Neighborhood Housing Cost Sensitivities *

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Note: Extended Abstract with Initial Results.

Abstract

This paper documents the effects of aggregate mortgage rate shocks on neighborhood housing costs. We employ zip code level home price and rental data from Zillow along with the structural shocks to national mortgage rates from Ben-David, Towbin, and Weber (2024) to estimate the effects of a decline in mortgage rates on rental and home price growth in each zip code from 2000-2017. Our preliminary results suggest that lower income areas tend to experience the largest appreciation in housing costs, which has important implications for assessing the distributional effects and transmission of monetary policy. We assess the extent to which of demand factors, supply factors, and other conditions account for heterogeneity in the local housing cost sensitivity to national mortgage rate shocks.

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1 Introduction

This paper quantifies neighborhood-level housing cost sensitivities to mortgage rate shocks. Recent periods of expansionary monetary policy have spurred inquiry into the link between interest rates and inequality (e.g., Coibion et al. (2017), Beraja et al. (2019), Auclert (2019)). A seemingly unrelated concern is the trend of rising housing costs in low-income neighborhoods (gentrification) over the past few decades (e.g., Baum-Snow and Hartley (2020), Couture and Handbury (2020), Couture et al. (2024)). Much of the work examining the causes and consequences of low-income housing costs has focused long-term trends and has abstracted from the role of interest rates. Yet borrowing costs and housing markets are intricately linked, and housing cost inequality is a potential consequence of changing borrowing costs.

How have changes in borrowing costs affected the distribution of housing costs? Isolating a link between borrowing costs and housing costs is challenging due to the high-frequency and endogenous nature of changes in interest rates and the low frequency and limited sample for which measures of housing costs are available. Our paper addresses these challenges by leveraging estimates of mortgage rate shocks from the structural decomposition of the national housing market in Ben-David, Towbin, and Weber (2024) (henceforth BTW). BTW identify structural shocks in the national housing market, including a mortgage rate shock.

For each zip code, we estimate the sensitivity of local housing costs to changes in national home values driven by the BTW mortgage rate shocks, conditional on other structural drivers of national housing markets and local economic conditions. Our measures of housing costs are quality-adjusted rental prices and, separately, home prices. We obtain precisely estimated home price sensitivities for most zip codes. The median rental price response is negative (consistent with the national-level evidence from Dias and Duarte (2019)) but features larger standard errors due to the shorter sample. The median home price response is positive, and in both the rental and home price responses, there is substantial dispersion.

With housing-cost sensitivities in hand, we address two primary questions. First, do housing cost sensitivities differ across the income distribution? Second, what are the fundamental drivers of the heterogeneity in housing cost sensitivity (HCS)?

We find that for both types of housing costs, the HCS is decreasing in zip code median household income, indicating that expansionary mortgage rate shocks are highly regressive. We also test for a non-linear relationship between zip code income and HCS by categorizing zip codes with homogeneous income among residents. Specifically, using tax return data from the IRS Individual Income Statistics, we categorize zip codes into one of five income categories —very low-income, low-income, middle-income, high-income, or not classified (for zip codes with dispersed income among residents). Our cross-sectional analysis finds that all income groups experience higher home price and rental rate appreciation relative to high-income areas. For example, housing values in the lowest-income areas appreciate between 54 and 77 basis points more than in high-income zip codes, while rental rates are on average 150 basis points higher.

To understand the drivers of heterogeneity in rental price and home price HCS, we collect

data on pre-sample zip code characteristics. These characteristics include housing supply elasticities and local amenities that are likely to influence demand for local housing and hence the response of both measures of housing costs to changes in borrowing costs. These supply and demand factors account for much of the variation in HCS across CBSAs. However, the HCS measures exhibit different quantitative dependencies on these factors, in some instances drastically and with different signs. For example, natural amenities are associated with a much stronger home price HCS but have a negligible influence on the rental price HCS.

The different influence of supply and demand factors on rental HCS and home price HCS raises the question of whether these factors capture fundamental supply and demand factors or other unobserved fundamentals. We verify that these factors can indeed be interpreted as supply and demand fundamentals by estimating zip-level quantity sensitivities (QS) to mortgage-shock-driven changes in national housing markets. These quantities include the local housing stock and household mortgage debt. Quantity sensitivities are influenced by these factors as expected. For example, a lower housing supply elasticity is associated with lower QS. Likewise, higher levels of natural amenities predict larger QS.

Although housing supply and demand factors primarily affect differences in HCS across CBSAs, other factors explain within-CBSA variation in HCS. We categorize these factors that vary within CBSAs as those related to the quality of the housing stock (which has been identified by Murphy (2024) as a key determinant of housing-cost-pass-through) and those related to the mix of renter-occupied and owner-occupied homes on the local housing market.

We document that zip codes with lower-quality homes exhibit substantially stronger pass-through from mortgage rate shocks to housing costs. The pass-through is particularly acute for rental prices. The influence of others factors on HCS differ by housing cost type. Our preliminary results indicate the prevalence of disintegrated rental and housing markets.[1] This lack of integration implies differential impacts of housing market shocks by type of occupancy (and, relatedly, by income level). These results provide a guide for local communities to assess how housing costs are likely to respond to changes in mortgage rates, depending on residents' characteristics and the conditions of the local housing stock.

