Upzoning and Neighborhood Change: Evidence from Los Angeles

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Abstract

Housing affordability is a pressing challenge in the United States, with rising costs placing significant financial strain on communities. In response, local governments are exploring policies to enhance residential development and increase housing supply. A common strategy is upzoning, which involves relaxing land use regulations to facilitate denser housing. Using property characteristics and consumer trace data, I show that easing zoning requirements increases housing supply, as measured by the number of units, without altering the size of units. I also find that upzoning leads to higher house prices. The zoning change also triggers demographic shifts, including a greater share of in-migrant households that are non-Hispanic White. On the other hand, out-migration does not vary by race or ethnicity. I also find that in-migrants do not come from higher-income neighborhoods, but out-migrants tend to move to tracts with slightly higher median incomes. Additionally, I assess spillover effects within a 2-mile radius of the treated zones, revealing delayed increases in housing units, and house prices within a mile of Transit Oriented Communities (TOC) areas. These findings are robust to a triple-difference-in-differences specification, which helps rule out confounding factors. The results for housing development and demographics remain consistent with the baseline findings, while the estimates for property prices are directionally similar but no longer statistically significant.

JEL Codes: I31, R14, R23, R31, R52

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1 Introduction

Housing affordability is a major challenge across the nation, affecting many cities as they strive to provide residents with affordable and suitable housing. As housing costs rise, they create significant financial strain on communities. In response to this pressing issue, local jurisdictions are actively exploring policies aimed at fostering residential development, increasing the housing supply, and reducing housing costs. One such policy gaining attention is various forms of upzoning, which involves relaxing land use regulations to facilitate denser housing developments.

Upzoning enables the construction of multifamily housing such as apartments and townhouses, thereby expanding the housing supply to curb rising prices (Glaeser et al. (2005); Schuetz (2009); Manville et al. (2020)). However, despite its potential benefits, many politicians and voters argue that new market-rate development contributes to rising home prices and the displacement of minority and low-income households. This concern may be driven by a positive correlation between new market-rate housing units and nearby housing prices (Pearsall (2010); Zahirovich-Herbert and Gibler (2014)). However, these studies generally overlook the selection bias that determines the location of new market-rate development.[1] To move beyond these correlations, this study provides causal evidence on the local impacts of upzoning on development, prices, and demographics.

In the City of Los Angeles, where housing affordability is a significant issue, a 2017 bill established the Transit Oriented Communities (TOC) program. This initiative relaxes floor area ratio (FAR) and parking requirements in exchange for the inclusion of affordable housing units within 0.5 miles of major transit stops. The program also streamlines approvals by allowing developers to pursue by-right projects, bypassing the lengthy and uncertain discretionary approval process.

Nearly half of all new housing built in Los Angeles between 2017 and 2021 was located in TOC-designated areas, up from 40 percent in the years just before the policy. This sharp increase underscores the program's central role in shaping the city's housing market and makes it a valuable case study for understanding the effects of easing land use restrictions in transit-accessible neighborhoods. The TOC program, adopted in Los Angeles in 2017, therefore provides an early and policy-relevant opportunity to evaluate how upzoning affects housing development, property values, demographics, and spillover effects. The study is also timely as California considers a statewide expansion of transit-oriented upzoning through Senate Bill 79, which would allow more multifamily housing near major transit stops with the goal of increasing supply, improving affordability, and supporting public transportation.

[1] Boustan et al. (2023) test the existence of such bias and find a robust positive correlation between new condominium units and pre-existing concentrations high income residents, highlighting developers' tendency to select areas attractive to high-income households for condo construction.

Theoretically, upzoning can affect local housing markets and demographics through three channels. First, by relaxing regulatory constraints, it increases the capacity for new development, which should reduce prices in the long run, although these effects may emerge with a lag. Second, by expanding redevelopment potential, it raises the option value of land, leading to short-run increases in property prices even before construction occurs. Third, it can reshape neighborhood composition through amenity-driven sorting, as new development and associated commercial activity make upzoned areas more attractive to different demographic groups than those historically residing there.

To address these questions, I assemble a uniquely rich dataset that brings together multiple large-scale administrative and proprietary sources. This includes parcel-level assessor data retrieved from the Los Angeles County Assessment Portal, data on Transit Oriented Communities (TOC) from Los Angeles City Planning, and consumer trace data acquired from DataAxle (previously InfoGroup). Constructing this dataset require substantial data collection and cleaning across millions of records, yielding one of the most detailed parcel- and block-level datasets of housing development and neighborhood change in Los Angeles to date. Using this dataset, I employ an event study framework that exploits geographic and temporal variation to compare outcomes in upzoned areas with those in control areas within the city.

A key challenge in identifying the program's impact is the potential existence of spillover effects. The implementation of the TOC program may have affected not only the directly treated areas but also adjacent neighborhoods, potentially through spillover effects that could stimulate development in nearby areas or divert it away (Freemark (2020); Greenaway-McGrevy and Phillips (2023); Büchler and Lutz (2024)). To address this concern, I follow the method proposed by Clarke (2017) and Butts (2021), where I control for areas within 0–1 mile and 1–2 miles of TOC boundaries to capture possible spillover effects. This approach should yield unbiased estimates under the assumption that spillover effects do not extend beyond 2 miles from the TOC areas.

The findings indicate three main results. First, the TOC program led to a significant increase in housing development within treated areas, with unit counts rising consistently though unit size did not change. Second, property prices increased relative to the control group, but these gains were concentrated in blocks with little prior permitting activity, where supply growth was slower. Third, demographic change followed: TOC neighborhoods experienced increases in the share of non-Hispanic White in-migrants. In addition, out-migrants tended to relocate to slightly higher-income neighborhoods, suggesting that these were voluntary moves. As a complementary analysis, I use American Community Survey (ACS) data. Although ACS is coarser and noisier, it provides information not available in the microdata and points to a decline in average age, modest increases in educational attainment, and higher median household income in TOC areas, consistent with the new developments attracting younger, more educated, and higher-income residents.

I also look at the spillover effects of the policy within a 2-mile radius surrounding the TOC areas. To do so, I use the baseline regression and plot the point estimates for the spillover areas. The findings reveal a delayed increase in the number of housing units within the 0-1 mile range from the TOC areas; however, this effect is smaller than the direct effect observed within the treated zones and diminishes beyond the 1-mile threshold. Furthermore, I find a small and marginally statistically significant increases in property prices within the spillover areas. On the other hand, I do not find any changes in the race and ethnicity of in-migrants or out-migrants in the spillover areas. The ACS analysis, however, points to modest increases in the share of college-educated residents in these neighborhoods, though not to higher incomes or younger populations.

To ensure the robustness of the findings, it is important to verify that the observed changes are not driven by broader citywide shocks that could disproportionately impact the treatment and control groups. To address potential confounding variables, I employ a triple-differences strategy using all parcels in Los Angeles County. For instance, if the City of Los Angeles experienced a surge in housing demand due to a countywide employer expansion or new regional infrastructure investment, this could increase development or prices near transit stops throughout the region, regardless of zoning changes. In such cases, a simple difference-in-differences design could mistakenly attribute those broader shifts to the TOC program. The triple-difference approach addresses this by comparing TOC-eligible areas not just to other areas in the city, but also to similar areas outside the city, helping isolate the effect of the policy. This strategy exploits variations in three dimensions: (1) being in close proximity, 0.5 miles, to a major transit stop, (2) the timing of the policy, and (3) being located in the City of Los Angeles. This analysis confirms that the findings are not driven by unobserved common shocks and can be attributed to the TOC program.

Overall, the triple-difference specification is more demanding and produces wider standard errors. For housing development outcomes, the results remain robust and consistent with the baseline findings. For property prices, the point estimates remain in the same direction as the baseline but are no longer statistically significant, so we cannot rule out the possibility of no price effects. For demographic outcomes, the triple-difference results are consistent with the baseline findings and yield estimates of similar magnitude and significance.

This paper is related to literature examining the effects of land use policies on the housing market. Much of the literature on land use policies focuses on the impact of zoning restrictions on house prices and construction (Thorson (1997); Mayer and Somerville (2000); Burge and Ihlanfeldt (2006); Ihlanfeldt (2007); Glaeser and Ward (2009); Zabel and Dalton (2011); Kok et al. (2014); Gyourko and Krimmel (2021)), finding that more restrictive zoning leads to an increase in house prices, a decrease in residential construction and in residential density. In contrast, the literature examining the effects of upzoning has only recently begun to emerge (Freemark, 2020; Anagol et al., 2021; Liao, 2022; Greenaway-McGrevy and Phillips, 2023; Brueckner et al., 2024; Büchler and Lutz, 2024). This paper contributes to this growing body of work by providing new evidence on the local impacts of upzoning.

This paper also contributes to the literature on the effects of land use policies on neighborhood change. While a substantial body of research examines the impact of place-based affordable housing programs on neighborhood composition (Baum-Snow and Marion, 2009; Freedman and McGavock, 2015; Davis et al., 2018; Diamond and McQuade, 2019), the literature on the effects of land use policies remains more limited. This gap is largely due to the challenge of identifying exogenous variation in land use reforms. Nevertheless, understanding how these policies influence neighborhood demographics is important, particularly since concerns about upzoning often stem from the demographic shifts and potential displacement associated with new construction.

Lastly, this paper contributes to the literature on the spillover effects of land use policies on nearby development and residential sorting. Land use policies not only shape the density and types of development in the directly zoned areas but can also significantly impact surrounding neighborhoods. By influencing where development is concentrated, these policies can shift the dynamics of nearby areas. Although this topic has not been deeply explored, some studies suggest that reducing land use restrictions can have unintended consequences on adjacent areas, potentially discouraging development as developers favor the newly upzoned areas where it is more profitable to build (Freemark (2020); Greenaway-McGrevy and Phillips (2023)). However, another possibility is that increased development in treated areas could create positive spillovers, encouraging further development even in nearby neighborhoods without zoning changes. For instance, Büchler and Lutz (2024) find a weak positive effect of large upzonings on the housing stock in neighboring areas. Despite the growing focus on spillovers in terms of development, no study has examined how these shifts affect neighborhood demographics. This paper addresses that gap by being the first to explore how zoning changes influence the demographic composition of areas adjacent to the treated zones, offering a more comprehensive understanding of the broader impacts of land use policies.

The rest of this paper is organized as follows. Section 2 presents a conceptual framework outlining the potential mechanisms. Section 3 provides an overview of the TOC Program in Los Angeles. Section 4 describes the data and sample characteristics. Section 5 explains the econometric framework, and Section 6 discusses the results. Section 7 concludes.

2 Conceptual Framework

Upzoning policies such as Los Angeles's TOC program are intended to increase housing production and improve affordability near transit. However, the effects of such policies are not limited to physical development. They can also influence land values, migration patterns, and the amenities available in surrounding areas. This study considers three primary channels through which upzoning may affect local housing markets and neighborhood demographics: housing supply, redevelopment incentives, and amenity-driven residential sorting.

First, by relaxing regulatory constraints on density, floor area ratio (FAR), and parking, upzoning creates the legal capacity for more housing units to be constructed. This supply channel suggests that over time, increases in housing production could alleviate price pressures and expand access to housing. However, new development often requires considerable time, especially in cities with lengthy permitting processes and high construction costs. As a result, the full effect of upzoning on prices and population may only materialize several years after policy adoption. Prior work emphasizes the lags between regulatory changes and realized construction (Malpezzi and Wachter, 2005; Bertaud and Brueckner, 2005), underscoring the importance of distinguishing short- and long-run responses.

Second, even before new housing is built, upzoning can affect land values by increasing the development potential of existing parcels. This "option value" channel operates through changes in the financial return from redevelopment. Parcels that are underbuilt relative to their new zoning capacity may become more attractive for future development, and this anticipated value can be capitalized into property prices. Theoretical and empirical work shows that zoning changes often increase land prices even in the absence of new construction, particularly for parcels with lower existing development (Clapp and Salavei, 2010; Greenaway-McGrevy et al., 2021; Leather, 2023).

Third, upzoning may alter the composition of who moves into and out of neighborhoods. Denser housing near transit may attract different types of households than those historically residing in the area, particularly if the new housing stock is newer, more amenity-rich, or better connected to employment centers. In addition, if development is accompanied by improvements to neighborhood amenities – such as the opening of restaurants, retail, or other commercial services – then upzoned areas may become more desirable to higher-income or more mobile residents. This sorting mechanism, documented in studies of gentrification and urban change, (such as in Roback (1982); Brueckner et al. (1999); Brueckner and Rosenthal (2009); Davis (2021); Asquith et al. (2023)), suggests that zoning policy can indirectly affect neighborhood demographics through changes in amenities.

Table 1 provides a summary of these three channels. The supply channel predicts that new housing development will eventually reduce prices, though the demographic consequences are less clear and depend on who the newly built units attract. Because development takes time, these effects emerge with a delay. The option value channel reflects the immediate capitalization of redevelopment potential into land prices, without directly changing the resident population. Finally, the amenities and sorting channel operates in the long run: as new businesses open and households with higher incomes or education levels move in, neighborhood demand rises, contributing to higher prices and shifts in the racial and socioeconomic composition of residents.

Table 1: Summary of Conceptual Channels

Channel	**Price Effects**	**Demographic Effects**	**Timing**
Supply (new development)	↓ Prices (long run)	Ambiguous	Delayed
Option value	↑ Land prices (short run)	None direct	Immediate
Amenities and sorting	↑ Prices (via demand)	Changes in race, income, education	Delayed

In this paper, I examine each of these mechanisms. I assess the timing of changes in development activity and property values, and I analyze how upzoning affects the characteristics of in-migrants and out-migrants, including their racial and ethnic composition and the types of neighborhoods they migrate from and to. I also evaluate whether changes in the local business landscape, especially in consumption-oriented industries, help explain shifts in neighborhood appeal and composition.

3 Transit Oriented Communities Program in Los Angeles

Los Angeles faces one of the most severe housing affordability challenges in the country. As shown in Figure 1, the house price-to-income ratio in the Los Angeles-Long Beach-Anaheim metro area has consistently exceeded that of other U.S. metros over the past four decades. This gap has widened substantially since the early 2000s, reaching nearly 11:1 by 2020. In other words, home prices in Los Angeles are more than 11 times the median household income—well above the national average of 5. These high costs place substantial strain on housing affordability, particularly for low- and middle-income households.

In response to the growing housing affordability concern, the City of Los Angeles enacted the Transit Oriented Communities (TOC) program in 2017. This policy relaxes FAR and parking requirements, and provides density bonuses for residential developments that include affordable housing units within a 0.5-mile radius of major transit stops. For example, under the TOC program, development projects situated within 0.5 miles of rail stations can receive a density increase of 70 percent if 10 percent of the housing units are

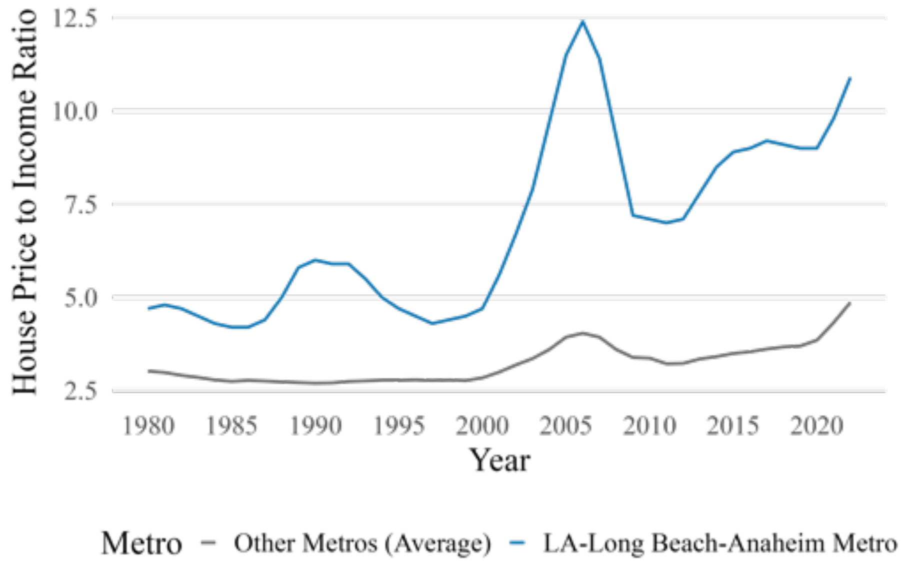


Figure 1: Trend in House Price-Income Ratio: Los Angeles-Long Beach-Anaheim Metro vs. Other Metros
Note: Values reflect annual averages. *Data Source: Harvard Joint Center for Housing Studies.*

affordable to households earning 30 percent or less of the Area Median Income (AMI). Additionally, these projects may be exempt from parking requirements based on their proximity to major transit stops. The TOC program also simplifies the development process by enabling developers to undertake by-right projects, which reduces the time and uncertainty linked to the permitting process.[2]

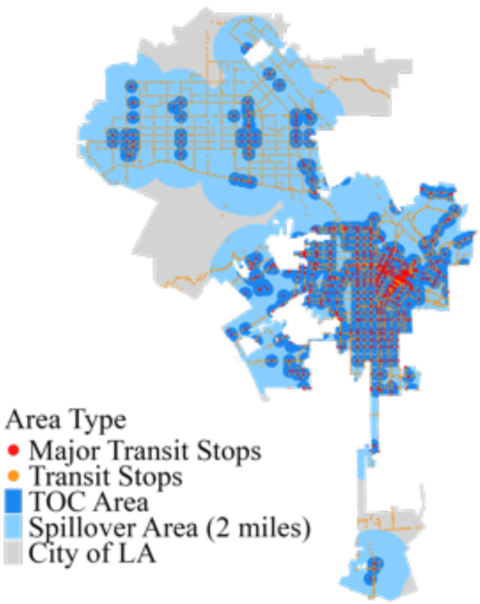
Although TOC areas may change from year to year, primarily due to the addition or removal of bus stops, most treated areas remain stable over time. For the purposes of this analysis, I use the initial TOC assignment in 2017 as the treatment assignment, as it provides a consistent baseline for assessing the impact of the program. As a robustness check, I also exclude all areas that are eventually treated.

Figure 2 illustrates the areas covered by the TOC program in 2017, along with the borders of the City of Los Angeles. Panel A shows the location of transit stops in orange and major transit stops in red across the city.[3] The widespread presence of transit stops should make these areas especially comparable to the TOC regions, as both types of areas are centered around transportation access, which is likely to influence housing development patterns. These untreated areas share similar access to transit but lack the TOC designation, providing an opportunity to examine how the TOC designation could influence development patterns in areas with comparable transit access.

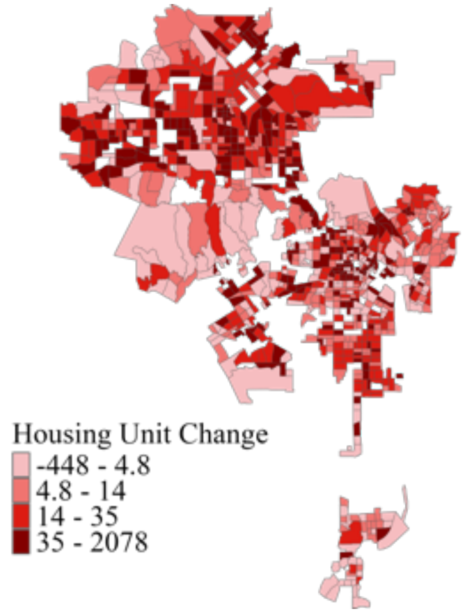
Furthermore, the dark blue shaded regions in Panel A of Figure 2 represent the TOC areas, defined as a

[2]Appendix A.1 provides a detailed overview of the TOC program's tier structure, eligibility criteria, and the different zoning incentives available.

[3]In California, a major transit stop is defined as a rail station or bus stop located within half a mile of a major transit corridor, such as bus or rail lines with frequent service. The stop must be served by transit operating at 15-minute intervals or less during peak hours (morning and evening) (California Public Resources Code (2008)).



(A)



(B)

Figure 2: TOC Areas and Change in Housing Units (2017–2021) in the City of Los Angeles. *Source: City of Los Angeles Planning Department, Los Angeles County Assessor*
Note: In Panel A, the dark blue shaded areas represent the regions covered by the TOC program, while the light blue areas indicate spillover areas—defined as the 2-mile buffer surrounding TOC boundaries. The orange dots indicate transit stops, and the red dots represent major transit stops. In Panel B, the map shows the change in the number of housing units between 2017 and 2021 across the City of Los Angeles. Tracts are shaded by quantiles of unit change, where darker shades indicate higher increases.

