Redevelopment and Gentrification in General Equilibrium*

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Abstract

Housing redevelopment is a key source of new housing supply, but it is often associated with neighborhood gentrification. This paper examines the interaction between redevelopment and gentrification, as well as the effect of a teardown tax policy intended to curb both. Using a spatial difference-in-differences approach, we estimate that a $15,000 teardown tax implemented in two Chicago neighborhoods reduced demolitions by 58% within the treated areas. We complement this result with evidence that redevelopment activity substantially increased neighborhood average income. Motivated by these findings, we develop a general equilibrium model featuring forward-looking landlords and heterogeneous households with varying willingness to pay for housing quality. Landlords decide when to redevelop and how many housing units to build, with new housing being of high quality that depreciates over time and filters to low-income households. Counterfactual results reveal that an expanded $60,000 teardown tax targeted at five neighborhoods in Chicago significantly shifts redevelopment and gentrification to other parts of the city, particularly neighborhoods with a more affordable housing stock. These findings have important implications for local governments considering anti-gentrification policies.

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

JEL Codes: R21, R31, R38

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1 Introduction

Understanding housing supply is crucial for addressing the affordability challenges. In dense urban areas, a major source of new housing supply comes through redevelopment (McMillen and O'Sullivan, 2013; Baum-Snow and Han, 2024). However, housing redevelopment tends to replace older buildings with newer, higher-quality housing that is preferred by rich households, and this replacement is often associated with neighborhood gentrification (Rosenthal, 2008; Guerrieri et al., 2013). In order to protect incumbent residents in gentrifying neighborhoods, many city governments are implementing policies to restrict housing redevelopment,[1] but their effects remain understudied. Understanding the heterogeneous welfare impacts of housing redevelopment is an important and policy-relevant issue.

In this paper, we develop a dynamic general equilibrium model to examine the interaction between housing redevelopment and gentrification that is driven by income sorting. We apply the model to analyze the impact of a tax on housing teardowns implemented in two Chicago neighborhoods. Our empirical analysis shows that the policy significantly reduces redevelopment in the targeted neighborhoods. Model counterfactuals reveal that the policy preserves affordable housing and benefits low-income households. However, middle- and high-income households are worse off due to reduced supply of high-quality housing. Moreover, the model predicts that housing redevelopment increases in other neighborhoods as a result of the teardown tax, particularly those with a more affordable housing. This leads to increases in housing rent and displacement of low-income residents in such neighborhoods. These results suggest that anti-gentrification policies that target certain neighborhoods have heterogeneous welfare impacts and unintended consequences, bringing important implications for municipal governments.

The paper consists of four parts. In the first part, we empirically assess the effect of the teardown tax in Chicago. In March 2021, the Chicago City Council approved a demolition surcharge ordinance in two neighborhoods, the Pilsen and 606 Trail, which have experienced significant housing redevelopment and gentrification. The policy imposes a maximum charge of \$15,000 and \$5,000 per demolished unit for a demolition permit to be issued, and it was planned to last for three years.To estimate the causal effect of the policy, we employ a spatial regression discontinuity and difference-in-difference design, comparing address-level construction activities within 500 meters of the boundaries of the treated areas. Using geo-coded

[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, the lengthy, complicated, and expensive review processes for the granting of demolition and construction permits by municipalities restrict redevelopment.

construction permit data, we find that the policy effectively reduced housing redevelopment in the treated neighborhoods: it decreased demolition permits by 58% and construction permits by 43%. The policy was implemented over too short a period of time to induce changes in housing supply that could significantly affect the neighborhood income composition. To further explore the relationship between redevelopment and income sorting, we complement these findings with evidence that redevelopment activity substantially increased neighborhood average incomes, using variation from decadal changes across neighborhoods in Chicago.

The reduced-form policy evaluation is informative about the direct policy effect but cannot illuminate on the policy's general equilibrium effect on untreated neighborhoods nor its welfare implications on the residents. In the second part of this paper, we develop a general equilibrium model to address these important questions. The model features forward-looking landlords and households that vary on income levels. Our model builds on the filtering framework of Sweeney (1974) and Brueckner and Rosenthal (2009), as well as the matching framework of Landvoigt, Piazzesi and Schneider (2015). The city consists of a set of neighborhoods that vary by their amenity value to households of different incomes, and each neighborhood contains a set of parcels owned by individual landlords. Existing residential buildings on these parcels differ both in the number of housing units and quality. Each period, landlords draw a blueprint – the option to build at a given quality level – and decide whether to redevelop their parcel, choosing the number of units to build if redevelopment occurs and incurring both a fixed and variable cost of construction. If redevelopment is not chosen, existing buildings depreciate in quality. Households, in turn, choose a neighborhood and the quality of their housing unit. Low-income households choose lower quality housing, and so depreciating buildings filter to low-income households over time. Moreover, we allow neighborhood amenity to respond to neighborhood income, as in Guerrieri et al. (2013) and Almagro and Domínguez-Iino (2024).

In equilibrium, demand and supply conditions give rise to a pricing function over housing quality in each neighborhood. The structure of this pricing function is important for income sorting and housing redevelopment. On the one hand, all else equal, high-income households prefer neighborhoods with a "flatter" pricing function; that is, where the price elasticity of quality is low. The intuition is that high-income households spend more on housing, and the marginal utility of spending an additional dollar on housing is greater when the pricing function has a low elasticity of quality. On the other hand, a flatter pricing function decreases the landlords' incentive to redevelop, as the gains from quality upgrading are smaller. Consequently, redevelopment is more likely to happen in neighborhoods where high-quality housing is relatively scarce, which supports a steeper pricing function. Redevelopment replaces low-quality housing with high-quality housing, which attracts high-income households and displaces low-income ones from redeveloping neighborhoods. This sorting is driven in equilibrium by a flattening of the pricing function.

In the third part of the paper, we estimate the parameters of the structural model. The main datasets we use are the assessment data and the transaction deeds data from 2000 to 2023, which are obtained from the Cook County Assessor's Office. The assessment data covers a rich set of building characteristics, such as the building and land square footage, numbers of bedrooms and bathrooms, construction materials, lot size, and building age for the universe of single-family housing and multi-family housing with no more than seven units. We observe housing redevelopment through the observation of a building's date of construction. The transaction deeds data records the sales price and transaction date.

Housing quality is a key input in the model. We estimate housing quality with a hedonic regression that allows for flexible, neighborhood-specific pricing functions that our theory predicts is important for understanding neighborhood income sorting. From this regression, we construct a panel dataset of housing quality and recover estimates of the quality depreciation rate. We obtain neighborhood income distributions from the American Community Survey and choose income-specific neighborhood amenity values to match these income distributions.

We estimate the construction cost parameters using information on housing redevelopment from the assessment data. First, we identify the housing unit supply elasticity for new developments, with identifying variation coming from demand shocks driven by an employment shift share instrument, as in Saiz (2010) and Baum-Snow and Han (2024). Second, we leverage variation in the fixed costs of redevelopment driven by the teardown tax to estimate the elasticity of redevelopment with respect to its opportunity cost. Third, we calibrate the neighborhood-level variable and fixed costs of construction to match observed redevelopment rates and the number of housing units per redeveloped parcel, respectively.

In the fourth part of the paper, we use the estimated model to quantify the general equilibrium effects of anti-gentrification policies. We simulate a \$60,000 demolition surcharge in five neighborhoods. As a succession to the three-year Demolition Surcharge, this new policy expands neighborhood coverage and increases the demolition fee, aiming to protect more low-income residents from rising housing costs and displacement. We show that the policy effectively reduces housing redevelopment in the treated neighborhoods. This preserves low-quality, affordable housing units, leading to decreases in average rent. However, the policy significantly increases housing redevelopment in untreated neighborhoods, especially those with initially more affordable housing. This implies that the policy does not completely resolve gentrification and affordability issues; instead, it "exports" them elsewhere. This has the effect of increasing average rent city-wide. These findings echo that of LaVoice (2024), who shows that a federal urban renewal program targeting blighted neighborhoods significantly increased housing rents in untreated neighborhoods. We argue that anti-gentrification policies that target certain neighborhoods have unintended consequences for other neighborhoods, and that such policies may not be effective at improving housing affordability at large.

Related Literature. Our work is related to several strands of literature. First, we contribute to the literature on neighborhood housing cycles and filtering. Earlier work includes Sweeney (1974) and Brueckner (1980), who analyzed the economics of housing maintenance, redevelopment or filtering dynamics. More recently, Rosenthal (2008) and Rosenthal (2014) provide empirical evidence on neighborhood change and the filtering process, emphasizing the role of building age and redevelopment. Brueckner and Rosenthal (2009) formalize the process of filtering in a model and characterize how the variation in building ages affects neighborhood income segregation. Our model extends this literature by incorporating landlord decisions and heterogeneous household preferences, allowing us to capture the dynamic interactions between redevelopment incentives, neighborhood filtering, and neighborhood demand that underlie the gentrification process. Our model is also rich enough for use in policy analysis. More broadly, this work relates to papers that study demand-driven gentrification (Brueckner et al., 1999; Guerrieri et al., 2013; Couture et al., 2023) and the effects of new housing construction on housing affordability (Pennington, 2021; Asquith et al., 2021; Baum-Snow and Han, 2024).

Second, we contribute to the literature on quantitative spatial models (Ahlfeldt et al., 2015; Monte et al., 2018; Hsieh and Moretti, 2019), including those with dynamics (Kleinman et al., 2023; Greaney et al., 2024). Studies in this literature model the housing market through the supply and demand for floorspace, often overlooking the granularity of choosing among heterogeneous housing units. In contrast, the literature that studies household housing demand, such as Bayer et al. (2007) and Bayer et al. (2016), adopts the discrete choice framework, where households choose from housing units with differentiated characteristics. Most related to this work, Määttänen and Terviö (2014) and Landvoigt et al. (2015) develop an assignment model with indivisible housing units and heterogeneous households. These studies typically investigate households' preference for housing characteristics in partial equilibrium settings where housing supply is fixed, limiting the ability to evaluate policy counterfactual on housing regulations. Our work integrates these approaches by providing a general equilibrium framework that accounts for endogenous housing supply. We stress that the structure of the pricing function that arises in these models causes income sorting across neighborhoods and is directly affected by policies that restrict redevelopment.[2]

Third, we contribute to the literature that studies housing regulations. The existing literature has focused on the effects of various aspects of land-use restrictions on housing supply, such as minimum lot size regulation (Zabel and Dalton, 2011; Song, 2021), building height limits (Brueckner and Singh, 2020), and land-use zoning (Shertzer et al., 2018). These studies investigate the impact of such restrictions on housing prices, income segregation, and economic activities. Others have studied housing policies that promote affordability, such as rent control (Diamond et al., 2018), affordable housing provision (Almagro et al., 2024), and rental subsidies (Eriksen and Ross, 2015). We contribute to this literature by studying a new form of housing policy designed to promote affordability by preventing the construction of new, high-quality housing.

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 the anti-gentrification policy. Finally, Section 7 concludes.

2 Data

In this Section, we describe the data sources that support our empirical analysis and serve as inputs in our quantitative spatial model.

Property assessments and transactions. We use the annual assessment data and transaction deeds data from the Cook County Assessor's Office and Cook County Recorder of Deeds. The assessment data provides detailed property characteristics for the universe of parcels in Cook County, covering from 2000 to 2023. For single- and multi-family housing, the set of characteristics include the build year, the building and land square footage, the number of housing units, the number of bedrooms and bathrooms, and information about the attic, porch, air conditioning, basement and garage. For multi-family housing, the assessment data only covers buildings with up to 6 units.

The transaction deeds data contains information on the sale price, the sale date, the buyer's and seller's names, and the deed type for the universe of parcel transactions from 2000 to 2023. To keep the transaction that are arms-length, we exclude the transactions (1) with prices below $10,000 or with missing prices, (2) with special deeds types (e.g. quit claim and executor) and (3) that are transacted at the same value multiple times within a year. As we

[2]A similar idea has been studied by Banzhaf and Mangum (2019) in the context of minimum lot size regulation.

focus on redevelopment activities, we only keep the transactions involving land and building sales. We match the property assessment data with the transaction data using the parcel identification number.

Building permit. We obtain building permit data from the Chicago municipal government. This dataset covers all significant building alterations, demolitions, and new construction in the city. It provides a wealth of detailed information including issue date, address, permit type, work description and estimated cost. The dataset also records detailed work description of a permit. For example, a construction permit can be applied to "replace existing porch in new location per plans" or to "construct foundations for proposed 2-story single family home". In our empirical analysis, we will only include construction and demolition permits that involves an entire building unit.[3] The building permit dataset covers from 2006 to 2023.

LEHD Origin-Destination Employment Statistics (LODES) Data. We use 2005-2019 Residential Area Characteristics (RAC) dataset, which is part of LODES. This dataset records employment by each 2-digit NAICS industry at the block group level.

American Community Survey. We use block group level demographic and income data from the 2009-2019 American Community Survey (ACS). The National Historical Geographic Information System (NHGIS) provides ACS tabulations at the block group level, which is the most detailed geographic unit available to the public. In total, the Chicago Metropolitan Area contains approximately 6,000 block groups, with about 2,200 located within the city limits.

We present the summary statistics in Table C.1, comparing the two treated neighborhoods, Pilsen and the 606-Trail, to citywide averages. See Figure C.1 for the two policy areas. The table highlights that residential buildings in the treated neighborhoods are more likely to consist of multi-family housing, have smaller average unit sizes, and were built earlier than those in the city overall. While these neighborhoods have lower median incomes than the city average, they have experienced faster income growth and rent growth, which indicates significant gentrification. One difference between the two areas is the level of building activity: the 606-Trail has seen more demolition and new construction compared to the city average, whereas Pilsen has experienced relatively less development.

[3] We use ChatGPT to select the permits. The prompt we provide to ChatGPT is "Can you determine whether this description of a housing permit involve 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 second floor addition to an existing building. Some permits may involve work on only a part of a housing unit, such as the roof and electrical system. Please return 1 if so and 0 if not.".

3 Empirical analysis

3.1 Impact of Demolition Surcharge 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 of Chicago Council has implemented a series of policies aimed at preserving affordable housing options and limiting housing redevelopment. We study the "The 606-Pilsen Demolition Permit Surcharge Ordinance", approved in March 2021.[4] The Ordinance imposes a permit surcharge, set at the maximum of \$15,000 and \$5,000 per demolished residential unit, for demolishing residential buildings. It aims to preserve existing multifamily housing from being torn down and replaced with higher quality single family homes. Revenues from the surcharge will support the Chicago Community Land Trust (CCLT), which provides subsidies for homeownership. The Surcharge Ordinance policy is a three-year pilot policy that plans to terminate on April 1, 2024.

