The Effect of Mortgage Rates on Neighborhood Housing Costs *

Daniel Murphy[†] DeShawn Vaughan[‡]

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Abstract

We estimate zip-level "housing cost sensitivities" (HCS)—the percent change in local home prices or rents per 1% increase in national home prices caused by Ben-David et al. (2024) mortgage-rate shocks. Using Zillow home-value and rent indices for over 13,000 zip codes, we find wide heterogeneity. Across the interquartile range, local home prices rise between 0.3% to 2.0%, while rents range from −1.5% to 1.1%. We find the HCS are strongly regressive: lower-income zips exhibit substantially larger responses for both prices and rents. Zip-level home-price HCS are highly correlated with the city-level inverse supply elasticity of Guren et al. (2021), yet meaningful unexplained variation remains. Beyond supply constraints, we find that demand amplification (natural amenities), land-cost pass-through, and housing-market liquidity all shape HCS. Our results quantify where mortgage-rate movements most strongly transmit into local housing costs and clarify the mechanisms underlying that heterogeneity.

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†University of Virginia Darden School of Business

‡University of Virginia Department of Economics

1 Introduction

Local housing affordability depends on how aggregate housing demand shocks transmit to neighborhood-level home prices and rents. This paper studies that transmission for a specific and policy-relevant shock: changes in borrowing costs. We combine structural estimates of national mortgage-rate shocks from Ben-David et al. (2024, henceforth BTW) with ZIP-code housing data to estimate neighborhood housing cost sensitivities (HCS) at a one-year horizon. Our analysis makes three contributions. First, we estimate short-horizon housing-cost responses to an identified mortgage-rate shock, whereas much of the existing literature studies broader housing-demand shocks over longer horizons. Second, we estimate responses for both home prices and rents, allowing us to distinguish responses in the owner-occupied and rental housing markets. Third, we use the resulting ZIP-level heterogeneity to study how local characteristics shape the pass-through of borrowing-cost changes into housing costs.

Our results show that these distinctions matter. We find substantial dispersion in both home-price and rent HCS across ZIP codes, and locations with stronger home-price responses need not exhibit stronger rent responses. The median rent response is negative, but rents rise in roughly 45% of ZIP codes, indicating that the positive local responses are economically important rather than confined to a small tail of the distribution. Distinguishing the two markets is also important for distributional analysis because low-income households are disproportionately likely to rent. We find that expansionary mortgage-rate shocks generate larger home-price and rent responses in lower-income ZIP codes, implying that declines in borrowing costs can have regressive effects on local housing affordability. We also show that, while home-price HCS are strongly related to the city-level inverse housing supply elasticity of Guren et al. (2021), supply responsiveness alone does not explain the observed heterogeneity.

Our empirical strategy isolates the component of national home-price movements attributable to the mortgage-rate shock in BTW and estimates its pass-through to Zillow home values and rents at a one-year horizon. We condition on the other BTW structural drivers—housing supply, housing consumption, and expectations—as well as local earnings and employment, thereby limiting the extent to which the estimated HCS reflect other aggregate housing shocks or measured local labor-market responses. Because multiple structural models satisfy the identifying restrictions, we augment the BTW identification with narrative restrictions and propagate the resulting set of admissible decompositions through the ZIP-level and cross-sectional regressions. We report both estimates based on the BTW median decomposition and posterior summaries that incorporate this first-stage uncertainty. Our home cost measures are quarterly quality-adjusted Zillow indices covering more than 17,000 ZIP codes for home values since 2000 and more than 13,000 ZIP codes for rents since 2010.

Home-price HCS are estimated relatively precisely for most ZIP codes, while the shorter rental panel produces noisier rent HCS. The median home-price response is positive and the median rent response is negative, consistent with the national-level effects documented by Dias and Duarte (2019), but both distributions exhibit substantial local heterogeneity. Our HCS estimates are closely related to the (inverse) housing supply elasticities estimated at the city level by Guren et al. (2021), but differ in geographic unit (city versus zip code), the nature of the housing demand shock (general versus mortgage-rate shock), and the time horizon. We find it reassuring that despite these differences there is a strong, precisely estimated relationship between our ZIP-level home-price HCS and the city-level GMNS inverse supply elasticity.

With housing-cost sensitivities in hand, we address two primary questions. First, do housing cost sensitivities differ across the income distribution? This question is important for assessing the distributional implications of mortgage-rate changes, including those driven by monetary policy shocks.[1] Second, what are the fundamental drivers of heterogeneity in housing cost sensitivity? Home-price responses to housing demand shocks have traditionally been interpreted through the lens of housing supply elasticities. However, price changes in response to demand shocks may reflect supply elasticities, amplification of the initial demand shock, lack of liquidity in local housing markets, or differential pass-through from land prices into housing costs.

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 grouping ZIP codes with relatively homogeneous resident incomes. Using tax-return data from the IRS Individual Income Statistics, we classify these ZIP codes into one of five income groups —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 lower-income areas experience higher home-price and rental appreciation than high-income areas, while middle income areas also show elevated home-price responses. For example, following a mortgage-rate shock that increases national home prices by 1%, rental prices in very-low- and low-income areas appreciate between 81 and 140 basis points more than in high-income ZIP codes within the same CBSA. Home prices in these areas appreciate roughly 50 basis points more than in high-income ZIP codes. Since most low-income households are renters, the substantially larger rental-price increase in low-income areas implies that mortgage-rate reductions disproportionately increase the cost of living for low-income households.

To explain the heterogeneity in HCS, we organize pre-sample ZIP-code characteristics around five channels: conventional housing-supply constraints, housing-market liquidity, demand amplification through local amenities, financing constraints, and differential pass-through associated with structure quality. The cross-sectional estimates should be interpreted as conditional stylized facts rather than as causal estimates of isolated mechanisms. A given local characteristic can reflect more than one channel, so we form sign predictions for each based on the dominant mechanism each is expected to capture and then assess whether the conditional associations conform to those predictions.

The first channel is conventional housing-supply responsiveness. A positive housing-demand shock should generate greater home-price and rent appreciation where additions to the housing stock are more difficult. We measure this channel primarily using the city-level inverse supply elasticity of Guren et al. (2021), supplemented by the more geographically granular elasticities of Baum-Snow and Han (2024) and an indicator for proximity to down-

[1] Monetary policy shocks account for as much as 64% of the variation in mortgage-rate shocks, as we discuss in Appendix E.

town. Because these measures are generally estimated from longer-horizon responses to broad housing-demand shocks, they need not fully capture the short-run response to the specific mortgage-rate shocks we study.

The second channel is housing-market liquidity. Even for a fixed housing stock, short-run price adjustment depends on the number of homes available for sale and the ease with which buyers and sellers can transact (Head et al., 2014). We use population and homeownership rates to proxy for the thickness of the owner-occupied market, and resident age to proxy for turnover, since older homeowners are less likely to move (Joint Center for Housing Studies, 2023). These variables should matter most for home-price HCS because they more directly describe the market for owner-occupied homes than the supply of rental units.

The third channel—and the channel that is new to this paper—is demand amplification through natural amenities. Existing work generally treats amenities as determinants of the level of local housing demand. We show that amenities can also affect the *sensitivity* of housing demand to borrowing costs. In particular, under broad conditions, lower costs of accessing amenities increase the interest-rate elasticity of housing demand, so an otherwise identical decline in mortgage rates generates a larger outward demand shift in a high-amenity location. Appendix C establishes this result in settings with both immobile and mobile households, and Appendix C.3 embeds it in a model with housing supply, land and structures, and financing constraints. We examine natural amenities as the principal proxy for this mechanism and crime as a local disamenity, although the empirical evidence is considerably sharper for natural amenities.

The fourth channel operates through financing constraints. Mortgage-rate declines can amplify housing demand by extending credit to households near the margin of mortgage access (Mian and Sufi, 2009; Bhutta and Ringo, 2021). At the same time, lower rates do not directly relax a binding down-payment requirement, so high housing values can dampen the demand response among prospective buyers who are liquidity constrained (Fuster and Zafar, 2021; Davis et al., 2020; Greenwald and Guren, 2025). We use pre-sample mortgage denial rates to proxy for the extensive margin of credit access. We use land values and, more directly, the ratio of home values to renter income to proxy for the down-payment burden facing households near the margin of homeownership. The two credit margins have opposing predictions: a larger pool of households near mortgage approval can amplify the shock, whereas more binding down-payment constraints can attenuate it.