1.1 Related literature

This paper is related to the literature that examines the effects of macroeconomic shocks on inequality. Recent work (see Auclert (2019), Auerbach, Gorodnichenko, and Murphy (2024), Coibion et al. (2017), Kaplan, Moll, and Violante (2018)) finds that expansionary monetary and fiscal policy can reduce inequality. In related work, Piazzesi and Schneider (2016) and Garriga and Hedlund (2020), highlight the importance of housing markets in transmitting aggregate shocks. Our findings indicate that aggregate shocks to mortgage rates induce disproportionately higher responses in housing costs for low-income households. This suggests that the housing cost channel can mitigate some of the distributional benefits of expansionary monetary policy that has been highlighted in prior work.

[1] In classic models of housing markets such as Poterba (1984) and Topel and Rosen (1988), home values and rental rates are intricately linked by an asset pricing equation. Home prices and rental rates can depart from this condition when markets are segmented.

Our findings and methodology are most closely related to Murphy (2024), who finds that MSA-wide housing demand shocks lead to relatively higher frequency movements in downtown gentrification. Our paper differs in two key aspects. First, our focus is on estimating heterogeneity in the housing-cost response across zip codes rather than the effect of housing expansions on downtown gentrification. Second, our identification employs structural estimates of nationwide mortgage rate shocks from a vector autoregression, and zip code level housing value and rental data. This contrasts to Murphy (2024) where the source of the demand shock is not explicit. By isolating the source of the housing demand shock, our paper provides guidance on the likely effects of changes in borrowing costs driven, for example, by monetary policy.

Our work is also complementary to the literature that examines the returns to housing investments. For example, Damen, Korevaar, and Van Nieuwerburgh (2025) find that rentals with the lowest rent levels provide the higher returns to their owners. Our results complement these findings by suggesting that rental rates in lower-income areas appreciate more, which may reflect both increased demand from potential property owners and developers, and greater challenges for renters in purchasing homes or moving to alternative rental markets.

2 Data and Methodology

Our empirical analysis proceeds in two steps. First, we estimate zip code-level housing cost responses to national mortgage rate shocks. Second, we document heterogeneous housing cost sensitivities across zip codes and examine the determinants of this heterogeneity.

2.1 Estimating Neighborhood Housing Cost Sensitivities

Ben-David, Towbin, and Weber (2024) (BTW henceforth) estimate a structural VAR to isolate orthogonal shocks in the national housing market. Our primary interest is in the neighborhood-level effects of the national mortgage rate shock. We briefly summarize the BTW housing shock identification strategy, then describe how we use these shocks to estimate neighborhood housing cost sensitivities.

2.1.1 National Housing Market Shocks

BTW identify a set of four orthogonal shocks in the national housing market: mortgage rate shocks, housing supply shocks, housing consumption shocks, and expectations shocks. Each shock is defined as a specific combination of reduced form innovations within a structural vector autoregression (SVAR). Mortgage rate shocks are structural innovations that decrease real mortgage rates, increase national home prices, increase the quantity of housing, and are orthogonal to the other structural shocks.[2] Each structural shock is normalized to imply an increase in national home prices.

[2]Housing supply shocks are characterized by a reduction in the housing supply and vacancy rates, and an increase in home prices. Housing consumption shocks are designed to capture movements in national home

The reduced form VAR in their paper is given by

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \quad u_t \sim N(0, \Sigma_u), \ \forall t = 1, \ldots, T, \tag{2.1}$$

which has a corresponding structural form

$$B_0 y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + \epsilon_t. \tag{2.2}$$

The model consists of quarterly measures of the real Case-Shiller home price index (ΔP_t), (ΔS_t), vacancy rates (V_t), real mortgage rates (I_t), the rent-to-price ratio (inferred by the rental component of CPI and the nominal Case-Shiller home price index), ($R_t - P_t$), net household formation (ΔHH_t), and real GDP ($\Delta RGDP_t$) such that

$$y_t = (\Delta P_t, \Delta S_t, V_t, I_t, R_t - P_t, \Delta HH_t, \Delta RGDP_t)'. \tag{2.3}$$

Real mortgage rates are defined as the difference between the nominal contract rate on purchases of existing single-family homes and blue-chip, ten-year ahead inflation forecasts. The real home price index, permits, rent-to-price ratio, and real GDP variables enter the VAR as log differences, while mortgage and vacancy rates enter as levels. Each series spans from the first quarter of 1974 to the first quarter of 2018.

The authors construct four mutually orthogonal structural shocks to expectations, mortgage rates, housing supply, and housing consumption by defining unique combinations of simultaneous reduced form innovations u_t in (2.1)[3]. Under the assumption that the VAR is covariance stationary, the structural impulse response functions Θ_i can be used to derive the contribution of each shock to the historical variation of each of the time series in (2.1):

$$\hat{y}_t = \sum_{s=0}^{t-1} \Theta_s \begin{pmatrix} \epsilon_{M,t-s} \\ \epsilon_{HS,t-s} \\ \epsilon_{Exp,t-s} \\ \epsilon_{HC,t-s} \end{pmatrix} = \sum_{s=0}^{t-1} \Theta_s \epsilon_{t-s} \tag{2.4}$$

The left-hand side of equation (2.4) is a vector of predicted values of the time series derived from shocks to expectations, mortgage rates, housing supply, and housing consumption to variables in Equation 2.3 (the historical decompositions). Our objects of interests are the contribution of the structural shocks to national home prices. The decomposition of an arbitrary variable i in the VAR system is given by

$$\hat{y}_{i,t} = \sum_{s=0}^{t-1} \sum_{j=1}^{4} \theta_{ij,s} \epsilon_{j,t-s}, \tag{2.5}$$

prices driven by consumers upgrading their current home or moving to larger homes. They are defined by an increase in the housing supply, higher mortgage rates, and lower vacancies. Price expectation shocks are characterized by increases in home prices, the housing supply, vacancies and mortgage rates.