0.5-mile radius around major transit stops. These zones were designated as TOC to encourage higher-density development near transit hubs. While TOC areas are clustered in certain parts of the city, they are often surrounded by untreated areas that are in close proximity, suggesting potential spillover development pressures from the TOC zones to neighboring, untreated areas. To account for this, I designate the surrounding 2-mile buffer zones, shown in light blue, as spillover areas. The remaining gray regions serve as the reference group for interpreting the estimated effects.

In Figure 2 Panel B, we observe the change in the number of housing units between 2017 and 2021 across the city. The map is shaded by quantiles of unit change, where darker shades represent areas that have experienced higher increases in housing units. Notably, TOC areas and the surrounding areas appear to have seen more significant increases in housing development compared to untreated areas. The clustering of higher development in and around the TOC zones suggests that these areas could be experiencing not only direct effects from the program but also indirect effects on neighboring areas, potentially due to the increased desirability and investment surrounding transit-oriented developments.

Figure 3 shows the change in the number of housing units within TOC and non-TOC areas in the City of Los Angeles from 2013 to 2021. Prior to 2017, unit growth trends in both areas are relatively similar.

After 2017, the year the policy was implemented, the gap begins to widen at an increasing rate. The smaller, but noticeable, increase in non-TOC areas also suggests the possibility of positive spillover effects. This suggests that this program had a substantial impact on the number of housing units, either through new development or conversion of existing spaces. Given its significant impact on the Los Angeles housing market, this policy presents an opportunity to explore the potential outcomes of reducing land use restrictions in densely populated areas.

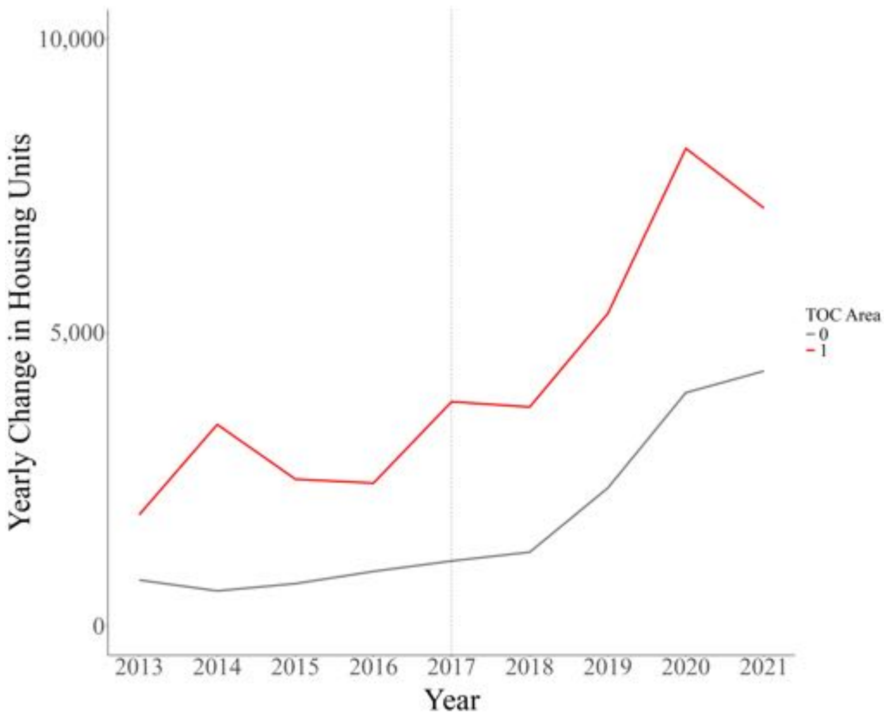


Figure 3: Change in the Number of Housing Units in TOC and non-TOC parcels in LA
Note: The dashed line marks the year of implementation of the TOC program. The red line shows the yearly change in the number of units on the TOC Area and the gray line shows the change in the number of units in non-TOC areas. *Data Source: Los Angeles County Assessment Portal.*

4 Data and Sample Characteristics

4.1 Data

I use data from several sources for this study. First, I use longitudinal assessment data from 2013 to 2021 retrieved from the Los Angeles County Assessment Portal. This dataset contains key attributes of houses and lots, including location, the number of housing units, size of the main building, and transaction information. Los Angeles County gathers data on property characteristics from various sources, including deeds and other recorded documents from the Clerk-Recorder's Office, building permits from municipal and county agencies, self-reported information through the State Board of Equalization, as well as trade publications and public filings. Since the housing unit and size information are likely derived from building permits, it is likely that the variables for additional units and size reflect permitting activity, hence the beginning stages of development. In addition to the assessor data, I use the Transit Oriented Communities (TOC) area map from LA City Planning to identify the treated areas.

For the demographic change outcomes, I utilize consumer trace data obtained from DataAxle, a commercial consumer reference dataset that compiles residential location, demographic, and socioeconomic information from a variety of sources.[4] These include USPS address change files, property records, and public databases. The dataset provides individual- and household-level characteristics at the address level, making it suitable for tracking migration patterns over time. Similar datasets, such as Infutor and LexisNexis, have been used in recent academic work on neighborhood change and mobility.[5] These raw micro-data files provide extensive information on a significant portion of the U.S. population, though they require data validation. Key features of the dataset include a unique household identifier, allowing to track household trajectories over time; precise location information, enabling accurate identification of household residences for each year; and additional columns that offer insights into demographic characteristics, such as individuals' names and ages. I conduct several validation exercises in Appendix A.2, which show that the DataAxle sample aligns closely with patterns observed in American Community Survey (ACS).

To build the sample, I limit the data to individuals who resided in Los Angeles County at any time between 2012 and 2022. For individuals living in the county during this period, I extract their location, enabling me to track household movements, even when migrations occur across counties or states. The unit of analysis is the head of household, as my focus is on household migration rather than individual movement. I use the head of household for tracking migration because they are less likely to leave the household abruptly, and their influence is likely to play a significant role in the decision to move.

I supplement the consumer trace data with imputed information on the race and ethnicity of the head of household following the method proposed by Imai and Khanna (2016). This approach first estimates the prior probabilities of race and ethnicity and then applies Bayes' Rule to calculate the posterior probability that an individual is non-Hispanic White, Hispanic, African-American, Asian and Pacific Islander, Native American, or other, conditioning on the individual's first and last names and the race and ethnicity distribution from the

[4]DataAxle compiles residential data using the USPS National Change of Address database, the Locatable Address Coding System, and the Delivery Point Verification database. These sources are supplemented with public records, including property deeds and tax assessor data. Using proprietary methods, DataAxle derives demographic and household characteristics such as race, age, education, and household structure. Kennel and Li (2009) estimate an undercoverage rate of 8.4% nationally and 14.3% for California households. These rates are comparable to other consumer reference datasets, which generally exhibit undercoverage between 10% and 20% (Asquith et al., 2023; Mast, 2021). Prior academic studies that have used the InfoUSA/DataAxle dataset include Greenlee (2019); Baker et al. (2021); Wang et al. (2024); Pan et al. (2020).

[5]See, for example, Diamond et al. (2019); Ling et al. (2019); Mast (2021); Downes et al. (2022); Phillips (2020).

2010 census tract. From this vector of posterior probabilities, I identify the race with highest probability and use it as the imputed race/ethnicity of the head of household. Using this method, I impute the race/ethnicity of 99 percent of individuals in my analysis sample.[6]

In addition to the imputed race and ethnicity categories, I am interested in the types of neighborhoods that migrants move from and into. To approximate neighborhood quality, I use the median household income of census tracts from the 2009–2013 American Community Survey for both origin and destination tracts. By examining the median income of origin and destination tracts, I explore the types of neighborhoods that in-migrants move from and whether incumbent residents are being displaced to lower-income neighborhoods. I collect the median income levels for both origin and destination tracts from American Community Survey 2009–2013.

Lastly, to analyze the impact of upzoning on the business environment, I use business license data published by the Office of Finance Department on the City of Los Angeles Open Data Portal, which provides detailed records of active and closed businesses over time. These data allow me to track openings, closures, and shifts in industry composition via NAICS codes. By incorporating this dataset in the analysis, the study offers an assessment of how zoning reforms affect not only residential outcomes but also neighborhood-level commercial dynamics.

4.2 Sample Characteristics

In this section, I examine the differences in parcel-level housing characteristics and census block-level demographic attributes between areas inside and outside TOC boundaries, prior to the zoning change. Documenting these differences provides important context for interpreting the results, offering deeper insight into how zoning changes influence development, neighborhood dynamics, and patterns of residential mobility. I also compare in- and out-migration patterns within and outside TOC boundaries; however, these results are discussed in detail in Appendix A.4. For the summary statistics, I focus on data from 2015, as it is the year preceding the passing of the zoning policy, providing a clear view of these patterns without the potential anticipation and direct impacts of the policy.

Table 1 shows the comparison in parcel characteristics between TOC and non-TOC areas. Parcels within TOC boundaries have, on average, a larger number of units (2.6 units per parcel) and a smaller square footage per unit (1,314 square feet), compared to non-TOC properties, which have 1.5 units and a mean size of 1,757 square feet per unit. This difference in unit count and size suggests that TOC parcels are designed to accommodate higher density, which aligns with the objective of TOC policy aimed at increasing housing

[6] Imai and Khanna (2016) report a false-positive rate below 3% for Latino registrants and below 6% for African American registrants, while maintaining true positive rates above 80%. A more detailed explanation of the method, along with additional validation exercises, can be found in Appendix A.3

supply in transit-rich areas. Additionally, the average sale price within TOC parcels is slightly lower than that of parcels outside, potentially reflecting differences in development intensity or housing demand.

I also compare the demographic characteristics at the block level for census blocks within and outside of TOC boundaries, as shown in Table 2. Consistent with the housing characteristics, this table also suggests that the TOC blocks are denser, as they accommodate more households on average.In TOC areas, a significantly higher share of householders are Black and Hispanic, at 15.7 percent and 43 percent, respectively, compared to non-TOC areas, where Black householders constitute just 5.3 percent and Hispanic households 36 percent. In contrast, non-TOC areas are predominantly White, with 48.4 percent of the householders identified as non-Hispanic White, compared to 30.7 percent in TOC blocks. These demographic patterns indicate that TOC areas are more racially diverse compared to the non-TOC areas.

Table 2: Parcel Characteristics

Panel 1: Parcels in TOC Boundaries	Number of Observations	Mean	SD
Number of Units	298,898	2.6	9.0
Sqft per Unit	292,783	1,314.1	759.8
Sale Price (in dollars)	28,620	687,907.5	2,998,669.0
Panel 2: Parcels outside TOC Boundaries	Number of Observations	Mean	SD
Number of Units	426,242	1.5	5.0
Sqft per Unit	422,964	1,757.3	1,079.5
Sale Price (in dollars)	39,954	722,718.2	1,480,112.3

Note: The table presents the parcel characteristics for the year 2015. The changes in the number of observations are due to missing values for specific variables. For instance, the number of observations for sale price is substantially lower because only 28,620 sales occurred within TOC parcels in 2015.

Table 3: Census Block Characteristics

Panel 1: Blocks in TOC Boundaries	Number of Observations	Mean	SD
Number of Households	7,197	85.5	88.4
API Householder Share	7,197	9.4	12.9
Black/AA Householder Share	7,197	15.7	23.8
Hispanic Householder Share	7,197	43.0	29.1
White Householders Share	7,197	30.7	30.5
Panel 2: Blocks outside TOC Boundaries	Number of Observations	Mean	SD
Number of Households	7,493	75.2	84.0
API Householder Share	7,493	8.5	8.2
Black/AA Householder Share	7,493	5.3	15.8
Hispanic Householder Share	7,493	36.0	28.1
White Householders Share	7,493	48.4	29.1

Note: The table presents the census block characteristics for the year 2015. Shares indicate the percentage of total households that have a householder belonging to each racial/ethnic group. API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders.

5 Econometric Framework

5.1 Baseline Methodology

To estimate the effects of the TOC program, I use an event study framework that leverages geographic and temporal variations to compare outcomes in upzoned areas to those in areas not exposed to the zoning policy. A key concern in this analysis is the potential presence of spillover effects in neighboring areas, which could bias the estimated impacts if not properly accounted for.

Evaluating the effects of place-based policies is challenging due to potential violations of the stable unit treatment value assumption (SUTVA). Since land use policies shape the density and types of developments, their influence often extends beyond the directly targeted zones to nearby areas. Thus, these policies not only affect the treated zones but can also have significant effects on adjacent neighborhoods.

Although this topic has not been extensively studied, existing research suggests that easing land use restrictions in one area can either hinder or promote development in neighboring locations, depending on developers' responses (Freemark, 2020; Greenaway-McGrevy and Phillips, 2023). For instance, developers may prefer to build in upzoned areas where regulations are less stringent, potentially decreasing construction in surrounding regions and leading to positively biased estimates. Conversely, increased development in treated areas could encourage further development nearby, resulting in negatively biased estimates.

To account for potential spillovers, I implement a modification to the standard difference-in-differences approach proposed by Clarke (2017) and Butts (2021). Their method involves designating untreated areas located within a certain distance, 2 miles in this case, from the boundaries of the treated area as spillover areas, while locations beyond this distance serve as the reference group.[7] This approach ensures that the estimates remain unbiased, provided there are no spillover effects in the furthest distance category. In particular, I estimate the following equation for housing market outcomes (where the unit of observation is parcels) and neighborhood composition outcomes (where the unit of observation is census blocks):

$$\begin{aligned} y_{it} = \delta_i + \gamma_t + &\sum_{k=2013, k\neq 2016}^{2021} \beta_k (NearMTS_i \times Year_k) \\ &+ \sum_{m=1}^{2} \sum_{k=2013, k\neq 2016}^{2021} \theta_k^m (SpilloverArea_i^m \times Year_k) + \varepsilon_{it} \end{aligned} \tag{1}$$

where y_{it} is the outcome for parcel (or block) i in year t, δ_i represents parcel (or block) fixed effects, and

[7] Diamond and McQuade (2019) find that the spillover effects of new housing supply, specifically Low-Income Housing Tax Credit (LIHTC) developments, are highly localized. Their research indicates that house prices located just 0.3 to 0.4 miles away may take 5 to 10 years to fully adjust to the impacts of such developments. Considering these findings, a 2-mile spillover area should be more than sufficient to control for the potential spillover effects.

γ_t is year fixed effects. The variable $NearMTS_i$ is an indicator variable that equals 1 if parcel (or block) i is within 0.5 miles to a major transit stop, corresponding to a TOC area in the City of Los Angeles. $Year_k$ captures the year dummy variables. $SpilloverArea_i^m$ is a binary variable equal to 1 for untreated parcels (or blocks) within spillover areas. These areas are categorized into three distance bands: 0-1 mile ($m = 1$), and 1-2 miles ($m = 2$) from the TOC boundaries. The interaction term $SpilloverArea_i^m \times Year_k$ allows the spillover effects to vary over time and by distance. Here, β_k measures the effect of the policy in treated areas for each year, while θ_k^m captures the spillover effects for neighboring parcels across the study period for each distance category.

The outcomes of interest include housing market variables, such as the number of housing units, square footage per unit, and sale price, as well as neighborhood composition outcomes, such as the racial and ethnic composition of in-migrants and out-migrants, and the median household income in origin and destination tracts for in-migrants and out-migrants. Standard errors are clustered at the level of the nearest major transit stop to account for similarities among observations near the same stop, as the treatment is defined relative to these transit stop locations. The key assumption needed for the identification strategy is the parallel trends assumption, which requires that, in the absence of the treatment, the introduction of zoning relaxation, the evolution of outcomes for both treated and control units would have followed a similar path. In other words, to interpret the results as causal, there must be no parcel-specific time-varying shocks that are correlated with both the upzoning implementation and housing market outcomes, nor any block-specific time-varying shocks correlated with upzoning and neighborhood composition outcomes.

While the parallel trends assumption cannot be directly tested, observing statistically insignificant point estimates for β_k where $k < 2016$ suggests a common trend in outcomes across treated and control areas prior to the policy change. Conversely, β_k where $k \geq 2017$ captures the average treatment effect (ATT) for each year following the implementation of the TOC program.

5.2 Triple Difference-in-Differences

The baseline analysis uses a standard difference-in-differences approach with treated and control areas within the City of Los Angeles to estimate the impact of the TOC program on housing and demographic outcomes. Using only parcels within the City of Los Angeles is particularly helpful because treated and untreated parcels are more comparable in terms of administrative regulations, geographic context, and demographic characteristics. Nonetheless, to ensure that the observed treatment effects are not driven by confounding factors or differential trends across the treatment and control groups, I also employ a triple difference-in-differences approach.

While a standard differences-in-differences strategy controls for time-invariant differences between treated and control units, it assumes that both groups would have followed the same trends in the absence of treatment. However, this assumption may be violated if there are unobserved shocks, policy changes, or other external factors that disproportionately impact either group. For example, other zoning changes or citywide housing policies could affect treated and control units differently, making it challenging to attribute observed changes solely to the TOC program.

The triple differences approach addresses this concern by incorporating a third group, which is not exposed to the TOC policy and is not influenced by the city-level changes: other cities in Los Angeles County. This setup allows for controlling not only for differences between treated and control units but also for any differential effects driven by citywide shocks or concurrent policy interventions. This framework exploits differences across (1) areas within 0.5 miles of a major transit stop versus those located more than 0.5 miles away, (2) the time periods before and after the policy change, and (3) the City of Los Angeles in relation to other jurisdictions in Los Angeles County that did not receive any treatment. By comparing across these dimensions, the triple differences strategy helps account for any citywide trends or shocks that could have simultaneously affected treated and control areas, thereby isolating the true causal effect of the zoning reform. This approach offers a more nuanced and robust identification strategy by ensuring that any observed impacts on housing and neighborhood outcomes are attributable to the policy intervention, rather than other concurrent policy changes, external shocks, or differential trends affecting the treatment and control groups independently.

For the triple differences specification, I estimate the following equation:

$$\begin{aligned} y_{it} = \delta_i + \gamma_t &+ \sum_{k=2013, k\neq 2016}^{2021} \alpha_k (NearMTS_i \times Year_k) \\ &+ \sum_{k=2013, k\neq 2016}^{2021} \mu_k (CityLA_i \times Year_k) \\ &+ \sum_{k=2013, k\neq 2016}^{2021} \beta_k (NearMTS_i \times CityLA_i \times Year_k) \\ &+ \sum_{m=1}^{2} \sum_{k=2013, k\neq 2016}^{2021} \theta_k^m (SpilloverArea_i^m \times Year_k) + \varepsilon_{it} \end{aligned} \tag{2}$$

where $CityLA_i$ is an indicator variable for whether a parcel (or block) is located within the City of Los Angeles; and all other variables are defined as in Equation 1. In this equation, β_k is the parameter of interest, capturing the ATT for the years following the implementation of the TOC program. This parameter can also be used to test whether the parallel trends assumption holds by examining the years prior to the program's introduction. The assumption needed for this identification strategy is similar to the one needed for the traditional difference-in-differences, where the parallel trends assumption must hold. Specifically, the parallel trends assumption must apply to the triple interaction term, ensuring that treated and control units would have followed a similar path over time in the absence of the TOC program.

