Assessing the effects of place-based policy on spatial inequality and the distribution of household income: Evidence from tax increment financing

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Abstract

This research examines the effects of tax increment financing (TIF) on spatial inequality from 1990 to 2014 in Cook County, Illinois. I first explore the effects of TIF on (real) income and income distribution. Then, I proceed to examine whether the effects lead to a reduction in spatial inequality. To address the second research question, I construct dependent variables that assess the probability of TIF increasing upward mobility on the (real) income ladder and catching up with other areas. The results show beneficial distributional effects, but the effects are much attenuated when examining changes in the probability of moving up in the rankings, indicating that the effects of TIF are limited in reducing spatial inequality in the region.

1. Introduction

For policy makers and researchers, persistent economic differences and unequal distribution of welfare across places have both served as sources of inspiration and concern (Capello and Nijkamp, 2007). And various place-based policies have been introduced aiming to address these social issues and find means to reduce spatial inequality. Nonetheless, scholars have paid very little attention to evaluating place-based policy (PBP)'s equity-based motivation. This is primarily due to the existing approach to PBP assessment that overlooks broader and regional context. When evaluating the PBPs, most of the existing literature identify the effects of PBPs on economic outcomes by comparing them to those of the control groups with similar socio-economic characteristics (Billings, 2009; Bondonio and Greenbaum, 2007; Ehrlich and Seidel, 2018; Elvery, 2008; Lester, 2014; Neumark and Kolko, 2010; Reynolds and Rohlin, 2015; Yadavalli and Landers, 2017; Czurylo, 2023). The findings from such comparison reveal, for example, that lagging places where a particular PBP was implemented have experienced faster income growth than similarly lagging places where the PBP was not implemented. This identification setup is useful to show how well the treated areas perform relative to the control areas.

However, the setup does not show whether the treated places have been catching up with other more flourishing places and whether the adoption of PBP reduces spatial inequality in the region. That is, even if the analysis finds relatively positive effects on the neighborhoods (treated) compared to similarly lagging neighborhoods (controlled), the surrounding areas with better economic conditions may have experienced a faster rate of income growth over the same time frame.[1] Such cases would demonstrate that the initially lagging neighborhoods have *not* been able to keep up with other more flourishing neighborhoods in the same region and imply that, while the PBP aids in performing better than similarly lagging areas, the success was only partial. Accordingly, the question we need to ask in order to investigate the effects of PBPs on spatial inequality is: Do place-based policies make a difference in relative neighborhood economic status *in the region* (not only compared to the control groups)? In essence, this paper takes a different approach to looking at the effects of PBP on spatial inequality by employing an alternative baseline in contrast to previous studies.

To answer this question, I first examine the effects of tax increment financing (TIF), as an example of PBP which has been adopted in 49 states and the District of Columbia since 1952 (Merriman, 2018), on (real) income and income distribution. Then, I proceed to examine whether the effects (if any) lead to a reduction in spatial inequality.

TIF districts, generally designated in more “blighted” and economically lagging areas (Czurylo, 2023; Lester, 2014) are intended to facilitate economic development, induce jobs and investments, and enhance the economic well-being of the designated areas. Investments and assistance in the designated areas are likely to affect the local economy and the economic well-being of the areas and residents through the local labor market or, more indirectly, through upgrades to schools, transport facilities, the provision of affordable housing and high-end residential development, or any other infrastructure improvements.

To assess the effects of these investments and subsequent economic development projects, previous studies have focused on labor market outcomes and property values. As a result, various analyses have been accumulated (Byrne, 2010; Drucker et al., 2019; El-Khattabi & Lester, 2019; Kane & Weber, 2016; Lester, 2014; Weber et al., 2007; Yadavalli & Landers, 2017). However, the results are inconsistent and mixed. And one area that remains unexplained is the effects of TIF on income and income distribution, which may more directly indicate changes in the economic status and well-being of the designated area and residents. Thus, this study aims to fill the gap in the literature by examining the effects of TIF on income in addition to (and as a means of measuring) the effects on spatial inequality. Specifically, I analyze TIF districts in Cook County, Illinois from 1990 to 2019. For identification, this research integrates a linear probability model into a staggered difference-in-difference (DID) method which will examine the likelihood of neighborhood upward mobility in TIF districts. This study aims at informing PBP studies about a new approach in evaluating the effects of PBPs.

2. Related literature

2.1. Place-based policy and its equity-based rationale

Place-based policy is a spatially immobile intervention in a particular area that is economically lagging relative to regional or national trends (Olfert et al., 2011). In the U.S., a myriad of PBPs has been implemented by governments, with resources invested at the national and local levels estimated to total more than $95 billion per year (Kline and Moretti, 2014). They come in many types, typically offering financial or other business assistance such as tax breaks and hiring incentives. The widespread use of PBPs is essentially based on the view that PBPs will have a positive influence on job creation, reduction of spatial inequality, and likely persistent differences in development.

The conventional view of neoclassical urban economists on spatial inequality and the role of PBPs differs from the perspective presented above. They argue that, without PBPs, there will be no distortion in the spatial market, and that the market will naturally reach its spatial equilibrium (SE) through migration of labor and capital. Under the unhindered mobility assumption of labor and capital, seeming or short-term differences in income level do not last for a very long time and do not imply that there are differences in utility level across space. And in the long run, high incomes are arbitraged away by high prices and utility level, which is frequently measured with a real income, is equalized across places and neighborhoods (Roback, 1982; Rosen, 1974). Critics of PBPs also claim that PBPs distort migration decisions of people and businesses and artificially lower economic activities and concentration. They contend that PBPs favor less productive regions with less skilled and innovative labor while penalizing more productive regions where workers are skilled and efficient (Kraybill and Kilkenny (2003).

However, as equilibrating migrations have been reduced since the 1980s, recent studies report exacerbating and persistent spatial inequality in contrast to the expectation based on the SE model (Ganong and Shoag, 2017). From the 1990s to the 2010s income convergence at various geographical scales from state to neighborhood slowed down, with less than half the historical convergence rate (Ganong and Shoag, 2017; Sampson, 2019; Shambaugh and Nunn, 2018). These recent phenomena have prompted urban economists to reevaluate PBP's contribution to closing the spatial gap (Austin et al., 2018; Shambaugh and Nunn, 2018). Yet, the equity-based motivation of PBPs has drawn significantly less attention among scholars thus far.

Most of the previous studies that measure the effects of PBPs show whether the outcomes of the treated area outperform those of the control area, which is often constructed either using the propensity score strategy (Bondonio and Greenbaum, 2007; Elvery, 2008; Hanson and Rohlin, 2013; Lester, 2014; Reynolds and Rohlin, 2015; Yadavalli and Landers, 2017) or geographical nearness to the treated area (e.g., a spatial discontinuity approach) (Billings, 2009; Ehrlich and Seidel, 2018; Neumark and Kolko, 2010). For instance, Yadavalli and Landers (2017) examine whether block groups that are designated as a TIF district experience an increase in employment and property values compared to matched block groups using propensity score matching based on residential, demographic, and economic conditions. Similarly, Neumark and Kolko (2010) assess how enterprise zones perform in comparison to areas just outside the enterprise zones (i.e., 1,000 feet) on the presumption that other economic characteristics are likely to be similar to the designated area.

With this identification setup, previous studies have revealed whether treated areas are better off than they would have otherwise. However, as these prior investigations focus on the comparison between the outcomes of the treated areas to the control groups, they have not shed light on the overall performance of the treated areas within the broader region, beyond the comparison to similarly economically lagging areas. Therefore, this study aims to fill this gap and advance understanding of the effects of PBP on spatial inequality. Addressing this knowledge gap is critical because persistent geographical inequality may be exacerbated by vicious, circular and cumulative processes that are intertwined with race and class (Myrdal, 1957; Soja, 2013).

2.2. Tax increment financing

TIF is one of the most widely used economic development tools in the U.S. (Warner and Zheng, 2013). For instance, as of 2020, more than $1 billion (38%) of Chicago's property tax revenue flowed into TIF districts (Cherone, H., 2021). TIF has grown in popularity over the years primarily because it helps three major stakeholders in achieving their respective goals. For local officials and residents, the program allows them to create employment opportunities and reinvigorate the local economy beyond the level of what would have occurred otherwise without raising tax rates. Developers, on the other hand, benefit from the TIF because TIF is commonly used as a subsidy for developers to cover expenses such as land acquisition and the hard costs of construction.

The detailed methods and processes that a local government follows to establish a TIF district vary by state. However, in general, a municipality first designates a TIF district in a particular geographically defined area. The area or a group of parcels must be "blighted" and unattractive, and the area must be a place where economic activity or development is not expected or would not have occurred "but for" designation of a TIF district. Then, the increased assessed property values resulting from (re)development are earmarked for a TIF district and used as a revenue source of a TIF fund for approximately 20 years (e.g., 23 years in Illinois). In the meantime, the existing bodies rely on property taxes that are assessed and frozen based on the property values at the time of designation.

The TIF fund is usually utilized to prepare the area for (re)development, to improve infrastructure, and to provide financial incentives. The fund helps (re)develop a site by land and property acquisition and site preparation. It can also be used to finance infrastructure improvement projects, such as adding parking spaces, roads, and street lighting. Job training programs and relocation assistance that help induce and retain jobs within TIF districts are other areas where municipalities frequently invest money. Lester's (2014) research shows how TIF revenues have been spent specifically by typology in Chicago. According to the analysis, approximately 42% of TIF revenues are allocated to a category referred to as "traditional economic development," which includes redevelopment agreements between the City of Chicago and private developers, land assembly, and site development costs. In contrast, approximately 54% of TIF revenues are allocated to "public facilities" and "infrastructure," which encompass lighting, sewer improvements, streetscaping, other infrastructure improvements, and upgrades to public schools, parks, and transit facilities.

In consideration of this financing mechanism, the majority of earlier studies evaluating the effectiveness of TIF have concentrated on property values and/or employment. For instance, one of the early studies by Man and Rosentraub (1998) finds that TIF districts in Indiana cities are associated with a higher median value of owner-occupied housing. Dye and Merriman (2000) also show that TIF adoption increased equalized assessed value in the Chicago metropolitan area. Since then, analyses on the effects of TIF have expanded with longer-term and granular data. More recent studies conduct analyses using sub-municipal level data such as block group or parcel level (Funderburg, 2019b; Smith, 2006; Weber et al., 2003) which is more likely to align with the actual boundaries of TIF districts. There have also been advancements in terms of identification methods. Lester (2014), and Yadavalli and Landers (2017) adopt propensity score matching or weighting to find more comparable control groups and address selection bias.

Despite these various efforts, the findings from previous analyses on both property values and employment have not been consistent, ranging from positive (Man and Rosentraub, 1998; Smith, 2006; Byrne, 2010; Czurylo, 2023; Man, 1999; Carroll, 2008) to insignificant or even negative effects (Drucker et al., 2019; El-Khattabi and Lester, 2019; Funderburg, 2019; Lester, 2014). Furthermore, existing evidence is particularly scarce in one dimension: how TIF affects the lives of residents in the designated area. It is true that in the majority of redevelopment plans devised for TIF districts, the goal of boosting economic activity is more overt than improving residents' well-being.[2] But, investments and improvements in transport, schools, and neighborhoods are likely to improve amenities and affect income, either directly or indirectly. Also, as Fisher and Bruner (2003) point out, the underlying goal of TIF designation and what policy-makers would ultimately like to see from improved economic performance is greater well-being for the residents and assistance in preventing them from being left behind. Analyzing the effects of TIF on income, the distribution of income, and real income would address the question of well-being directly as other PBP studies (Busso et al., 2013; Ehrlich and Seidel, 2018; Reynolds and Rohlin, 2015).

3. Data and variables

3.1 Data

I obtain detailed demographic and other economic characteristics of block groups including income, race, education, rent and property value, housing units, owner rate, and unemployment rate from a commercial firm called Geolytics Ltc. as well as the 2008-2012 and 2015-2019 U.S. Census Bureau American Community Survey. [3] For studies using longitudinal data, Census geographic unit boundaries changing over time often presents a challenge. Geolytics data address this issue by providing 1990 and 2000 data with fixed 2010 census boundaries. [4] As for the income data, Geolytics provides data at 16 points in the distribution of annual household income that is normalized to 2010 block group boundaries. To reduce complexity and measurement errors that may arise once Geolytics normalize the data, I merge some categories and create three groups (i.e., low, middle, and high-income household groups) based on the median household income of Cook County in 2010, which was $53,942 (U.S. Census, 2010). When households' income is in between 75% and 125% of the median household income, those households are classified as middle-income households. Under and above the middle-income household range are categorized as low-income households and high-income households respectively.

The data on TIF come from the Cook County Clerk's Office (CCCO) and the City of Chicago Data portal through both their website and Freedom of Information Act (FOIA) request. [5] I restrict the analyses to TIF districts established after 1990 considering the availability of the Decennial Census and the fact that approximately 90% of TIF in Cook County are created after 1990. [6]

The boundaries of TIF districts designated from 1990 to 2014 are corresponded to 2010 block groups. Since the boundaries of TIF districts are mostly irregular and are not directly matched with census geographies, I adopt a threshold criterion to define TIF areas ‘. Block groups are considered to be treated when more than 30% of the area is covered by a TIF district.[7] and as a result, 509 TIF districts and 12,014 block groups are included in the analysis (see Table A2 in Online Appendix for the number of observations by designation year).

One may raise a question of which geographical scale should be used to assess changes in (real) income and income distribution because the analysis based on the block group level is prone to underestimation since many individuals who work in TIFs but do not live there are excluded. Conversely, the use of a broader geographical unit would likely result in greater inclusion of those who both work and live in TIFs, thus reducing the possibility of underestimation. However, this approach is limited in its ability to capture the effects on workers in TIFs due to difficulties in distinguishing between those directly affected by TIF and those who do not live or work within TIFs. Additionally, the use of a broader geographical unit may increase the likelihood of bias from the effects of simultaneous economic development policies. Thus, this study uses a more refined geography in the analysis that facilitates the identification of the boundaries and spheres of influence of TIF with greater precision, thereby enabling a more accurate and conservative estimation of the effects of TIF.

3.2 Variables

To estimate the effects of TIF on the lives of residents, I first look at median household income as an outcome variable. Most PBP studies have also predominantly focused on income at mean or median (Reynolds and Rohlin, 2015). However, it does not reveal the redistributive nature of PBP and who or which income groups actually drive a change in income. Thus, I also look at the effects of TIF on the share of different categories of household income to examine possible distributional effects. If, for example, the analysis results show decreases in the share of low-income households, it could be due to income gains from the improved labor market and local economy or low-income households being priced out by higher housing prices. Alternatively, a more likely scenario is a combination of the two. As for the share of high-income households, it is expected that the share would rise as dilapidated facilities are replaced with new and better-quality buildings and development.

Next, the effects on median house values and median gross rents are investigated. I use housing values and rents as a foundation for assessing and interpreting the TIF effects on real income. I anticipate that new, redeveloped, and improved infrastructure will cause both rents and housing values to rise.

Even if TIF areas experience increases in nominal income, the increase could be canceled out by a higher cost of living. Thus far, only a couple of PBP studies take this possibility into consideration and examine the effects on real income (Busso et al., 2013; Ehrlich and Seidel, 2018). This study extends the current limited understanding of TIF's effects on real income.

The cost of living here is computed solely based on housing prices since differences in the cost of living are mostly caused by housing prices (Beeson and Eberts, 1989) and prices for non-housing are not expected to vary significantly between neighborhoods in the same county. As a result, a real income variable is calculated as log(median household income) – 0.30 * log(median rents).[8,] The analysis results shed light on how TIF affects the real income of renters, who account for about 50% of the population in the designated areas, according to Table A1 in the Online Appendix.

The last group of dependent variables is constructed to measure the probability of moving up in the *rankings* of outcomes. Specifically, the rankings of the outcomes are determined for each year; if the rankings are higher than the previous year, it is coded as 1 and 0 otherwise. With the dependent variables created in this manner, the regression results will show how the treated areas are more (or less) likely to be ranked higher (lower) in the distribution of the outcomes compared to the control group. And TIF is considered to have positive effects only when the treated group moves up to a higher ranking (i.e., catching up with other more affluent block groups in Cook County).[9]

As for the treatment variable, it is coded 1 if a TIF district covers more than 30% of a block group, and 0 otherwise. In the estimation, I compute propensity scores to find control groups. Covariates used for the calculations of propensity scores include minority shares (i.e., the share of non-white), median household income, median gross rent, median housing values, the share of the population with a bachelor's degree or higher, unemployment rate, and Enterprise Zone dummy.

Table A1 in Online Appendix compares average characteristics and standard deviations for block groups in TIF districts and block groups not in TIF districts. As expected, median household income, gross rent, property value, and the share of high-income households are higher in non-TIF block groups while TIF areas have higher unemployment rates, a higher share of low-income households, lower homeownership rates, and a lower share of bachelor or higher degree holders. These characteristics are often associated with economically lagging areas and they reveal that TIF districts are generally targeted and located in those more disadvantaged areas as shown in other studies (Czurylo, 2023; Lester, 2014).[10] Also, this fact suggests that TIF generally functions as a more equity-based policy, as opposed to the efficiency-based arguments of classical urban economists, which recommend investments to be made in areas that are already more productive.

4. Empirical Approach

To explore the effects of TIF on spatial inequality, I propose to compare how the treated areas are more (or less) likely to be ranked higher (lower) in the distribution of the outcomes compared to the control group.

I integrate the linear probability model[11] into Callaway and Sant'Anna, (2021)'s estimator to employ a new way of measuring the effects of PBP. Also, instead of the two-way fixed effects (TWFE) model, which has been one of the most popular approaches in evaluating PBPs, I follow Callaway and Sant'Anna (2021) to avoid possible bias identified in recent studies (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021).[12]

The following specification is used to estimate the group-time average treatment effects for the treatment time group g at a varying time, denoted as $ATT_{(g,t)}$

$$ATT_{(g,t)} = E\left[\left(\frac{G_g}{E[G_g]} - \frac{\frac{p_g(X)(1-D_t)(1-G_g)}{1-p_g(X)}}{E\left[\frac{p_g(X)(1-D_t)(1-G_g)}{1-p_g(X)}\right]}\right)(Y_t - Y_{g-1} - m_{g,t}^{not-yet}(X))\right]$$

where G_g is a binary variable equal to 1 if a block group is first treated in time g. Y_t denotes the potential outcomes at varying time t. $p_{g,t}(X)$ is a propensity score that is calculated based on covariates X and on either being treated in time g (i.e., $G_g = 1$) or a not-yet-treated group by time t (i.e. $(1 - D_t)(1 - G_g) = 1$). D_t is a dummy variable equal to 1 if a block group is treated in period t or 0 otherwise. And $m_{g,t}^{not-yet}(X) = E[Y_t - Y_{g-1}|X, D_t = 0, G_g = 0]$.