[3]In practice, the procedure leverages Bayesian estimation methods and employs normal inverse-Wishart priors over the reduced form VAR coefficient matrices (A_i) and covariance matrix (Σ_u). When combined with the sampling algorithm of Rubio-Ramírez, Waggoner, and Zha (2010) the reduced form draws are transformed to provide estimates of the structural VAR coefficients in (2.2). This procedure uncovers sets of orthogonal shocks. We follow BTW and focus on the set of structural shocks that is central to the impulse response distribution.

where $\theta_{ij,s}$, is the impulse response coefficient of variable i, to shock j, at horizon s. Let national home prices, P_t, be the first equation in the VAR, and $\epsilon_{M,t}$ be the first element of ϵ_t. We use equation (2.5) to express the contribution of mortgage rate shocks to home prices as $M_t \equiv \hat{y}_{1,t}^{(1)} = \hat{P}_t^M$.

$$M_t \equiv \hat{y}_{1,t}^{(1)} = \hat{P}_t^M = \sum_{s=0}^{t-1} \theta_{PM,s} \epsilon_{M,t-s} \tag{2.6}$$

The contribution of the housing supply, expectation shocks, and housing consumption shocks are defined in the same manner, which we denote HS_t, Exp_t, and HC_t, respectively.

2.1.2 Neighborhood Housing Cost sensitivities

For each zip code, we estimate the sensitivity of housing costs to the evolution of national home values driven by each of the structural housing market shocks. We are interested in the sensitivity to the component of national home values driven by mortgage rate shocks, but we include other historical decompositions as controls. Our specification is run at the quarterly frequency, and we include a host of additional controls to isolate the role of mortgage rate shocks. Specifically, we estimate

$$c_{it} = \beta_{c,i}^{M} \Delta M_t + \beta_{c,i}^{HS} \Delta HS_t + \beta_{c,i}^{Exp} \Delta Exp_t + \beta_{c,i}^{HC} \Delta HC_t + \sum_{j=0}^{p} X_{i,t-j} \beta_{c,i,j} + \alpha_{c,k} + \epsilon_{cit}. \tag{2.7}$$

Where c_{it} is the year-over-year (four-quarter) growth of either the housing (ZHVI) or rental (ZRI) index for zip code i at time t. $\Delta M_t, \Delta HS_t, \Delta Exp_t, \Delta HC_t$ denote the respective year-over-year changes in the structural decompositions of national home prices due to mortgage rate, housing supply, expectation, and housing consumption shocks. $X_{i,t-j}$ is a vector of macro- and zip-level controls at lag j to capture the contemporaneous and lagged effects from variables such as inflation or local labor market conditions. α_k is a quarter fixed effect that we include to capture any seasonal or time-specific effects on the housing cost response. The object of interest, β_i^M, captures the percentage change in local home values to a unit change in the historical contribution of mortgage rate shocks.[4]

2.2 Heterogeneity

Our cross-sectional analysis explores the differential responses in home costs across zip codes. The primary objectives are twofold. First, we document the distributional effects of mortgage rate shocks by examining the home value and rental responses across zip codes with homogeneous incomes. We classify zip codes based on adjusted gross income (AGI) IRS data, as detailed in Section 2.3 and Table (1). We then regress these sensitivities on the income classifications:

[4]Including additional macroeconomic controls has little effect on the estimates of the coefficient of interest, which indicates that the structural decompositions and local controls sufficiently condition on other factors relevant for local housing costs. We provide summary statistics of alternative specifications in the Appendix.

$$\hat{\beta}^{M}_{c,i} = \gamma_c + \delta_1 VL_i + \delta_2 L_i + \delta_3 MI_i + \delta_4 NC_i + u_{i,c}. \tag{2.8}$$

The controls on the right-hand side of (2.8) are indicator variables corresponding to a zip code being labeled as either very low- (VL_i), low- (L_i), middle-income (MI_i), or not classified (NC_i). The coefficients δ_j reflect the average differences in housing cost responses relative to high-income zip codes across CBSAs. For example, $\delta_1 > 0$ would suggest that very low-income zip codes experience higher appreciation of housing costs, relative to high-income zip codes. We also estimate a version of Specification 2.8 that includes CBSA fixed effects, in which case the coefficients reflect within-CBSA differences across the income groups.

Our second objective is to explore mechanisms that can account for heterogeneity in the estimated sensitivities. The existing literature suggests that local housing market dynamics may depend on a variety of pre-existing factors, such as housing quality, economic demographics, credit conditions, and the land share of property values[5]. We gather data related to these factors in a vector Z_i, using pre-sample measurements, and estimate the following model:

$$\hat{\beta}^{M}_{c,i} = \gamma_c + Z_i'\phi + u_{i,c}. \tag{2.9}$$

Equation (2.9) allows us to quantify the extent to which local characteristics drive heterogeneity in housing costs within and across CBSAs. The coefficients in the vector ϕ capture the marginal impacts of these local factors, providing insights into the mechanisms underlying housing market responses.

2.3 Data

Our analysis leverages an unbalanced panel of home value and rental indices from Zillow[6]. We choose our sample based on periods where we observe both housing costs and the BTW historical decompositions. Due to differences in coverage between the ZHVI and the ZRI, our final sample consists of 17,451 zip codes for the home value regressions (spanning 2000-2017) and 13,389 for the rental specification (spanning 2010-2017). In specifications of equation (2.7) that include additional zip-level controls we use growth rates in employment, firm counts, and earnings derived from the QCEW. Because the QCEW data is reported at the county level, we construct zip-level measurements by taking weighted averages based on the share of zip code residents within a given county for zip codes that are associated with multiple counties.