We run the following address-level difference-in-difference regression to investigate the impact of the policy on housing demolitions and new constructions:

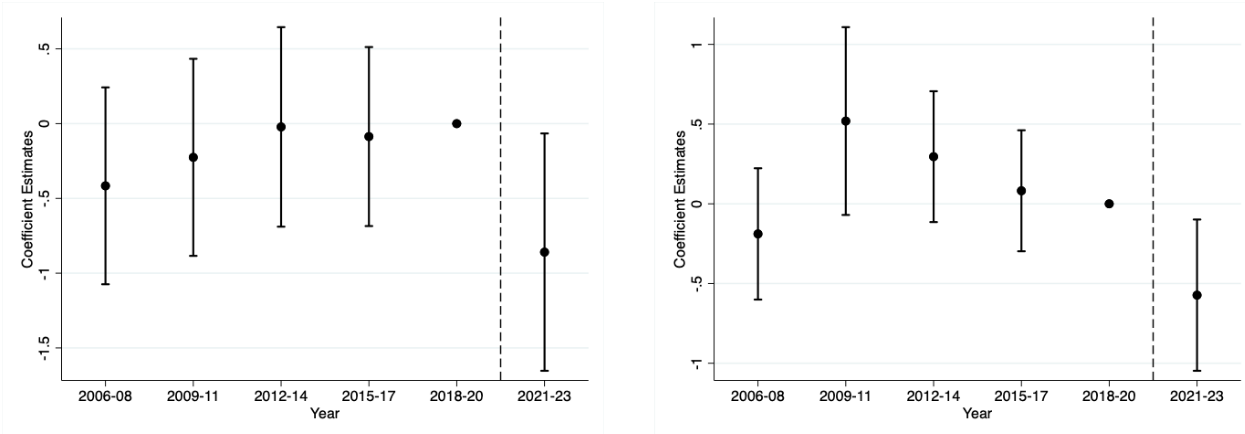
$$D_{it} = \text{logistic}\left(\sum_{k=-5}^{1} \delta_t \times 1_{t=k} \times Trt_i + \mu_i + \alpha_t\right) + \epsilon_{it} \tag{1}$$

where i indexes an address, t indexes time, D_{it} is a dummy variable representing new demolition/construction permit at address i at time t, $Trt_i = 1$ if address i is in the treatment area and 0 if not, μ_i is the address fixed effect, α_t is the time fixed effect, and ϵ_{it} is the error term. The coefficient δ_t is the parameter of interest, which captures the average treatment effect of the policy on housing demolitions and constructions. Since housing demolition and construction occur infrequently, we conduct the regression (1) using data at three-year intervals.[5] Period 2021-2023 is the treatment period and 2018-2020 is the baseline period. We estimate a logistics regression for the binary dependent variable.[6]

[4]Details on the policies can be found here. Two other related policies are worth noting. First, there is an "Anti-Deconversion" policy implemented in the same two neighborhoods, approved in January 2021. Anti-deconversion ordinances require that new construction projects maintain density levels comparable to the buildings being replaced. Second, the city council enacted a six-month ban on demolition permits in part of the 606's Bloomingdale Trail neighborhood on February 1, 2020. This temporary ban was extended to end on February 1, 2021 – a month before the enactment of the Surcharge Ordinance.

[5]Specifically, only about 0.2% of addresses in Chicago are approved a demolition permit and 0.3% of addresses are approved a construction permit in each year from 2010 to 2020. The corresponding proportions are 0.2% and 0.5% in the policy areas.

[6]There exist several addresses on which more than one demolition or construction permit are applied within a period. We censor these observations such that there is a maximum of one permit per address-



(a) Demolition Permits (b) Construction Permits

Figure 1: Different-in-Difference Results on Demolition and Construction

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

A naive comparison of housing activities in treated and untreated neighborhoods in the city would give biased estimates of the policy effect. One reason is that the existing two-to-eight-unit housing stocks that are abundant in the two neighborhoods are deemed profitable for housing redevelopment. Another reason is that the rising demand for amenities provided in the two neighborhoods significantly contributes to the increases in local housing supply. Hence, absent of the policy intervetion, we may expect that housing demolitions and constructions would have been increasing by more in these areas, making the untreated area not comparable.

To deal with the first concern, we include in the regression the address fixed effect μ_i to control for time-invariant unobservables such as the build year and the number of housing units. With the inclusion of the address fixed effect, the regression captures a within-address comparison before and after the policy intervention. To deal with the second concern, we employ a spatial discountinuity design. Specifically, we include only addresses that are within 500 meters around the polcy area boundaries.[7] The identification assumption is that, absent of the policies, housing demolition and construction activities would have followed the same trend in the narrow bands around the boundaries.

Figure 1 plots the estimated δ coefficients of equation (1), with robust standard error clustered at the address level. The two panels show the effects on demolition and construction permits, respectively. The estimated δ's prior to the policies in both regressions are insignif-

period for each permit type.

[7]The 500-meter buffer area covers 5,207 of 6,437 buildings in the 606-Trail neighborhood, and 3,558 of 3,648 buildings in the Pilsen neighborhood.

icant at the 5% significance level, indicating parallel trends inside and outside the treatment area boundary within the 500 meters buffer. The lack of significant pre-trends of the demolition permits also suggests that the temporary demolition ban prior to the Demolition Permit Surcharge Ordinance in the 606 neighborhood did not significantly reduce housing teardown. The insignificant but gradually declining coefficient estimates for construction permits over time may reflect a persistent reduction in available empty land lots within the treated areas. Table C.2 shows that the pre-trends for construction activity are more comparable within a tighter 250-meter buffer. The declining trend in construction combined with the stable trend in demolitions highlights the growing significance of redevelopment in housing supply.

The estimated post-treatment δ is -0.86 for demolition and -0.56 for construction, which translate to a reduction in demolition permits by 57.7% and a reduction in construction permits by 42.9% in the treated area.[8] These estimates show the policy effectively reduced housing redevelopment in treated areas. The estimated effect on construction is smaller than that on demolition, although the difference is not statistically significant. This may be attributed to the availability of empty land lots for construction after the policy's implementation, which do not require the teardown of pre-existing buildings. The policy does not impose a tax on housing construction on vacant lots.

We perform several robustness checks for our main result. In Table C.2, we conduct robustness checks with different buffers, including 250m, 1km, and 3km. For demolition permits, the estimated effect is insignificant at the 250m buffer, likely due to the small number of addresses in the narrow band and low probability of housing permits. Beyond the buffer of 500m, the estimated effect is significant and stable as the buffer zone is expanded. For construction permits, the estimated effects are significant and of similar magnitudes at all buffers. In Figure C.3, we report 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.

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. In our case, the teardown tax likely incentivizes redevelopment just outside the policy boundary, where housing demand conditions may resemble those of the treated areas. Although the reduced-form design cannot isolate the general equilibrium effect, we will be able to disentangle it using our model, which will be introduced in Section 4. Nonetheless, we argue that such a general equilibrium spillover effect is likely small in this context. Given that the policy was intended to last only three years, developers might prefer to wait for the

[8]We show in Figure C.4 that the policy does not have a significant impact on renovation permits, suggesting limited substitution between housing redevelopment and renovation.

tax to expire rather than incur the costs of searching for alternative properties to redevelop. In Figure C.2, we show that the average construction and demolition rates right outside the boundary do not increase after the policy, suggesting limited spillover effects.

3.2 Evidence on Redevelopment and Income Sorting

We have shown that a small surcharge was effective in reducing demolitions and new construction. Would it also be effective at reducing neighborhood value for high income households, slowing down the process of gentrification? Ideally, we would like to exploit the demolition surcharge policy to study this relationship. However, the policy was implemented over too short a period of time to induce changes in housing supply that could meaningfully affect the neighborhood income composition. Any statistical test would likely lack power.

To this end, we study the causal effect of exogenous redevelopment activity on the neighborhood income composition using broader sources of variation. Specifically, we run regressions of decadal changes in log median income on changes in median building age at the Chicago census block group level, from 2009 to 2019.[9] The change in building age measures the extent of housing development in a neighborhood – a decrease in building age indicates that more new buildings have been constructed, while the change in log median income captures the shift in composition of the residents.[10] We posit that the median income will increase in a neighborhood with more redeveloped housing units as wealthier residents move in. The regression specification is

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

where b represent a block group. This regression specification should be thought of as a neighborhood demand equation, with the error ϵ_b representing all unobserved demand factors that caused neighborhood income sorting between 2009-2019.

A naive OLS regression suffers from a simultaneity bias: unobserved demand shocks are likely to cause changes in the neighborhood income distribution and incentivize developers to upgrade the quality of the housing stock. For example, Pilsen may have been gentrifying because it is within commuting distance of high-skill jobs that experienced wage growth, which caused redevelopment activity within the neighborhood.

To address these concerns, we develop an instrumental variable that is inspired by the one in Diamond (2016). The instrument we construct is an interaction between a Bartik-

[9] We take the median building age from the assessment data, which has much broader coverage than the 5% sample ACS.

[10] We use median as the measure of neighborhood income and build age to mitigate the effect from outliers. Results are robust to averages.

Table 1: Change in Building Age and Income

	(1)	(2)	(3)	(4)
	Δ log Income	Δ log Income	Δ log Income	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
First Stage 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.

style shift-share variable and the share of housing units that are built before 1910. We pick the year of 1910 because it is the average build year of housing units being redeveloped in our sample (see Figure C.5 for a histogram of the build year). The Bartik-style variable is constructed by aggregating the 2009-2019 county-level change in employment by 2-digit NAICS industry, weighted by the 2005 neighborhood-level employment share by industry. It aims to capture local labor demand shocks that come from exogenous employment changes outside the neighborhood, which could spur changes in housing demand. We describe how we construct the Bartik instrument in more detail in Section 5.2.

With the instrument, identification comes from the fact that housing redevelopment should be more responsive to housing demand shocks in neighborhoods with a higher share of older buildings. In contrast, the housing demand shocks should be met by more new construction instead of redevelopment in neighborhoods with a few older buildings. We additionally control for the initial 2009 log median income, initial average building age, and the change in log neighborhood employment, all of which are 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 first two columns are the results of OLS regressions and the last two are the IV regressions. Column (1) shows that a one-standard-deviation decrease in the change in building age is associated with a 6.8 log point increase in median income. Column (2) shows that the coefficient estimate remains unchanged when controlling for the log initial median income.

The IV estimates reported in Column (3) is slightly larger in magnitude, suggesting that a one-standard-deviation decrease in the change in building age is associated with about 10.7 log point increase in median income. Adding initial log income as a control does not materially change the IV estimate. We report the first-stage estimation results in Table C.3. It shows that census blocks with higher demand shocks and older housing stocks underwent significant decreases in building age, which is consistent with our expectations. The F-statistics of the first stage are well above the threshold of 10, indicating that the instrument is strong.

The main reason for the larger IV estimates (in absolute value) is that the change in building age in the OLS regression captures the effect of both new constructions that are associated with increases in local housing supply. This quantity change shifts up the local housing supply curve and lead to a decrease in rents, which in turn may attract more low-income households. The IV regressions, on the other hand, are identified from different neighborhood-level exposures to housing redevelopment due to initial housing stocks and demand shocks. Therefore, conditional on the control variables, the variations in changes in the building age are thus solely from housing redevelopment activities. We interpret this as the causal evidence that housing redevelopment leads to income sorting of households across neighborhoods.[11]

3.3 Taking Stock

We have provided evidence that (1) the teardown tax effectively reduced housing redevelopment, and (2) housing redevelopment drives income sorting across neighborhoods. Next, we develop a model to capture the relationship between endogenous redevelopment and income sorting. This model will also enable us to conduct counterfactual analyses of housing policies, examine their general equilibrium effects, and assess the welfare implications.

4 Model

4.1 Environment

Consider a city that consist of a set of neighborhoods, indexed by $x \in \boldsymbol{X}$, and an outside option $\boldsymbol{o}$. Each neighborhood contains a set of land parcels $i \in \boldsymbol{I}_x$. The parcel and the

[11] In Appendix Table C.4, we show evidence that newly redeveloped buildings in higher-income neighborhoods tend to have fewer units and a higher floorspace per unit.

residential building built on it are owned by an immobile landlord. Each residential building varies by its housing quality $q \in \boldsymbol{Q}$ and the number of units $h \in [0, \infty)$. Housing quality depreciates over time, with the depreciation rate given by δ.

Each household ω differs in their (continuous) income type $z_\omega \in (0, Z_{max}]$ and initial neighborhood $x_{\omega,0} \in \boldsymbol{X}$. There are an exogenous measure $\bar{L}(z, x_0)$ of each household type. neighborhoods differ in type-specific exogenous amenities, denoted by $\bar{A}(x, z)$. Amenities also respond endogenously to the average income of the neighborhood, which is described later. Households can choose to live in a neighborhood x within the city, or to live outside the city that provides a normalized utility level of 1. All households in the city rent one unit of housing. We model a finite-horizon economy where time is indexed by $t \in \{1, 2, ..., T\}$. We omit the time index t and the household index ω when there is no ambiguity

4.2 The Household's Problem

We present the household problem backwardly. First, given the choice of a neighborhood x, households choose the quality of housing q to rent in that neighborhood. The matching mechanism between heterogeneous housing units and households follows the framework of Landvoigt et al. (2015). Second, given the neighborhood characteristics (housing supply and amenities), households choose from the neighborhoods in the city and the outside location to live in.

Housing quality choice

Consider the problem of a household ω with income z_ω who has decided to reside in neighborhood x (not including the outside option). The household chooses to rent one housing unit with quality q and consume the numeraire good y, with the utility given by

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

s.t.

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

where β is the utility weight on housing quality. The pricing function $P(q, x)$ represents the housing rent for one housing unit of quality q in neighborhood x, which is determined in equilibrium by housing supply and demand conditions. We assume that the neighborhood choice does not affect the household's income z.

We first show that the three following properties hold:

Proposition 1 *The following hold under the stated utility function:*

1. *The pricing function $P(q, x)$ increases in quality q, $\forall x$.*

2. *Given a smooth pricing function $P(q)$ that strictly increases in q, $q^*(z_1) > q^*(z_2)$ iff $z_1 > z_2$.*

3. *Suppose $\boldsymbol{Q} = [0, \infty)$. Assume the pricing function is isoelastic in each neighborhood, or $P(q, x) = k(x)q^{\nu(x)}$. Then, for any neighborhoods x_1 and x_2 and income levels $z_1 < z_2$, we have*

$$\frac{U(x_1, z_1)}{U(x_2, z_1)} < \frac{U(x_1, z_2)}{U(x_2, z_2)}$$

if and only if $\nu(x_1) < \nu(x_2)$.