Essentially, the Callaway and Sant'Anna (2021) estimator is a weighted average of the differences in outcome. The propensity scores computed from a group of covariates in the latest pre-treatment year work as weights in the first term while the second term is a regression that measures the change in outcomes for the not-yet-treated group (i.e., block groups that have not yet been treated by time period t) between years t and $g-1$.

The not-yet-treated block groups are used in the estimation because, firstly, the true counterfactual cannot be observed and, secondly, they are eventually treated in the later period and thus, likely to have more analogous (un)observable characteristics with treated block groups. Also, contiguous block groups to TIF districts that may have been more directly affected are excluded from the control group to account for possible spillover effects. Standard errors are clustered at the city level to account for possible spatial and temporal dependence. Instead of point-wise confidence intervals, simultaneous confidence intervals are used to control for the dependence across the group-time coefficients.

The main estimates are computed by summarizing the reduced form effect of TIF on outcomes rather than interpreting each $ATT(g,t)$, most of which are estimated based on relatively fewer number of observations and include compositional changes in observations that could complicate the interpretation of the results.[13] Thus, to get the summary measure, I first estimate group-time treatment effects for every length of exposure e including pre-treatment periods ($e < 0$) by averaging the treatment effect over the entire treatment time groups. The resulting coefficients for each length of exposure or event-time e are analogous to event-study parameters. I also report the *overall* average treatment effects (i.e., overall ATT). It is a weighted average of $ATT(g,t)$ for $t \geq g$ across all time groups and time periods.

5. Results

As in other PBP studies, first, the average treatment effects on outcomes are reported in Panel A of Figures 1 to 7. Then, I turn to the estimates that show how more likely it is for TIF districts to advance to a higher ranking in each outcome compared to the non-TIF areas. The results for the second group of outcomes are included in Panel B of Figures 1 to 7, highlighting the differentiating effects on the two groups of outcomes. Also, I combine time window into two-year bins to improve the power of the estimation and smooth out the noisier estimation results caused by the staggered adoption of treatment and compositional changes in the observation.[14] The event-time coefficients in the Figures show the TIF effects by two-year bins relative to the designation of TIF. Pre-treatment periods are also included to identify any differential pre-trends between the treated and the propensity-score-weighted not-yet-treated group. *Overall ATT* shows overall average treated effects on the treated. Furthermore, I estimate the effects of TIF using the standard TWFE event-study models for robustness check purposes and comparability with other studies (see Figures B9 to B15 in Online Appendix). The key findings are unaffected and remain same.

5.1. The effects on the distribution of household income and spatial inequality

[Figure 1 here]

Figure 1 presents the effects of TIF on median household income. First, in both Panel A and B, the event-time coefficients for pre-treatment periods (before 0-1 years bin) indicate no differential pre-trends between the treated and control areas, supporting a causal interpretation of the estimates. Next, in Panel A, the event-time coefficients for the treatment period show the positive effects of TIF on median household income in most cases (10 out of 13 coefficients), with 5 coefficients reaching statistical significance at the 95% confidence level. The treatment effects are less evident until years 10-11 with fluctuating coefficients. And the estimates start to show evidence of the positive effects of TIF around 10-11 years bin after TIF designation. Specifically, for instance, TIF areas experience a 9% increase in median household income compared to the non-TIF areas in 10-11 years bin and the positive trend continues up until the last estimation window (i.e., 24-25 years bin). The positive effects observed in the later years rather than in the immediate periods could be attributed to the intrinsic nature of (re)development projects. Usually, (re)development projects for building such as large new residential buildings or improvements of vehicular flow with newly-created roads generally require time-consuming construction. Additionally, the protracted negotiations over the terms and conditions of (re)development, as well as filing of related lawsuits for demolishing the existing properties and site preparation, which frequently takes years, also delay the realization of the TIF effects. And even if redevelopment projects are eventually initiated, it takes additional time to collect property tax increments.

Then, do these positive effects help TIF districts not only outperform similarly lagging areas but also help them catch up with more affluent neighborhoods? Panel B in Figure 1 addresses this question.

Overall, the event-time coefficients show insignificant results. The majority of the coefficients (8 out of 13) have positive signs, but they are essentially not informative except for the 0-1 years bin. Combined with Panel A, the estimation results for the median household show that TIF areas experience increases in median household income in comparison to non-TIF block groups; however, it does not appear that outperforming similarly lagging block groups will always result in catch-up growth and a decline in spatial inequality. That is, it implies that there may be a sizable number of cases where they experience an increase in income relative to the control group, even though they still lag behind other areas in the region.

The next question this paper explores is to identify the distributional effects of TIF. For illustration, suppose a simple scenario of how TIF could increase median household income. An increase in the proportion of high-income households may be the primary factor driving improvements in median household income (either through in-migration or new jobs paying higher wages), with no change or a decrease in the share of low-income households. So, I examine the TIF effects on household income by three categories – high, middle, and low.

[Figure 2 here]

The regression results are depicted in Figures 2 to 4. First, as seen in Panel A of Figure 2, TIF reduces the share of low-income households and the beneficial effects are observed again in the later periods. 10 years after designation, the share of low-income households starts to show clearer positive effects of TIF. As expected, coefficients from the 10-11 years bin through the last 24-25 years bin suggest that TIF decreases the share of low-income households compared to non-TIF groups and the shares fall by 7% to 19%. When it comes to the probability of changes in ranking, Panel B of Figure 2 demonstrates the same anticipated signs but insignificant TIF effects as those seen in the median income model. Decreases in the share of low-income households may be driven by two possible mechanisms. First, low-income households may have been displaced due to redevelopment and resulting higher housing prices. But, considering that rent has not risen particularly faster in TIF districts than in other areas, as will be discussed in the next section, displacement of the share of low-income households does not appear to have a significant impact on the outcomes. Alternatively, it is possible that TIF has helped low-income households in locating employment with higher wages and induced higher-income households. This latter scenario may have played a larger role in reducing the share of low-income households and seems more plausible, but unfortunately, without individual mobility data, it is not possible to distinguish between these explanations.

[Figure 3 here]

Figure 3 shows the effects of TIF on middle-income households. Similar to the low-income households model, TIF areas appear to have positive effects on the share of middle-income households with marginally significant results. Of the entire 13 estimates, 11 have positive signs and again the significant positive TIF effects are identified around 10 years after designation, with fewer number of significant estimates. In contrast, the TIF effects on the probability of changes in the ranking (Panel B in Figure 3) are mostly insignificant and the coefficients fluctuate more. The mixed estimates indicate that TIF is not likely to increase the share of middle-income faster than other areas in the region.

[Figure 4 here]

The same pattern is observed in Figure 4 which shows the effects on high-income households. While not all estimates with positive signs are statistically significant, the positive TIF effects start to emerge several years after designation as seen in the preceding results, and continue until the 20-21 years period. Then, the estimates begin to lose significance and start to show negative signs as the estimation window gets closer to the endpoint. Such a trend might indicate that the effects of TIF vary by their designation time frame. Stricter requirements on the “blighted” condition applied to the earlier TIFs may have affected the differentiating outcomes, suggesting TIFs designated around the early 1990s may particularly have not been as economically successful as other TIFs designated in the later period. Or, relatively larger confidence intervals in the last two estimation windows simply result from fewer observations that can be used.[15]

Unlike Panel A in Figure 4, the positive TIF effects mostly disappear with only a couple of significant estimates observed in the 14-15 and 16-17 years bins. Taking Panel A and B in Figure 4 together, the results imply that businesses that offer higher wages may have relocated to TIF districts to benefit from various incentives. Also, newly created or rehabilitated buildings and their increased prices may have attracted higher-income households to the TIF districts. Despite that, it seems that the positive TIF effects are not large enough to catch up with other areas in terms of the share of high-income households.

To sum, TIF improves median household income and the distribution of income compared to the non-TIF areas and it is fueled by a combination of a decrease in the share of low-income households and a slight increase in the share of middle- and high-income households. The beneficial effects are much attenuated in the probability models, supporting the idea that measuring the effects on outcomes that are based solely on the comparison with the control group may produce incomplete or inaccurate conclusions from the perspective of spatial inequality or equity-based goals of PBP.

5.2. The effects on rent, housing values, and real income

Even if TIF increases income, people's lives may not improve if the cost of living also rises and the positive effects on income are canceled out. In this section, I explore this possibility. Rents and housing values are used as outcomes to measure the effects of TIF on the cost of living. Then I move on to real income. To calculate real income, rents rather than housing values are used following the lead of Busso et al. (2013). The examination on housing values is still critical since it is the source of revenues and the success of TIF is contingent on growth in property values.

[Figure 5 here]

The results for median gross rent (Panel A) are first presented in Figure 5. Most of the coefficients have positive signs. From the fourth time period (8-9 years bin) the magnitudes of the positive effects on rent increase, but only a couple of the coefficients are significant. The results in the probability model (Panel B) are even less statistically significant, indicating that TIF and an increase in rent are not strongly correlated in both models.

[Figure 6 here]

The effects of TIF on median housing value are more distinct and statistically distinguishable from the non-TIF areas. As presented in Panel A of Figure 6, TIF increases housing values. Again, 10-11 years after designation, the beneficial effects become more consistent and significant. The magnitudes of the positive effects also increase and reach a peak at the 20-21 years bin (about 60% increase), although the confidence interval is wider and the lower bound of its estimates is less than the previous period (about 27% increase). This finding on the positive effects coincides with previous research (Man & Rosentraub, 1998; Smith, 2006). Then, the positive effects are no longer identified after 20-21 years. Again, it might be because of the timing when TIF is designated.

Then why and how does the TIF significantly increase housing values while having much less substantive effects on rental prices? One possible reason is that various housing rental assistance programs that are often co-located with TIF and they contribute to less major rent fluctuations when compared to housing values. For instance, property owners who participate in the Housing Choice Voucher program in Chicago must submit a request to the Chicago Housing Authority (CHA) for a rent increase and the requests are only approved when the requested rent increase is consistent with the amount determined by the CHA's market analysis. The Low-Income Tax Credit (LIHTC) program also imposes maximum rent limits based on the tenant's household size and income, making rent more rigid and challenging to be raised in the area. Or, the differences in the results may be due to unobserved factors that are not captured in the regression models. The propensity scores weighting ought to control for a great portion of such factors; however, it may not be able to fully eliminate their influence.

As for the TIF effects on the probability of moving up to a housing value ranking in Panel B of Figure 6, they are not significant. Most of the time, the estimates show consistent positive signs as in Panel A, but I fail to find significant increases in the probability of moving up in the ranking. Thus, the evidence does not support the claim that housing values in the TIF areas grow faster than in other areas in the region.

[Figure 7 here]

Lastly, I explore how real income in TIF districts is different from the non-TIF areas and measure whether TIF actually improves the economic well-being of residents in the designated areas. I find, again, evidence of the positive TIF effects on real income in Panel A of Figure 7. Looking at, again, 10 years after designation, all estimates show positive signs except for 14-15 years with 4 achieving significance. But they are limited compared to the nominal income model in Figure 1 – the number of estimates that are significant has decreased from 6 to 4 and the magnitudes of the effects have also fallen. In other words, the benefits are subdued when measured with real income relative to Figure 1, and the beneficial TIF effects seem to weakly outweigh the increase in housing costs, particularly in the later period. In Panel B, the effects of TIF are not significant and inconsistent. It seems that TIF's modest effects on median income in the probability model are almost offset by increases in rent, leading to even less clear positive effects on the probability of moving up to a higher ranking.

6. Conclusion

This paper examines distributional implications of TIF and whether TIF reduces spatial inequality, in Cook County, Illinois. In the regressions, I find that TIF increases median household income relative to not-yet-treated areas. It is driven by a combination of a lower share of low-income households and a marginally higher share of middle to high-income households. However, TIF areas do not show a greater probability of moving up to a higher income ranking compared to non-TIF areas. The results indicate that TIF areas have been able to outperform the control group, but they were unable to catch up with relatively affluent areas.

The effects of TIF on rent are less pronounced and significant while housing values show more distinct increases. On average, rent is not significantly affected by TIF designation and estimation results for the probability model show mixed and insignificant coefficients. In contrast, TIF designation seems to have resulted in an increase in housing values. The presence of various housing rental assistance programs that make rent more rigid and set a ceiling on the rent level may explain why rent is particularly less affected by TIF relative to housing values. From another perspective, the results imply that renters, who are more likely to be considered a key target group by policymakers, may not have been subject to huge pressure due to soaring rent and displacement.

Next, I estimate the TIF effects on real income, a proxy for quality of life, considering the possibility that increases in household income may be offset if rent increases concurrently. The results show only weak evidence of improvement in quality of life in TIF districts relative to similarly lagging areas but it does not help TIF areas move up rankings. It should be noted that the effects of TIF may be a bit weaker and underestimated in this study because a more conservative, yet potentially more accurate approach is taken to estimate the effects of TIF, using a stricter threshold to define TIF areas and more precise geographic boundaries than in previous studies.

Generally, I find more significant results in the models that simply compare TIF areas to the control group. Relatively better income than similarly lagging areas might not show the entire picture of what policymakers would want to know and ultimately aim to achieve in terms of spatially equitable development. Examining changes in the probability of moving up in the ranking is useful in that it provides how TIF areas have performed in the broad region and whether TIF has been helpful in the reduction of spatial inequality.

There are some limitations to the results that suggest further research areas. As in other event-study type regressions, compositional changes in observations remain the same. Due to this, some event-time coefficients have larger confidence intervals which makes them less reliable. More work with extended time frames or data at a finer geographical level could be helpful to enhance the reliability of estimates for each event-time.

Also, comprehensive and accurate information on the types of development projects that have occurred and individual-level mobility data could also be useful in understanding the underlying reasons for the effects of TIF. Due to the lack of publicly available data, this study is unable to provide a complete picture of whether the positive effects on reducing the share of low-income groups is a result of TIF's contribution to increasing their income or simply displacing them through rising prices. Nevertheless, the insignificant TIF effects on rents in the analysis results suggest a lower possibility of mass displacement.

As many researchers have argued, the identified positive effects for the TIF district residents might have come at the expense of other overlapping taxing districts (Weber et al., 2008). The cost-benefit analysis that incorporates the effects on those taxing bodies could provide a broader assessment and societal implications of TIF designation.

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[1] Conversely, a negative effect could imply that the gap between the treated areas and other areas in the region could widen even further if other areas experience higher economic growth. Or, it could signify that spatial inequality decreases if other areas perform even worse.

[2] However, still, many redevelopment plans include and aim to enhance the economic well-being of the residents and the area. To provide a few examples, the redevelopment plans for the 35th & Halsted TIF district (Louik\Schneider & Associates, Inc., 1996, p.14) and the Irving Park and Elston TIF district (Ernest R. Sayer Enterprise, Inc., 2009, p.11) explicitly aim to enhance the "economic well-being" of their respective areas. Additionally, the redevelopment plan for the 107th & Halsted TIF district states a goal to "establish an economically diverse, affordable, and mixed-use neighborhood through the creation and preservation of affordable, low-cost, and mixed-income housing" (Camiros, Ltd, 2014, p.12). While the inclusion of these goals in the redevelopment plans does not guarantee their actualization, it does provide a rationale for examining the effects of TIF on income and income distribution.

[3] Generally, the 5-year estimates are considered a proxy for the middle year on the assumption that change during the 5-year period is linear (Theodos et al., 2022).

[4] Over time, census boundaries may merge or split. Thus, to normalize data to a fixed geography, Geolytics first created population-based weights at census block level. When a block group is split, the presence of streets in a census block is used to determine the level of population on the assumption that people live on or close to streets. When blocks merge, the numbers are simply added. Once the data at census block level are computed, they sum up the blocks to obtain the numbers for block groups. A more detailed description and the data used in this study can be found and purchased at http://www.geolytics.com

[5] The Cook County open data portal provides information on the boundaries of TIF districts. However, the data provided is limited to TIF districts that were active as of 2018. Thus, I submitted FOIA request to collect data on the boundaries of the expired TIF districts.

[6] TIF districts that are expired during the study period are excluded since the estimation method I use allows a switch from being a treated unit to an untreated unit.

[7] I also test the 50% threshold following the previous studies (Lester, 2014; Yadavalli and Landers, 2017). The findings are consistent and the effects are more significant. The results are included in Online Appendix Tables A6 to A8 and Figures B2 to B8. I choose to use a more conservative and possibly more accurate estimation method in the analysis for the following two reasons. First, the 50% threshold used in the existing studies has been chosen for practical research purposes rather than theoretical or empirical background. Second, the results measured with the 50% threshold may be more significant partly because only larger TIFs are considered.

[8] According to Consumer Expenditures report (Bureau of Labor Statistics, 2002), the share of gross income spent on housing was 27% in 2000. Thus, I use 30% as the expenditure share on housing in the main analysis. I also test 25%. The findings are consistent and included in Online Appendix Figure B1. The equation implies that 1 percent increase in rent requires income to increase by 0.3 percent for utility to remain the same. The variables are log-transformed to reduce skewness of the distributions and for ease of interpretation.

[9] To be more specific, if one simply compares changes in median income between TIF areas and non-TIF areas, and concludes that TIF has positive effects, it may not actually show 1) *real* positive effects 2) whether TIF areas catch up with other affluent areas. For example, if median income in TIF areas changes from $10,000 to $9,900 while median income in non-TIF areas changes from $10,000 to $9,800, this would lead to a conclusion that TIF has positive effects (when TIF areas do not actually experience improvements in median income). Nor does it show whether TIF helps the designated areas catch up with other wealthy areas. By contrast, by examining how rankings of outcomes change from one year to the next and only coding them as 1 if the rankings are higher than the previous year, the treated group is considered to have positive effects only when it actually moves up to higher rankings. This design also allows me to show how likely it is that TIF improves the rankings that show the relative economic status in the region.

[10] TIF has been criticized for being set up in places that are already economically developed or for relaxing and adjusting the criteria initially required by Tax Increment Allocation Redevelopment Act (the Act). In the early days of TIF districts in Illinois, the designated area needed to be "blighted," although the term "blighted" was not completely clear, leaving room for different interpretations. But, since 1999, a TIF district does not necessarily need to be a blighted area at the time of designation. Instead, the requirement was changed to the area only needing to be likely to become blighted based on three or more blighting factors (e.g., age of buildings, lack of ventilation). However, in many cases, eligibility studies included in the redevelopment plans (e.g., Ernest R. Sayer Enterprise, Inc.,2009; S.B.