In our cross-sectional analysis, we classify zip codes as low-, middle-, or high-income using the adjusted gross income (AGI) bins reported in the 2010 IRS Statistics of Income (SOI). The SOI data reports the total number of tax filers and their average AGI for six distinct income bins: (i) Less than \$25,000; (ii) \$25,000 - \$50,000; (iii) \$50,000 - \$75,000 (iv) \$75,000-\$100,000 (v) \$100,000 - \$200,000 (vi) More than \$200,000. Our classifications are constructed

[5]Pre-sample measurements are not available for all the series of interest. For instances where observations are not available in the year 2000 we use the earliest set of observations we can.

[6]We opt for the year-over-year change in these series, but the results are robust to using the level of the decompositions.

using the share of total tax filers within a given AGI bin, as a fraction of the total number of filers within the zip code. For example, if a zip code has 75% of its filers reporting an AGI between $25,000 and $75,000, it would be classified as *Low Income*. Our approach allows us to identify the zip codes that are relatively homogeneous in terms of income so that we can capture any differential responses in housing costs across these areas. Zip codes that have a heterogeneous income profile are not put into one of the income bins and instead labeled as *Not Classified*.

We control for local credit conditions using the zip code level averages of credit growth, credit scores, number of mortgage applications, and income insight scores from Experian and HMDA. The panel structure of the data also allows us to estimate the response of variables like debt-to-income ratios to the same decompositions we use to estimate the housing cost responses.

Table 1: Zip code income classifications.

Class	**Criteria**
Very low income	Share of tax filers with an AGI less than $25,000 exceeds 55%.
Low income	Share of tax filers with an AGI between $25,000 and $75,000 exceeds 55%.
Middle income	Share of tax filers earning between $75,000 and $200,000 exceeds 30% and those earning more than $200,000 are less than 15%.
High income	Share of tax filers earning more than $200,000 is greater than 15%.
Not classified	Areas not meeting any of the criteria above.

Note: This table reports the criteria for the zip code income classifications. Each zip code is sorted into one of the classes listed in the first column, and the criteria for the classification is reported in the second column. When the variables are used in the cross sectional regressions we omit the *High Income* variable so that the marginal effects are measured relative to high income areas. Source: IRS Individual Income Statistics.

We employ Census data from NHGIS to provide measurements of demographic and housing characteristics. The 2000 decennial census is the primary source, but in cases where variables are not available we use ACS 5-year estimates (2007–2011). We measure tightness in local housing markets using vacancy rates, and use median age of the home (as of 2000) as a proxy for housing quality. Additionally, the Census reports data on physical and financial conditions of the housing stock based on survey responses regarding inadequate plumbing, kitchen facilities, overcrowding, and high cost burdens[7]. Because we do not observe which

[7]Households are asked to respond to whether their current unit is: 1) lacking complete plumbing facilities, 2) lacking complete kitchen facilities, 3) with 1.01 or more occupants per room, 4) selected monthly owners costs as a percentage of household income greater than 30 percent, and 5) gross rent as a percentage of household income greater than 30 percent

response the household is reporting, our variable of interest is the number of units reporting multiple conditions as a share of total units in the zip code.[8] As a proxy for local housing supply elasticities, we use population density and the fraction of units within structures of five or more units. We are also able to merge a subset of our zip codes with direct estimates of housing supply elasticities from Guren et al. (2021) and Saiz (2010) , and provide the associated tables in the appendix.

Existing work finds that low-income households are particularly vulnerable to housing demand shocks due to a higher proportion of land costs in property values Murphy (2024). To account for the land cost channel, we incorporate property value data from Davis et al. (2021), which provides zip-code-level estimates of the average land value share. Furthermore, we control for the effects associated with local regulatory conditions using the Wharton Residential Land Usage Regulation Index (WRLURI) from Gyourko, Hartley, and Krimmel (2021).

3 Empirical results

We begin by summarizing the distributions of our housing cost sensitivities (β_i^M from Equation 2.7). Sensitivity coefficients for each housing cost exhibit fairly symmetric distributions. The home value coefficients, depicted in Figure (1a), have a mean of 1.1 suggesting that local home values tend to appreciate by about 1% when national home values appreciate by 1% driven my mortgage rate shocks. The rental coefficients, depicted in Figure (1b) exhibit much flatter responses, with an average of roughly -0.23 (i.e. a decline of 23 basis points). In other words, our findings are directly in line with basic economic theory. Lower mortgage rates lead to higher demand for homes, and slightly less demand for rentals across US zip codes. These average responses are in line with the effects of monetary policy on national rental prices documented in Dias and Duarte (2019).