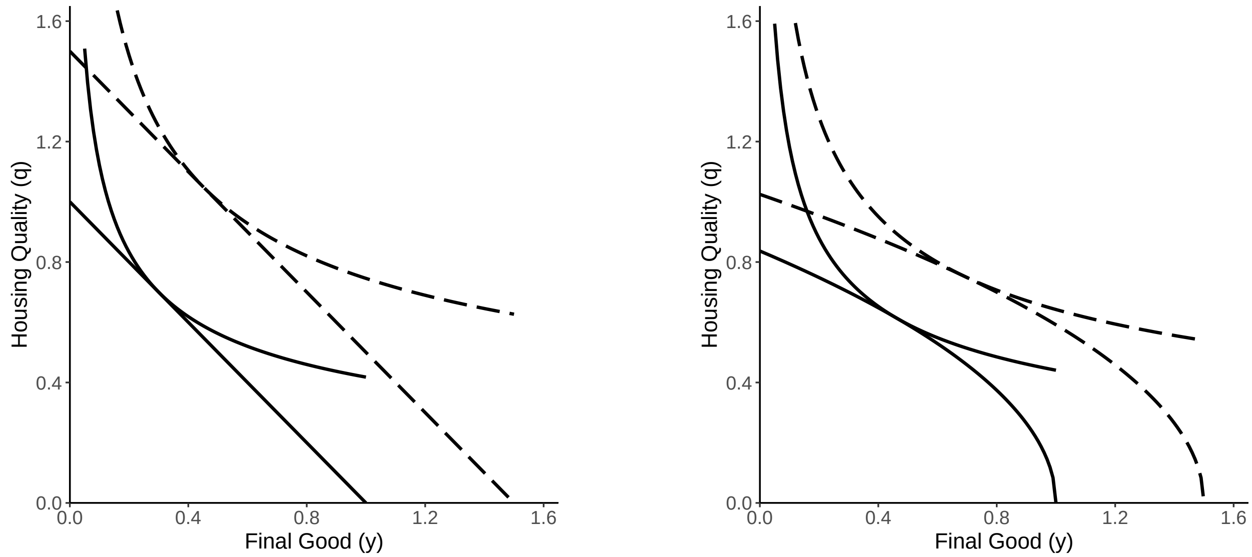
The first part of the proposition is intuitive: if a higher quality level costs less than a lower quality level, demand for the lower-quality housing would be zero, and the price function would fail to clear the market with strictly positive housing supply. The second part follows from Topkis (1978), as the utility function is supermodular in q and z and the pricing function $P(q, x)$ increases with q.

The third part requires a detailed explanation to better understand households' quality and neighborhood choice. Assuming that the price function is first-order differentiable, the first-order conditions with respect to the choices of q and y give rise to the following optimality condition

$$\frac{\beta}{1-\beta} = \epsilon_q^P(z, x) \cdot \frac{P\left(q^*(z, x), x\right)}{z - P\left(q^*(z, x), x\right)} \tag{5}$$

where $\epsilon_q^P(z, x) = \frac{\partial P(q^*(z,x),x)/P(q^*(z,x),x)}{\partial q^*(z,x)/q^*(z,x)}$ is the price elasticity of quality in neighborhood x. This optimality condition illustrates how the pricing function influences a household's quality choice. First, note that with linear pricing of housing quality, i.e. $\epsilon_q^P = 1$, each household spends β share of income on housing and $1 - \beta$ share of income on the final good, and the utility function is homothetic in household income z. More generally, when the pricing function is non-linear in quality, the utility function becomes non-homothetic in z. This is because the relative price of high- and low-quality housing affect the relative welfare of high- and low-income households who prefer to consume these different segments. Consequently, variations in ϵ_q^P across neighborhoods can lead to income sorting by creating differences in the relative value of neighborhoods for high and low income households.

To illustrate this better, we consider a special case when the pricing functions are iso-elastic, i.e. $P(q, x) = \kappa(x)q^{\nu(x)}$. The result on relative neighborhood-level utility for households with different income is illustrated in Figure 2. In Panel (a), we set $\nu = 1$. The household problem becomes a standard one of homothetic Cobb-Douglas preference and a linear budget constraint. A well-known result is that utility level is linear in income z. In



(a) $\nu = 1$ (b) $\nu = 2$

Figure 2: Utility maximization under two pricing functions for two income-type 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) $\beta = 0.7$, (2) $z_L = 1$ and $z_H = 1.5$, (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.

Panel (b), we set $\nu = 2$. Under Cobb-Douglas utility, the share of income spent on housing is the same across all income types.[12] However, the greater amount of housing expenditure results in less housing quality improvement for higher-income individuals, due to the convex pricing function. In other words, the marginal utility from spending one more dollar on housing is smaller as income increases. As a result, the utility gap between high- and low-income individuals is smaller.

There are four additional noteworthy points. First, the prior discussion is a partial equilibrium statement on how the pricing function could induce income sorting. In full general equilibrium, the pricing function is co-determined by neighborhood housing demand and supply. Second, in more general cases where ϵ_q^P varies with q, income sorting based on the pricing function becomes more complex, as different quality choices also influence elasticity across neighborhoods. In Appendix A.2, we prove the third part of Proposition 1 with a general pricing function, which requires some additional assumptions. It remains true that higher-income households prefer neighborhoods where the marginal utility from greater housing expenditure is higher. Third, it abstracts away from the impact of amenity values

[12] In the non-linear pricing case, the share of income spent on housing also relates to the parameter ν, which can be seen in Equation (A.3).

on households' neighborhood choices, which we introduce next. Importantly, income-type specific amenities can also affect sorting and local housing demand for different housing qualities. Therefore, to empirically test part 3 of the proposition, one would need an instrumental variable that is orthogonal to these local unobserved amenity values. Fourth, it sheds light on the distributional welfare impact of housing redevelopment. As redevelopment activities tend to replace low-quality houses with higher-quality ones, this resulting change in housing supply makes the pricing function flatter and thus benefits high-income household relatively more than low-income ones.[13]

Neighborhood choice

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

$$V_{\omega t}(x_0, z_\omega, \vec{\xi_t}) = \max_x \tau(x; x_{\omega 0}) \cdot U_t(x, z_\omega) A_t(x, z) \xi_{\omega t}(x) + \beta \mathbb{E}_{\vec{\xi}}\, V_{t+1}(x_0, z_\omega, \vec{\xi}_{\omega t+1}) \tag{6}$$

where x_0 is the original neighborhood, τ is the mobility cost, $A(x, z)$ is the type-specific amenity of neighborhood x, $\vec{\xi}$ is a vector of neighborhood-specific idiosyncratic preferences.

A number of assumptions follow. First, following Guerrieri et al. (2013) and Almagro and Domínguez-Iino (2024), we assume that the neighborhood amenity endogenously respond to the local residents composition:

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

where $\bar{A}$ is the exogenous neighborhood amenity, $\bar{z}$ is the average neighborhood income, and η is the endogenous amenity spillover elasticity. Second, we assume that the idiosyncratic preferences, $\{\xi_t(x)\}_{x,t}$, are drawn i.i.d. from a Frechet distribution with its dispersion governed by parameter σ_x, i.e. $F(\xi) = \exp\left(-\xi^{-\sigma_x}\right)$. Third, the utility of a household contains a cost of residing in neighborhood x other than the original neighborhood of a household, i.e. $\tau(x; x_0) < 1$ if $x \neq x_0$ and $\tau(x_0; x_0) = 1$. It reflects the idea that households may have a strong attachment to their original neighborhood; hence, displacement causes a welfare loss. Similar to Desmet et al. (2018), the assumption on the mobility cost makes the household's neighborhood choice problem a static one. This is because τ only shifts household utility in the current period, and households can move back to their original neighborhood anytime in the future to avoid such a cost. We can then obtain the law of motion for household

[13] The absolute welfare effect would also depend on the changes in the number of housing units caused by redevelopment. We will discuss this margin later in the landlord's problem.

allocation across types and neighborhoods as

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

and the expected welfare of a type-z household originally from neighborhood x_0 in period t as

$$\bar{U}_t(z,x_0) = \Gamma\left(\frac{\sigma_x - 1}{\sigma_x}\right) \cdot \left[\sum_{x \in \boldsymbol{X}} [\tau(x;x_0) \cdot U_t(x,z)A_t(x,z)]^{\sigma_x} + \tau(\boldsymbol{o};x_0)^{\sigma_x}\right]^{\frac{1}{\sigma_x}}, \tag{9}$$

where $\Gamma(\cdot)$ represents the Gamma function.

4.3 The Landlord's Problem

Each landlord aims to maximize the expected value of the parcel i. The discount rate of the landlord is ρ. We denote $s_{it} = (q_{it}, h_{it})$ as the vector of state variables of parcel i in period t, which contains the housing quality q and quantity h information. In each period t, we assume that landlord i receives a building blueprint $\hat{q}_{it}$, drawn from a quality distribution $G(\hat{q}), \hat{q} \in \boldsymbol{Q'} \subseteq \boldsymbol{Q}$. The landlord can choose to redevelop the parcel according to the blueprint $q_{i,t+1} = \hat{q}_{it}$ and decide the housing units $h_{i,t+1}$. Redevelopment incurs a cost $C_i(\hat{q}, h)$ depending on the new housing quality and quantity, which is specified as

$$C_i(\hat{q}, h) = \Omega_x \cdot \hat{q} \cdot h^\gamma + F_x. \tag{10}$$

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. Ω_x is a neighborhood-specific variable cost shifter, and F_x is the neighborhood-specific fixed cost parameter, which includes the construction cost of teardowns and the regulatory cost of redevelopment – including the teardown tax.[14] We assume that redevelopment takes one period to complete. The blueprint gets destroyed if not used, and the landlord will draw a new one in the next period. Housing investment is irreversible, so the landlord obtains zero salvage value from the demolished housing.

If the landlord chooses not to redevelop, she collects housing rent $P_t(q_{it}, x) \cdot h_{it}$ and faces housing quality depreciation by a constant rate δ, i.e. $q_{i,t+1} = (1-\delta)q_{it}$. We assume that the minimum housing quality is q_{min}, and that housing units do not further depreciate after reaching q_{min}. Let $V_{it}(s_{it}, \hat{q}_{it})$ be the value of parcel i, which incorporates the capitalization of future rent streams and the option value of potential redevelopment, with the current

[14] The fixed cost can be a function of the number of units being destructed, in the way which the teardown tax is levied in the 606-Pilsen Demolition Permit Surcharge Ordinance.

housing state s_{it} and blueprint $\hat{q}_{it}$. The landlord's problem can be written recursively as

$$V_{it}(s_{it}, \hat{q}_{it}, \vec{\xi}_{it}) = \max \Bigg\{ P_t(q_{it}, x)h_{it} + \frac{1}{\sigma_c}\xi_{it}^N + \rho\mathbb{E}_{\hat{q}_{it+1},\, \vec{\xi}_{it+1}} V_{i,t+1}\left(q_{it+1}, h_{it}, \hat{q}_{i,t+1}, \vec{\xi}_{it+1}\right), \\ \max_h \left\{ -C_i(\hat{q}, h) + \frac{1}{\sigma_c}\xi_{it}^R + \rho\mathbb{E}_{\hat{q}_{it+1},\, \vec{\xi}_{it+1}} V_{i,t+1}\left(\hat{q}_{it}, h, \hat{q}_{i,t+1}, \vec{\xi}_{it+1}\right) \right\} \Bigg\},\ t < T \tag{11}$$

where $q_{it+1} = (1-\delta)q_{it}$ if $(1-\delta)q_{it} > q_{min}$ and $q_{it+1} = q_{min}$ otherwise, ξ_{it}^N and ξ_{it}^R are the idiosyncratic cost shocks of not redeveloping and redeveloping the parcel, which are drawn i.i.d. over time and space from a Type-I Extreme Value distribution with its variance scaled by σ_c. At the terminal period T, $V_{iT}(s_{iT}, \hat{q}_{iT}) = \overline{V}_{iT}(s_{iT})$; we assume the steady state has been reached before period T. We do not model housing developers or construction firms directly. We implicitly assume a perfectly competitive land market and construction sector, implying that the full value of the land is captured by the landlord.

4.4 Perfect Foresight Equilibrium

We assume that the landlords have perfect foresight over the future housing prices over the quality distribution, $\{P_t(q,x)\}_{\forall t,q,x}$. We hereby define the perfect foresight equilibrium as follows.

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 $\{L(q,x,z)\}_{\forall q,x,z}$, 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 equations (5) and (6).*

2. *Each landlord makes the redevelopment decision to optimize the value of the parcel, according to equation (11).*

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

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

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

5 Estimation of Model Parameters

In this section, we discuss how we estimate the parameters of the model to assess the consequences of the teardown tax. Our spatial unit of analysis is the official Chicago neighborhood, as defined by the municipality. There are 98 of these neighborhoods. For model computation, we aggregate contiguous neighborhoods into 22 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.6 maps these neighborhood groups. For the remainder of this paper, we use the term "neighborhoods" and "neighborhood groups" interchangeably unless a distinction is required.

Our estimation approach involves three steps. First, we estimate housing quality from the assessment and transactions data using a hedonic regression. Second, we use these as inputs to estimate the construction cost function, exploiting observed redevelopment decisions. Third, we calibrate neighborhood amenity values and other preference parameters to rationalize the observed neighborhood income distribution in the steady state. We describe each step below.

5.1 Measuring Quality, Depreciation, and Pricing Functions

We first describe our strategy to estimate housing quality from the data. We start with the assumption that the quality index q is log linear in both observed and unobserved housing characteristics:

$$\log q_{it} = \underbrace{-\delta \times \text{Building Age}_{it}}_{\text{Depreciation}} + \underbrace{\sum_{c\in\mathcal{C}} \alpha_c \log M_{c,it}}_{\text{Observed quality characteristics}} + \underbrace{\log \epsilon^q_{it}}_{\text{Unobserved quality characteristics}} \tag{13}$$

where δ is the depreciation rate, $\mathcal{C}$ is a set of observed housing characteristics, M_c is the value of each characteristic, and ϵ^q contains all unobserved characteristics. Consider an iso-elastic pricing function for housing quality q in each neighborhood x

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

where $\kappa(x)$ and $\nu(x)$ govern the average price and the price elasticity of quality, respectively. Ideally, we would like to run the hedonics regression using housing rent, which maps to the equilibrium pricing function in the model. However, we do not have good access to unit-level rent data. Instead, we use sales price from the transaction data to run the regression. The estimated quality would be the same if the rent-to-price ratio does not vary by quality q within each neighborhood x, which we assume to hold.[15] Notably, we do not impose an iso-elastic form for the pricing function when solving the model. Instead, we obtain housing quality from the hedonic regression using sales price, which, given housing demand, endogenously generates the equilibrium pricing function, $P(q, x)$. The equilibrium pricing functions we solve closely approximates the iso-elastic ones estimated from equation (14), which supports our assumption on rent-to-price ratio.

Combining equations (13) and (14) yields a hedonic regression model for residential building i in neighborhood x

$$\log \tilde{V}_{it} = \log \kappa(x) + \nu(x) \left[-\delta \times \text{Building Age}_{it} + \sum_{c \in \mathcal{C}} \alpha_c \log M_{c,it} \right] + \nu(x) \log \epsilon^q_{it} \tag{15}$$

where $\tilde{V}_{it}$ is the observed sales price of the property per housing unit. We estimate it using a nonlinear least squares (NLS) estimator, under a parameter normalization that the elasticity of quality is on average one, or $\frac{1}{|X|} \sum_{x \in X} \nu(x) = 1$.[16] The normalization implies that quality is proportional to house values in a neighborhood with the average quality elasticity.

To estimate (15), we leverage assessment data for single-family housing and multi-family housing below seven units. We incorporate durable housing features in $\mathcal{C}$, including floorspace per housing unit, numbers of bedrooms and bathrooms, construction materials, and lot sizes (and their interactions with the number of housing units on the parcel). We choose characteristics that are unlikely to be influenced by depreciation because they would otherwise be bad controls for the estimation of δ. We pool all transactions from 1999-2023 and parse out year-month fixed effects from sales prices.[17] We exclude structures built before 1900, which are likely to have been well-maintained or abnormally durable, to mitigate survivorship bias in estimating the depreciation rate (Rosenthal, 2014).