Friedman & Company, 2005) still show that more than three blighting factors are present, even though they are not required by the law. This may explain why TIFs tend to be located in more economically lagging areas, on average, according to summary statistics.

[11] The linear probability model applies to the second groups of outcomes (i.e., outcomes that show the probability of moving up in the rankings of outcomes). I was not able to estimate the effects of TIF with logit or probit models since Callaway and Sant'Anna's estimator does not support logit or probit models with a staggered difference-in-differences design in their current software packages (The 'did' package version 2.1.2 in R or the 'CSDID' Stata module version 1.6). It may be worth investigation in detail in future studies.

[12] TWFE models use early-treated groups as controls, which should not be used, especially when there are heterogeneous effects across time and treatment groups.

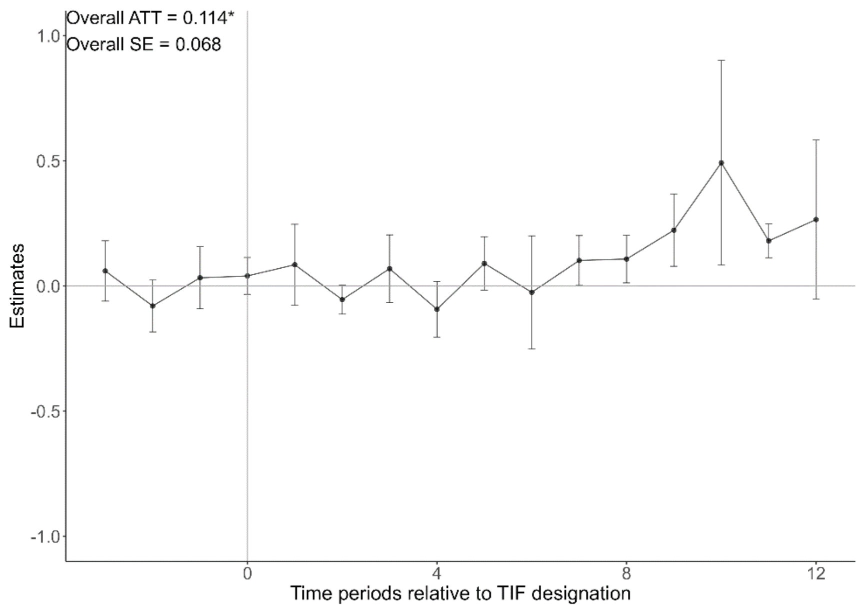
[13] The issue of compositional changes remains as in the event-study type regressions used in other TIF studies (El-Khattabi and Lester, 2019; Lester, 2014). For example, the number of TIF districts designated in 1990s was relatively small while more TIF districts were created in 2000s, leading to different number observations and larger confidence intervals for the later treatment window. It is possible to circumvent this issue by only including treatment groups that have received treatment for at least a few years. However, such an alternative approach could also jeopardize reliability and informativeness because fewer treatment groups must inevitably be used for estimation (Callaway and Sant'Anna, 2020).

[14] Specifically, year 0 and year 1 are combined for the first two-years bin post treatment (i.e., t =0). The following bins are for years 2 through 3, 4, and 5 and so on. For the estimates, I compute averages for each of the two-year bin and estimate standard errors through the influence function used for the estimation of $ATT(g,t)$ and a bootstrap procedure. More detailed discussion can be found in Callaway and Sant'Anna (2020). Estimated results with year-by-year are also included in Online Appendix Table A3-A5. As expected, the results are noisier, but findings are consistent.

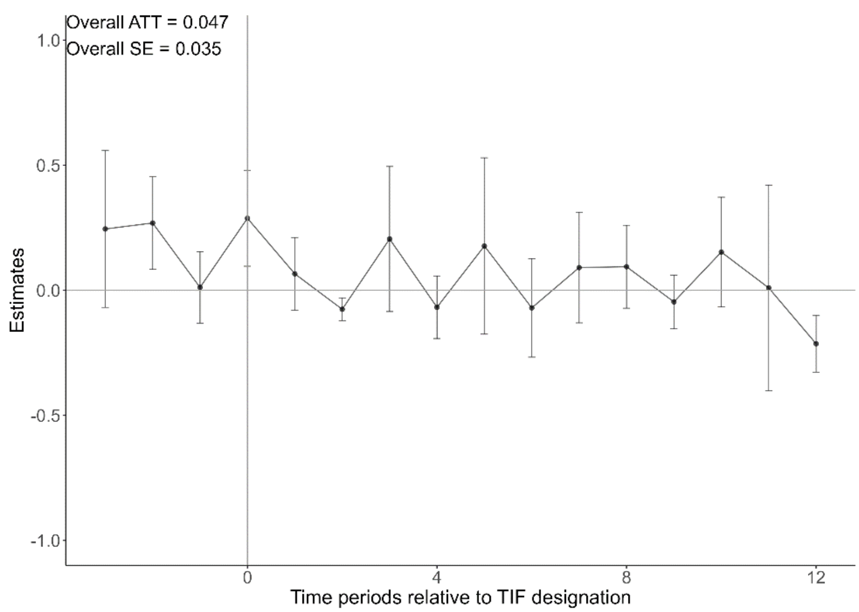
[15] Analyzing possible differentiating effects based on the distribution of TIFs' designation time frame may be worth a new detailed study.

Figure 1. The effects of TIF on median household income and probability of moving up in the ranking of median household income.

Panel (A) Log median household income



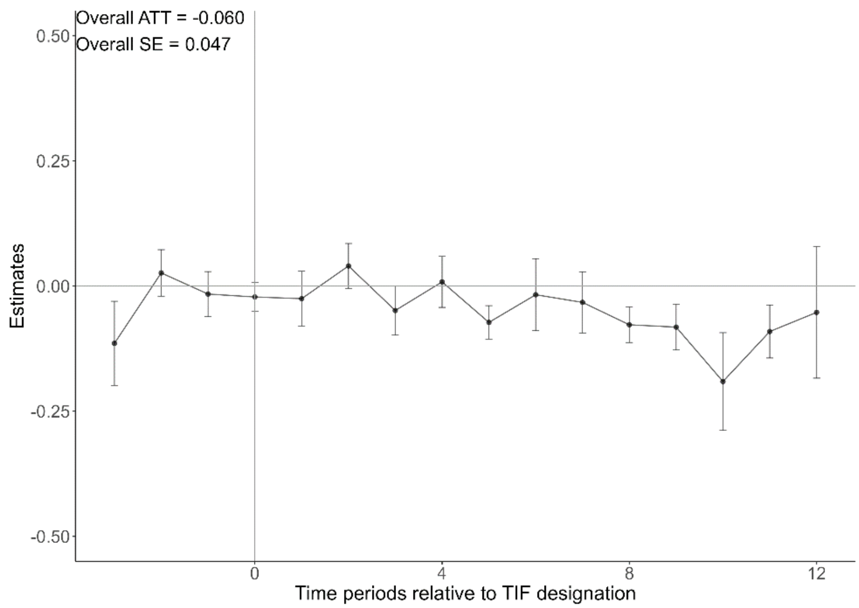
Panel (B) Probability of moving up in the ranking



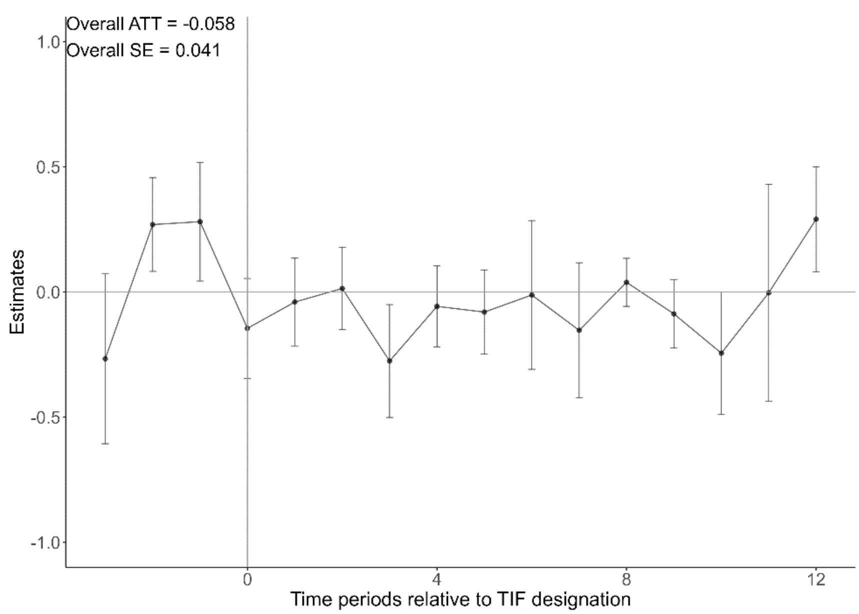
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval. Standard errors are clustered by city. The coefficients at event time 5 is significant at the 90% confidence interval with lower confidence intervals of 0.001.

Figure 2. The effects of TIF on the share of low-income households and the probability of moving up in the ranking of the share of low-income households

Panel (A) Share of low-income households



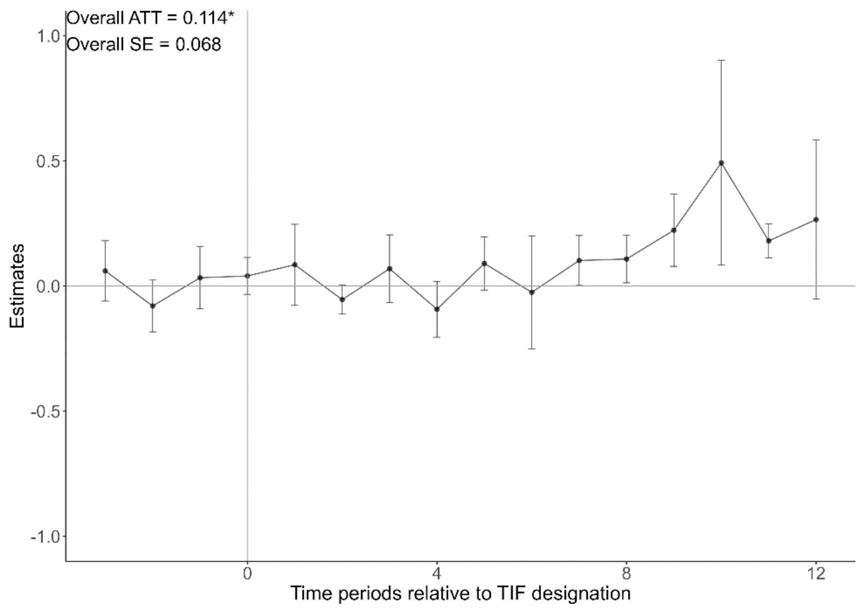
Panel (B) Probability of moving up in the ranking



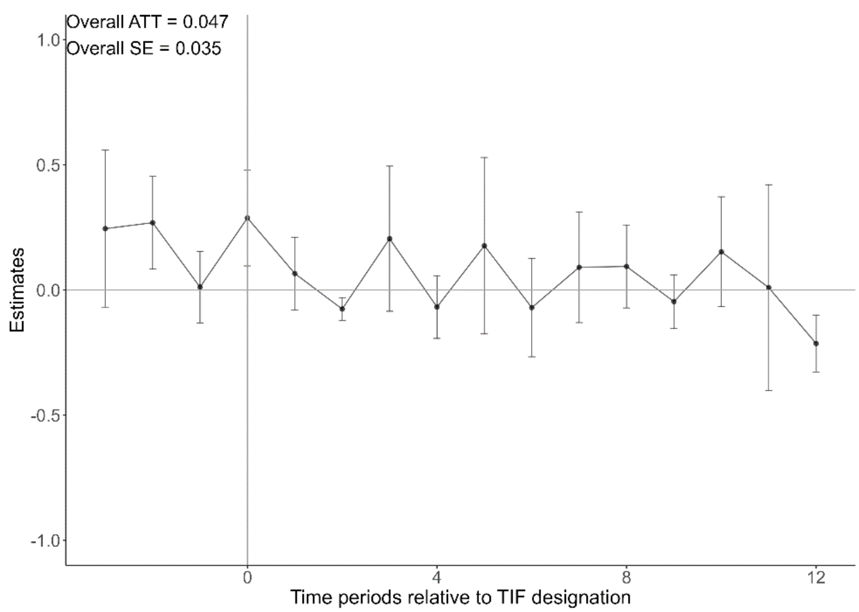
Notes: The vertical line (t =0) presents the first two-year post designation period. The bars present the 95% confidence interval. Standard errors are clustered by city.

Figure 3. The effects of TIF on the share of middle-income households and the probability of moving up in the ranking of the share of middle-income households

Panel (A) Share of middle-income households



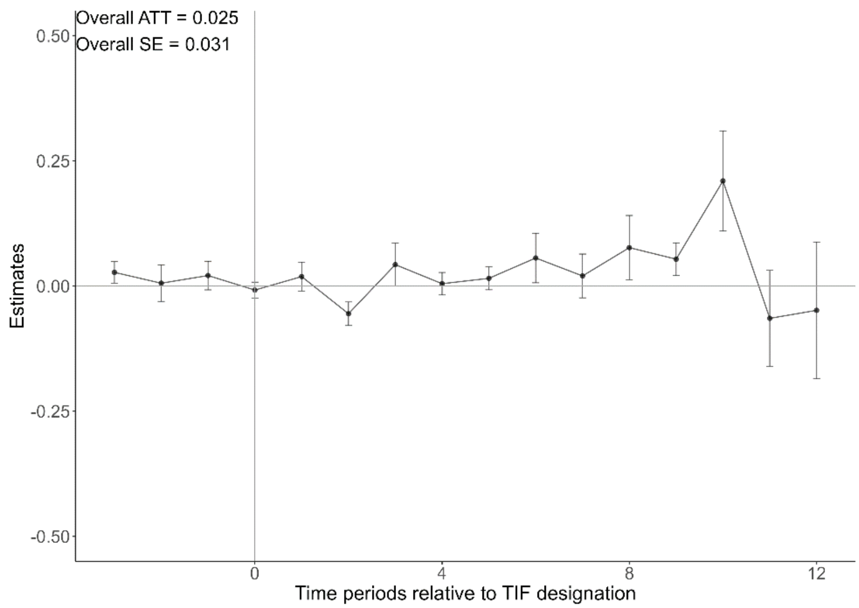
Panel (B) Probability of moving up in the ranking



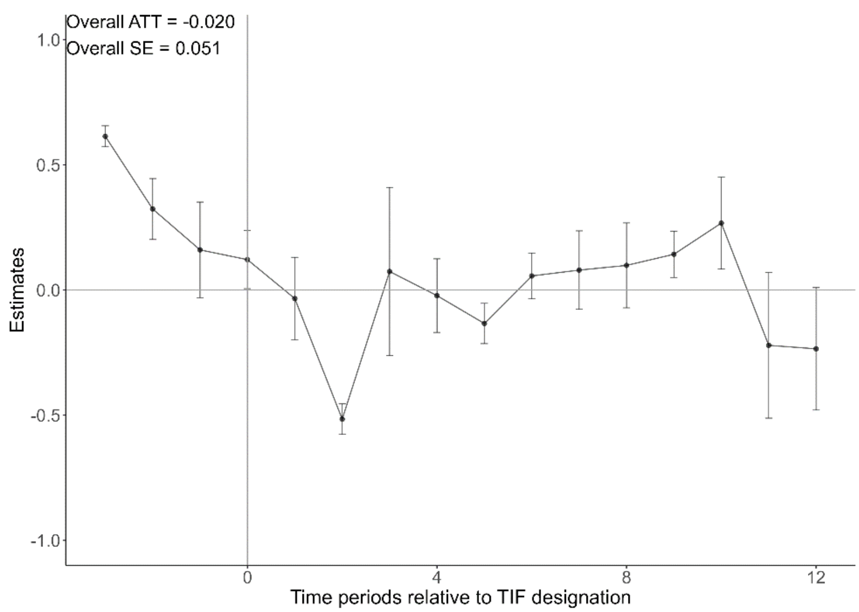
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval. Standard errors are clustered by city.

Figure 4. The effects of TIF on the share of high-income households and the probability of moving in the ranking of the share of high-income households

Panel (A) Share of high-income households



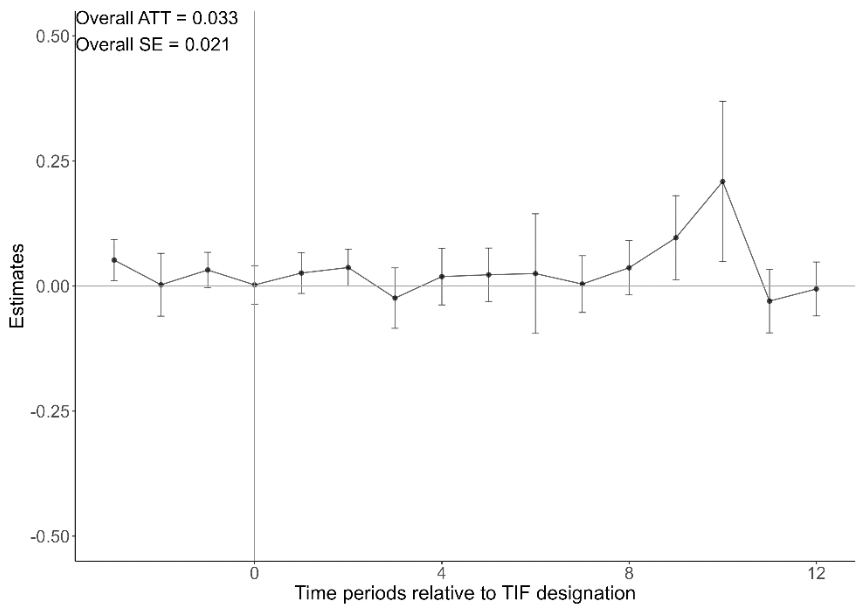
Panel (B) Probability of moving up in the ranking



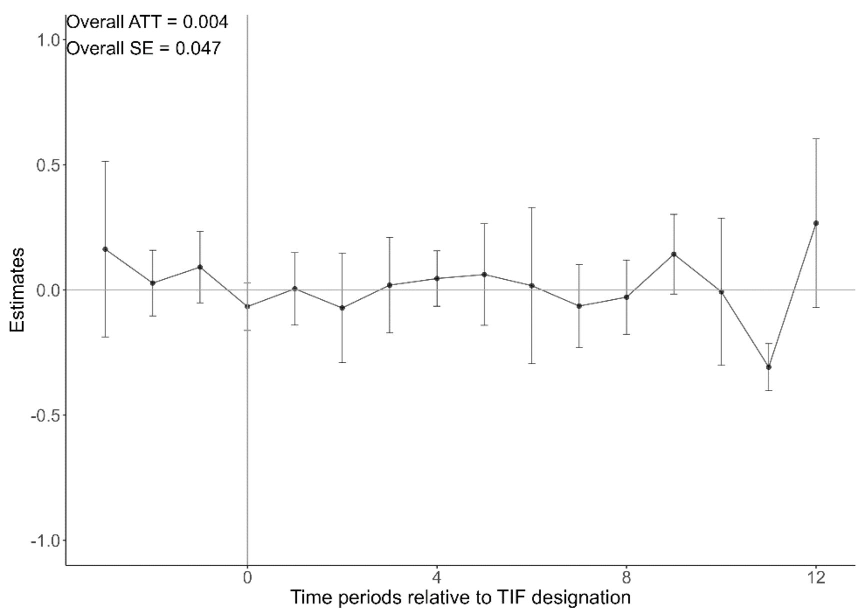
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval. Standard errors are clustered by city.