Table 2: Distributional statistics of the home value and rental sensitivities

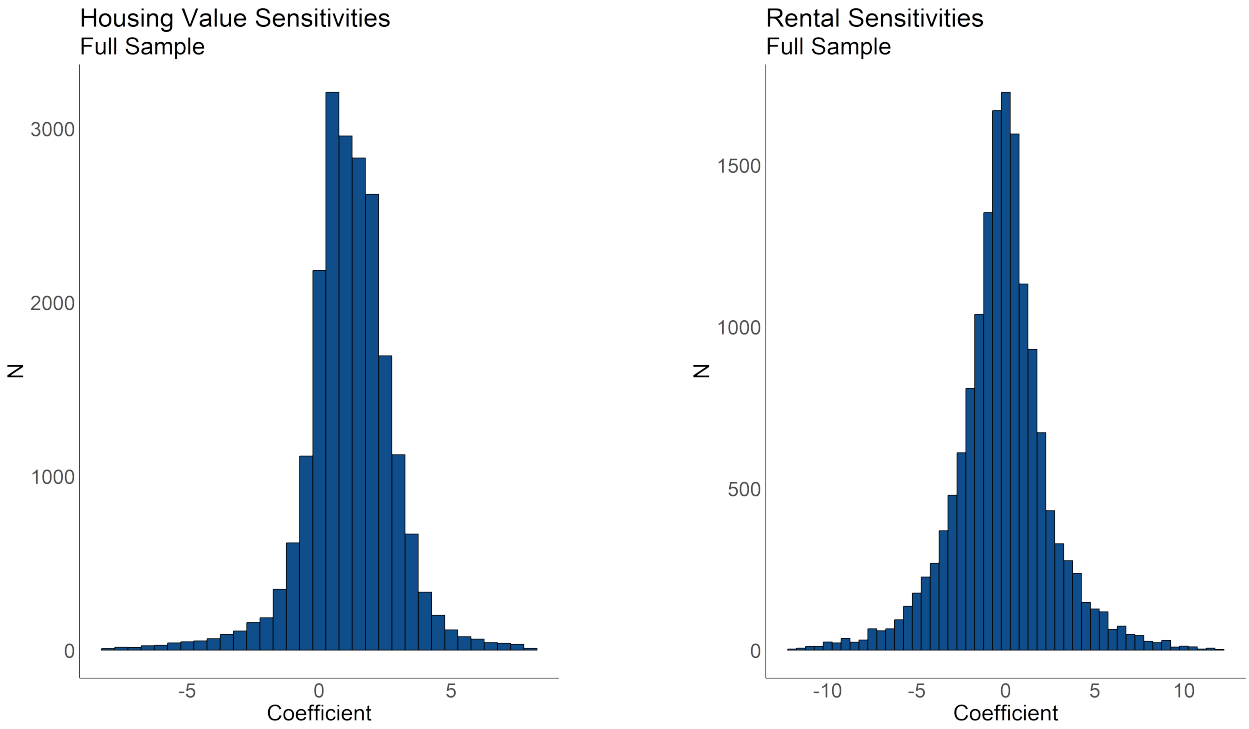
	P.25	Mean	P.50	P.75	P.90	N
β_{HV}^M	0.303	1.161	1.121	2.041	2.908	17,451
$se(\beta_{HV}^M)$	0.149	0.372	0.247	0.429	0.756	17,451
β_R^M	−1.505	−0.211	−0.177	1.091	2.711	13,389
$se(\beta_R^M)$	0.484	1.048	0.807	1.353	2.082	13,389

Note: The table presents the distributional statistics associated with the home value (β_{HV}^M) and rental (β_R^M) sensitivities and their associated standard errors. The columns P.25, P.50, P.75, and P.90 denote the values at the 25th, 50th, 75th and 90th percentiles, respectively.

The distributional statistics in Table 2 indicate that local home values tend to move fairly closely with national trends and have more precisely estimated responses. The rental dis-

[8] In Section 4 we explicitly control for the number of units reporting two or three or more conditions as a share of total units within the zip code.

tribution has a fatter left tail and much larger standard errors. One contributing factor to the lack of precision of these estimates is the length of the sample. The earliest observations we have for the ZRI begin in 2011, and the majority of zip codes in our sample don't begin reporting until 2012. Whereas the ZHVI data extend back to 2000.

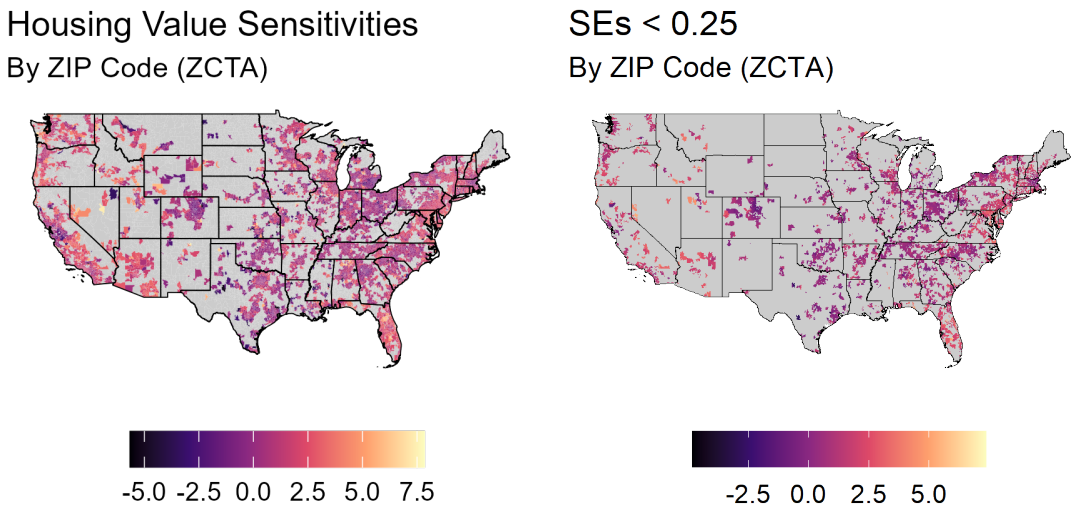


(a) Home Value Sensitivities

(b) Rental Sensitivities

Figure 1: The figures depict the distribution of home value and rental sensitivities to mortgage rates from equation (2.7). The home value sample is from 2000-2017, and the rental sample is from 2010-2017.