Depreciation rate δ We estimate a quality depreciation rate of 0.3% per year. This is slightly smaller than the nationwide annual depreciation rate estimates reported by Rosenthal (2014), which are 0.4% for rental housing and 0.8% for owner-occupied housing. Baum-Snow (2023) shows the teardown rate is significantly smaller in large metros. This difference may

[15] Admittedly, Equation (11) implies that the rent-to-price ratio should be lower for low-quality housing. This is because the value of the building reflects not only the present value of the housing rent stream but also the option value tied to potential redevelopment. In addition, the average level of rent-to-price ratio can vary across neighborhoods, which is captured by $\kappa(x)$.

[16] A normalization is required for parameter identification because the quality index q has no cardinal interpretation. This normalization thus indexes quality to be proportional to the pricing function for a neighborhood with a quality elasticity of one, which is the average estimate across neighborhoods in the sample.

[17] This requires assuming that the quality elasticity $\nu(x)$ is time invariant.

suggest greater maintenance and renovation efforts in Chicago, contributing to a smaller average depreciation rate.

Neighborhood pricing parameters $\kappa(x)$ and $\nu(x)$ We estimate substantial variation in both pricing parameters across neighborhoods. First, the estimated fixed effect $\log \kappa(x)$ has a standard deviation of 0.5 across neighborhoods, indicating significant variation in housing prices. It is also strongly and positively correlated with neighborhood income. Second, the estimated slope parameter $\nu(x)$ ranges from 0.4 to 1.5 across neighborhoods with a standard deviation of 0.2. The estimated slope $\nu(x)$ is positively correlated with neighborhood income, with a coefficient of 0.3. The varying slopes of the pricing function across neighborhoods reflect differences in both the distribution of housing quality and amenity values across neighborhoods. Figure C.7 plots both $\kappa(x)$ and $\nu(x)$ across neighborhoods, along with other characteristics.

Quality The quality index can be estimated for both sold and unsold properties using estimates of δ and each α_c:

$$\hat{q}_{it} = -\hat{\delta} \times \text{Building Age}_{it} + \sum_{c \in \mathcal{C}} \hat{\alpha}_c \log M_{c,it}. \tag{16}$$

Figure C.7 shows this average housing quality across neighborhoods. The quality index is highly correlated with income across neighborhood: it is lower on Chicago's south and west Sides and higher in areas along and north of the central city. The standard deviation in log quality across neighborhoods is 0.55, which is smaller than the deviation in log housing prices of 0.7. Differences in the variation between housing quality and prices are driven by disparities in neighborhood amenities, which affect housing demand, and variations in the number of housing units available in each neighborhood.

5.2 Construction Cost Parameters

The construction cost parameters to be estimated are the cost convexity parameter γ, the variable cost parameter Ω, and the fixed cost parameter F. We allow Ω and F to vary across neighborhoods x, to account for the spatial variation in housing production technologies and land-use regulations. We assume that the cost parameters do not change over time.

We define redevelopment if the build year of a parcel changes in the assessment data. We then obtain the transaction price of the redeveloped building from the transaction deeds data. To capture the market value of each newly redeveloped housing unit, we retain only the first transaction, provided it occurs within three years of the redevelopment year. We then estimate the housing supply parameters using the following steps.

The Variable Cost Parameters: γ and Ω

The parameter γ is identified from the observed building unit choices of the redeveloped buildings. The more convex the cost function (i.e. larger γ), the fewer building units the landlord will choose, conditional on the price per unit. Due to irreversibility of housing investment, the new unit choice is not affected by the original building that it demolished. From the profit maximization problem, we can obtain the following estimation equation for redeveloped parcels:[18]

$$\log h_{it+1} = \Gamma + \frac{1}{(\gamma-1)}\left(\log \frac{\partial \tilde{V}_{i,t+1}\left(q_{it+1}, h\right)}{\partial h} - \log q_{it+1}\right) - \frac{1}{(\gamma-1)}\log \Omega_x + \frac{1}{(\gamma-1)}\epsilon^{\gamma}_{it+1} \quad (17)$$

where $\Gamma \equiv -\frac{1}{(\gamma-1)}(\log\gamma - \log\rho)$ is a constant, h_{it+1} is the number of housing units of the new building, $\partial\tilde{V}\left(q,h\right)/\partial h$ is the price per unit at quality q, ϵ^{γ} is the error term, which contains the measurement error of quality q and unobserved cost shocks ξ.

Two notes are in order. First, the unit price needs to be adjusted by the quality of the building when estimating the estimating equation. The estimated slope $1/(1-\gamma)$ would be downward biased if we instead use the unadjusted price. This is because high-quality buildings are not only more expensive but also more costly to build, making it optimal to build fewer units. Hence, we use the estimated quality index of each redeveloped unit from equation (16) to adjust the unit price.

Second, one would also worry that the error term contains the unobserved cost shocks that are correlated with the price per unit and quality. As pointed out by Baum-Snow and Han (2024), neighborhoods with rising housing prices may also have greater housing regulation, which makes more housing units difficult to build. In addition, the quality measured using the hedonic regression and transaction prices from the deeds data may contain measurement error. These issues may lead to a downward bias in the OLS estimate. To address these issues, we construct a shift-share Bartik-style instrument that leverages industry-specific city-level labor demand shocks and neighborhood-level variations in exposure to these shocks, forming a housing demand shifter at the neighborhood level. Specifically, the instrument is constructed as

$$Bartik_{x,t} = \sum_{ind\neq \text{Cons}}\left(\frac{EMP_{x,ind,t_0}}{\sum_{ind\neq\text{Cons}} EMP_{x,ind,t_0}}\right)\Delta\log EMP_{msa,ind} \quad (18)$$

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

[18] Appendix B.1 provides the derivation of the estimation equation.

the entire MSA level. We leverage the LEHD Origin-Destination Employment Statistics (LODES) Residential Area Characteristics (RAC) dataset, which records employment by each 2-digit NAICS industry at the block group level, to construct the instrument. We calculate the employment share in 2005, i.e. $t_0 = 2005$, and the decadal employment changes from 2010 to 2019.[19] We construct the instrument at the census block group level, rather than the broader neighborhood group level, to exploit the greater geographical variation in housing demand. We exclude the construction industry from the instrument because its employment is likely to be affected by the local construction productivity shocks that enters equation (17) as an error term.

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 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. Columns (1)–(2) use the unadjusted price per unit, while Columns (3)–(4) use the quality-adjusted price per unit. Columns (1) and (3) are the OLS estimates, while Columns (2) and (4) show the IV estimation result. Comparing between the results using the two price measures, we see that adjusting the housing price by quality significantly increases the estimate in both specifications. Both the OLS estimates are negative, but they are likely downward biased, as higher housing prices are probably associated with the tightening of local housing regulations.

The IV estimates of the supply elasticity are 0.07 using the unadjusted price and 0.09 using the adjusted price, respectively. Our 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).[20] The higher quality-adjusted supply elasticity results from the fact more expensive neighborhoods supply high-quality housing, as shown by our motivating

[19]The LODES dataset starts from 2002. We find that the Bartik shock constructed using pre-2010 data (e.g. 2005-2009) is only weakly correlated with the housing price, which is also pointed out by Baum-Snow and Han (2024).

[20]This is reported in Column (5) Table 4 of the Baum-Snow and Han (2024).

Table 2: Estimation of the 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 (17). Columns (1)-(2) use the unadjusted price per unit, while Columns (3)-(4) use the quality-adjusted price per unit. 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 employment2010-2019 block group employment growth, and year-month fixed effects. Standard errors are clustered at the census block group level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

facts. Our preferred specification is Column (4), which transforms to a γ parameter of 12.0. The F-statistics of the first stage are 13.1 and 9.5, which is around the rule-of-thumb threshold of 10. The low F-statistic is primarily due to limited statistical power, as the sample size is small and the Bartik IV only vary at the block group level.

With γ estimated, we can then recover neighborhood-specific variable cost parameter Ω_x from equation (17):

$$\log \Omega_x = \mathbb{E}_{i \in x} \left[\log \left(\frac{\rho}{\gamma} \right) + \left(\log \frac{\partial \tilde{V}_{i,t+1}\left(q_{it+1}, h\right)}{\partial h_{it+1}} - \log q_{it+1} \right) + (1-\gamma) \log h_{it+1} \right]. \tag{19}$$

with the assumption that ϵ^{γ}, which include the idiosyncratic unobserved cost shocks and measurement errors, are mean-zero at the neighborhood level. For neighborhoods that have fewer than 30 redevelopments during the period, we set their Ω_x to be the mean at the city level. The average Ω of the city is estimated to be 309, which translates to a variable building cost of around $\$116,000$ for an average newly redeveloped building.[21] Neighborhoods that are more costly to build are found to be more expensive. The correlation between Ω_x and quality adjusted price (unadjusted price) is 0.48 (0.52).

[21] The average building has 1.1 units and a quality index of 121.

The Cost Dispersion Parameter: σ_c

We leverage the demolition tax policy to identify the parameter σ_c, which governs the dispersion of the unobserved cost shocks $\{\xi^N, \xi^R\}$. The intuition is that the more dispersed these shocks, the smaller the decline in demolition rate caused by the demolition tax. Specifically, using the property of the extreme-value distributed shocks, σ_c can be identified from the following equation

$$\Delta \log \frac{P^R}{1-P^R} = \frac{1}{\sigma_c}\Delta(V^R - V^N) \tag{20}$$

where Δ represents a difference-in-difference operator, i.e. $\Delta y = [\mathbb{E}_{i\in\Omega^T} y_{it} - \mathbb{E}_{i\notin\Omega^T} y_{it}] - [\mathbb{E}_{i\in\Omega^T} y_{it-1} - \mathbb{E}_{i\notin\Omega^T} y_{it-1}]$, where t is the treatment period and Ω^T represents the set of houses in the treatment area; $V^R - V^N$ represents the difference in redevelopment value and non-redevelopment value of a parcel.

One important aspect of the policy is that it was designed to be temporary pilot policy that lasts only three years, from March 2021 to March 2024.[22] As a result, this temporary demolition tax should not be capitalized into the future value of the parcels in the treatment area, but only decreases the value of redevelopment during the policy period. In other words, the landlords can choose to wait to redevelop after the policy ends to avoid the demolition tax. This temporary feature of the policy results in $\Delta(V^R - V^N) = -\$15,000$.[23] Based on the estimate from equation (1), which indicates that the demolition tax reduces the log odds ratio of redevelopment by 0.86, we infer a semi-elasticity of housing redevelopment of $1/\sigma_c = 0.57/\$10,000$.

The Fixed Cost Parameter: F

The neighborhood-specific fixed cost parameter F_x is identified by matching the redevelopment rate. Intuitively, the higher the fixed cost, the lower the likelihood of redevelopment should be in a neighborhood. Formally, we can express the redevelopment probability from the model as

$$P^R_{it}(h_{it}, q_{it}) = \frac{\exp\left[-\left(\Omega_x \cdot q_{it+1} \cdot h^{\gamma}_{it+1} + F_x\right) + \rho V_{i,t+1}(h_{it+1}, q_{it+1})\right]^{1/\sigma_c}}{\exp\left(V_{i,t}\left(h_{it}, q_{it}\right)\right)^{1/\sigma_c} + \exp\left[-\left(\Omega_x \cdot q_{it+1} \cdot h^{\gamma}_{it+1} + F_x\right) + \rho V_{i,t+1}(h_{it+1}, q_{it+1})\right]^{1/\sigma_c}}. \tag{21}$$

The challenge of estimating F_x from the equation above is that we do not observe the optimal unit and quality decision for the houses that did not undergo redevelopment. We thus make use of the model structure to infer these choices. For now, we assume that all

[22] The policy is extended to the end of 2024. We assume that the extension is unexpected to the landlords.

[23] The policy sets the demolition tax to be the greater of $\$15,000$ and $\$5,000$ per building units. For now, we under-count the demolition tax by setting uniformly to $\$15,000$. As a result, the σ estimate should be interpreted as an upper bound.

houses are redeveloped to the same quality level, q_{new}, which varies across neighborhoods. We obtain q_{new} as the median quality of all the redeveloped houses city-wide. Then, we solve for the optimal housing unit decision h_{it+1} from the first-order condition, i.e. equation (B.2).[24] We then compute the redevelopment value as $V_{it+1}(h_{it+1}, q_{it+1}) = P_{t+1}(q_{it+1}, x) \cdot h_{it+1}$. For the parcels underwent redevelopment, we observe their quality and unit before redevelopment, and use the information to construct their value V^N. We trim observations whose computed gains from redevelopment fall below the 1st percentile or exceeds the 99th percentile. We assume redevelopment takes three years to complete and $\rho = 0.97^3$. We estimate the fixed cost parameter using the Maximum Likelihood Estimator (MLE) for each neighborhood, using the assessment records up to 2020 (before the demolition surcharge policy).

The average F_x across all neighborhoods is estimated to be $\$225,000$. There is significant variation across neighborhoods, ranging from $\$94,000$ to $\$326,000$. Neighborhoods with higher fixed costs tend to have a higher average house price, with correlation coefficient of 0.8.

5.3 Calibration of Other Parameters in the Steady State

To perform counterfactual exercises, we define a baseline economy in steady state. We use three key inputs into this baseline economy. First, using our estimated quality distribution, we construct a discrete quality grid. The maximum quality level in this grid is the median redevelopment quality we estimate above of $q = 102$. Assuming a time period in this model to be 10 years, we fill the grid backwards with 10-year cumulative depreciation at the estimated annualized rate of 0.3% per year. With this procedure, we define 46 discrete quality levels spanning from $q = 28$ to 102; these form our quality space $\boldsymbol{Q}$. In this iteration of the paper, we define the support of the blueprint distribution $\boldsymbol{Q'}$ as the singleton q_{new}. In future iterations of the paper, we will choose a larger support to match important variation in redevelopment qualities across neighborhoods we observe in the data.

Secondly, we use previously estimated values of the housing production parameters directly in our model. This means we do not choose fixed and variable costs F_x and Ω_x to match neighborhood redevelopment rates or to target quality distributions as a steady state directly. We discuss model fit with this approach in the next subsection.

Third, we identify the neighborhood amenity distribution $A(x, z)$ and the preference parameter β by targeting both the population distribution across neighborhoods by income

[24] The optimal housing unit implied from the first-order condition does not vary within a neighborhood. This implies that the optimal housing unit h_{it+1} solved from the first-order condition does not vary within a neighborhood. We interpret this model-implied optimal unit as the average redevelopment housing unit for each neighborhood. We plan to allow for quality variation to generate within-neighborhood variation in (q, h) for newly-redeveloped houses.

and aggregate spending on rents. We abstract from neighborhood displacement costs in this iteration of the paper by setting $\tau(x', x) = 1$ for all $x, x' \in \boldsymbol{X}$, and we follow to Macek (2024) calibrate the elasticity of amenity values to income as $\eta = 0.24$. To obtain population data by income, we posit that the income distribution of all neighborhood groups is lognormal. We then choose the log mean and log standard deviation of these distributions to match those of the discrete distributions reported in the 2015-2019 ACS tabulations. We then rescale this distribution by the amount of housing units in our assessment sample to arrive at a household density function $L(x, z)$ for each neighborhood group.We also obtain an outside option density $L(\boldsymbol{o}, z)$, which we take to be the remainder of the Chicago MSA not including the City of Chicago.[25] Lastly, we measure housing expenditure shares via Chicago's rent-to-income ratio from the ACS.