Figure 5. The effects of TIF on median gross rent and the probability of moving up in the ranking of median gross rent

Panel (A) Median gross rent



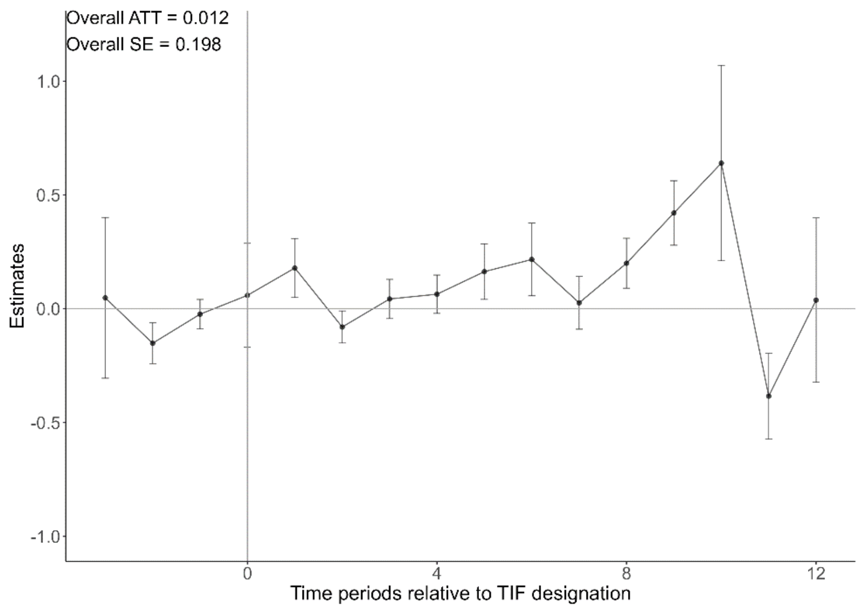
Panel (B) Probability of moving up in the ranking



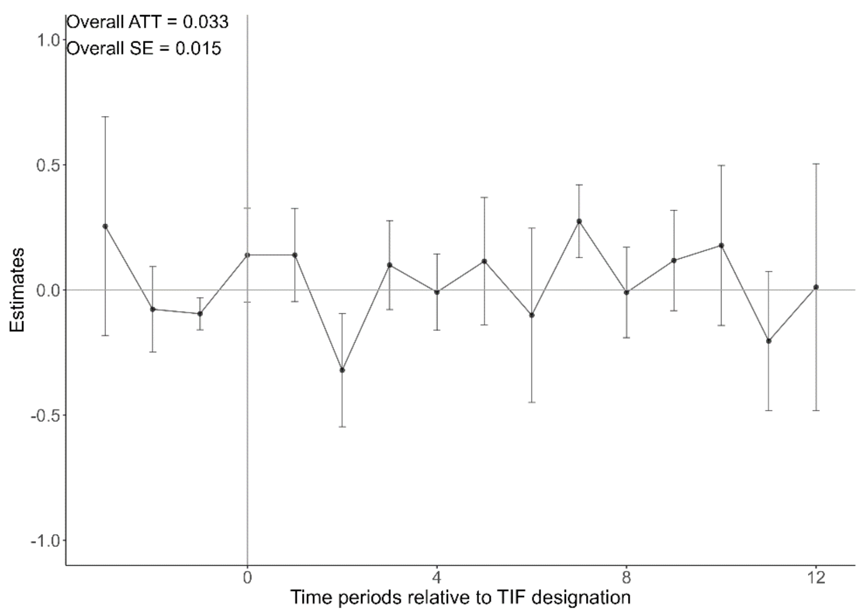
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval. Standard errors are clustered by city.

Figure 6. The effects of TIF on median housing value and the probability of moving up in the ranking of median housing value

Panel (A) Median housing value



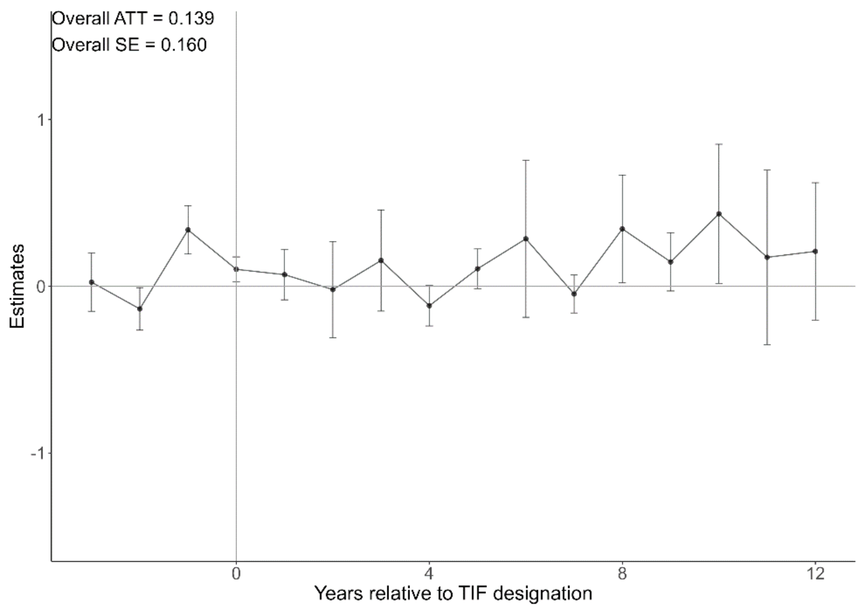
Panel (B) Probability of moving up in the ranking



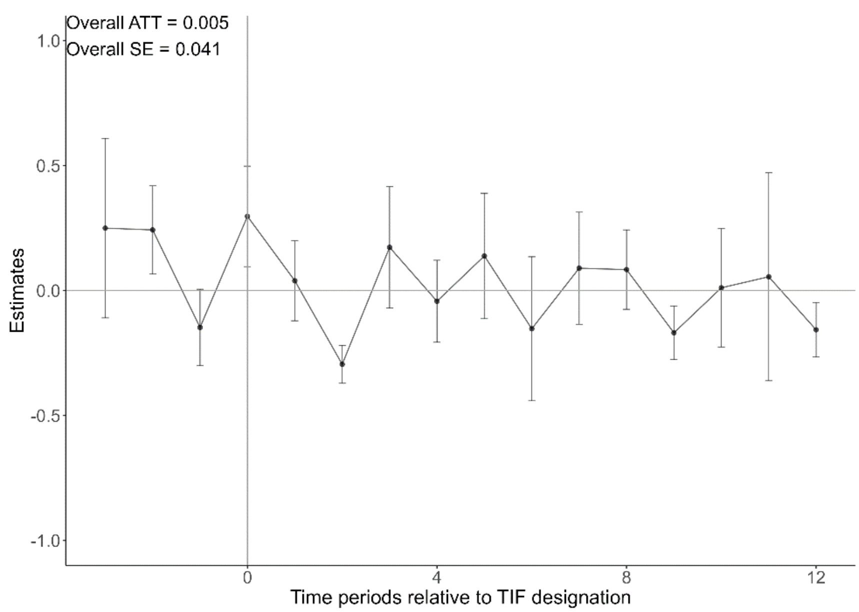
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval. Standard errors are clustered by city.

Figure 7. The effects of TIF on real income and the probability of moving up in the ranking of real income

Panel (A) Real income



Panel (B) Probability of moving up in the ranking



Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval. Standard errors are clustered by city. The coefficients at event time 5 and 9 in Panel A are significant at the 90% confidence interval with lower confidence intervals of 0.004 and 0.003 respectively.

Online Appendix

Table A1. Summary Statistics for TIF areas and non-TIF areas

Variables	TIF areas		Non-TIF areas	
	Mean	Std. Dev.	Mean	Std. Dev.
Log median income	10.313	0.612	10.876	0.511
Log median property value	11.375	2.191	12.045	1.113
Log median rent	6.465	0.582	6.517	1.171
Log real income	5.938	0.671	6.649	0.96
Bachelor*	0.188	0.187	0.331	0.235
Unemployment rate*	0.164	0.117	0.075	0.073
Owner rate*	0.494	0.257	0.651	0.228
Share of minority*	0.706	0.324	0.327	0.308
Housing unit*	490.831	241.247	522.398	251.529
TIF (designation year)	2001.893	4.78	0.000	0.000
Enterprise Zone*	0.701	0.458	0.256	0.437
Share of low-income households	0.610	0.207	0.399	0.198
Share of middle-income households	0.233	0.113	0.296	0.114
Share of high-income households	0.157	0.162	0.306	0.213
Changes in median household income rank	0.394	0.489	0.355	0.479
Changes in median property value rank	0.333	0.472	0.242	0.429
Changes in median gross rent rank	0.158	0.365	0.176	0.381
Changes in real income rank	0.365	0.482	0.352	0.478
Changes in income rank for low-income households	0.349	0.477	0.412	0.492
Changes in income rank for middle-income households	0.519	0.5	0.378	0.485
Changes in income rank for high-income households	0.369	0.483	0.357	0.479

Notes: Income, property value, and rent are log-transformed; Bachelor denotes the share of adults with bachelor's degree or higher; Households earning less than $40,000 income are classified as low-income households; Households earning between $40,000 and $75,000 are in the middle-income group while households earning more than $75,000 are in the high-income group. Real income is calculated using log(monthly income)-0.30*(rent). Changes in ranks are coded as 1 when the rank is higher than the previous year, and 0 otherwise. An asterisk indicates variables used to calculate the propensity scores.

Table A2. Number of associated block groups by TIF designation year

TIF Designation year	Associated block groups
1990	16
1991	20
1992	18
1993	27
1994	24
1995	48
1996	71
1997	52
1998	285
1999	334
2000	455
2001	324
2002	286
2003	83
2004	40
2005	39
2006	30
2007	183
2008	69
2009	72
2010	92
2011	59
2012	4
2013	32
2014	79

Notes: Block groups are considered to be treated when more than 30% of the area is covered by a TIF district. As discussed in the manuscript, some of the years have fewer number of observations and thus, the issue of compositional changes remains as in the event-study type regressions used in other TIF studies (El-Khattabi and Lester, 2019; Lester, 2014). Note that larger confidence intervals for the later treatment window could be due to fewer observations that can be used.

Table A3. The effects of TIF on median household income and probability of moving up in the ranking of median household income

Years Since Designation	Median Household Income	
	Log Income	Probability
(-6)	0.132	-0.033
	(0.149)	(0.404)
(-5)	-0.012	0.524***
	(0.020)	(0.049)
(-4)	-0.118**	0.048
	(0.043)	(0.140)
(-3)	-0.041	0.489***
	(0.133)	(0.079)
(-2)	0.066**	0.053
	(0.023)	(0.075)
(-1)	-0.0004	-0.030
	(0.073)	(0.284)
(0)	0.058***	0.160
	(0.009)	(0.098)
(1)	0.023	0.416***
	(0.015)	(0.068)
(2)	0.081	-0.102
	(0.276)	(0.215)
(3)	0.089	0.233***
	(0.063)	(0.066)
(4)	-0.008	-0.307
	(0.092)	(1.169)
(5)	-0.101***	0.154***
	(0.026)	(0.030)
(6)	0.080	0.192
	(0.120)	(0.463)
(7)	0.058	0.218
	(0.080)	(0.197)
(8)	-0.185***	0.057
	(0.017)	(0.107)
(9)	-0.002	-0.195
	(0.359)	(0.109)
(10)	0.116***	0.303
	(0.013)	(0.132)
(11)	0.064	0.051
	(0.159)	(0.441)
(12)	0.003	0.083
	(0.211)	(0.040)
(13)	-0.054**	-0.224
	(0.019)	(0.202)
(14)	0.100	0.123
	(0.806)	(0.366)
(15)	0.104***	0.058
	(0.035)	(0.087)
(16)	0.088	0.017
	(0.069)	(0.220)
(17)	0.127	0.171
	(0.103)	(0.134)
(18)	0.200***	-0.028
	(0.045)	(0.021)
(19)	0.246***	-0.065
	(0.031)	(0.126)

Years Since Designation	Median Household Income	
	Log Income	Probability
(20)	0.728***	0.175***
	(0.015)	(0.027)
(21)	0.257	0.131
	(0.400)	(0.993)
(22)	0.139	-0.075
	(0.102)	(0.044)
(23)	0.222	0.094
	(0.113)	(0.438)
(24)	0.086	-0.646*
	(1.675)	(0.267)
(25)	0.437***	0.219***
	(0.061)	(0.064)

Notes: Column (1) presents years relative to TIF designation. The first dependent variable is log-transformed median household income. The second dependent variable is the probability of moving up in the ranking of median household income. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table A4. The effects of TIF on the share of each household income group and the probability of moving up in the rankings of outcomes

Years Since Designation	Low Income		Middle Income		High Income	
	Share	Probability	Share	Probability	Share	Probability
(-6)	-0.084	-0.012	0.042	0.394***	0.048	0.545***
	(0.114)	(0.443)	(0.092)	(0.042)	(0.027)	(0.098)
(-5)	-0.151***	-0.522***	0.143***	0.090	0.023***	0.681***
	(0.010)	(0.036)	(0.008)	(0.105)	(0.007)	(0.045)
(-4)	0.031*	-0.091	0.013	0.186	-0.016	-0.064
	(0.013)	(0.117)	(0.013)	(0.168)	(0.029)	(0.162)
(-3)	0.022	0.630***	-0.055	-0.394***	0.041	0.688***
	(0.046)	(0.081)	(0.018)	(0.054)	(0.030)	(0.133)
(-2)	-0.003	0.535***	-0.006***	-0.437***	0.063***	0.118
	(0.010)	(0.037)	(0.013)	(0.129)	(0.012)	(0.057)
(-1)	-0.027***	0.027	0.007	-0.019	-0.010	0.221***
	(0.004)	(0.938)	(0.004)	(0.301)	(0.113)	(0.056)
(0)	-0.009	-0.019	0.031***	0.040	-0.011**	-0.003
	(0.005)	(0.022)	(0.005)	(0.191)	(0.004)	(0.026)
(1)	-0.043***	-0.272	0.044***	0.336**	-0.008	0.259**
	(0.008)	(0.109)	(0.008)	(0.114)	(0.010)	(0.092)
(2)	0.010	0.159	0.006	-0.068	-0.021	-0.226
	(0.202)	(0.166)	(0.145)	(0.212)	(0.049)	(0.233)
(3)	-0.068	-0.239***	0.034	-0.130	0.053	0.146**
	(0.034)	(0.078)	(0.014)	(0.099)	(0.031)	(0.054)
(4)	0.019	-0.244	-0.058***	-0.235	0.025	0.049
	(0.090)	(0.806)	(0.017)	(0.484)	(0.404)	(0.713)
(5)	0.087***	0.273***	0.023	0.173	-0.137***	-0.864***
	(0.021)	(0.033)	(0.016)	(0.105)	(0.012)	(0.070)
(6)	-0.067	-0.284	0.075	0.057	0.034	0.070
	(0.099)	(0.455)	(0.063)	(0.175)	(0.139)	(0.408)
(7)	-0.027	-0.267***	-0.010	0.071	0.034	0.041
	(0.025)	(0.084)	(0.024)	(0.059)	(0.019)	(0.140)
(8)	0.011	0.025	-0.003	0.042	-0.002	0.028
	(0.010)	(0.036)	(0.010)	(0.120)	(0.006)	(0.075)
(9)	-0.018	-0.140	0.005	-0.008	0.007	-0.060
	(0.194)	(0.067)	(0.118)	(0.237)	(0.046)	(0.263)
(10)	-0.116***	-0.294***	0.085***	0.038	0.043***	0.214***
	(0.010)	(0.036)	(0.009)	(0.058)	(0.013)	(0.030)
(11)	-0.053***	0.133	0.035	0.036	0.013	-0.552
	(0.012)	(0.198)	(0.029)	(0.026)	(0.077)	(0.341)
(12)	-0.007	-0.184	0.029	-0.132	0.013	-0.023
	(0.051)	(0.095)	(0.014)	(0.062)	(0.031)	(0.109)
(13)	-0.024	0.160	-0.055	-0.450***	0.104***	0.079
	(0.038)	(0.228)	(0.048)	(0.098)	(0.028)	(0.052)
(14)	-0.090	-0.250	0.029	-0.049	0.032	-0.079
	(0.337)	(1.112)	(0.032)	(1.781)	(0.188)	(1.144)
(15)	-0.035	-0.056	0.029	-0.140	0.012	0.241***
	(0.031)	(0.045)	(0.033)	(0.076)	(0.017)	(0.052)
(16)	-0.046***	0.162***	0.082	-0.147	0.056	0.143
	(0.015)	(0.045)	(0.021)	(0.278)	(0.166)	(0.580)
(17)	-0.135***	-0.085	0.062***	-0.084	0.107***	0.049
	(0.012)	(0.037)	(0.012)	(0.109)	(0.018)	(0.030)
(18)	-0.074***	-0.180***	0.051**	0.055	0.050***	0.221***
	(0.016)	(0.035)	(0.010)	(0.114)	(0.010)	(0.033)
(19)	-0.102***	0.005	0.024	-0.003	0.066*	0.034
	(0.009)	(0.163)	(0.050)	(0.050)	(0.026)	(0.163)