6 Results

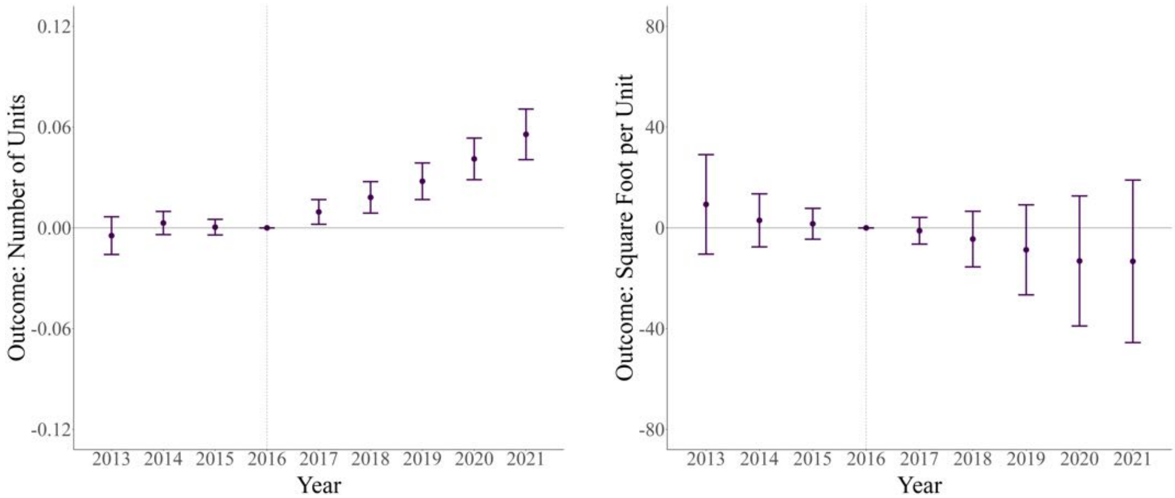
6.1 Baseline Results

This section presents the baseline findings on the impact of the TOC program on housing market and demographic composition. The event study framework is used to formally test whether the parallel trends assumption is violated and to analyze how the effect of upzoning evolves over time. For the parallel trends assumption to be valid, the estimated coefficients for the pre-treatment period (2015 and earlier) should not be statistically different from zero. I check this by examining the point estimates in the pre-treatment period, as shown in all event study figures. If there is no systematic pattern of significance in these coefficients, it suggests that the parallel trends assumption is satisfied.

Reviewing the event study plots, there is no consistently significant trends for any of the outcomes prior to treatment, indicating that the evolution of outcomes in the treatment and control parcels was comparable in the absence of the policy, conditional on the controls.

6.1.1 Housing Market

After establishing that the parallel trends assumption is not violated, the findings can be interpreted as causal relationships. Figure 4 and Figure 5 demonstrate the impact of the policy on housing market outcomes. Panel A in Figure 4 displays the effect on the number of housing units per parcel. By 2021, four years after the policy was implemented, TOC areas experience a cumulative increase in total housing units per parcel relative to the control group—an average of 0.06 additional units, or about 2 percent based on a mean of 2.6 units per parcel. This increase could result from new construction or conversions of existing structures into additional units. Extrapolating the average effect of 0.06 additional units per parcel to the full set of treated parcels implies that the TOC program resulted in the production of approximately 17,934 housing units by 2021. On the other hand, Panel B in Figure 4 shows that the square footage per unit does not change significantly following the policy, though there is a slight, insignificant decrease in point estimates over time.



(A) Number of Housing Units

(B) Square Footage Per Unit

Figure 4: Housing Development Outcomes

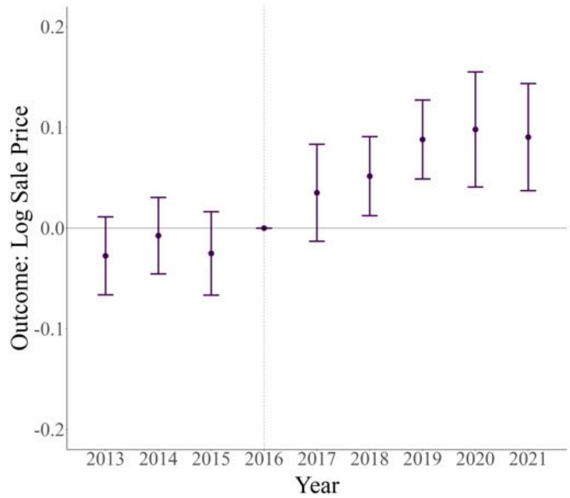
Note: Figure 4 plots the β_k event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are the number of units (Panel A), and square footage per unit (Panel B). The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include parcel and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

I also examine the changes in house prices in response to the zoning change. For this outcome, I adopt a more sparse specification that uses block fixed effects instead of parcel fixed effects. This choice is motivated by data limitations: to measure market prices rather than assessed values, I restrict the sample to properties that transact.[8] However, because many parcels are not sold repeatedly, including parcel fixed effects would limit identification to a selected subset of parcels with frequent transactions. By using block fixed effects, the identification comes from changes over time in transacted properties within similar neighborhoods, rather than from the exact parcel.

Figure 5 shows a consistent and substantial increase in house prices, up to 10 percent, in TOC areas following the zoning change. Given the mean house price in treated areas, this translates to an average increase of approximately $68,790. This result is somewhat surprising, as an increase in housing supply would typically be expected to reduce, not raise, prices. In Appendix A.6, I explore whether this increase can be explained by changes in the characteristics or qualities of homes being sold. When I control for house characteristics alone, the effect persists. However, once I interact those characteristics with year dummies, the estimated price effect disappears. This suggests that the policy not only changed the composition of homes on the market, but also shifted how certain features were valued over time.

[8]California's Proposition 13 caps annual increases in assessed values at 2 percent, except upon sale or substantial improvement. As a result, assessed values often differ significantly from market values, depending on the timing of the last transaction or construction. Restricting the sample to transacted properties ensures that the outcome accurately reflects current market conditions.

For example, a single-family home with 1,500 square feet may have transacted at a certain price level before the policy. But after the TOC program was implemented, that same home might be seen as more valuable—not because it physically changed, but because buyers now see potential to convert part of it into an additional unit. In this case, the observed price increase reflects a shift in the housing market tied to the policy environment. The interaction of housing characteristics with year dummies captures this change in valuation, helping to explain the upward trend in prices even as supply increases.[9]



(A) Sale Price

Figure 5: House Price Outcome
Note: Figure 5 plots the β_k event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variable is the log sale price (Panel A). The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

There are two important considerations when using transacted parcels to estimate price effects. First, transaction activity may be endogenous if treated parcels are systematically more or less likely to sell following the policy change. To assess this, I look at whether the probability of sale changes after the policy. In Appendix A.5, I show that treated parcels are no more or less likely to transact than control parcels in the years before 2021, which supports a causal interpretation of the price effects during that period. However, by 2021, treated parcels become significantly less likely to transact, indicating potential selection in the later period. As such, the price estimates, particularly for 2021, should be interpreted with caution and may not fully reflect causal effects.

Second, even if the likelihood of sale remains stable, the composition of transacted properties may change over time. I do not control for time-varying property characteristics in the baseline regressions, as many of

[9] Additional analyses using American Community Survey (ACS) data support several of the observed patterns in housing market outcomes, including increases in house prices and rents. While some point estimates differ in precision or magnitude, the overall direction of effects is consistent. Appendix A.10 provides further discussion.

these attributes (e.g., number of bedrooms or owner occupancy) are themselves potential outcomes of interest. Including them would introduce bias by conditioning on variables affected by the treatment. Nevertheless, changes in property characteristics may partially explain the observed price effects. In Appendix A.6, I test whether the price increases are driven by compositional shifts in the types of properties being sold. Price effects remain after adding static property controls but attenuate with year interacted controls, suggesting shifts in how certain property characteristics are valued under the new zoning.

6.1.2 Housing Market: Heterogeneous Effects by Development History

To better understand the sources of the observed development and price effects, I conduct a heterogeneous effects analysis by prior permit history. This test aims to assess whether the estimated changes in housing outcomes are concentrated in areas with different baseline development patterns. To do so, I estimate a triple-interaction event study specification that allows treatment effects to vary by local development context:

$$\begin{aligned} y_{it} = \delta_i + \gamma_t + &\sum_{k=2013, k\neq 2016}^{2021} \beta_k \left(NearMTS_i \times Year_k \times I(PriorDevelopment_i) \right) \\ + &\sum_{m=1}^{2} \sum_{k=2013, k\neq 2016}^{2021} \theta_k^m \left(SpilloverArea_i^m \times Year_k \right) + \varepsilon_{it} \end{aligned} \tag{3}$$

where y_{it} is the housing outcome of interest for parcel i in year t. The main coefficients of interest, β_k, capture year-specific effects of the policy, interacted with an indicator for being near a major transit stop and in an area with either high permitting activity before the policy or high housing supply elasticity, depending on the analysis. The term $I(PriorDevelopment_i)$ equals one for parcels located in blocks that had above-median permitting activity between 2013 and 2017 in the first analysis.[10] The year 2016 is normalized to zero. All regressions include parcel (or block for house prices) and year fixed effects, and standard errors are clustered at the level of the nearest major transit stop.

To examine heterogeneity by prior development intensity, I use permitting activity between 2013 and 2017 to classify blocks as either high- or low-development blocks. This proxy captures where developers were already active before the policy took effect. As shown in Figure 6, treatment effects differ meaningfully across these groups. First, Panel A shows that in high-permit blocks, the number of housing units rises immediately

[10] In Appendix A.11, I present a complementary analysis that replaces baseline development patterns with tract-level housing supply elasticity estimates from Baum-Snow and Han (2024). Tracts are classified as above- or below-median elasticity using the 2011 quadratic finite mixture model (FMM) specification. While this provides a useful exercise, the block-level permitting measure in the main text is more granular and conceptually stronger, as it captures realized development activity and within-tract heterogeneity that tract-level indices may obscure.

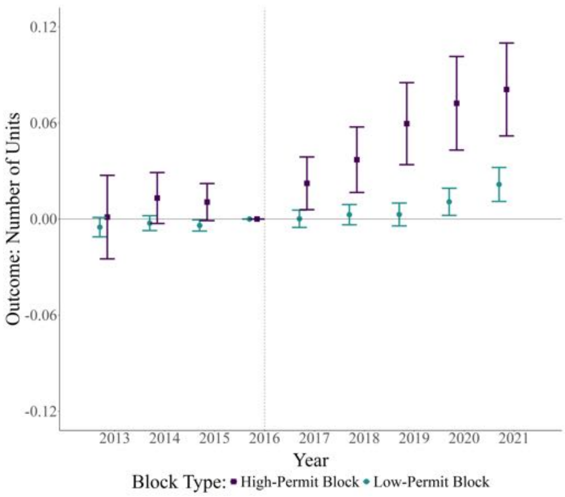
following the policy implementation, and the growth rate continues to outpace that in low-permit blocks. In contrast, new development in low-permit areas emerges later and at a slower pace. Second, Panel B indicates that the additional units in high-permit blocks tend to be smaller, consistent with a shift toward higher-density construction. Finally, Panel C reveals an asymmetry in price dynamics: house prices increase more sharply in low-permit blocks, while price reductions are visible primarily in high-permit blocks where new construction occurs.

This timing is consistent with the option value theory of land markets. In areas where development was not previously active, the zoning change raised expectations about the future profitability of redevelopment, which was capitalized into higher land prices even before substantial new supply was built. By contrast, in places where construction actually accelerated, the supply response began to dampen prices. In other words, appreciation appeared first where the option value of redevelopment increased, while price reductions followed in areas where the new supply was realized.

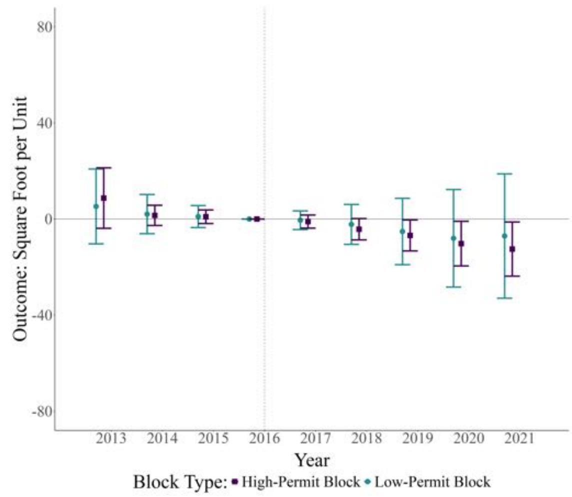
6.1.3 Housing Market: Spillover Effects

Upzoning policies can generate not only direct effects within the areas where zoning changes are implemented but also indirect spillover effects in surrounding neighborhoods. To capture the broader impact of the TOC policy on housing markets, I examine how outcomes such as housing construction and prices evolve in areas just outside the treated zones. Specifically, I estimate effects within a 2-mile radius beyond the TOC boundaries, allowing for a more comprehensive view of how policy-induced development pressure may extend into nearby areas.

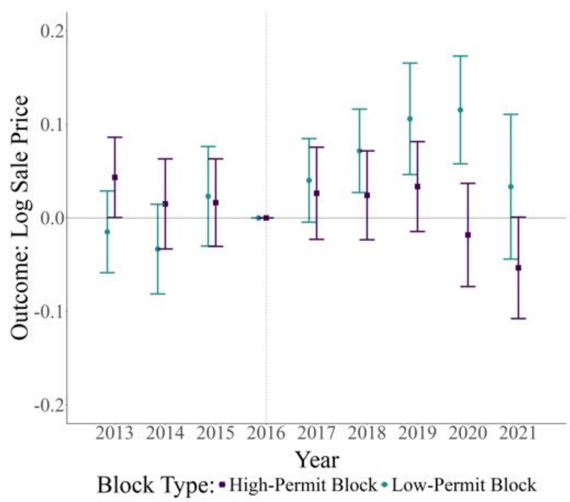
Panel A in Figure 7 illustrates how the number of housing units changes in areas surrounding the TOC zones, using 1-mile distance thresholds. The results show a delayed, statistically significant, and positive impact of the policy on the number of units within 0-1 mile outside the TOC boundaries. The size of the effect is about fifteen percent of what is observed in the TOC zones themselves, suggesting modest but still meaningful development right outside of the TOC boundaries. To translate into numbers, by 2021, the number of units increases by roughly 0.01 per parcel, translating to around 2,600 additional units across the 260,676 parcels in this spillover area. Beyond 1 mile, the effect becomes indistinguishable from zero. Panel B examines square footage and finds no meaningful changes in unit size in nearby untreated areas. Panel C shows a slight increase in sales prices within the 0–1 mile band, though the effect is somewhat noisy. Overall, the results suggest some spillover in construction and prices immediately outside the treated areas, but the effects are highly localized.



(A) Number of Housing Units



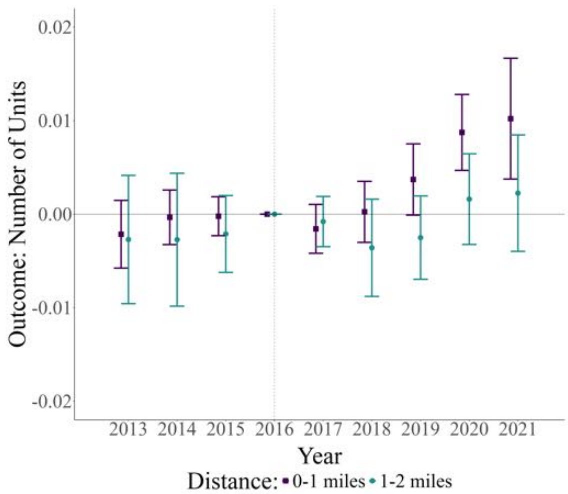
(B) Square Footage Per Unit



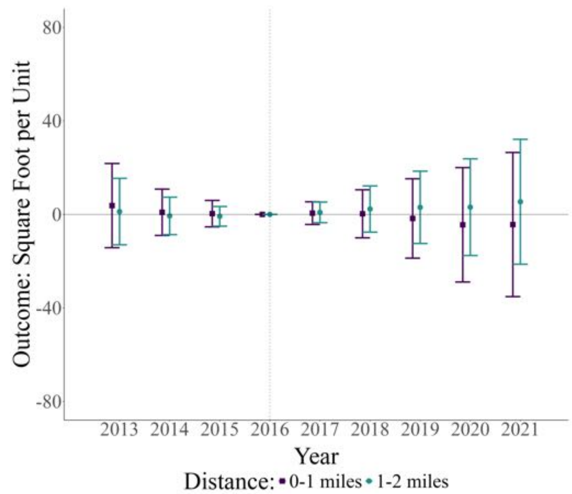
(C) Log Sale Price

Figure 6: Housing Market Outcomes by Prior Development Intensity

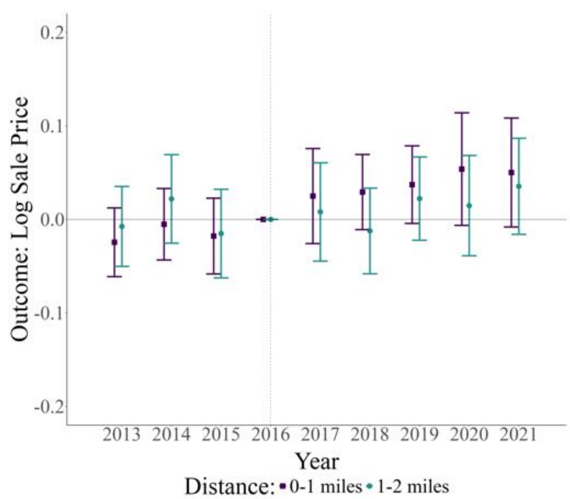
Note: Figure 6 plots the β_k event study coefficients estimated from a regression of the form given in Equation 3, where the dependent variables are the number of units (Panel A), square footage per unit (Panel B), and log sale price (Panel C). High-permit blocks are defined as those with above-median permitting activity between 2013 and 2017; low-permit blocks fall below the median. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include parcel (or block for house prices) and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.



(A) Number of Housing Units



(B) Square Footage Per Unit



(C) Log Sale Price

Figure 7: Spillover Effects by Distance to TOC Boundaries: Housing Market Outcomes

Note: Figure 7 plots the θ_k^m event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are the number of units (Panel A), square footage per unit (Panel B), and log sale price (Panel C). The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include parcel (or block for house prices) and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

6.1.4 Neighborhood Demographics

The next question that arises is: Who moves into the new housing units? To address this question, I use the same event study framework used for housing market outcomes, but now focusing on demographic changes at the block level. I now define treated blocks as those where at least 50 percent of the area falls within the treatment boundary. I compare migration patterns in these blocks to those in adjacent untreated blocks and to the broader reference group. Additionally, for this analysis, I focus on the subset of households for which I have detailed migration information to analyze in-migrant and out-migrant characteristics. Specifically, I limit the sample to in-migrant households where I can identify their previous location and out-migrant households where I know their future destination. This approach allows me to analyze the characteristics of the tracts migrants are moving to and from, and to better understand the migration patterns that drive changes in neighborhood composition. Figure 8 shows the results.

Panels A and B of Figure 8 provide a detailed breakdown of in-migrant and out-migrant households by race and ethnicity. Panel A indicates that following the implementation of the TOC program, a larger proportion of in-migrant households are non-Hispanic White, up to a 5 percentage point increase in 2019, while there is no consistent pattern for other race and ethnicity groups. On the other hand, Panel B does not show any clear or consistent pattern in the racial or ethnic composition of households moving out of the TOC blocks after the zoning changes, suggesting that the demographic shifts are primarily driven by changes in in-migration.

While data on household income are not available, analyzing the characteristics of the origin tracts can provide insight into the types of households moving into the treated areas, and examining the destination tracts can indicate whether displacement may be occurring. Panels C and D in Figure 8 present the origin and destination tract characteristics of migrant households to explore potential shifts in the incomes of residents. For instance, if the median household income of the origin tracts is higher for in-migrants after the zoning relaxation, this could imply that the new housing units are attracting higher-income households. Conversely, if the median household income of the destination tracts is lower for out-migrants, it might suggest that existing households are being pushed out to lower-income areas, or that the moves are involuntary. Addressing these patterns is important, as new construction and zoning reforms often raise concerns about attracting higher-income residents and potentially displacing incumbent residents.

