Redevelopment and Gentrification in General Equilibrium*

Guangbin Hong — Michigan State University
James Macek — University of Alberta

November 10, 2025

Abstract

Redevelopment is a major source of housing supply in dense cities, but it is spatially concentrated and often associated with gentrification and displacement. This paper studies the equilibrium consequences of redevelopment and of policies that restrict it. We first empirically evaluate a teardown tax implemented in two Chicago neighborhoods using a spatial difference-in-differences design and find that it substantially reduced demolitions and modestly curbed displacement. We then develop a dynamic general equilibrium model with forward-looking landlords who choose when to redevelop and heterogeneous households who choose across neighborhoods and vertically differentiated housing units. Redevelopment affects income sorting across neighborhoods and generates filtering dynamics over time. Model counterfactuals show that a spatially targeted teardown tax preserves old, affordable housing in treated areas but shifts redevelopment to untreated areas, raising rents there. The policy benefits low-income households but harms middle- and high-income households, with the largest losses for the middle. Land values fall in treated areas and rise elsewhere. We conclude with a discussion of the policy implications of our findings.

Keywords: Housing redevelopment, gentrification, filtering, anti-gentrification policy.

JEL Codes: R21, R31, R38

*Hong: honggua2@msu.edu. Address: 478 W Circle Dr 204B, East Lansing, MI 48824, USA; Macek: jmacek@ualberta.ca. Address: 11211 Saskatchewan Dr NW, Edmonton, AB T6G 2R6, Canada. We thank Carlos Flores Komatsu for superb research assistance. Special thanks to the discussants Olivier Schöni and Ying Fan, and to Tom Davidoff for detailed comments on an earlier draft. For helpful discussions, we thank Milena Almagro, Nate Baum-Snow, Victor Couture, Gilles Duranton, Robert French, Joshua Gottlieb, Stephan Heblich, Kevin Lim, Jeffrey Lin, Andrii Parkhomenko, Jordan Rosenthal-Kay, Allison Shertzer, Tsur Somerville, Joe Steinberg, William Strange, Pablo Valenzuela-Casasempere, and Yue Yu. We also thank conference participants at 2024 UEA European Meeting, 2025 Chinese Economist Society North American Conference, 2025 Spring Midwest Macro Meeting, and 2025 AREUEA National Meeting, as well as the seminar at Chicago Fed.

1 Introduction

Understanding housing supply is crucial for addressing the affordability challenges (Glaeser and Gyourko, 2018). In dense urban areas, a major source of new housing supply is housing redevelopment (McMillen and O'Sullivan, 2013; Baum-Snow and Han, 2024), which involves replacing older, affordable housing with newer, high-quality housing. At the city level, increasing supply of high-quality housing can have a "trickle-down" effect that improves housing affordability across all quality segments (Nathanson, 2025) and filter towards low-income households over time (Rosenthal, 2014). However, as housing redevelopment tends to be spatially concentrated (Munneke and Womack, 2015), it can also lead to neighborhood gentrification and displacement of local incumbents (Brueckner and Rosenthal, 2009; Guerrieri, Hartley and Hurst, 2013). In response, many cities have adopted policies that explicitly restrict redevelopment.[1] Despite the policy salience of this tension, the heterogeneous welfare consequences of redevelopment across space, time, and households remain under-studied.

In this paper, we develop a dynamic general equilibrium model to study the welfare effects of housing redevelopment. We embed the assignment framework (Määttänen and Terviö, 2014; Landvoigt, Piazzesi and Schneider, 2015), which allows tractably matching between heterogeneous households and heterogeneous housing units within neighborhoods, into a quantitative spatial model featuring income sorting across neighborhoods and endogenous neighborhood amenities. The model also incorporates forward-looking redevelopment decisions by landlords and quality depreciation over time. Taken together, these elements allow us to comprehensively analyze the long-run, heterogeneous welfare effects of housing redevelopment and of policies that changes the housing quality distribution, such as teardown taxes and public housing demolition.

We apply the model to analyze a housing demolition tax policy targeted at two Chicago neighborhoods between 2021 and 2024. Our empirical analysis shows that the policy reduced both teardowns and displacement of incumbent residents. We then use the model to evaluate a scaled-up version of the policy that targets all below-median-income neighborhoods in Chicago. The counterfactuals reveal that, while the policy preserves affordable housing in the targeted neighborhoods and benefits low-income households, it also induces substantial redevelopment spillovers to untreated neighborhoods and generates heterogeneous welfare effects across the households. Among renters, low-income households benefit from the policy, whereas middle- and high-income households are worse off as average housing quality

[1] For example, Chicago introduced a demolition surcharge and an anti-deconversion ordinance in two neighborhoods. San Francisco imposes a high demolition fee and requires replacing rent-controlled units. Seattle requires developers to either include affordable units or a contribute to a housing fund. More broadly, lengthy and costly municipal permitting processes implicitly restrict redevelopment.

decreases at the city level. In particular, the scarcity of high-quality housing has a positive, trickle-down effect on the rent in the middle quality segment, yielding the largest welfare losses for middle-income renters. Among homeowners, land values in treated neighborhoods decline sharply as the tax erodes the option value of redevelopment, while land values in untreated neighborhoods rise as middle- and high-income households move in. We conclude that a spatially targeted teardown tax can serve as a redistributive policy, albeit with substantial unintended consequences.

We begin by empirically evaluating the teardown tax implemented in Chicago. In March 2021, the city council of Chicago approved a demolition surcharge ordinance to be levied in two neighborhoods, the 606-Trail and Pilsen, which have experienced significant housing redevelopment and gentrification. To identify the causal effect of the policy, we employ a spatial difference-in-differences design comparing outcomes just inside versus just outside the treated boundaries. We find that the policy significantly reduced housing demotion in the treated areas, showing the policy's success in its goal. We estimate negative, though statistically insignificant, effects on displacement, housing rents, and sales prices, plausibly due to the short policy horizon limiting its impact on the housing stock. We complement the policy evaluation with evidence that a greater amount of housing redevelopment raises neighborhood average income, leveraging the variation in decadal changes in building age across Chicago block groups and an instrument that exogenously shifts redevelopment.

The reduced-form analysis is informative about the direct policy effect, but it does not illuminate on the general equilibrium consequences in untreated neighborhoods nor the welfare implications. We develop a general equilibrium model to address these questions. The model extends the assignment framework of Määttänen and Terviö (2014) and Landvoigt, Piazzesi and Schneider (2015) by endogenizing neighborhood-level housing supply and demand, which in their setting is taken as given, and it embeds realistic neighborhood heterogeneity into the filtering framework of Sweeney (1974) and Brueckner and Rosenthal (2009). The city consists of a set of neighborhoods, each containing a set of parcels owned by forward-looking landlords, and households that differ in income. Residential structures differ in both the number of indivisible units and housing quality. Each period, households choose a neighborhood — based on the rental prices by quality and amenities — and then select a housing unit within that neighborhood. Landlords draw a blueprint, i.e., the option to build at a given quality, and decide whether to redevelop the parcel; if so, they choose the number of units and pay a construction cost. Housing quality depreciates over time, and households can relocate across neighborhoods subject to mobility costs. Neighborhood amenities are endogenous and respond to neighborhood income, as in Guerrieri, Hartley and Hurst (2013).

In equilibrium, neighborhood-level supply and demand determine a rental pricing function over housing quality. The shape of this pricing function governs both income sorting and redevelopment. On the demand side, holding amenities fixed, high-income households prefer neighborhoods with a flatter pricing function (i.e., a low price elasticity of quality), because they spend more on housing and gain more utility from an additional dollar of housing when the marginal price increase with quality is small. On the supply side, a steeper pricing function raises the return to supplying high-quality units, increasing landlords' incentives to redevelop. Therefore, redevelopment is more likely in neighborhoods where high-quality housing is relatively scarce and the pricing function is steep. By replacing low-quality with high-quality units, redevelopment flattens the pricing function and attracts higher-income households. Gentrification pressures are further amplified by endogenous amenities: as income rises, amenity levels increase and in turn induce greater inflows, reducing affordability for incumbents across the quality distribution.

We discipline the model parameters using property assessment and transaction deed data from the Cook County Assessor's Office, as well as rental listing data from RentHub. We first estimate housing quality using a hedonic regression of posted rent on a large set of housing characteristics from the assessment data. We allow for flexible, neighborhood-specific pricing functions in the hedonic regression, as our theory predicts these are important for understanding income sorting and redevelopment. From this regression, we obtain an estimate of the quality depreciation rate and recover the housing quality distribution by neighborhood. For the housing supply elasticities, we identify the housing unit supply elasticity using revealed decisions of unit choices of new developments, with identifying variation coming from demand shocks driven by an employment shift share instrument following Saiz (2010) and Baum-Snow and Han (2024). We set the elasticity of redevelopment to match the reduced-form estimates of the teardown tax on demolition. We calibrate the rest of model parameters to match the model steady state to salient facts in the data on the income and quality distributions across neighborhoods and the expenditure shares spent on housing by households with different income.

We use the estimated model to evaluate a \$60,000 teardown tax in all below-median-income neighborhoods in Chicago. This mirrors the city's effort to expand the 606-Pilsen Demolition Surcharge policy given its success in reducing demolitions.[2] The counterfactuals show that the policy benefits low-income households citywide by preserving old, low-quality housing, but harms middle- and high-income households and reduces land values in treated neighborhoods. Interestingly, the welfare effect is non-linear in income: middle-income households are harmed the most. This is because changes in housing rents are non-monotonic across

[2] As a succession to the three-year Demolition Surcharge, the city council approves a new policy that expands neighborhood coverage and increases the demolition fee to \$60,000, aiming to protect more low-income residents from rising housing costs and displacement. See more details on the policy here.

the quality distribution. The reduction in high-quality supply causes high-income households to downgrade, pushing up rents in the middle-quality segment more than in the high-quality segment and disproportionately harming middle-income households. Moreover, middle- and high-income households relocate to untreated neighborhoods, raising land values there and increasing redevelopment, particularly in relatively affordable untreated neighborhoods prior to the policy. This highlights substantial spatial spillovers from neighborhood-level housing supply operating through migration, analogous to the impact of city-level housing supply on migration studied in Howard and Liebersohn (2021) and Nathanson (2025). We further show that endogenous amenities play a crucial role in generating the general equilibrium spillovers to untreated neighborhoods. Without amenity adjustment, the migration of middle- and high-income households towards untreated areas is much weaker, and consequently the redevelopment response is also attenuated.

Related Literature. Our work is related to several strands of literature. We contribute to the literature on filtering in the housing market. Earlier work by Sweeney (1974) and Brueckner (1980) develops frameworks in which housing is a depreciating asset that filters down the income distribution over time. More recently, Rosenthal (2008) and Brueckner and Rosenthal (2009) provide empirical evidence that neighborhood income declines as the housing stock ages, highlighting the role of housing depreciation and redevelopment. Rosenthal (2014) empirical estimates a sizable housing filtering rate at the individual building level. Our model extends this literature by explicitly modeling landlords' redevelopment choices and heterogeneity in household housing demand, which together generate the dynamic feedback between housing redevelopment, filtering, and spatial income sorting.

This paper contributes to the assignment model literature by building on Määttänen and Terviö (2014) and Landvoigt et al. (2015), who study the matching of vertically differentiated housing units to households with different income.[3] Abramson and Landvoigt (2025) apply the framework to evaluate demand- and supply-side policies aimed at curbing housing costs. Nikolakoudis (2024), Hacamo (2024), and Nathanson (2025) extend this framework to analyze how income-specific credit conditions, mortgage interest rates, and quality-segment-specific housing supply changes affect housing affordability across the distribution, respectively. We contribute to this literature in two ways. First, we endogenize housing supply by modeling forward-looking landlords who make redevelopment decisions in response to market conditions; prior work takes the housing supply as given. Second, we embed the assignment mechanism in a dynamic model, allowing us to study the long-run effects of supply changes. The long-run perspective of studying housing supply is important given the durability and

[3] More broadly, the assignment framework has been used to study matching in the labor market (Costinot and Vogel, 2010), neighborhood choice (Davis and Dingel, 2020; Couture et al., 2023), and school choice (Epple and Romano, 2003) among other topics.

irreversibility of housing investment (Baum-Snow and Duranton, 2025).

Our work adds to the empirical literature that studies the impact of new housing development and demolition on local affordability, income and demographic composition, and neighborhood amenities. This includes work on the impact on low-income housing development (Baum-Snow and Marion, 2009; Diamond and McQuade, 2019), market-rate building development (Pennington, 2021; Asquith, Mast and Reed, 2023; Mast, 2021; Kennedy and Wheeler, 2023), and public housing demolition (Almagro, Chyn and Stuart, 2024; Blanco, 2023). We contribute to this work by providing a unifying, general equilibrium framework that permits analysis of both local and city-wide effects of policies that induce changes in housing quantity and quality. In addition, we introduce a new identification approach to estimate the causal effect of housing redevelopment on income sorting. More broadly, this paper is related to the literature on demand-driven neighborhood gentrification (Brueckner, Thisse and Zenou, 1999; Guerrieri, Hartley and Hurst, 2013; Couture, Gaubert, Handbury and Hurst, 2023), adding a complementary channel of neighborhood change through housing quality upgrading.

Lastly, we contribute to the literature on quantitative spatial models (Ahlfeldt, Redding, Sturm and Wolf, 2015; Monte, Redding and Rossi-Hansberg, 2018; Hsieh and Moretti, 2019), including those with dynamics (Kleinman, Liu and Redding, 2023; Greaney, Parkhomenko and Van Nieuwerburgh, 2024). This class of models typically assumes housing is invisible and clears the housing market by equating neighborhood-level floorspace demand and supply, thereby abstracting from the granular choice over heterogeneous housing units that is standard in discrete-choice approaches to housing (e.g., Bayer, Ferreira and McMillan (2007)). We incorporate heterogeneous housing units into the quantitative spatial model and shows that the housing quality distribution is an important determinant of income sorting across space.

Outline. The rest of paper is organized as follows. We describe our data in Section 2 and present the empirical analysis of the demolition surcharge policy in Chicago in Section 3. We then introduce the general equilibrium model in Section 4. Section 5 describes the estimation of the model. Section 6 presents the counterfactual analysis of a teardown tax policy. Finally, Section 7 concludes.

2 Data

In this section, we outline the data sources used in our empirical analysis and structural model estimation. Throughout the analysis, we focus on neighborhoods within the city of Chicago, with neighborhood boundaries obtained from the Chicago Data Portal.

Property assessments and transactions. We use annual assessment data and transaction deeds from the Cook County Assessor's Office and the Cook County Recorder of Deeds. The assessment data provide parcel-level assessment records from 2000 to 2023, with a unique parcel identification number (PIN) for each parcel. For single- and small multi-family buildings, the assessment records include detailed characteristics such as build year, building and land square footage, number of units, bedrooms, bathrooms, and information on attics, porches, air conditioning, basements, and garages. For condominium buildings, the data are recorded at the unit level but contain a more limited set of characteristics—specifically, square footage and the number of bedrooms and bathrooms. In addition, the assessment data cover only multi-family buildings with up to six units; large apartment buildings with more than six units are therefore not included in our data.

The transaction data include information on each deed, including the PIN, sale price, sale date, buyer and seller names, and deed type, covering the universe of parcel transactions from 2000 to 2023. To restrict the sample to arm's-length transactions, we exclude (1) sales with prices below $10,000 or with missing prices, (2) sales involving special deed types (e.g., quit or executor claim), and (3) transactions recorded at the same value multiple times within a year. Given our focus is on redevelopment activities, we further exclude sales of vacant land parcels. We then match the property assessment data to the transaction data using the PIN.

Building permit. We obtain building permit data from the City of Chicago Data Portal, which record all major building alterations, demolitions, and new construction in the city from 2006 to 2023. The dataset provides detailed permit-level information including the issue date, address, work type, work description, processing time, and estimated cost. The work descriptions are highly detailed; for instance, a permit might state "replace existing porch in new location per plans," "construct foundations for a proposed two-story single-family home," or "revision to permit #...".

We restrict the sample to permits for residential buildings, excluding those for commercial or public structures. In addition, many permits are filed for modifications of prior approvals or for partial alterations of an existing structure. We use ChatGPT to select the construction and demolition permits that involve erecting or tearing down an entire housing unit. The prompt instructs: "Can you determine whether this description of a housing permit involves an entire housing unit? Adding or demolishing one or more floors of a building would count as a permit on an entire unit, such as a second-floor addition to an existing building. Some permits may involve work on only part of a unit, such as the roof or electrical system. Please return 1 if so and 0 if not."

RentHub data. We obtain rental information from RentHub, which has provided nationwide residential rental listings since 2014. The data are collected through weekly web scraping of more than 100 publicly accessible websites. Each listing reports the advertised monthly rent, posting date, unit characteristics, address, and longitude-latitude coordinates. RentHub also constructs unique unit identifiers, allowing us to track rent changes within the same unit over time. We keep the rental listings within Chicago. To reduce the influence of outliers, we exclude the top and bottom 1 percent of rental prices and unit square footage. We then geocode all addresses, identify those within the treated neighborhoods, and merge the listings with property assessment data by address to obtain additional building characteristics.

Verisk Address History data. We use the Verisk Address History data to track individual mobility. Verisk (formerly Infutor) compiles address information from a wide range of private and public sources, including USPS change-of-address records, county assessor files, magazine subscriptions, and phone directories. Although the data inevitably omit some moves, Asquith et al. (2023) show that coverage does not systematically vary with local characteristics. The vintage of the dataset we use includes individuals whose most recent activity recorded by Verisk occurred between 2012 and 2024, thereby providing coverage up to four years after the teardown tax policy. We follow the data-cleaning procedure outlined in Diamond et al. (2020) to construct an individual–year panel of address histories for those who have lived in Chicago after 2012, defining each person's location in a given year as their address on January 1.

Block-Group Level Characteristics. We obtain block-group level data from two sources. First, the 2005–2019 Residential Area Characteristics (RAC) files from the LEHD Origin-Destination Employment Statistics (LODES) dataset provide employment by 2-digit NAICS industry. Second, the 2009–2019 American Community Survey (ACS) provides demographic and income tabulations at the block-group level. We construct tract-level characteristics using block-group level data.

3 Empirical analysis of the Teardown Policy

In this section, we empirically evaluate the effects of Chicago's teardown tax on housing demolition and construction activities, housing rents and prices, and population displacement in treated neighborhoods. We also provide causal evidence on how redevelopment affects income sorting across neighborhoods. Before presenting the empirical results, we begin by describing the policy.

3.1 The Teardown Tax Policy in Chicago

Many neighborhoods in Chicago have undergone rising rents, upscale developments, and a changing demographic landscape. As wealthier residents are drawn to newly developed housing and neighborhood amenities, long-standing residents face displacement and housing affordability issues. To address these issues, the City Council of Chicago implemented a series of policies aimed at preserving affordable housing options and limiting housing redevelopment.

We study the 606–Pilsen Demolition Permit Surcharge Ordinance, implemented from April 2021 to April 2024. The ordinance was designed to preserve existing multifamily housing from being torn down and replaced by higher-end single-family homes. It imposes a surcharge on demolitions, set at the greater of $15,000 and $5,000 per demolished residential unit, in the 606 Trail and Pilsen neighborhoods. See Figure C.1 for the policy areas.[4] Revenues are directed to the Chicago Community Land Trust (CCLT), which provides subsidies for affordable homeownership. [5] Though originally designed as a three-year pilot, the ordinance was extended through the end of 2024 and later renewed with broader neighborhood coverage and a surcharge four times the original amount.

Two other related policies are worth noting. First, an anti-deconversion policy was implemented simultaneously in the same two neighborhoods, which require that construction projects cannot reduce the number of housing units. The permits issued for housing deconversion are classified as renovation/alteration permits in the building permit data, as such projects often involves consolidates housing units within an existing structure without substantial exterior work.[6] Therefore, this anti-deconversion policy complements the teardown tax in preserving the multi-family housing. Later, we will show that this policy indeed reduces the renovation permits that are related to deconversion.

Second, there was a demolition ban in part of the 606 neighborhood from February 2020, which is then replaced by the Demolition Surcharge Ordinance. One might worry that this ban could have changed the housing market conditions prior to the policy. We show later that this temporary ban did not have a significant impact on housing demolition in a narrow band across the boundary, which is required for our empirical strategy. In addition, had

[4]The political economy context is important. Chicago is divided into 50 wards, each represented by an alderperson who also serves on the City Council. Alders wield substantial influence over ward-level zoning and permitting decisions and are highly responsive to local constituencies and interest groups. The surcharge ordinance was co-sponsored by the mayor and the alderpersons of Wards 1 and 35, which border the 606 Trail, and supported by the alderperson of Ward 25, which covers Pilsen.

[5]The demolition surcharge is waived if the demolition is required to address imminently hazardous housing conditions, or if the replacement building reserves at least 50% of its units for low-income residents. More details are available here.

[6]A demolition permit is required for construction projects to to demolish an entire building or structure, to demolish substantially all of the above-grade portion of a building or structure, or to alter an existing building and permanently reduce its building area.

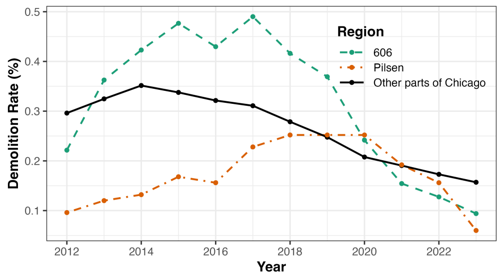
the temporary ban had a significant effect, we would expect to see a rebound in demolition activities after the ban was lifted, which would imply that we underestimate the treatment effect of the teardown tax policy.

Figure 1 illustrates that both neighborhoods were experiencing rapid redevelopment, affordability challenges, and displacement pressures prior to the policy. Panels (a) and (b) show that construction and demolition rates—measured as the share of addresses issued each type of building permit each year—were higher in 2020 in the treated neighborhoods than in the city overall. This reflects heightened redevelopment activity, though the trajectories differed across the two areas: in the 606, construction activity peaked around 2016, whereas in Pilsen it rose steadily through 2020. Panels (c) and (d) show that average rental and sales prices in both neighborhoods increased much faster than in the rest of the city, highlighting growing affordability pressures. Panels (e) and (f) show rising in-migration and out-migration rates in the two treated neighborhoods, indicating greater population churn. The mobility rates increase by more in Pilsen, consistent with its rising construction activity. Panels (g) and (h) further show that in-migrants to the two neighborhoods increasingly originated from higher-income tracts, while out-migrants moved to tracts with below-average incomes. Taken together, these patterns underscore the displacement pressures generated by rising inflows of higher-income households and the corresponding outflows of lower-income incumbents.

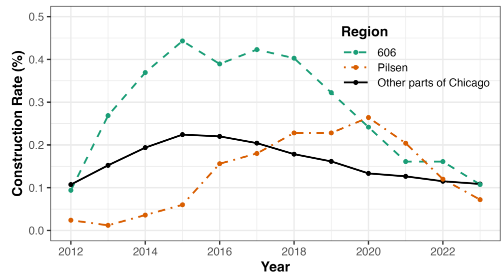
It is also evident from Figure 1 that, since the start of the policy, demolition and construction activity have declined markedly. Growth rates in housing rents and prices have been lower relative to the city average, as well. It is more difficult to draw conclusions from the mobility rates, given the substantial population movements during the COVID-19 pandemic. These time-series patterns, however, cannot be interpreted as causal effects of the ordinance. The observed patterns may reflect broader city-level housing market conditions or neighborhood-specific trends unrelated to the policy. For example, it is possible that after the COVID-19 pandemic, high-income households increasingly sort into suburban neighborhoods, lowering the housing demand for 606 and Pilsen. To credibly identify the policy's impact, we turn in the next section to a spatial difference-in-differences framework.