Years Since Designation	Low Income		Middle Income		High Income	
	Share	Probability	Share	Probability	Share	Probability
(20)	-0.292***	-0.399***	-0.045	0.415***	0.312***	0.357***
	(0.011)	(0.026)	(0.021)	(0.011)	(0.010)	(0.092)
(21)	-0.169	-0.090	0.038	0.102	0.040	0.177
	(0.711)	(2.056)	(0.229)	(1.982)	(0.542)	(1.006)
(22)	-0.047	-0.083	0.191***	0.422***	-0.128**	-0.477***
	(0.032)	(0.056)	(0.039)	(0.039)	(0.040)	(0.129)
(23)	-0.116	0.076	0.226	0.468***	0.017	0.038
	(0.178)	(1.052)	(0.092)	(0.068)	(0.091)	(1.113)
(24)	-0.103	0.415***	0.086	-0.096	0.005	-0.181
	(0.761)	(0.034)	(0.604)	(1.550)	(0.859)	(1.018)
(25)	-0.056	0.167	0.065	0.074	0.009	-0.207
	(0.043)	(0.060)	(0.065)	(0.133)	(0.010)	(0.263)

Notes: Column (1) presents years relative to TIF designation. The shares of each household income group are the first dependent variables of the models. The second dependent variables are the probability of moving up in the rankings of the shares of each income group. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table A5. The effects of TIF on median rent, median housing value, real income, and probability of moving up in the rankings of each outcome

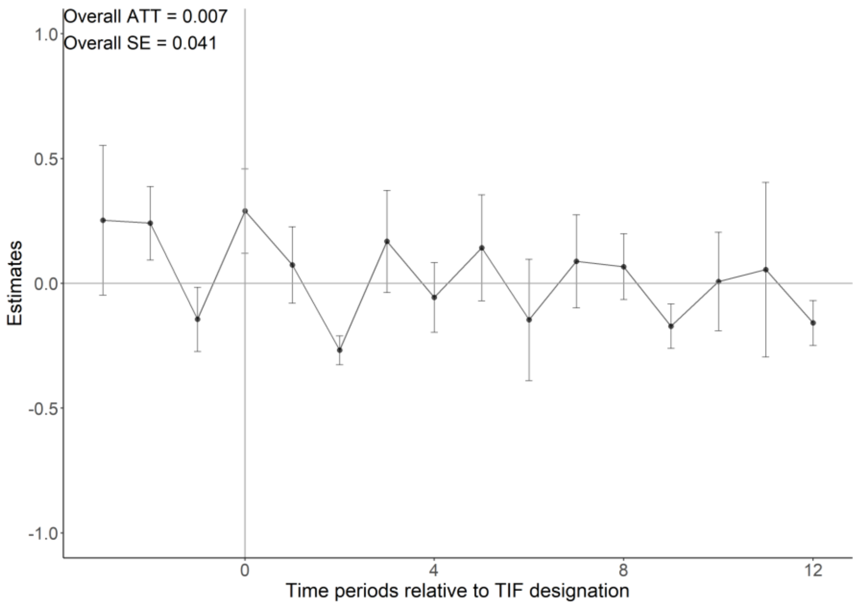
Years Since Designation	Median Rent		Median Value		Real Income	
	Log rent	Probability	Log value	Probability	Real Income	Probability
(-6)	0.069	-0.073	0.151	0.215	0.110	0.008
	(0.041)	(0.061)	(0.336)	(0.245)	(0.226)	(0.467)
(-5)	0.035	0.399	-0.054	0.295	-0.061	0.491***
	(0.172)	(0.038)	(0.090)	(0.054)	(0.040)	(0.036)
(-4)	-0.054	-0.032	-0.155***	-0.115	-0.070	0.109
	(0.056)	(0.106)	(0.023)	(0.224)	(0.058)	(0.091)
(-3)	0.059	0.088	-0.148**	-0.040	-0.202	0.376***
	(0.061)	(0.187)	(0.052)	(0.099)	(0.252)	(0.108)
(-2)	0.025	0.163	0.012	-0.053	0.716***	-0.189***
	(0.016)	(0.101)	(0.042)	(0.037)	(0.124)	(0.044)
(-1)	0.040	0.020	-0.061	-0.137	-0.039	-0.106
	(0.047)	(0.133)	(0.054)	(0.141)	(0.486)	(0.255)
(0)	0.043	-0.054	0.017	0.098	0.209***	0.206***
	(0.040)	(0.164)	(0.072)	(0.147)	(0.013)	(0.024)
(1)	-0.038	-0.079**	0.101***	0.181***	-0.006	0.388***
	(0.031)	(0.011)	(0.021)	(0.052)	(0.035)	(0.072)
(2)	0.079	0.076	0.076	0.123	0.041	-0.067
	(0.084)	(0.250)	(0.064)	(0.262)	(0.240)	(0.129)
(3)	-0.025	0.019	0.282***	0.156**	0.099	0.145
	(0.021)	(0.049)	(0.038)	(0.062)	(0.062)	(0.075)
(4)	0.073	0.136	0.032	-0.153	-0.223	-0.364
	(0.041)	(0.215)	(0.472)	(0.835)	(0.355)	(0.934)
(5)	0.001	-0.280**	-0.193***	-0.488***	0.183	-0.227**
	(0.019)	(0.069)	(0.041)	(0.118)	(0.141)	(0.082)
(6)	-0.039	0.053	0.049	0.082	0.370	-0.027
	(0.034)	(0.158)	(0.215)	(0.289)	(1.040)	(0.526)
(7)	-0.009	-0.015	0.038	0.117	-0.061	0.373***
	(0.070)	(0.029)	(0.137)	(0.134)	(0.062)	(0.076)
(8)	0.015	-0.075	0.136**	-0.098	-0.146***	-0.064
	(0.027)	(0.038)	(0.056)	(0.047)	(0.047)	(0.052)
(9)	0.023	0.167	-0.009	0.081	-0.087	-0.022
	(0.266)	(0.310)	(0.067)	(0.264)	(0.176)	(0.210)
(10)	0.059***	0.188**	0.359***	0.157***	0.308***	0.205***
	(0.018)	(0.065)	(0.102)	(0.043)	(0.050)	(0.045)
(11)	-0.014	-0.064	-0.033	0.073	-0.099	0.072
	(0.026)	(0.078)	(0.114)	(0.304)	(0.308)	(0.319)
(12)	0.024	0.053	0.120	-0.045	0.274	-0.015
	(0.019)	(0.146)	(0.052)	(0.159)	(0.199)	(0.065)
(13)	0.033	-0.018	0.314***	-0.157***	0.295	-0.292
	(0.020)	(0.024)	(0.050)	(0.028)	(0.556)	(0.202)
(14)	0.028	-0.269	0.088	0.172	-0.103	0.127
	(0.060)	(0.620)	(0.983)	(1.319)	(1.878)	(0.768)
(15)	-0.020	0.141	-0.035	0.378***	0.010	0.052
	(0.034)	(0.065)	(0.052)	(0.062)	(0.070)	(0.083)
(16)	-0.033	-0.123	0.025	0.131	0.332	0.068
	(0.033)	(0.203)	(0.150)	(0.326)	(0.531)	(0.238)
(17)	0.106	0.065	0.376***	-0.151	0.356***	0.099
	(0.106)	(0.150)	(0.112)	(0.122)	(0.088)	(0.041)
(18)	0.146***	0.263*	0.420***	0.120	0.062	-0.155***
	(0.023)	(0.115)	(0.116)	(0.067)	(0.044)	(0.053)
(19)	0.048	0.024	0.422***	0.116	0.231	-0.184
	(0.033)	(0.021)	(0.103)	(0.058)	(0.140)	(0.141)

Years Since Designation	Median Rent		Median Value		Real Income	
	Log rent	Probability	Log value	Probability	Real Income	Probability
(20)	0.374***	0.089***	0.920***	0.240***	0.887***	0.031
	(0.012)	(0.009)	(0.103)	(0.044)	(0.141)	(0.148)
(21)	0.045	-0.103	0.366	0.117	-0.017	-0.009
	(0.349)	(0.563)	(3.563)	(1.871)	(0.483)	(1.665)
(22)	-0.044	-0.383**	-0.800***	-0.356***	-0.192	0.003
	(0.047)	(0.079)	(0.098)	(0.085)	(0.229)	(0.127)
(23)	-0.017	-0.233	0.031	-0.052	0.539	0.107
	(0.144)	(0.130)	(0.395)	(0.663)	(0.979)	(0.334)
(24)	-0.017	0.319	-0.236	0.085	-0.245	-0.627***
	(0.050)	(1.642)	(1.363)	(2.285)	(0.775)	(0.109)
(25)	0.005	0.215**	0.313	-0.062	0.664***	0.312***
	(0.021)	(0.054)	(0.197)	(0.042)	(0.060)	(0.059)

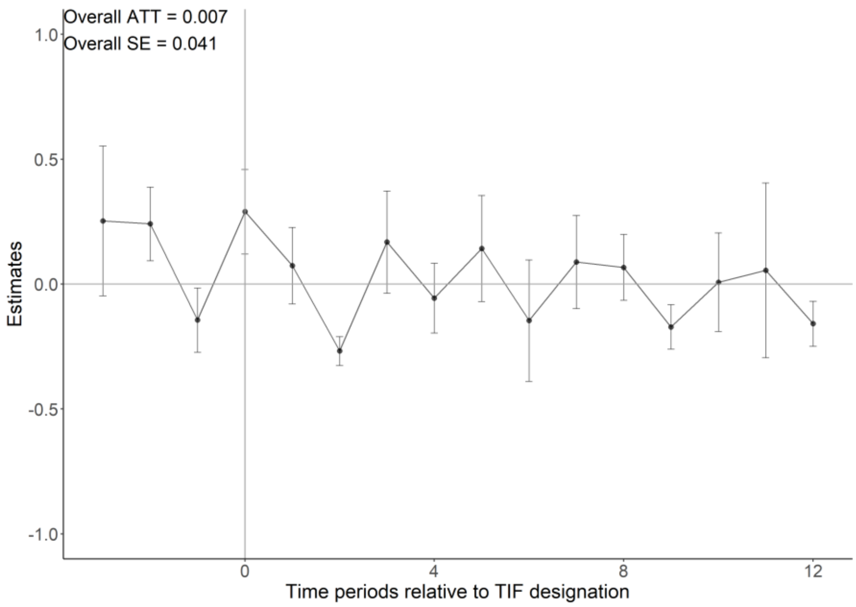
Notes: Column (1) presents years relative to TIF designation. The first dependent variables for the median rent and median value models are log-transformed. Real income is calculated using log(monthly income)-0.30*(rent). The second dependent variable is the probability of moving up in the rankings of outcomes. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Figure B1. The effects of TIF on real income (calculated with a 25% threshold) and the probability of moving up in the ranking of real income

Panel (A) Real income



Panel (B) Probability of moving up in the ranking



Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 90% confidence interval. Standard errors are clustered by city.

Table A6. The effects of TIF (measured with a 50% threshold) on median household income and probability of moving up in the ranking of median household income

Years Since Designation	Median Household Income	
	Log Income	Probability
(-4)	-0.037	-0.023
	(0.104)	(0.089)
(-3)	-0.199***	-0.566***
	(0.063)	(0.111)
(-2)	0.073***	-0.017
	(0.021)	(0.056)
(-1)	0.018	-0.038
	(0.011)	(0.034)
(0)	0.166***	0.078***
	(0.007)	(0.022)
(1)	0.052***	0.172***
	(0.013)	(0.046)
(2)	0.196	0.005
	(0.095)	(0.225)
(3)	0.084	0.172***
	(0.095)	(0.053)
(4)	0.120	0.189
	(0.690)	(5.245)
(6)	0.101	0.272
	(0.230)	(0.290)
(7)	-0.065	0.232
	(0.071)	(0.116)
(8)	0.019	-0.025
	(0.029)	(0.088)
(9)	0.070**	-0.171*
	(0.028)	(0.069)
(10)	0.339***	0.137
	(0.048)	(0.090)
(11)	0.054	-0.038
	(0.055)	(0.060)
(12)	0.227	0.022
	(0.555)	(0.182)
(13)	0.460**	-0.241
	(0.185)	(0.227)
(14)	0.155	0.083
	(2.234)	(1.824)
(15)	0.093	0.050
	(0.073)	(0.115)
(16)	0.235***	0.212
	(0.066)	(0.098)
(17)	0.535***	0.066
	(0.031)	(0.035)
(18)	0.149***	0.050
	(0.047)	(0.045)
(19)	0.293	-0.004
	(0.174)	(0.188)
(20)	1.308***	0.218***
	(0.042)	(0.054)

Years Since Designation	Median Household Income	
	Log Income	Probability
(21)	0.394	0.188
	(2.170)	(1.459)
(23)	0.147	0.512
	(0.398)	(0.298)
(25)	0.380***	0.364***
	(0.040)	(0.053)

Notes: Column (1) presents years relative to TIF designation. The first dependent variable is log-transformed median household income. The second dependent variable is the probability of moving up in the ranking of outcome. Asterisks denotes significance at the 1% (***), 5% (**), and 10% (*) levels. The missing event time coefficients are due to the lack of corresponding block groups when using the 50% threshold.

Table A7. The effects of TIF (measured with a 50% threshold) on the share of each household income category and the probability of moving up in the rankings of outcomes

Years Since Designation	Low Income		Middle Income		High Income	
	Share	Probability	Share	Probability	Share	Probability
(-4)	0.013	-0.145	-0.024	0.113	0.004	0.276
	(0.033)	(0.084)	(0.034)	(0.357)	(0.015)	(0.188)
(-3)	0.047	0.475***	-0.060***	-0.037	0.005	0.541***
	(0.028)	(0.172)	(0.014)	(0.190)	(0.020)	(0.097)
(-2)	-0.010	-0.013	-0.041***	0.084	0.019	0.025
	(0.012)	(0.072)	(0.013)	(0.068)	(0.012)	(0.057)
(-1)	-0.011	0.000	0.012	0.168*	-0.006	-0.173
	(0.006)	(0.052)	(0.010)	(0.072)	(0.007)	(0.151)
(0)	-0.013	0.028	0.031***	0.125	-0.013	-0.040
	(0.007)	(0.039)	(0.007)	(0.286)	(0.008)	(0.111)
(1)	-0.036***	-0.151***	0.035**	0.180***	-0.005	-0.003
	(0.010)	(0.037)	(0.013)	(0.017)	(0.005)	(0.064)
(2)	-0.024	-0.047	0.030	0.032	-0.013***	-0.179
	(0.012)	(0.034)	(0.014)	(0.106)	(0.003)	(0.114)
(3)	-0.036	-0.099	0.006	-0.117	0.026	0.157***
	(0.042)	(0.101)	(0.015)	(0.199)	(0.054)	(0.043)
(4)	0.021	-0.018	0.023	-0.009	-0.086	0.044
	(0.085)	(3.605)	(0.265)	(1.531)	(1.320)	(3.714)
(6)	-0.106	-0.184	0.096	-0.012	-0.003	-0.019
	(0.199)	(0.309)	(0.106)	(0.457)	(0.059)	(0.431)
(7)	0.014	-0.040	0.039*	0.060	-0.014	-0.066
	(0.018)	(0.163)	(0.015)	(0.139)	(0.018)	(0.080)
(8)	-0.005	-0.046	0.000	-0.034	0.004	-0.081
	(0.014)	(0.073)	(0.020)	(0.212)	(0.009)	(0.087)
(9)	-0.042***	-0.062	0.039***	-0.005	0.013	0.180
	(0.007)	(0.046)	(0.011)	(0.325)	(0.014)	(0.084)
(10)	-0.096***	-0.181	0.066***	-0.031	0.032***	0.196
	(0.025)	(0.092)	(0.018)	(0.035)	(0.009)	(0.113)
(11)	-0.029	-0.058	0.006	-0.064	0.014	0.039
	(0.019)	(0.075)	(0.015)	(0.051)	(0.023)	(0.071)
(12)	-0.079	-0.200	0.021	-0.057	0.043	0.077
	(0.108)	(0.316)	(0.021)	(0.041)	(0.085)	(0.278)
(13)	-0.107	0.308*	-0.098***	-0.507***	0.191***	0.248**
	(0.066)	(0.125)	(0.028)	(0.087)	(0.024)	(0.097)
(14)	-0.037	-0.123	0.001	-0.305	0.054	-0.040
	(0.846)	(3.247)	(0.201)	(3.293)	(0.335)	(1.916)
(15)	-0.008	-0.013	0.001	-0.131	0.012	-0.087
	(0.024)	(0.125)	(0.018)	(0.119)	(0.010)	(0.071)
(16)	-0.073***	0.010	0.057***	-0.173***	0.037	0.298
	(0.023)	(0.248)	(0.014)	(0.051)	(0.031)	(0.134)
(17)	-0.126***	0.151	0.054***	-0.124	0.080***	0.047
	(0.016)	(0.142)	(0.015)	(0.079)	(0.017)	(0.107)
(18)	-0.058***	-0.175**	0.002	0.037	0.055***	0.158**
	(0.019)	(0.062)	(0.015)	(0.063)	(0.013)	(0.055)
(19)	-0.079***	0.042	0.030	-0.031	0.026	-0.030
	(0.018)	(0.224)	(0.060)	(0.142)	(0.026)	(0.205)
(20)	-0.311***	-0.445***	-0.050**	0.539***	0.295***	0.268***

Years Since Designation	Low Income		Middle Income		High Income	
	Share	Probability	Share	Probability	Share	Probability
	(0.033)	(0.105)	(0.020)	(0.024)	(0.008)	(0.066)
(21)	-0.114	-0.329	0.012	0.184	0.056	0.220
	(1.234)	(0.721)	(0.456)	(1.623)	(0.525)	(1.140)
(23)	-0.124	-0.114	0.196***	0.434*	-0.096	0.008
	(0.219)	(1.133)	(0.020)	(0.182)	(0.161)	(1.221)
(25)	-0.041	0.223	0.029	0.046	0.006	-0.106
	(0.029)	(0.389)	(0.017)	(0.123)	(0.010)	(0.090)

Notes: Column (1) presents years relative to TIF designation. The shares of each household income group are the first dependent variables of the models. The second dependent variables are the probability of moving up in the rankings of the shares of each income group. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels. The missing event time coefficients are due to the lack of corresponding block groups when using the 50% threshold.