The heterogeneity in the estimates is apparent when looking across geographies. Figure 2 reports the distribution of the housing value sensitivities across the continental United States. Due to the limited sample of home values in some of the zip codes we report full sample estimates in Figure (2a), and those with more precise estimates (standard errors $<$ 0.25, slightly less than the 25th percentile) in Figure (2b). The responses of zip codes within the sand states (Arizona, California, Florida, and Nevada) and Pacific Northwest tend to experience sharper increases in home prices. Whereas the majority of areas within the rust and bible belts tend to exhibit dampened or negative responses.



(a) Home Values

(b) Precise Home Value Estimates

Figure 2: Housing value sensitivities by US zip codes. The left panel plots the full sample of estimates, and the right panel plots the sample with standard errors less than 0.25.

3.1 Distributional Effects

Table 3 presents the estimates from equation (2.8). Columns (1) and (2) report coefficients based on housing value sensitivities, whereas columns (3) and (4) show results using rental sensitivities. The findings indicate that lower-income areas experience a higher rate of housing cost appreciation across and within CBSAs. For example, column (1) shows that areas classified as "Very Low Income" exhibit a housing value sensitivity that is 54 basis points higher, on average, than that of high-income areas. The effects, regardless of specification, indicate that areas at middle and lower quantiles of the income distribution experience disproportionately higher appreciations in housing costs.

We also find that areas that did not fit into one of the distinct income bins experience relatively higher housing costs. Unlike the homogeneous groups (e.g. Very Low, Low, and Middle Income), these areas have more heterogeneous income profiles. The positive coefficient for the "Not Classified" areas may partly reflect the influence of gentrification in some neighborhoods. Lower mortgage rates might have spurred additional investment, increased demand for homes, and triggered an inflow of highly educated residents alongside an outflow of lower-income residents, as documented in Murphy (2024). However, income diversity does not necessarily imply gentrification, and the estimate may capture other market dynamics. Further analysis is needed to establish this link in our context.

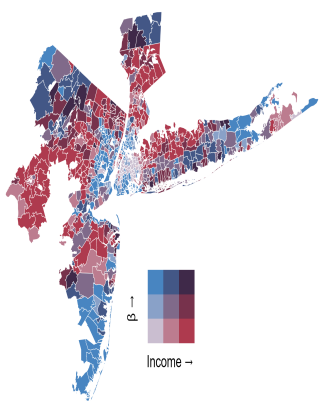
Table 3: Housing cost appreciation by AGI classification

Dependent Variables:	Home price HCS			Rental HCS		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Very Low Income (AGI)	0.54***	0.77***		1.5***	1.5***	
	(0.08)	(0.12)		(0.15)	(0.25)	
Low Income (AGI)	0.32*	0.62***		3.3***	2.6***	
	(0.17)	(0.17)		(0.70)	(0.68)	
Middle Income (AGI)	0.49***	0.48***		0.75***	0.62***	
	(0.05)	(0.07)		(0.14)	(0.17)	
Not Classified (AGI)	0.42***	0.59***		0.96***	0.92***	
	(0.04)	(0.09)		(0.13)	(0.18)	
Median HH Income (2000)			-0.19***			-0.53***
			(0.03)			(0.07)
Fixed-effects						
cbsa		Yes			Yes	
Fit statistics						
Observations	17,139	17,139	17,451	13,322	13,322	13,389

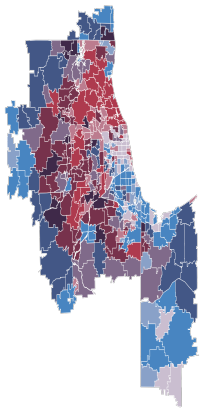
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The variable *High Income* is omitted from the estimated models so that the marginal effects are measured relative to the high-income zip codes. Since every zip code in our sample is categorized into one of the five classes depicted in Table 1, inclusion of the *High Income* variable would induce perfect collinearity in the regressors.

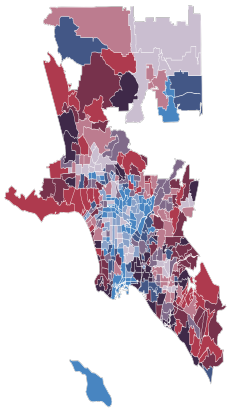
We provide visual context for our home value estimates using bivariate choropleth maps in Figures (3a - 3c) for Chicago, Los Angeles, and New York City. Each region within a map corresponds to a zip code, and the color shading reflects the quantile pairing of the home value coefficient and median household income. Brighter shades of red (blue) reflect higher quantiles of the respective variable. For example, bright red regions are zip codes with low home value sensitivities (first quantile) and high median income (third quantile), bright blue regions are low income high sensitivity areas, and dark purple regions are high income and high sensitivity areas.