The fifth channel is differential pass-through associated with structure quality. In Murphy (2024), housing-demand shocks bid up the price of land, while structures constitute a separately valued component of the housing bundle. The resulting pass-through into total housing costs is stronger where structures are less valuable conditional on land values. We therefore use median housing age and direct estimates of structure values from Davis et al. (2021) to capture this channel.

The empirical results are broadly consistent with the predictions implied by these channels. Across CBSAs, conventional supply responsiveness is central: the GMNS inverse supply elasticity is strongly related to home-price HCS and accounts for more than half of the variation explained by our observable characteristics. Natural amenities are the next most important predictor of home-price HCS across CBSAs. The positive coefficient on natural amenities supports the new demand-amplification mechanism: mortgage-rate shocks generate larger home-price responses in locations where natural amenities make housing demand more sensitive to borrowing costs. The evidence for amplification through mortgage access is weaker, as the coefficients on pre-sample denial rates are generally imprecise.

Within CBSAs, structure quality and housing-market liquidity are the most prominent correlates of home-price HCS. Structure values are negatively associated with both home-price and rent HCS conditional on land values, consistent with stronger pass-through where structures constitute a smaller or lower-quality component of housing value. Higher homeownership rates are also associated with lower home-price HCS, consistent with thicker owner-occupied markets attenuating short-run price responses. Higher land values and higher home-value-to-renter-income ratios are associated with lower home-price HCS, although the latter relationship is imprecisely estimated after propagating first-stage uncertainty. We interpret these negative relationships as evidence consistent with down-payment constraints.[2]

We interpret the dependence of HCS on ZIP characteristics through the lens of the mechanism associated with each category. To assess the likelihood that each underlying mechanism is indeed responsible for the estimated relationships, we separately derive ZIP-code-level debt-to-income sensitivities (DS) that capture the responsiveness of consumer leverage to national home-price fluctuations driven by mortgage-rate shocks. The ZIP-level DS are estimated analogously to the HCS and similarly exhibit substantial dispersion across ZIP codes. For each characteristic, we hypothesize its conditional relationship to DS given the observed relationship to HCS. For example, the large influence of natural amenities on home-price sensitivity implies that natural amenities should also be associated with stronger DS because debt is typically required to finance the purchase of more expensive homes. We then test the relationship between DS and ZIP characteristics. The relationships between DS and ZIP characteristics generally align with the hypothesized patterns.

Taken together, the results show that a conventional housing-supply elasticity is not sufficient to characterize the short-run local incidence of mortgage-rate shocks. Pass-through also depends on whether local demand is amplified by amenities, whether the owner-occupied market is liquid, whether marginal buyers face binding financing constraints, and how housing value is divided between land and structures. These channels also operate differently in owner-occupied and rental markets. Understanding the distributional effects of changes in borrowing costs therefore requires attention not only to the average national housing response, but also to the local characteristics that govern the size and composition of that response.

1.1 Related literature

A large body of research has been devoted to estimating the response of home prices or the stock of housing to housing demand shocks at the city level (e.g., Saiz, 2010; Guren et al.,

[2] Land values are equilibrium outcomes that reflect several forces, including amenity capitalization, supply scarcity, and the financing burden facing marginal buyers. Conditional on natural amenities, supply responsiveness, structure values, and the other controls, the negative land-value coefficient is consistent with high required down payments dampening the response to lower mortgage rates.

2021) and, more recently, at the census tract level (Baum-Snow and Han, 2024). Much of this work estimates elasticities over long-term (5+ year) horizons. We contribute to this literature by estimating short-horizon (one-year) housing-cost responses to an identified mortgage-rate shock. We also examine both major forms of housing costs —home prices and rents —whereas much of the prior literature has focused primarily on home prices. Our analysis reveals that locations with stronger home-price responses need not have stronger rental-price responses. Since most low-income households are renters, distinguishing between these two forms of housing costs is particularly important for understanding the distributional implications of housing demand shocks.

Our results also complement recent evidence that, at the CBSA level and over long horizons, the effects of housing-demand growth on prices and quantities are not well explained by standard measures of housing supply elasticities (e.g., Louie et al., 2025). Relatedly, Davidoff (2013) finds little role for supply elasticity in the cross section of the 2000s boom–bust, and Davidoff (2016) reinforces this point by showing that such elasticities are correlated with observable demand-side factors. In contrast, we focus on short-horizon effects of mortgage-rate shocks at the ZIP level and show that, while external CBSA-level measures of supply responsiveness such as GMNS are relevant, there remains an important role for cross-sectional heterogeneity in demand-shock amplification at the ZIP level. We further relate this amplification to underlying local characteristics, including amenities, market liquidity, and credit conditions.

Our evidence that expansionary mortgage-rate shocks increase housing costs more in low-income ZIP codes contributes to a growing literature on the effects of macroeconomic shocks on inequality. Recent work (e.g. Auclert, 2019; Auerbach et al., 2025; Coibion et al., 2017; Kaplan et al., 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 larger increases 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 highlighted in prior work.[3]

Our distributional findings are closely related to Murphy (2024), which documents that broad housing-market expansions generate stronger home-price and rent appreciation in lower-income downtown neighborhoods. Rather than interpreting our findings as establishing the existence of this regressive housing-cost channel for the first time, we directly identify and quantify its operation for a specific aggregate shock. We use structurally identified mortgage-rate shocks to estimate nationwide ZIP-level responses of both home prices and rents, show that the distributional pattern extends beyond downtown neighborhoods, and assess which local characteristics govern the strength of pass-through.

Methodologically, our approach uses aggregate structural shocks to identify heterogeneous local responses, as in Coibion et al. (2017) and Cloyne et al. (2019). Unlike designs based on cross-sectional exposure to external monetary-policy instruments, we use historical decom-

[3] In Appendix Table E.4.12, we document that most of the variation in BTW mortgage-rate shocks is explained by prior monetary-policy shocks.

positions from a structural housing-market VAR to isolate the contribution of mortgage-rate shocks to national home prices. We then propagate uncertainty over the admissible structural models through the ZIP-level and cross-sectional regressions. This approach delivers shock-specific local pass-through measures while preserving uncertainty from the aggregate identification stage.

2 Data and Methodology

Our empirical analysis proceeds in two steps. First, we estimate ZIP-code-level housing cost sensitivities (HCS) to aggregate mortgage-rate shocks using quarterly data on local home prices and rents. Second, we use cross-sectional variation in these HCS estimates to study two questions: how mortgage-rate shocks affect housing affordability across the income distribution, and which local characteristics account for heterogeneity in pass-through across places.

A central challenge is that mortgage rates, local housing costs, and local economic conditions are jointly determined. Our approach addresses this challenge by combining structural estimates of aggregate housing-market shocks from BTW with local housing-market data. The key idea is to isolate the component of national home-price movements attributable to mortgage-rate shocks, then estimate how strongly that component transmits to ZIP-code home prices and rents. We also propagate uncertainty from the first-stage structural decomposition into the ZIP-level and cross-sectional regressions. Appendix D provides full details.

2.1 Estimating Neighborhood Housing Cost Sensitivities

Ben-David et al. (2024) estimate a structural VAR that identifies orthogonal shocks in the national housing market. Our interest is in the local effects of their mortgage-rate shock. We briefly summarize the BTW identification strategy and then describe how we use the implied historical decompositions to estimate neighborhood housing cost sensitivities. Because our empirical object is local pass-through rather than the aggregate VAR itself, we keep the discussion of the national model concise here and provide additional details in Appendix D.

2.1.1 National Housing Market Shocks

BTW identify four mutually orthogonal shocks in the national housing market: mortgage-rate shocks, housing-supply shocks, housing-consumption shocks, and expectation shocks. Identification is based on sign restrictions on the responses of national housing-market variables, and each accepted shock is normalized to imply an increase in national home prices. We use the posterior draws from this model to recover the contribution of each structural shock to national home-price movements over time.

Let y_t denote the vector of aggregate housing-market variables in BTW, and let Θ denote a posterior draw of the structural parameters. For each accepted draw, the model implies a sequence of structural shocks, impulse responses, and historical decompositions. Our object of interest is the historical contribution of the mortgage-rate shock to national home prices, since this is the component that we use to estimate local housing-cost pass-through.

The reduced form VAR in their paper is given by

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

which has a corresponding structural form

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

The model consists of quarterly measures of the real Case-Shiller home price index (ΔP_t), housing permits (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.