Table A8. The effects of TIF (measured with a 50% threshold) on median rent, median housing value, real income, and probability of moving up in the rankings of each outcome

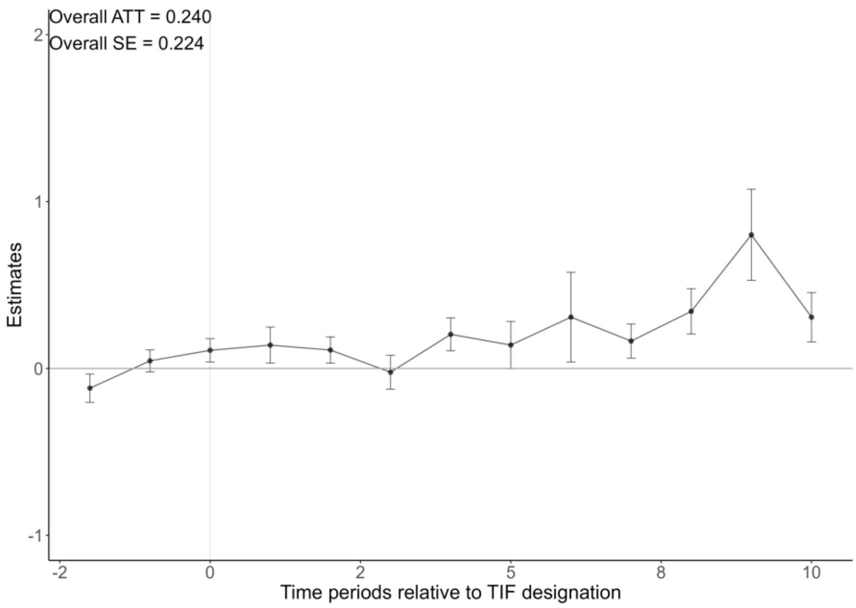
Years Since Designation	Median Rent		Median Value		Real Income	
	Log rent	Probability	Log value	Probability	Real Income	Probability
(-4)	0.334	0.066	-0.076	-0.073	-0.109	0.088
	(0.147)	(0.185)	(0.049)	(0.225)	(0.106)	(0.084)
(-3)	0.024	0.404***	0.008	-0.137	-0.214	-0.475***
	(0.158)	(0.029)	(0.036)	(0.177)	(0.086)	(0.152)
(-2)	-0.222***	0.025	0.033	-0.020	0.116***	-0.011
	(0.032)	(0.030)	(0.075)	(0.033)	(0.021)	(0.070)
(-1)	-0.056	-0.023**	0.052	-0.195***	-0.004	0.001
	(0.051)	(0.009)	(0.086)	(0.055)	(0.023)	(0.025)
(0)	0.080	0.000	0.006	-0.026	0.212***	0.136***
	(0.066)	(0.030)	(0.083)	(0.302)	(0.013)	(0.020)
(1)	0.007	-0.062***	0.133***	0.224***	0.030	0.124***
	(0.027)	(0.012)	(0.038)	(0.055)	(0.018)	(0.026)
(2)	0.090	0.055	0.106	0.031	0.169	-0.095
	(0.054)	(0.164)	(0.057)	(0.094)	(0.117)	(0.156)
(3)	0.115	0.037	0.193***	0.167	0.010	-0.008
	(0.210)	(0.057)	(0.055)	(0.099)	(0.097)	(0.061)
(4)	-0.031	-0.182	0.196	0.190	0.110	-0.002
	(0.846)	(0.855)	(2.824)	(2.678)	(1.381)	(2.385)
(6)	-0.726	-0.082	0.087	0.115	0.325	-0.149
	(1.672)	(0.068)	(0.239)	(0.447)	(0.512)	(0.641)
(7)	0.628	-0.084	0.112***	0.354	-0.242***	0.029
	(0.437)	(0.078)	(0.035)	(0.202)	(0.038)	(0.096)
(8)	0.081	-0.008	0.090***	0.015	0.065	0.091
	(0.110)	(0.091)	(0.031)	(0.293)	(0.038)	(0.071)
(9)	0.510	0.176	0.010	-0.064	-0.014	-0.229
	(0.249)	(0.162)	(0.025)	(0.543)	(0.036)	(0.146)
(10)	0.159	0.068	0.408***	0.205***	0.336***	0.328***
	(0.180)	(0.063)	(0.096)	(0.053)	(0.056)	(0.046)
(11)	0.402***	0.084	0.272***	0.174***	-0.039	0.097
	(0.086)	(0.067)	(0.070)	(0.050)	(0.047)	(0.070)
(12)	0.000	0.102	0.281	0.173	0.260	-0.020
	(0.114)	(0.250)	(0.141)	(0.167)	(0.592)	(0.100)
(13)	-0.357	0.071	0.490***	-0.112***	0.558	-0.402
	(1.330)	(0.100)	(0.130)	(0.040)	(0.274)	(0.240)
(14)	0.596	-0.525	0.221	0.215	-0.022	0.028
	(0.755)	(0.415)	(2.573)	(2.732)	(2.497)	(2.135)
(15)	0.168	-0.033	0.096**	0.022	0.106	0.008
	(0.282)	(0.033)	(0.035)	(0.202)	(0.067)	(0.116)
(16)	0.905*	0.147	0.051	0.180	0.048	-0.030
	(0.412)	(0.128)	(0.054)	(0.120)	(0.071)	(0.091)
(17)	0.655	0.003	0.436***	-0.209***	0.390***	-0.122***
	(0.264)	(0.022)	(0.122)	(0.045)	(0.049)	(0.042)
(18)	0.477***	0.033	0.354***	0.084	0.008	-0.031
	(0.113)	(0.036)	(0.089)	(0.056)	(0.045)	(0.074)
(19)	-0.045	-0.072	0.383***	0.066	0.286	-0.188
	(0.298)	(0.034)	(0.126)	(0.098)	(0.252)	(0.219)

Years Since Designation	Median Rent		Median Value		Real Income	
	Log rent	Probability	Log value	Probability	Real Income	Probability
(20)	0.644***	-0.146***	0.908***	0.244***	0.927***	-0.238***
	(0.054)	(0.015)	(0.093)	(0.017)	(0.104)	(0.040)
(21)	1.483	-0.122	0.615	0.199	0.081	-0.023
	(2.769)	(0.384)	(7.454)	(4.363)	(0.645)	(1.679)
(23)	0.677	-0.167	-0.118	0.075	-0.185	0.435***
	(0.581)	(0.080)	(0.236)	(1.264)	(0.181)	(0.113)
(25)	-1.483***	0.180***	0.300	-0.094*	0.657***	0.164***
	(0.117)	(0.046)	(0.185)	(0.038)	(0.056)	(0.045)

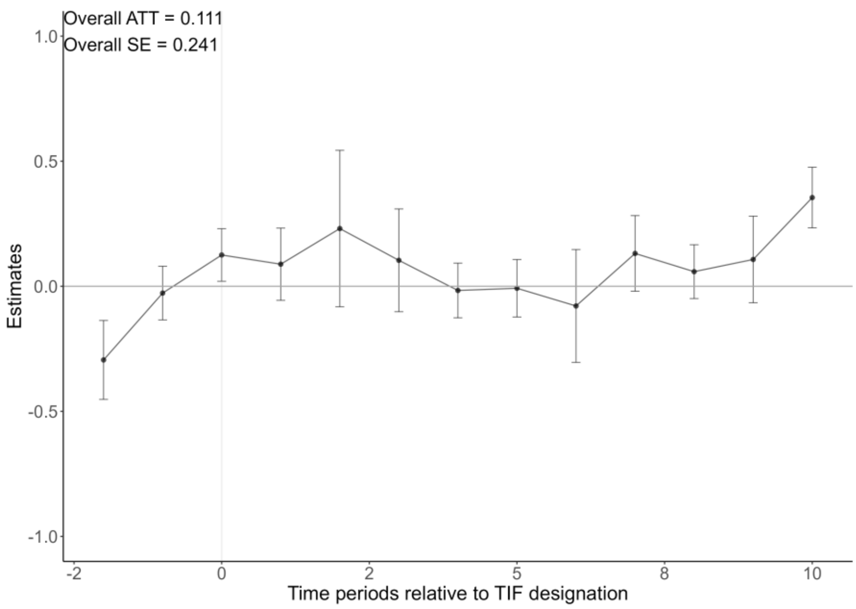
Notes: Column (1) presents years relative to TIF designation. The first dependent variables for the median rent and median value models are log-transformed. Real income is calculated using log(monthly income)-0.30*(rent). The second dependent variable is the probability of moving up in the rankings of outcomes. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels. The missing event time coefficients are due to the lack of corresponding block groups when using the 50% threshold.

Figure B2. The effects of TIF (measured with a 50% threshold) on median household income and probability of moving up in the ranking of median household income

Panel (A) Log median household income



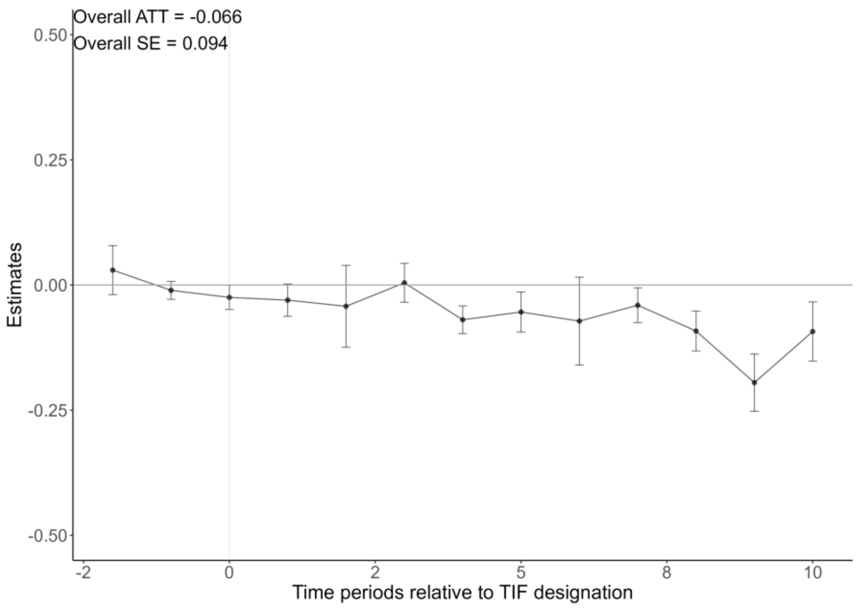
Panel (B) Probability of moving up in the ranking



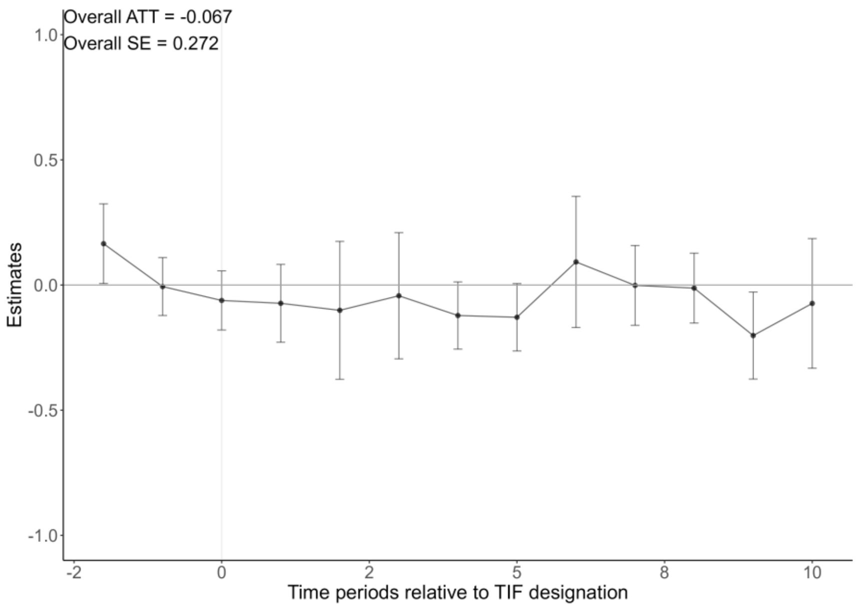
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 90% confidence interval. Standard errors are clustered by city. Due to lack of corresponding block groups when using the 50% threshold, event-time coefficients for years 5, 22, 24 are omitted. The 2-year bins have been adjusted accordingly.

Figure B3. The effects of TIF (measured with a 50% threshold) on the share of low-income households and the probability of moving up in the ranking of the share of low-income households

Panel (A) Share of low-income households



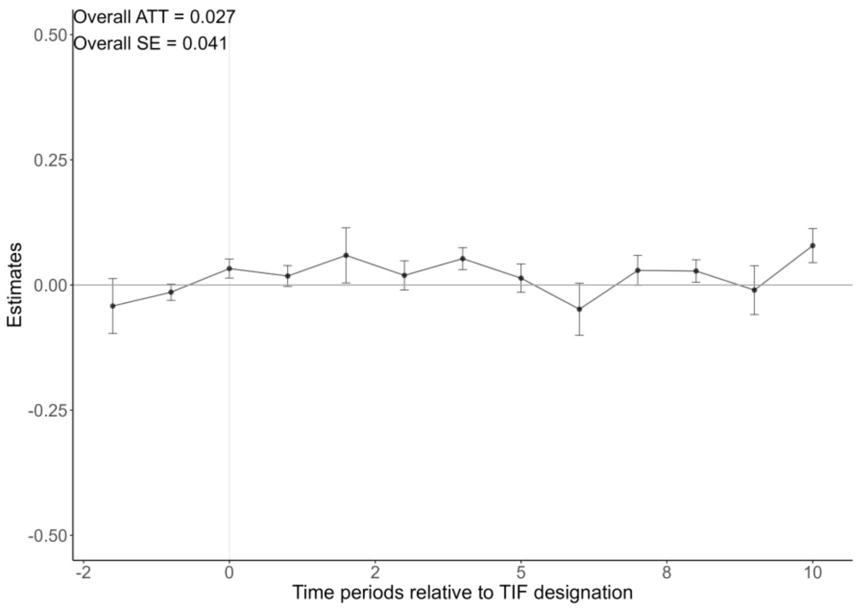
Panel (B) Probability of moving up in the ranking



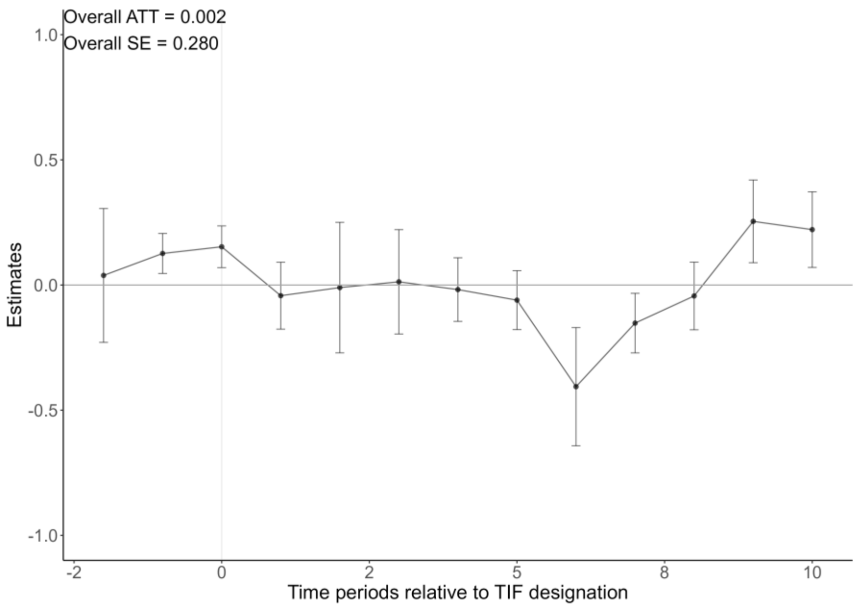
Notes: The vertical line (t =0) presents the first two-year post designation period. The bars present the 90% confidence interval. Standard errors are clustered by city. Due to lack of corresponding block groups when using the 50% threshold, event-time coefficients for years 5, 22, 24 are omitted. The 2-year bins have been adjusted accordingly.

Figure B4. The effects of TIF (measured with a 50% threshold) on the share of middle-income households and the probability of moving up in the ranking of the share of middle-income households

Panel (A) Share of middle-income households



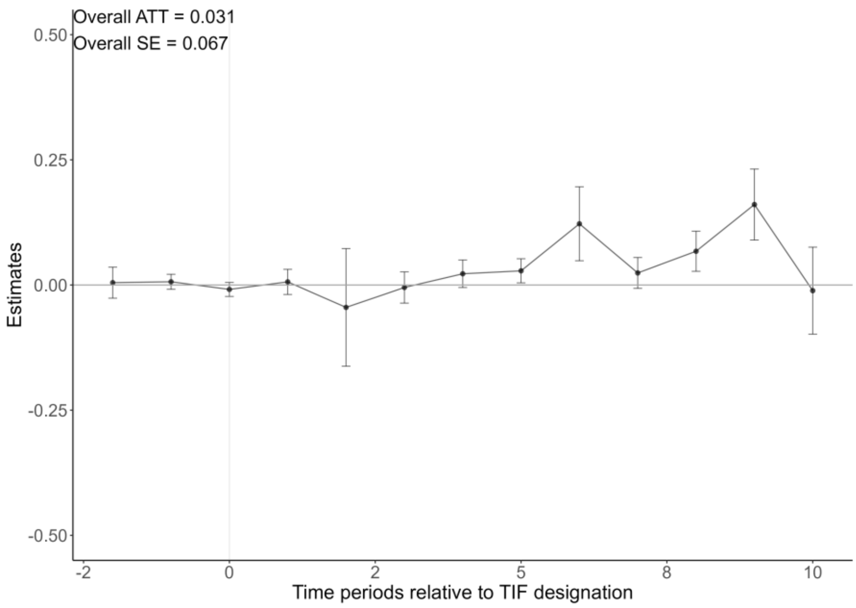
Panel (B) Probability of moving up in the ranking



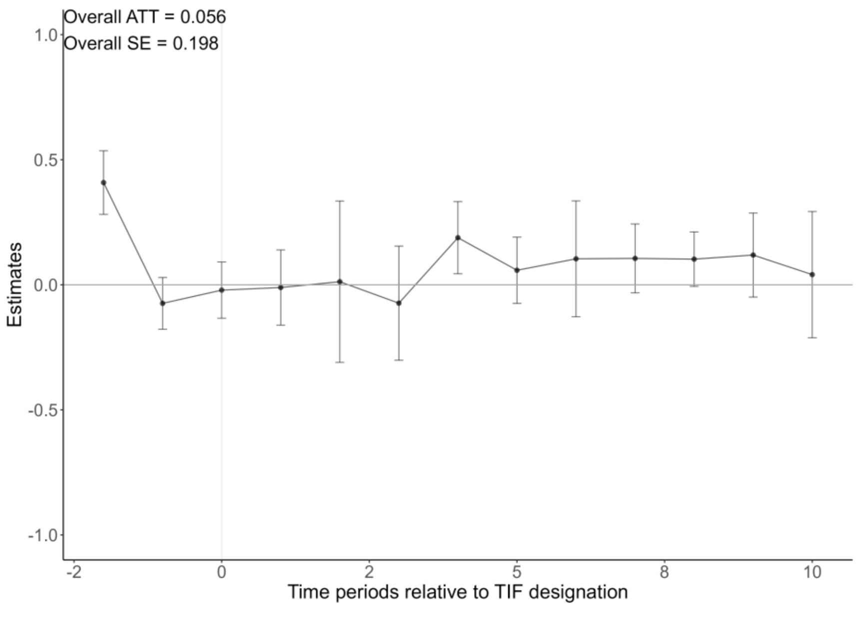
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 90% confidence interval. Standard errors are clustered by city. Due to lack of corresponding block groups when using the 50% threshold, event-time coefficients for years 5, 22, 24 are omitted. The 2-year bins have been adjusted accordingly.