Panel C and Panel D in Figure 8 show that concerns about displacement may not be strongly substantiated in the context of Los Angeles. Panel C shows that in-migrant households in TOC areas come from tracts with similar median household incomes as those of in-migrants in the control group. In contrast, Panel D shows that TOC out-migrant households tend to relocate to tracts with slightly higher median incomes, up to seven percent, compared to out-migrants from control blocks after the policy implementation. Therefore, while in-migrant households to TOC neighborhoods come from tracts with comparable income levels as before the policy, out-migrants tend to move to higher-income tracts, suggesting no evidence of displacement. If anything, the positive point estimate may reflect selective out-migration among higher-income households, potentially motivated by a preference for lower-density neighborhoods.[11]

These results indicate that while the zoning change stimulates demographic shifts, these changes are primarily driven by an increase in the non-Hispanic White population. The findings also suggest that the TOC program has not resulted in a significant outflow of minority residents from the treated areas, challenging common concerns related to displacement. Instead, the evidence suggests that existing communities are remaining in place, even as the demographic composition evolves.[12]

6.1.5 Neighborhood Demographics: Spillover Effects

Similar to housing outcomes, demographic shifts resulting from upzoning may extend beyond the immediate boundaries of treated areas. To assess these potential spillover effects, I analyze changes in racial and ethnic composition, incomes, and migration patterns within a 2-mile radius of the TOC zones. This analysis complements the main findings by illustrating whether neighborhood change also occurs in nearby neighborhoods or remains localized in the directly treated areas. While I focus on the outcomes that show notable patterns, event studies for all outcomes are reported in Appendix A.8.

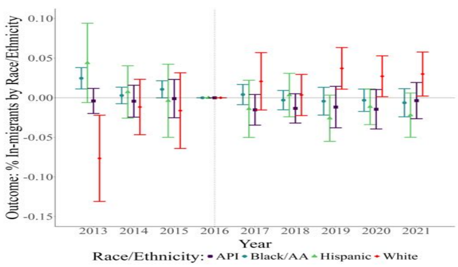
Figure 9 Panel A shows shows that the share of White in-migrants moving into the spillover areas does not change following the policy implementation. Panel B shows a similar pattern to the direct effects in the nearest spillover area, where out-migrants are more likely to relocate to tracts with higher median incomes. As both the treated and nearby spillover areas become denser, it is plausible that households with greater resources and a stronger aversion to density are among the first to move. I report additional migration outcomes in Appendix A.8, which show no statistically significant effects in the spillover areas.

6.1.6 Neighborhood Demographics: Using ACS Data

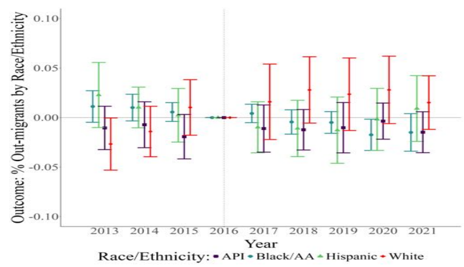
To complement the main analysis, I draw on an alternative, publicly available dataset that provides information on age and income. Although the unrestricted version of the ACS data are only available at the block group level and reported in five-year averages, they add an important dimension for understanding

[11] To examine owner–renter differences, I compare these groups in Appendix A.12 and find that the positive effects are driven by owner-occupant outmigrants, while renters do not move to lower-income neighborhoods (point estimates are small and statistically insignificant).

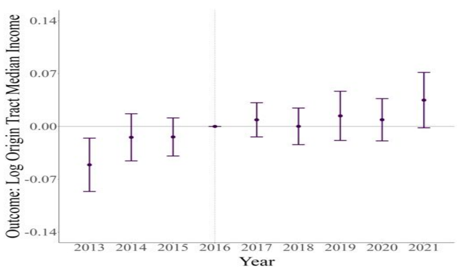
[12] Additional analyses using American Community Survey (ACS) data reinforce many of the findings on neighborhood demographic change, including increases in the non-Hispanic White population and minimal changes among other groups. Differences in magnitude and statistical significance are discussed in Appendix A.10.



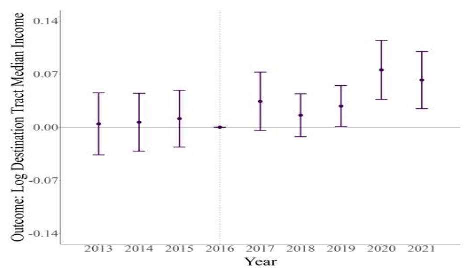
(A) In-migrant Households Race and Ethnicity Share



(B) Out-migrant Households Race and Ethnicity Share



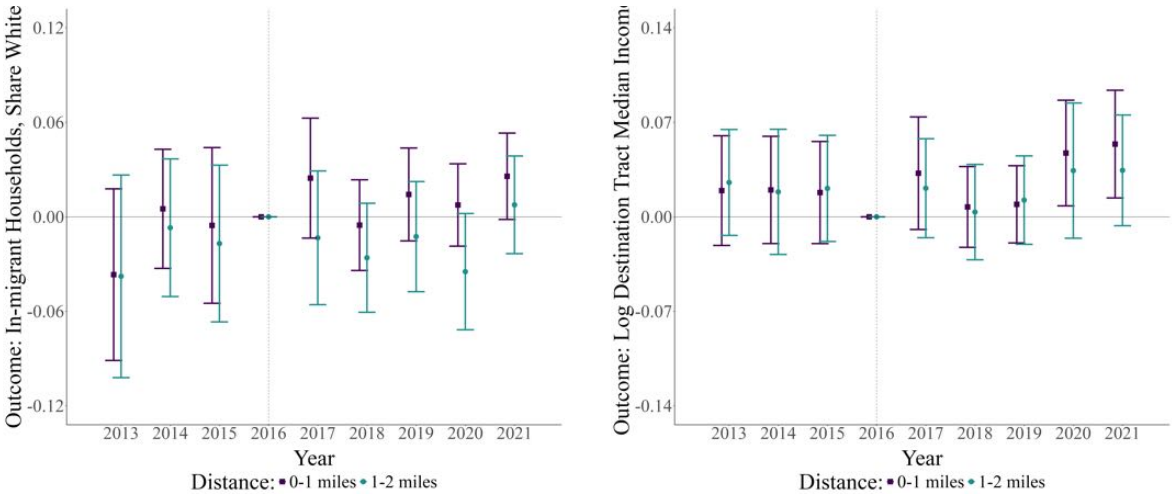
(C) Origin Tract Median Household Income of In-migrants



(D) Destination Tract Median Household Income of Out-migrants

Figure 8: Population Change Outcomes

Note: Figure 8 plots the β_k event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are the racial and ethnic composition of in-migrant households (Panel A), the racial and ethnic composition of out-migrant households (Panel B), the origin tract median household income for in-migrant households (Panel C), and the destination tract median household income for out-migrant households (Panel D). In Panels A and B, API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.



(A) Share of non-Hispanic White In-migrants

(B) Destination Tract Median Household Income of In-migrants

Figure 9: Spillover Effects by Distance to TOC Boundaries: Population Change Outcomes

Note: Figure 9 plots the θ_k^m event study coefficients estimated from a regression of the form given in Equation 1, where the variables are the share of non-Hispanic White in-migrants (Panel A), and the destination tract median household income for out-migrant households (Panel B). The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

how neighborhood demographic characteristics change. I estimate a standard difference-in-differences model using 5-year ACS averages for the pre-policy period (2012–2016) and the post-policy period (2018–2022):

$$y_{bt} = \delta_b + \gamma_t + \beta_1(\text{NearMTS}b \times \text{Post}t) + \beta_2(\text{Spillover0–1}, b \times \text{Post}t) + \beta_3(\text{Spillover1–2}, b \times \text{Post}t) + \varepsilon_{bt} \quad (4)$$

where y_{bt} is the outcome of interest for block group b in period t, $NearMTS_b$ is an indicator equal to 1 if the majority of parcels in block group b fall within the TOC area, and $Post_t$ is an indicator for the post-policy period (2018–2022). The term δ_b captures block group fixed effects, and γ_t captures year fixed effects. Standard errors are clustered at the level of the nearest major transit stop.

Since ACS data are reported at the block group level, treatment assignment in mixed or border areas may be noisy, and the estimates should be interpreted cautiously. The goal of this exercise is not to recover precise treatment effects but to explore broader patterns in demographic change, particularly along dimensions such as age, education level, and income that are not well captured in the microdata.

The results, reported in Table 4, indicate that treated block groups experienced a decline in average age, suggesting an influx of younger residents.[13] They also show modest increases in the share of college-educated

[13] I also look at the ages of in-migrants and out-migrants using the consumer data in Appendix A.7, where I find that the

residents. Finally, the ACS results suggest increases in median household income in TOC areas. While the baseline analysis indicates that in-migrants tend to come from neighborhoods with similar median incomes as earlier movers, ACS data provide a more direct measure and points to rising household income levels within TOC neighborhoods.

Table 4: Effect of TOC Policy on Neighborhood Characteristics

Dependent Variable:	Median Age	Share College Educated	log(Median HH Income)
TOC × Post2017	-4.5***	0.02**	0.11***
	(1.5)	(0.01)	(0.03)
0–1mi × Post2017	-1.2	0.02**	0.04
	(1.6)	(0.01)	(0.03)
1–2mi × Post2017	0.73	0.009	0.03
	(1.5)	(0.010)	(0.03)
Fixed Effects			
Block Group	✓	✓	✓
Year	✓	✓	✓
Fit Statistics			
Observations	5,275	5,276	5,066
R^2	0.95382	0.94652	0.91797

Standard errors are clustered at the level of the nearest major transit stop.

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

average age of in-migrant householders declines following the TOC program, suggesting an influx of younger residents. While I also observe a decline in the age of out-migrants, this trend begins before the policy change, making it difficult to interpret as a causal effect. Overall, the results point to modest demographic turnover driven by younger in-migrants.

6.1.7 Mechanisms: Amenities Channel

Amenities play a central role in shaping neighborhood quality and residential sorting. To assess whether this channel helps explain the effects of the TOC program, I examine changes in the local business environment following the TOC implementation. In particular, I focus on consumption-oriented industries, such as restaurants, retail, and office services, that contribute to the perceived quality of a neighborhood.

Prior research shows that food, cultural, and creative establishments often precede shifts in neighborhood composition and serve as early indicators of gentrification (Behrens et al., 2024). If the TOC program made neighborhoods more desirable—not only by adding new housing but also by improving amenities, one would expect to see increased activity in these sectors. Such a change would also be consistent with the patterns observed in earlier sections, where treated neighborhoods experience higher house prices and an influx of non-Hispanic White households.

To evaluate changes in business activity around TOC zones, I use block-level data on business openings and closures. I disaggregate openings by sector—focusing on restaurants, retail, and office-related services—to assess how commercial composition shifts after upzoning. Closure data, however, contain more limited industry information and do not allow for breakdowns by sector. I estimate:

$$y_{bt} = \delta_b + \gamma_t + \beta_1(\text{NearMTS}_b \times \text{Post}_t) + \beta_2(\text{Spillover}_{0\text{–}1,b} \times \text{Post}_t) + \beta_3(\text{Spillover}_{1\text{–}2,b} \times \text{Post}_t) + \varepsilon_{bt} \quad (5)$$

where y_{bt} is the outcome of interest (e.g., an indicator for any business opening) for block b in year t, NearMTS_b is an indicator for whether the block is in a TOC area, and Post_t indicates the post-policy period. The terms δ_b and γ_t represent block and year fixed effects, and standard errors are clustered at the level of the nearest major transit stop. I consider several outcome variables, including a binary indicator for any new business opening, as well as the number of new openings for restaurants/cafes, retail establishments, and offices or business services. I also look at a binary indicator for any business closing. The binary measures are helpful because they capture whether any commercial activity occurred at all in a given block-year. This is especially useful in lower-density areas where openings and closings are infrequent, and the raw counts may be too sparse or noisy to detect meaningful patterns. Nonetheless, Appendix A.9 presents event study estimates for all outcomes, where I show that there is no evidence of pre-trends in business activity outcomes, supporting the causal interpretation of the point estimates.

Table 5 reports the estimated effects of the TOC policy and its spillovers on the likelihood of a new business opening or closure, along with estimates for industry-specific openings for restaurants/cafes, retail, and office services. Column (1) shows no significant change in the overall likelihood of business openings in treated areas. However, Columns (2) and (3) show statistically significant increases in the number of restaurant and retail openings, suggesting that sectors associated with foot traffic and often viewed as early indicators of gentrification have grown following upzoning. Notably, these increases are concentrated within the treated areas and do not extend to surrounding neighborhoods. By contrast, Column (4) shows a significant decline in the number of new office or business service establishments, possibly reflecting a shift in land use away from commercial activity toward residential or mixed-use development, both within TOC areas and in the 1-mile spillover area. Lastly, Column (5) indicates that businesses located in the TOC areas are less likely to close, which may reflect increased business stability as there is more demand following upzoning, possibly due to higher foot traffic and a larger customer base.

Overall, these findings suggest that the TOC program contributed to a compositional shift in the local business environment, favoring sectors more responsive to increased foot traffic such as restaurants and retail, while reducing office-related activity. These shifts in business activity support the idea that the TOC program made neighborhoods more appealing, which partially explains the observed increases in housing demand, prices, and changes in migration patterns.

Table 5: Effect of TOC Areas and Proximity on Businesses

Dependent Variable:	I(Any Opening) (1)	Restaurant/Cafe (2)	Retail (3)	Office Services (4)	I(Any Closing) (5)
TOC × Post2017	-9.7×10^{-5}	0.010***	0.02***	-0.04***	-0.06***
	(0.009)	(0.003)	(0.006)	(0.008)	(0.01)
0–1mi × Post2017	-0.01	0.0009	0.006	-0.03***	-0.02
	(0.010)	(0.002)	(0.006)	(0.007)	(0.01)
1–2mi × Post2017	-0.02*	-0.0007	0.002	-0.02	-0.007
	(0.01)	(0.002)	(0.007)	(0.01)	(0.01)
Fixed Effects					
Census Block	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
Fit Statistics					
Observations	196,659	196,659	196,659	196,659	196,659
Adjusted R^2	0.25737	0.16457	0.23722	0.36398	0.20501
Dependent variable mean	0.45413	0.02920	0.11706	0.22752	0.38745

Note: Standard errors are clustered at the level of the nearest major transit stop. Approximately 65 percent of business closures are missing NAICS codes, which is why I do not analyze closings by industry.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6.2 Triple Difference-in-Differences Results

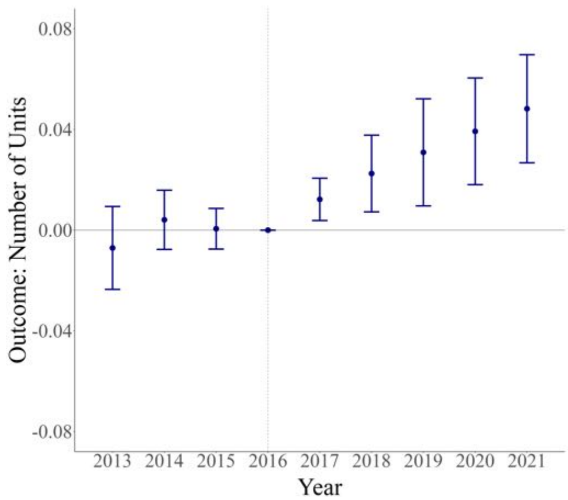
In this section, I analyze the the impact of the TOC program on housing market and demographic composition outcomes using a triple differences approach. This method leverages data from Los Angeles County to exploit additional variations and ensure that the observed effects are not driven by unobserved confounding variables. While the triple differences approach addresses these concerns, expanding the analysis to include other counties could introduce less comparable groups. Thus, I test the parallel trends assumption by examining the β_k coefficients for the pre-treatment period (2015 and earlier) in Equation 2. The results are shown in Figure 10 and Figure 11. If these coefficients do not show a consistent pattern of significance before the policy was implemented, this suggests that the parallel trends assumption is not violated.

Analyzing the event study plots reveals that there are no consistently significant trends for any of the outcomes, besides the origin tract incomes of in-migrants in Panel C in Figure 11. The lack of pre-trends in the remaining outcomes suggest that the outcomes in both the treatment and control parcels evolved similarly in the absence of the policy, after accounting for the controls.

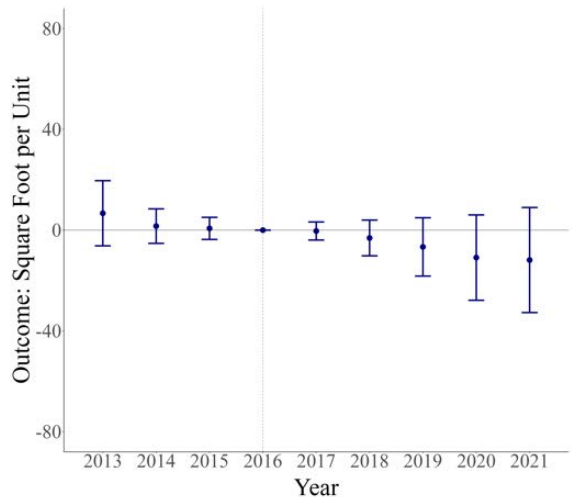
Figure 10 shows the findings for the housing market outcomes. While the direction of point estimates are similar to the baseline results, the point estimates are slightly smaller and more noisy for the triple differences approach. The increased noise in the estimates is expected, as the triple differences methodology aims to reduce bias by accounting for confounding factors, which can inherently lead to larger standard errors compared to the traditional difference-in-differences approach. Additionally, while the size of the point estimates are similar for house price outcome, Panel C, the standard errors become too noisy in triple differences, making the point estimates insignificant. This could highlight increasing price patterns in untreated areas near major transit stops, either due to expectations in these areas also becoming upzoned or increased development interest in areas near transit. This also necessitates caution in interpreting the baseline estimates as causal. Nonetheless, the similar patterns of point estimates with the baseline findings, particularly for the housing development outcome, enhance the reliability of the findings, indicating that the baseline results are robust to the alternative specification.

Panel A of Figure 11 shows an increase in the share of non-Hispanic White householders moving into TOC blocks following the zoning change, consistent with the baseline findings. At the same time, the shares of Asian and Pacific Islander and Hispanic in-migrants show small and noisy declines, with point estimates close to zero. Panel B examines out-migration patterns and finds a slight increase in the share of White out-migrants and a modest decline for Hispanic householders, though again, these estimates are not consistent over time.

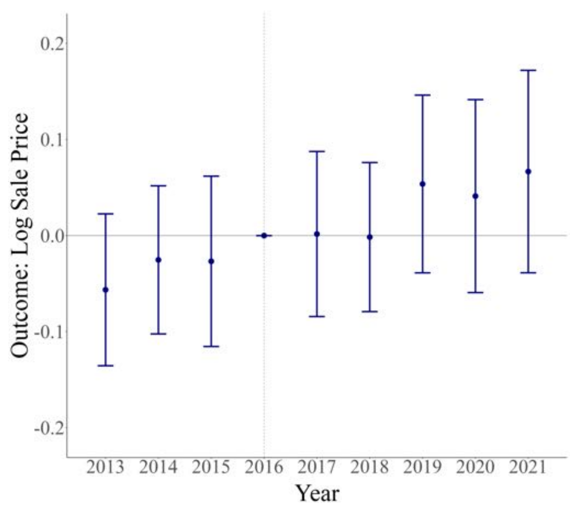
Finally, Panels C and D in Figure 11 present the median household income of the tracts from which in-migrants to TOC blocks come from and the areas into which out-migrants move. In Panel C, while the pre-trends make it difficult to interpret the results for incomes of in-migrants, there seems to be no statistically significant changes in the incomes of the tracts that they come from. In Panel D, I also find that out-migrants are moving into tracts with slightly higher incomes. These findings are consistent the baseline conclusions, suggesting that there is no evidence that the upzoning attracts higher-income households or displaces lower-income residents.



(A) Number of Housing Units



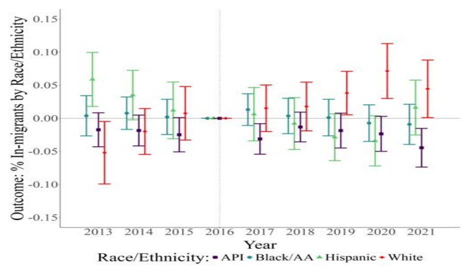
(B) Square Foot Per Unit



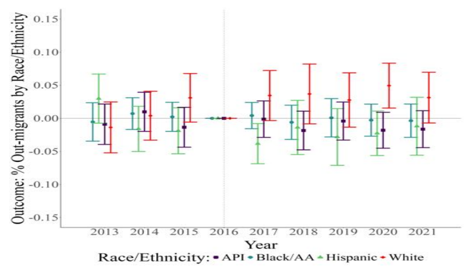
(C) Sale Price

Figure 10: Triple Differences Specification: Housing Market Outcomes

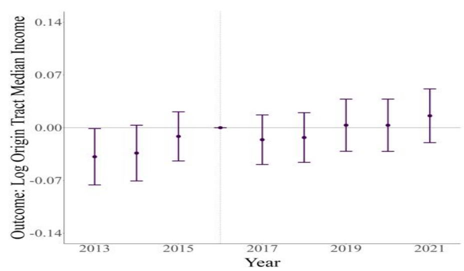
Note: Figure 10 plots the estimated β_k coefficients for the triple interaction term from an event study regression of the form given in equation 2, where the dependent variables are the number of units (Panel A), and the square footage per unit (Panel B). The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include parcel (or block for house prices) and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.



