie and Bernardo Modenesi (Jan. 10, 2022). "What Is a Labor Market? Classifying Workers and Jobs Using Network Theory". In: *Unpublished Manuscript*.

Hyman, Benjamin et al. (Nov. 2022). "Firm Responses to State Hiring Subsidies: Regression Discontinuity Evidence from a Tax Credit Formula". In: *Unpublished Manuscript*.

Manson, Steven et al. (2022). "IPUMS National Historical Geographic Information System". In: URL: http://doi.org/10.18128/D050.V17.0.

Wheeler, Harrison (Nov. 2022). "Locally Optimal Place-Based Policies: Evidence from Opportunity Zones". In: *Working Paper*.

Asquith, Brian J., Evan Mast, and Davin Reed (Mar. 3, 2023). "Local Effects of Large New Apartment Buildings in Low-Income Areas". In: *The Review of Economics and Statistics* 105.2, pp. 359–375.

Cook County Government (2023). "Cook County Open Data". In: URL: https://datacatalog.cookcountyil.gov.

Czurylo, Todd (2023). "The Effect of Tax Increment Financing Districts on Job Creation in Chicago". In: *Journal of Urban Economics* 134.103510, pp. 1–19.

Ferreira, Fernando, Jeanna Kenney, and Benjamin Smith (2023). "Household Mobility, Networks, and Gentrification of Minority Neighborhoods in the US". In: *Unpublished Manuscript*.

Jarosch, Gregor, Jan Sebastian Nimczik, and Issac Sorkin (2023). "Granular Search, Market Structure, and Wages". In: *Unpublished Manuscript*.

Nimczik, Jan Sebastian (2023). "Job Mobility Networks and Data-driven Labor Markets". In: Unpublished Manuscript.

Pollmann, Michael (Jan. 2023). "Causal Inference for Spatial Treatments". arXiv: 2011.00373v2 [econ.EM].

Wang, Ye et al. (Mar. 9, 2023). "Design-Based Inference for Spatial Experiments under Unknown Inference". arXiv: 2010.13599v4 [stat.ME]. URL: https://arxiv.org/abs2010.13599.

Alves, Guillermo, William H Burton, and Sebastian Fleitas (Sept. 17, 2024). "Difference-in-Differences in Equilibrium: Evidence from Place-Based Policies". In: *Unpublished Manuscript*.

Gaubert, Cecile, Gordon H. Hanson, and David Neumark (2024). "Introduction". In: *Economics of Place-Based Policies*. National Bureau of Economics Research.

Mast, Evan (2024). "Off the Beaten Tract: Constructing a New Neighborhood Geography from Migration Data". In: *Working Paper*.

Wing, Coady, Seth M. Freedman, and Alex Hollingsworth (Jan. 2024). "Stacked Difference-in-Differences". In: *NBER Working paper* 32054.