For a given draw of the reduced form parameters, the structural coefficients, $\Theta = (B_0, B_+)$, are constructed using the mappings $A_j = B_0^{-1} B_j$, and $\mathbb{E}[u_t u_t'] = \Sigma_u = (B_0 B_0')^{-1}$, where $B_+ = [B_1, \ldots, B_p, c]$. Define the companion matrix

$$\mathcal{A}(\Theta) = \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ \mathbf{I}_n & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_n & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & & \ddots & & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I}_n & \mathbf{0} \end{bmatrix}. \tag{2.4}$$

and let $J = [\mathbf{I}_n \ \ \mathbf{0}_{n \times n(p-1)}]$. The structural impulse response matrix at horizon k is

$$\mathbf{\Psi}_k(\Theta) = J \, \mathcal{A}(\Theta)^k \, J' \, B_0^{-1}, \tag{2.5}$$

so that element (i, j) of $\mathbf{\Psi}_k(\Theta)$, denoted $\psi_{ij,k}(\Theta)$, gives the response of variable i to shock j at horizon k.

Each of the four structural shocks is identified by imposing sign restrictions on $\psi_{ij,k}(\Theta)$ over the first K horizons. Mortgage-rate shocks are structural innovations that decrease real mortgage rates, increase national home prices, and increase the quantity of housing. Housing-supply shocks are characterized by a reduction in the housing supply and vacancy rates, and an increase in home prices. Housing-consumption shocks capture movements in national home prices driven by consumers upgrading or moving to larger homes; they are defined by an increase in the housing supply, higher mortgage rates, and lower vacancies. Expectation shocks are characterized by increases in home prices, the housing supply, vacancies, and mortgage rates. A candidate draw Θ is retained only if the implied impulse responses satisfy all of these restrictions.[4] Each structural shock is normalized to imply an increase in national home prices.

Given an accepted draw Θ, the structural shocks are recovered from the reduced form residuals as $\epsilon_t(\Theta) = B_0\, u_t$. The historical decomposition expresses each variable as the cumulative contribution of all structural shocks from the beginning of the sample:

$$\begin{aligned} \hat{y}_{i,t}(\Theta) &= \sum_{k=0}^{t-1}\sum_{j=1}^{n} \psi_{ij,k}(\Theta)\, \epsilon_{j,t-k}(\Theta), \\ &= \sum_{k=0}^{t-1} \mathbf{\Psi}_k(\Theta) \begin{pmatrix} \epsilon_{M,t-k} \\ \epsilon_{HS,t-k} \\ \epsilon_{Exp,t-k} \\ \epsilon_{HC,t-k} \\ \tilde{\epsilon}_{t-k} \end{pmatrix}. \end{aligned} \tag{2.6}$$

Equation (2.6) expresses each aggregate variable as the cumulative contribution of the identified structural shocks, and the 3×1 vector of unidentified residual shocks in the system $\tilde{\epsilon}_{t-k}$. In our application, the relevant object is the contribution of mortgage-rate shocks to national home-price growth.

The historical decomposition can also be expressed over a particular event period as shown in Antolín-Díaz and Rubio-Ramírez (2018). The contribution of the jth shock to the unexpected change in variable i over an event window $[t, t+h]$ is

$$H_{ij,t,t+h}(\Theta) = \sum_{\ell=0}^{h} \psi_{ij,\ell}(\Theta)\, \epsilon_{j,t+h-\ell}(\Theta), \tag{2.7}$$

which isolates the cumulative effect on variable i of the realizations of shock j between dates t and $t+h$, propagated through the impulse response function.

Our objects of interest are the contributions of the structural shocks to national home prices. Let $\epsilon_{M,t}$ denote the structural mortgage-rate shock. The contribution of the structural mortgage-rate shocks to home prices is

$$M_t^{(\Theta)} \equiv \hat{P}_t^{M}(\Theta) = \sum_{k=0}^{t-1} \psi_{PM,k}(\Theta)\, \epsilon_{M,t-k}(\Theta). \tag{2.8}$$

The contributions of the housing-supply, expectation, and housing-consumption shocks are defined analogously and denoted $HS_t^{(\Theta)}$, $Exp_t^{(\Theta)}$, and $HC_t^{(\Theta)}$, respectively. Figure 1 reports

[4] 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 et al. (2010) the reduced form draws are transformed to provide estimates of the structural VAR coefficients in (2.2).

the year-over-year changes in the median historical decompositions over our sample period. These series provide the aggregate shock variation that underlies our ZIP-level pass-through estimates.

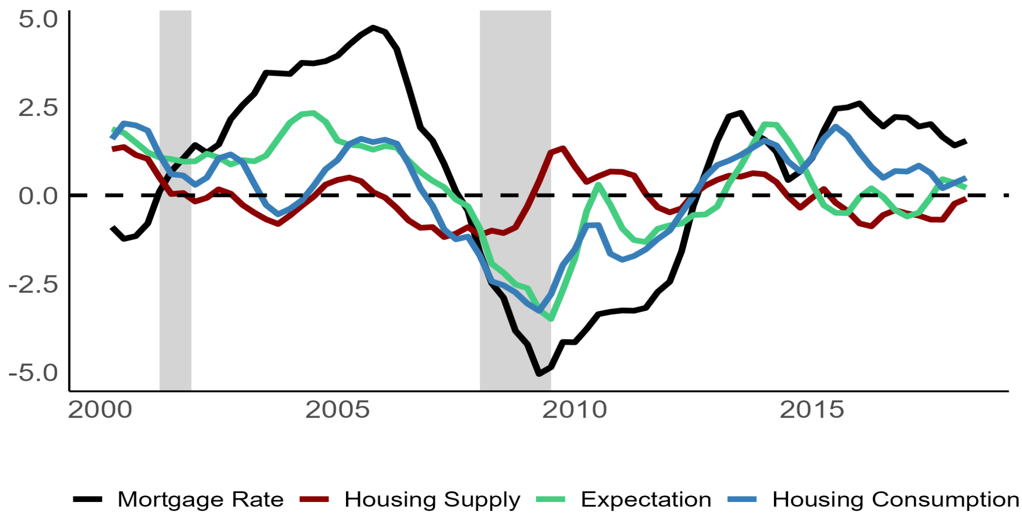


Figure 1: The figures depict the year-over-year changes in the BTW historical decompositions from 2000–2017.

2.2 Identification with Narrative Restrictions

The BTW historical decompositions are summary measures across structural models $\Theta \in \boldsymbol{\Theta}$ that satisfy the identification restrictions. In Appendix D, we provide details on how we account for multiple admissible structural VAR models in our cross-sectional estimates. Here we briefly discuss how we narrow the set of admissible models (and hence limit the uncertainty that propagates to cross-sectional inference) by drawing on narrative episodes of important events in mortgage markets, following the methodology of narrative restrictions from Antolín-Díaz and Rubio-Ramírez (2018, henceforth ADRR). These restrictions sharpen inference on the historical decompositions that we use in the ZIP-level regressions. Since our first-stage objects are generated from a structural VAR, reducing the set of admissible draws improves the precision and interpretability of the downstream HCS estimates.

Narrative restrictions add historical discipline to the usual sign-restriction approach by requiring accepted draws to be consistent with well-understood episodes in mortgage and bond markets. In practice, this discards draws that imply implausible historical decompositions and yields a sharper posterior for the mortgage-rate component of national home prices.

We use three episodes in which sharp mortgage-rate movements can plausibly be linked to mortgage-rate shocks associated with monetary-policy developments: the 1994 bond market episode, the first quantitative easing announcement (QE-1), and the 2013 Taper Tantrum. These episodes are useful because they provide historically grounded information about both the sign of the mortgage-rate shock and its importance in explaining observed rate movements.

As noted by ADRR, the 1994 bond market crash is often attributed to an unanticipated contractionary monetary-policy decision, and the authors also use it as an episode within their monetary-policy VAR. We use QE-1 as a narrative episode because the Fed's asset purchases were directly aimed at stimulating mortgage markets by purchasing agency mortgage-backed securities (MBS). Krishnamurthy and Vissing-Jorgensen (2011) find that these policies were particularly effective in mortgage and MBS markets relative to QE-2, which only targeted Treasuries. The 2013 Taper Tantrum refers to the sharp movement in bond markets following Chairman Bernanke's May 2013 speech suggesting a tapering of asset purchases.

Figure 2 plots the real mortgage-rate series and highlights the episode windows used in the narrative restrictions.