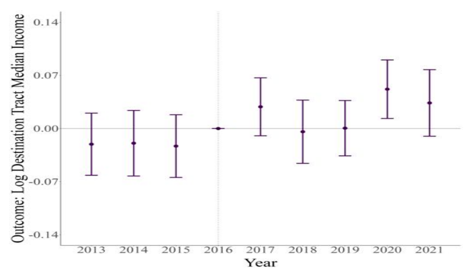
(A) In-migrant Households Race and Ethnicity Share



(B) Out-migrant Households Race and Ethnicity Share



C) Origin Tract Median Household Income of In-migrants



(D) Destination Tract Median Household Income of Out-migrants

Figure 11: Triple Differences Specification: Population Change Outcomes

Note: Figure 11 plots the estimated β_k coefficients for the triple interaction term from an event study regression of the form given in equation 2, where the dependent variables are the racial and ethnic composition of in-migrant households (Panel A), the racial and ethnic composition of out-migrant households (Panel B), the origin tract median household income for in-migrant households (Panel C), and the destination tract median household income for out-migrant households (Panel D). In Panels A and B, API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders. The Hispanic group includes individuals of any race identified as Hispanic. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

6.3 Robustness Check

6.3.1 Dropping Future Treatment Areas

In the main analysis, I define treated areas using the 2017 TOC boundaries. However, some areas in the control group eventually become eligible for TOC incentives as new bus lanes or rail lines are added. These future treatment areas could introduce noise if they start to see spillover effects or if developers begin responding in anticipation of future eligibility.

To test whether these changes affect the results, I drop parcels (or blocks) in the control group that later become treated. These areas make up a relatively small share of the sample—by 2021, about 8% of initially untreated parcels or blocks are later become TOC areas. Figure 12 and Figure 13 show that dropping these areas and re-estimating the models produces results that are very similar to the baseline. This suggests that any contamination from eventual eligibility does not affect the main findings.

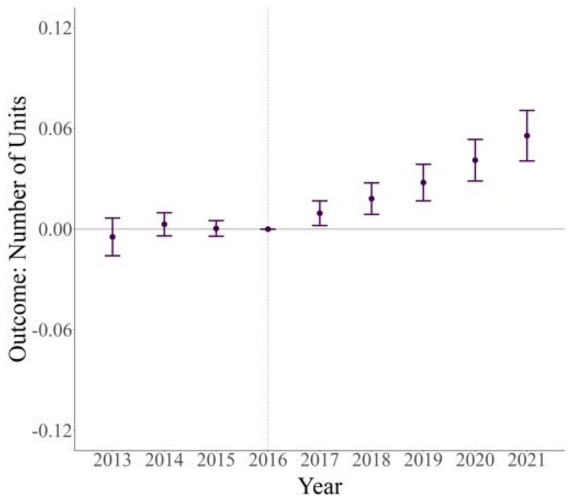
6.3.2 San Fernando Valley Exercise

A large share of the treatment areas under the TOC program are concentrated in central Los Angeles, particularly near Downtown, where the zoning incentives apply across a large set of parcels. However, treatment in the San Fernando Valley, located in the northern portion of the city, is more fragmented, with smaller and more spatially dispersed TOC zones. To test whether the effects of the TOC program are driven primarily by large-scale, contiguous treatment zones like those near Downtown, I re-estimate the core specifications focusing only on the San Fernando Valley.

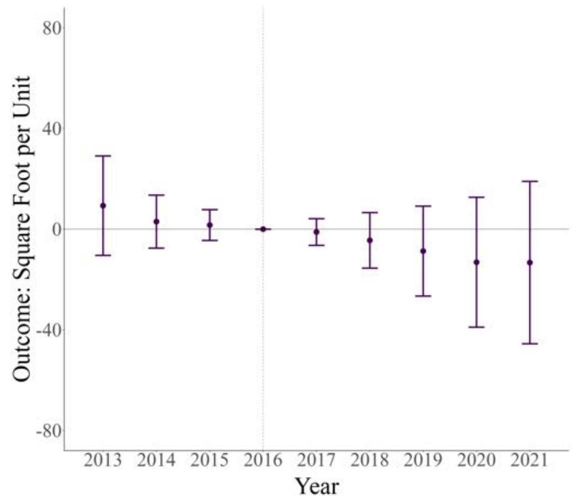
Figure 14 displays the geographic scope of this analysis. The purple-shaded area highlights the San Fernando Valley, and I only use the parcels located within this region in this robustness check. The TOC areas within the Valley are generally more limited in size and less concentrated than those in central LA, making this a useful test of whether the observed effects hold in a less intensely treated environment.

Figure 15 presents the housing market outcomes for the San Fernando Valley subsample. Panel A shows a post-policy increase in the number of housing units in treated areas, though the effects kick in later than in the citywide analysis. Still, by 2021, the magnitude of the effect is similar to the baseline, suggesting that development picks up in the Valley after a short lag. Panel B shows no change in average square footage per unit. Panel C shows a positive trend in log sale prices, similar to the baseline, though with larger standard errors. The price increases also subside by 2021, which could reflect supply catching up to demand.

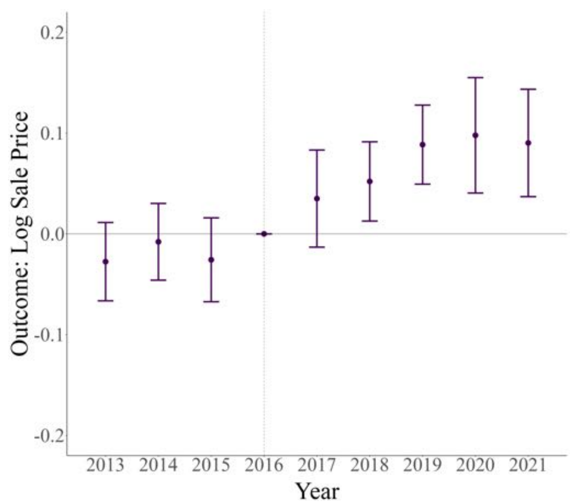
Figure 16 shows the corresponding demographic outcomes. Unlike the citywide results, Panel A shows no increase in the share of in-migrant households who are non-Hispanic White. In fact, the share of Black in-migrants increases slightly following the policy. As in the baseline analysis, Panel B shows no significant



(A) Number of Housing Units



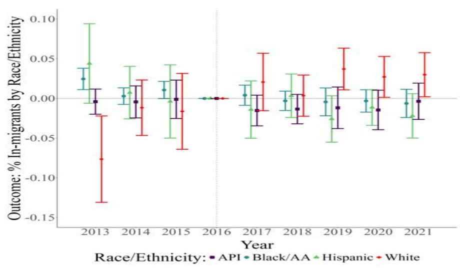
(B) Square Footage Per Unit



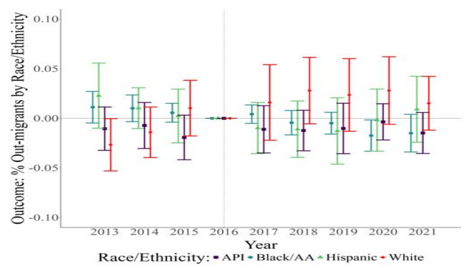
(C) Log Sale Price

Figure 12: Dropping Future Treatment Areas: Housing Market Outcomes

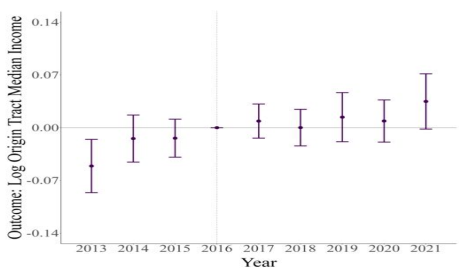
Note: Figure 12 plots the β_k event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are the number of units (Panel A), square footage per unit (Panel B), and log sale price (Panel C). The sample excludes blocks that eventually are treated by the program. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include parcel (or block for house prices) and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.



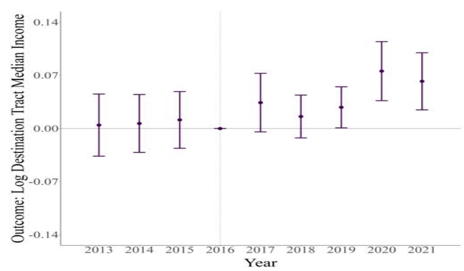
(A) In-migrant Households Race and Ethnicity Share



(B) Out-migrant Households Race and Ethnicity Share



(C) Origin Tract Median Household Income of In-migrants



(D) Destination Tract Median Household Income of Out-migrants

Figure 13: Dropping Future Treatment Areas: Population Change Outcomes

Note: Figure 13 plots the β_k event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are the racial and ethnic composition of in-migrant households (Panel A), the racial and ethnic composition of out-migrant households (Panel B), the origin tract median household income for in-migrant households (Panel C), and the destination tract median household income for out-migrant households (Panel D). The sample excludes blocks that eventually are treated by the program. In Panels A and B, API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

changes in the racial or ethnic composition of out-migrants. Panels C and D show no evidence that in-migrants are coming from higher-income neighborhoods or that out-migrants are moving to more affluent areas. This could reflect the lower overall density and different housing stock in the Valley, which may attract different households and lead to distinct patterns of migration.

Overall, the findings suggest that the effects of the TOC program extend beyond the dense, high-intensity treatment areas near central Los Angeles. Even in a more dispersed context like the San Fernando Valley, the program leads to increased housing supply, rising housing prices—though only in the short run—and changes in demographic characteristics, although in different ways. While the estimates are somewhat noisier, likely due to the smaller scale of treatment and different context, the overall patterns remain consistent with the main results, reinforcing the robustness of the broader findings.

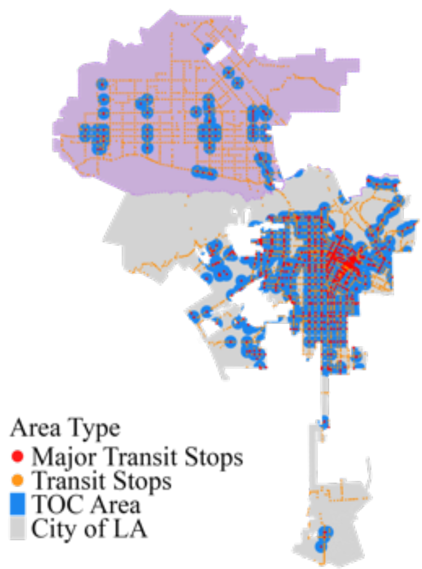
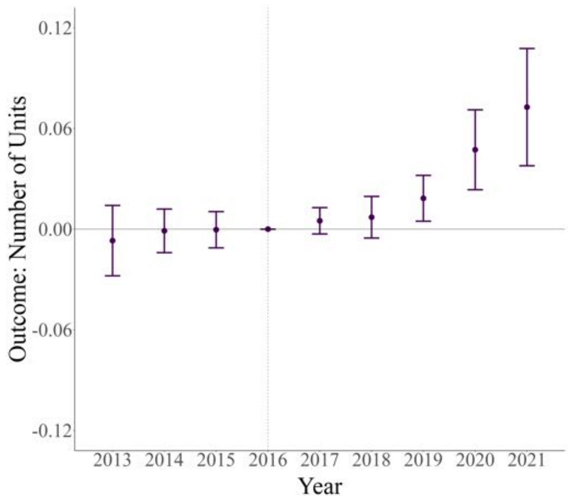


Figure 14: San Fernando Valley.
Note: The purple shaded area highlights the San Fernando Valley.

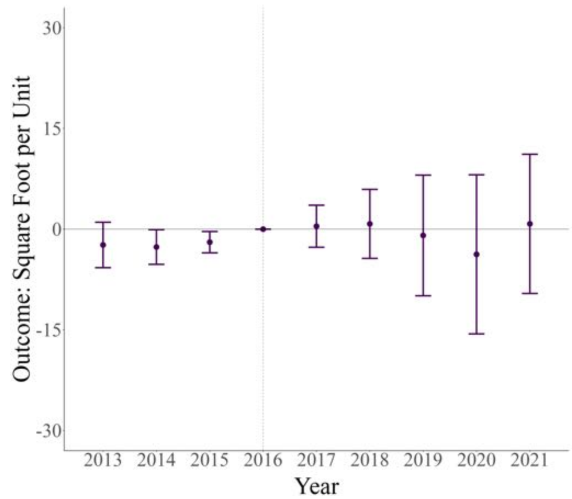
7 Conclusion

This study explores the impact of the Transit Oriented Communities (TOC) program on housing market and neighborhood change in the City of Los Angeles. To do so, I employ standard difference-in-differences and triple difference-in-differences approaches and account for the potential SUTVA violation by incorporating the spillover area in the regression models. The findings reveal several key insights into the effects of upzoning policies in urban settings.

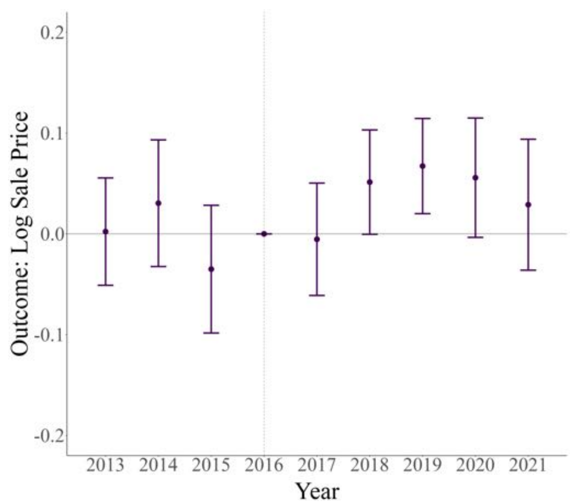
First, the results show that the TOC program increased the number of housing units in treated areas, without significantly changing the average square footage per unit. I also find evidence of rising house prices



(A) Number of Housing Units



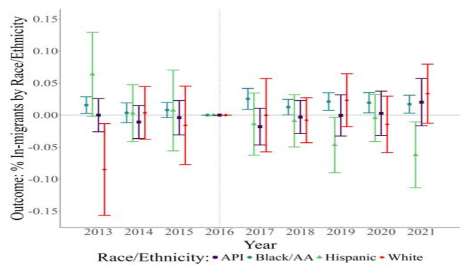
(B) Square Footage Per Unit



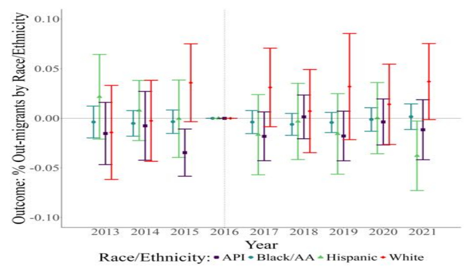
(C) Log Sale Price

Figure 15: San Fernando Valley: Housing Market Outcomes

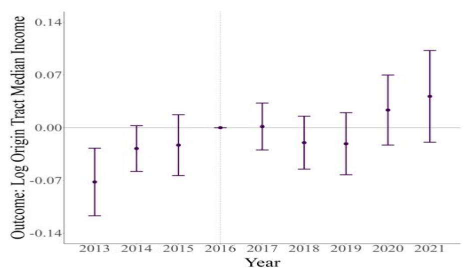
Note: Figure 15 plots the β_k event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are the number of units (Panel A), square footage per unit (Panel B), and log sale price (Panel C). The sample excludes blocks that eventually are treated by the program. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include parcel (or block for house prices) and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.



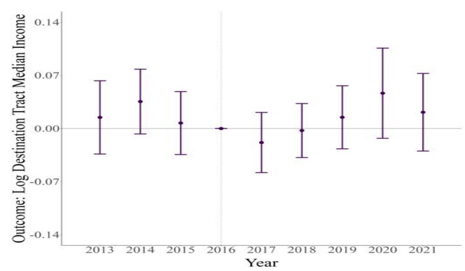
(A) In-migrant Households Race and Ethnicity Share



(B) Out-migrant Households Race and Ethnicity Share



(C) Origin Tract Median Household Income of In-migrants



(D) Destination Tract Median Household Income of Out-migrants

Figure 16: San Fernando Valley: Population Change Outcomes

Note: Figure 16 plots the β_k event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are the racial and ethnic composition of in-migrant households (Panel A), the racial and ethnic composition of out-migrant households (Panel B), the origin tract median household income for in-migrant households (Panel C), and the destination tract median household income for out-migrant households (Panel D). The sample excludes blocks that eventually are treated by the program. In Panels A and B, API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

in these areas, though this effect is less robust in the triple-differences specification. These price increases appear concentrated in blocks with little prior permitting activity, consistent with an option-value mechanism in which land values rise faster than supply materializes.

Second, demographic change follows. TOC neighborhoods see an increase in the share of non-Hispanic White in-migrants, while the composition of out-migrants remains largely unchanged. The origin and destination tract characteristics of movers show no clear pattern of households moving from higher-income tracts or incumbent residents moving into lower-income tracts, suggesting that the demographic shifts are not the result of involuntary moves or displacement. Instead, they reflect new demand for treated neighborhoods. Complementary ACS evidence shows consistent patterns, showing that TOC neighborhoods become somewhat younger, more educated, and higher-income, even though in-migrants originate from neighborhoods with similar median incomes. Together, these results indicate that zoning reform reshapes neighborhood composition by attracting a different demographic profile of residents.

Third, I examine spillover effects on nearby neighborhoods. The analysis shows that the TOC program led to delayed increases in housing units within a 1-mile radius of treated areas, though the magnitude of these effects is much smaller than the direct impacts. Price effects also appear just outside treated areas, though noisier than within TOC boundaries. These spillover effects suggest that upzoning policies can influence housing dynamics beyond the directly targeted areas, underscoring the importance of considering adjacent neighborhoods when evaluating broader policy impacts. In contrast, demographic shifts appear more localized, with little evidence of spillovers beyond treated blocks. The ACS analysis provides a slight exception, showing modest increases in educational attainment in nearby areas, even though broader demographic changes are not evident. These findings suggest that the demographic changes associated with the TOC program are even more localized than its effects on the housing market.

Finally, I explore how neighborhood amenities may contribute to these dynamics. Evidence suggests that new development coincides with changes in the local business environment, particularly in consumption-oriented sectors, which likely enhance the attractiveness of TOC neighborhoods and reinforce the demographic shifts observed in both the microdata and ACS.

More broadly, the findings highlight multiple mechanisms through which upzoning affects urban neighborhoods: direct supply growth, option-value capitalization into land prices, and amenity-driven sorting. A key takeaway is that while supply increases, the supply effects materialize only gradually, whereas prices, land values, and neighborhood composition can adjust more quickly. This dynamic underscores the importance of policy design that not only expands zoning capacity but also accelerates its translation into actual housing—by reducing permitting delays, construction barriers, and other frictions. Without mechanisms to speed up development, short-run pressures from rising demand and land values may outpace the longer-run benefits of supply growth.

In summary, this study contributes new evidence to the growing literature on land use policies by showing that upzoning can simultaneously stimulate development, raise land values, and alter neighborhood demographics. By documenting the nuanced effects of the TOC program, it underscores the importance of evaluating zoning reforms with attention to both their intended outcomes and their unintended consequences. Future research should continue to track the long-run impacts of such reforms, especially how house prices and neighborhood composition evolve as the supply response unfolds over time.

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A Appendix

A.1 TOC Program Details

The Transit Oriented Communities (TOC) Incentive Program grants a bundle of development incentives to residential projects near major transit stops, with the level of benefit determined by the project's proximity to transit and the frequency of service. Projects are grouped into four tiers, with Tier 1 offering the least generous incentives and Tier 4 the most. Tier eligibility is based on distance to major transit stops, such as Metro rail stations, Metrolink stations, or intersections served by Rapid Bus lines, and the type of transit available. For example, Tier 4 applies to projects within 750 feet of a Metro rail station or the intersection of two Rapid Bus lines. By contrast, Tier 1 applies to projects located between 750 and 2,640 feet (0.5 mile) from transit stops with lower service frequency (e.g., two regular buses). Figure A1 shows the TOC tiers in the City of LA.