3.2 Empirical Strategy

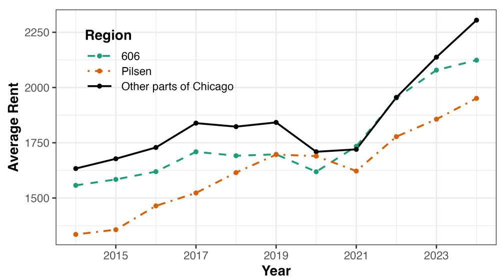
In this section, we study the impact of the Demolition Permit Surcharge Ordinance on the treated neighborhoods. The outcome variables we examine are construction and demolition permits, population displacement, rental prices, and housing transaction prices. To identify the causal effect, we employ a spatial difference-in-difference strategy that compares areas within 500 meters inside the boundary to areas within 500 meters just outside. The empirical



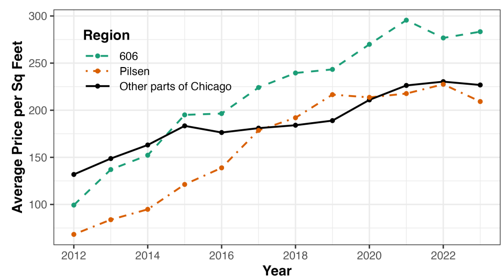
(a) Demolition Rate



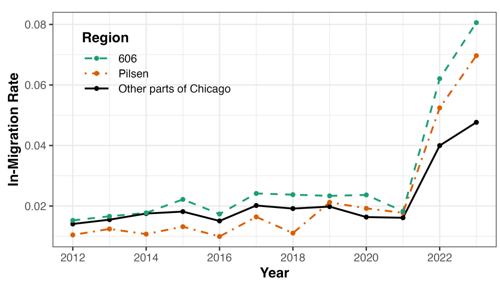
(b) Construction Rate



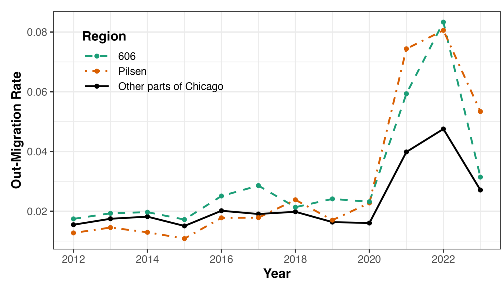
(c) Average Rent



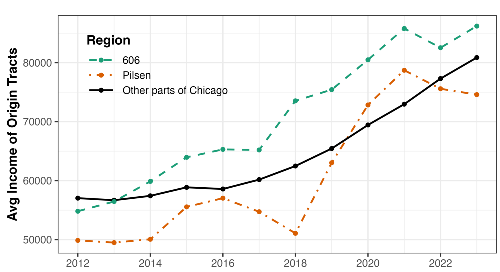
(d) Average Price



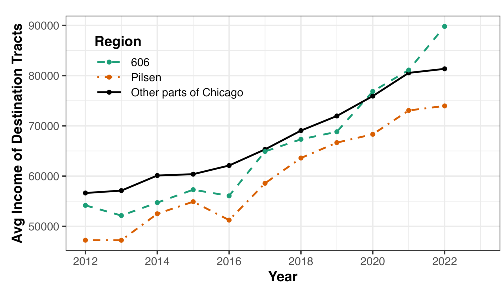
(e) In-Migration Rate



(f) Out-Migration Rate



(g) Avg Origin Tract Income of In-Migrants



(h) Avg Dest. Tract Income of Out-Migrants

Figure 1: Construction Activities, In-Migration and Out-Migration in 606 and Pilsen

Note: Data Sources: Building Permit Data, RentHub Data, Transaction Deeds Data, Verisk Address History Data, and the American Community Survey (ACS). Panels (a) and (b) report demolition and construction rates, defined as the share of addresses issued each type of building permit, where the address set is derived from the Chicago Building Footprints data. Panels (c) and (d) trim the top one percent of listed rental prices and sales prices per square foot, respectively. Panels (e) and (f) define in-migration and out-migration rates as the number of individuals entering or leaving an area relative to its total population. For the remainder of Chicago, we first calculate migration rates at the census-tract level and then take a population-weighted average. Panels (g) and (h) use tract-level average household income from the ACS to calculate the average income of migrants' origin and destination tracts.

specification is given by:

$$Y_{it} = \delta_0 + \sum_{k=-t_0}^{t_1} \delta_t \times 1_{t=k} \times Trt_i + \beta_{xt} X_{it} + \mu_i + \alpha_{xt} + F_{xt}(LON_{it}, LAT_{it}) + \epsilon_{it} \tag{1}$$

where i indexes the observational unit (parcel, individual, or rental unit), t indexes time, and x indexes neighborhoods (606 and Pilsen); the dependent variable Y_{it} represents one of the outcomes of interest (construction and demolition permit dummy, displacement dummy, log rental price, and log sales price); $Trt_i = 1$ indicates that the unit is located within the treated neighborhoods; X_{it} is a vector of control variables and we allow their effect to differ by neighborhood and time through β_{xt}; α_{xt} denotes neighborhood-by-time fixed effects, $F_{xt}(LON_i, LAT_i)$ represents neighborhood-time-specific polynomial of each unit's geographic coordinates, and ϵ_{it} is the error term. We will provide further details on the construction of the outcome variables and on the set of control variables used in each regression. Our parameter of interest, δ_t, captures the dynamic average treatment effect of the policy.

We include a range of control variables and fixed effects to control for observed and unobserved differences across the treatment boundary. To account for unobserved heterogeneity, we include unit fixed effects μ_i for all outcomes except sales prices, since repeated transactions of the same property within a short period are rare and potentially selected. Identification for these outcomes therefore comes from within-unit variation before and after the policy intervention. For the sales price regressions, as repeated sales are rare within a short period, controlling for unit fixed effects are infeasible. We instead control for a set of housing characteristics—including the number of bedrooms, bathrooms, building age, number of units, and building square footage—to capture quality differences across properties.

We additionally include neighborhood-time-specific polynomials in latitude and longitude to absorb granular local shocks. This helps ensure that identification comes from differential changes across the policy boundary. For example, if rental prices gradually increased with distance from the city center due to the rise of remote work in 2021, such spatial trends would be absorbed by these controls, leaving the policy effect identified from the discontinuous change at the boundary. We also control for neighborhood-specific time fixed effects to account for neighborhood-level time-varying shocks.

The identification assumption is that the areas right inside and outside the policy boundary share the same housing demand conditions, conditional on the extensive set of controls. The choice of a 500-meter buffer is motivated by two considerations. First, it provides sufficient sample size for statistical power — in particular for the building permits. Second, we believe 500 meters is narrow enough to ensure that areas inside and outside the boundary share the same housing demand conditions. In Table C.1, we provide a balance test between the 500 meter buffer areas inside and outside the treatment boundaries. We find no significant difference of a set of housing characteristics and the sales price, though the housing rent is slightly lower inside the treatment boundary.[7] Notably, the policy overlaps with the COVID-19 pandemic, which significantly shifted housing supply and demand conditions. Our identification relies on the assumption that these shifts do not differentially affect the areas right across the treatment boundaries.

As discussed by Baum-Snow and Ferreira (2015), the treatment effect estimated from any spatial difference-in-differences design includes the general equilibrium effect on control neighborhoods. Although the reduced-form design cannot isolate general equilibrium effects, we incorporate them in the structural model introduced in Section 4. In practice, however, such spillover effects are likely small given the policy's short duration and limited coverage. As shown in Figure C.2, average construction and demolition rates just outside the boundary do not increase following the policy. In particular, the average demolition rate in the control area declines at a pace similar to the citywide rate, indicating limited spatial spillovers.

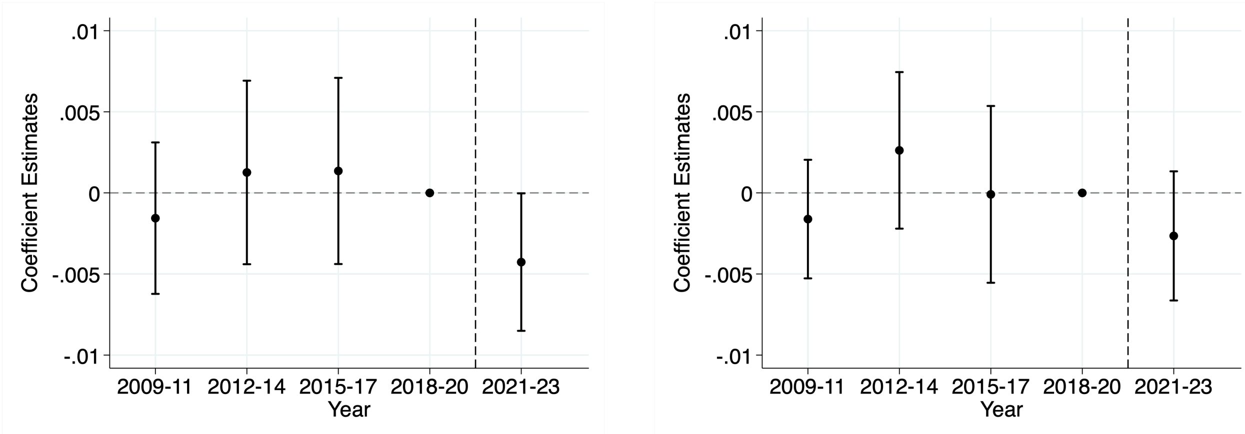
3.3 Housing Demolition and New Construction

We start from the policy effect on demolition and construction activities. Because these are rare events at the address level as shown in Figure 1, we construct three-year periods and run the spatial difference-in-difference using the address-period-level panel data. The dependent variables are dummy variables which equal one if address i is issued a demolition and construction permit in period t, respectively. The set of addresses are obtained from the Chicago Building Footprints data.

Figure 2 shows that the teardown policy reduced the probability of demolition permits in the treated areas by about 0.5 percentage points, significant at the 5% level, and the probability of construction permits by about 0.3 percentage points, though the latter is not statistically significant. The estimated effect on construction is smaller than the effect on demolition. Construction permits are not taxed and can come from follow-up construction after demolition in the previous period or from new development on parcels that were initially empty. The estimated δ's prior to the policy are all insignificant at the 5% level in both regressions, lending support to the parallel trends assumption. It also implies that the temporary demolition ban enacted before the ordinance in the 606 neighborhood did not significantly reduce teardowns in the treated area.

We perform several robustness checks for our main result. In Table C.3, we conduct robustness checks with different buffer widths of 250 meters and 1,000 meters. With the

[7] Table C.2 shows that relative to the rest of the city, housing the treated neighborhoods have more units, larger building square footage, smaller lot size, and greater build age. Average sales price before the policy are greater, while average rent is lower.



(a) Demolition Permits

(b) Construction Permits

Figure 2: Difference-in-Difference Results on Demolition and Construction Permits

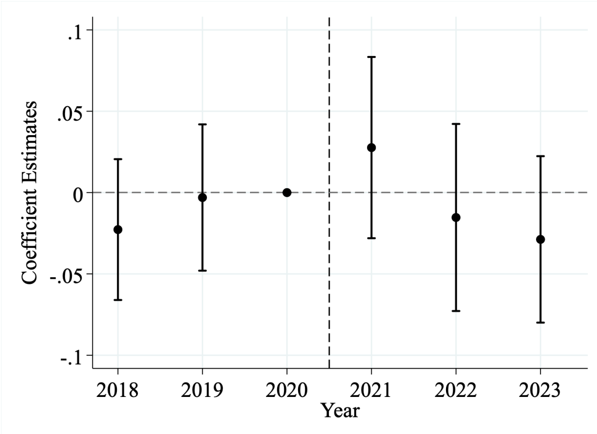
Note: The figure shows the logistic estimation results of equation (1) at the three-year frequency with 500 meter buffers. Robust standard errors clustered at the address level. Confidence intervals are at the 95% significance level.

250 meters buffer, the estimated effect on demolition permits becomes insignificant, likely due to a lack of power from the smaller sample of addresses. Using the 1,000 meters buffer, the estimated effect on demolition permits is similar to the baseline, whereas the effect on construction permits becomes significantly negative. Figure C.3 reports estimation result of equation (1) at the yearly frequency. The results are similar to the baseline specification using the three-year frequency, though we find greater effects in 2021, the first year after the policy. Figure C.4 shows the policy does not increase processing time of building permits in the treated area, indicating that the estimated treatment effect is not driven by administrative delays.

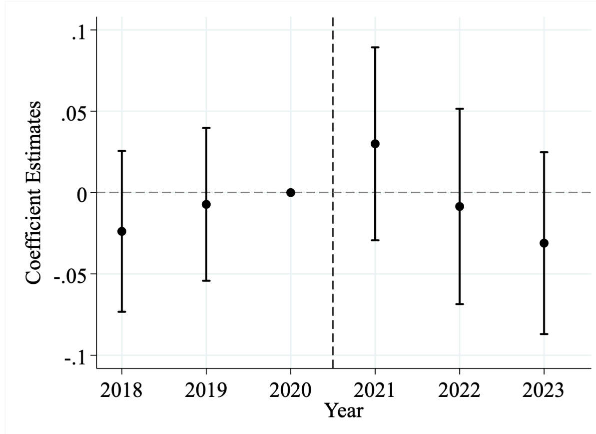
In addition to demolition and construction permits, we assess the policy's impact on renovation permits and find no significant effects (see Panel (a) of Figure C.5). We also use ChatGPT to classify renovation permits into four categories based on the work descriptions: additions, remodeling, repairs, and deconversions. Among these, we find a marginally significant negative effect on deconversion permits, while the other three categories show no significant increase (see Panels (b)–(e) of Figure C.5). This pattern suggests limited substitution from new construction to renovation as a means of supplying higher-quality housing in response to the policy.

3.4 Population Displacement

We use the Verisk Address History data to study the policy's impact on the displacement of incumbent residents in the treated neighborhoods. The estimation sample is constructed from



(a) Neighborhood-Level Displacement



(b) Address-Level Displacement

Figure 3: Difference-in-Difference Results on Displacement

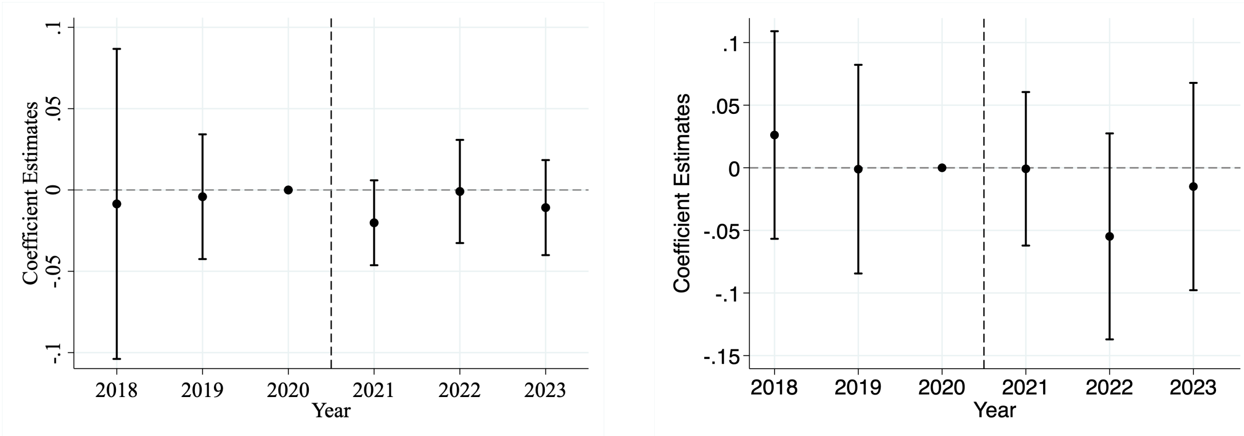
Note: The figure shows the estimation results of equation (1) for displacement outcomes. See the main text for details on the two displacement outcomes. Robust standard errors are clustered at the individual level. Confidence intervals are at the 95% significance level.

a balanced individual–year address panel spanning 2014–2024. To isolate the effect of the policy on long-term incumbents, we restrict the sample to who had lived within 500 meters of the treatment boundaries from 2014 to 2018. We then use the address records of these incumbents from 2018 to 2024 to estimate the spatial difference-in-differences regression. Once an individual moved out from the treatment and control area areas, we exclude all subsequent observations from the estimation sample, since these later location choices are no longer directly affected by the policy. We expect the policy to lower displacement by preserving older, affordable housing stock valued by low-income incumbents, although the effect may be modest given the policy's short duration.[8]

Displacement is measured in two ways. The first is a neighborhood-level measure, which is set to one if an individual moves out of the buffer area in a year—that is, the 500-meter ring just inside or outside the boundary—and zero otherwise. The second is an address-level measure, which is set to one if an individual moves between addresses in a year and zero otherwise. The latter measure captures the broadest definition of displacement, since even intra-neighborhood relocations can incur moving costs on households.

The results show in Figure 3 suggest that the policy has a negative yet statistically insignificant effect on displacement in the treated neighborhoods after the first year of its implementation. The pre-treatment coefficients for both displacement measures are small and insignificant, indicating that treated and control neighborhoods were subject to similar

[8]Recent work by Garin, Jenkins, Mast and Stuart (2025) shows that individuals experiencing earnings growth tend to move out of poorer neighborhoods. Our research design examines how changes in housing supply—arguably orthogonal to incumbents' earnings changes—affect mobility.



(a) Rental Price (b) Sales Price

Figure 4: Difference-in-Difference Results on Housing Rental and Sales Prices

Note: The figure shows the estimation results of equation (1) for log housing rental and sales prices. In panel (a), we include the unit fixed effect and apply two-way clustering by unit ID and month. We weight each rental listing by the inverse of the number of listings that RentHub records for each unit within a year. Robust standard error clusted at the unit level. In panel (b), we control for a set of housing characteristics, including the building age, number of bedrooms and bathrooms, number of units, land square feet, and average unit square feet, and interact them with year-month dummies and neighborhood dummies to capture time-varying demand for these housing characteristics. Conley standard errors reported. Both regressions include year-month-neighborhood-specific polynomials of longitude and latitude. Confidence intervals are at the 95% significance level.

displacement pressures prior to the policy. Turning to the treatment effects, we find that both measures of displacement respond in a similar way. Displacement in the treated areas rises slightly in 2021 but gradually declines to negative values after 2022, although none of the estimates are statistically significant. The 2023 coefficient suggests that the policy reduced the displacement rate by about 3 percentage points—an effect that is imprecisely estimated yet economically meaningful relative to the average post-2020 annual moving rate of 5 percent, as calculated from the Verisk data.

Table C.5 reports robustness checks using alternative buffer widths. As expected, the estimated treatment effects based on the 250-meter buffer are not statistically significant. Expanding the buffer to 1,000 meters yields an estimated effect of –0.04 in 2023, significant at the 10% level. This comparison suggests limited statistical power to detect displacement effects when the buffer is too narrow, while individuals located farther from the boundary may be less comparable.

3.5 Rental and Sales Prices

We now turn to the policy's impact on housing rents and prices. Two mechanisms could plausibly generate downward pressure in the treated neighborhoods. First, by preventing demolitions, the policy modestly increases the stock of older housing, thereby expanding the rental supply and reducing developer demand for existing units. Given the short policy horizon and the low annual demolition rate, however, this effect is likely limited. Second, by reducing the displacement of incumbent residents, the policy helps preserve neighborhood amenities tailored to the existing population, which in turn dampens demand from prospective gentrifiers.

Sales prices provide an additional lens because they reflect expectations of future supply and demand conditions. A concern one may have is that the policy might have been anticipated before it was implemented or might have been expected to extend beyond the planned end date. If so, these expectations should be capitalized into housing values—particularly for older properties—since a prolonged teardown tax erodes the option value of redevelopment and lowers the price of existing structures. The results we will soon show provide no evidence of such expectations.

The regression results on rental and sales prices are in Figure 4. We estimate insignificant and negative policy effects on the rental prices (Panel (a)) and on quality-adjusted sales price (Panel (b)) in the treated area, which are as expected. The pre-trends for both prices are insignificant, indicating parallel trends and a lack of anticipation prior to the policy. The insignificant effect on the sales price throughout 2018–2023 also suggests a lack of market expectation that the teardown tax would be extended. Table C.4 shows that these results are robust to alternative buffer widths. Figure C.6 further shows that the policy lowered the average age of buildings sold in 2021–2022, with the prices of older buildings also declining modestly. There is also a slight increase in the building age of listed rental properties, indicating a policy-induced expansion in rental supply of old housing.

3.6 Evidence on Redevelopment and Income Sorting

We now examine whether redevelopment causally affects income sorting. Ideally, we would exploit the demolition-surcharge policy as a source of variation. However, the policy window was too short to generate meaningful shifts in neighborhood income composition, and we do not observe micro-level income data to run the spatial different-in-difference regression. We therefore turn to citywide block-group variation in decadal changes in building age to provide complementary evidence. Specifically, we regress 2009-2019 block-group level changes in log median income, obtained from ACS, on changes in median building age, measured using the assessment data, as follows.

$$\Delta \log \text{Median Income}_b = \beta_0 + \beta_1 \Delta \text{Median Building Age}_b + \beta_c \text{X}_b + \epsilon_b \tag{2}$$

where Δ represents the change from 2009 to 2019, b indexes a block group, X_b is a set of control variables, and ϵ is the error term. The change in building age proxies for the extent of housing redevelopment, while the change in log median income captures shifts in resident composition.[9] We expect median income to rise in block groups where median building age declines, i.e., higher-income households sort into neighborhoods with newer housing stock. The first-difference specification accounts for all time-invariant neighborhood characteristics. Equation (2) can be interpreted as a neighborhood demand equation, with ϵ_b being the unobserved demand shocks affecting income sorting between 2009–2019.

A naive OLS regression suffers from a simultaneity bias: unobserved demand shocks can both shift the neighborhood income distribution and incentivize housing redevelopment. For example, Pilsen might have been gentrifying because it is within commuting distance of high-skill jobs that experienced wage growth, which in turn spurred redevelopment in the neighborhood.

To address these concerns, we construct an insutrmental variable in the spirit of Diamond (2016). The instrument is the interaction between a Bartik-style shift–share measure, which generates exogenous housing demand shocks, and the 2009 share of housing units built before 1910. With this instrument, identification comes from heterogeneous responses to housing demand shocks: for a given positive demand shock, neighborhoods with a larger stock of older buildings should have more redevelopment. We use 1910 because it is the average build year of redeveloped units in our sample (see Figure C.7). The Bartik shock aggregates 2009–2019 MSA-level employment changes by 2-digit NAICS industry, using 2005 neighborhood employment shares as weights, capturing local labor-demand shocks originating outside the neighborhood that shift housing demand. The construction of the shift-share variable is described in detail in Section 5.2. We also control for initial (2009) log median income, initial average building age, and changes in neighborhood employment, all of which are possibly correlated with unobserved neighborhood demand shocks.

The results are shown in Table 1. We cluster the standard error at the official Chicago neighborhood level, as the demand and supply factors for Census block groups within a neighborhood might be correlated. The IV estimates reported in Columns (3)–(4) are both larger in magnitude than the OLS counterparts reported in Columns (1)–(2). The estimate in Column (3) indicates that a one-standard-deviation decrease in the change in building age is associated with about 10.7 log point increase in median income. The IV estimate changes by little when initial log income is added as a control, implying that the estimated negative effect of redevelopment on income is not driven by the mean reversion process in

[9] We use medians for both income and age to reduce sensitivity to outliers; results are robust to using means.

Table 1: Change in Building Age and Income

	(1) Δ log Income	(2) Δ log Income	(3) Δ log Income	(4) Δ log Income
Δ Median Building Age	-0.068***	-0.086***	-0.107***	-0.105**
	(0.012)	(0.015)	(0.036)	(0.046)
Δ log Employment	-0.009	-0.052	-0.008	-0.053
	(0.037)	(0.036)	(0.038)	(0.036)
Initial Median Building Age	-0.001	-0.003***	-0.001	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Initial log Income		-0.269***		-0.276***
		(0.028)		(0.030)
Observations	2,268	2,268	2,268	2,268
R^2	0.038	0.143	0.025	0.140
Specification	OLS	OLS	IV	IV
KP F-Stat	.	.	29.7	38.2

Note: All regressions are weighted by the initial number of housing units. Change in building age is normalized to have a standard deviation of 1 year (originally 3.7 years). Standard errors are clustered at the official Chicago neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

neighborhood income. The F-statistics of the first stage are well above the conventional threshold of 10, confirming instrument strength. Table C.6 shows that in the first stage, blocks with larger demand shocks and older housing stock experienced significantly larger declines in building age, consistent with our expectations.

3.7 Taking Stock

We have shown that (1) the teardown tax effectively reduced housing redevelopment and had negative, statistically insignificant effects on displacement, housing rent and prices, and (2) housing redevelopment cause income sorting across. In the next section, we develop a model that endogenizes housing redevelopment and household neighborhood sorting decisions for an entire city. This model will enable us to theoretically analyze the relationship between redevelopment and gentrification, conduct counterfactual analyses of housing policies, and assess these policies' general equilibrium effects and welfare implications.

4 Model

Consider a city that consist of a set of neighborhoods, indexed by $x \in \mathbb{X}$, and a location representing an outside option o.[10] Neighborhoods differ by exogenous amenities that vary by income type, denoted by $\bar{A}(x, z)$. Amenities also respond endogenously to the average income of the neighborhood, which we describe later. In each neighborhood, there is a set of land parcels $i \in \mathbb{I}_x$. The parcel and the residential building on it are owned by an immobile landlord. Each residential building varies by its housing quality $q \in \mathbb{Q}$ and the number of units $h \in [0, \infty)$, with $h = 0$ representing an empty parcel.

Households, indexed by ω, differ in their income $z_\omega \in [0, Z_{max}]$ and initial neighborhood of residence $x_{\omega,0} \in \mathbb{X} \cup \{o\}$. There are an exogenous measure $\bar{L}(z, x_0)$ of each household type. Households can choose to live in a neighborhood x within the city, or to live outside the city that provides a normalized, exogenous utility level of 1. We assume all households are renters. Within a neighborhood, each household chooses one housing unit to rent. Moving between neighborhoods is costly.

The model is dynamic, with time is indexed by t. Housing quality depreciates over time, with the depreciation rate given by δ. Both landlords and households are forward-looking when making housing supply and neighborhood choice decisions. For notational convenience, we omit the time index t and the household index ω when there is no risk of confusion.

4.1 The Household's Problem

The household's problem consists of two choices. First, given the choice of a neighborhood x, households choose the quality q of a housing unit to live in that neighborhood. Second, given the characteristics of the neighborhood (a schedule of housing rent and amenities), households choose one of the neighborhoods of the city or the outside location to live in. We present these two problems below.