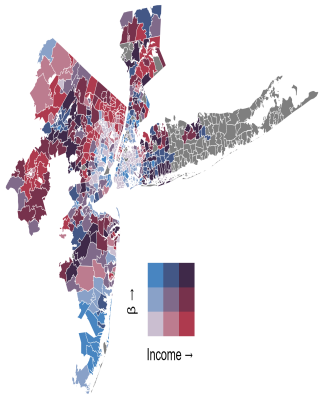
(a) New York City



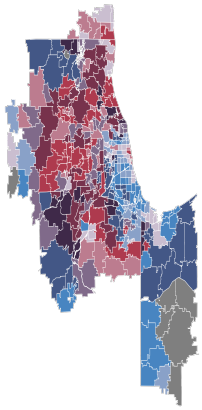
(b) Chicago



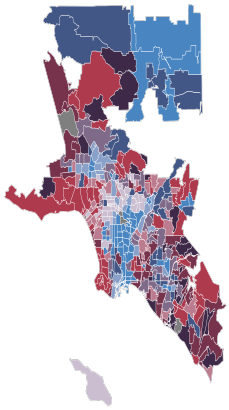
(c) Los Angeles



(d) New York City (Rentals)



(e) Chicago (Rentals)



(f) Los Angeles (Rentals)

Figure 3: The figures depict the relationship between our housing cost sensitivities and median income across the New York City, Chicago, and Los Angeles CBSAs. The first row (panels a-c) depicts the housing value sensitivities, and the second row (panels d-f) use the rental sensitivities.

The results from the choropleth maps align with what we document in Table 3. Within CBSAs, zip codes with lower income levels typically display the most pronounced increases in housing costs, while those in higher-income brackets generally exhibit more subdued sensitivities. Notably, high-income and high-sensitivity zip codes tend to be fairly uncommon.

An immediate question that arises is whether there are substantial differences in the housing and economic characteristics between zip codes in these CBSAs that contribute to the estimated responses. Table 4 reports summary statistics on local credit, housing quality, and amenity characteristics. What is clear in the CBSAs depicted is that the areas with higher HCSs, tend to have lower credit scores and more inelastic housing supplies. The high-income

areas that exhibit larger HCS responses also tend to have much higher natural amenities. We explore the validity of these findings more rigorously in the cross sectional analysis in Section 4.

Table 4: Summary statistics of local characteristics by income-HCS pairings.

Statistic	N	Mean	St. Dev.	Min	Max
Low-income high-HCS					
Vantage score	251	645.290	33.254	569.058	731.386
Presample housing age (median)	251	43.355	9.784	19	61
Home ownership rate	251	41.145	22.174	0.889	89.441
Vacancy rate	251	8.747	11.779	1.866	78.510
WRLURI	173	5.738	11.236	−9.936	21.573
Saiz elasticity	210	0.885	0.328	0.627	1.755
Unemployment rate	251	0.098	0.037	0.000	0.317
Natural amenity index	251	1.939	4.276	−3.580	10.330
High-income high-HCS					
Vantage Score	69	706.531	12.338	675.397	733.709
Presample housing age (median)	69	32.710	10.585	5	61
Home ownership rate	69	73.084	14.352	36.496	96.917
Vacancy rate	69	4.846	4.460	0.859	20.370
WRLURI	64	10.090	9.358	−9.936	21.573
Saiz elasticity	42	0.794	0.258	0.627	1.755
Unemployment rate	69	0.057	0.018	0.016	0.103
Natural amenity index	69	4.658	5.172	−2.850	10.330
High-income low-HCS					
Vantage scores	222	722.049	15.441	658.242	748.160
Presample housing age (median)	222	34.473	14.177	1	61
Home ownership rate	222	78.631	14.055	8.856	94.879
Vacancy Rate	222	4.126	6.063	0.659	65.136
WRLURI	206	6.609	8.113	−9.936	21.573
Saiz elasticity	159	0.951	0.316	0.627	1.755
Unemployment rate	222	0.052	0.021	0.000	0.157
Natural amenity index	222	1.901	3.589	−2.410	10.330

Note: The table reports summary statistics of local housing characteristics in the low-income and high-HCS (blue), high-income low-HCS (red), and high-income high-HCS (purple) groups depicted in Figure 3.

4 Factors driving Heterogeneous HCSs (In progress)

We examine the determinants of the HCS estimates across CBSAs in Table 5. The table depicts the results of estimating equation (2.9) without CBSA fixed effects. We distinguish local factors related to housing demand (e.g. crime and natural amenities) from those related to supply (e.g. housing quality and supply elasticities).

On the demand side, our results—especially in the more precisely estimated subsample—suggest that areas with greater access to natural amenities experience higher pass-through from mortgage rates into housing costs. Crime rates emerge as the largest factor on the demand side, but surprisingly, have different signed coefficients. Higher crime is associated with less pass-through into home values, but *more* pass-through into rental rates. One possible explanation is that homeowners in these areas migrate to areas with lower crime when rates fall. If this were true, then you would expect this to create a surplus of available homes and that may entice renters in the area to purchase a home. However, less demand for rental would manifest as a negative coefficient in these regression which is the opposite of what we find. An alternative explanation is that these findings are indicative of redevelopment activity in high-crime areas, where deteriorating conditions and lower property values might spur investment and renovation efforts.

The largest coefficients are associated with supply factors. Our measurements of housing quality, the share of housing units that report low-quality conditions, and the median pre-sample age of housing units in the zip code, taken together, suggest that areas with lower-quality housing experience less pass-through into home prices and more pass-through into rental rates. These results are intuitive for home values as lower quality should reflect less demand. All else equal, one might expect the same to hold for rentals. Our results again suggest the opposite. Higher shares of low-quality housing units are associated with higher pass-through into rental rents.

We control for population density and the preexisting stock of rentals by calculating the ratio of multi-unit complexes to the total number of housing units in the zip code. In every specification, we find a negative and highly significant association between the multi-unit share and the HCS estimates. Areas with high shares of multi-unit complexes tend to have smaller housing stocks and less demand. On the rental side, the presence of larger units likely indicates a greater supply of rentals and also present more challenges for redeveloping.