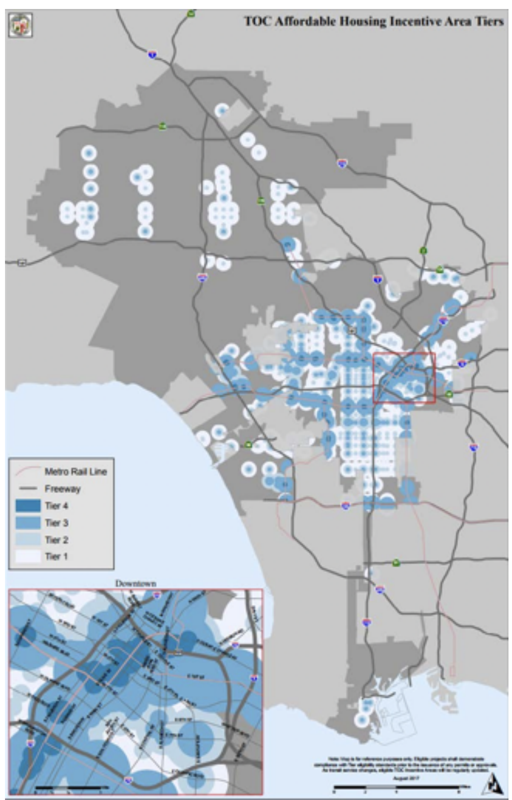


Figure A1: TOC Tier Map
Note: Image Source: City of Los Angeles TOC Guidelines https://planning.lacity.gov/ordinances/docs/toc/tocguidelines.pdf, last accessed 06/11/2025

Each tier requires a minimum share of on-site affordable housing in exchange for the zoning incentives. These requirements vary by both income level and tier. For instance, a Tier 1 project must set aside at least

8 percent of total units for Extremely Low Income (ELI) households, or 11 percent for Very Low Income (VLI) households. Tier 4, by comparison, requires 11 percent ELI or 15 percent VLI units to qualify for maximum benefits. In return, developers receive substantial increases in allowable density and floor area ratio (FAR). Residential density bonuses range from 50 percent in Tier 1 to 80 percent in Tier 4. Similarly, FAR increases range from 40 percent (or a minimum FAR of 2.75:1 in commercial zones) in Tier 1 to 55 percent (or at least 4.25:1) in Tier 4. These bonuses allow developers to build substantially more housing units than would otherwise be permitted under base zoning rules.

The TOC program also significantly relaxes parking requirements, which are often cited as a barrier to infill development. In Tiers 1 through 3, required parking is capped at 0.5 spaces per bedroom, while Tier 4 eliminates residential parking minimums entirely. Projects that are 100 percent affordable (excluding manager units) are eligible for full parking waivers in any tier. In addition, non-residential parking requirements can be reduced by up to 10–40 percent, depending on the tier. These changes can substantially lower development costs and increase site feasibility, especially on small or irregular lots.

Beyond the base incentives, TOC projects may request up to three "additional incentives" related to site layout, design, or bulk regulations. These include reduced yard setbacks, increased lot coverage, decreased open space requirements, and added building height. For example, Tier 4 projects may receive up to a 35 percent reduction in two yard setbacks and a 25 percent reduction in open space, as well as up to three additional stories or 33 feet in building height. The program also relaxes transitional height standards, particularly in the higher tiers, allowing buildings to be taller even when located near lower-density residential areas. These additional incentives offer developers flexibility to accommodate more units and reduce construction costs, further enhancing the feasibility of mixed-income housing in transit-oriented areas.

A.2 Validation of Consumer Reference Data

A.2.1 Comparing the Number of Households in Consumer Reference Data to American Community Survey

To validate the consumer reference Data against the American Community Survey (ACS), I compare the total number of households in Los Angeles County tracts across both datasets. For this analysis, I use the 2021 sample from the consumer reference Data and the 2017–2021 ACS sample.

Figure A1 compares household counts by tract for the two datasets. While the consumer data is generally representative of Los Angeles tracts, it does not capture the entire population, as indicated by the difference in the number of individuals in Table **??**. To gain further insights into the types of households included in the consumer reference data, I compare household characteristics between the ACS sample and the consumer data sample in the following section.

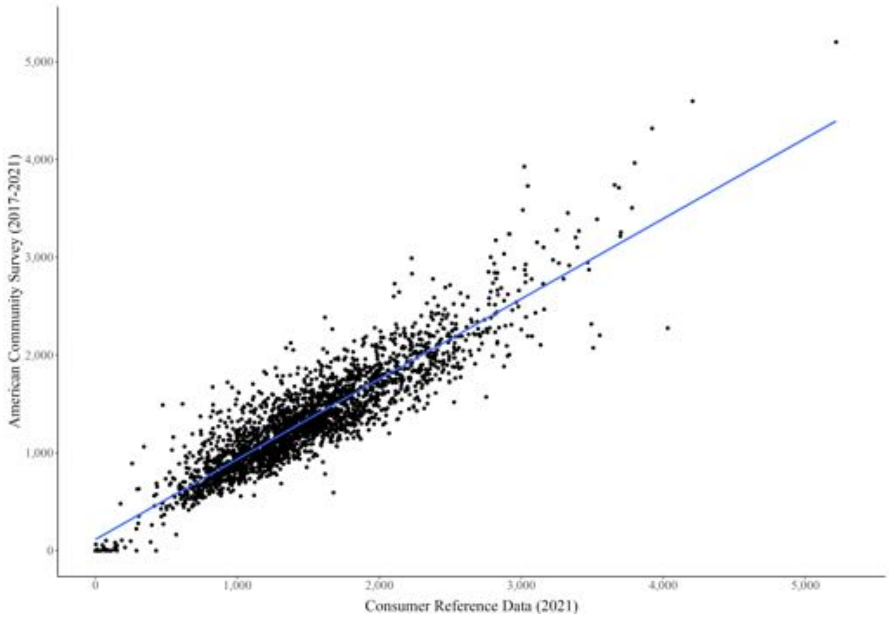


Figure A2: Total Number of Households in Los Angeles Tracts
Note: The figure compares the number of households identified in 2021 in Los Angeles County tracts using the two data sources.

A.2.2 Comparing Household Characteristics

To further validate the consumer reference data sample, I compare household characteristics from this dataset to those in the 2017-2021 ACS sample, as shown in Table A1. Although the consumer reference data includes a greater number of households, it reports fewer individuals than the ACS. This discrepancy arises from the DataAxle's definition of households, which relies heavily on last names to differentiate households at the same address. For instance, if a married couple has different last names, the consumer data may count them as two separate households. Consequently, while this increases the household count in the consumer data, it captures only about 75 percent of individuals in a tract on average.

Regarding homeownership, the consumer data tends to sample households that are more likely to be homeowners. Since the consumer data records are collected from sources such as mailing address, the dataset may be biased toward households with greater housing stability and a higher ownership rate.

Table A1 also shows that the consumer data captures the movement of renter households more effectively compared to the the ACS, as the average length of residence is shorter for renters in the consumer data. For homeowners, however, the average length of residence is similar between the two datasets. Overall, while the consumer data sample is more representative of owner households, likely due to its reliance on address

Table A1: Comparison of Tract Level ACS and Consumer Data

Variable	ACS	Consumer Reference Data
Average Number of Households	1,341.4	1,496.5
	[541.2]	[595.9]
Average Number of Individuals	4,020.7	2,902.3
	[1,459.5]	[1,300.6]
Percentage of Owner Households	46.5	62.8
	[26.7]	[33.1]
Average Length of Residence for Renters (in years)	6.9	3.8
	[2.4]	[2.1]
Average Length of Residence for Owners (in years)	17.6	17.1
	[5.2]	[4.6]

Note: Standard deviations in brackets. ACS sample uses the 2017-2021 vintage and consumer reference sample uses the 2021 data aggregated to the tract level.

records, it still effectively captures migration patterns for renter households.

A.3 Imputing Race and Ethnicity of Individuals

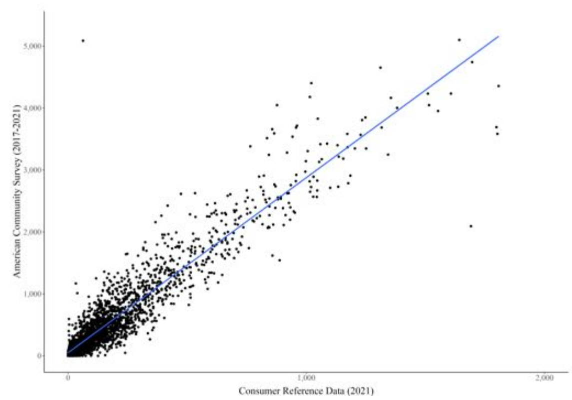
I estimate the ethnicity of each householder in the consumer data sample using the approach presented in Imai and Khanna (2016). This approach combines the Census Bureau's Surname List with demographic information from voter registration records to create a training set. Using Bayes' rule, the method calculates the posterior probability that an individual belongs to one of five ethnic groups: Asian and Pacific Islander, Black, Hispanic, White, or Other. I implement this method through the R package 'wru', using first name, last name, and race and ethnicity distribution of census tracts, which returns probability estimates for each observation in the sample. I then assign the race and ethnicity category corresponding to the highest probability. Figure A2 compares the number of individuals in each race and ethnicity category from the ACS sample with the number of householders in each category from the consumer data sample for Los Angeles County tracts.

The scatter plots in Figure A2 demonstrate a strong correlation between the imputed race and ethnicity counts from the consumer data and the corresponding values from the ACS. This suggests that the imputation method performs well in accurately deriving race and ethnicity variable. Additionally, comparing the mean distributions of different race and ethnicity categories can help better assess the accuracy of the consumer data in capturing the diversity of the population in Los Angeles. Table A2 presents the mean percentages of various race and ethnicity groups across Los Angeles County tracts, highlighting how representative the consumer trace data is in reflecting the demographic composition of Los Angeles tracts.

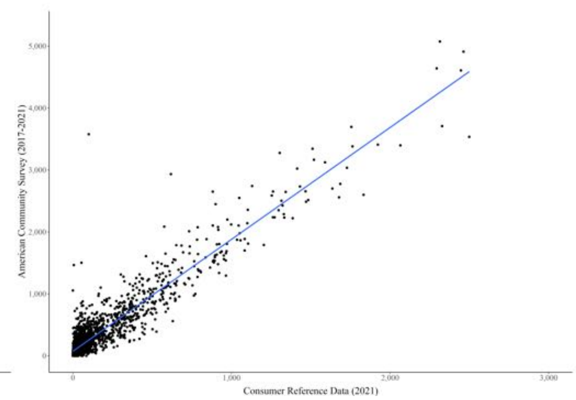
Table A2: Race and Ethnicity Distribution in Los Angeles County Tracts

Variable	ACS	Consumer Reference Data
Percentage of API Population	14.5	12.6
	[15.9]	[14.6]
Percentage of Black/AA Population	7.6	8.4
	[11.9]	[14.8]
Percentage of Hispanic Population	47.5	46.9
	[28.6]	[27.3]
Percentage of White Population	26.7	30.8
	[24.6]	[26.4]
Percentage of Other Population	3.8	1.7
	[4.2]	[2.3]

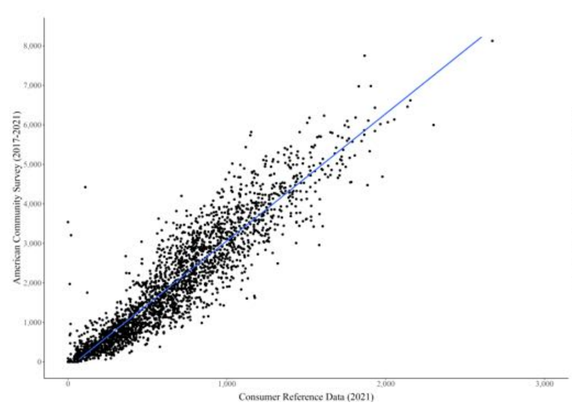
Note: Standard deviations in brackets. ACS sample uses the 2017-2021 vintage and consumer reference sample uses the 2021 data aggregated to the tract level. Percentages are calculated by dividing the number of individuals in each race/ethnicity category by the total tract population for the ACS data. Since the unit of observation for the consumer data is households, the number of householders in each race/ethnicity group is divided by the total number of households in the tract. API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders.



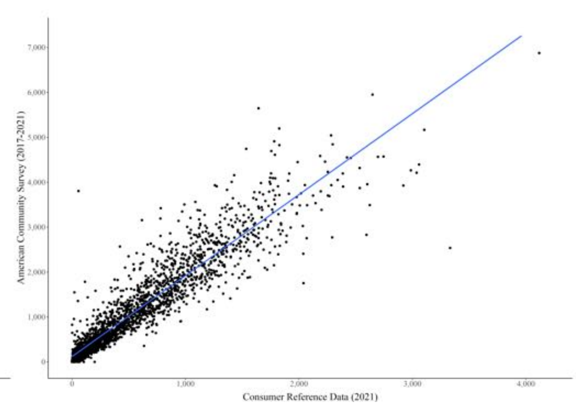
(A) API Households



(B) Black/AA Households



(C) Hispanic Households



(D) White Households

Figure A3: Total number of individuals (ACS) and householders (consumer data) in each race/ethnicity category in Los Angeles County

Note: The ACS sample is based on 2017-2021 data, while the consumer reference sample uses 2021 data aggregated at the tract level. In the ACS, values represent the number of individuals, whereas in the consumer data, the values reflect the number of householders. API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders.

A.4 Summary Statistics for In-migrant and Out-migrant Households

In this section, I compare the characteristics of in-migrant and out-migrant households between TOC and non-TOC areas. Table A3 reveals the dynamics between the in-migrant households in the treated blocks and untreated blocks. While both TOC and non-TOC areas experience in-migration, the racial and ethnic composition of the in-migrant householders differs notably. In TOC areas, a significant share of in-migrant householders are Hispanic (34.9%) and Black (13.8%), whereas non-TOC areas have a slightly smaller share of Hispanic (32.2%) in-migrants and a considerably lower percentage of Black (5.1%) in-migrants. This table also highlights that White householders constitute a larger share of in-migrants in non-TOC blocks, at 52.4%, compared to 39.8% in TOC blocks. This pattern suggests that TOC areas may be more accessible to minority in-migrant households, possibly due to relatively lower property values. Additionally, Table A3 shows that the median household income of origin tracts for in-migrants moving into TOC areas is lower, at $56,627, compared to $68,415 for those relocating to non-TOC areas.

Table A4 presents the characteristics of out-migrants from blocks located inside and outside TOC boundaries. Consistent with the patterns observed for in-migrants, TOC areas show a larger share of Hispanic (36.7%) and Black (15.9%) households among out-migrants compared to non-TOC areas, which have a significantly lower proportion of Black households (5.4%) and a higher share of White out-migrants (52.8%). The median household income of the destination tracts for out-migrants from TOC areas is also lower ($58,896) compared to those moving out of non-TOC areas ($72,669).

These tables show that the in-migrant households in TOC areas generally originate from lower-income backgrounds and are more racially diverse. Similarly, out-migrants from TOC areas show comparable trends, with a higher share being minority households and moving into tracts with lower median household incomes compared to the tracts where out-migrants from non-TOC blocks move. Conversely, non-TOC areas display a higher proportion of White in-migrant and out-migrant households, suggesting distinct demographic dynamics between the two regions.

Table A3: In-migrant Characteristics

Panel 1: Blocks in TOC Boundaries	Number of Observations	Mean	SD
Number of In-migrant Households	7,197	3.7	5.1
API Householder Share	7,197	10.1	23.1
Black/AA Householder Share	7,197	13.8	30.2
Hispanic Householder Share	7,197	34.9	39.9
White Householder Share	7,197	39.8	40.4
Origin Tract Median Household Income	7,195	56,626.8	22,919.4
Origin Tract White Population Share	7,195	35.2	25.7
Panel 2: Blocks outside TOC Boundaries	**Number of Observations**	**Mean**	**SD**
Number of In-migrant Households	7,493	3.3	4.7
API Householder Share	7,493	8.4	21.5
Black/AA Householder Share	7,493	5.1	18.7
Hispanic Householder Share	7,493	32.2	39.5
White Householder Share	7,493	52.4	41.7
Origin Tract Median Household Income	7,491	68,414.9	26,612.6
Origin Tract White Population Share	7,491	46.1	24.1

Note: The table presents the census block characteristics for the year 2015. Shares indicate the percentage of total in-migrant households that have a householder belonging to each racial/ethnic group. API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders.

Table A4: Out-migrant Characteristics

Panel 1: Blocks in TOC Boundaries	Number of Observations	Mean	SD
Number of Out-migrant Households	7,184	3.6	4.9
API Householder Share	7,184	9.9	22.9
Black/AA Householder Share	7,184	15.9	32.9
Hispanic Householder Share	7,184	36.7	40.8
White Householder Share	7,184	36.5	40.3
Destination Tract Median Household Income	7,184	58,896.4	24,095.3
Destination Tract White Population Share	7,184	34.8	25.6
Panel 2: Blocks outside TOC Boundaries	**Number of Observations**	**Mean**	**SD**
Number of Out-migrant Households	7,551	3.1	4.5
API Householder Share	7,551	8.3	21.7
Black/AA Householder Share	7,551	5.4	20.2
Hispanic Householder Share	7,551	32.1	40.1
White Householder Share	7,551	52.8	42.5
Destination Tract Median Household Income	7,544	72,668.9	28,134.3
Destination Tract White Population Share	7,544	47.4	24.1

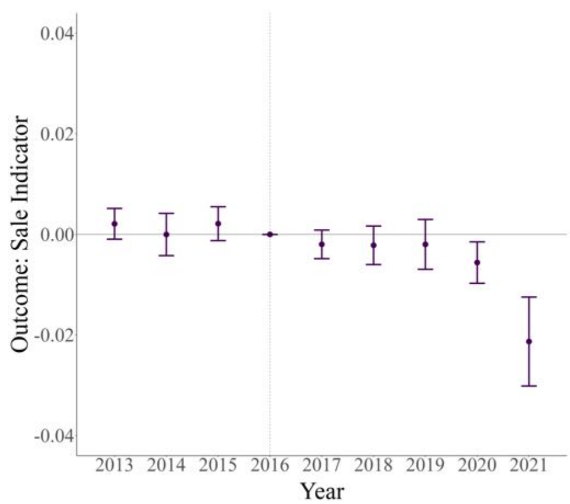
Note: The table presents the block characteristics for the year 2015. Shares indicate the percentage of total out-migrant households that have a householder belonging to each racial/ethnic group. API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders.

A.5 Probability of Transaction

Panel A in Figure A4 shows the estimated effects of the TOC policy on the annual probability that a property is sold, using the event study specification used in the baseline results, which use Equation 1. For the first few years after the policy change, there is no significant change in sale probability. A noticeable decline appears in 2021, and it is statistically significant.

This pattern is helpful for interpreting the sale price results. One concern in using transaction prices is the potential endogeneity of the sale decision. For example, if the policy causes certain types of properties to be sold more frequently, the observed prices might reflect changing composition rather than actual appreciation. The fact that sale probabilities remain stable through most of the post-treatment period suggests that selection into sales is not the main driver of the observed price increases.

That said, it is still important to be cautious. Even if the overall likelihood of a sale does not change much, the types of properties or owners transacting could still shift in ways that affect observed prices, e.g., if more investor-owned or newly entitled parcels begin to sell. So while the stability in transaction rates supports a more causal interpretation of the price effects, the results should still be interpreted with some caution.