Housing quality choice

We adopt the assignment framework of Määttänen and Terviö (2014) and Landvoigt, Piazzesi and Schneider (2015) for the quality choice problem. Consider a household ω with income z_ω who has chosen neighborhood x. The household chooses to rent one housing unit with quality q and the quantity of the numeraire good y to maximize the following utility function:

$$U(x, z_\omega) = \max_{q,y} (q - \bar{q})^\alpha y^{1-\alpha} \tag{3}$$

[10] An outside option o is needed as the number of households in the city needs to equal to the number of housing units, which is an endogenous variable, as we do not allow for homelessness or shared occupancy.

s.t.

$$P(q, x) + y = z_\omega \tag{4}$$

where α and $\bar{q}$ are household preference parameters, and $P(q, x)$ is the housing rent for one housing unit of quality q in neighborhood x. $P(q, x)$ is an equilibrium object determined by housing supply and demand conditions. Parameter α governs the average expenditure share on housing. Parameter $\bar{q} > 0$ is the minimum quality demanded by households. This parameter controls the rate at which the expenditure share on rent declines with household income (Couture et al., 2023; Albouy et al., 2016). If the pricing function is differentiable, the optimal quality choice of household ω satisfies:

$$\underbrace{\frac{\alpha}{1-\alpha}\frac{z_\omega - P(q, x)}{q - \bar{q}}}_{\text{MRS of housing for numeraire}} = \frac{\partial P(q, x)}{\partial q} \tag{5}$$

Equation (5) is derived from household's first-order conditions and is a standard condition that equalizes the marginal rate of substitution (MRS) to the price ratio, with the final good y being the numeraire. Moreover, for any strictly increasing pricing function $\frac{\partial P(q,x)}{\partial q} > 0$, the MRS is strictly decreasing in q. This immediately implies that, within a neighborhood, higher income residents match to strictly higher quality housing (Määttänen and Terviö, 2014).

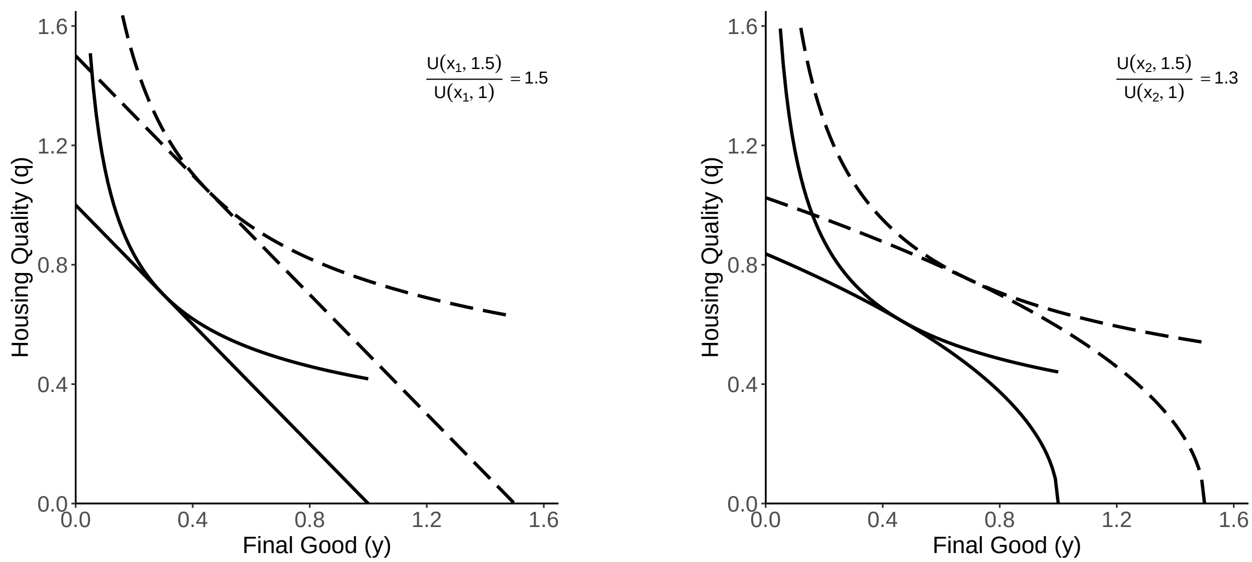
The pricing function $P(q, x)$ is an important equilibrium object. It characterizes how housing costs vary across the quality distribution, and thus how housing affordability varies across the income distribution given the positive assortative matching between housing quality and household income. In particular, Proposition 1 shows that high-income households derive relatively greater utility than low-income households in neighborhoods where high quality housing is relatively cheap; equivalently, in neighborhoods where the pricing function is less elastic.

Proposition 1 *Suppose $\bar{q} = 0$, i.e., preferences are Cobb-Douglas. Consider two neighborhoods x_1 and x_2 and households $z_2 > z_1$. Then,*

$$\forall q \in \mathbb{Q}, \quad \frac{\partial \log P(q, x_2)}{\partial \log q} > \frac{\partial \log P(q, x_1)}{\partial \log q} \implies \frac{U(x_1, z_2)}{U(x_1, z_1)} > \frac{U(x_2, z_2)}{U(x_2, z_1)}.$$

Proof. See Appendix A. ■

To illustrate Proposition 1, we consider a partial-equilibrium case where the pricing functions are iso-elastic: $P(q, x) = \kappa(x)q^{\nu(x)}$, where $\kappa(x)$ and $\nu(x)$ are neighborhood-specific parameters. Figure 5 compares the optimal choices and utility of two types of households in the two neighborhoods with $\nu(x_2) > \nu(x_1)$. In Panel (a), where $\nu(x_1) = 1$, the household



(a) Neighborhood 1, $\nu(x_1) = 1$

(b) Neighborhood 2, $\nu(x_2) = 2$

Figure 5: Utility maximization under two pricing functions for low- and high-income households

Note: Each figure plots the budget constraints and the optimized indifferent curves for two types of households and in a neighborhood. The solid lines are for the low-income household, and the dashed lines are for the high-income household. The specification is as follows: (1) $\alpha = 0.7$, (2) $z_1 = 1$ and $z_2 = 1.5$, (3) $\nu = 1$ in panel (a), and $\nu = 2$ in panel (b), (4) we normalize κ to 1 in panel (a), while in panel (b), we set κ such that the optimal bundle of (q, y) for each type of individual in panel (a) is still affordable.

problem becomes one with a standard linear budget constraint. With Cobb-Douglas preferences, it is well-known that the utility level is linear in income z. In Panel (b), where we set $\nu(x_2) = 2$, the greater amount of housing expenditure results in less housing consumption for higher-income households; this is a consequence of the convex pricing function. In other words, the marginal utility of spending one more dollar on housing becomes smaller as income increases. As a result, the utility gap between high- and low-income households (discerned by the distance between the indifference curves) is smaller in the neighborhood with the elastic pricing function.

By setting $\bar{q} = 0$, Proposition 1 abstracts from non-homothetic preferences for housing. The purpose of this abstraction is to show how the non-linear structure of the pricing function affects welfare inequality across neighborhoods. When $\bar{q} > 0$, the level of the pricing function ($\kappa(x)$ in our simple example) also affects variation in the relative utility across neighborhoods, as is well known (Couture et al., 2023; Finlay and Williams, 2025).

Proposition 1 is a partial-equilibrium statement about the pricing function and household welfare. However, it has two important implications that underpin our entire general equilibrium theory. First, redevelopment tends to replace low-quality housing units with high-quality housing units. The increase in supply of high-quality housing benefits high-income households, and this benefit is manifested in equilibrium by a lower price elasticity of quality (to clear housing markets). Second, high-income households sort into neighborhoods with lower price elasticities of quality because they derive relatively more value from them than low-income households. In what follows, we show how our model of housing supply and neighborhood choice captures both of these effects.

Neighborhood choice

In each period t, each household ω chooses a neighborhood x to reside in, according to the following problem:

$$V_{\omega t}(z_\omega, x_{0\omega}, \vec{\epsilon}_t) = \max_x \; \tau(x; x_{\omega 0}) \cdot U_t(x, z_\omega) A_t(x, z_\omega) \epsilon_{\omega t}(x) + \beta \mathbb{E}_{\vec{\epsilon}} \, V_{t+1}(z_\omega, x_{\omega 0}, \vec{\epsilon}_{\omega t+1}), \tag{6}$$

where $x_{\omega 0}$ is the household ω's original neighborhood, $\tau(x; x_{\omega_0})$ is the mobility cost associated with moving to x, $A(x, z)$ is the income-specific amenity of neighborhood x, $\vec{\epsilon}_{\omega t} = (\epsilon_{\omega t}(1), ..., \epsilon_{\omega t}(X), \epsilon_{\omega t}(o))$ is a vector of neighborhood-specific idiosyncratic preferences, β is the discount factor.

A number of assumptions follow. First, following Guerrieri et al. (2013), we assume that the neighborhood amenity responds endogenously to the average income:

$$A_t(x, z) = \bar{A}(x, z) \cdot \bar{z}_t(x)^\eta, \tag{7}$$

where $\bar{A}(x, z)$ is the exogenous income-specific neighborhood amenity, $\bar{z}$ is the average neighborhood income, and η is the endogenous amenity spillover elasticity. Second, the moving cost takes the form of a utility shifter associated with living in a neighborhood other than the original neighborhood, i.e., $\tau(x; x_{\omega 0}) < 1$ if $x \neq x_{\omega 0}$ and $\tau(x; x) = 1, \forall x$. It reflects the idea that households may have a preferential attachment to their original neighborhood and thus moving to another neighborhood is associated with a welfare loss. As in Desmet, Nagy and Rossi-Hansberg (2018), the mobility-cost assumption renders the household's neighborhood choice problem static: households can always move back to their original neighborhood in the future to avoid this cost. Third, we assume that the idiosyncratic preferences, $\{\epsilon_{\omega t}(x)\}_{\forall \omega, t, x}$, are drawn i.i.d. from a Type-II Extreme Value distribution with its dispersion governed by parameter σ_x, i.e., $F(\epsilon) = \exp\left(-\epsilon^{-\sigma_x}\right)$.

The assumption on idiosyncratic preference shocks allows us to solve for the mass of households that chooses to live in neighborhood x in each period t:

$$L_t(x, z, x_0) = \bar{L}(z, x_0) \cdot \frac{[\tau(x; x_0) \cdot U_t(x, z) A_t(x, z)]^{\sigma_x}}{\sum_{x' \in \mathbb{X}} [\tau(x'; x_0) \cdot U_t(x', z) A_t(x'; z)]^{\sigma_x} + \tau(o; x_0)^{\sigma_x}}, \tag{8}$$

where $L_t(x, z, x_0)$ is the mass of households choosing x that are of type (z, x_0), and $\bar{L}(z, x_0)$ are the exogenous mass of households of type (z, x_0). The utility term $U_t(x, z)$ is defined in equation (3), and the last term in the denominator represents the utility of living in the outside option o, which is normalized to one and multiplied by the moving cost $\tau(o; x_0)$.

Equation (8) shows that households sort into neighborhoods that provide relatively high utility value, and this sorting is potentially heterogeneous by income. Combining equation (8) with Proposition 1 implies that heterogeneity in the price elasticity of quality across neighborhoods induces income sorting. We summarize this result in Corollary 1.

Corollary 1 *Suppose $\bar{q} = 0$, i.e., preferences are Cobb-Douglas. Consider two neighborhoods x_1 and x_2, and households with income levels $z_2 > z_1$ that start in the same origin neighborhood x_0. Assume there is no variation in amenities between these neighborhoods. Then,*

$$\forall q \in \mathbb{Q}, \quad \frac{\partial \log P(q, x_2)}{\partial \log q} > \frac{\partial \log P(q, x_1)}{\partial \log q} \implies \frac{L(x_1, z_2, x_0)}{L(x_1, z_1, x_0)} > \frac{L(x_2, z_2, x_0)}{L(x_2, z_1, x_0)}, \ \forall x_0.$$

That is, the neighborhood with lower price elasticity of quality has a greater share of high-income households from the same origin. If there is no moving cost, then the condition on the pricing functions imply $\frac{L(x_1,z_2)}{L(x_1,z_1)} > \frac{L(x_2,z_2)}{L(x_2,z_1)}$, where $L_t(x, z) \equiv \sum_{x_0 \in \mathbb{X} \cup \{\boldsymbol{o}\}} L_t(x, z, x_0)$.

Proof. Follows directly from Proposition 1 and equation 8. ∎

A well-established result is that with homothetic preferences and divisible housing, variation in housing rents does not generate income sorting across neighborhoods (Diamond and Gaubert, 2022; Finlay and Williams, 2025). Corollary 1 shows that this result no longer holds when housing is indivisible: even under homothetic preferences, differences in the non-linear pricing functions can induce income sorting.

Corollary 1 forms one of the key bases for understanding general equilibrium in this model. Redevelopment, which replaces low-quality housing with high-quality housing, will induce income sorting across neighborhoods by flattening the pricing function. Imposing a tax on redevelopment would achieve the opposite outcome. In what follows, we formulate the redevelopment decisions of forward-looking landlords and discuss how these decisions both influence and are influenced by the pricing function in general equilibrium.

4.2 The Landlord's Problem

Each landlord maximizes the expected value of the parcel it owns, which correspond to the discounted stream of future housing rents. The discount factor is β. We denote $s_{it} = (q_{it}, h_{it})$ as the vector of state variables of parcel i in period t, consisting of housing quality q and the number of housing units h. In each period t, we assume that landlord i receives a building *blueprint* $\hat{q}_{it}$, drawn from a quality distribution $G(\hat{q}), \hat{q} \in \mathbb{Q}' \subseteq \mathbb{Q}$. Blueprints endow the landlord with the option, but not the obligation, to redevelop a parcel with quality $\hat{q}_{it}$. If the landlord redevelops, they also decide on the number of housing units h_{it} for the new structure. Redevelopment incurs a cost $C_i(\hat{q}, h)$ depending on the new housing quality and quantity, which is specified as

$$C_i(\hat{q}, h) \;=\; \underbrace{\Omega_x \cdot \hat{q} \cdot h^{\gamma}}_{\text{Variable costs}} \;+\; \underbrace{F_{\hat{q}x}}_{\text{Fixed costs}} \quad . \tag{9}$$

The cost function C_i contains a variable and a fixed cost component. The variable cost relates to the blueprint quality $\hat{q}$ and the choice of housing units h, with a convex cost parameter γ, and a neighborhood-specific variable cost shifter Ω_x. Building high-quality units is more costly, and the marginal cost of increasing additional housing units grows with the number of units. The fixed cost of redevelopment is $F_{\hat{q}x}$, which varies by the blueprint quality and neighborhood. It includes the cost of teardowns and site preparation for new construction, the cost of acquiring the blueprint, and the regulatory cost of redevelopment – including the teardown tax. We implicitly assume a perfectly competitive construction sector, so the landlord captures all surplus from redevelopment. As housing investment is irreversible, a demolished structure yields zero salvage value.

If the landlord chooses not to redevelop, she collects housing rent $P_t(q_{it}, x) \cdot h_{it}$. The housing quality of all units depreciates at a rate δ.[11] The current period blueprint is then destroyed, and the landlord draws a new one in the next period. We assume that once a structure reaches the minimum quality $\bar{q}$, it ceases to depreciate further. We interpret such units as vacant—they are sufficiently dilapidated so as to provide zero housing services.

Let $V_{it}(s_{it}, \hat{q}_{it}, \vec{\xi})$ be the value of parcel $i \in \mathbb{I}_x$, which incorporates the capitalization of future rent streams and the option value of potential redevelopment, given the current housing state s_{it} and blueprint $\hat{q}_{it}$. The landlord's problem can be written recursively as

$$V_{it}(s_{it}, \hat{q}_{it}, \vec{\xi}_{it}) = \max \left\{ \; V_{it}^N(s_{it}) + \frac{1}{\sigma_c}\xi_{it}^N, \; V_{it}^R(\hat{q}_{it}) + \frac{1}{\sigma_c}\xi_{it}^R \; \right\} \tag{10}$$

where the value of no redevelopment V_{it}^N is the sum of rents this period and the continuation value:

$$V_{it}^N(s_{it}) = P_t(q_{it}, x)h_{it} \; + \beta \mathbb{E}_{\hat{q}_{it+1},\, \vec{\xi}_{it+1}} V_{i,t+1}\left(q_{it}^D, h_{it}, \hat{q}_{i,t+1}, \vec{\xi}_{it+1}\right)$$

[11] We abstract from endogenous renovation and maintenance decisions. This simplification is motivated by our empirical evidence, which shows little substitution from demolitions to renovations in response to the teardown tax.

and the value of redevelopment V_{it}^R is the discounted rent stream minus construction costs for the profit maximizing development:

$$V_{it}^R(\hat{q}_{it}) = \max_h \left\{ -C_i(\hat{q}, h) + P_t(\hat{q}_{it}, x)h + \beta \mathbb{E}_{\hat{q}_{it+1},\, \vec{\xi}_{it+1}} V_{i,t+1}\left(\hat{q}_{it}^D, h, \hat{q}_{i,t+1}, \vec{\xi}_{it+1}\right) \right\}$$

where we used the depreciation operator $q_{it}^D = (1-\delta)q_{it}$ if $(1-\delta)q_{it} > \bar{q}$, or $\bar{q}$ otherwise. Note that the redevelopment value V^R does not vary by the state variable s_{it}, as housing investment is completely irreversible. ξ_{it}^N and ξ_{it}^R are the idiosyncratic cost shocks of not redeveloping and redeveloping the parcel, which we assume are drawn i.i.d. over time and space from a Type-I Extreme Value distribution, i.e., $F(\xi) = \exp(-\exp(-\xi))$, with its variance scaled by parameter σ_c. A larger σ_c implies less dispersion in idiosyncratic shocks, making redevelopment decisions more responsive to the deterministic components of the payoff. We can then obtain the probability of redevelopment given state variables as

$$P_{it}^R(s_{it}, \hat{q}_{it}) = \frac{e^{\sigma_c V_{it}^R(\hat{q}_{it})}}{e^{\sigma_c V_{it}^R(\hat{q}_{it})} + e^{\sigma_c V_{it}^N(s_{it})}}. \tag{11}$$

Our model of housing supply has important implications for understanding the general equilibrium response to a teardown tax. The probability of redevelopment is closely tied to the equilibrium housing quality distribution. This is because the production of high-quality structures can only be achieved through redevelopment. If the redevelopment probability is low (for example, because of a teardown tax), there will be relatively more buildings that have low quality in the steady state. In general equilibrium, an increase in the abundance of low-quality housing and the scarcity of high-quality housing will then manifest in a higher price elasticity of quality, attracting more low-income households to the neighborhood (Proposition 1 and Corollary 1).

Rents and the incentives for redevelopment. We showed that the structure of the pricing function matters for neighborhood sorting. The structure of the pricing function also matters for understanding landlords' incentives to redevelop to high-quality housing relative to low-quality housing. The redevelopment payoff, given by $V^R(\hat{q}) - V^N(q, h)$, depends on the value of the current structure, construction costs, and the value of the structure after redevelopment. Crucially, the value of a new structure depends on the shape of the pricing function: when the pricing function is steeper in quality (or more elastic), high-quality units generate higher rental returns, increasing incentives to redevelop housing at higher quality.

This point can be illustrated with the following thought experiment. Suppose there is an inflow of high-income households into a neighborhood. This shift in the income distribution pushes up the housing rent in the high-quality segment of the local housing market, which, in turn, induces more redevelopment by the landlords to reap the higher return from high-quality housing. This thought experiment explains why a teardown tax targeted to specific neighborhoods increases redevelopment in untreated neighborhoods (see Section 6). In Appendix A.2, we formalize this logic and prove that higher rent gradients will cause more redevelopment to high quality segments.[12]

The role of random blueprints. We do not explicitly model the landlord's optimal choice of redevelopment quality. Instead, drawing from the macro literature (e.g., Luttmer (2011)), we introduce random development blueprints that affect the landlord's decision to redevelop. The random blueprint captures, in a reduced form way, the matching frictions between landlords and heterogeneous construction firms that generate heterogeneity in redevelopment outcomes. This modeling choice is consistent with growing evidence on the inability of housing investors to respond to arbitrage opportunities across segmented housing markets. Damen, Korevaar and Van Nieuwerburgh (2025) document excess returns to low-quality rental housing that is accompanied by a lack of entry into the sub-market. Greenwald and Guren (2025) show that imperfect substitution across housing submarkets is necessary for credit to play a causal role in the U.S. housing boom. One could instead model quality choice by landlords under explicit housing market frictions in a way that can be disciplined by data. We leave such an extension to future work.

4.3 Equilibrium Definitions

We assume that landlords have perfect foresight over future rent schedules across the entire quality distribution. This assumption allows us to define the equilibrium for the model.

Definition 1 *Given the initial housing conditions* $\{s_{i0}\}_{\forall i}$*, income distribution for each original neighborhood* $\{\bar{L}(z, x_0)\}_{\forall z, x_0}$*, a perfect foresight equilibrium is a set of housing prices* $\{P_t(q, x)\}_{\forall t,q,x}$*, housing quality distributions* $\{H_t(q, x)\}_{\forall t,q,x}$*, households' quality and neighborhood choices* $\{L(q, x, x_0, z)\}_{\forall q,x,x_0,z}$*, and landlord value functions* $\{V_{it}(s, \hat{q}, \vec{\xi})\}_{\forall i,t,s,\hat{q},\vec{\xi}}$ *such that in each period* t

1. *Each household chooses housing quality and neighborhood to maximize utility according to (3) and (6).*

2. *Each landlord makes the redevelopment decision to optimize the value of the parcel, according to equation (10).*

[12] Our proof considers an empirically-relevant environment where depreciation and the probability of redevelopment are arbitrarily small. We discuss this assumption and its implications in Appendix A.2.

3. The housing markets clear in all neighborhoods and housing quality types, such that

$$\int_{z\in\mathbb{Z}_t(q,x)} L_t(x,z) = H_t(q,x), \forall q,x,t. \tag{12}$$

where $\mathbb{Z}_t(q,x)$ *is the income set of households choosing* q *in* x *at* t, $H_t(q,x) \equiv \sum_{i\in\mathbb{I}_x} \mathbb{1}\{q_{it} = q\} \cdot h_{it}$, *and* $L_t(x,z) \equiv \sum_{x_0\in\mathbb{X}\cup\{o\}} L_t(x,z,x_0)$.

We define the steady-state equilibrium of the model as follows.

Definition 2 *A steady-state equilibrium is one in which the rent functions* $\{P_t(q,x)\}_{\forall t,q,x}$, *housing quality distributions* $\{H_t(q,x)\}_{\forall t,q,x}$, *household allocations* $\{L(q,x,x_0,z)\}_{\forall q,x,x_0,z}$ *are constant over time.*

4.4 Illustrating the Effect of a Teardown Tax

Before turning to the quantitative analysis, we present a simple example that illustrates how a change in the housing quality distribution affects a neighborhood's income distribution and pricing function. In the example shown in Figure 6, we model the effect of a teardown tax by introducing a downward shift in the neighborhood's housing quality distribution and we abstract from endogenous redevelopment. To clarify the roles of the household mobility and endogenous amenities in mediating the effects of shift in housing quality, we proceed in four steps. We begin with a baseline equilibrium (see the note to Figure 6 for details). We then shift the housing quality distribution while keeping the income distribution fixed. Next, we allow households to relocate while holding neighborhood amenities constant. Finally, we allow both household mobility and neighborhood amenities to adjust endogenously. In each scenario, we solve for the pricing function and the income distribution as equilibrium outcomes.

With the income distribution held fixed, a deterioration in the housing quality distribution raises rents across all quality levels – this is known as the "trickle down" effect in assignment models (Nathanson, 2025; Nikolakoudis, 2024). When high-quality housing becomes scarce, high-income households are forced to move down the quality ladder. This reallocation shifts the housing assignment such that, at every quality level, the income of the occupying household increases. According to equation (5), the slope of the rent function at any quality level equals the marginal rate of substitution (MRS) between housing and the numeraire good. Since high-income households spend more on the numeraire good, their MRS of housing is higher, which steepens the rent function and raises rents throughout the quality spectrum. This comparative statics exercise highlights an important insight: in the absence of household mobility, preserving low-quality housing at the expense of reducing high-quality housing supply can worsen, rather than improve, housing affordability for types of housing.

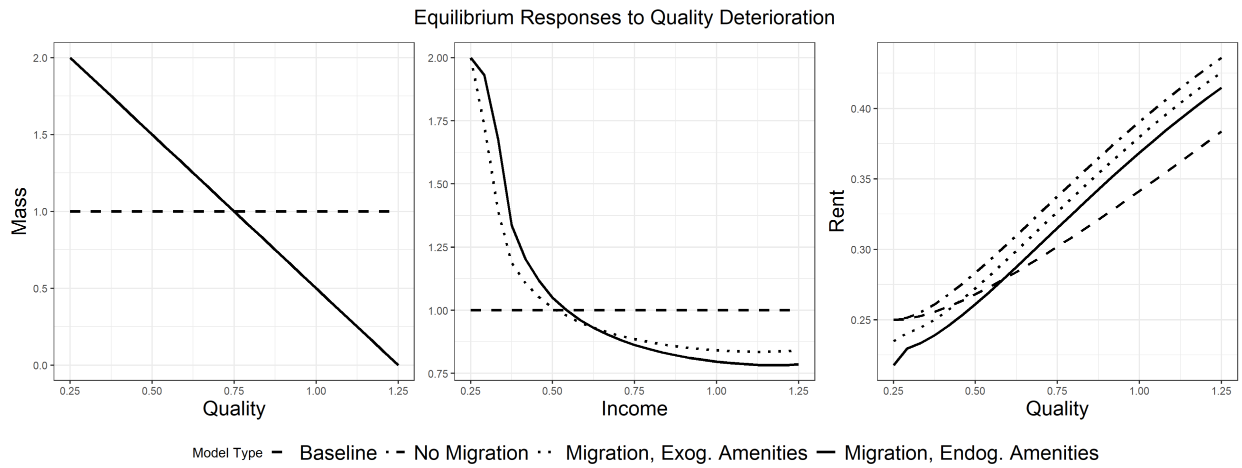


Figure 6: Illustrating the Effect of a Teardown Tax

Note: We simulate a model with one focal neighborhood and an additional outside-option location that provides exogenous utility value. We then compare the income distribution and rent function in the focal neighborhood across four equilibria. In the baseline equilibrium (dashed line), the neighborhood has uniform distributions of housing quality and income over the interval $[0.25, 1.25]$. For the remaining equilibria, we shock the housing quality distribution. This new housing quality distribution is first-order stochastically dominated by the baseline one. In the teardown tax, no-mobility equilibrium (dotted and dashed line), we simulate the effects of this shock on rents holding the set of households in the neighborhood fixed at baseline. In the teardown tax, mobility with exogenous amenities equilibrium (dotted line), we allow household mobility but keep neighborhood amenities fixed. Finally, in the full equilibrium (solid line), we allow for both mobility and endogenous amenities.