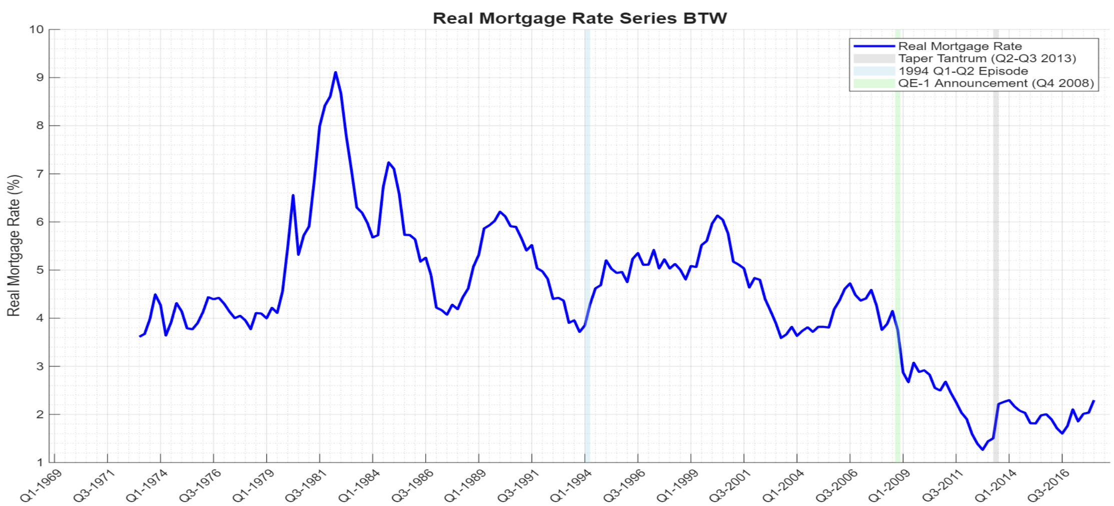


Figure 2: This figure depicts the difference between the nominal contract rate on purchases of existing single-family homes and the 10-year-ahead forecast of the inflation rate. Shaded regions indicate the events used for the narrative restrictions. Data are from Ben-David et al. (2024).

Following Antolín-Díaz and Rubio-Ramírez (2018), we impose two types of restrictions for each episode. First, we require the structural mortgage-rate shock to have the historically appropriate sign over the episode window. Second, we impose that the mortgage-rate shock be the single largest contributor to the unexpected movement in the real mortgage rate during that episode.

More formally, in addition to requiring that the impulse responses $\psi_{ij,k}(\Theta)$ satisfy the sign restrictions described above, the historical decomposition from a candidate draw of the structural coefficients Θ must satisfy

$$\left|H_{ij,t,t+h}(\Theta)\right| > \max_{j' \neq j} \left|H_{ij',t,t+h}(\Theta)\right|, \tag{2.9}$$

which requires that shock j is the single most important contributor to the unexpected movement in variable i over the episode $[t, t+h]$.[5]

At each episode we also enforce that the structural mortgage-rate shock take a particular sign:

$$e'_{j,n}\epsilon_{t_v} \lesseqgtr 0 \quad \text{for } 1 \leq v \leq s_j. \tag{2.10}$$

Table 1 describes the full set of additional narrative restrictions we employ.

Table 1: Narrative Restriction Episodes

Episode	Window	Shock Sign	Key Reference
1994 Bond Market	Q1–Q2 1994	$\varepsilon_{M,t} < 0$	Antolín-Díaz and Rubio-Ramírez (2018)
QE-1 Announcement	Q4 2008	$\varepsilon_{M,t} > 0$	Krishnamurthy and Vissing-Jorgensen (2011)
2013 Taper Tantrum	Q2–Q3 2013	$\varepsilon_{M,t} < 0$	Sinha and Smolyansky (2022)

Notes: Shock sign refers to the required sign of the structural mortgage-rate shock $\varepsilon_{M,t}$ at each date within the episode window. A negative shock corresponds to contractionary mortgage-rate movements, or increases in rates; a positive shock corresponds to expansionary movements, or decreases in rates.

2.2.1 Neighborhood Housing Cost Sensitivities

Our objective is to estimate how strongly local housing costs respond when mortgage-rate shocks move national home prices. A standard endogeneity problem arises because home prices, mortgage conditions, and local economic outcomes are jointly determined. Our setting is not well suited to a shift-share design because mortgage rates exhibit limited cross-sectional variation across U.S. locations (e.g., Bhutta and Ringo, 2021). Instead, we use the BTW historical decompositions to isolate the component of national home-price growth attributable to mortgage-rate shocks, while controlling for the other identified aggregate housing shocks and for local economic conditions.

For each Θ, we estimate the pass-through of the mortgage-rate component of national home-price growth into ZIP-code home prices or rents. This yields a ZIP-specific coefficient that we interpret as a housing cost sensitivity: the percent change in local housing costs associated with a one percent change in national home prices induced by mortgage-rate shocks.

Specifically, we estimate

$$c_{it} = \beta^{M(\Theta)}_{c,i}\Delta M^{(\Theta)}_t + \beta^{HS(\Theta)}_{c,i}\Delta HS^{(\Theta)}_t + \beta^{Exp(\Theta)}_{c,i}\Delta Exp^{(\Theta)}_t + \beta^{HC(\Theta)}_{c,i}\Delta HC^{(\Theta)}_t + \sum_{j=0}^{p} X_{i,t-j}\beta^{(\Theta)}_{c,i,j} + \alpha_{c,k} + \epsilon^{(\Theta)}_{cit}. \tag{2.11}$$

[5] This is a Type A restriction in the terminology of Antolín-Díaz and Rubio-Ramírez (2018). Their Type B restriction replaces the max with a sum over $j' \neq j$, requiring the contribution of shock j to exceed the combined absolute contributions of all other shocks. See their equations (6)–(9).

In equation (2.11), c_{it} is the year-over-year growth rate of either the Zillow Home Value Index (ZHVI) or the Zillow Rental Index (ZRI) for ZIP code i at time t. The variables $\Delta M_t^{(\Theta)}$, $\Delta HS_t^{(\Theta)}$, $\Delta Exp_t^{(\Theta)}$, and $\Delta HC_t^{(\Theta)}$ are the year-over-year changes in the mortgage-rate, housing-supply, expectation, and housing-consumption components of national home-price growth implied by the draw of structural coefficients Θ. The vector $X_{i,t-j}$ includes contemporaneous and lagged local controls such as employment and earnings growth, and $\alpha_{c,k}$ denotes quarter (seasonal) fixed effects.

The coefficient of interest, $\beta_{c,i}^{M(\Theta)}$, measures the percent change in local housing costs per one percent increase in national home prices caused by mortgage-rate shocks. Since the decompositions we are utilizing from the VAR are identified at a national level, their associated coefficients are identified off time series variation.[6]

We estimate specification 2.11 for each admissible structural model, including for the summary set of historical decompositions from BTW. For the cross-sectional analysis discussed below, we report results based on the summary BTW historical decomposition along with estimates across the distribution of $\beta_{c,i}^{M(\Theta)}$ from the set of admissible models' historical decompositions. Appendix D provides details.

2.3 Heterogeneity

We use the estimated HCS measures for two distinct cross-sectional exercises. First, we study who is most exposed to mortgage-rate-driven housing-cost increases by examining how HCS varies across the income distribution. Second, we study why HCS differs across locations by relating it to local characteristics that proxy for supply constraints, housing-market liquidity, demand amplification, and land-cost pass-through.

To study distributional exposure, we classify ZIP codes using adjusted gross income (AGI) data from the IRS; Table 3 reports the classification rules. We then estimate:

$$\hat{\beta}_{c,i}^{M(\Theta)} = \delta_0^{(\Theta)} + \delta_1^{(\Theta)} VL_i + \delta_2^{(\Theta)} L_i + \delta_3^{(\Theta)} MI_i + \delta_4^{(\Theta)} NC_i + u_{i,c}^{(\Theta)}. \tag{2.12}$$

The indicators on the right-hand side classify a ZIP code as very low income (VL_i), low income (L_i), middle income (MI_i), or not classified (NC_i), with high-income ZIP codes omitted as the reference group. The coefficients therefore measure how much more or less sensitive each income group is relative to high-income ZIP codes. We also estimate versions with CBSA fixed effects, in which case the coefficients capture within-CBSA differences in exposure across the income distribution.

[6] Including additional aggregate controls has little effect on the estimates of the coefficient of interest, suggesting that the structural decompositions and local controls adequately capture other macroeconomic factors relevant for local housing costs. We use county-level QCEW measures of employment, and earnings, aggregated to the ZIP-code level using population-based crosswalk weights.