(A) Probability of Sale

Figure A4: Probability of Property Sale

Note: Figure A4 plots the β_k event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variable is an indicator variable for a sale occurring. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include parcel and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

A.6 House Prices: Alternative Specifications

To assess whether the price increases observed in the baseline analysis are driven by compositional shifts in the types of properties being sold, I estimate two alternative specifications using parcel-level data on transacted properties. The goal of this exercise is to examine whether controlling for property characteristics attenuates the estimated treatment effects. While including post-treatment characteristics risks introducing bad controls, since attributes like square footage or owner-occupancy may themselves be outcomes of the policy, this analysis helps to evaluate whether changes in composition can explain the observed price dynamics. The specification follows the event study framework outlined in the following equation:

$$\begin{aligned} y_{it} = X_i'\gamma + \delta_b + \gamma_t + \sum_{k=2013,k\neq 2016}^{2021} \beta_k (NearMTS_i \times Year_k) \\ + \sum_{m=1}^{2} \sum_{k=2013,k\neq 2016}^{2021} \theta_k^m (SpilloverArea_i^m \times Year_k) + \varepsilon_{it} \end{aligned} \tag{6}$$

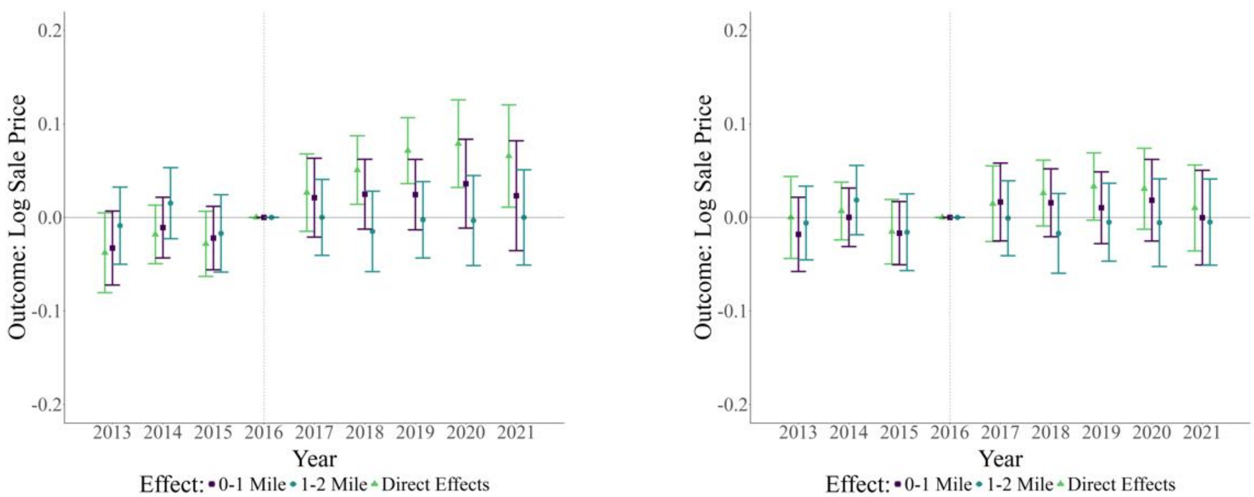
where y_{it} is the log of sale price for parcel i in year t, δ_b and γ_t denote block and year fixed effects, and X_i' includes parcel characteristics such as number of bedrooms, bathrooms, square footage, year built, owner occupancy status, and distance to CBD. $NearMTS_i$ is an indicator for whether a parcel is located within a TOC area (defined as within 0.5 miles of a major transit stop), and $SpilloverArea_i^m$ indicates proximity to TOC boundaries within 0–1 mile ($m = 1$) and 1–2 miles ($m = 2$). The coefficients β_k capture the evolution of the treatment effect in TOC areas, and θ_k^m captures spillover effects over time and by distance.

I estimate two versions of this model. Model 1 includes static parcel characteristics (Panel A of Figure A5), while Model 2 interacts the property controls with year fixed effects (Panel B), allowing for more flexible trends in property attributes over time. Both models restrict the sample to parcels that were sold during the study period and include fixed effects for block and year. Standard errors are clustered at the level of the nearest major transit stop.

Figure A5 presents the estimated treatment effects on log sale prices across two specifications. In Panel A, which includes static parcel-level controls, point estimates increase after the 2017 zoning change and remain statistically significant in several post-treatment years. These patterns are consistent with the baseline results, suggesting that upzoning is associated with higher sale prices even after controlling for observable differences in property characteristics.

In Panel B, where property characteristics are interacted with year dummies, the estimates become noisier and are no longer statistically significant. This attenuation may be partly mechanical, as the more flexible controls absorb time-varying changes in composition. But it may also reflect more substantive shifts in the types of properties being sold: upzoning may have made certain parcels more attractive to developers, e.g., those with larger lot sizes, fewer physical constraints, or aging structures. These parcels could be sold for higher prices not because of their existing features, but because their redevelopment potential increased under the new zoning.

In this sense, the disappearance of the price effect once controls are interacted with time may indicate that what matters is not just the physical characteristics of the home, but how the market perceives those characteristics under the new regulatory environment. For example, an older single-family home in a high-allowance TOC area might have limited value before 2017, but after the policy change, the same home may be viewed as a teardown opportunity with multifamily potential. As a result, the policy may have reshaped how buyers, particularly institutional or investor-driven buyers, value the development potential of certain parcels. Together, these findings reinforce the idea that upzoning increases land values through improved redevelopment opportunities.



(A) Property Characteristics Controls

(B) Property Characteristics Controls Interacted with Year Dummies

Figure A5: House Prices: Alternative Specifications

Note: Figure A5 plots the β_k event study coefficients estimated from a regression of the form given in Equation 6, where the dependent variables are log sale price in both regressions. While Panel A regression uses parcel level controls, Panel B uses these controls interacted with year dummies. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

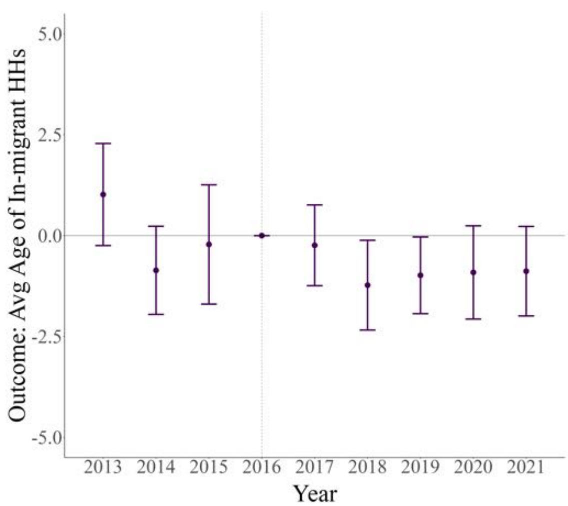
A.7 Age of Migrants

Understanding who moves into and out of neighborhoods after a zoning change can help explain the demographic shifts observed in treated areas. One important characteristic is age, which often reflects housing preferences and mobility. Here, I examine how the average age of in-migrant and out-migrant householders changes in response to the TOC program.

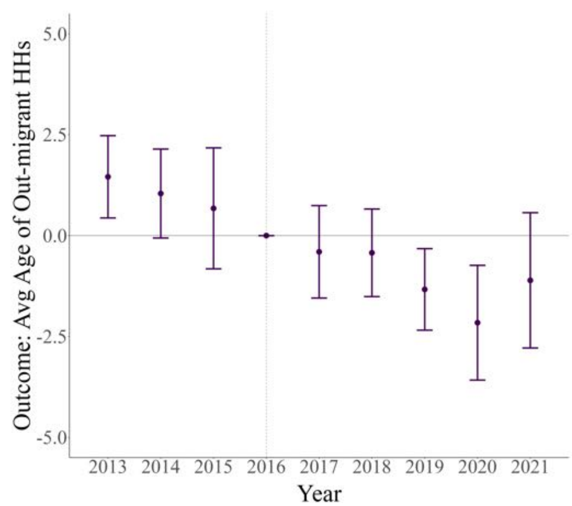
Figure A6 shows the event study estimates, which use the framework described in Equation 1. Panel A plots the average age of householders moving into TOC blocks. After the policy goes into effect, I find a modest decline in the age of in-migrants, with several years showing statistically significant differences. This suggests that younger households are more likely to move into TOC neighborhoods, consistent with the idea that the new housing or improved neighborhood conditions appeal more to younger households.

Panel B, which shows the average age of out-migrants, also reveals a downward trend. However, there is a notable pre-trend in the years leading up to the policy, with estimates beginning to decline before the zoning change takes effect. This makes it difficult to causally attribute the post-policy effects to the TOC program alone. It is possible that these areas were already seeing some demographic turnover even before the TOC program, or that residents were responding to anticipated changes in the neighborhood.

Overall, the results suggest that upzoning contributed to a shift toward younger in-migrants. While the out-migration patterns are less clear due to pre-existing trends, the consistent decline in in-migrant age supports the idea that the TOC program attracted younger households and contributed to modest demographic change in treated areas.



(A) Age of In-migrants

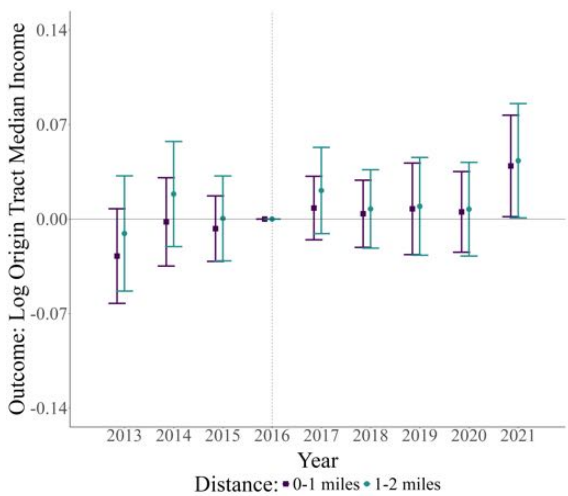


(B) Age of Out-migrants

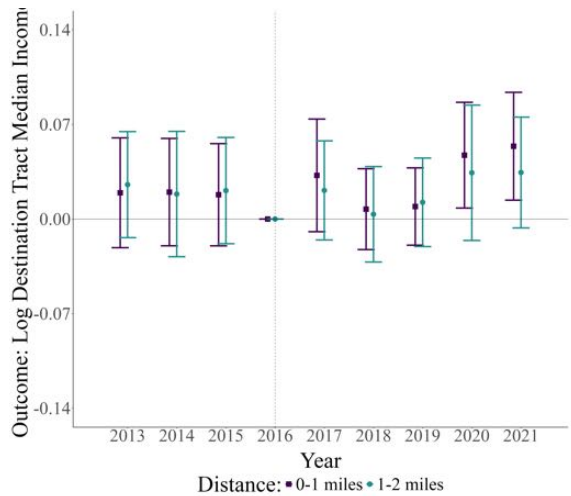
Figure A6: Age of Movers

Note: Figure A6 plots the β_k event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are ages of the head of household for migrant households. While Panel A looks at the ages of in-migrants, Panel B looks at the ages of out-migrants. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

A.8 Spillover Effects for All Migration Outcomes



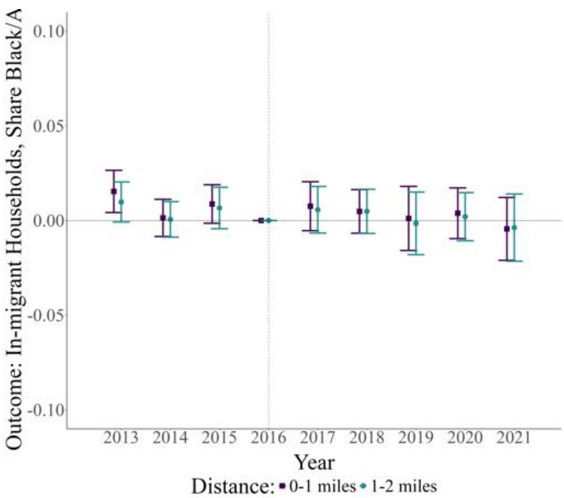
(A) Origin Tract Median Household Income of In-migrants



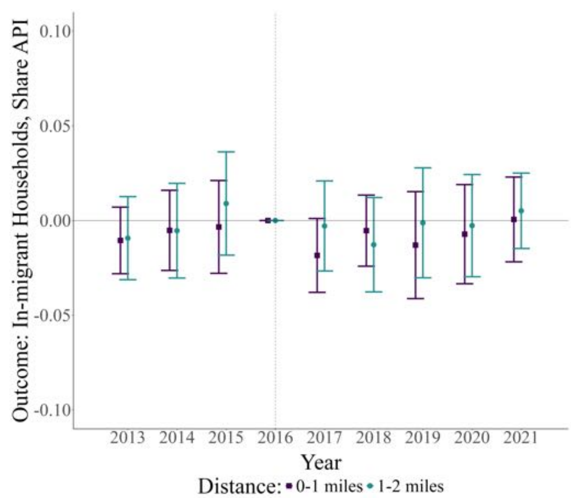
(B) Destination Tract Median Household Income of In-migrants

Figure A7: Population Change Outcomes

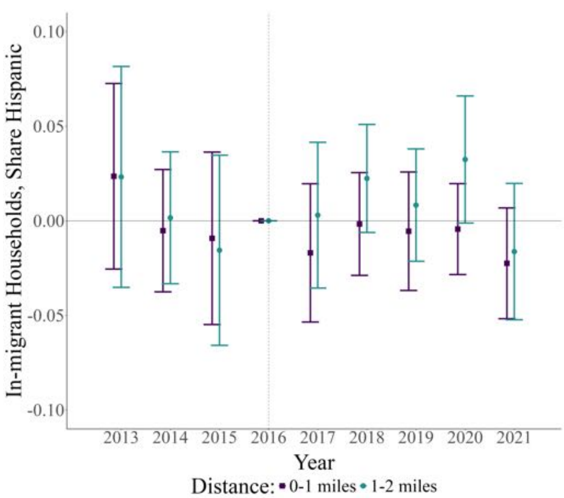
Note: Figure A7 plots the θ_k^m event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are the origin tract median household income for in-migrant households (Panel A), and the destination tract median household income for out-migrant households (Panel B). The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.



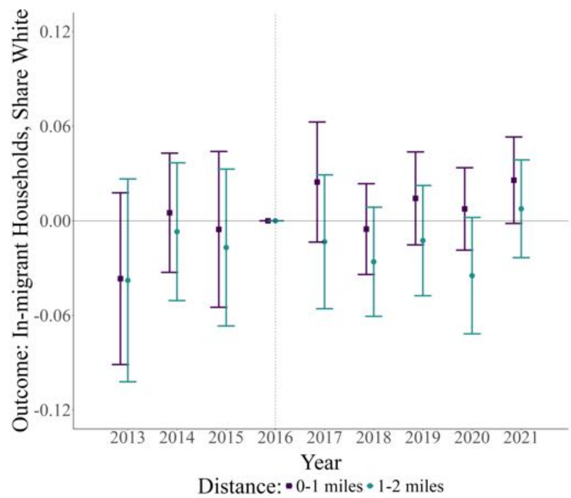
(A) Share of Black/AA In-migrant Households



(B) Share of API In-migrant Households



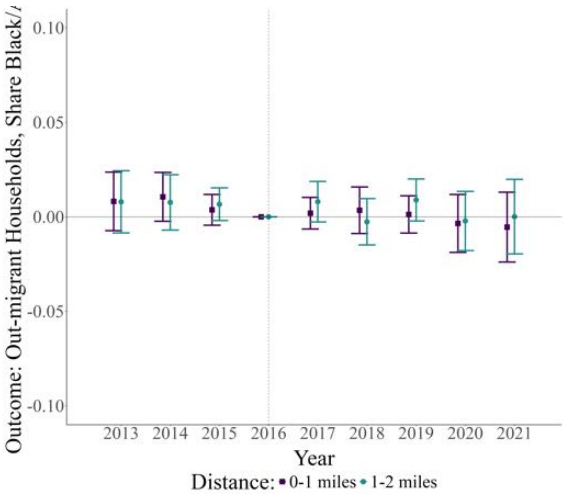
(C) Share of Hispanic In-migrant Households



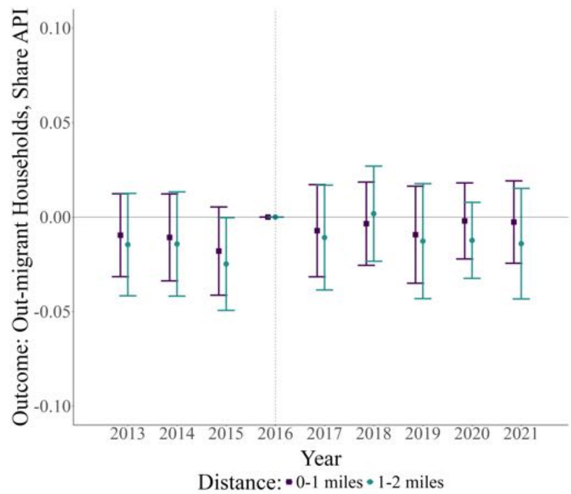
(C) Share of non-Hispanic White In-migrant Households

Figure A8: In-migrant Race and Ethnicity Outcomes

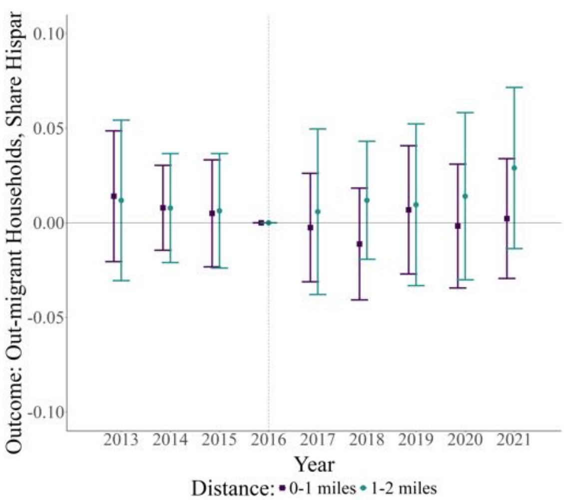
Note: Figure A8 plots the θ_k^m event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are the share of Black/AA in-migrant households (Panel A), the share of API in-migrant households (Panel B), the share of Hispanic in-migrant households (Panel C), the share of non-Hispanic White in-migrant households (Panel D). API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders. The Hispanic group includes individuals of any race identified as Hispanic. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.



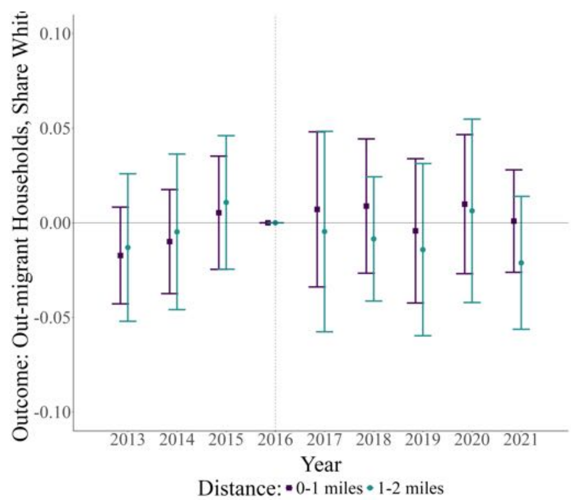
(A) Share of Black/AA Out-migrant Households



(B) Share of API Out-migrant Households



(C) Share of Hispanic Out-migrant Households



(D) Share of non-Hispanic White Out-migrant Households

Figure A9: Out-migrant Race and Ethnicity Outcomes

Note: Figure A9 plots the θ_k^m event study coefficients estimated from a regression of the form given in Equation 1, where the dependent variables are the share of Black/AA out-migrant households (Panel A), the share of API out-migrant households (Panel B), the share of Hispanic out-migrant households (Panel C), the share of non-Hispanic White out-migrant households (Panel D). API refers to Asian and Pacific Islander; Black/AA denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders. The Hispanic group includes individuals of any race identified as Hispanic. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

A.9 Event Studies for Business Outcomes

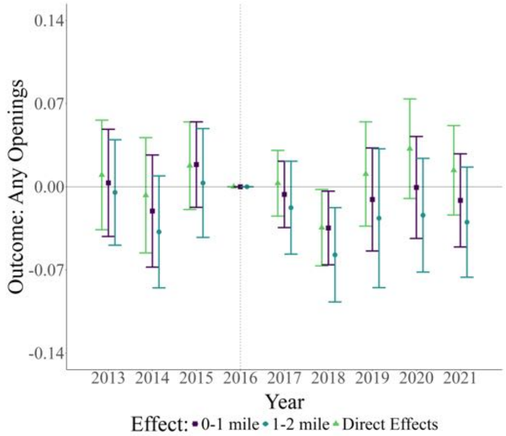
To evaluate the dynamic effects of the TOC program on commercial activity, I estimate an event study specification of the form:

$$
\begin{aligned}
y_{bt} = \delta_b + \gamma_t + &\sum_{k=2013, k\neq 2016}^{2021} \beta_k (\text{NearMTS}_b \times \text{Year}_k) \\
&+ \sum_{m=1}^{2} \sum_{k=2013, k\neq 2016}^{2021} \theta_k^m (\text{Spillover}_b^m \times \text{Year}_k) + \varepsilon_{bt}
\end{aligned}
\tag{7}
$$

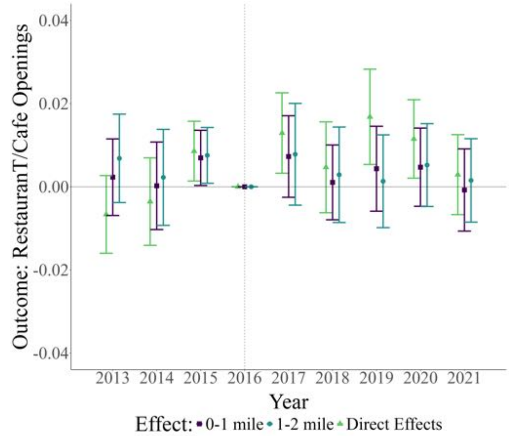
where y_{bt} denotes the business outcome for block b in year t. The variable NearMTS_b indicates whether a block falls within a TOC-eligible area, while Spillover_b^m identifies blocks in spillover zones within 0–1 mile ($m = 1$) or 1–2 miles ($m = 2$) of TOC boundaries. Block and year fixed effects, δ_b and γ_t, absorb time-invariant block-level characteristics and common temporal shocks. The year 2016 is normalized to zero, and standard errors are clustered by the nearest major transit stop.