The income distribution changes significantly once households are allowed to re-optimize their neighborhood choices. As discussed in Section 4.1, high-income households dislike neighborhoods where high-quality housing is relatively more expensive. The steepening of the rent function therefore induces many high-income households to move out, who are substituted by lower-income households. Nevertheless, a substantial share of high-income households remains, driven by idiosyncratic preferences or attachment to local amenities. This re-sorting shifts down the neighborhood's rent function. Most importantly, low-quality housing becomes cheaper relative to the baseline equilibrium, which is the intended outcome of the teardown tax policy.

When neighborhood amenities endogenously respond to income, the rent function shifts further downward. As neighborhood amenities deteriorate, equilibrium rents must decline across all housing units to clear the housing market. A small share of the top-income households move out as amenities and the rent function adjust. This illustrates the amplifying effect of endogenous amenities on housing rents: the out-migration of high-income households not only reduces competition for low-quality housing but also lowers neighborhood attractiveness, both of which contribute to improved housing affordability.

This illustrative exercise holds the utility level of the rest of the city constant. In the full general equilibrium analysis, which we investigate in Section 6, amenities in other neighborhoods will improve as high-income households move in, making the neighborhood subject to the policy even less attractive. In addition, the migration of high-income households into the untreated neighborhoods will raise the demand for high-quality housing there, thus increasing the incentive of the local landlords to redevelop. These general equilibrium adjustments will further amplifies the rent-reducing effect of the teardown tax on the treated neighborhoods and generate significant ripple effects on the untreated neighborhoods.

5 Estimation of Model Parameters

In this section, we discuss how we estimate the parameters of the model. First, we estimate hedonic regressions using the rental listing data to obtain neighborhood-specific pricing function parameters and the quality depreciation rate δ. A byproduct of this hedonic regression is an empirical measure of quality at the property-year level. Second, we estimate the intensive-margin housing supply elasticity γ from observed redevelopment and estimate the extensive-margin housing supply elasticity σ_c by matching the spatial difference-in-difference estimate of the teardown tax on demolition. Finally, we calibrate remaining parameters by matching empirical moments and by following the estimates from the literature.

Our spatial unit of analysis is the official Chicago neighborhood, as defined by the municipality. There are 98 of these neighborhoods, and they are larger than the policy areas considered in Section 3. For model computation, we aggregate contiguous neighborhoods into 24 neighborhood groups using a spatial clustering algorithm based on neighborhood housing density and average income. On average, each neighborhood group has 50,000 housing units. Figure C.8 maps these neighborhood groups. For the remainder of this paper, we use the term "neighborhoods" and "neighborhood groups" interchangeably unless a distinction is required.

5.1 Estimating the Pricing Functions

We start with estimating the pricing functions. We assume that housing quality is a unidimensional measure that is log-additive in the observed and unobserved components:

$$\log q_{it} = \underbrace{-\delta \times \text{Building Age}_{it}}_{\text{Depreciation}} + \underbrace{\sum_{c \in \mathcal{C}} \alpha_c \log X_{it}^c}_{\text{Other observed characteristics}} + \underbrace{\log \epsilon_{it}^q}_{\text{Unobserved characteristics}}, \tag{13}$$

where δ is the depreciation rate, $\mathcal{C}$ is a set of observed housing characteristics, X^c is the value of each characteristic, and ϵ^q is the unobserved quality component. We then estimate neighborhood-specific iso-elastic pricing functions:

$$\log P(q,x) = \log \kappa(x) + \nu(x) \log q, \tag{14}$$

where $\kappa(x)$ and $\nu(x)$ are the neighborhood-x-specific fixed effect and the quality gradient, respectively. A larger κ raises the rent level at any given quality; a larger ν steepens the rent-quality schedule.

Combining equations (13) and (14) yields a hedonic regression model:

$$\log P_{it} = \log \kappa(x) + \nu(x) \left[-\delta \times \text{Building Age}_{it} + \sum_{c\in\mathcal{C}} \alpha_c \log X_{it}^c \right] + \nu(x) \log \epsilon_{it}^q, \tag{15}$$

where P_{it} is the listed rent of housing unit i in year t. Equation (15) is estimated by a nonlinear least squares (NLS) estimator, up two sets of normalization. We normalize the average quality elasticity is to be one, $\frac{1}{|X|}\sum_{x\in X} \nu(x) = 1$.[13] We then recover housing quality as $\hat{q}_{it} = -\hat{\delta} \times \text{Building Age}_{it} + \sum_{c\in\mathcal{C}} \hat{\alpha}_c \log X_{it}^c$ using the parameter estimates for all the parcels in the assessment data.

We estimate the hedonic regression using rental listing data from RentHub. We merge RentHub data with property assessment data to obtain a more complete set of housing attributes. The set of housing characteristics $\mathcal{C}$ includes unit floor space, number of bedrooms and bathrooms, land parcel size, number of floors, number of housing units in the building (categorized as single-family, small multi-family [$\leq$4 units], and large multi-family [>4 units]), types of construction material, the heating system and porch, and the presence of garage. We deliberately select characteristics that are plausibly time-invariant with respect the structure age, as time-varying attributes (renovation and maintenance conditions) would be bad controls for identifying the depreciation rate δ. Therefore, our estimate of δ should be interpreted as the gross depreciation rate that incorporate both physical wear and the impact pf endogenous maintenance and renovation over a property's life cycle.

We exclude buildings constructed before 1940, for two reasons, First, the U.S. Bureau of Economic Analysis (BEA) assigns an 80-year service life to 1–4 unit residential structures. Properties exceeding this lifespan likely reflect exceptional maintenance. Second, historic buildings may possess historical charm that increase their market value. Both factors would bias the estimated depreciation rate downward.

One might be concerned that unobserved quality characteristics ϵ_{it}^q may be correlated with observed attributes, which introduces a classic omitted variable issue. To address this,

[13]Because the quality index q has no cardinal scale, the normalization anchors quality so that a neighborhood with $\nu = 1$ has rent proportional to q.

we follow Diamond and Diamond (2024) to proxy unobserved quality with property-specific percentile ranks of past sale prices. Specifically, we compute percentiles within cells defined by year $\times$ neighborhood $\times$ build-year decade and merge these ranks to the listing data. The constructed percentiles capture a unit's relative unobserved quality within its local market and are, by construction, orthogonal to building age. We limit the sample to listings with prior sales and control for a quadratic in the percentile rank in (15).

Depreciation rate δ Our preferred specification, which includes sales price percentiles as controls, yields an annual quality depreciation rate of approximately 0.21%. Excluding the sales price percentile controls slightly lowers the estimate to 0.19%. The downward bias in the depreciation rate arises from a negative correlation between unobserved quality and building year, suggesting that lower-quality newer houses are more likely to appear in the rental market than higher-quality ones.

Our estimated depreciation rate of 0.21% is below the nationwide estimate of 0.4% for rental housing reported by Rosenthal (2014). This lower rate likely reflects greater maintenance and renovation efforts in Chicago, as developable open land is scarce (Baum-Snow, 2023). In addition, Rosenthal (2014) estimates higher depreciation rate of 0.8% for owner-occupied housing; this likely reflects relatively greater maintenance efforts for rental housing. We do not want to limit our focus to rental housing, as the policies we study affect the entire housing market. For this reason, we adjust the depreciation rate in our model to 0.3%.

Pricing Function and Quality Figure C.9 reveals substantial between-neighborhood variation in the estimated levels and quality gradients of the pricing functions, $\log \kappa(x)$ and $\nu(x)$. The standard deviations of $\log \kappa(x)$ and $\nu(x)$ are 0.26 and 0.19, respectively. The former indicates that, holding housing quality constant, a one–standard-deviation increase in neighborhood rent level corresponds to a 29.4% higher rent; the latter implies that a one percent quality increase translates to a 19% greater increase in housing rent in a neighborhood where the rent-to-quality elasticity is one–standard-deviation larger.

Table C.9 shows that at the neighborhood level, newer housing stock and higher income are associated with higher housing rent, rent level as measured by the fixed effect and average housing quality. The elasticity of rent with respect to quality decreases with building age but shows no systematic relationship with neighborhood median income. While higher-income households favor neighborhoods with flatter pricing schedules, their sorting simultaneously raises demand for high-quality units, thereby steepening the rent–quality gradient. This lack of a correlation is directly analogous to a traditional supply and demand model where prices and quantities may be uncorrelated.

5.2 Housing Supply Elasticities

We detail how we estimate two housing supply elasticity parameters: the housing unit cost elasticity γ and the redevelopment elasticity σ_c. Parameter γ governs, conditional on redevelopment, how strongly the number of housing units per parcel changes with housing prices (the intensive margin of new housing supply). We estimate γ by leveraging housing demand shocks induced by labor market shocks, following Baum-Snow and Han (2024). Parameter σ_c governs how strongly the redevelopment responds to changes in the value of redevelopment (the extensive margin of housing supply). We estimate σ_c by matching the empirical estimate of the effect of the teardown tax, which exogenously lowered the value of redevelopment.

Housing unit cost elasticity γ

We use the assessment data and transaction deeds data to estimate the housing unit cost elasticity γ. We detect redevelopment if the build year of a parcel changes across assessment records of different years. We then obtain the transaction price of the newly constructed building from the transaction deeds data. We retain only the first transaction after each redevelopment, provided it occurs within three years after the redevelopment. To align with the timing of the shift-share instrument, we restrict redevelopments between 2010 and 2019.

The parameter γ is identified from the observed building unit choices of the redeveloped buildings. When the cost function is more convex (i.e., larger γ), the fewer additional housing units will be developed in response to an increase in housing demand. As housing investment is irreversible, the choice on the new building is not affected by the characteristics of the demolished building. From the landlord's profit maximization problem, we can obtain the following estimation equation for redeveloped parcels:

$$\log h_{it} = \Gamma + \frac{1}{(\gamma-1)}\left(\log \frac{V_{it}\left(q_{it}, h\right)}{h} - \log q_{it}\right) - \frac{1}{(\gamma-1)}\log \Omega_x + \frac{1}{(\gamma-1)}\epsilon_{it}^{\gamma} \tag{16}$$

where $\Gamma \equiv -\frac{1}{(\gamma-1)}(\log\gamma - \log\beta)$ is a constant, h_{it} is the number of housing units of the new building, $V(q,h)/h$ is the per-unit price at quality q,[14] Ω_x and ϵ^{γ} comprise the error term in this regression: the former is the neighborhood-level cost shifter, and the latter contains measurement error in quality estimation and parcel-level unobserved construction costs that are not explicitly modeled in Section 4.

There are two important considerations when estimating equation (16). First, the unit price needs to be adjusted by the housing quality. Because higher-quality buildings both

[14] Strictly speaking, unit choice depends on the marginal value $\partial V/\partial h$, which we approximate by average value per unit $V(q,h)/h$. The two differ only because the number of units affects the option value of future redevelopment embedded in V; for newly built properties this effect is small. See Appendix B.1 for details on the derivation.

command higher prices and cost more to construct, omitting quality q would downward bias the estimate of $1/(\gamma - 1)$. We obtain q for the redeveloped buildings from our hedonic regression estimates (equation (13)).

Second, the error term contains unobserved supply-side cost shocks that are correlated with parcel values and quality. Neighborhoods with rising house prices often face tighter regulation, which can hinder unit additions. Moreover, our quality proxies—constructed from hedonic estimates and deed prices—are measured with error. Together, these forces bias the OLS estimate downward. To address these issues, we construct a shift–share Bartik-style instrument as below:

$$Bartik_{x,t} = \sum_{ind \neq \text{Cons}} \left(\frac{EMP_{x,ind,t_0}}{\sum_{ind \neq \text{Cons}} EMP_{x,ind,t_0}} \right) \Delta \log EMP_{msa,ind} \tag{17}$$

where $EMP_{x,ind,t}$ is the number of individuals who live in neighborhood x, work in industry ind, at time t, and $\Delta \log EMP_{msa,ind}$ is the change in log employment in industry ind at the MSA level. We use the LEHD Origin–Destination Employment Statistics (LODES) Residential Area Characteristics (RAC) to construct exposure weights at the block-group level (by 2-digit NAICS), aggregate them to neighborhoods, and compute baseline employment shares in $t_0 = 2005$. The shifters are MSA-level industry employment growth over 2010–2019.[15]

The shift–share instrument measures each neighborhood's exposure to MSA-wide industry shocks, yielding predicted changes in local labor demand. It is relevant because higher local labor demand raises housing demand through income effects. We construct the instrument at the census block group level, rather than the broader neighborhood group level, to exploit the granular variation in housing demand. We follow Borusyak and Hull (2023) in assuming that MSA-level industry shocks are exogenous to individual block groups. We exclude the construction industry from the instrument because its employment is likely affected by the local construction productivity shocks.

We further control for the log of 2005 block group employment and employment growth from 2010 to 2019 at the census block group level, accounting for potential correlations between unobserved housing supply factors and the levels and changes in housing demand. neighborhoods that face high housing demand may respond by increasing housing regulations. As pointed out by Davidoff (2016), more supply-constrained areas also tend to have greater productivity and housing demand growth. Furthermore, the Bartik-style instrument is designed to leverage the industry-level labor demand shocks outside the neighborhood to shift the neighborhood's housing demand. Controlling for changes in local employment

[15] Consistent with Baum-Snow and Han (2024), Bartik shocks constructed from pre-2010 data (e.g., 2005–2009) are only weakly correlated with housing prices.

Table 2: Estimation of the intensive housing supply elasticity

Dependent Variable:	Log(Housing Units)			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Log(Price Per Unit)	-0.114^{***}	0.068^{*}		
	(0.018)	(0.040)		
Log(Adj. Price Per Unit)			-0.037^{*}	0.091^{*}
			(0.022)	(0.052)
Num. obs.	3304	3304	3304	3304
R^2	0.155	-0.059	0.076	0.007
First Stage F-stat		13.1		9.5

Note: The table shows the estimation result of equation (16). Columns (1)–(2) use the unadjusted price per unit (V/h), while Columns (3)–(4) use the quality-adjusted price per unit ($V/(hq)$). Columns (1) and (3) report the OLS estimates, while Columns (2) and (4) report the IV estimates. All columns control for log 2005 block group employment, 2010-2019 block group employment growth, and year-month fixed effects. Standard errors are clustered at the census block group level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

ensures that we only exploit labor demand shock outside of the census block group for identification. Our identification assumption is that the pre-determined industry employment shares in each neighborhood, conditional on the controls, are uncorrelated with unobserved construction costs Ω_x.

We report the estimation result in Table 2. The full specification (Column (4)) gives a unit supply elasticity of 0.09, which transforms to the value of γ as 12.0. The F-statistics of the first stage is 9.5, around the rule-of-thumb threshold of 10. The low F-statistic largely reflects limited statistical power, since the Bartik instrument varies only at the block-group level rather at the parcel level. Adjusting the housing price by quality significantly increases the estimate in both specifications. The IV estimates are significantly greater than the corresponding OLS estimates, which are downward biased. The estimated unadjusted supply elasticity of 0.07 is at the ballpark of the average unit supply elasticity of 0.03 for redevelopment reported by Baum-Snow and Han (2024).

The Cost Dispersion Parameter: σ_c

We leverage the teardown tax policy to identify the parameter σ_c. Specifically, σ_c is related to the change in log odds ratio caused by change in the redevelopment payoff:

$$\Delta \log \frac{P^R}{1 - P^R} = \sigma_c \; \Delta(V^R - V^N) \tag{18}$$

where P^R is the probability of redevelopment, Δ is a change operator, $V^R - V^N$ represents the redevelopment payoff, which is the difference between the value of redevelopment and non-redevelopment.

We exploit the teardown tax policy to identify σ_c using equation (18). The left-hand side corresponds to the estimate of the treatment effect from a logistic counterpart of the spatial difference-in-difference regression (1), which is -0.90. The change in redevelopment payoff is the teardown tax of $-\$15,000$. The semi-elasticity of housing redevelopment is thus obtained as $\sigma_c = (-0.90/-\$15,000) \times \$1000 = 0.06$ (measured in thousands of dollars).

The temporary feature of the policy enables the credible identification of σ_c. First, because it lasts only three years, the demolition tax should not be capitalized into future parcel values; it only affects the redevelopment payoff during the policy period. Figure 4 shows that the policy did not significantly affect housing prices. Panel (c) of Figure C.4 further indicates that the policy had no discernible impact on the estimated costs of new construction permits, a proxy of building quality. Together, these findings suggest that the teardown tax influenced redevelopment decisions primarily by raising fixed costs rather than by altering the value or the quality choice of newly constructed structures. Second, the short duration and small treated areas (around 5,000 buildings on average) also limit the city-wide general-equilibrium effects of the policy. For this reason, we interpret the estimated σ_c as the intertemporal elasticity of housing supply; that is, how shifts in the redevelopment payoff affect the timing of redevelopment. [16]

5.3 Calibration of Other Parameters

Lastly, we describe how we choose the remaining parameters. We internally calibrate a set of parameters to target three sets of empirical moments: the neighborhood-level pricing functions, the neighborhood-level population and income distribution, and the housing expenditure shares of households with different income levels. Matching these moments is essential for the model to plausibly capture neighborhood-level demographic dynamics and

[16] This interpretation is consistent with the nature of the landlord's decision in the model, which is to choose the timing of redevelopment of its own parcel. An alternative model one can write down is that developers cross-sectionally choose between parcels to redevelop and receive part of the payoff. Our assumption of a perfect construction sector abstract away from rent sharing and the choice of the developers.

to evaluate the welfare effects of the teardown tax. We calibrate the rest of the parameters using standard values from the literature. Internal calibration comprises a demand block and a supply block, which we describe below.

Demand Block

Calibration of the demand block involves choosing a discretized quality grid $\mathbb{Q}$ and housing preference parameters $(\alpha, \bar{q})$. For the quality grid, we use the empirical distribution of housing quality obtained from the hedonic regression (15) and set the upper and lower bounds of the quality space to three standard deviations above and below the mean, respectively. We then discretize the quality space into 61 equally spaced levels. We then choose the housing preference parameters $(\alpha, \bar{q})$ to minimize the distance between rent expenditure shares across ten income deciles calculated using the ACS and those implied by our model under the empirically estimated rent function $P(q, x)$. This procedure yields an approximate value of $\alpha = 0.09$, indicating that a top-income households spend slightly more than 9% of their expenditure on rent. The estimated minimum quality level, $\bar{q}$, implies that a bottom-income household spends at least \$5,850 per year on housing, given the average pricing function across neighborhoods in Chicago.

With only two parameters, our model matches rent expenditure share deciles closely, with errors never exceeding one percentage point. This accuracy is consistent with findings in the literature using similar preference specifications (Couture et al., 2023).[17] The estimated rent function and housing preference parameters generate a model-implied housing quality distribution, $H(q, x)$, through households' problem (3). In the next step, we choose the remaining housing supply parameters to match this quality distribution.

Supply Block

Calibration of the supply block involves choosing the blueprint distribution $G(\hat{q})$, and fixed costs of construction $F_{\hat{q}x}$ to match the model-implied quality distributions $H(q, x)$. To reduce the computational burden, we assume that the support of the blueprint distribution, $\mathbb{Q}'$, comprises only three quality levels corresponding to the upper bounds of the tertiles of the empirical quality distribution.

Within each neighborhood, both fixed costs and the blueprint distribution play crucial roles in determining the steady-state quality distribution. However, they cannot be separately identified using $H(q, x)$ alone. Intuitively, if higher-quality blueprints are more likely to be drawn, more high-quality housing will be supplied in equilibrium. The same outcome would arise if the fixed costs of constructing high-quality housing were lower. For this reason, we

[17] The minimum quality level, $\bar{q}$, is included as the lowest value in the quality grid $\mathbb{Q}$. Given our preference specification, demand for this segment is always zero.

assume that the blueprint distribution G is uniform across quality segments. We interpret the blueprint distribution G as a reduced-form representation of market frictions rather than a literal technological process (see Section 4).

For each neighborhood, there are 3 different fixed costs $F_{\hat{q}x}$ to calibrate, each corresponding to a point on the support of the blueprint distribution. Specifically, we calibrate the fixed costs to reproduce the observed shares of housing units within four equally-spaced quality segments. The variation in the calibrated fixed costs likely reflects, in part, cross-neighborhood differences in housing regulations that shape the equilibrium quality distribution of housing (Macek, 2024). They may also capture regulatory fees and other barriers that make high-quality development relatively more costly.

The remaining housing supply parameters to be calibrated are the unit cost shifters, Ω_x, and the total mass of parcels by neighborhood. The parameter Ω_x is chosen to match the average number of housing units per parcel in each neighborhood, as observed in the assessment data: lower construction costs directly imply a higher density of units for any given building value function. The total mass of parcels is then selected to ensure that neighborhood sizes, measured by the total number of housing units, are consistent with the data. Because some parcels remain vacant (with quality $q = \bar{q}$), the number of parcels always exceeds the minimum required to match neighborhood sizes. Under our calibration, these vacant parcels represent less than 1

Construction Cost Estimates Our procedure yields reasonable construction costs that vary across neighborhoods. In Figure B.1, we plot both total and fixed construction costs broken down by neighborhoods and each of the three blueprint quality levels we consider. The figure shows that, to construct a structure at a quality level in the 33rd percentile of housing quality, fixed and total costs are on average only $\$120,000$ and $\$200,000$, respectively. To build a home in the top quality percentile, these costs are exponentially greater, at 1.4 and 1.8 million dollars, respectively.[18] Fixed costs comprise almost 75% of total construction costs, and a greater share for higher quality blueprints. Construction costs vary almost as much across neighborhoods as they do across quality segments. Higher-income neighborhoods have both higher average fixed costs and a greater dispersion of fixed costs across quality segments. This reflects stringent land use regulations set by affluent homeowners.

[18]EcoBuild Plus is a Chicago area contractor that specializes in the construction of single family and low-density multifamily homes. They estimate that the total costs of building an average home range from $\$450,000$ and $\$700,000$ inclusive of land acquisition costs. For luxury homes, costs can easily exceed millions, with prices up to \$500 per square foot. These costs are inclusive of additional fixed costs for architecture and interior design consultation. See their article here.

Remaining Parameters

There are a few remaining parameters we take from the literature. We set the discount factor to be 0.97. We follow Baum-Snow and Han (2024) to calibrate a migration elasticity of $\sigma_x = 8.5$. We abstract from the estimation of neighborhood displacement costs in this iteration of the paper and set $\tau(x'; x) = 0.75$ for all $x \neq x' \in \mathbb{X}$. This means that a household receives a disutility approximately equal to 25% of income when moving to another neighborhood. This welfare cost is, on average, much lower than those of dynamic models of moving costs that often have estimates exceeding $\$100,000$ (e.g., Kennan and Walker (2011)). Using estimates from Macek (2024), we calibrate the elasticity of amenity values to income as $\eta = 0.24$. Exogenous amenities $\bar{A}(x, z)$ are then chosen to rationalize observed income distributions as neighborhood choices in the model. We take the outside option o to be the remainder of the Chicago–Naperville–Elgin, IL-IN-WI MSA, excluding the municipality itself.

6 Counterfactual Analysis

We use the model to evaluate the general equilibrium effect of the teardown tax policy. In the counterfactual, we impose a \$60,000 teardown tax on all neighborhoods with income below the median that lasts 50 years. This counterfactual analysis mirrors the City of Chicago's efforts to stop redevelopment in more neighborhoods. Before the 606–Pilsen Demolition Surcharge Ordinance expired, the City Council approved an enlarged policy—the Northwest Side Preservation Ordinance—which expands geographical coverage, raises the surcharge amount to \$60,000, and is set to expire in 2030. See the policy description here.

To highlight the heterogeneity in spillover effects, among the untreated neighborhoods we report results separately for those with relatively high and relatively low average income. See Figure C.10 for a map of these three groups of neighborhoods. We solve for the full transition path from the initial steady state to the new equilibrium and compare outcomes along the transition. Because housing depreciates slowly (0.3% per year), solving the full transition path at annual frequency is computationally challenging. We therefore set one period in the model to be 10 years and adjust our parameters at an annual frequency accordingly.