With these inputs, we solve for a steady state, yielding key endogenous variables defining our baseline model: the rent function $P(q, x)$, 10-year redevelopment rates, and quality distributions for each neighborhood while targeting neighborhood income distributions from the data. We obtain a spending share parameter $\beta = 0.22$ to target a spending share on rents of 0.21. We summarize our calibration algorithm in Appendix B.2.

6 Counterfactual Analysis

We use the model to evaluate the impact of a permanent Demolition Surcharge of \$60,000, extending its scope to include Logan Square, Humboldt Park, Avondale, West Town, and Hermosa, in addition to Pilsen and the 606-Trail area. Approved in September 2024, the new Northwest Side Preservation Ordinance expands the treated area of the three-year pilot policy and increases the surcharge amount.[26]

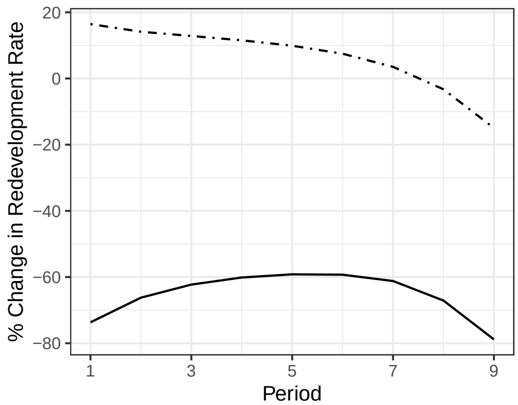
We model the surcharge as an increase in the fixed cost of redevelopment and solve the model assuming the tax revenue is not rebated back to landowners or households. We focus on the policy impacts on housing redevelopment, housing rent, housing quality and neighborhood composition in the treated neighborhoods versus untreated ones, which are presented in Figure 3.

Treated Neighborhoods

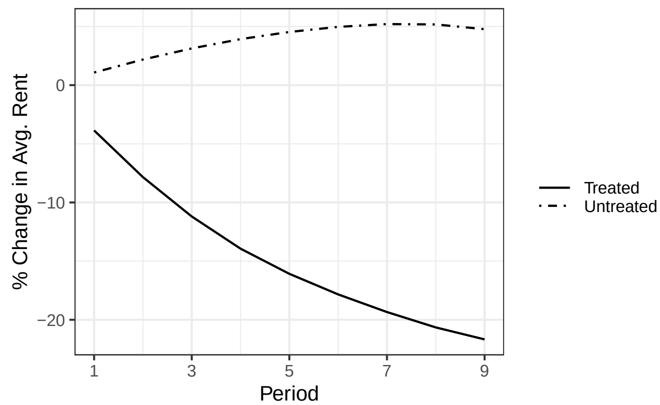
Panel (a) shows that the policy is effective at decreasing housing redevelopment treated neighborhoods. The average redevelopment rates of treated neighborhoods decrease by 74% in the first period, with the effect being persistent over time. As a result of the reduction

[25]We take the total number of housing units in the outside option from the 2020 Census. However, this count includes structures with greater than 7 housing units per lot. To address this, we rescale this housing unit count by our fraction of housing units in 1-7 unit structures measured from the assessments.

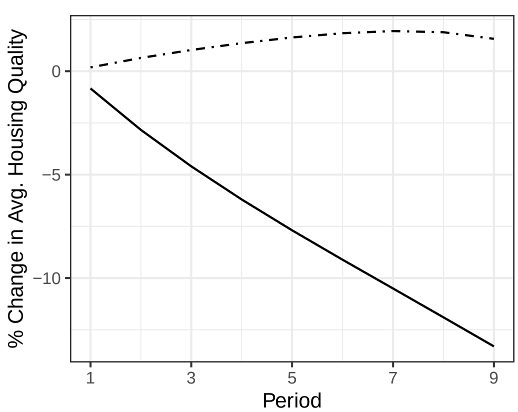
[26]See the description of the policy here.



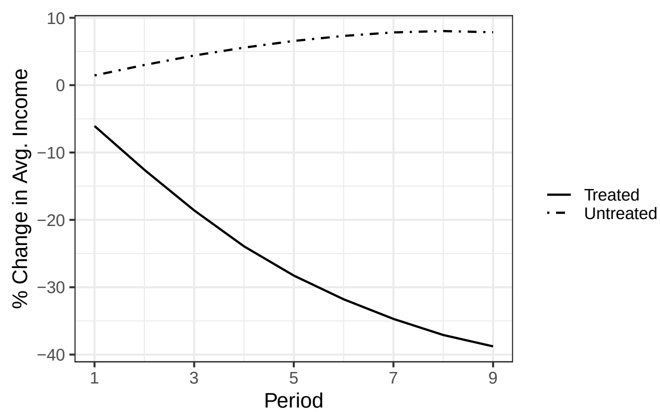
(a) Redevelopment Rate



(b) Average Housing Rent



(c) Average Housing Quality

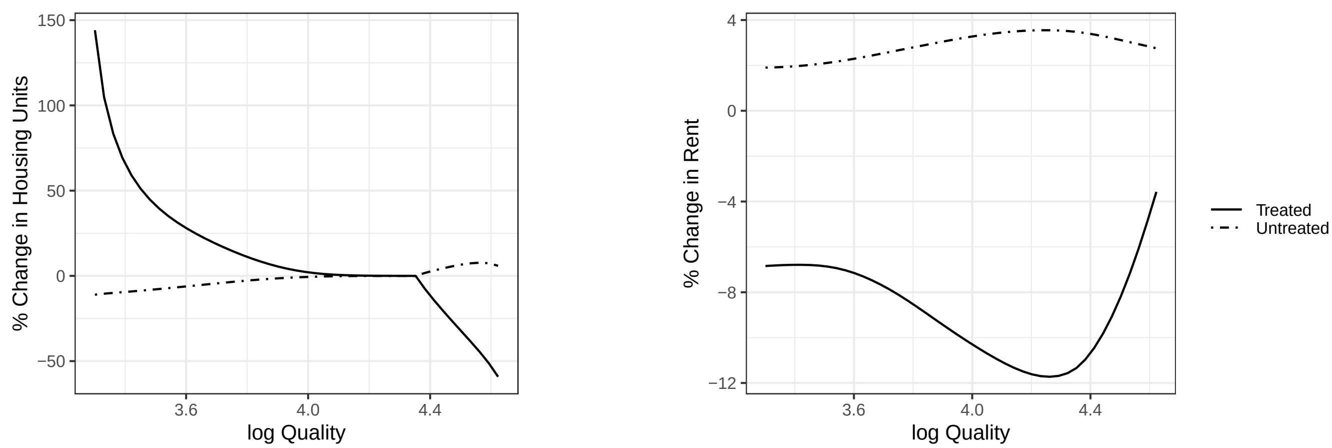


(d) Average Neighborhood Income

Figure 3: The Policy Impacts of the Demolition Surcharge

in housing redevelopment, we observe a decrease in housing rent, housing quality and neighborhood income in both treated neighborhoods, as shown in Panels (b)-(d). The effects on these three neighborhood outcomes all increase over time. The persistent decrease in housing redevelopment not only increases the supply of housing units but also leads to a decrease in average housing quality. Moreover, the shift in housing quality distribution also attracts low-income households to move into the treated neighborhoods. All of these contribute to the decrease in housing rent. These results indicate that the Demolition Surcharge is effective at reducing housing redevelopment and promoting housing affordability in the treated neighborhoods.

In Figure 4, we further examine the effect of the policy on the quality distribution and the pricing function. We present the average results over the nine periods we simulate. It could be seen from Panel (a) of Figure 4 that the policy significantly increases the number



(a) Quality Distribution

(b) Pricing Function

Figure 4: The Policy Impacts on Pricing Function and Quality Distribution

of low-quality housing units yet decreases high-quality housing units in the treated neighborhoods. As we have shwon before, redevelopment is often associated with deconversion in the gentrifying neighborhoods. Another effect of the Demolition Surcharge is that it increases the total numbers of housing units supplied in the treated neighborhoods by 1.6%.

In Panel (b) of Figure 4, we present the results of the changes in the pricing functions. Low-quality housing rent decreases significantly in the treated neighborhoods, while high-quality housing rent decreases by less. Notably, the housing rent for medium-quality units decreases by more than the low-and high-quality units. This may seem surprising in light of the discussion about how the structure of the pricing function causes neighborhood sorting (Section 4.2). The teardown tax decreases the supply of high-quality housing, presumably leading to a increase in the price of high quality relative to low quality. However, this assumes that amenity values are held fixed. In the baseline model, the decline in average income in the treated neighborhoods is instead associated with a decrease in amenity values. This induces the households with relatively higher income to move from treated neighborhoods, which in turn decrease the demand for medium- and high-quality housing units. On the supply side, only the number of highest-quality housing units decreases caused by the Demolition Surcharge. These joint changes in demand and supply conditions lead to a larger decrease in rent for medium-quality housing units than other types of housing. We confirm that the changes in the pricing function follow our theoretical predictions when amenity values are exogenous, shown in Figure C.8.

Untreated Neighborhoods

On the contrary to the treated neighborhoods, we observe remakable increases in housing redevelopment, housing rent, housing quality and neighborhood income in untreated neighborhoods, as shown in Figure 3. For example, the redevelopment rate increases by 16% in Period 1. Although the increase in redevelopment diminishes over time, it significantly shifts the quality distribution and the pricing function, which can be seen in Figure 4.

The average effects on the untreated neighborhoods may mask significant heterogeneity among them. To uncover such heterogeneity, we regress changes in the key outcomes in each untreated neighborhood on their initial neighborhood redevelopment rate, average rent, average quality, and average income. We present the results in Table 3. The regression result reveals that the policy tends to increase in housing redevelopment in neighborhoods started with higher redevelopment rate, lower rent, and lower housing quality.

These results convey an important message for the policymakers, that is, an implementation of anti-gentrification policies in selected neighborhoods will intensify gentrification in the untreated neighborhoods, especially the ones that are already subject to redevelopment. The policy-induced decrease in housing redevelopment in the treated neighborhoods leads to a decrease in high-quality housing supply. High-income households move from the those neighrboudhood towards the ones with high-quality housing. On impact, it increases the demand for high-quality housing in the untreated neighborhoods, pushing up housing rent. Such a shift in the pricing function leads to an increase in housing redevelopment in the untreated neighborhoods, reducing low-quality housing supply. Furthermore, the inflow of higher-income households increases neighborhood amenities, which put further upward pressure on housing rent. All else equal, neighborhoods abundent with cheaper and lower-quality housing are more likely to experience a higher increase in housing redevelopment, due to the lower opportunity cost of teardown.

Welfare Implications

The teardown tax causes both a fall in rents and a deterioration of housing quality – how do these changes map to household welfare by income level? In Figure 5, we map average flow welfare over time for households making 30k, 50k, 100k, and 200k per year. We measure welfare changes as the equivalent variation of an average z-household.[27] In Panel (a), we measure welfare under the baseline model with endogenous neighborhood amenities. We find that households making around 30k per year are better off, but most households above this income level are made significantly worse off over time (upwards of 0.4% of income). These results suggest that policy that lowers rents by reducing housing quality will come at a cost to many middle-and high-income households.

[27] That is, we measure the equivalent variation as a uniform cash injection for households in all locations from the baseline equilibrium that would make the average household as well off as after the policy change. By average, we mean an average taken with respect to idiosyncratic location taste shocks within an income level.

Table 3: Heterogeneous Effects on Untreated Neighborhoods

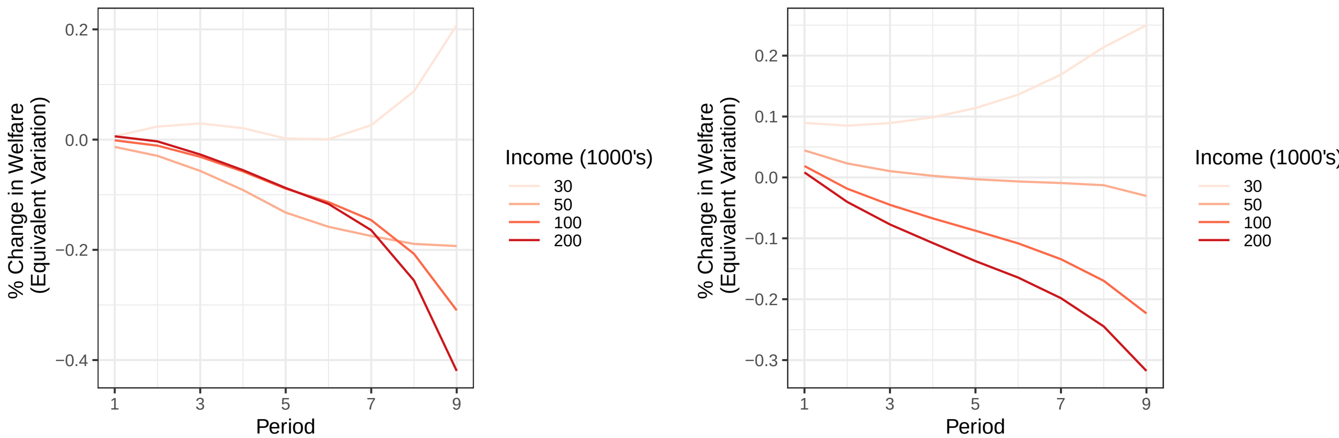
Log changes in	(1) Redev. Rate	(2) Rent	(3) Quality	(4) Income
Log(Initial Redev. Rate)	4.795**	0.543	0.243	1.031
	(2.254)	(0.361)	(0.176)	(0.737)
Log(Initial Rent)	−0.305	−0.151**	−0.033	−0.202
	(0.375)	(0.060)	(0.029)	(0.123)
Log(Initial Quality)	−10.899**	−1.143	−0.490	−2.417
	(5.452)	(0.875)	(0.426)	(1.783)
Log(Initial Income)	0.139	0.132**	0.024	0.145
	(0.407)	(0.065)	(0.032)	(0.133)
Period FE	Yes	Yes	Yes	Yes
Num. obs.	171	171	171	171
R^2	0.125	0.146	0.087	0.096

Notes: We include nine-period observations of the nineteen untreated neighborhoods. The regressions are weighted by initial neighborhood population. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

We also find that all households are made worse off by endogenous neighborhood amenities changes after the policy. To show this, we plot the same welfare effects under a parametrization of the model with exogenous amenities ($\eta = 0$) in Panel (b). Households making above 50k observe an additional 0.1 percentage point decrease in welfare in Panel (a) relative to (b). The fall in aggregate neighborhood amenities comes primarily from an in-migration of lower skill households into treated neighborhoods from outside the city.