Figure B5. The effects of TIF (measured with a 50% threshold) on the share of high-income households and the probability of moving in the ranking of the share of high-income households

Panel (A) Share of high-income households



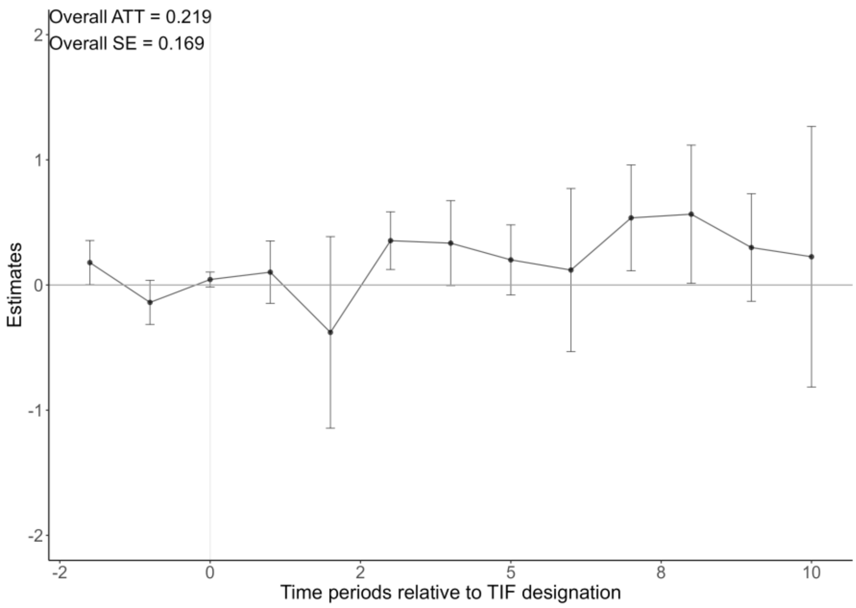
Panel (B) Probability of moving up in the ranking



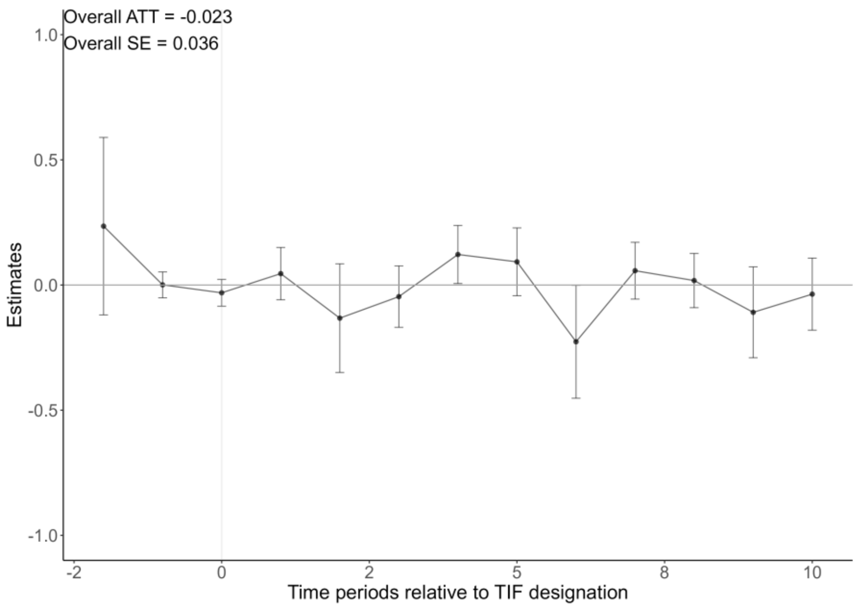
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 90% confidence interval. Standard errors are clustered by city. Due to lack of corresponding block groups when using the 50% threshold, event-time coefficients for years 5, 22, 24 are omitted. The 2-year bins have been adjusted accordingly.

Figure B6. The effects of TIF (measured with a 50% threshold) on median gross rent and the probability of moving up in the ranking of median gross rent

Panel (A) Median gross rent



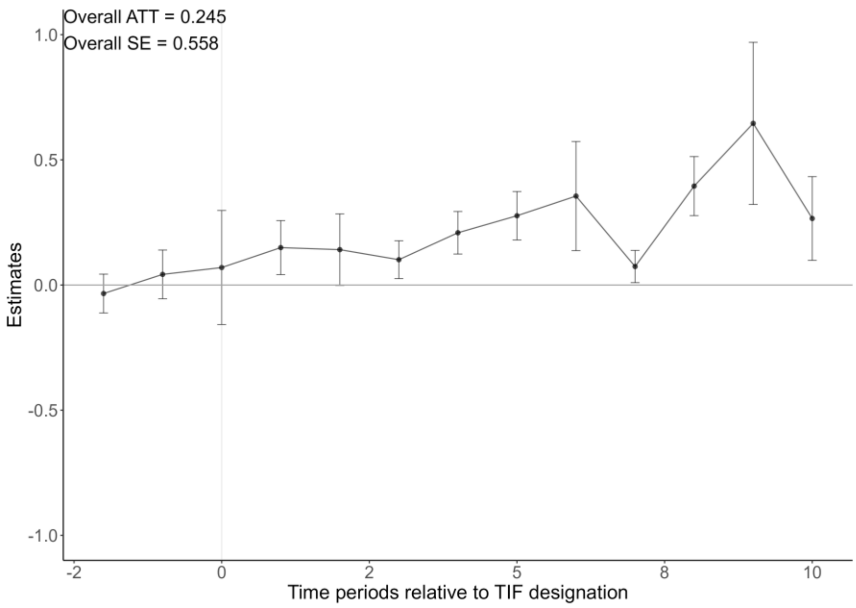
Panel (B) Probability of moving up in the ranking



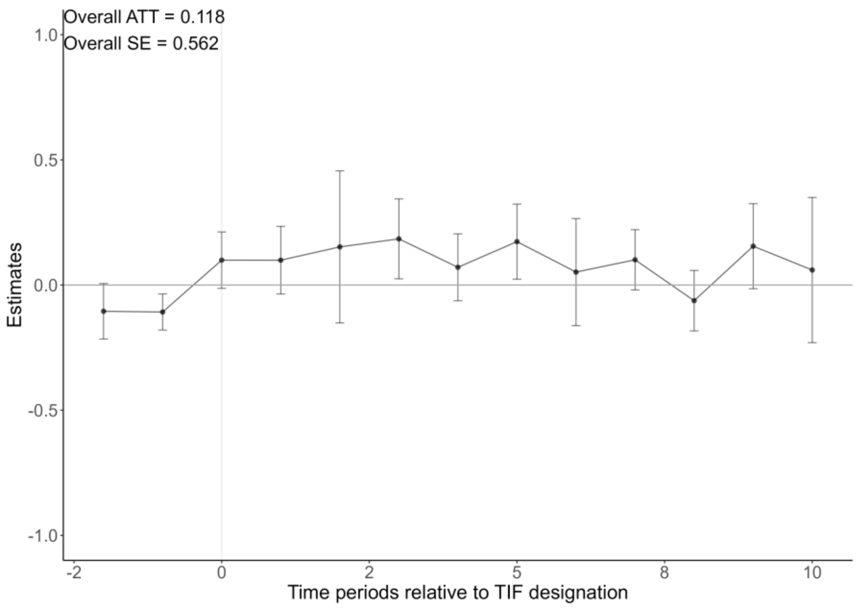
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 90% confidence interval. Standard errors are clustered by city. Due to lack of corresponding block groups when using the 50% threshold, event-time coefficients for years 5, 22, 24 are omitted. The 2-year bins have been adjusted accordingly.

Figure B7. The effects of TIF (measured with a 50% threshold) on median housing value and the probability of moving up in the ranking of median housing value

Panel (A) Median housing value



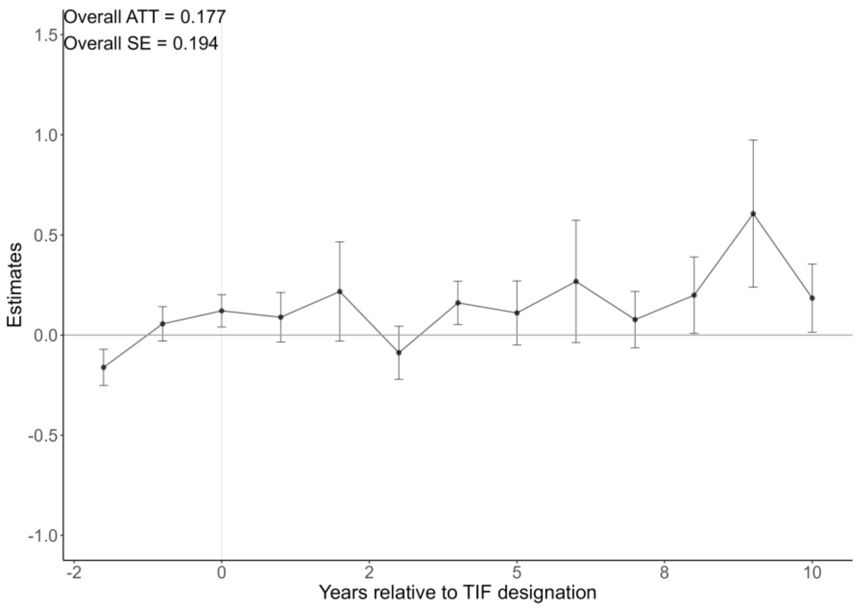
Panel (B) Probability of moving up in the ranking



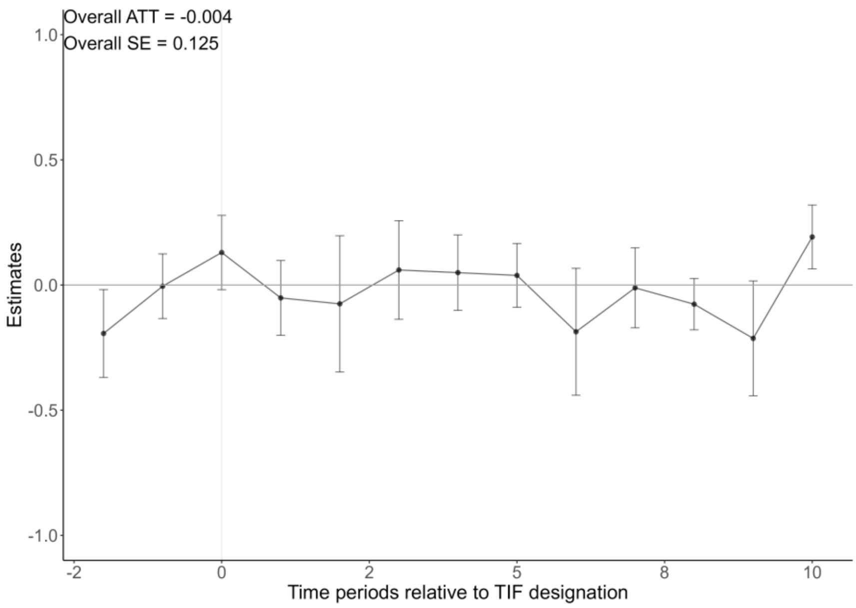
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 90% confidence interval. Standard errors are clustered by city. Due to lack of corresponding block groups when using the 50% threshold, event-time coefficients for years 5, 22, 24 are omitted. The 2-year bins have been adjusted accordingly.

Figure B8. The effects of TIF on real income and the probability of moving up in the ranking of real income

Panel (A) Real income



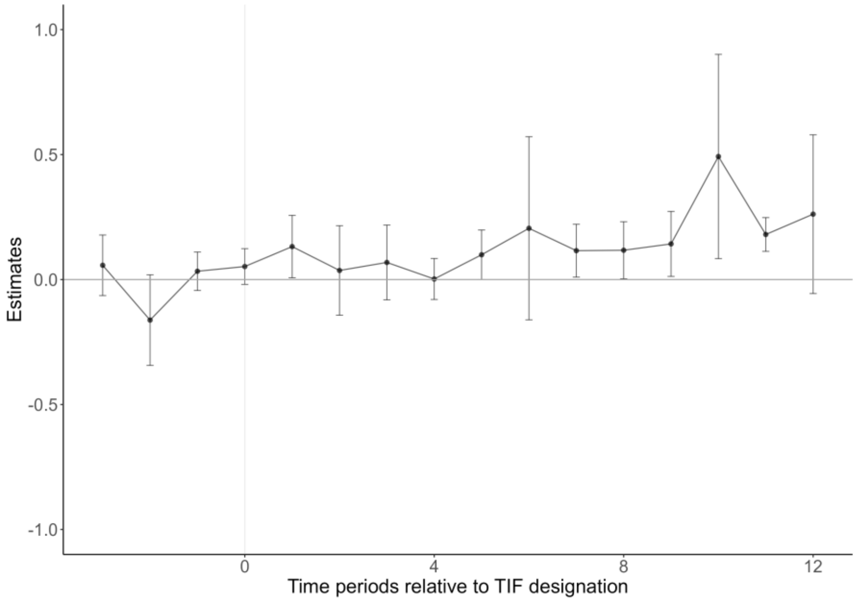
Panel (B) Probability of moving up in the ranking



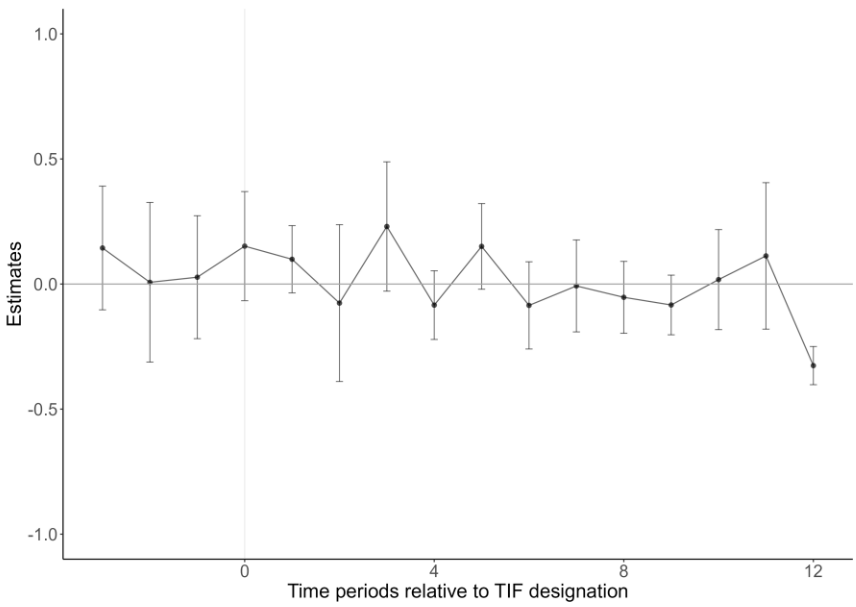
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 90% confidence interval. Standard errors are clustered by city. Due to lack of corresponding block groups when using the 50% threshold, event-time coefficients for years 5, 22, 24 are omitted. The 2-year bins have been adjusted accordingly.

Figure B9. The effects of TIF on median household income and probability of moving up in the ranking of median household income, obtained from the TWFE model

Panel (A) Log median household income



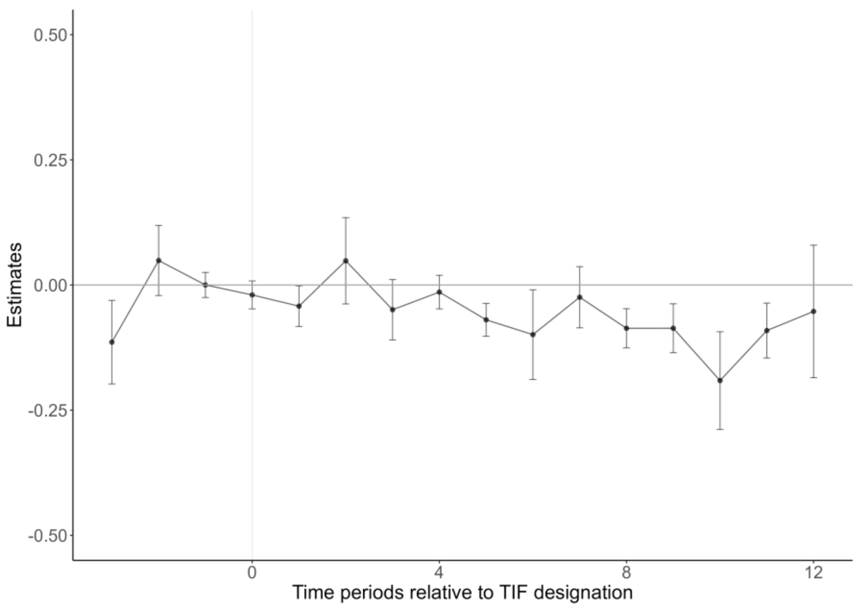
Panel (B) Probability of moving up in the ranking



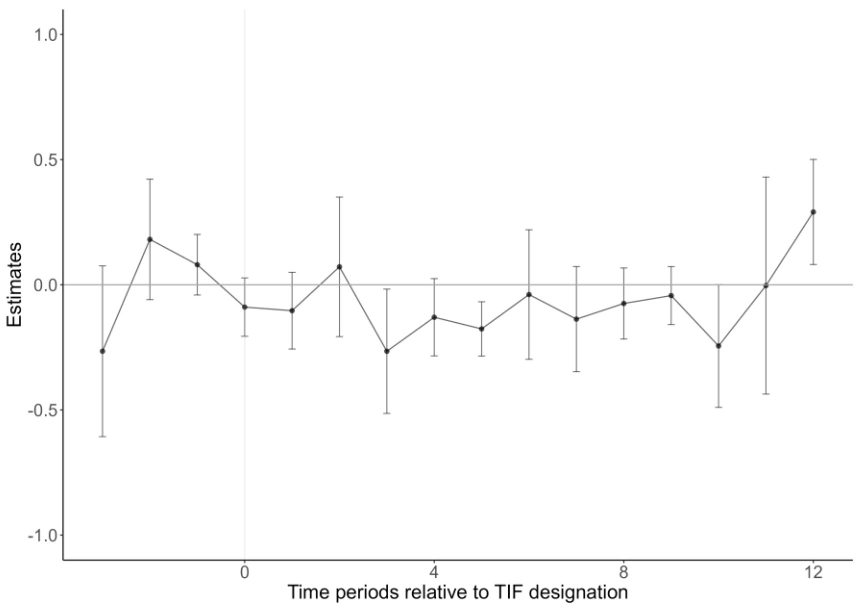
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval.