6.1 Policy Effect across Neighborhoods

Figure 7 presents the policy's effect on redevelopment rate, average rent, average housing quality, and average income across the city up to 10 periods. The top-left panel reveals significant intertemporal and interregional substitution in housing redevelopment induced by the teardown tax. In treated neighborhoods, the redevelopment rate falls by roughly one-

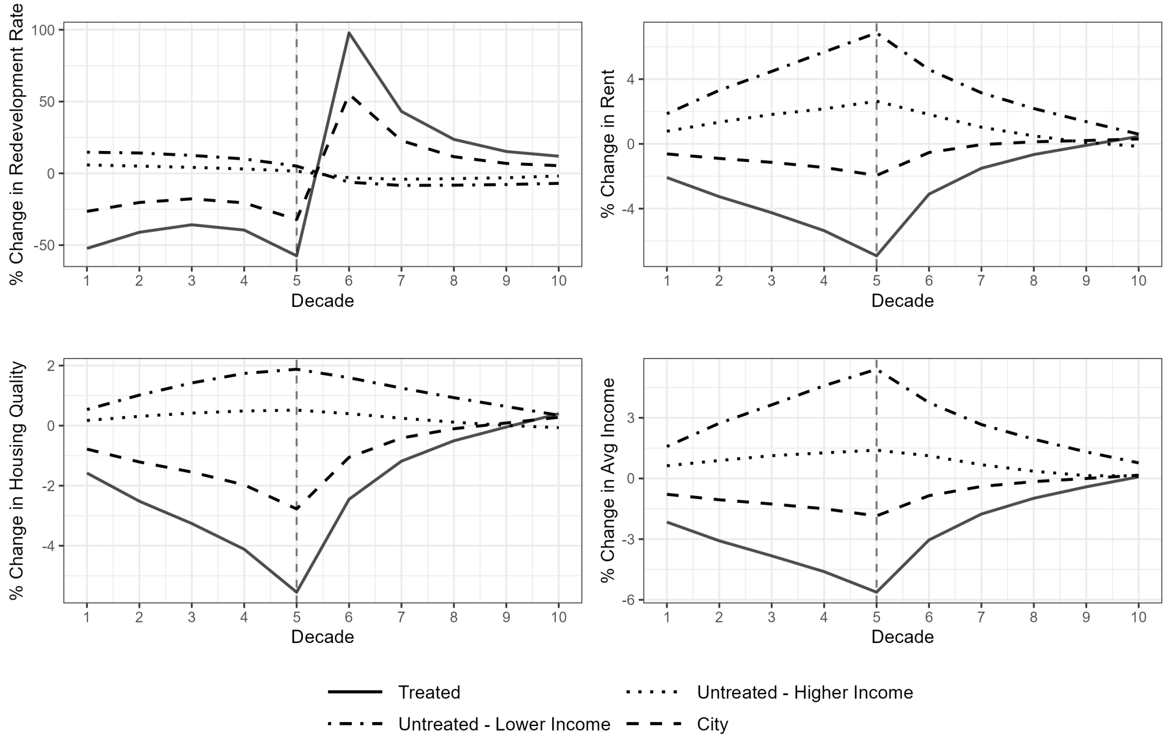


Figure 7: The Impact of a 50-Year Teardown Policy on Housing Redevelopment, Rent, Quality and Neighborhood Income

half while the policy is in force, then overshoots—nearly doubling—once the policy expires, before gradually converging back to its initial steady state level. In untreated neighborhoods redevelopment increases during the policy and declines after it is lifted, although the magnitudes are much smaller in absolute terms. On average, the redevelopment rate increases by 25% during the policy period. The cross-neighborhood substitution effect arises because the policy pushes high-income households out of treated areas, raising demand for higher-quality housing in untreated areas and thus increasing redevelopment there. Since roughly half of the city is covered by the tax, the citywide redevelopment rate also declines during the policy period and rises afterward, with magnitudes about half as large. These shifts in redevelopment lead to a decline in housing quality in treated neighborhoods and an upgrade in untreated ones, as shown in the bottom-left panel.

Among untreated neighborhoods, the increase in redevelopment is more than twice as large in low-income areas as in high-income areas — the decadal redevelopment rate in the untreated low-income group rises by roughly 6 percentage points more than in the untreated high-income group. The heterogeneity in redevelopment spillovers arises from selective migration. As housing quality deteriorates in treated neighborhoods, households at the top of

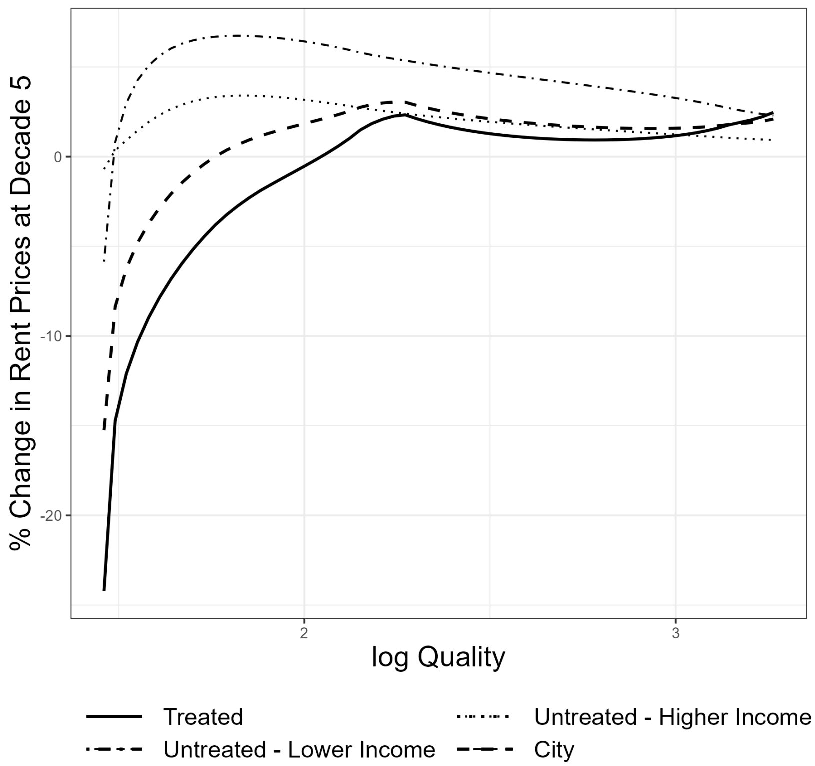


Figure 8: The Impact of a 50-Year Teardown Policy on the Rent Function

the income distribution in these areas, the majority of whom are middle-income households in the city, move out. By revealed preference, these households will sort into neighborhoods with a higher pre-policy share of similar-income households. Meanwhile, low-income households also move from untreated into treated neighborhoods. Consequently, the low-income untreated neighborhoods receive a greater inflow of high-income households from treated areas and a greater outflow of low-income households. Their average income therefore rises about 5.0% in period five, more than the rise of 1.5% in high-income untreated neighborhoods, as shown in the bottom-right panel. The greater increase in average income leads to faster rent growth in these neighborhoods, shown in the top-right panel, incentivizing redevelopment to a greater extent. City-level average income also decreases significantly by about 1.7% in period five, resulting from selective migration into and out from the outside option.

Figure 8 illustrates how housing rents vary along the quality distribution across different groups of neighborhoods in period 5. In treated neighborhoods, rents decline sharply for low-quality units but rise modestly for high-quality units. This change in the rent function is qualitatively consistent with the illustrative example in Section 4.4. As the housing quality distribution deteriorates, lower-income households move into the treated neighborhoods, reducing local amenities. These adjustments shift the rent function downward, particularly in the low-quality segment where housing supply expands. In contrast, high-quality units become relatively more expensive due to their scarcity and demand from higher-income households who choose to stay.

Interestingly, in untreated neighborhoods,especially those with lower average income,housing rents exhibit a hump-shaped change along the quality distribution. Rents decline for low-quality units but rise more strongly for middle-quality units than for high-quality ones. This is because the increase in redevelopment is insufficient to meet the demand for high-quality units from the households moving in. This generates a "tickle-down" effect on the rent along the quality distribution as high-income households downgrade in quality. Moreover, most households moving out of the treated neighborhoods are middle-income, further increasing demand for middle-quality units in the untreated areas and pushing up housing rent. Rents for low-quality units decline as the overall citywide supply of low-quality housing expands. These forces jointly result in the hump-shaped rent changes in the non-treated neighborhoods.

Lastly, Figure C.11 reveals significant changes in land values across the city. As a result of demand shifts in the rental markets, the average land value in treated neighborhoods falls by 4.9%, while land values in untreated low-income and high-income neighborhoods rise by 3.75% and 1.25%, respectively. This result shows that the targeted teardown tax—designed to assist low-income renters—is regressive for homeowners, which helps explain the opposition among homeowners in the policy areas (see local news coverage here).

6.2 Welfare Effect across Households

Figure 9 shows that the policy generates significantly heterogeneous welfare effects on households by income and initial neighborhoods. During the policy period, low-income households in the treated neighborhoods benefit the most: their welfare, measured in equivalent variation, increases by 1% at the beginning of the policy, which rises to 4% before the policy concludes. Low-income households in untreated neighborhoods also benefits significantly, as they can move to the treated neighborhoods to live in cheap, low-quality units. Due to moving costs, their welfare gains are smaller than the low-income households already living in the treated neighborhoods.

Most middle- and high-income households suffer from sizable welfare losses, except for the richest who are initially in the untreated neighborhoods. Those who begin in treated neighborhoods suffer from greater welfare loss due to moving costs. Similar to the non-linear changes in rent with respect to quality, the welfare effect is also non-monotonic in income: holding fixed the initial location, the highest-income households lose less than middle-income ones. Two forces account for this. First, as a result of non-homoethetic preference, high-

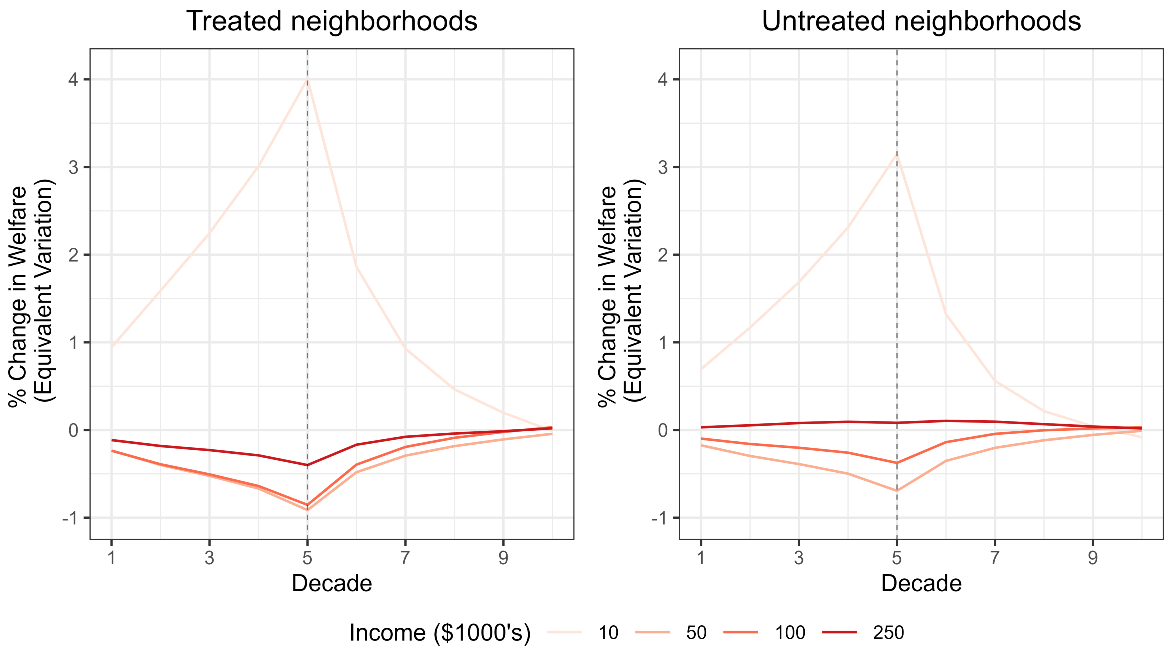


Figure 9: The Impact of a 50-Year Teardown Policy on Welfare by Income and Initial Neighborhood

income households spend a smaller share of their income on housing, so the same increase in rent translates into a smaller welfare loss. Second, rent increases are larger for middle-quality housing than for top-quality housing in the untreated neighborhoods (Figure 8) in which most middle- to high-income households reside after the policy. For the highest-income households initially in the non-treated neighborhoods, the amenity improvement from having higher-income neighbors outweigh the slight increase in the housing rent at the very top of the quality distribution. After the end of the policy, welfare of all types of households return back to the initial level, indicating that the teardown policy serves purely as redistributive tool in the short run.

6.3 The Role of Endogenous Amenities

To isolate the role of endogenous amenities in mediating the policy's effects, we re-simulate the policy while holding neighborhood amenities fixed. The results are reported in Figure 10. Without endogenous amenities, the spillover effect of the teardown tax on redevelopment in untreated neighborhoods is much smaller, and the effects on average rent and income are correspondingly weaker. Absent amenity adjustments, the return to relocating from treated to untreated neighborhoods for high-income households is greatly reduced. In period five, the increase in average income in the untreated low-income neighborhoods is 3.8%, compared with 0.75% in the baseline model with endogenous amenities. The attenuated

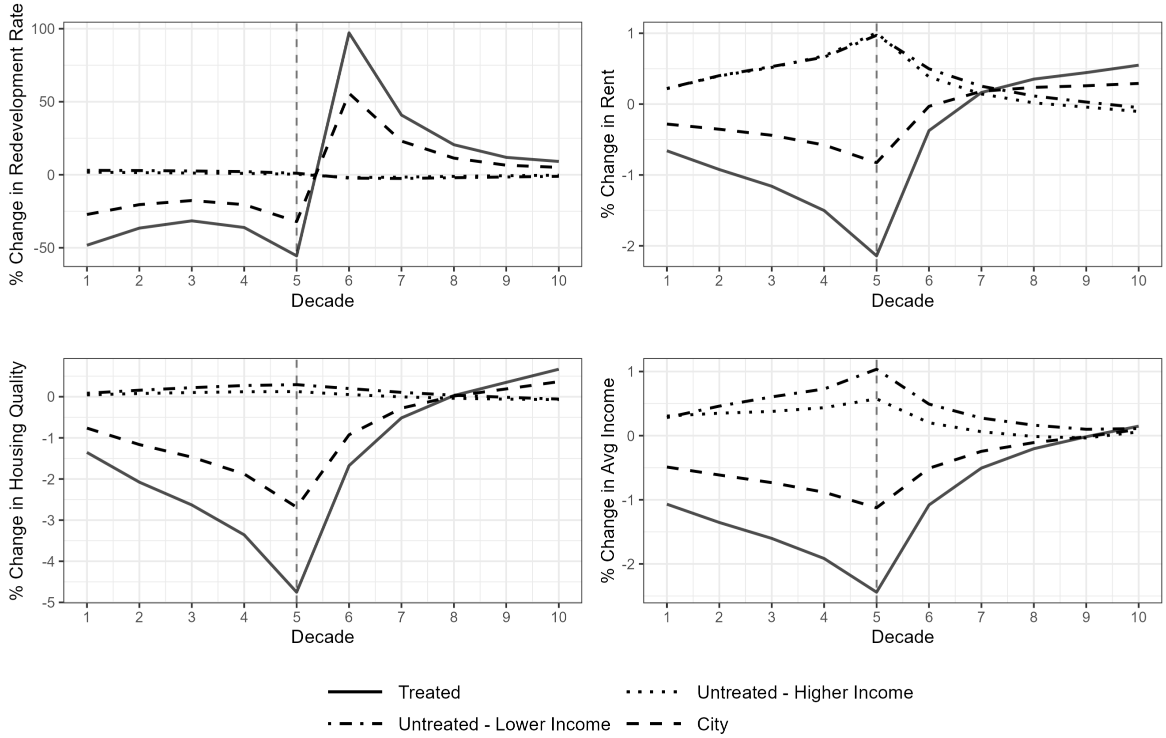


Figure 10: The Impact of a 50-Year Teardown Policy without Endogenous Amenities on Housing Redevelopment, Rent, Quality and Neighborhood Income

mobility response weakens rent growth, which in turn dampens redevelopment incentives, further suppressing subsequent sorting into untreated areas. This comparison reveals a strong complementarity between housing redevelopment and endogenous amenities in mediating neighborhood changes as a result of local shocks.

6.4 The Role of Policy Duration

Figure C.12 shows that the 20-year policy produces a larger decline in redevelopment in treated neighborhoods, while the spillover to untreated neighborhoods is slightly smaller. When the policy is short-lived, landlords in treated neighborhoods have stronger incentives to delay redevelopment to avoid the tax. Meanwhile, landlords in untreated neighborhoods do not increase redevelopment by much, as they anticipate that high-quality housing supply will increase soon in the treated neighborhoods. Consequently, the 20-year policy generates quicker and larger negative effects on average quality, rent, and income in treated neighborhoods than the 50-year policy. This helps explain why even a small, temporary 606–Pilsen teardown tax can have a large impact on demolitions.

6.5 Discussions on Policy Implications

Although an optimal policy design is beyond the scope of the paper, we provide a discussion on the source of market inefficiency and corresponding policy implications from our analysis. In the model, the only inefficiency arises from endogenous amenities: households do not internalize how their location choices affect neighborhood quality. This leads middle-income households to over-sort into high-income neighborhoods, free-riding on amenities and generating negative externalities. Such an externality is analogous to fiscal externalities that arise from the provision of local, congested public goods (Calabrese et al., 2012).

A welfare-improving policy would therefore discourage low-income households' entry into high-income neighborhoods and compensate affected households through monetary transfers, analogous to the optimal spatial policy framework of Fajgelbaum and Gaubert (2020). With moving costs, the optimal policy will also need to balance the gain from reallocation against the moving costs associated with it. However, such a policy is unlikely to be politically feasible: it would increase income segregation within the city and carry adverse long-run social consequences. In the space of housing policy, this logic points toward incentivizing redevelopment in high-income neighborhoods rather than restricting it in low-income ones.

Without endogenous amenities, no policy can achieve a Pareto improvement. Even then, waves of redevelopment generate sizable distributional effects that may warrant policy attention. When households are mobile with moving costs, redevelopment benefits high-income households and harms local low-income households.[19] Taxing redevelopment is not desirable in the long run, since high-quality housing eventually filters down to low-income households. A redistributive policy should therefore avoid distorting the housing supply margin. A better policy option is to compensate displaced households — for example through housing vouchers — rather than restrict redevelopment.

7 Conclusion

Housing redevelopment is a major source of new housing supply in dense urban areas, yet its welfare consequences remain understudied. At the city level, expanding the stock of high-quality units can generate a "trickle-down" effect, reducing housing rent across the quality distribution. However, as housing redevelopment is spatially concentrated, waves of new construction often trigger gentrification and displacement, resulting in welfare losses on incumbent households. In addition, housing is durable and depreciates over time, so redevelopment persistently alters citywide housing supply and generates long-lasting effects.

[19] When households are immobile, replacing low-quality with high-quality housing reduces rents across the quality distribution in the neighborhood (Nathanson, 2025).

Taken together, these features make the welfare implications of redevelopment difficult to analyze.

In this paper, we develop a dynamic general equilibrium framework to study the welfare consequences of housing redevelopment. We embed an assignment model — which tractably matches heterogeneous households to housing units within each neighborhood and delivers a local pricing function — into a quantitative spatial model that allows income sorting across neighborhoods. We further incorporate forward-looking landlords who endogenously choose redevelopment timing, together with quality depreciation over time. We theoretically show that housing redevelopment induces income sorting through its effect on the pricing function. In addition, the model allows neighborhood amenities to respond to income, capturing further neighborhood dynamics induced by redevelopment.

We apply the model to evaluate a three-year teardown tax implemented in two neighborhoods in Chicago, designed to curb redevelopment in low-income, gentrifying areas and protect incumbent residents. Using a spatial difference-in-differences design, we show empirically that the policy substantially reduced housing teardowns and population displacement in the targeted neighborhoods. The model counterfactuals reveal richer general-equilibrium effects. The policy induces out-migration of high-income households from the treated areas, thereby increasing redevelopment and rents in untreated neighborhoods. As a result, low-income households gain, while middle- and high-income households suffer from welfare losses, with the largest losses borne by the middle of the income distribution. Overall, we conclude that the teardown tax act as redistributive instruments that are net welfare-decreasing, primarily because they induce costly relocations and worsens amenities by decreasing average income in the city.

Although we focus on a specific form of anti-redevelopment policy, the model is well suited to study the long-run consequences of a broad class of housing policies that involves changing the local housing quality distribution. Some examples are the Low-Income Housing Tax Credit and demolition of public housing. Finally, we deliberately abstract from modeling the labor market and commuting choices to keep the model tractable. Future work can incorporate these aspects to study the how local labor market shocks affect housing quality across the city, as well as how the housing quality distribution affects the spatial distribution of productive activities through its impact on income sorting.

References

Abramson, Boaz and Tim Landvoigt, "Curbing Rising Housing Costs: A Model-Based Policy Comparison," *Journal of Economic Perspectives*, August 2025, *39* (3), 27–44.

Ahlfeldt, Gabriel M, Stephen J Redding, Daniel M Sturm, and Nikolaus Wolf, "The economics of density: Evidence from the Berlin Wall," *Econometrica*, 2015, *83* (6), 2127–2189.

Albouy, David, Gabriel Ehrlich, and Yingyi Liu, "Housing Demand, Cost-of-Living Inequality, and the Affordability Crisis," Working Paper 22816, National Bureau of Economic Research November 2016.

Almagro, Milena, Eric Chyn, and Bryan A Stuart, "Neighborhood Revitalization and Inequality: Evidence from Chicago's Public Housing Demolitions," 2024.

Asquith, Brian J., Evan Mast, and Davin Reed, "Local Effects of Large New Apartment Buildings in Low-Income Areas," *The Review of Economics and Statistics*, 03 2023, *105* (2), 359–375.

Baum-Snow, Nathaniel, "Constraints on City and Neighborhood Growth: The Central Role of Housing Supply," *Journal of Economic Perspectives*, May 2023, *37* (2), 53–74.

_ **and Fernando Ferreira**, "Causal inference in urban and regional economics," in "Handbook of regional and urban economics," Vol. 5, Elsevier, 2015, pp. 3–68.

_ **and Gilles Duranton**, "Chapter 6 - Housing supply and housing affordability," in Dave Donaldson and Stephen J. Redding, eds., *Handbook of Regional and Urban Economics*, Vol. 6 of *Handbook of Regional and Urban Economics*, Elsevier, 2025, pp. 353–461.

_ **and Justin Marion**, "The effects of low income housing tax credit developments on neighborhoods," *Journal of Public Economics*, 2009, *93* (5), 654–666.

_ **and Lu Han**, "The Microgeography of Housing Supply," *Journal of Political Economy*, 2024, *132* (6), 1897–1946.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan, "A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, 2007, *115* (4), 588–638.

Blanco, Hector, "Pecuniary effects of public housing demolitions: Evidence from Chicago," *Regional Science and Urban Economics*, 2023, *98*, 103847.

Borusyak, Kirill and Peter Hull, "Nonrandom Exposure to Exogenous Shocks," *Econometrica*, 2023, *91* (6), 2155–2185.

Brueckner, Jan and Stuart Rosenthal, "Gentrification and Neighborhood Housing Cycles: Will America's Future Downtowns Be Rich?," *Review of Economics and Statistics*, 2009, *91* (4), 725–743.

Brueckner, Jan K., "A vintage model of urban growth," *Journal of Urban Economics*, 1980, *8* (3), 389–402.

— **, Jacques-François Thisse, and Yves Zenou**, "Why is central Paris rich and downtown Detroit poor?: An amenity-based theory," *European Economic Review*, 1999, *43* (1), 91–107.

Calabrese, Stephen M., Dennis N. Epple, and Richard E. Romano, "Inefficiencies from Metropolitan Political and Fiscal Decentralization: Failures of Tiebout Competition," *The Review of Economic Studies*, 2012, *79* (3), 1081–1111.

Costinot, Arnaud and Jonathan Vogel, "Matching and Inequality in the World Economy," *Journal of Political Economy*, 2010, *118* (4), 747–786.

Couture, Victor, Cecile Gaubert, Jessie Handbury, and Erik Hurst, "Income Growth and the Distributional Effects of Urban Spatial Sorting," *Review of Economic Studies*, 04 2023, *91* (2), 858–898.

Damen, Sven, Matthijs Korevaar, and Stijn Van Nieuwerburgh, "An Alpha in Affordable Housing?," Working Paper 33470, National Bureau of Economic Research Feb 2025.

Davidoff, Thomas, "Supply Constraints Are Not Valid Instrumental Variables for Home Prices Because They Are Correlated With Many Demand Factors," *Critical Finance Review*, 2016, *5* (2), 177–206.

Davis, Donald R. and Jonathan I. Dingel, "The comparative advantage of cities," *Journal of International Economics*, 2020, *123*, 103291.

Desmet, Klaus, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg, "The Geography of Development," *Journal of Political Economy*, 2018, *126* (3), 903–983.

Diamond, Rebecca, "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *American Economic Review*, March 2016, *106* (3), 479–524.

— **, Adam Guren, and Rose Tan**, "The Effect of Foreclosures on Homeowners, Tenants, and Landlords," Working Paper 27358, National Bureau of Economic Research June 2020.