Lastly, we control for local land regulations from Gyourko, Hartley, and Krimmel (2021), and the housing supply elasticities from Guren et al. (2021) (GMNS) and Saiz (2010). We find that higher land regulations tend to be associated with slightly higher home value appreciation and slightly lower rental rates. Of these measures, our HCS estimates have the strongest correlations with the GMNS inverse elasticities. The positive sign on these coefficients suggest that ares with more inelastic housing supplies tend to experience larger appreciation in housing costs. These findings are in line with the results from Murphy (2024).

Table 5: Cross zip regressions: local demand and supply factors

Dependent Variables:	Home price HCS		Rental HCS	
Model:	(1)	(2)	(3)	(4)
Demand				
Natural amenity index	0.008	0.02***	-0.04***	0.04**
	(0.007)	(0.007)	(0.01)	(0.02)
Total arrests (log)	-0.09***	-0.11***	0.18***	0.18***
	(0.01)	(0.01)	(0.03)	(0.03)
Supply				
Poor housing conditions share	-1.8**	-2.4**	2.4**	1.9
	(0.70)	(0.94)	(1.2)	(1.8)
Median presample housing age (log)	0.10***	0.20***	0.08	-0.04
	(0.03)	(0.03)	(0.07)	(0.07)
Multi-unit share	-0.76***	-1.2***	-3.4***	-1.6***
	(0.22)	(0.23)	(0.41)	(0.56)
Saiz elasticity	-0.08***	-0.10***	-0.05	-0.03
	(0.02)	(0.02)	(0.04)	(0.06)
GMNS inv elasticity	0.64***	0.78***	0.34***	0.59***
	(0.05)	(0.05)	(0.11)	(0.17)
WRLURI	0.04***	0.04***	-0.003	-0.04***
	(0.004)	(0.003)	(0.007)	(0.008)
Other				
Home ownership rate	-0.007**	-0.009***	-0.04***	-0.01*
	(0.003)	(0.003)	(0.005)	(0.007)
Vacancy rate	0.009***	0.006*	-0.009	0.0008
	(0.003)	(0.003)	(0.007)	(0.01)
Fit statistics				
Observations	6,982	4,038	5,413	1,749
R^2	0.09687	0.23306	0.04038	0.06812

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Columns (1) and (3) correspond to full sample estimates based on zip codes that have both HSC estimates and values for the regressors. Column (2) is the subset with home value HCSs standard errors less than 0.25. Column (4) is the subset of rental HCSs with standard errors less than 0.5.

4.1 Quantity Sensitivities (Forthcoming)

4.2 Credit Factors (Forthcoming)

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Appendix

A Appendix Tables and Figures

Table A.0.1: Distributional of the home value and rental sensitivities (precise)

	P.25	Mean	P.50	P.75	P.90	N
β_{HV}^{M}	0.375	1.115	1.020	1.816	2.471	$8,829$
$se(\beta_{HV}^{M})$	0.105	0.149	0.151	0.197	0.227	$8,829$
β_{R}^{M}	-0.889	-0.105	-0.063	0.723	1.604	$3,533$
$se(\beta_{HV}^{M})$	0.253	0.333	0.344	0.424	0.470	$3,533$

Note: The table presents the distributional statistics associated with the home value sensitivities for the subsample with standard errors less than 0.25, and rental sensitivities with standard errors less than 0.5.

Table A.0.2: Summary Statistics (full sample)

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max	N
Housing Value Beta	1.16	1.50	−5.66	0.30	1.12	2.04	7.84	17,451
Rental Beta	−0.21	2.50	−8.94	−1.50	−0.18	1.09	8.55	13,389
WRLURI	1.26	4.78	−10.69	−0.79	0.32	2.12	21.57	11,148
In-migration share	9.36	4.82	0.00	6.16	8.72	11.76	53.30	17,451
Poor housing conditions share	0.02	0.03	0.00	0.004	0.01	0.02	0.34	17,451
Land Share (std)	0.24	0.16	0.02	0.14	0.19	0.29	2.00	14,770
Median Age (log)	3.72	0.16	2.97	3.63	3.73	3.82	4.30	17,451
log Pop Density	5.83	2.04	−1.27	4.22	5.66	7.59	11.68	17,451
Median Contract Rent (log)	6.13	0.39	4.60	5.86	6.10	6.39	7.60	17,451
Median Income 1999	45,289.36	16,886.94	7,236	34,243	41,667	52,325.5	200,001	17,451
Median Income 2010	57,276.73	22,745.62	2,499	42,056	52,515	67,140	250,001	17,449
Median Inc Growth 2000-2010	−7.48	15.75	−343.81	−16.19	−7.59	0.83	131.29	17,449
Unemployed Prime Age Workers	0.23	0.09	0.00	0.18	0.22	0.28	1.00	17,447
Δ% Establishments	20.74	26.87	−32.52	2.72	14.16	34.39	248.65	17,440
Δ% Employment	11.60	24.36	−59.51	−1.40	7.22	19.74	1,348.93	17,440
LTV Beta	1.24	4.29	−21.30	−0.85	1.15	3.41	26.22	17,387
DTI Beta	0.73	1.86	−7.24	−0.28	0.65	1.67	9.41	17,212
Foreign Born Population Share	6.86	9.73	0.00	1.20	3.08	7.99	79.74	17,451
Home Ownership Beta	0.57	2.06	−5.86	−0.50	0.55	1.61	7.71	13,815
Housing Unit Beta	−0.05	0.20	−1.54	−0.14	−0.03	0.07	0.61	13,831