3 Determinants of Heterogeneous HCS

Our second cross-sectional exercise asks which local characteristics account for heterogeneity in the estimated HCS measures. Large price responses to demand shocks are often interpreted as evidence of inelastic housing supply. In our setting, however, heterogeneity in pass-through may also reflect amplification of the initial demand shock, limited liquidity in local housing markets, or differential pass-through from land costs into housing costs. We therefore organize the ZIP-level controls according to these four mechanisms: supply constraints, housing-market liquidity, demand-shock amplification, and land-cost pass-through.

Cross-Sectional Empirical Specification Let Z_i denote the vector of pre-sample ZIP-level characteristics. To study the determinants of HCS heterogeneity, we estimate:

$$\hat{\beta}_{c,i}^{M(\Theta)} = \gamma_c + Z_i'\phi^{(\Theta)} + u_{i,c}. \tag{3.1}$$

Equation (3.1) relates the estimated mortgage-rate HCS for ZIP code i to local characteristics measured prior to the sample period. The coefficients in $\phi^{(\Theta)}$ summarize how strongly each characteristic is associated with stronger or weaker local pass-through. Because the dependent variable is itself estimated, we estimate equations (2.12) and (3.1) by weighted least squares, weighting each ZIP code by the inverse variance of its first-stage HCS estimate ($1/\hat{\sigma}_\beta^2$) so that more precisely estimated sensitivities receive more weight, and we cluster standard errors at the CBSA level. Throughout the paper, we report both estimates based on the median historical decomposition and estimates that propagate the first-stage VAR uncertainty.

3.1 Supply Factors

We begin with variables intended to capture conventional housing-supply constraints. These include the city-level inverse supply elasticity of Guren et al. (2021) and the tract-level housing-supply elasticities of Baum-Snow and Han (2024). Because these measures are constructed from longer-horizon responses to housing-demand shocks, they need not fully capture the short-horizon pass-through measured by our HCS estimates. We therefore also include an indicator for whether a ZIP code is near downtown, which may proxy for local scarcity of developable land and related short-run supply constraints (e.g., Couture et al., 2024).

We also consider liquidity-related features of the owner-occupied housing market. The stock of homes available for purchase depends not only on the total housing stock, but also on how easily potential buyers and sellers match. Motivated by Head et al. (2014), we use ZIP-code population, homeownership rates, and resident age as proxies for local housing-market liquidity. Population and homeownership rates proxy for the thickness of the owner-occupied market, while resident age proxies for turnover, since older homeowners are less likely to sell (Joint Center for Housing Studies, 2023). If illiquid markets transmit housing-demand shocks more strongly into prices, these variables should help explain HCS heterogeneity.

3.2 Demand Shock Amplifiers

We next consider mechanisms through which local characteristics may amplify the initial effect of a mortgage-rate shock on housing demand. The core idea is that if the sensitivity of housing demand to borrowing costs depends on local fundamentals, then otherwise similar mortgage-rate shocks can generate different local demand shifts.

3.2.1 Natural Amenities as Demand Amplifiers

Here we briefly formalize how an initial shock to housing demand can have differential effects on the housing demand shift depending on the level of natural amenities; Appendix C provides extended formalization under alternative scenarios for household mobility.

The simple intuition is based on the assumption that the cost of a bundle of housing and amenities depends both on the user cost of housing and the cost of accessing the amenities. In high-amenity areas, the cost of accessing amenities is low, so the user cost of housing accounts for the majority of the cost of the housing bundle. In low-amenity areas, households must pay a transportation cost to access amenities. Interest rate reductions directly affect the user cost of housing but not the (transportation) cost of amenities. Therefore, there is stronger pass-through from interest rates to housing (bundle) costs in high-amenity areas. This leads to stronger increases in housing demand, holding fixed households' nominal incomes.

Consider a representative household's Marshallian demand function,

$$H^d = \frac{I}{c_H + \psi^{-\sigma}(1-\psi)^{\sigma} c_H^{\sigma} c_O^{1-\sigma}}, \tag{3.2}$$

where I is income, c_H are the relevant housing costs, and c_O are other local costs of living. σ determines how easily households are willing to substitute between housing and other local goods O.[7] Housing costs c_H are those that adjust to clear the housing market, whereas c_O includes the price of goods produced non-locally (and hence set on national or international markets) as well as transportation costs. In Appendix C, c_O is the cost of enjoying local amenities (including transportation costs) and c_H is the cost of homes.

Our focus in this paper is on a particular housing-demand shock: a decline in mortgage rates. Following the user-cost model of housing in Poterba (1984), we specify c_H as housing user costs equal to the interest rate r times the asset value of housing V_H,

$$c_H = rV, \tag{3.3}$$

such that for a given interest rate r, V adjusts to clear the housing market.

Definition. Demand-shock amplification occurs when the elasticity of H^d with respect to the interest rate depends on the determinants of housing demand. Specifically, demand-shock

[7]This demand function is based on a CES utility function, as is explicitly shown in Appendix C.

amplification occurs when there exists $x \in \{I, c_O, c_H\}$ such that

$$\frac{\partial}{\partial x}\left(\frac{\partial \ln H^d}{\partial \ln r}\right) \neq 0.$$

This definition is quite inclusive but rules out a unit elasticity of substitution between housing and other goods. In particular, if $\sigma = 1$, then $\frac{\partial \ln H^d}{\partial \ln r} = -1$, which violates the requirement that $\frac{\partial}{\partial x}\left(\frac{\partial \ln H^d}{\partial \ln r}\right) \neq 0$ for some x.

Turning back to the more general case with $\sigma \neq 1$, some algebra yields

$$\frac{\partial \ln H^d}{\partial \ln r} = -\left[\,\sigma - (\sigma - 1)s_H\,\right], \tag{3.4}$$

where s_H is the initial expenditure share on housing: $s_H \equiv (c_H H^d)/I$. Equation (3.4) shows that the housing-demand response to interest-rate changes depends on the initial housing expenditure share when $\sigma \neq 1$. The dominant mechanism depends on whether σ exceeds unity. When $\sigma < 1$, places where housing costs account for a larger share of expenditure experience stronger outward demand shifts when mortgage rates fall. When $\sigma > 1$, lower amenity-access costs still amplify the housing-demand response, but the mechanism is instead substitution between amenities and housing. Under either scenario, since high-amenity locations tend to have higher housing shares of spending, this framework predicts stronger pass-through of mortgage-rate shocks in such places. Appendix C formalizes this mechanism more fully.

3.2.2 Credit Channels

Credit-Expansion Amplification. Mortgage-rate shocks may also be amplified through local credit conditions. Mian and Sufi (2009) and Bhutta and Ringo (2021) show that credit expansions disproportionately improve mortgage access for households near borrowing constraints. This suggests that ZIP codes with more households near the extensive margin of credit access may respond more strongly to mortgage-rate declines.

Credit-Expansion Dampening. At the same time, recent evidence indicates that the quantitative effect of lower mortgage rates on willingness to pay for housing may be modest (Fuster and Zafar, 2021; Davis et al., 2020). A decline in interest rates raises unconstrained housing demand by lowering the flow user cost of owning. However, this demand response is attenuated when marginal buyers are constrained by the down-payment requirement rather than by the user-cost margin. Since the required down payment is proportional to the level of home values, expensive markets — those with high land values or high structures values — have a larger share of marginal buyers for whom lower interest rates do not substantially relax the binding constraint. As a result, the effective interest-rate elasticity of housing demand is lower in high-value markets, muting home-price appreciation. This attenuation can be reinforced if high-value markets are populated by richer or less leveraged households whose housing demand is less sensitive to financing costs.

We therefore view the relative importance of credit amplification and dampening as an empirical question. We consider pre-sample mortgage denial rates as a proxy for households near the extensive margin of credit (which amplify credit expansions), and we examine land values as a proxy for down-payment constraints that dampen credit expansions. To capture down-payment constraints more directly, we also consider the ratio of the ZIP-code median home value to the median income of renter households. Renters constitute the natural pool of prospective first-time buyers, so a higher ratio implies a larger required down payment relative to the resources of households on the margin of homeownership, which should dampen the local demand response to mortgage-rate declines.

3.3 Differential Pass-Through from Land Costs to Housing Costs

A final mechanism is differential pass-through from land costs into housing costs. Murphy (2024) develops a framework in which housing is produced using land and structures, and positive demand shocks primarily bid up land prices. In that environment, the pass-through from demand shocks to housing costs is larger where structures are a smaller share of total housing value. Put differently, areas with lower-quality structures conditional on land values should exhibit stronger housing-cost responses to mortgage-rate shocks.