— **and Cecile Gaubert**, "Spatial Sorting and Inequality," *Annual Review of Economics*, 2022, *14* (Volume 14, 2022), 795–819.

— **and Tim McQuade**, "Who wants affordable housing in their backyard? An equilibrium analysis of low-income property development," *Journal of Political Economy*, 2019, *127* (3), 1063–1117.

— **and William F. Diamond**, "Racial Differences in the Total Rate of Return on Owner-Occupied Housing," NBER Working Papers 32916, National Bureau of Economic Research, Inc Sep 2024.

Epple, Dennis N and Richard Romano, "Neighborhood schools, choice, and the distribution of educational benefits," in "The economics of school choice," University of Chicago Press, 2003, pp. 227–286.

Fajgelbaum, Pablo D and Cecile Gaubert, "Optimal Spatial Policies, Geography, and Sorting*," *Quarterly Journal of Economics*, 01 2020, *135* (2), 959–1036.

Finlay, John and Trevor C. Williams, "Housing demand, inequality, and spatial sorting," *Journal of International Economics*, 2025, *158*, 104171.

Garin, Andrew, Ethan Jenkins, Evan Mast, and Bryan A Stuart, "Dynamic Individuals, Static Neighborhoods: Migration and Earnings Changes in Poor Neighborhoods," 2025.

Glaeser, Edward and Joseph Gyourko, "The Economic Implications of Housing Supply," *Journal of Economic Perspectives*, February 2018, *32* (1), 3–30.

Greaney, Brian, Andrii Parkhomenko, and Stijn Van Nieuwerburgh, "Dynamic Urban Economics," *Available at SSRN 4897077*, 2024.

Greenwald, Daniel L. and Adam Guren, "Do Credit Conditions Move House Prices?," *American Economic Review*, October 2025, *115* (10), 3559–96.

Guerrieri, Veronica, Daniel Hartley, and Erik Hurst, "Endogenous gentrification and housing price dynamics," *Journal of Public Economics*, 2013, *100*, 45–60.

Hacamo, Isaac, "Interest rates and the distribution of house prices," *Available at SSRN 2687277*, 2024.

Howard, Greg and Jack Liebersohn, "Why is the rent so darn high? The role of growing demand to live in housing-supply-inelastic cities," *Journal of Urban Economics*, 2021, *124*, 103369.

Hsieh, Chang-Tai and Enrico Moretti, "Housing constraints and spatial misallocation," *American economic journal: macroeconomics*, 2019, *11* (2), 1–39.

Kennan, John and James R. Walker, "The Effect of Expected Income on Individual Migration Decisions," *Econometrica*, 2011, *79* (1), 211–251.

Kennedy, Patrick and Harrison Wheeler, "High-End Housing and Gentrification: Evidence from a San Francisco Lottery," *Working paper*, 2023.

Kleinman, Benny, Ernest Liu, and Stephen J. Redding, "Dynamic Spatial General Equilibrium," *Econometrica*, 2023, *91* (2), 385–424.

Landvoigt, Tim, Monika Piazzesi, and Martin Schneider, "The Housing Market(s) of San Diego," *American Economic Review*, April 2015, *105* (4), 1371–1407.

Luttmer, Erzo G. J., "On the Mechanics of Firm Growth," *The Review of Economic Studies*, 02 2011, *78* (3), 1042–1068.

Macek, James, "Housing Regulation and Neighborhood Sorting Across the US," 2024.

Mast, Evan, "JUE Insight: The effect of new market-rate housing construction on the low-income housing market," *Journal of Urban Economics*, 2021, p. 103383.

McMillen, Daniel and Arthur O'Sullivan, "Option value and the price of teardown properties," *Journal of Urban Economics*, 2013, *74*, 71–82.

Monte, Ferdinando, Stephen J. Redding, and Esteban Rossi-Hansberg, "Commuting, Migration, and Local Employment Elasticities," *American Economic Review*, December 2018, *108* (12), 3855–90.

Munneke, Henry J. and Kiplan S. Womack, "Neighborhood renewal: The decision to renovate or tear down," *Regional Science and Urban Economics*, 2015, *54*, 99–115.

Määttänen, Niku and Marko Terviö, "Income distribution and housing prices: An assignment model approach," *Journal of Economic Theory*, 2014, *151*, 381–410.

Nathanson, Charles G, "Trickle-down housing economics," 2025.

Nikolakoudis, Georgios, "The Economics of Segmented Housing Markets," *Available at SSRN 4251925*, 2024.

Pennington, Kate, "Does Building New Housing Cause Displacement?: The Supply and Demand Effects of Construction in San Francisco," 2021.

Rosenthal, Stuart S., "Old homes, externalities, and poor neighborhoods. A model of urban decline and renewal," *Journal of Urban Economics*, 2008, *63* (3), 816–840.

_ , "Are Private Markets and Filtering a Viable Source of Low-Income Housing? Estimates from a "Repeat Income" Model," *American Economic Review*, February 2014, *104* (2), 687–706.

Saiz, Albert, "The Geographic Determinants of Housing Supply," *Quarterly Journal of Economics*, 2010, *125* (3), 1253–1296.

Sweeney, James L, "A Commodity Hierarchy Model of the Rental Housing Market," *Journal of Urban Economics*, 1974, *1* (3), 288–323.

Appendix

A Additional model details

A.1 Proof of Proposition 1

To prove Proposition 1, note that it is sufficient to show that

$$\frac{\partial \log U(x_2, z)}{\partial z} < \frac{\partial \log U(x_1, z)}{\partial z}$$

for every z (so that lower income households derive relatively higher utility in location x_2). By the envelope theorem, we can express each derivative as

$$\frac{\partial \log U(x, z)}{\partial z} = \frac{\partial}{\partial z} \max_q \log q^\alpha (z - P(q, x))^{1-\alpha} = (1 - \alpha) \frac{1}{z - P(q^\star(x, z), x)}$$

where $q^\star := \text{argmax}_q q^\alpha (z - P(q, x))^{1-\alpha}$. Note that this means

$$\frac{\partial \log U(x_2, z)}{\partial z} < \frac{\partial \log U(x_1, z)}{\partial z} \iff P(q^\star(x_2, z), x_2) < P(q^\star(x_1, z), x_1)$$

for all income levels z. However, it can be easily shown that the quality choice solving the maximization problem $q^\star$ must solve the equation

$$P(q, x) = \frac{\alpha}{\alpha + (1 - \alpha)\epsilon(q, x)} z$$

where $\epsilon := \frac{\partial \log P(q,x)}{\partial \log q}$ is the price elasticity of quality. If $\epsilon(q, x)$ is always greater in x_2 for any quality choice $q^\star$, then households of all income levels spend less on housing in x_2. This is sufficient to complete the proof.

A.2 The Incentives to Redevelop to High Quality Blueprints

In this section of the appendix, we consider how the structure of the pricing function affects the probability of redevelopment into high quality segments. In settings with no depreciation and when the probability of redevelopment is low (i.e. in instances where construction costs are high) we prove that neighborhoods with higher rent gradients experience more redevelopment to high quality segments. This is because the returns to holding high quality housing are greater relative to low quality housing when rent gradients are high.

Proposition 2 *Consider two neighborhoods x_1 and x_2 that are identical but for the following: there exists a steady-state equilibrium pricing function $P(q, x)$ and a focal quality level $q^\star$ such that*

$$P(q, x_1) > P(q, x_2) \quad \textit{for all} \quad q < q^\star$$
$$P(q, x_1) < P(q, x_2) \quad \textit{for all} \quad q > q^\star$$

That is, the rent gradient is larger in neighborhood x_2 and the pricing functions exhibit a single-crossing property. Then, when $\delta = 0$ and in the limit where the probability of redevelopment is low,

$$\hat{q} > q^\star \textit{ and } q < q^\star \quad \implies \quad P^R_{x_1}(q, h, \hat{q}) < P^R_{x_2}(q, h, \hat{q}) \tag{A.1}$$

where P^R_x is the probability of redevelopment in neighborhood x. That is, there is more redevelopment that accompanies quality upgrading in neighborhood x_2.

Proof.

First, we consider a smooth, once-differentiable path between the two pricing functions in either neighborhood $P(q, x_1)$ and $P(q, x_2)$ indexed by $s \in [0, 1]$. That is, $P_s(q)$ is continuous and differentiable in (q, s) and and $P_0(q) = P(q, x_1)$ with $P_1(q) = P(q, x_2)$. For every s, assume $\frac{\partial P}{\partial s} < 0$ if and only if $q < q^\star$. Such a smooth path is guaranteed to exist that satisfies all properties.

Fix any q, $\hat{q}$ such that $q < q^\star$ and $\hat{q} > q^\star$ and assume (for simplicity) a **finite** quality space $\mathbb{Q}$. For the purposes of this proof, we can write the average value function of a firm (average taken with respect to idiosyncratic fixed cost shocks) as solving the recursive equation:

$$V_s(q, h, \hat{q}) = \frac{1}{\sigma_c} \log \left[e^{\sigma_c V^N_s(q,h)} + e^{\sigma_c V^R_s(\hat{q})} \right]$$

with (assuming $\delta = 0$)

$$V^N_s(q, h) = P_s(q)h + \beta \sum_{\tilde{q} \in \mathbb{Q}'} V_s(q, h, \tilde{q}) g(\tilde{q})$$
$$V^R_s(\hat{q}) = \max_h \; P_s(\hat{q})h - \Omega \hat{q} h^\gamma - F_{\hat{q}} + \beta \sum_{\tilde{q} \in \mathbb{Q}'} V_s(\hat{q}, h, \tilde{q}) g(\tilde{q})$$

where $g(.)$ is the pdf of the blueprint distribution, and noting that V is continuous in δ, we can work in this limiting case. The log-odds ratio of the probability of redevelopment can also be expressed as follows:

$$\log \frac{P^R_s(q, h, \hat{q})}{1 - P^R_s(q, h, \hat{q})} = \sigma_c [V^R_s(\hat{q}) - V^N_s(q, h)]$$

It is sufficient to show that the log odds ratio is strictly increasing in s to complete the proof. This is the objective in what follows. Note that the Envelope Theorem implies

$$\frac{\partial V_s^R(\hat{q})}{\partial s} - \frac{\partial V_s^N(q,h)}{\partial s} = \underbrace{\frac{\partial P_s(\hat{q})}{\partial s} h_s^\star(\hat{q}) - \frac{\partial P_s(q)}{\partial s} h}_{\text{One-period rent}} + \underbrace{\beta \sum_{\tilde{q}\in\mathbb{Q}'} g(\tilde{q}) \left[\frac{\partial V_s(\hat{q}, h_s^\star(q), \tilde{q})}{\partial s} - \frac{\partial V_s(q,h,\tilde{q})}{\partial s} \right]}_{\text{continuation values}}$$

where $h_s^\star(\hat{q}) > 0$ solves the maximization problem in V^R (where we applied the envelope theorem). To prove the statement, it is then sufficient to show that the "continuation values" term is strictly positive, since the"one period rent" term is strictly positive by the assumptions of $q < q^\star$, $\hat{q} > q^\star$, and the antecedents of the proof, that is, $\frac{\partial P_s(q)}{\partial s} > 0$ if and only if $q < \bar{q}$.

To this end, we define the average change in the value function (average taken with respect to the blueprint distribution)

$$\mathbf{EV}_s(q,h) = \sum_{\tilde{q}\in\mathbb{Q}'} g(\tilde{q}) \frac{\partial V_s(q,h,\tilde{q})}{\partial s}$$

By deriving the derivative of $V_s(q,h,\hat{q})$ with respect to s, it is simple to show that $\mathbf{EV}_s(q,h)$ is defined recursively by

$$\mathbf{EV}_s(q,h) = \left[\sum_{\tilde{q}\in\mathbb{Q}'} (1 - P_s^R(q,h,\tilde{q})) g(\tilde{q}) \left(\frac{\partial P_s(q)}{\partial s} h + \beta \mathbf{EV}_s(q,h) \right) \right] + \left[\sum_{\tilde{q}\in\mathbb{Q}'} P_s^R(q,h,\tilde{q}) g(\tilde{q}) \left(\frac{\partial P_s(\tilde{q})}{\partial s} h_s^\star(\tilde{q}) + \beta \mathbf{EV}_s(\tilde{q}, h_s^\star(\tilde{q})) \right) \right]$$

(we also applied the Envelope theorem again). Define $P_s^{RT}(q,h) := \sum_{\tilde{q}\in\mathbb{Q}'} P_s^R(q,h,\tilde{q}) g(\tilde{q})$ as the average probability of redevelopment across all blueprint draws. This statement can be simplified to

$$\mathbf{EV}_s(q,h) = \underbrace{\frac{1 - P_s^{RT}(q,h)}{1 - \beta(1 - P_s^{RT}(q,h))} \frac{\partial P_s(q)}{\partial s} h}_{\text{Change in Discounted rents on current structure}} + \tag{A.2}$$

$$\underbrace{\frac{\sum_{\tilde{q}\in\mathbb{Q}'} P_s^R(q,h,\tilde{q}) g(\tilde{q}) \left(\frac{\partial P_s(\tilde{q})}{\partial s} h_s^\star(\tilde{q}) + \beta \mathbf{EV}_s(\tilde{q}, h_s^\star(\tilde{q})) \right)}{1 - \beta(1 - P_s^{RT}(q,h))}}_{\text{Discounted profits from redevelopment option value}} \tag{A.3}$$

Next, we take the limit as $F_{\hat{q}} \to \infty$ (a pointwise limit such that fixed costs become arbitrarily large over **all** blueprint draws). Importantly, $h_s^\star$ is a constant function of $F_{\hat{q}}$, so we need not worry about how the optimal number of constructed units varies with fixed costs. Then, we have that

$$P_s^R(q, h, \tilde{q}) \to 0$$

uniformly for every $(q, \tilde{q})$ and a fixed h. This directly implies that

$$\lim_{F_{\hat{q}} \to \infty} \mathbf{EV}_s(q, h) = \frac{1}{1-\beta} \frac{\partial P_s(q)}{\partial s} h$$

uniformly for all $s \in [0, 1]$ and $q \in \mathbb{Q}$ for a given h. Uniform convergence over (s, q, h) follows from assuming h takes on values in a bounded, closed, and strictly positive interval. (One such interval can be chosen such that all maximizers $h_s^\star(\hat{q})$ are interior solutions. This is because we assumed a finite quality space and continuity of prices in s; and thus bounded prices. Moreover, we have convex costs of housing unit construction that become arbitrarily large as $h \to \infty$ and small as $h \to 0$).

Deriving the limiting case, we can complete the proof. We know that, for $q < q^\star$ implies $\frac{\partial P_s}{\partial s} < 0$, so $\lim_{F_{\hat{q}} \to \infty} \mathbf{EV}_s(q, h) = \frac{1}{1-\beta} \frac{\partial P_s(q)}{\partial s} h < 0$. Symmetrically, $\hat{q} > q^\star$ implies $\lim_{F_{\hat{q}} \to \infty} \mathbf{EV}_s(\hat{q}, h_s^\star(\hat{q})) > 0$. Substituting into the expression for $V^R - V^N$ above, we can prove $V_s^R - V_s^N > 0$ for all (s, q, h) which is sufficient to prove that $P_s^R(q, h, \hat{q})$ is strictly increasing in s when fixed costs are large and $q < q^\star < \hat{q}$. This completes the proof.

■

Our proof of Proposition 2 relies on a stylized environment where redevelopment probabilities are low and there is no depreciation. How crucial are these assumptions? First, we stress the point that these assumptions are empirically relevant – both depreciation and redevelopment rates we measure empirically are each less that 0.3% per year. Second, low probabilities of redevelopment are necessary to establish the proof because of complications arising from the option value of *future* redevelopment. Differences in rent gradients may change how valuable the expected value of future redevelopment is (with the expectation taken with respect to the entire distribution of future blueprint draws). This corresponds to the additional term A.3 that prevents ascribing a signed value to $\mathbf{EV}_s(q, h)$. When redevelopment probabilities are low, this option value is unimportant and can be ignored.

With non-zero depreciation, a landlord also needs to consider how a steeper rent gradient will affect returns on housing in the future as the structure they intend to build depreciates down the quality ladder. The condition for this proof becomes:

$$\sum_{t=0}^{\infty}\beta^t\frac{\partial P_s[(1-\delta)^t q]}{\partial s}h < \sum_{t=0}^{\infty}\beta^t\frac{\partial P_s[(1-\delta)^t \hat{q}]}{\partial s}h_s^\star(\hat{q})$$

for $q < q^\star < \hat{q}$ and all s (and redevelopment probabilities are low). That is, the discounted stream of rents for a high quality development need to be greater than that of low quality below the focal quality $q^\star$. Higher rent gradients make this condition more likely to hold, especially when either 1) $\beta \to 0$ (high discounting) or 2) $\delta \to 0$ (slow depreciation as in Proposition 2).

A.3 Solution Algorithm

We discretize the quality space $\boldsymbol{Q}$ into a grid $\boldsymbol{Q} = \{q_1, q_2, ..., q_{N_q}\}$, where $q_1 = \bar{q}$ and $q_n = (1-\delta)q_{n+1}, n \in \{1, 2, ..., N_q - 1\}$. The model is solved iteratively in the following steps:

1. Start by solving for the long run steady state equilibria. The policies we report in this paper are temporary, so this is just the baseline steady state.

2. Solve for the dynamic equilibrium up to a pre-specified terminal period T. Assume all value functions at the terminal period are given by the steady state value functions solved above. To do this, proceed in the following way:

   (a) Guess the entire stream of the pricing function $\{P_t(q,x)\}_{\forall t,q,x}$.

   (b) Given the pricing function, solve the household's problem by equations (3) and (6). This generates the housing demand $\{L_t(q,x,z)\}_{\forall t,q,x,z}$.

   (c) Given the pricing function, solve the landlord's problem backwardly (from $t = T$ to $t = 1$)in the following steps:

      i. In period T, set $V_T(s_{iT}, \hat{q}_{iT})$ to be the steady state value function solved in Step 1.

      ii. In period $t < T$, solve the problem given by equation (10). The value functions $V_{it+1}(\cdot,\cdot)$ are solved from the landlord's problem in the period $t+1$.

         A. Calculate the value of not redeveloping the parcel, net of the idiosyncratic cost shock:

$$V_{it}^N(s_{it}, \hat{q}_{it}) = P_t(q_{it}, x)h_{it} + \beta\mathbb{E}_{\hat{q}_{it+1}}V_{i,t+1}\left(q_{it+1}, h_{it}, \hat{q}_{i,t+1}\right).$$

B. Calculate the value of redeveloping the parcel, net of the idiosyncratic cost shock:

$$V_{it}^{R}(s_{it},\hat{q}_{it}) = -C_i(\hat{q}_{it}, h_{it}^{*}(\hat{q}_{it},x)) + P_t(\hat{q}_{it},x)h_{it}^{\star}(\hat{q}_{it},x) + \beta\mathbb{E}_{\hat{q}_{it+1}} V_{i,t+1}\left(\hat{q}_{it}^{D}, h_{it}^{*}(\hat{q}_{it},x), \hat{q}_{i,t+1}\right),$$

where $h_{i,t+1}^{*}(\hat{q}_{it},x) = \arg\max_{h_{i,t}} \left\{-C_i(\hat{q}_{it}, h_{i,t+1}) + \beta\mathbb{E}_{\hat{q}_{it+1}} V_{i,t+1}\left(\hat{q}_{it}, h_{i,t+1}, \hat{q}_{i,t+1}\right)\right\}$. Note that due to full irreversiblility of housing investment, the optimal housing unit $h_{i,t+1}^{*}(\hat{q}_{it},x)$ conditional on redevelopment is independent of the current housing characteristics s_{it}.

C. Calculate the share of parcels that choose to redevelop:

$$P^{R}(s_{it},\hat{q}_{it}) = \frac{\exp\left(V_{it}^{R}(s_{it},\hat{q}_{it})\right)^{1/\sigma_c}}{\exp\left(V_{it}^{N}(s_{it},\hat{q}_{it})\right)^{1/\sigma_c} + \exp\left(V_{it}^{R}(s_{it},\hat{q}_{it})\right)^{1/\sigma_c}}.$$

(d) Given the landlord's optimal redevelopment decisions $\{p(s_{it},\hat{q_{it}})\}_{i,t,s,\hat{q}}$ and $\{h_{it}^{*}(\hat{q}_{it})\}_{i,t,\hat{q}}$ solved in Step 3, and the initial mass of housing by quality across neighborhoods $\{s_{i0}\}_i$, calculate the housing supply $H_t(q,x)$ forwardly, from $t=1$ to $t=T$:

$$\begin{aligned} H_t(q,x) = & \sum_{i\in\boldsymbol{I}_x} \mathbf{1}\{q_{i,t-1} = \frac{1}{1-\delta}q\}\left(1-p(s_{it-1},\hat{q}_{it-1})\right)h_{it-1} + \sum_{i\in\boldsymbol{I}_x} p(s_{it-1},\hat{q}_{it-1})\cdot h_{it}^{*}(\hat{q}_{it-1},x) + \\ & \mathbf{1}\{q = q_{min}\}\sum_{i\in\boldsymbol{I}_x}\mathbf{1}\{q_{i,t-1} = q\}\left(1-p(s_{it-1},\hat{q}_{it-1})\right)h_{it-1}. \end{aligned}$$

(e) Check the market clearing condition:

$$\sum_{z\in\boldsymbol{Z}} L_t(q,x,z) = H_t(q,x), \quad \forall t\in\{1,2,...,T\}, q\in\boldsymbol{Q}, x\in\boldsymbol{X}$$

i. if the market clearing condition is satisfied, stop the iteration.

ii. if not satisfied, update the pricing function $\{P_t(q,x)\}_{\forall t,q,x}$ in a way proportional to excess demand; and go back to step 2.

B Calibration and estimation

In this appendix, we provide supplementary material for the empirical implementation of our model.

B.1 Housing Supply Estimation

B.1.1 The Housing Unit Cost Elasticity γ

We start with the estimation of the housing unit cost elasticity parameter γ. Conditional on redevelopment, the landlord chooses h_{it} to maximize profits, that is:

$$h_{it} = \text{argmax}_h \left\{ -\left(\Omega_x \cdot q_{it} \cdot h^{\gamma}\right) - F_{qx} + V_{i,t}\left(\hat{q}_{it}, h\right) \right\}. \tag{B.1}$$

where $V_{it}(q_{it}, h) = P(q_{it}, x)h + \beta \mathbb{E}_{\hat{q}_{it+1},\, \vec{\xi}_{it+1}} V_{i,t+1}\left([1-\delta]q_{it}, h, \hat{q}_{i,t+1}, \vec{\xi}_{it+1}\right)$ is the value of the building *cum-dividend* (including the current period's rents). The first-order condition of this problem is

$$\gamma \Omega_x \cdot q_{it} h^{\gamma-1} + \beta \frac{\partial V_{it}\left(q_{it}, h\right)}{\partial h} = 0. \tag{B.2}$$

Taking the logarithm and rearranging the first-order condition, we can obtain

$$\log h_{it} = -\frac{1}{(\gamma-1)}\left(\log\gamma - \log\beta\right) + \frac{1}{(\gamma-1)}\left(\log \frac{\partial V_{it}\left(\hat{q}_{it}, h\right)}{\partial h_{it}} - \log \hat{q}_{it}\right) - \frac{1}{(\gamma-1)} \log \Omega_x \tag{B.3}$$

Assuming that quality is measured with a measurement error and that there are additional unobserved marginal cost shocks ϵ^{γ} at the parcel level, we can derive the estimating equation (16). We find that, in our model calibration, the marginal value of adding an additional building is almost exactly constant. For this reason, we approximate $\frac{\partial V_{it}(q_{it},h)}{\partial h}$ in this equation with the average value per housing unit $V(q,h)/h$. This derives Equation (16).

B.1.2 Estimates of total construction costs

We use each of the estimated and internally calibrated parameters of the housing production function to construct model-based measures of total and fixed construction costs. We report these estimates for each neighborhood and blueprint quality level in Figure B.1.