It is worth noting that welfare effects in Figure 5 are small because we assume the city is "half-open". Under perfect labor mobility ($\sigma_x \to \infty$) in a standard open city Alonso-Muth-Mills model, any policy cannot affect the utility of households because they are fixed by the value of the outside option. These welfare measures also do not take into account additional losses for the landlords from falling land values in treated neighborhoods. In Figure C.9, we show that the land value in treated neighborhood significantly falls. This result suggests that the anti-gentrification policy benefits local renters at the expense of landlords, highlighting an additional aspect of the heterogeneous welfare implications.

In this iteration of the paper, the quantitative analysis abstracts away from two key policy issues that the teardown tax is thought to address. First, we assume no preferential attachment to an initial neighborhood, or $\tau(x, x') = 1$ for every neighborhood pair. Second, we assume fundamental amenity levels $\bar{A}(x, z)$ are unchanging over time, which abstracts from



(a) Endogenous Amenities

(b) Exogenous Amenities

Figure 5: The Welfare Impacts of the Teardown Tax

changes in location demand that has likely driven recent gentrification in Chicago. Taken together, these two features introduce an additional motive for implementing the teardown tax: to counteract costly household displacement arising from demand-driven neighborhood changes. We will incorporate these important features in future iterations of the paper. Including moving costs also allow us to quantify the heterogeneous welfare effects for residents in different parts of the city.

7 Conclusion

Housing redevelopment is a key way of housing supply in central cities, yet it often ensues gentrification. In this paper, we develop a general equilibrium framework to examine the dynamic interplay between housing redevelopment and income sorting. By incorporating forward-looking landlords and heterogeneous households with different income levels, our model captures the nuanced relationship between redevelopment decisions and neighborhood evolution over time. The model's inclusion of housing quality depreciation and subsequent neighborhood filtering provides valuable insights into the mechanisms driving neighborhoods housing cycles.

We apply to model to study the effect of a teardown tax policy in Chicago, which was designed to curb redevelopment in gentrifying neighborhoods as to protect the residents. While the reduced-form evidence shows significant reduction in redevelopment activities in the targeted neighborhoods, model counterfactuals reveal significant spillover effects. Redevelopment activities and rents increase in neighborhoods that were not targeted by the policy. As a result, the policy has significant and heterogeneous welfare consequences across different households, depending on their income and initial neighborhood residence. Overall, the average rent at the city level barely changes.

Our findings have important policy implications. First, anti-gentrification measures targeting specific neighborhoods can have unintended consequences on other urban areas, which results in higher rents and the displacement of low-income residents. Second, restricting new housing supply does not address the broader challenge of housing affordability faced by many U.S. cities. Future work should explore alternative policy tools, such as rental subsidies and the provision of affordable housing, to better support low-income residents in gentrifying neighborhoods and mitigate these unintended consequences.

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Appendix

A Additional model details

A.1 Proof of Proposition 1

We prove three statements:

1. **In equilibrium, the pricing function $P(q, x)$ increases in quality q.**

2. **Given a smooth pricing function $P(q, x)$ which increases in q, we have $q^*(z_1, x) > q^*(z_2, x)$ iff $z_1 > z_2$.**

   To prove this, it is sufficient to show that

$$\frac{\partial \tilde{U}}{\partial q \partial z} > 0 \tag{A.1}$$

   for $\tilde{U}(q, z, x) := q^\beta \big[z - P(q, x)\big]^{1-\beta}$, then directly applying Topkis' theorem. We have that

$$\frac{\partial \tilde{U}}{\partial q \partial z} = \beta(1-\beta)\left[q^{\beta-1}[z - P(q,x)]^{-\beta} + q^\beta [z - P(q,x)]^{-\beta-1} \frac{\partial P}{\partial q}\right] > 0$$

   since $\frac{\partial P}{\partial q} > 0$

3. **Assume the pricing function is isoelastic in each neighborhood, or $P(q, x) = k(x) q^{\nu(x)}$. Then, for any neighborhoods x_1 and x_2 and income levels $z_1 < z_2$, we have**

$$\frac{U(x_1, z_1)}{U(x_2, z_1)} < \frac{U(x_1, z_2)}{U(x_2, z_2)}.$$

   if and only if $\nu(x_1) < \nu(x_2)$

   We start with the parameteric assumptions of $p\,(q; x) = \kappa(x) q^{\nu(x)}$, where $\kappa(x)$ and $\nu(x)$ are neighborhood-specific pricing function intercept and elasticity parameters. From the first order condition

$$\frac{\beta}{1-\beta}=\epsilon_{p}^{q}\cdot\frac{p\left(q\left(x,z\right)\right)}{z-p\left(q\left(x,z\right)\right)} \tag{A.2}$$

we have

$$p\left(q\left(x,z\right)\right)=\frac{\beta}{\nu(x)\left(1-\beta\right)+\beta}\cdot z \tag{A.3}$$

then

$$q\left(x,z\right)=\left(\frac{1}{\kappa(x)}p\left(q\left(z,x\right)\right)\right)^{\frac{1}{\nu(x)}}. \tag{A.4}$$

With the optimal price and quality, and assuming that $a\left(x,z\right)=1,\forall x,z$, we can obtain the utility of type-z household in neighborhood x as

$$\begin{aligned}
U\left(x,z\right) &= q\left(x,z\right)^{\beta}\left(z-p\left(q\left(x,z\right)\right)\right)^{1-\beta} \\
&= \left(\frac{1}{\kappa(x)}p\left(q\left(x,z\right)\right)\right)^{\frac{\beta}{\nu(x)}}\left(z-p\left(q\left(x,z\right)\right)\right)^{1-\beta} \\
&= \left(\frac{1}{\kappa(x)}\frac{\beta}{\nu(x)\left(1-\beta\right)+\beta}\cdot z\right)^{\frac{\beta}{\nu(x)}}\left(z-\frac{\beta}{\nu(x)\left(1-\beta\right)+\beta}\cdot z\right)^{1-\beta} \\
&= \chi\cdot z^{1+\beta\left(\frac{1}{\nu(x)}-1\right)}
\end{aligned}$$

where in the last step we define $\chi\equiv\left(\frac{1}{\kappa(x)}\frac{\beta}{\nu(x)(1-\beta)+\beta}\right)^{\frac{\beta}{\nu(x)}}\left(\frac{\nu(x)(1-\beta)}{\nu(x)(1-\beta)+\beta}\right)^{1-\beta}$. It is straightforward to see that the utility function is log-submodular in income z and the pricing function elasticity $\nu(x)$:

$$\frac{\partial\log U\left(x,z\right)}{\partial z\partial\nu(x)}=-\frac{\beta}{\nu(x)^{2}}\cdot\frac{1}{z}<0.$$

Hence, for two neighborhoods with $\nu(x_2)>\nu(x_1)$ and two income types $z_1<z_2$, we have

$$\frac{U(x_1,z_1)}{U(x_2,z_1)}<\frac{U(x_1,z_2)}{U(x_2,z_2)}.$$

A.2 Derivation of Part 3 of Proposition 1 for a general pricing function

In this appendix, we prove the following statement that holds under a more general structure of the pricing function, including the case where the function is not isoelastic in quality:

For a continuum of neighborhoods indexed by x, if the pricing function $P(q,x)$ varies across neighborhoods smoothly such that

$$\frac{\partial \epsilon_q^P}{\partial x} > \frac{\partial P}{\partial x}\frac{\partial \epsilon_q^P}{\partial q}\left[\frac{\partial P}{\partial q}\right]^{-1}$$

for all q and x, then $U(x_1,z_1)/U(x_2,z_1) > U(x_1,z_2)/U(x_2,z_2)$ for $z_1 > z_2$ and $x_2 > x_1$.

To prove this, we start by deriving an analytical expression for $\frac{\partial \log U(x,z)}{\partial z}$ for $U(x,z)$ solving the full households' problem (Equation 4), for which it is sufficient to show that the difference across x_1 and x_2 are strictly decreasing in z.

Applying the Envelope theorem, we know that

$$\frac{\partial \log U(x,z)}{\partial z} = \frac{\partial \log \tilde{U}(q,x,z)}{\partial z}|_{q=q^\star(x,z)}$$

with $q^\star$ solving (4) or

$$\frac{\partial \log U(x,z)}{\partial z} = (1-\beta)\frac{1}{z - P(q^\star(x,z),x)} \tag{A.5}$$

Now, consider the equation

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

for any $x_2 > x_1$, which is strictly positive if and only if

$$(1-\beta)\frac{1}{z - P(q^\star(x_1,z),x_1)} > (1-\beta)\frac{1}{z - P(q^\star(x_2,z),x_2)}$$

or equivalently

$$P(q^\star(x_1,z),x_1) > P(q^\star(x_2,z),x_2) \tag{A.6}$$

That is, a sufficient condition for high income types to sort into neighborhood x_1 is that all income types would spend more on rent in x_1 than if they lived in x_2 given their choice of optimal quality. The objective is to show that the assumed conditions on how the pricing function varies across neighborhoods create this divergence in optimal spending on rent.

Recall the first order condition that implicitly defines the quality function $q^\star(x,z)$

$$\frac{\beta}{1-\beta} = \epsilon_q^P(q^\star, x)\frac{P(q^\star, x)}{z - P(q^\star, x)} \tag{A.7}$$

where ϵ_q^P is the elasticity of rent with respect to quality. This means that the elasticity of rent to quality multiplied by the relative expenditure on rent and other goods is equalized across neighborhoods for these preferences. We assume the left-hand side of (A.7) is strictly increasing in quality in order for this households maximization problem to have a unique global maximum. A sufficient condition is that the price elasticity ϵ_q^P is weakly increasing in quality, which we assume moving forward.

To complete the proof, we derive conditions on how the pricing function P varies between x_1 and x_2 to prove the inequality (A.6). Implicitly differentiating (A.7) over x gets us the following equation

$$\frac{1}{\epsilon_q^P}\frac{\partial \epsilon_q^P}{\partial x} + \frac{1}{\epsilon_q^P}\frac{\partial \epsilon_q^P}{\partial q}\frac{\partial q^\star}{\partial x} + \left[\frac{1}{P} + \frac{1}{z-P}\right]\left[\frac{\partial P}{\partial x} + \frac{\partial P}{\partial q}\frac{\partial q^\star}{\partial x}\right] = 0$$

which implies (after some algebra and substituting the definition of ϵ_q^P)

$$\frac{\partial q^\star}{\partial x} = -\frac{\frac{1}{\epsilon_q^P}\frac{\partial \epsilon_q^P}{\partial x} + \left[\frac{1}{P} + \frac{1}{z-P}\right]\frac{\partial P}{\partial x}}{\frac{1}{\epsilon_q^P}\frac{\partial \epsilon_q^P}{\partial q} + \frac{\epsilon_q^P P}{q}\left[\frac{1}{P} + \frac{1}{z-P}\right]}$$

a sufficient condition to prove that $P(q^\star(x,z), x)$ is strictly decreasing in x (to show A.6) is that $\epsilon_q^P(q^\star(x,z), x)$ is strictly increasing in x from Equation (A.7). This is equivalent to showing that the total derivative is strictly positive

$$\frac{\partial \epsilon_q^P}{\partial x} + \frac{\partial \epsilon_q^P}{\partial q}\frac{\partial q^\star}{\partial x} > 0$$

Substituting the expression for $\frac{\partial q^\star}{\partial x}$ yields the inequality

$$\frac{\partial \epsilon_q^P}{\partial x} - \frac{\partial \epsilon_q^P}{\partial q}\frac{\frac{1}{\epsilon_q^P}\frac{\partial \epsilon_q^P}{\partial x} + \left[\frac{1}{P} + \frac{1}{z-P}\right]\frac{\partial P}{\partial x}}{\frac{1}{\epsilon_q^P}\frac{\partial \epsilon_q^P}{\partial q} + \frac{\epsilon_q^P P}{q}\left[\frac{1}{P} + \frac{1}{z-P}\right]} \tag{A.8}$$

which is strictly positive if and only if (after simplifying A.8 and applying the inequality $\frac{\partial \epsilon_q^P}{\partial q} \geq 0$)

$$\frac{\partial \epsilon_q^P}{\partial x} > \frac{\partial P}{\partial x}\frac{\partial \epsilon_q^P}{\partial q}\left[\frac{\partial P}{\partial q}\right]^{-1}$$

that is, if the variation in the price-quality elasticity across neighborhoods is large relative to the product of the differences in prices and the quality elasticity itself. This is the inequality reported in the proposition.

A.3 Solution Algorithm

We discretize the quality space $\boldsymbol{Q}$ into a grid $\boldsymbol{Q} = \{q_1, q_2, ..., q_{N_q}\}$, where $q_1 = q_{min}$ 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. Guess the entire stream of the pricing function $\{P_t(q, x)\}_{\forall t,q,x}$.

2. Given the pricing function, solve the household's problem by equations (5) and (6). This generates the housing demand $\{L_t(q, x, z)\}_{\forall t,q,x,z}$.

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

   (a) In period T, set $V_T(s_{iT}, \hat{q}_{iT}) = P_T(q_{iT}, x) \cdot h_{iT}$. No landlord chooses to redevelop.

   (b) In period $t < T$, solve the problem given by equation (11). The value functions $V_{it+1}(\cdot, \cdot)$ are solved from the landlord's problem in the period $t + 1$.

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

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

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

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

      where $h_{i,t+1}^*(\hat{q}_{it}, x) = \arg\max_{h_{i,t+1}} \left\{-C_i(\hat{q}_{it}, h_{i,t+1}) + \rho \mathbb{E}_{\hat{q}_{it+1}} V_{i,t+1}\left(\hat{q}_{it}, h_{i,t+1}, \hat{q}_{i,t+1}\right)\right\}$. 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}.

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

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

      .

4. Given the landlord's optimal redevelopment decisions $\{p(s_{it}, \hat{q_{it}})\}_{i,t,s,\hat{q}}$ and $\{h^*_{it+1}(\hat{q}_{it})\}_{i,t,\hat{q}}$ 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 $t=T$:

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

5. Check the market clearing condition:

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

   (a) if the market clearing condition is satisfied, stop the iteration.

   (b) if not satisfied, update the pricing function $\{P_t(q,x)\}_{\forall t,q,x}$ according to the market clearing condition, and go back to step 2.

B Calibration and estimation

B.1 Estimating the Housing Supply Parameters

We start from the estimation of the elasticity parameter γ. Conditional on redevelopment, the landlord chooses h_{it+1} to maximize profits, that is:

$$h_{it+1} = \max_h \left\{ -\left(\Omega_x \cdot q_{it+1} \cdot h^\gamma\right) + \rho V_{i,t+1}\left(q_{it+1}, h\right) \right\}. \tag{B.1}$$

The first-order condition of this problem is

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

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

$$\log h_{it+1} = -\frac{1}{(\gamma-1)}(\log\gamma - \log\rho) + \frac{1}{(\gamma-1)}\left(\log \frac{\partial V_{i,t+1}\left(q_{it+1}, h\right)}{\partial h_{it+1}} - \log q_{it+1}\right) - \frac{1}{(\gamma-1)} \log \Omega_x. \tag{B.3}$$

Assuming that quality is measured with a measurement error and that there is idiosyncratic unobserved cost shocks, we can derive the estimating equation (17). And the variable cost parameter Ω_x could be calculated as:

$$\log \Omega_x = \mathbb{E}_{i\in x}\left[\log\left(\frac{\rho}{\gamma}\right) + \left(\log \frac{\partial V_{i,t+1}\left(q_{it+1}, h\right)}{\partial h_{it+1}} - \log q_{it+1}\right) + (1-\gamma)\log h_{it+1}\right]. \tag{B.4}$$

B.2 Calibration Algorithm

Our calibration algorithm proceeds as follows.