To capture this channel, we include proxies for the non-land component of housing quality, including median housing age and ZIP-level structure values from Davis et al. (2021).

Summary of Mechanisms. The literature has identified several primary channels through which housing demand shocks (and credit expansions in particular) can influence housing costs. In addition to channels identified by the literature, we propose a new channel through which natural amenities amplify demand shocks. We consider proxies for these channels to assess their quantitative relevance for the effect of mortgage rate shocks on local housing costs. These proxies are jointly determined, of course, and a single measure may proxy for more than one mechanism. For example, high land values may reflect low land supply elasticities or high amenities, and they can also generate down-payment constraints. Even though we classify proxy measures based on the most relevant mechanism, we cannot be sure that any given measure captures a unique mechanism. Rather, we hypothesize how each proxy is expected to influence mortgage-rate pass-through based on the primary relevant mechanism and conditional on other proxies, and we assess the quantitative relevance of each proxy. The empirical estimates provide stylized facts about the local determinants of housing-cost pass-through for local characteristics that proxy for relevant underlying mechanisms. Relative to a more typical approach of isolating plausibly exogenous variation to quantify a single mechanism, this approach provides guidance on the joint relevance of the dominant mechanisms driving housing cost pass-through.

Table 2 summarizes the predicted relationships based on the primary mechanism associated with each proxy. For example, traditional measures of inverse supply elasticities are associated with stronger home price and rental price responses. Conditional on measures of traditional supply elasticities and housing market liquidity, having more households on the margin of credit access can amplify the initial mortgage-rate shock. And conditional

Variable	Correlation with HCS: Home	Rent	Notes
Supply			
Traditional Supply Elasticity			
GMNS (Across)	+	+	Traditional supply elasticity
Near Downtown	+	+	Traditional supply elasticity
Housing Liquidity			
Home Ownership Rate	−	+	Liquid owner-occupied market; less liquid rental market
Median Resident Age	+	?	Illiquid owner-occupied market
Population	−	?	Thicker owner-occupied market
Demand Amplifiers			
Amenities			
Natural Amenity (Across)	+	+	No differential effect unless demand shock amplification
Crime Rate (Within)	−	−	No differential effect unless demand shock amplification
Credit			
Denial Rate	+	?	Extensive margin of credit
Land Value	−	?	Down-payment constraints, conditional on supply elasticity
Home Value to Renter Income	−	?	Down-payment burden of marginal (renter) buyers
Housing Quality			
Median Age of Home (Within)	+	+	Housing quality conditional on land values
Structure Value	−	−	Housing quality conditional on land values

Table 2: Hypothesized correlations with HCS estimates

on these proxies, higher land values can increase down-payment constraints and dampen pass-through. Finally, conditional on land values, higher-quality structures tend to dampen the effect of housing demand shocks on housing costs (Murphy, 2024). Appendix C presents the mechanism that is new to this paper (amenity-based demand amplification), and Appendix C.3 presents a model that jointly formalizes the predicted roles of housing supply, amenity-based amplification, credit frictions, and structure-quality-based pass-through.

3.4 Data

This subsection describes the construction of the local housing-cost measures and the ZIP-level characteristics used in the cross-sectional analysis. Unless otherwise noted, all covariates are measured prior to the estimation sample so that they can be interpreted as pre-determined correlates of HCS heterogeneity. Table A.2.1 summarizes each variable, its source, vintage, and native geography; Appendix A provides additional detail on variable construction.

3.4.1 Housing Costs

Our housing-cost data come from Zillow's quality-adjusted home-value and rent indices.[8] We select the sample to align with the period over which the BTW historical decompositions

[8]Appendix A summarizes the construction of the ZHVI and ZRI and discusses differences in their quality adjustment.

are available and with the coverage of the Zillow series. The final sample contains 17,451 ZIP codes for home values over 2000–2017 and 13,389 ZIP codes for rents over 2010–2017.

3.4.2 Income

We classify ZIP codes by income using adjusted gross income (AGI) bins from the 2010 IRS Statistics of Income. The data report the number of filers and average AGI in six income bins. We use the shares of filers in each bin to classify ZIP codes as very low income, low income, middle income, high income, or not classified. Table 3 reports the classification rules. The purpose of this classification is to identify ZIP codes with relatively homogeneous resident incomes and to compare their exposure to mortgage-rate-driven housing-cost changes.

Table 3: Zip code income classifications.

Class	**Criteria**	**Share**
Very low income	Share of tax filers with an AGI less than $25,000 exceeds 55%.	.05
Low income	Share of tax filers with an AGI between $25,000 and $75,000 exceeds 55%.	.07
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%.	.10
High income	Share of tax filers earning more than $200,000 is greater than 15%.	.02
Not classified	Areas not meeting any of the criteria above.	.75

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.

3.4.3 Supply Factors

We consider several measures of housing supply elasticity from the literature, including the CBSA-level elasticities of Saiz (2010) and Guren et al. (2021), and the tract-level measures of Baum-Snow and Han (2024). Our baseline across-CBSA specifications use the inverse elasticity from Guren et al. (2021), although the results are similar when we use Saiz (2010). We do not include the tract-level BSH elasticities in the baseline because they have limited explanatory power for our HCS estimates and because their interpretation is tied to a different shock and a longer horizon. Appendix B shows that including them does not materially change the main results.

Motivated by Couture et al. (2024) and Murphy (2024), we also include an indicator for whether a ZIP code is near downtown. This variable provides an alternative proxy for short-run scarcity and local supply tightness within CBSAs.

Housing Liquidity. We interpret housing liquidity through a search-and-matching lens: markets are more liquid when there are more sellers, such that matches with buyers are more likely. Our main proxies are pre-sample homeownership rates, resident age, and total population from the 2000 Census which we query from NHGIS[9].

3.4.4 Demand Factors

Our main demand-side variables are natural amenities and crime. Natural amenities are measured using the USDA Economic Research Service Natural Amenities Scale, a time-invariant county-level index based on climate, topography, and water access. We assign values to ZIP codes using county crosswalks. Because this measure varies primarily across rather than within CBSAs, it is most informative in regressions without CBSA fixed effects.

Crime is measured as the median annual county arrest rate per 100,000 residents over the pre-sample window 1991–2000, constructed from the county-level files of the FBI Uniform Crime Reporting (UCR) program. We construct an analogous rate for offenses known to police from the compiled UCR panel of Kaplan (2024). A limitation of these data is that reporting to the UCR is voluntary, so the set of agencies reporting within a county varies across counties and years. Appendix A details the construction and its limitations; because agency coverage is incomplete and non-random, the crime measures are likely measured with error, which may attenuate estimates of their influence on HCS toward zero.

Credit Conditions To measure local credit conditions, we construct pre-sample mortgage denial rates using 1996 HMDA data. Following Mian and Sufi (2009), we interpret higher denial rates as proxies for tighter credit conditions and greater scope for mortgage-credit expansions to amplify local responses. We compute denial rates as the ratio of denied applications to accepted-plus-denied applications after excluding pre-approvals, purchased loans, withdrawn applications, incomplete applications, and approvals not accepted. To proxy for the down-payment burden facing marginal buyers, we construct the ratio of the ZIP-code median home value to the median household income of renter-occupied households, with both inputs taken from the 2000 Census (Schroeder et al., 2025).

In Section 4.2.2 we use ZIP-level debt-to-income ratios from Experian as an auxiliary outcome. Because debt is required to finance more expensive owner-occupied housing, these data provide a useful way to assess whether the mechanisms that predict stronger HCS also predict stronger leverage responses.

3.4.5 Housing Quality

Across CBSAs, we proxy for housing quality using median housing age from the 2000 Census. Within CBSAs, we exploit estimates of land and structure values from Davis et al. (2021).

[9]NHGIS refers to the National Historical Geographic Information System, maintained by IPUMS (Schroeder et al., 2025).

4 Empirical Results

We begin by summarizing the distribution of the ZIP-level housing cost sensitivities implied by equation (2.11) when the first stage is evaluated at the median historical decomposition. Next, we estimate the dependence of home price and rental HCS on zip code characteristics. In the cross-zip regressions, we report the point estimates from the median BTW historical decomposition, along with credible intervals based on accepted narrative-restriction posterior draws of structural VAR models.