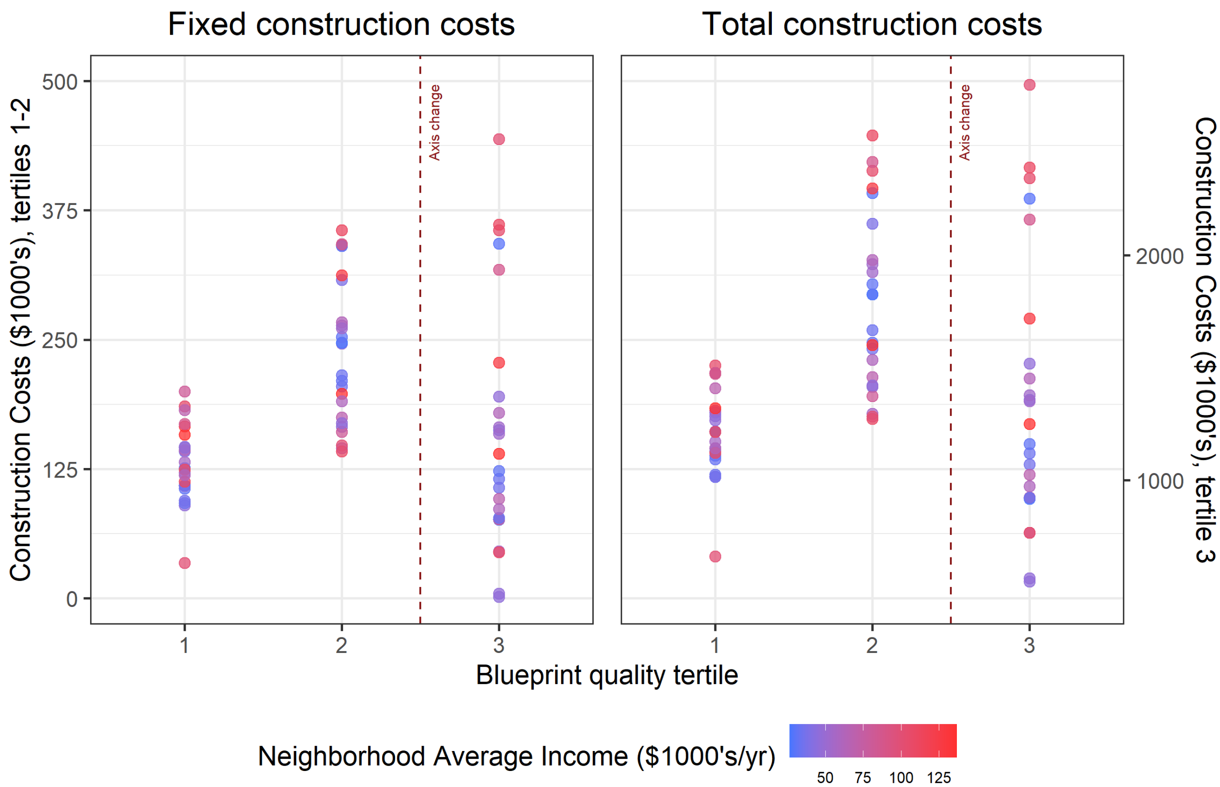


Figure B.1: Model-based construction costs; constructed using estimated and internally calibrated parameters in Section 5. The support of the blueprint distribution represent upper bounds of the 3 quality tertiles observed in the data. For example, the highest quality blueprint corresponds to the 99th percentile of housing quality, while the lowest quality blueprint is the 33rd percentile. The left scale is associated with the first two blueprint tertiles. The right scale is associated with the remaining tertile. Fixed costs take the lion's share of total construction costs. Construction costs for the highest quality blueprints are exponentially greater in all neighborhoods. Higher income neighborhoods tend to have greater fixed and variable costs of construction for any given quality blueprint. However, there is considerable noise in both fixed and variable costs for neighborhoods of identical incomes.

C Additional Figures and Tables

Table C.1: Balance Test between the Buffer Areas within and outside the Treatment Boundary

Variable	Treated Area Mean	Treated Area SD	Control Area Mean	Control Area SD	Difference Estimate	Difference SE
Panel A: Assessment data (2020)						
Bedrooms	4.57	(2.35)	4.38	(2.19)	0.20	(0.24)
Bathrooms	2.51	(1.26)	2.41	(1.17)	0.10	(0.15)
Unit Sq. ft.	2423.36	(1433.72)	2337.09	(1369.41)	86.28	(207.49)
Land Sq. ft.	3201.29	(899.91)	3198.47	(1104.07)	2.81	(233.91)
Single Family	0.34	(0.47)	0.41	(0.49)	-0.07	(0.09)
Building Units	2.14	(1.20)	1.97	(1.16)	0.16	(0.23)
Build Year	1909.87	(39.14)	1916.59	(38.35)	-6.72	(8.35)
Panel B: Transaction data (2015–2020)						
Bedrooms	4.09	(2.17)	3.71	(2.09)	0.38	(0.25)
Bathrooms	2.56	(1.21)	2.46	(1.19)	0.10	(0.09)
Unit Sq. ft.	2218.20	(1285.94)	2025.18	(1128.98)	193.01	(170.74)
Land Sq. ft.	3665.93	(2681.31)	3825.20	(2193.57)	-159.27	(289.06)
Single Family	0.44	(0.50)	0.50	(0.50)	-0.06	(0.11)
Building Units	2.72	(2.83)	3.51	(3.77)	-0.79***	(0.10)
Build Year	1929.76	(52.28)	1940.91	(51.00)	-11.15	(11.33)
log(Sale Price)	12.81	(0.62)	12.85	(0.66)	-0.04	(0.03)
log(Sale Price / Unit Sq. ft.)	5.23	(0.58)	5.35	(0.60)	-0.12	(0.09)
Panel C: Rental data (2015–2020)						
Bedrooms	2.24	(0.86)	2.18	(0.76)	0.06	(0.06)
Bathrooms	1.33	(0.56)	1.43	(0.58)	-0.10	(0.07)
Unit Sq. ft.	1130.35	(416.91)	1160.16	(385.79)	-29.81	(49.49)
Build Year	1898.49	(26.73)	1909.75	(32.40)	-11.26	(8.01)
log(Rent)	7.37	(0.33)	7.49	(0.33)	-0.12**	(0.06)
log(Rent / Unit Sq. ft.)	0.40	(0.28)	0.48	(0.29)	-0.08***	(0.02)

Note: Standard errors are clustered by 500-meter buffer. * p<0.1, ** p<0.05, *** p<0.01.

Table C.2: Balance Test: Treated Neighborhoods versus the Rest of the City

	Treated Area		The Rest of Chicago		Difference	
Variable	Mean	SD	Mean	SD	Estimate	SE
Panel A: Assessment data (2020)						
Bedrooms	4.55	(2.33)	3.75	(1.89)	0.80***	(0.00)
Bathrooms	2.49	(1.25)	1.91	(1.08)	0.58***	(0.00)
Unit Sq. ft.	2393.72	(1413.87)	1875.43	(1235.09)	518.29***	(0.00)
Land Sq. ft.	3217.97	(896.78)	3991.24	(1830.01)	-773.27***	(0.00)
Single Family	0.34	(0.47)	0.70	(0.46)	-0.36***	(0.00)
Building Units	2.12	(1.19)	1.46	(0.93)	0.65***	(0.00)
Build Year	1909.76	(38.57)	1932.63	(31.00)	-22.87***	(0.00)
Panel B: Transaction data (2015–2020)						
Bedrooms	4.05	(1.95)	3.37	(1.30)	0.68***	(0.00)
Bathrooms	2.47	(1.09)	1.83	(0.87)	0.64***	(0.00)
Unit Sq. ft.	2103.75	(942.36)	1670.15	(780.42)	433.60***	(0.00)
Land Sq. ft.	3495.19	(1234.90)	5214.29	(2128.79)	-1719.10***	(0.00)
Single Family	0.43	(0.50)	0.84	(0.36)	-0.41***	(0.00)
Building Units	2.60	(2.61)	1.75	(2.27)	0.84***	(0.00)
Build Year	1926.70	(51.02)	1948.95	(32.54)	-22.24***	(0.00)
log(Sale Price)	12.78	(0.62)	12.30	(0.81)	0.48***	(0.00)
log(Sale Price / Unit Sq. ft.)	5.22	(0.58)	4.96	(0.71)	0.26***	(0.00)
Panel C: Rental data (2015–2020)						
Bedrooms	2.12	(0.94)	1.79	(1.06)	0.33***	(0.00)
Bathrooms	1.32	(0.57)	1.34	(0.57)	-0.02***	(0.00)
Unit Sq. ft.	1115.04	(514.36)	1052.04	(517.10)	62.99***	(0.00)
Build Year	1899.03	(27.20)	1916.11	(33.29)	-17.08***	(0.00)
log(Rent)	7.41	(0.36)	7.47	(0.47)	-0.07***	(0.00)
log(Rent / Unit Sq. ft.)	0.52	(0.33)	0.67	(0.43)	-0.15***	(0.00)

Note: Standard errors are clustered at two levels: the treatment area and the remainder of the city. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table C.3: Event Study Results: Demolition and Construction Permits

	Demolition			Construction		
Buffer Width	0.25km	0.5km	1km	0.25km	0.5km	1km
	(1)	(2)	(3)	(4)	(5)	(6)
Treat ×						
2009–2011	-0.000	-0.002	-0.002	0.000	-0.002	-0.003*
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
2012–2014	0.002	0.001	-0.002	0.004	0.003	0.000
	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
2015–2017	0.005	0.001	0.001	0.003	-0.000	0.000
	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
2018–2020	-	-	-	-	-	-
2021–2023	0.002	-0.004**	-0.004**	0.001	-0.003	-0.004**
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Building FE	Yes	Yes	Yes	Yes	Yes	Yes
Period × Neighborhood FE	Yes	Yes	Yes	Yes	Yes	Yes
$F_{xt}(\text{Lon}, \text{Lat})$	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	30,985	58,055	95,025	30,985	58,055	95,025

The table shows the estimation results of equation (1). This specification includes the spatial pricing dynamic controls $F_{xt}(\text{Lon}, \text{Lat})$ discussed in Section 3, and excludes unit-specific controls X_{it} and fixed effects. Standard errors are clustered by Building ID. * p<0.1, ** p<0.05, *** p<0.01.

Table C.4: Event-Study Results: Rent and Sale Price

	Log Rent			Log Sale Price		
Buffer Width	0.25km	0.5km	1km	0.25km	0.5km	1km
	(1)	(2)	(3)	(4)	(5)	(6)
Treat ×						
2018	-0.012	-0.006	0.027	0.015	0.024	0.072*
	(0.017)	(0.029)	(0.016)	(0.059)	(0.040)	(0.040)
2019	-0.001	-0.001	-0.001	0.015	0.008	0.027
	(0.013)	(0.009)	(0.009)	(0.059)	(0.038)	(0.035)
2020	-	-	-	-	-	-
2021	-0.001	-0.013	0.001	-0.043	-0.011	0.003
	(0.013)	(0.009)	(0.007)	(0.043)	(0.029)	(0.024)
2022	0.002	0.001	0.003	-0.008	-0.053	-0.048
	(0.013)	(0.010)	(0.009)	(0.065)	(0.040)	(0.029)
2023	0.001	-0.005	0.001	0.039	-0.004	-0.004
	(0.013)	(0.010)	(0.009)	(0.073)	(0.040)	(0.031)
Unit FE	Yes	Yes	Yes	No	No	No
Unit Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Period × Neighborhood FE	Yes	Yes	Yes	Yes	Yes	Yes
$F_{xt}(\text{Lon}, \text{Lat})$	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	8,505	13,997	21,889	2,463	4,507	7,671

Note: The table shows the estimation results of equation (1). All regressions control for a neighborhood-time-specific polynomial of longitude and latitude. $F_{xt}(\text{Lon}, \text{Lat})$, and excludes unit-specific controls X_{it}. Rent regressions cluster standard errors by unit; sales price regressions use Conley standard errors. * p<0.1, ** p<0.05, *** p<0.01.

Table C.5: Event Study Results: Displacement

	Neighborhood-level			Address-level		
Buffer Width	0.25km	0.5km	1km	0.25km	0.5km	1km
	(1)	(2)	(3)	(4)	(5)	(6)
Treat ×						
2018	0.005	-0.023	-0.020	-0.007	-0.024	-0.027
	(0.028)	(0.022)	(0.018)	(0.030)	(0.025)	(0.020)
2019	0.039	-0.003	-0.006	0.034	-0.007	-0.009
	(0.029)	(0.023)	(0.017)	(0.029)	(0.024)	(0.018)
2020	-	-	-	-	-	-
2021	0.053	0.028	0.007	0.055	0.030	0.008
	(0.032)	(0.028)	(0.022)	(0.034)	(0.030)	(0.024)
2022	0.044	-0.015	-0.002	0.055	-0.009	-0.002
	(0.035)	(0.029)	(0.021)	(0.035)	(0.031)	(0.022)
2023	0.011	-0.029	-0.039*	0.021	-0.031	-0.041*
	(0.035)	(0.026)	(0.020)	(0.035)	(0.029)	(0.022)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Period × Neighborhood FE	Yes	Yes	Yes	Yes	Yes	Yes
$F_{xt}(\mathrm{Lon}, \mathrm{Lat})$	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	4,194	7,775	13,809	4,194	7,775	13,809

Note: The table shows the estimation results of equation (1) for the displacement outcomes. Neighborhood-level displacement is a dummy variable equal to one if an individual moves out of the rings of corresponding buffer widths, while address-level displacement equals one if an individual moves out of their previous address. Standard errors are clustered by individual. * p<0.1, ** p<0.05, *** p<0.01.

Table C.6: Change in Building Age and Income: First Stage

	(1) Δ Median Building Age	(2) Δ Median Building Age
Bartik×Median Building Age	-22.705***	-22.816***
	(4.143)	(3.667)
Initial Median Building Age	0.007***	0.004*
	(0.002)	(0.002)
Δ log Employment	0.108	0.049
	(0.096)	(0.081)
Initial log Income		-0.375***
		(0.118)
Num. Obs.	2,280	2,268
R^2	0.114	0.140
KP F-Stat	29.7	38.2

Note: All regressions are weighted by the number of initial number of housing units. Change in building age is normalized to have a standard deviation of 1 year (originally 3.7 years). Standard errors are clustered at the official Chicago neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table C.7: Redevelopment Across High-income and Low-income neighborhoods

	(1) log Units	(2) log Sqft	(3) Δ log Units	(4) Δ log Sqft
log Income	-0.108***	0.161***	-0.243***	0.054**
	(0.014)	(0.021)	(0.028)	(0.022)
Num. Obs.	24,621	24,419	6,691	6,605
R^2	0.027	0.044	0.038	0.002

Note: This table shows the regression of housing measures on neighborhood-level income for redeveloped buildings. neighborhood is defined as a census block group. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.8: Hedonic Regression Results

	(1)	(2)	(3)
Building age	-0.0020	-0.0019	-0.0021
Bedrooms	0.1477	0.1571	0.1572
Bedrooms^2	-0.0116	-0.0200	-0.0129
Bathrooms	0.1789	0.1715	0.1637
Bathrooms^2	-0.0201	-0.0201	-0.0199
Unit area (sq. ft.)	0.2825	0.2837	0.2880
Lot area (sq. ft.)	-0.0071	0.0061	-0.0120
Lot × unit area	0.0105	-0.0068	-0.0061
Single-family dwelling	0.4692	0.7526	0.8297
Medium multifamily building	0.0512	0.0512	0.0593
Construction quality = Poor	-17.6572	-19.3818	-14.0882
Construction quality = Deluxe	0.0696	0.0601	0.0542
Exterior wall: Frame/Masonry	-0.0552	-0.0396	-0.0242
Exterior wall: Frame	0.0402	0.0436	0.0407
Exterior wall: Stucco	-0.0397	-0.0483	-0.0372
Heating: Hot water/steam	-0.0139	-0.0047	-0.0939
Heating: Electric	-0.0028	-0.0417	-0.0381
Heating: None	-0.1507	-0.1548	-0.1475
Housing type: Two-story	0.0001	0.0114	0.0131
Housing type: Split-level	0.0048	0.0161	0.0161
Housing type: 1.5-story	0.0237	0.0314	0.0314
Enclosed porch (masonry)	-0.0213	-0.0184	-0.0171
Enclosed porch (frame)	-0.0007	0.0199	0.0201
Rank of prior sale price			0.0020
Rank of prior sale price^2			-0.0000
Neighborhood FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Num. Obs.	17,212	11,333	11,333
R^2	0.87	0.87	0.87

Notes: The table shows the results of the depreciation rate and the coefficient of different housing characteristics from Equation 15. Columns (2) and (3) are estimated using the subset of rental properties with observed past transactions.

Table C.9: Regressions of Estimated Pricing Function Parameters and Average Quality

Dependent variable:	Log rent	Elasticity	FE	Log avg quality
	(1)	(2)	(3)	(4)
Log(Building Age)	-0.458***	-0.201*	-0.219***	-0.258***
	(0.058)	(0.104)	(0.057)	(0.032)
Log(Median Income)	0.355***	0.014	0.410***	0.125***
	(0.055)	(0.099)	(0.055)	(0.031)
Num. obs.	23	23	23	23
R^2	0.917	0.221	0.876	0.889

Note: The table uses the estimated pricing function parameters and housing quality from equation (15). All regressions are conducted at the neighborhood group level and are weighted by the number of housing units. Median income, median rent, and the number of housing units information are obtained from the American Community Survey. Building age is from the assessment data. Average quality is normalized to be 1 at the city-level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table C.10: First Stage Results of the Supply Elasticity Estimation

Dependent Variable:	Log(Price Per Unit)	Log(Adj. Price Per Unit)
	(1)	(2)
Bartik IV	8.17***	6.07**
	(2.25)	(1.97)
Num. obs.	3304	3304
R^2	0.24	0.25
F statistic	13.13	9.46

Note: The table shows the first-stage estimation results of the IV specification in Table 2. Both columns control for log 2025 block group employment and 2010-2019 block group employment growth, and year-month fixed effects. Standard errors are clustered at the census block group level. * p<0.1, ** p<0.05, *** p < 0.01.

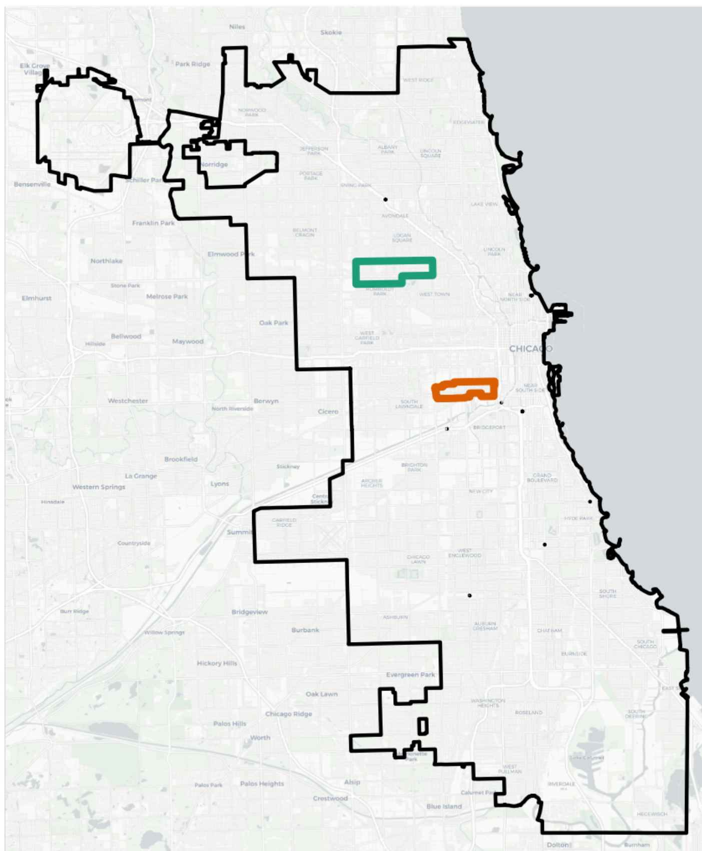
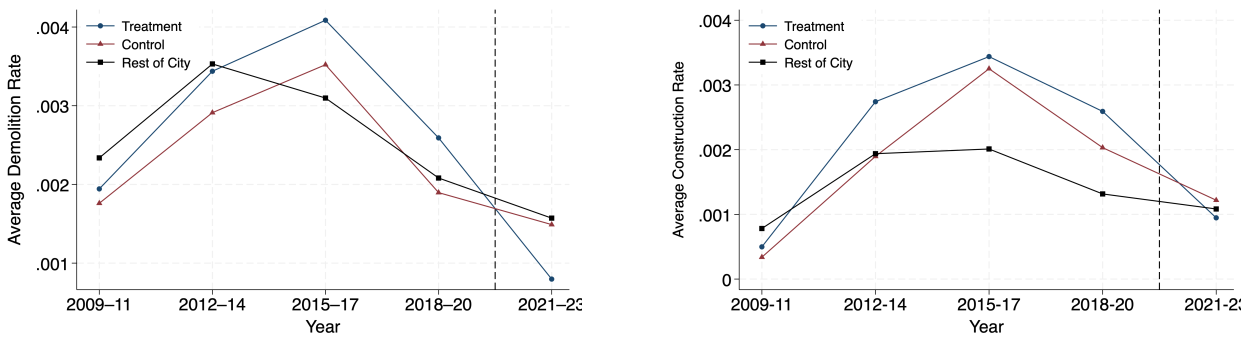


Figure C.1: Policy areas: The 606 and Pilsen neighborhoods

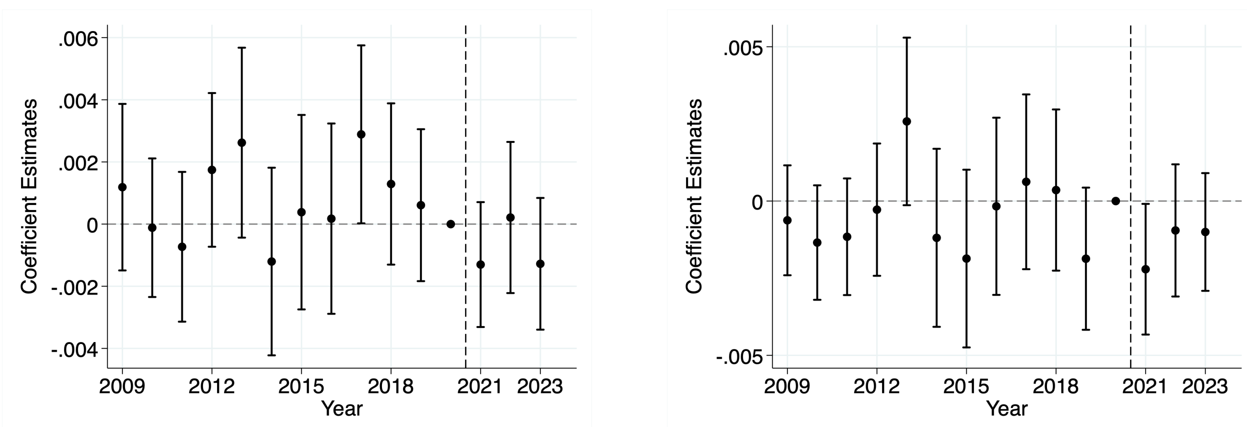
Note: The solid line represents the boundary of the city of Chicago. The upper-left area is 606-Trail; the other area is Pilsen.



(a) Demolition Permits (b) Construction Permits

Figure C.2: Average Demolition and Construction Rates within 500-meter Buffer Zones

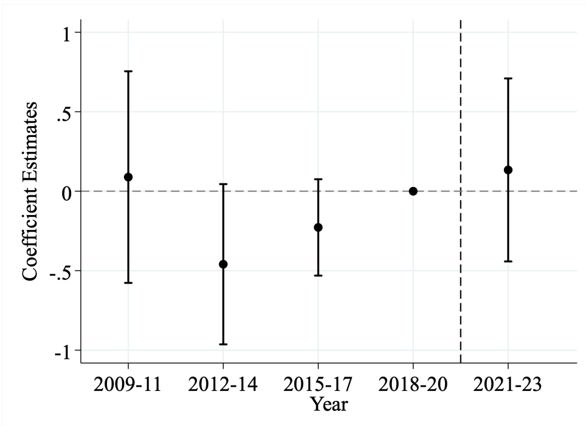
Note: The figure shows the average three-year probabilities of an address issued a demolition or a construction permit.



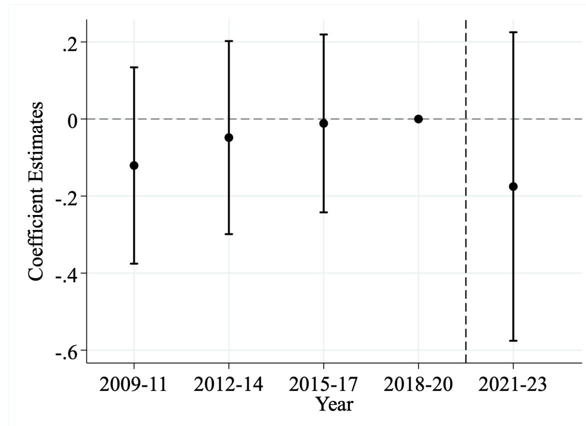
(a) Demolition Permits (b) Construction Permits

Figure C.3: Difference-in-Difference Results at Yearly Frequency

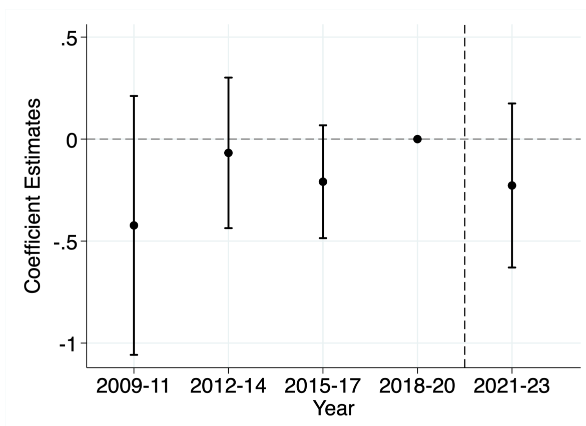
Note: The figure shows the estimation results of equation (1) at the one-year frequency with 500m buffer. Robust standard errors clustered at the address level. Confidence intervals are at the 95% significance level.