1. Initialize initial prices $P(q,x)$, error ϵ and excess demand error tolerance ϵ_{tol} and adjustment speed parameter $\Lambda > 0$

2. While $\epsilon > \epsilon_{\text{tol}}$ do:

   (a) Solve the producers problem

   (b) Obtain a steady state distribution of parcels by quality as well as their assigned number of housing units per parcel. Calculate total number of housing units in each neighborhood $H(x)$.

   (c) Choose β at prices $P(q,x)$ to target aggregate spending given the targeted population distribution $L(x,z)$

   (d) Adjust prices for lowest quality $P'(\min \boldsymbol{Q}, x) = P(\min \boldsymbol{Q}, x) + \Lambda[L(x) - H(x)]$, where $L(x)$ is the ACS total population in x

   (e) Solve for unique pricing function $P'(q,x)$ for all $q > \min \boldsymbol{Q}$ to solve the equilibrium matching relation $\mathbb{F}_x(z) = \mathbb{H}_x(q)$ for all $q \in \boldsymbol{Q}$, where $\mathbb{F}_x$ is the culumative distribution of z types in x and $\mathbb{H}_x$ is the cumulative quality distribution in x.

   (f) Adjust $P(q,x) = P(q,x) + \Lambda[P'(q,x) - P(q,x)]$, calculate new errors $\epsilon = \max_{q,x} |P'(q,x) - P(q,x)|$

3. Find indirect utility $U(x,z)$ associated with calibrated prices $P(q,x)$

4. Find amenities given $a(x,z)$ to rationalize targeted populations $L(x,z)$. Solves simple equation under baseline model where $\tau = 1$ (no displacement costs):

$$\frac{L(x,z)}{L(\boldsymbol{o},z)} = U(x,z)^{\sigma_x} a(x,z)^{\sigma_x}$$

C Additional Figures and Tables

Table C.1: Summary Statistics

Neighborhoods	Pilsen	606-Trail	Chicago
Panel A: Assessment Records (2000-2023)			
Building units	1.9	2.3	1.4
Floorspace (sf)	2209	2546	1819
Floorspace per unit (sf)	1217	1205	1343
Land lot (sf)	3368	2892	4131
Bedrooms	4.4	4.6	3.7
Bathrooms	2.3	2.5	1.8
Build year	1912	1899	1932
Number of assessment records	451,208	199,586	23,763,462
Panel B: Transaction Records (2000-2023)			
Median sales price (in '000)	368,000	302,000	295,500
Median sales price per unit (in '000)	119,000	66,500	119,000
Median sales price per sf	199	135	176
Number of transaction records	18,861	4,808	634,789
Panel C: Building Permits (2006-2023)			
Demolition permit probability	0.15%	0.17%	0.17%
Construction permit probability	0.26%	0.45%	0.28%
Renovation permit probability	2.37%	1.94%	2.40%
Panel D: Neighborhood Characteristics (2019)			
Median income	55,994	66,390	67,082
Median build year	1943	1943	1953
Average monthly rent	870	1,099	1,091
Changes in log median income (2009-2019)	0.43	0.36	0.20
Changes in median build year (2009-2019)	1.51	4.66	2.41
Changes in log avg monthly rent (2009-2019)	0.37	0.30	0.24

Notes: All monetary values are converted to 2019 dollars. Data sources: annual assessment data from the Cook County Assessor's Office, transaction deeds data from the Cook County Recorder of Deeds, building permits data from the Chicago municipal government, and American Community Survey block group level tabulations from the National Historical Geographic Information System (NHGIS)

Table C.2: Difference-in-Difference Results: Demolition and Construction Permits

	Demolition				Construction			
Buffer	0.25km	0.5km	1km	3km	0.25km	0.5km	1km	3km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat ×								
Period 1	-0.236	-0.416	-0.246	-0.408*	-0.0350	-0.189	-0.388**	-0.640***
	(0.424)	(0.336)	(0.267)	(0.218)	(0.295)	(0.210)	(0.165)	(0.139)
Period 2	0.508	-0.225	-0.406	-0.230	0.260	0.519*	0.364	-0.0452
	(0.472)	(0.336)	(0.261)	(0.218)	(0.432)	(0.300)	(0.225)	(0.174)
Period 3	0.195	-0.0220	-0.356	-0.444**	0.285	0.296	0.0850	-0.0650
	(0.458)	(0.340)	(0.257)	(0.212)	(0.301)	(0.209)	(0.161)	(0.131)
Period 4	0.262	-0.0865	-0.272	-0.0428	0.0723	0.0818	0.0102	-0.0578
	(0.401)	(0.305)	(0.234)	(0.192)	(0.269)	(0.194)	(0.151)	(0.125)
Period 5	-	-	-	-	-	-	-	-
Period 6	0.224	-0.859**	-0.899***	-0.885***	-0.650*	-0.573**	-0.708***	-0.654***
	(0.613)	(0.405)	(0.329)	(0.286)	(0.338)	(0.242)	(0.193)	(0.169)
Constant	-1.442***	-0.422	-0.242	-0.419***	-1.289***	-1.356***	-1.403***	-1.246***
	(0.457)	(0.269)	(0.180)	(0.0811)	(0.358)	(0.252)	(0.158)	(0.0693)
Mean Y	0.00486	0.00485	0.00518	0.00539	0.0109	0.0111	0.0112	0.0101
Observations	1,458	2,688	4,644	14,772	3,210	5,982	9,762	27,210

Note: The table shows the estimation results of equation (1). Standard errors are clustered at the address level.
* p<0.1, ** p<0.05, *** p<0.01.

Table C.3: 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)
Observations	2,280	2,268
R^2	0.114	0.140
First Stage 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.4: 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)
Observations	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.5: 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.

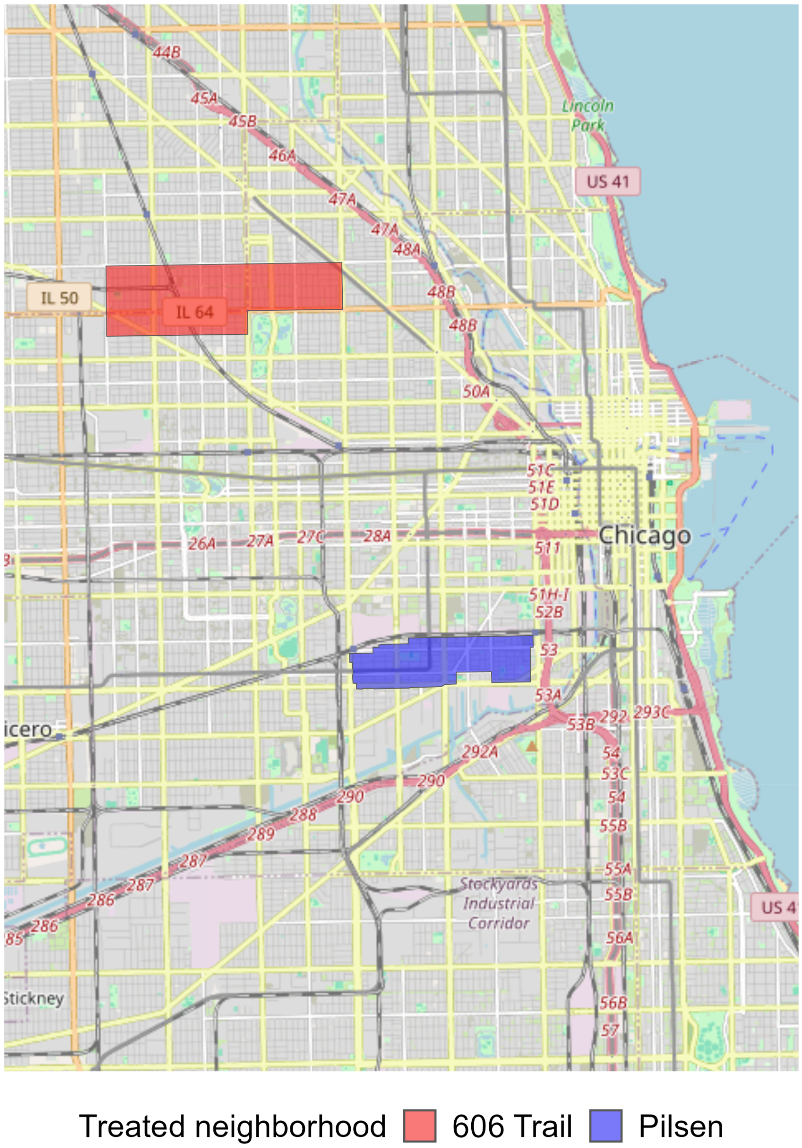
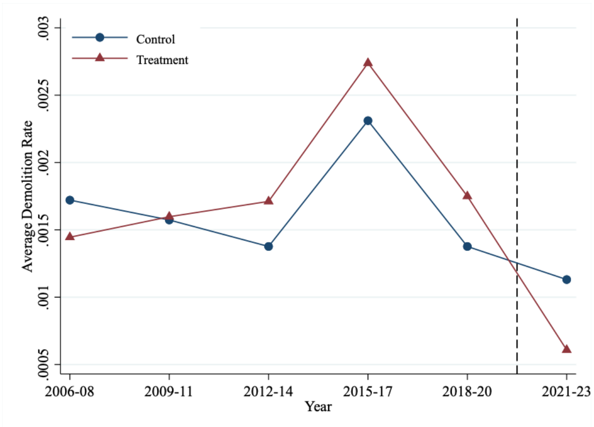
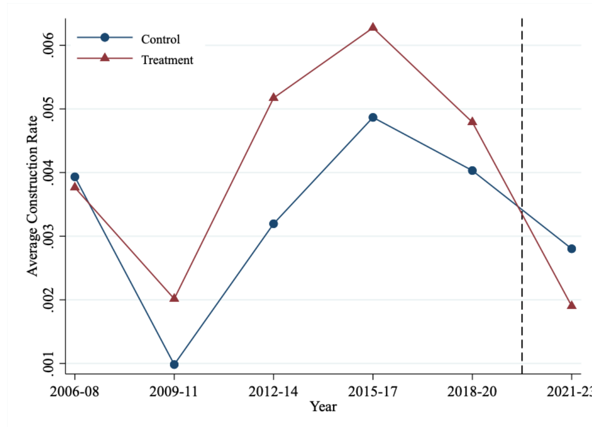


Figure C.1: Policy areas: The 606 and Pilsen neighborhoods



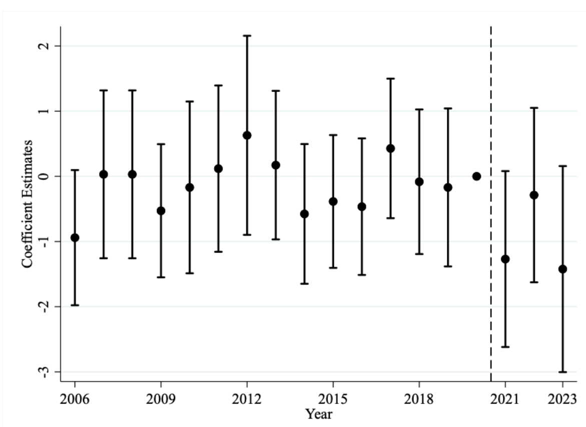
(a) Demolition Permits



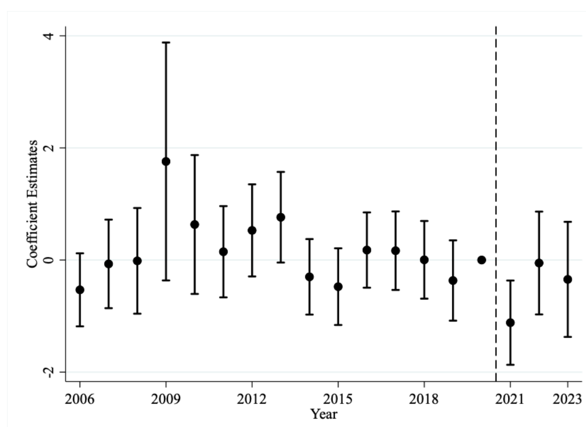
(b) Construction Permits

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: Different-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.