Two patterns are immediate from the HCS estimates derived from the BTW median historical decompositions. First, the distribution of home-price HCS are centered well above zero and are estimated relatively precisely for most ZIP codes. Second, rent HCS are more dispersed and substantially less precise, reflecting both genuine heterogeneity and the shorter rental sample.

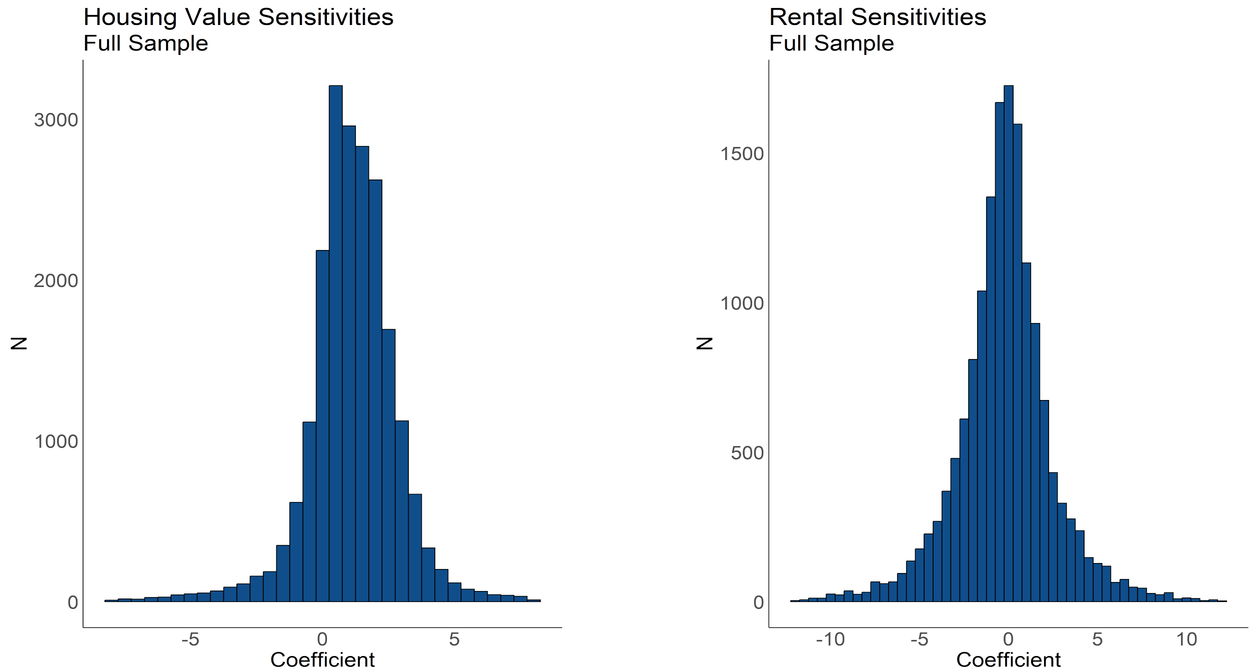
The home-price HCS distribution, shown in Figure 3a, has a mean of 1.16, implying that local home prices tend to rise by about 1 percent when national home prices rise by 1 percent due to mortgage-rate shocks. The rent HCS distribution, shown in Figure 3b, is flatter and centered slightly below zero, with a mean of roughly -0.21. This negative average rent response is consistent with Dias and Duarte (2019), but it should be interpreted more cautiously than the home-price result because the rental estimates are notably less precise.

Table 4: Distributional statistics of the home value and rental sensitivities

	P.25	Mean	P.50	P.75	P.90	N
β^M_{HV}	0.303	1.161	1.121	2.041	2.908	17,451
$se(\beta^M_{HV})$	0.149	0.372	0.247	0.429	0.756	17,451
β^M_R	−1.505	−0.211	−0.177	1.091	2.711	13,389
$se(\beta^M_R)$	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^M_{HV}) and rental (β^M_R) 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.

Table 4 confirms this difference in precision. In the home-price regressions, the mean and median R^2 are 0.64 and 0.68, respectively, when the specification includes only the historical decompositions and quarter fixed effects. In the analogous rent regressions, the mean and median R^2 are 0.51 and 0.52. The shorter sample and more limited coverage of the ZRI likely contribute to the wider standard errors in the rent HCS estimates.



(a) Home-price sensitivities

(b) Rent sensitivities

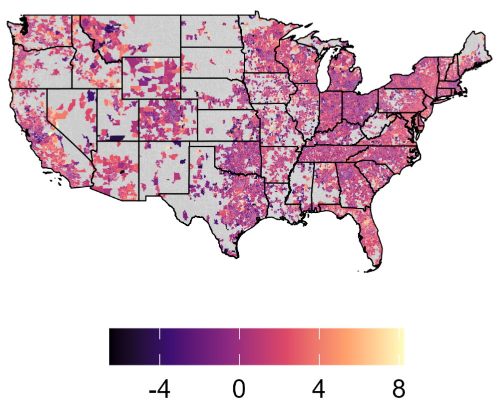
Figure 3: The figures depict the distribution of home-price and rent sensitivities to mortgage-rate shocks from equation (2.11). The home-price sample is 2000–2017, and the rent sample is 2010–2017.

While the median rent response is negative, Figure 3b shows that the rent HCS distribution is wide and roughly symmetric around its median of -0.18. Rents rise in 45% of rental ZIP codes when mortgage-rate shocks raise national home prices, and in about 21% this positive response is statistically significant ($|t| > 1.645$). The positive mass is not an artifact of the shorter rental sample. Rent HCS are statistically distinguishable from zero in 46.9% of rental ZIP codes, and among that precisely estimated subset 43.2% are positive, close to the 45% share overall. Screening on precision therefore leaves the positive share essentially unchanged, which is not the pattern one would expect if imprecision were generating the positive tail.

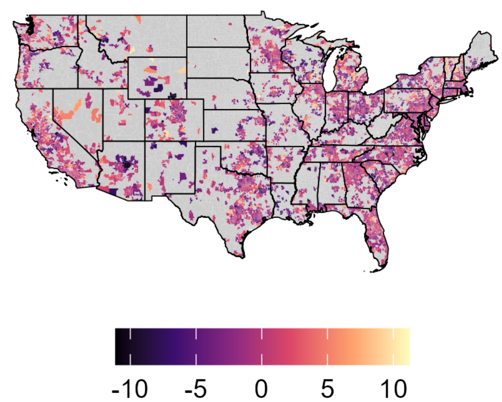
User-cost reasoning delivers a sharp prediction for home prices, where lower mortgage rates directly reduce the cost of owning. In the presence of integrated markets for owner-occupied and rental units, user-cost reasoning also implies that lower mortgage rates reduce rental prices: cheaper borrowing draws some households from renting into owning, which pushes rents down and is consistent with the negative national-level response documented by Dias and Duarte (2019).

However, these markets are likely to be segmented, which may limit extent to which mortgage rate reductions pass through to rental price reductions. Furthermore, mortgage rate shocks reduce interest costs more broadly and can increase investment in local services. Investment in local services can act as an amenity that increases demand for rental units. The prevalence of positive local rental HCS estimates suggests that these demand forces dominate in a substantial share of ZIP codes.[10]

The heterogeneity in HCS is also evident geographically. Figure 4a reports the home-price HCS across ZIP codes, and Figure 4b reports the rent HCS for ZIP codes with relatively precise rent estimates. Areas in the Sand States and parts of the Pacific Northwest tend to exhibit stronger home-price pass-through, while much of the Midwest and South exhibits weaker or even negative responses. These patterns suggest that local conditions materially shape the transmission of national mortgage-rate shocks.



(a) Home-price sensitivities



(b) Rent sensitivities

Figure 4: The figure reports the distribution of HCS estimates across U.S. ZIP codes. The left panel reports home-price HCS and the right panel reports the rental price HCS.

4.1 Distributional Effects

The strongest distributional result in the paper is that expansionary mortgage-rate shocks raise housing costs more in lower-income areas, especially on the rental margin. Since low-income households are disproportionately likely to rent, this pattern implies that declines in borrowing costs can have regressive effects on local housing affordability even if they stimulate aggregate activity.

Table 5 reports the estimates from equation (2.12). Columns (1) and (2) use home-price HCS as the dependent variable, while columns (3) and (4) use rent HCS. The estimates show that lower-income ZIP codes experience systematically larger housing-cost responses than high-income ZIP codes. For example, in column (2), very-low-income ZIP codes exhibit home-

[10]Our data do not allow us to test these investment-induced demand channels directly. Doing so would require measures of migration flows and neighborhood composition change at the ZIP level and at a frequency that aligns with the BTW VAR. We flag them as conjectures and leave a fuller account of positive rental pass-through to future work.

price sensitivities that are 53 basis points larger than high-income ZIP codes when the first stage is evaluated at the median decomposition. After propagating first-stage uncertainty, the corresponding median coefficient remains positive at 0.326, and the 68% credible interval excludes zero.