(a) Demolition Permits



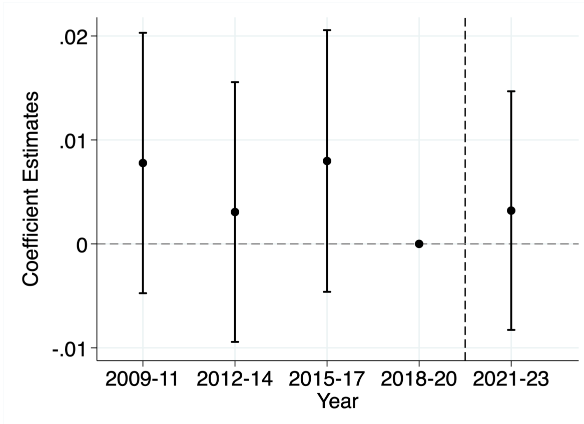
(b) All Permits



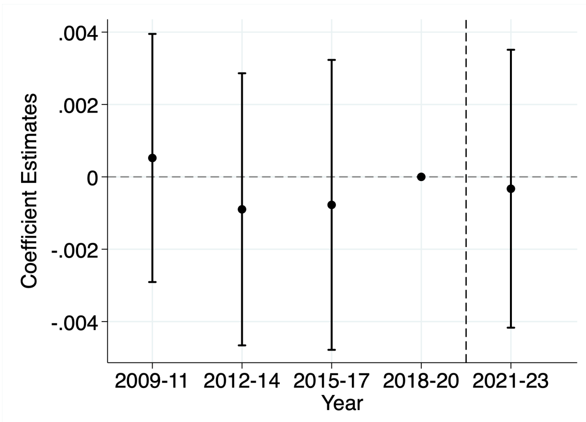
(c) Construction Cost

Figure C.4: Difference-in-Difference Results of Permit Processing Time and Estimated Cost of Construction Permits

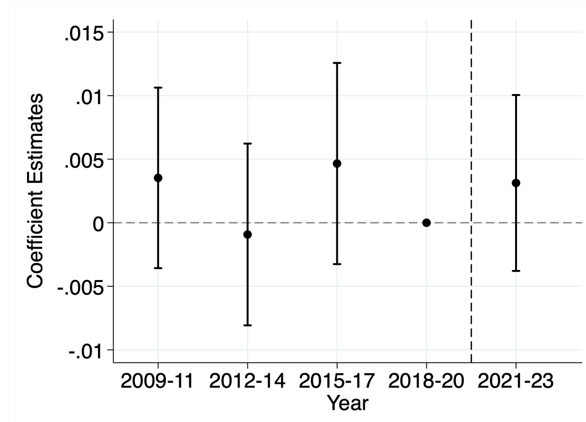
Note: The figure shows the spatial difference-in-difference results for log permit processing time (measured in days) and log estimated project costs of construction permits. All dependent variables are in log. Confidence intervals using heteroskedasticity-robust standard error are at the 95% significance level.



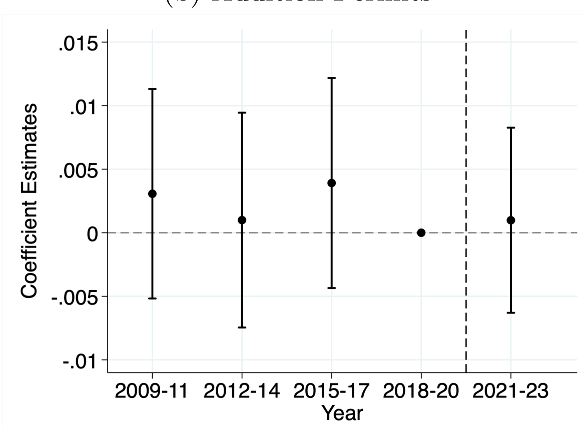
(a) All Renovation Permits



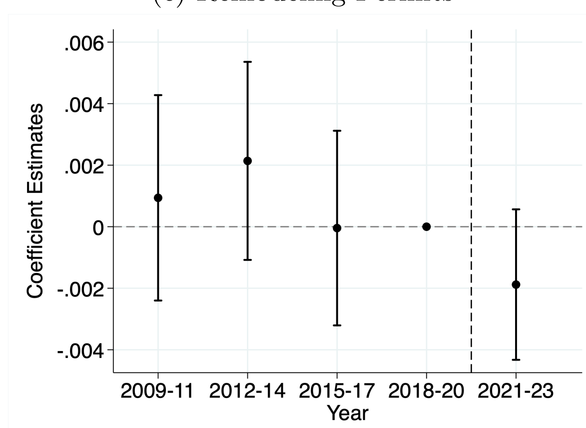
(b) Addition Permits



(c) Remodeling Permits



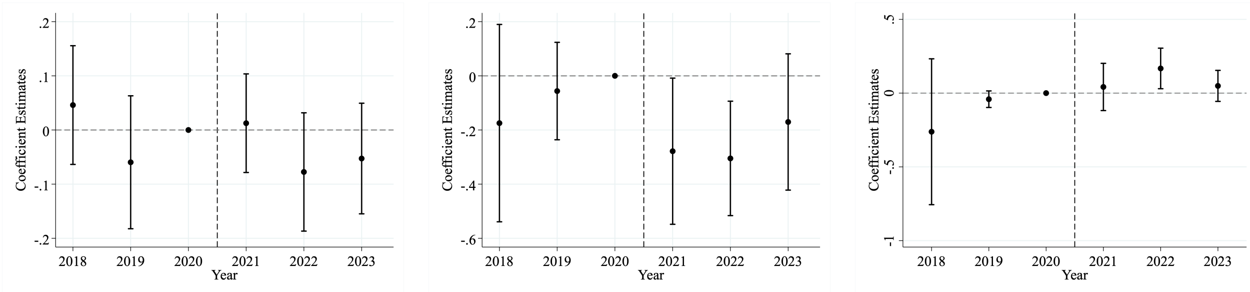
(d) Repairing Permits



(e) Deconversion Permits

Figure C.5: Difference-in-Difference Results of Renovation Permits

Note: The figure shows the spatial difference-in-difference results for renovation permits. We use ChatGPT to classify renovation permits into four types based on the work description: addition (adding an additional housing unit), remodeling, repairing and deconversion. Standard errors are clustered at the address level. Confidence intervals are at the 95% significance level.



(a) Sales Price (Old) (b) Build Age (Sales) (c) Build Age (Rental)

Figure C.6: Difference-in-Difference Results on Sales Price of Old Properties, Building Age of Sold and Rental Properties

Note: The figure shows the estimation results of equation (1) for log sales price of old properties and the build age of sold and rental properties. Old buildings are defined as the ones greater or equal to 80 years old. The regression for the rental properties building age (Panel (c)) uses a 250 meter buffer, as the 500 meter buffer sample violates the parallel trend assumption. All regressions include year-month-neighborhood-specific polynomials of longitude and latitude to control for local market dynamics. Confidence intervals are at the 95% significance level.

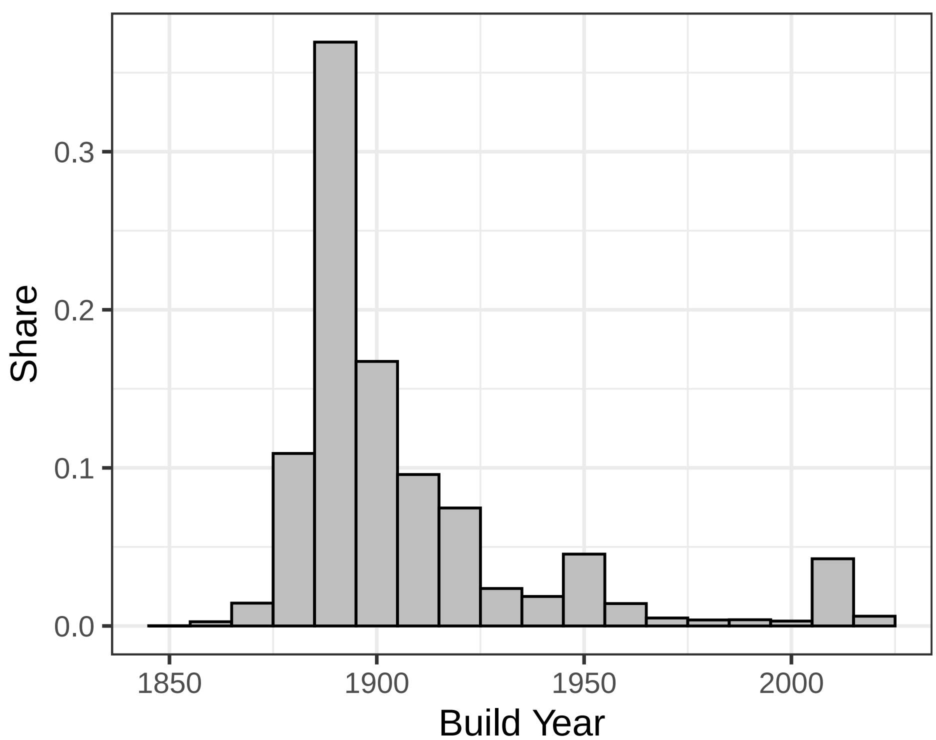


Figure C.7: Distribution of Build Year of Redeveloped Buildings

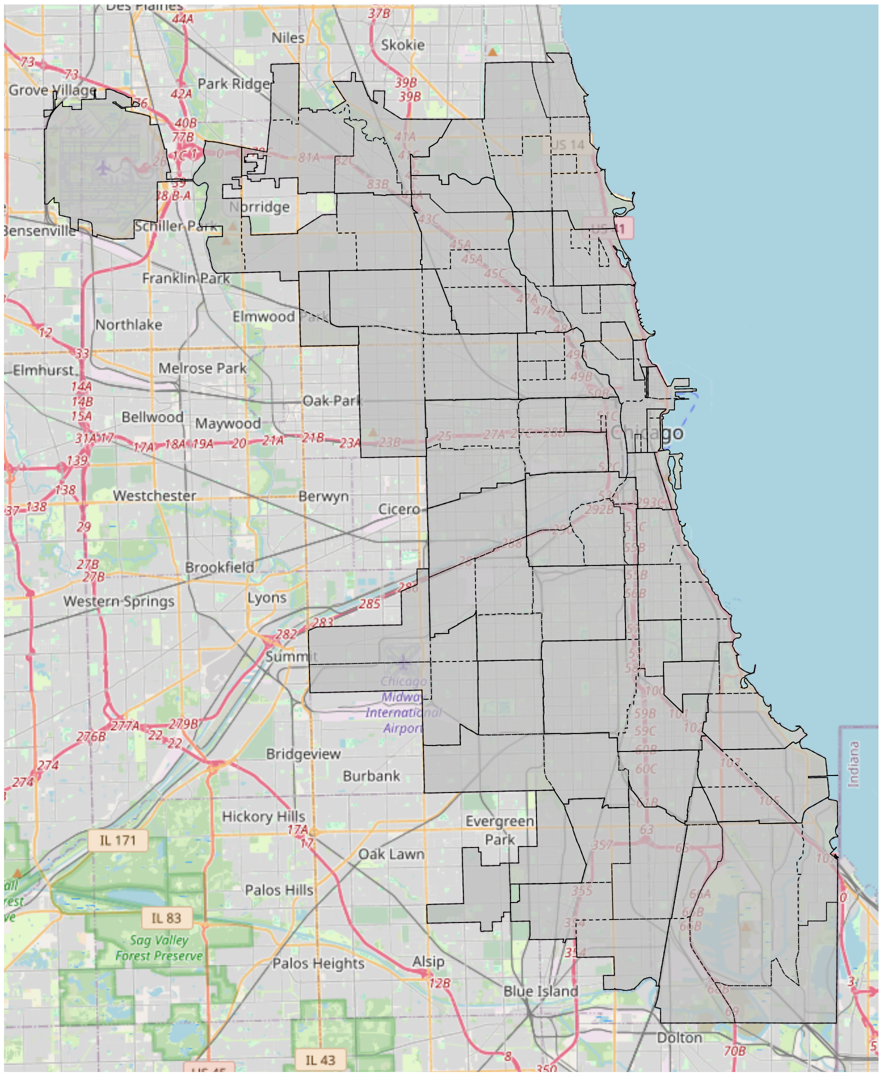


Figure C.8: A Map of Neighborhood Groups

Note: The solid lines represent our defined neighborhood groups; the dashed lines show the official neighborhood boundaries set by the City of Chicago.

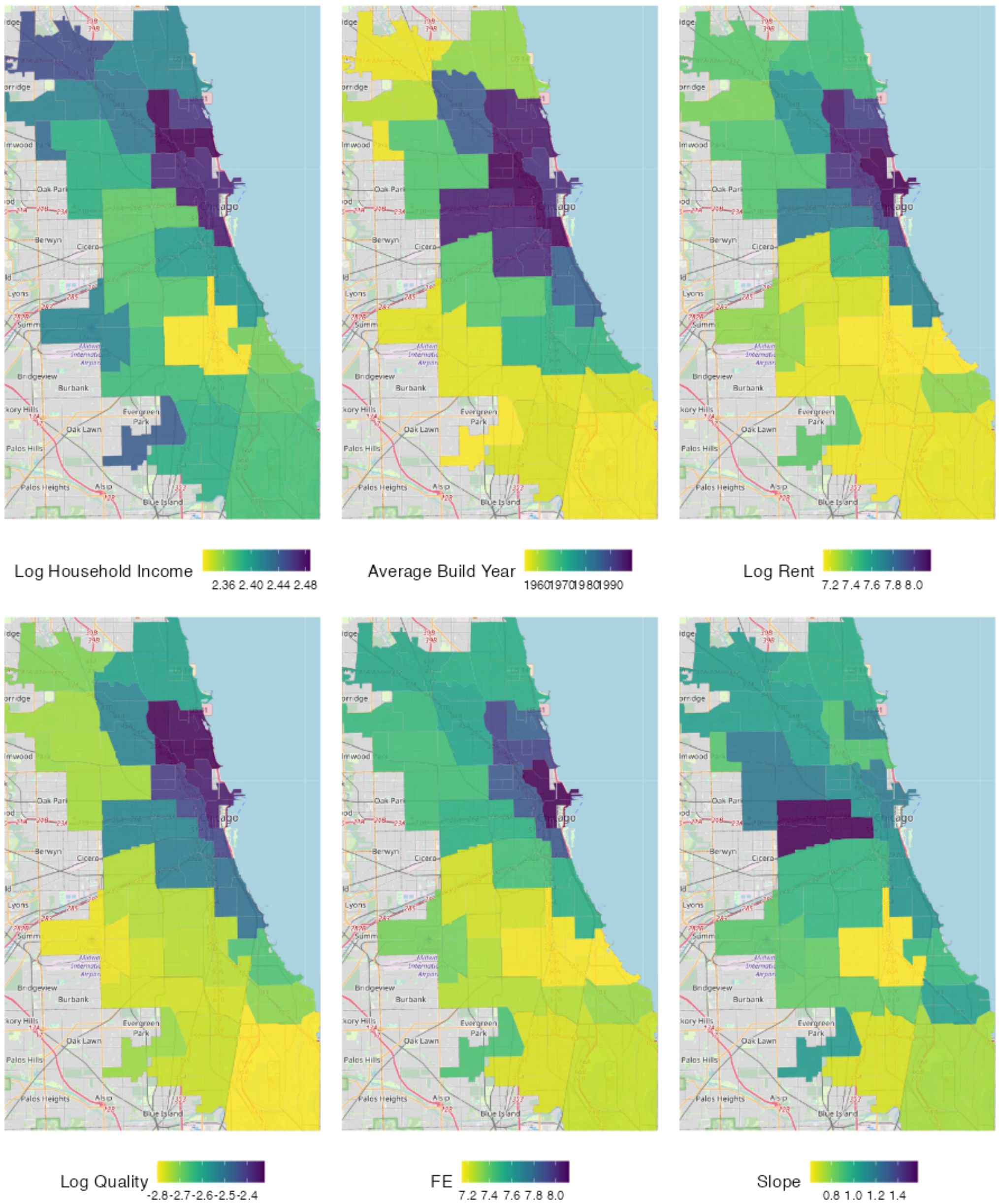


Figure C.9: Observed characteristics and estimated pricing functions across neighborhoods

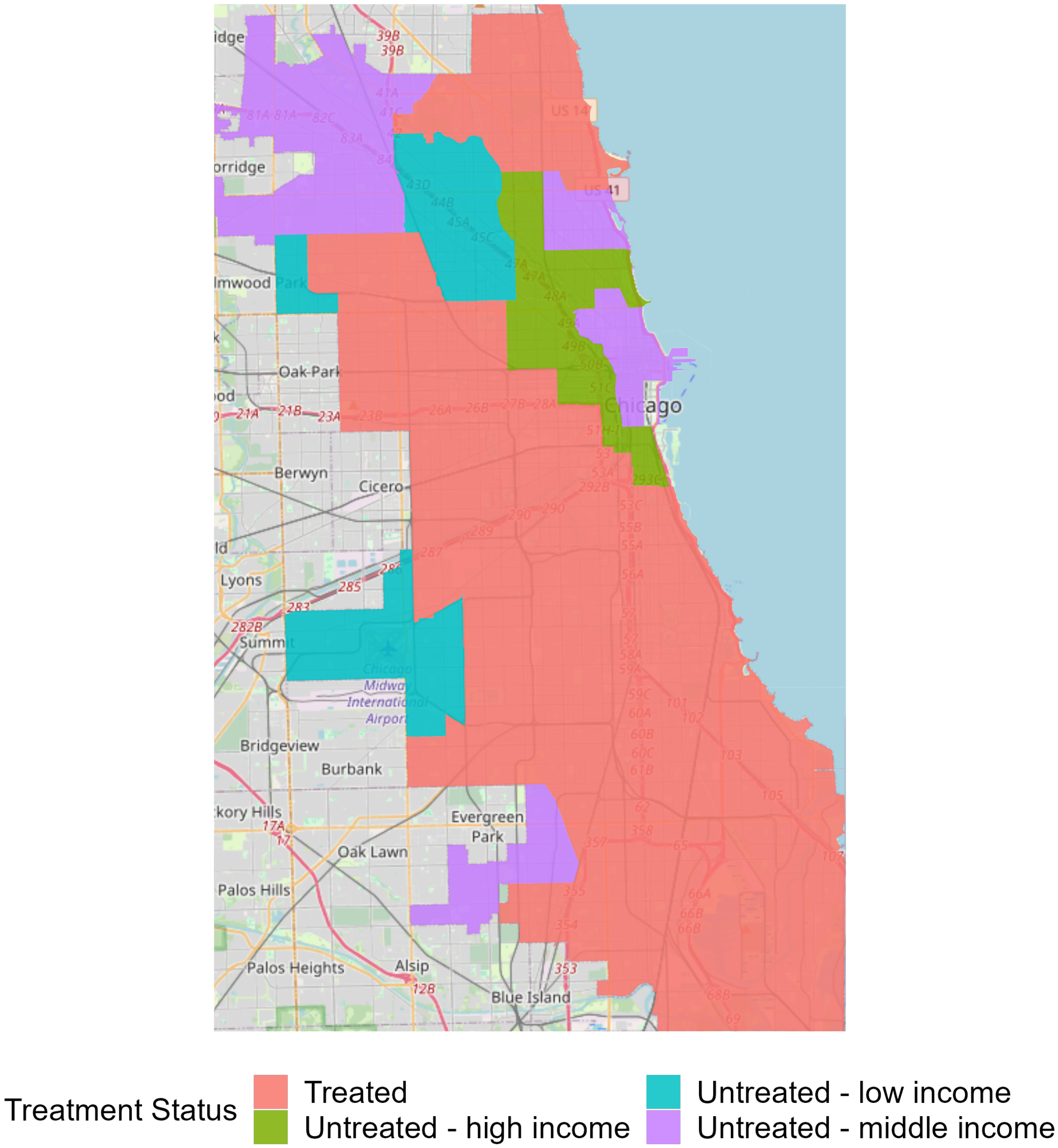


Figure C.10: Map of neighborhood groups by treatment status for the 50-year Teardown Policy

Note: Treatment area represents 60% of the total population of the Chicago municipality (approximately 700,000 housing units). Untreated areas take the remaining share.

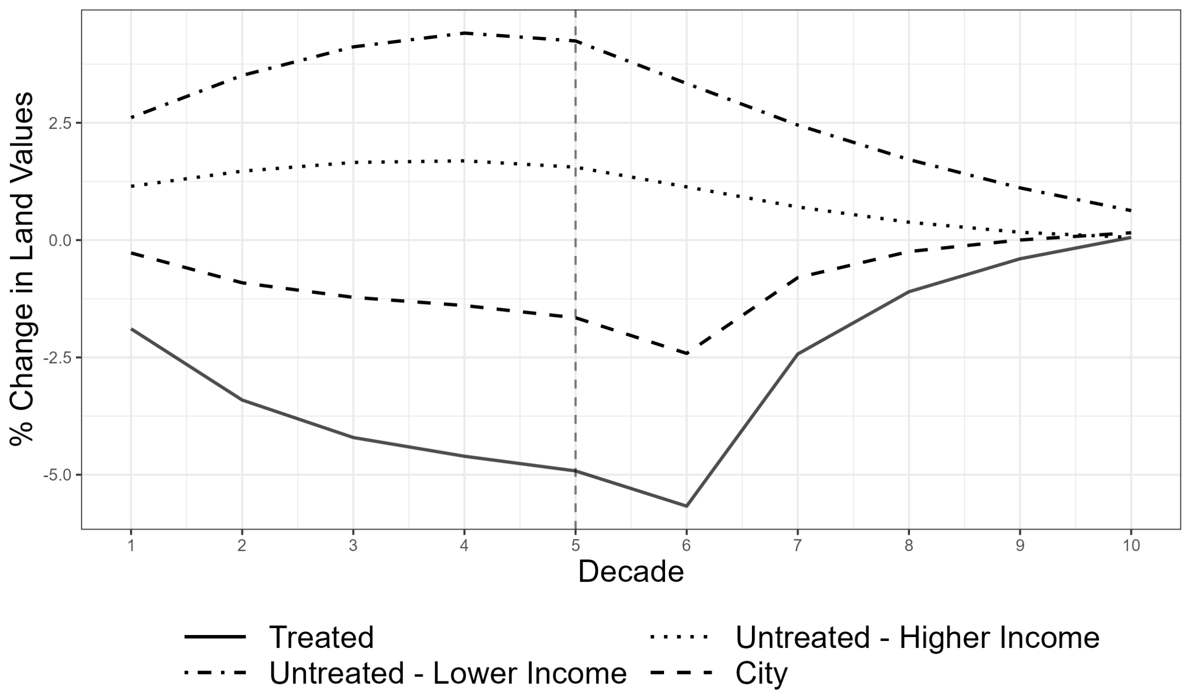


Figure C.11: The Impact of a 50-year Teardown Policy on Land Value across Neighborhoods

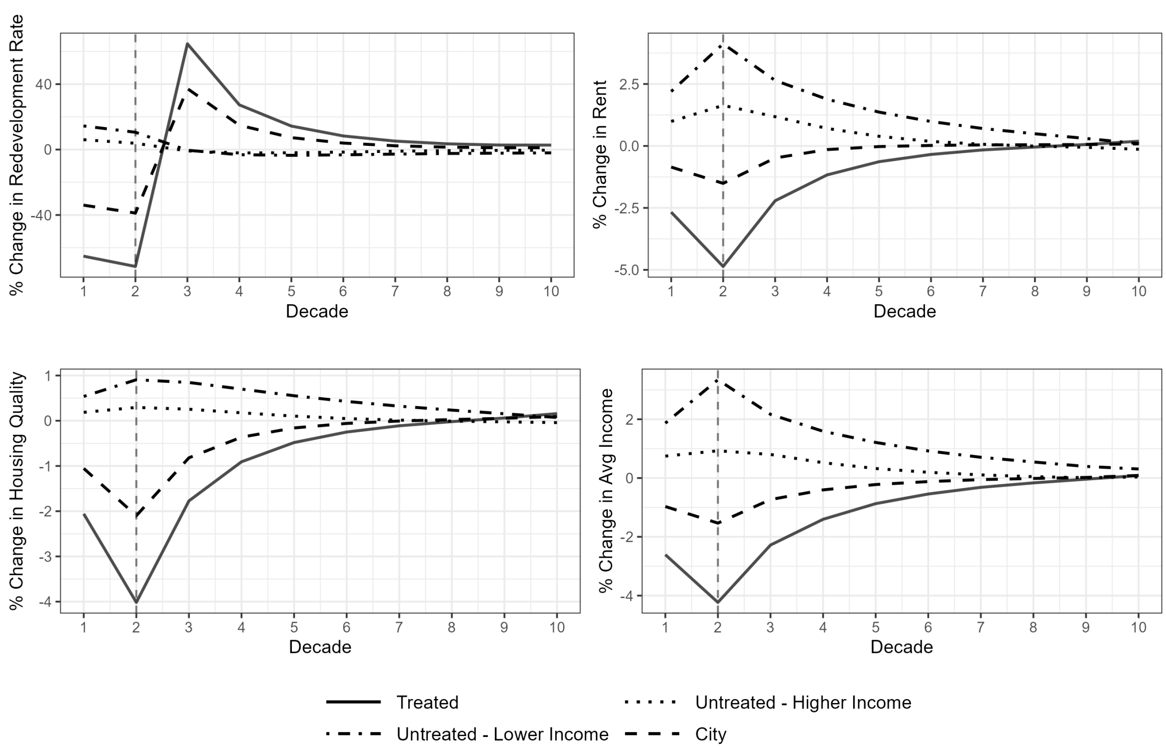


Figure C.12: The Impact of a 20-Year Teardown Policy on Housing Redevelopment, Rent, Quality and Neighborhood Income