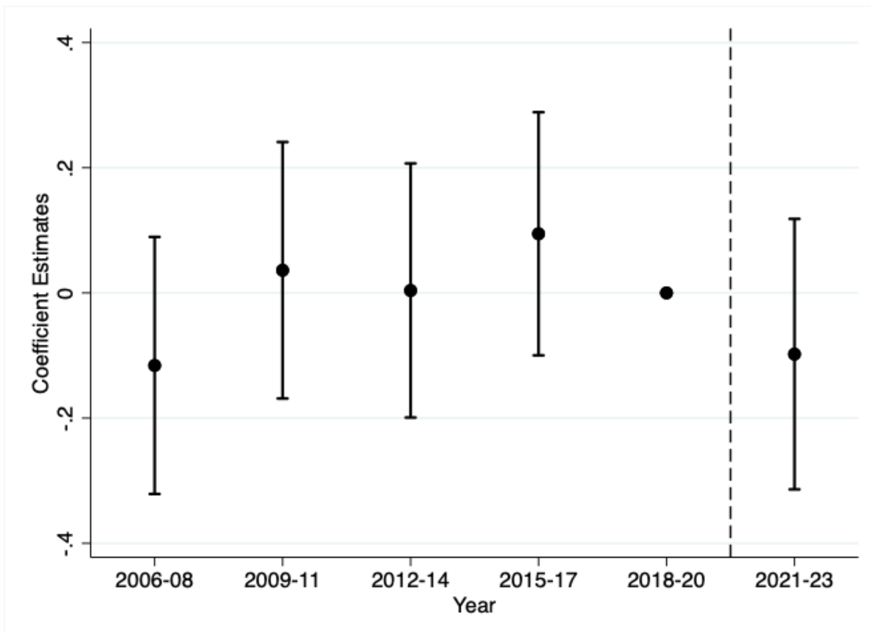


Figure C.4: Different-in-Difference Results of Renovation Permits

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

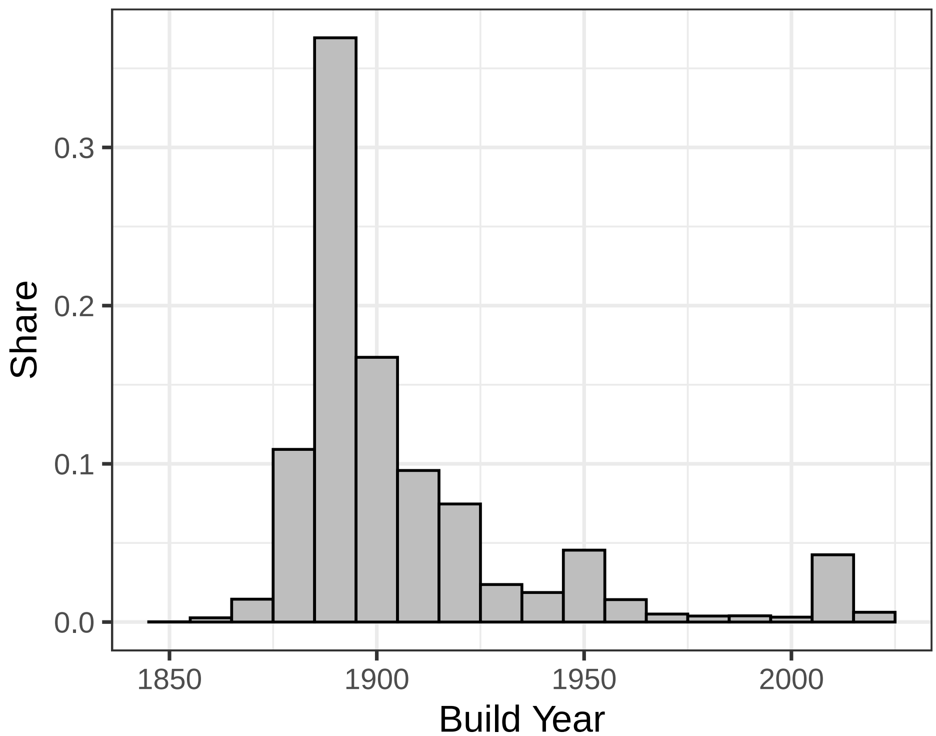


Figure C.5: Distribution of Build Year of Redeveloped Buildings

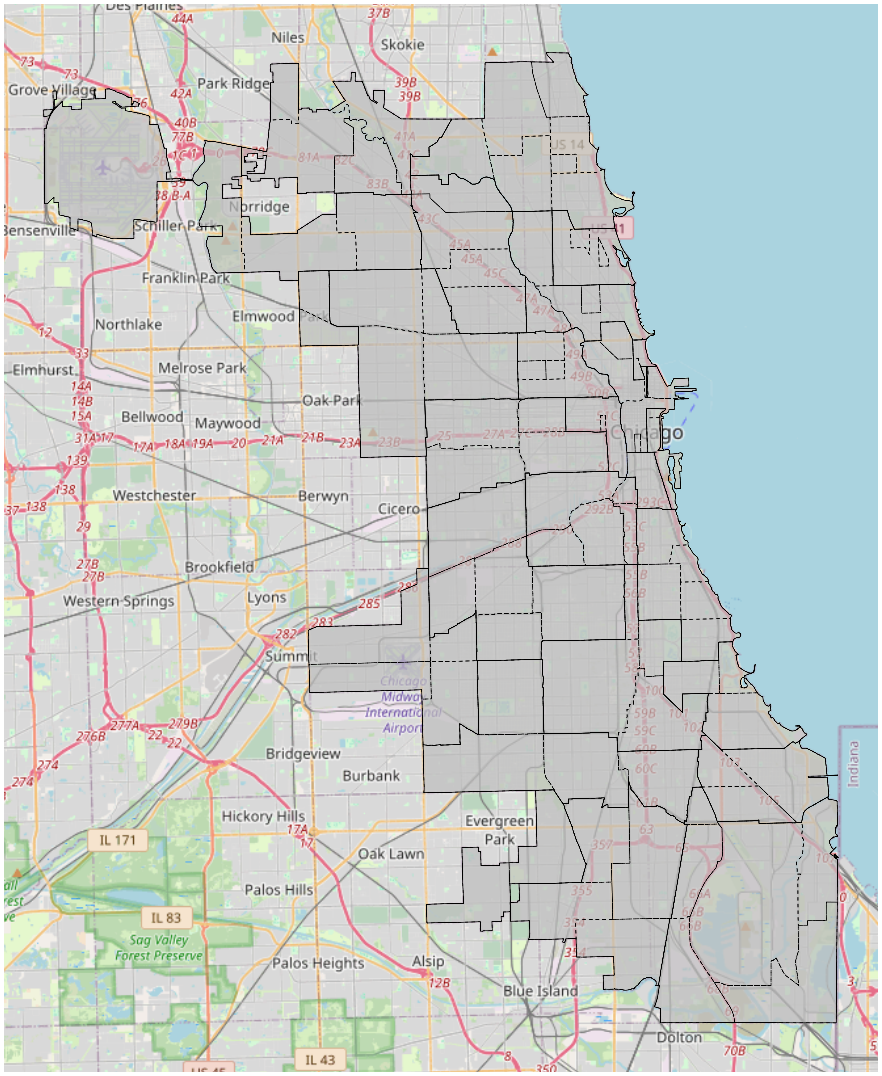


Figure C.6: A Map of Neighborhood Groups

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

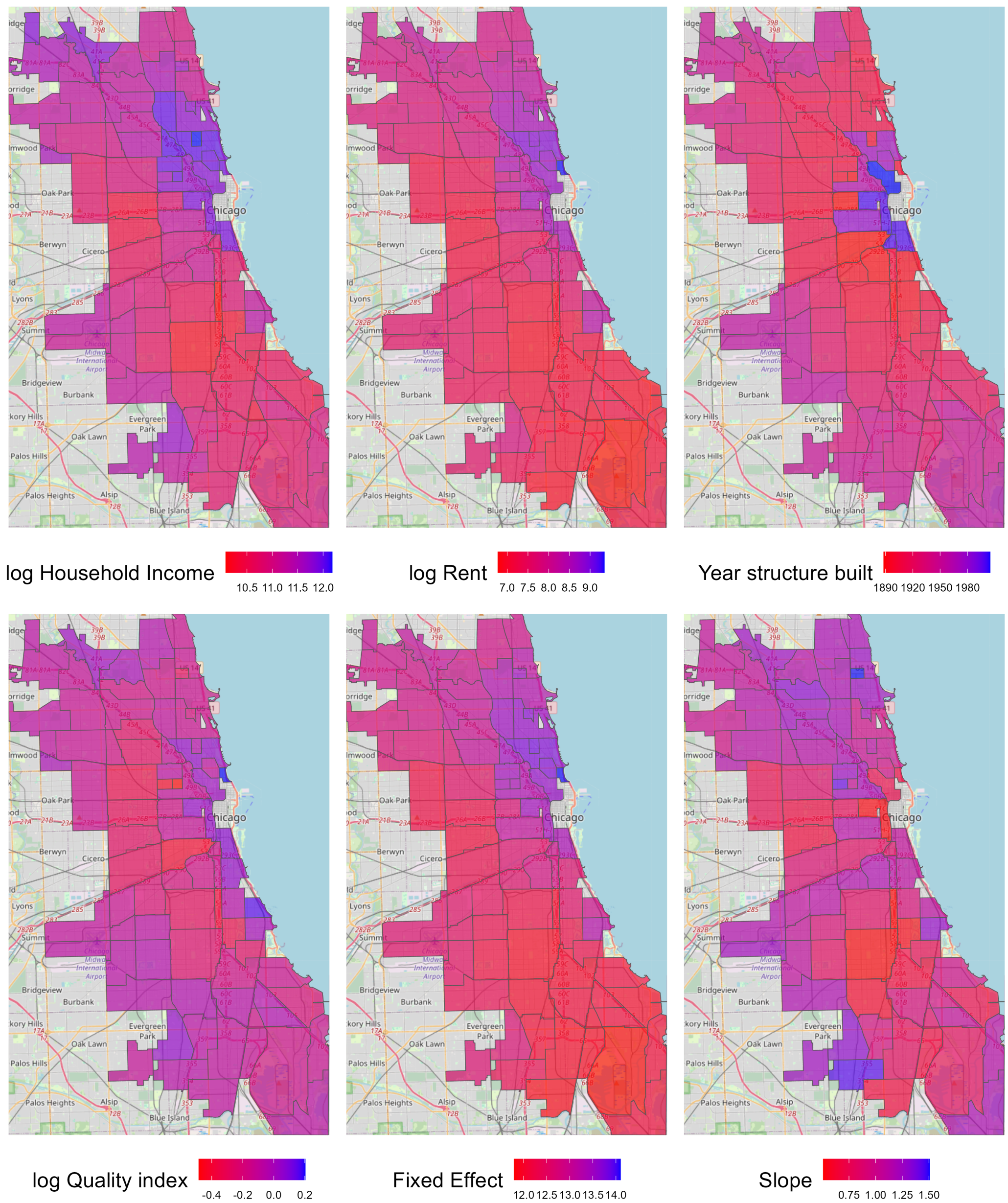


Figure C.7: Observed characteristics and estimated pricing functions across neighborhoods

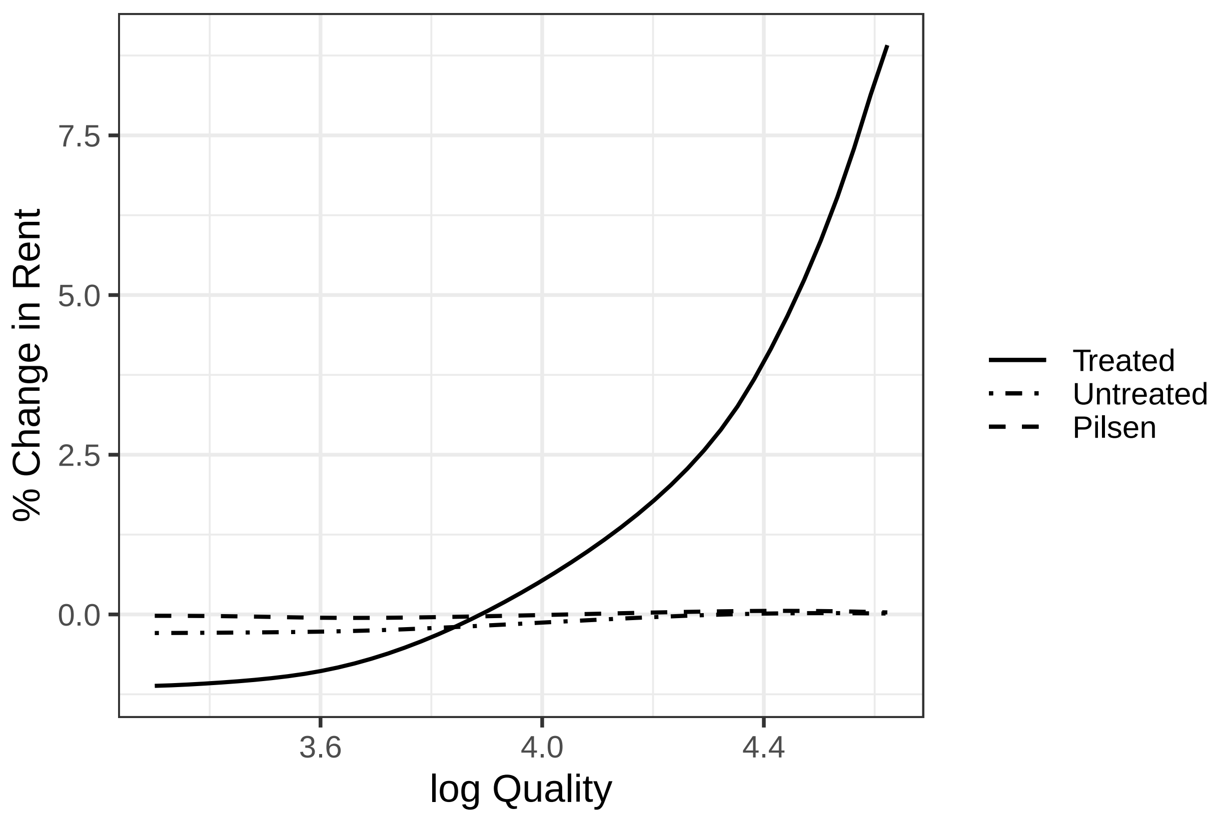


Figure C.8: Pricing function changes under the $60,000 northwest policy with no endogenous amenities ($\eta = 0$)

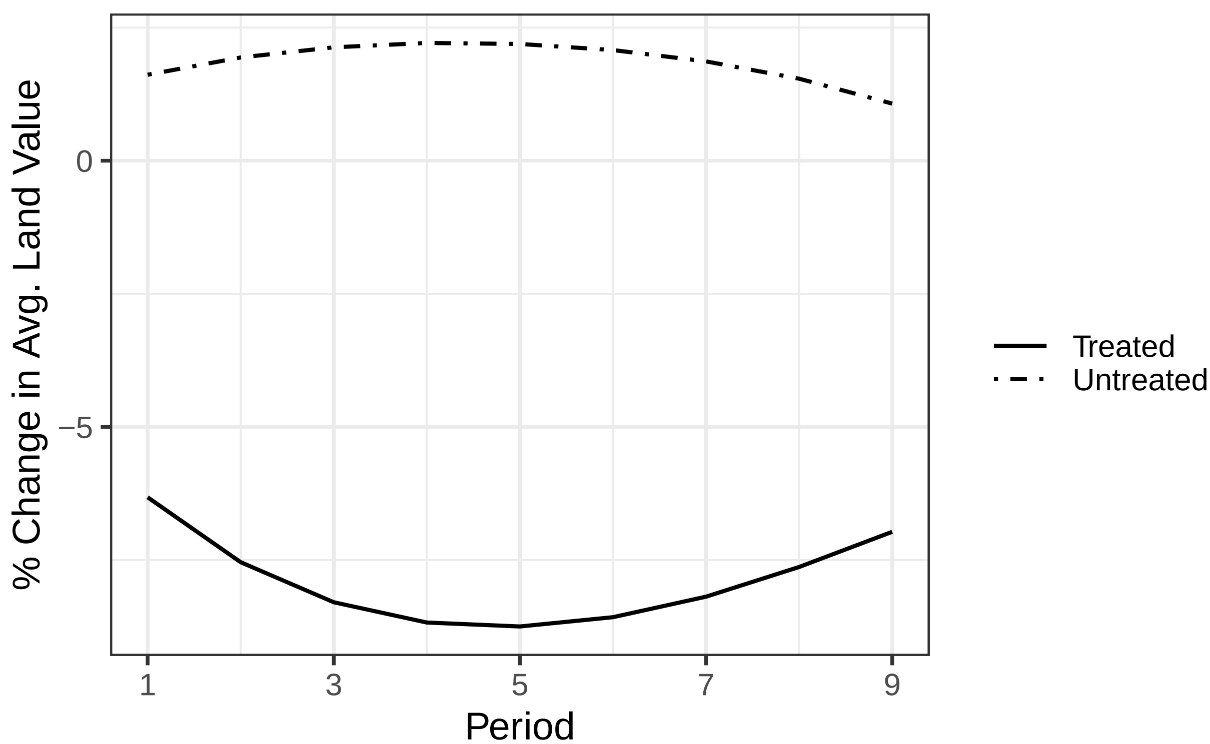


Figure C.9: Changes in Land Value under the $60,000 northest policy