Figure B10. The effects of TIF on the share of low-income households and the probability of moving up in the ranking of the share of low-income households, obtained from on the TWFE model

Panel (A) Share of low-income households



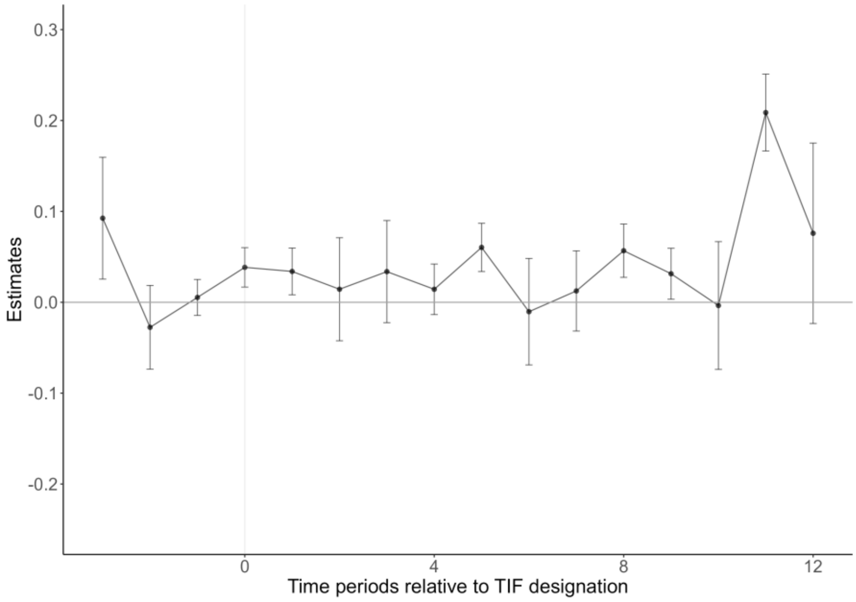
Panel (B) Probability of moving up in the ranking



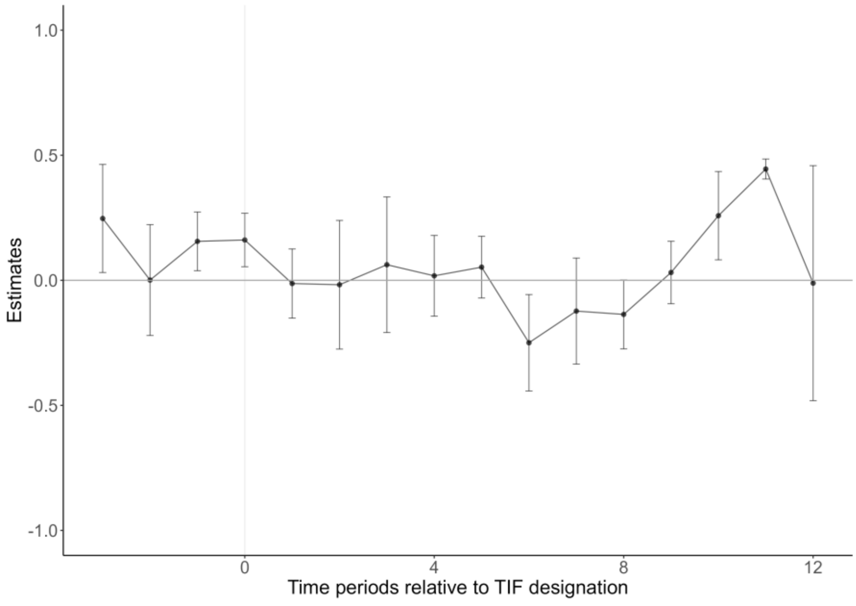
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval.

Figure B11. The effects of TIF on the share of middle-income households and the probability of moving up in the ranking of the share of middle-income households, obtained from on the TWFE model

Panel (A) Share of middle-income households



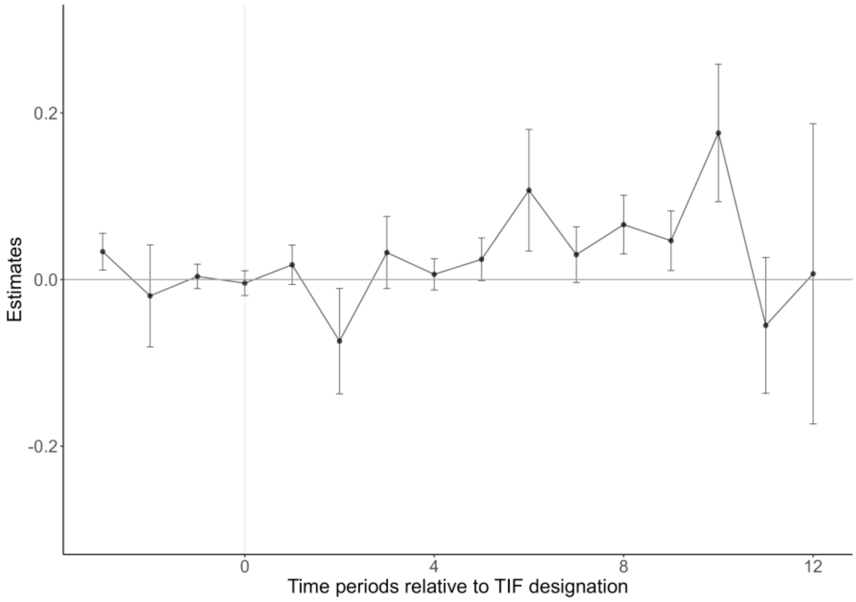
Panel (B) Probability of moving up in the ranking



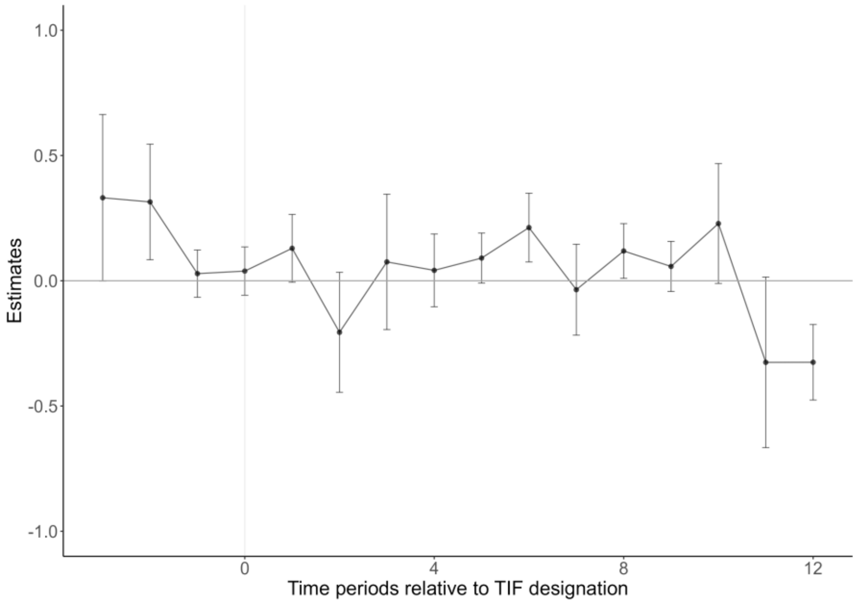
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval.

Figure B12. The effects of TIF on the share of high-income households and the probability of moving in the ranking of the share of high-income households, obtained from the TWFE model

Panel (A) Share of high-income households



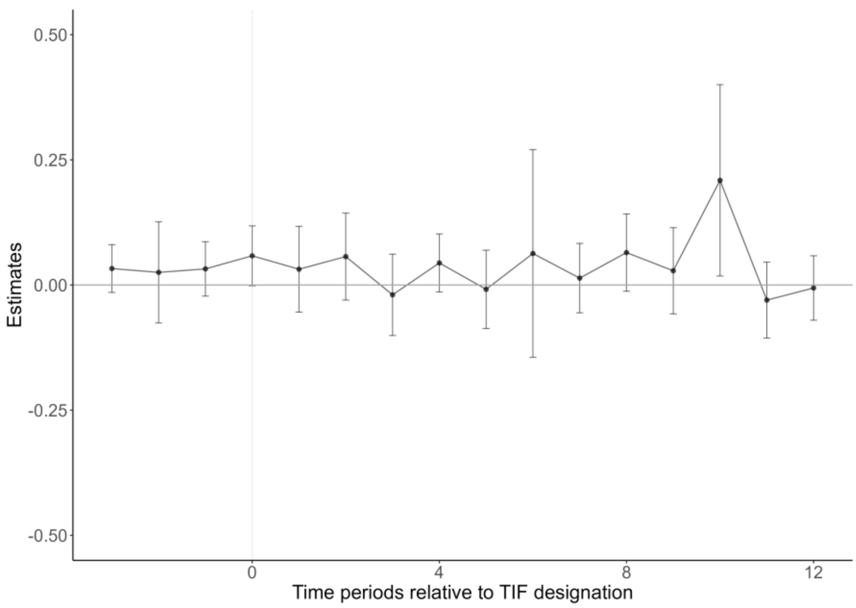
Panel (B) Probability of moving up in the ranking



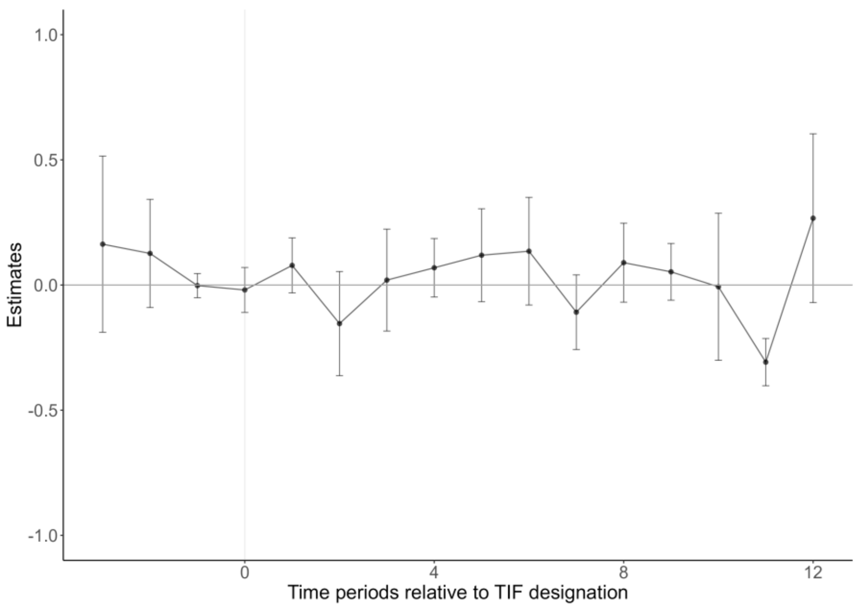
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval.

Figure B13. The effects of TIF (measured with a 50% threshold) on median gross rent and the probability of moving up in the ranking of median gross rent, obtained from the TWFE model

Panel (A) Median gross rent



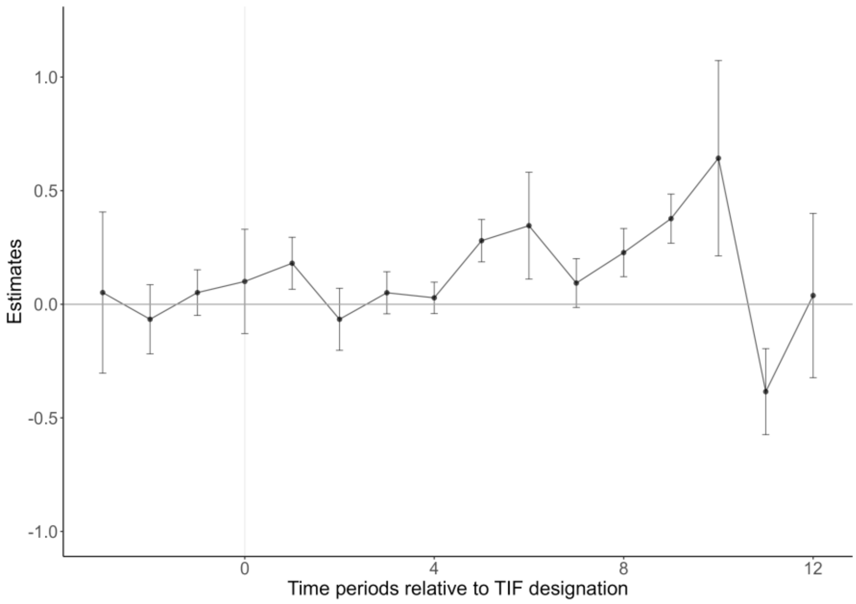
Panel (B) Probability of moving up in the ranking



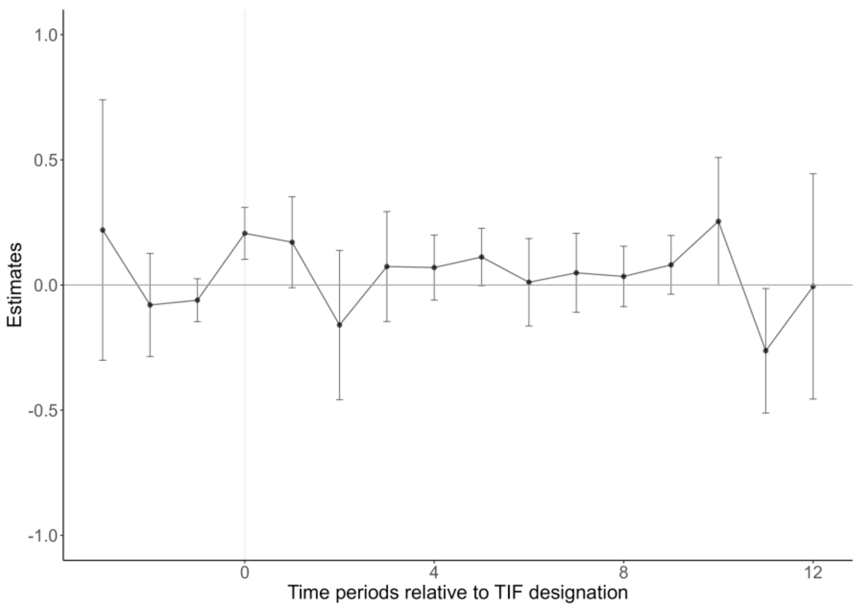
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval.

Figure B14. The effects of TIF (measured with a 50% threshold) on median housing value and the probability of moving up in the ranking of median housing value, obtained from the TWFE model

Panel (A) Median housing value



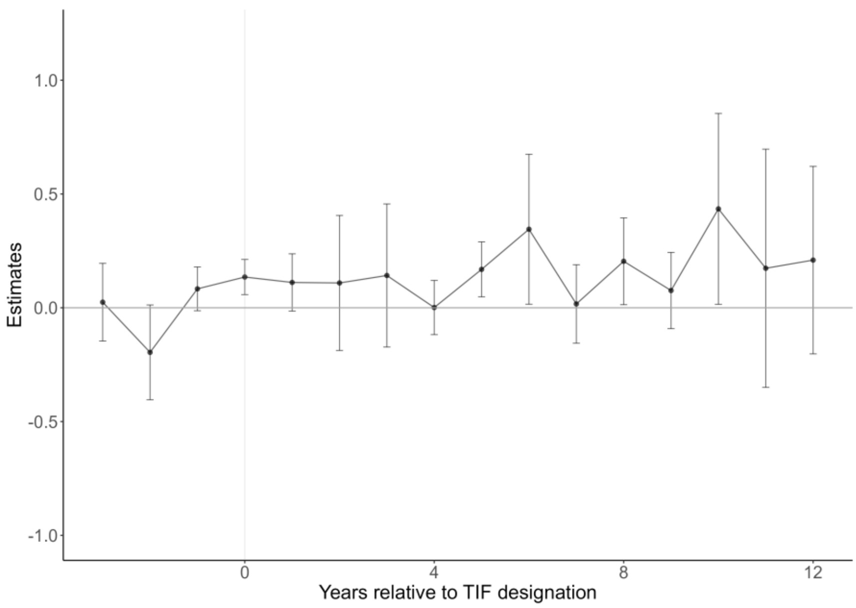
Panel (B) Probability of moving up in the ranking



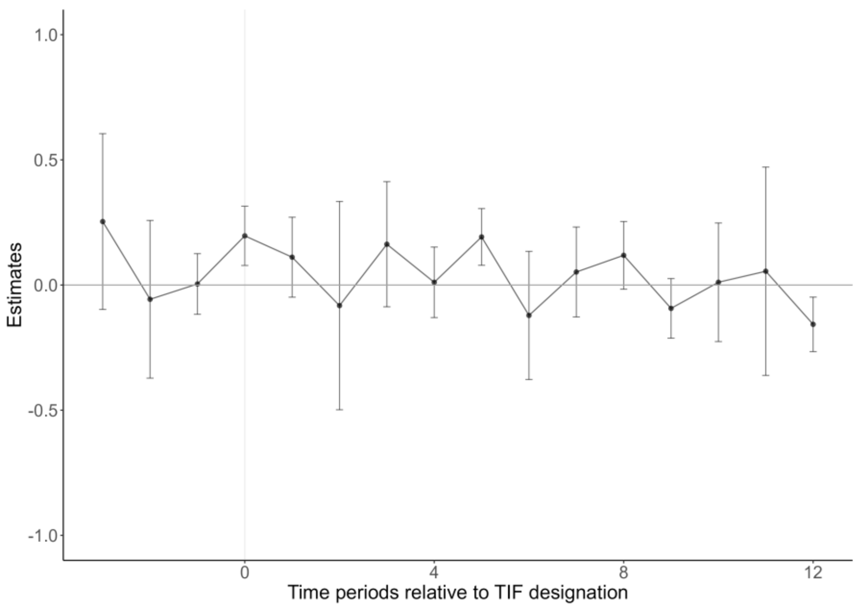
Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval.

Figure B15. The effects of TIF on real income and the probability of moving up in the ranking of real income, obtained from the TWFE model

Panel (A) Real income



Panel (B) Probability of moving up in the ranking



Notes: The vertical line (t =0) presents the first two-years post designation period. The bars present the 95% confidence interval.