Figure A10 presents the estimated β_k and θ_k^m coefficients for each outcome. While there is no consistent evidence of pre-trends overall, Panel B shows some anticipatory effects in 2015 for restaurant/cafe openings, and the estimates for closings indicate a decreasing pattern in treated areas, with a significant positive point estimate in 2013. Nonetheless, the lack of systematic and consistent pre-trends across all outcomes supports the identification strategy.

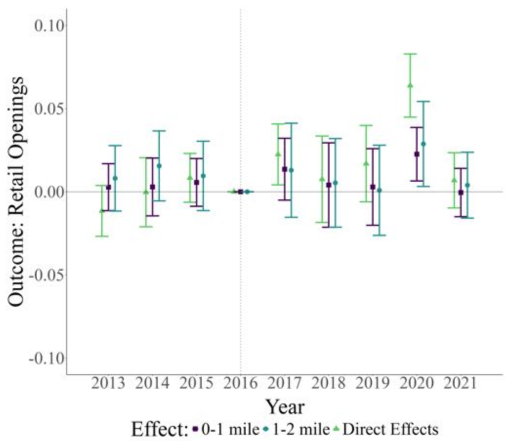
Most post-treatment estimates are small and imprecise, but there is some indication of increased openings in restaurants/cafes and retail, decreased openings in office/business services, and a decline in business closures in the years following the upzoning. These effects appear to be more pronounced in the treated areas and are generally noisier and less significant in the spillover areas. Overall, the findings suggest that the TOC program did not lead to large or immediate shifts in commercial activity, but may have contributed to gradual adjustments in local business composition, particularly within the service sector.



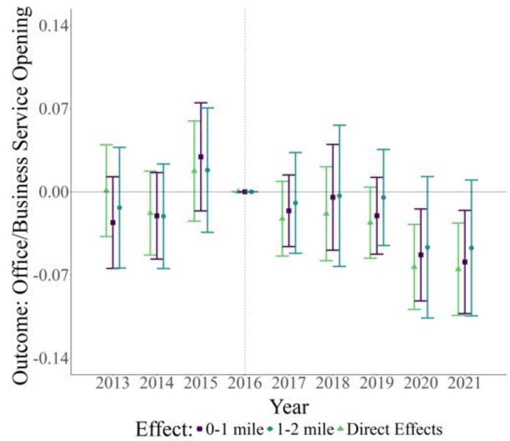
(A) Any Openings



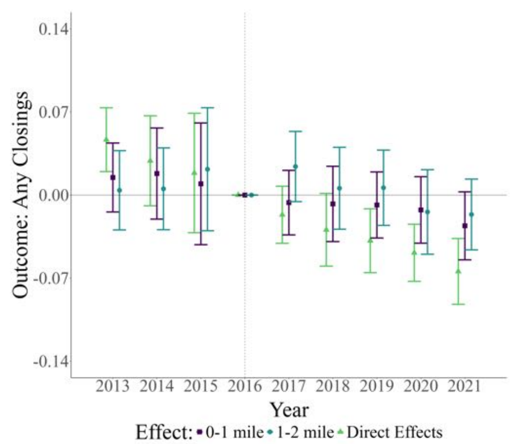
(B) Restaurant/Cafe Openings



(C) Retail Openings



(D) Offices/Business Service Openings



(E) Any Closings

Figure A10: Effects of TOC Policy on Business Activity

Note: Figure A10 plots β_k coefficients from an event study specification where the outcome is a binary or count indicator of new business openings by type. Panel A shows the effect on any new business opening, while Panels B through D show openings by business category: Restaurants/Cafes, Retail, and Offices/Business Services. Panel E shows the effect on any business closings. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include block and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

A.10 Using ACS Outcomes

As a complementary analysis, I use ACS data to estimate the effects of the TOC policy on housing market and demographic outcomes. In particular, I estimate a standard difference-in-differences model to serve as an independent check on the patterns observed in the parcel- and block-level microdata. Using 5-year average block group-level ACS data for the pre-policy period (2012–2016) and post-policy period (2018–2022), I estimate the following regression:

$$y_{bt} = \delta_b + \gamma_t + \beta_1(\text{NearMTS}_b \times \text{Post}_t) + \beta_2(\text{Spillover}_{0-1,b} \times \text{Post}_t) + \beta_3(\text{Spillover}_{1-2,b} \times \text{Post}_t) + \varepsilon_{bt} \quad (8)$$

where y_{bt} is the outcome of interest for block group b in period t, $NearMTS_b$ is an indicator equal to 1 if the majority of parcels in block group b fall within the TOC area, and $Post_t$ is an indicator for the post-policy period (2018–2022). The term δ_b captures block group fixed effects, and γ_t captures year fixed effects. Standard errors are clustered at the level of the nearest major transit stop.

Notably, these regressions use block group–level data, which are less granular than the parcel- and block-level microdata used in the main analysis. As a result, the estimates may be noisier and subject to greater measurement error, particularly in how treatment is assigned in mixed or border areas. The purpose of this analysis is not to recover precise treatment effects but to assess whether broad patterns in housing market and demographic shifts are consistent with the main results using a publicly available dataset.

Overall, the ACS results provide qualitatively similar results presented in the parcel- and block-level analyses. Treated areas exhibit an increase in housing activity, with significant increases in asking rents, median rents, and home values (Table A5). These patterns are consistent with the parcel-level price dynamics observed in Figure 5 and support the interpretation that housing prices increased following the TOC program, relative to control areas. However, the estimated increase in housing units is not statistically significant within TOC block groups, which is different from what I find in the main analysis. This discrepancy likely reflects both measurement issues and timing: assessor data capture new permits, while ACS counts finished and occupied units, which materialize more slowly. In addition, aggregating to the block-group level introduces noise, particularly in mixed or border areas, whereas the assessor data allow for precise parcel-level treatment assignment. Nonetheless, the ACS estimate for total housing units is positive—though not statistically significant—indicating that the direction of the effect is consistent with the assessor data.

In terms of demographic composition, Table A6 shows that the TOC policy is associated with a significant increase in the non-Hispanic White population, with no strong evidence of change among other racial or ethnic groups. This aligns with the finding that demographic shifts are largely driven by in-migration of non-Hispanic White households rather than out-migration of existing residents.

There are also notable differences in income-related patterns between the ACS and the consumer reference data. While the income information is not available in the consumer reference data, I opt to look at median household income in the origin and destination neighborhoods to explore whether in-migrants start coming from higher quality tract or whether out-migrants move to tracts with different income levels. The block-level analysis shows no substantial changes in in-migration in origin tract income, suggesting that the in-migrants come from similar neighborhoods. Nonetheless, the analysis that uses ACS data suggests modest increases in both income and educational attainment in TOC areas (Table 4). These differences likely reflect both variation in the underlying samples between the consumer reference data and the ACS, as well as differences in the specific measures used. For instance, in-migrants may originate from tracts with similar median incomes, yet still have higher individual incomes, given the income heterogeneity within tracts. As a result, the ACS data, which include self-reported income and education, may offer a more direct and less noisy estimate of demographic change.

Moreover, as shown in Column (1) of Table 4, treated block groups also experience a decrease in average age, suggesting an influx of younger residents. Using the consumer reference data, I also find a decline in average age among in-migrants, as shown in Appendix A.7, suggesting that the TOC program may be attracting younger residents. While a similar trend may exist among out-migrants, the noisier patterns in the out-migration data make the causal interpretation less clear.

Overall, the ACS results reinforce the core findings: the TOC program increased house prices, shifted the demographic composition of treated areas, and attracted higher-income, more White, and more educated residents. While the ACS offers a less granular, hence noisier, analysis than the parcel- and block-level analyses, it provides useful confirmation that the zoning reform reshaped both market and population characteristics in ways that are consistent with the main event study results.

Table A5: Effect of TOC Policy on Housing Market Outcomes

Dependent Variable:	log(Housing Units)	log(Asking Rent)	log(Median Rent)	log(Median Value)
TOC × Post2017	0.06	0.22**	0.08***	0.13***
	(0.05)	(0.09)	(0.02)	(0.04)
0–1mi × Post2017	0.06	0.26***	0.07***	0.10***
	(0.05)	(0.10)	(0.02)	(0.03)
1–2mi × Post2017	0.09*	0.05	0.06**	0.03
	(0.05)	(0.13)	(0.03)	(0.03)
Fixed Effects				
Block Group	✓	✓	✓	✓
Year	✓	✓	✓	✓
Fit Statistics				
Observations	5,279	2,469	4,907	4,554
R^2	0.84007	0.81984	0.90544	0.95657

Standard errors are clustered at the level of the nearest major transit stop.

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A6: Effect of TOC Policy on Demographic Composition

Dependent Variable:	log(Total Pop)	log(White)	log(Black)	log(API)	log(Hispanic)
TOC × Post2017	0.06	0.20***	-0.11	-0.10	0.05
	(0.05)	(0.06)	(0.13)	(0.11)	(0.06)
0–1mi × Post2017	0.06	0.10	-0.05	-0.07	0.01
	(0.05)	(0.06)	(0.13)	(0.10)	(0.07)
1–2mi × Post2017	0.12**	0.12**	-0.11	-0.07	0.12
	(0.05)	(0.06)	(0.19)	(0.13)	(0.08)
Fixed Effects					
Block Group	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
Fit Statistics					
Observations	5,276	4,936	4,356	4,598	5,224
R^2	0.80000	0.92479	0.82566	0.84621	0.88825

Note: Standard errors are clustered at the level of the nearest major transit stop. API refers to Asian and Pacific Islander; Black denotes Black or African American; Hispanic refers to individuals of Hispanic/Latino origin (of any race); and White refers to non-Hispanic White householders. The Hispanic group includes individuals of any race identified as Hispanic. *Significance levels:* *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

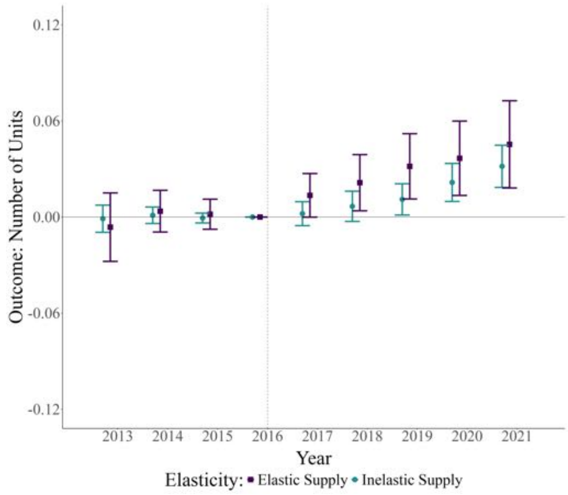
A.11 Housing Market: Heterogeneous Effects by Supply Elasticity

As a complementary exercise to prior development heterogeneity analysis, I also test for heterogeneity by local housing supply elasticity. Rather than using block-level permitting activity, this specification relies on tract-level elasticity estimates from Baum-Snow and Han (2024), which measure how easily new housing can be added given land use and regulatory conditions. Tracts are classified as either elastic or inelastic based on whether their elasticity measure lies above or below the citywide median, using the 2011 quadratic finite mixture model (FMM) specification.

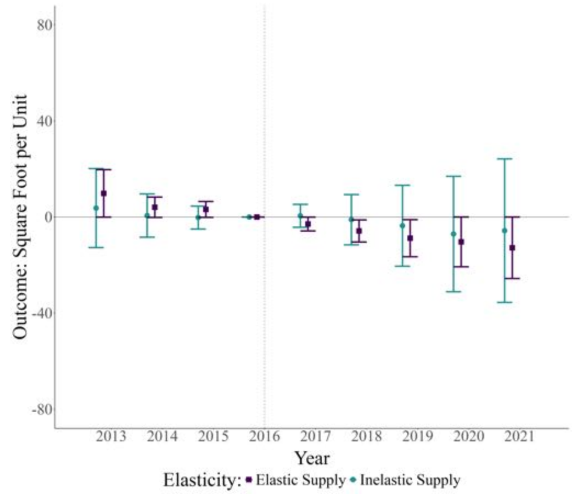
It is worth noting that the permitting-based measure used in the main text is more granular and arguably better suited for this context. Because it is constructed at the block level, it can capture within-tract heterogeneity that tract-level elasticity indices may overlook. Moreover, the permitting-based classification reflects realized development history rather than estimated elasticity, making it a more direct proxy for where developers had already been active before the policy.

Figure A11 presents results using the elasticity classification. Panels A and B show patterns broadly consistent with the permitting analysis: unit counts rise faster in elastic tracts, and the new units tend to be smaller, consistent with higher-density development. However, Panel C departs from the earlier findings: price increases are concentrated in elastic tracts rather than inelastic ones.

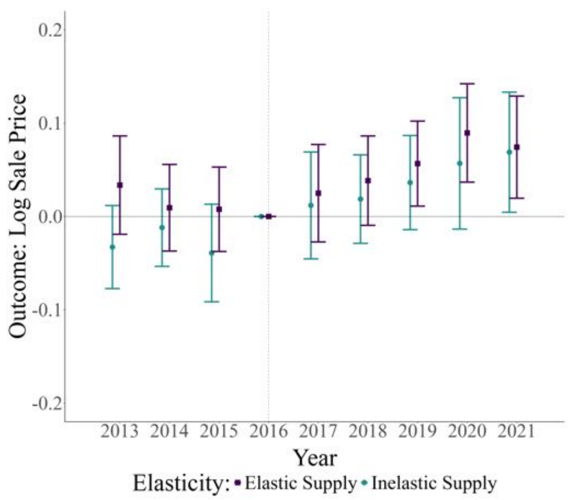
This divergence makes the elasticity-based results more ambiguous. One interpretation is that, even in elastic areas, supply responses lagged relative to strong demand pressures, producing short-run price appreciation. Another is that tract-level classifications obscure important within-tract variation, blurring the option-value dynamics that are more clearly evident in the block-level permitting analysis. For these reasons, while the tract-level results provide a useful complementary analysis, the permitting-based measure offers a more precise and conceptually grounded view of heterogeneous policy effects.



(A) Number of Housing Units



(B) Square Footage Per Unit



(C) Log Sale Price

Figure A11: Housing Market Outcomes by Housing Supply Elasticity

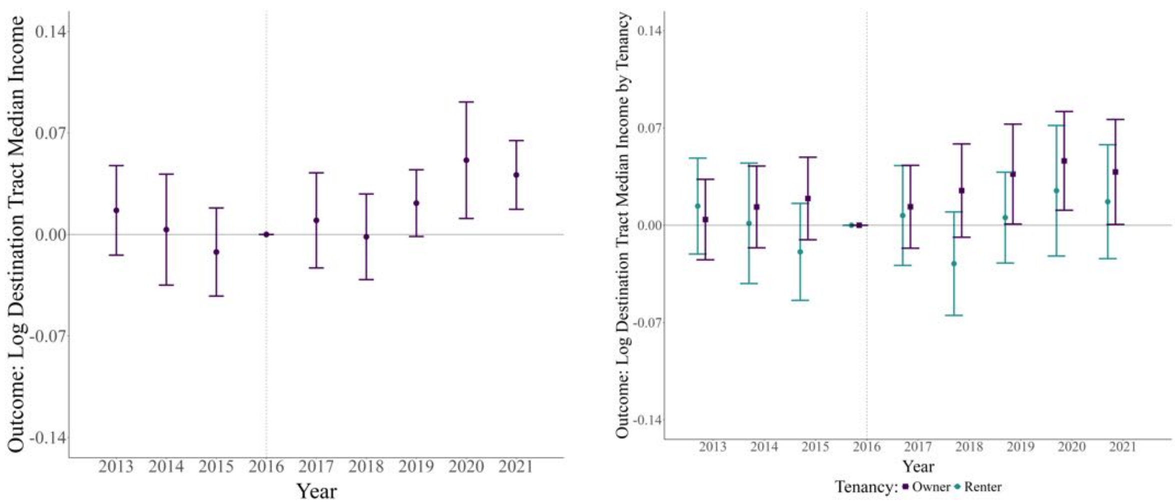
Note: Figure A11 plots the β_k event study coefficients estimated from a regression of the form given in Equation 3, where the dependent variables are the number of units (Panel A), square footage per unit (Panel B), and log sale price (Panel C). Elastic supply tracts are are defined as those with above-median elasticity according to Baum-Snow and Han (2024); low-elasticity tracts fall below the median. The event is defined as the implementation of the zoning change, in 2017, and the year prior to the event, 2016, is normalized to zero. All regressions include parcel (or block for house prices) and year fixed effects. The vertical lines reflect the 95% confidence intervals. Standard errors are clustered at the level of the nearest major transit stop.

A.12 Neighborhood Demographics: Heterogeneous Effects by Ownership Status

To examine whether the upzoning policy affected homeowners and renters differently, I test for heterogeneous effects in out-migration patterns by ownership status. This distinction is important because renters are generally more financially vulnerable, and thus more likely to experience displacement pressures. Homeowners, in contrast, may have greater ability to capitalize on price increases, and move voluntarily. To explore these differences, I estimate an interacted event study model where I estimate separate treatment effects for owner-occupied and non-owner-occupied parcels using the following specification:

$$\begin{aligned} y_{it} = \delta_i + \gamma_t + &\sum_{k=2013,\, k\neq 2016}^{2021} \beta_k \big(NearMTS_i \times Year_k \times I(OwnerOccupied_i)\big) \\ &+ \sum_{m=1}^{2} \sum_{k=2013,\, k\neq 2016}^{2021} \theta_k^m \big(SpilloverArea_i^m \times Year_k\big) + \varepsilon_{it} \end{aligned} \tag{9}$$

Figure A12 presents the results. Panel A shows the main finding that, on average, out-migrants from treated areas move to neighborhoods with slightly higher median incomes. Panel B disaggregates these effects by ownership status and shows that the positive effect is driven primarily by out-migrants from owner-occupied parcels. On the other hand, out-migrants from renter-occupied parcels move to neighborhoods with similar income levels as before, as the statistically insignificant point estimates indicate. These findings suggest that the modest increases in destination neighborhood income observed in the main analysis are primarily driven by owner-occupier households relocating to slightly higher-income areas, while renters tend to move laterally in terms of neighborhood income level.



(A) Parcel-level Destination Median Tract Income of Out-migrants

(B) Parcel-level Destination Median Tract Income of Out-migrants by Tenancy

Figure A12: Neighborhood Change Outcomes by Ownership Status