We find similar evidence for rents. Across CBSAs, both very-low-income and low-income ZIP codes exhibit substantially larger rent HCS than high-income ZIP codes, and these relationships remain visible after propagating VAR uncertainty. Because low-income households are more exposed to rents than to owner-occupied housing costs, the rent results provide the clearest evidence that mortgage-rate declines can worsen affordability at the lower end of the income distribution.

We also estimate specifications that use median household income rather than income-group indicators in Appendix Table E.2.10. These results point in the same direction, especially for rents, although they are generally less precise than the categorical specifications. Taken together, the evidence indicates that lower-income areas are more exposed to mortgage-rate-driven increases in both home prices and rents.

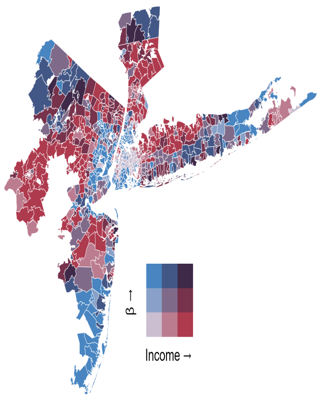
Within CBSAs, ZIP codes classified as "Not Classified" also tend to exhibit elevated HCS relative to high-income ZIP codes. Because these areas contain more heterogeneous income distributions, the interpretation is less direct than for the homogeneous income groups. One possibility is that this category captures neighborhoods undergoing composition change or localized redevelopment —the same compositional forces we discuss above in the context of positive rent responses —but we do not view the coefficient as definitive evidence of gentrification. More conservatively, it indicates that mixed-income ZIP codes often display stronger housing-cost pass-through than uniformly high-income areas.

Table 5: Housing Cost Sensitivity by AGI Classification

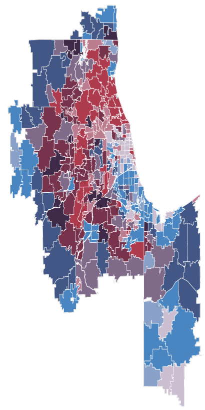
Dependent Variables:	Home Price HCS		Rental HCS	
Model:	(1)	(2)	(3)	(4)
Very Low Income (AGI)	0.48***	0.53***	0.81***	0.81***
	0.110	*0.326*	*0.178*	*0.210*
	[-0.220, 0.441]	[0.039, 0.634]	[0.004, 0.468]	[0.013, 0.511]
Low Income (AGI)	0.55***	0.49***	1.40***	1.40**
	-0.023	*0.240*	*0.288*	*0.305*
	[-0.231, 0.197]	[0.105, 0.420]	[0.070, 0.659]	[0.012, 0.779]
Middle Income (AGI)	0.37***	0.37***	0.05	0.04
	0.048	*0.146*	*-0.044*	*-0.046*
	[-0.078, 0.201]	[0.070, 0.255]	[-0.157, 0.090]	[-0.150, 0.081]
Not Classified (AGI)	0.34***	0.48***	0.51**	0.47***
	-0.044	*0.206*	*0.124*	*0.121*
	[-0.278, 0.187]	[0.078, 0.380]	[0.009, 0.298]	[-0.002, 0.291]
Fixed-effects				
cbsa		✓		✓
Fit statistics				
Observations	13,900	13,900	10,585	10,580
Posterior draws used	357	357	357	357

Notes: Coefficients and significance stars report the original weighted least squares estimates using the point-wise median historical decompositions, with clustering at the CBSA level. Italicized entries report the median coefficient estimate across accepted narrative-restriction posterior draws from the VAR-uncertainty propagation exercise. Bracketed entries report 68% credible intervals, formed from the 16th and 84th percentiles of the draw-by-draw coefficient distribution. The variable *High Income* is omitted so that the reported effects are measured relative to high-income zip codes. In the propagated specification, regressions are weighted by inverse first-stage variance ($1/\hat{\sigma}^2_{\beta_z}$) within each accepted narrative-restriction VAR draw.

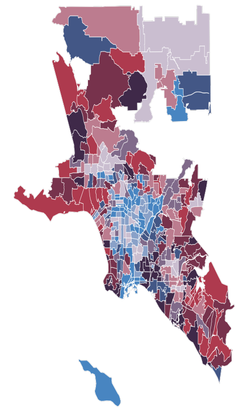
Figures 5a–5c provide visual evidence from New York, Chicago, and Los Angeles. The maps pair local HCS estimates with median household income within each city. A common pattern is that lower-income, high-sensitivity ZIP codes are widespread, whereas high-income, high-sensitivity ZIP codes are relatively rare. This visual pattern is consistent with the regression evidence in Table 5.



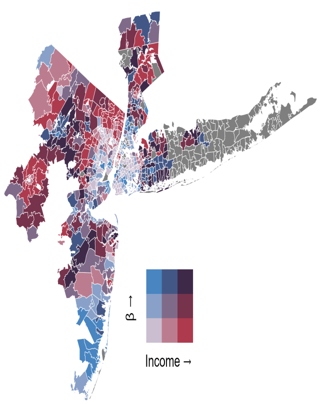
(a) New York City



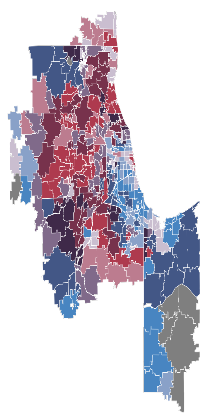
(b) Chicago



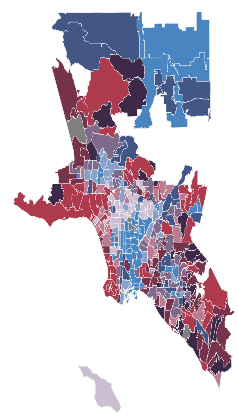
(c) Los Angeles



(d) New York City (Rents)



(e) Chicago (Rents)



(f) Los Angeles (Rents)

Figure 5: The figures depict the relationship between housing cost sensitivities and median income across the New York, Chicago, and Los Angeles CBSAs. The first row reports home-price sensitivities, and the second row reports rent sensitivities.

Table 6: Summary statistics of local characteristics by income-HCS pairings.

Statistic	N	Mean	St. Dev.	Min	Max
Low-income high-HCS					
Home-price HCS	242	2.42	0.94	0.81	5.77
Rent HCS	179	-0.03	2.69	-6.91	6.92
GMNS inverse elasticity	242	1.29	0.11	1.13	1.38
Home ownership rate	242	40.50	21.78	0.89	89.44
Denial rate (1996, %)	242	26.50	6.46	11.34	37.12
Median home price to renter income	242	6.06	3.55	0.00	40.28
Structure value (log, 2012)	81	12.27	0.40	11.51	13.36
Presample housing age (median)	242	44.08	9.60	14.00	61.00
Natural amenity index	242	2.13	4.38	-3.58	10.33
High-income high-HCS					
Home-price HCS	92	1.78	0.50	0.82	3.12
Rent HCS	82	0.27	2.00	-4.02	7.64
GMNS inverse elasticity	92	1.23	0.11	1.13	1.38
Home ownership rate	92	77.42	13.18	16.89	96.92
Denial rate (1996, %)	92	22.04	6.77	11.82	33.10
Median home price to renter income	92	5.69	2.23	0.00	19.31
Structure value (log, 2012)	77	12.32	0.23	11.79	12.84
Presample housing age (median)	92	29.85	11.57	5.00	61.00
Natural amenity index	92	3.30	5.13	-2.85	10.33
High-income low-HCS					
Home-price HCS	212	0.53	0.67	-2.93	1.48
Rent HCS	137	-0.85	2.98	-8.15	7.08
GMNS inverse elasticity	212	1.30	0.11	1.13	1.38
Home ownership rate	212	76.61	16.94	0.00	102.11
Denial rate (1996, %)	212	22.46	5.30	12.72	33.10
Median home price to renter income	209	7.88	4.55	0.00	33.37
Structure value (log, 2012)	143	12.57	0.30	11.83	13.48
Presample housing age (median)	212	35.28	13.93	0.00	61.00
Natural amenity index	212	2.10	3.82	-2.40	10.33

Notes: Groups pool ZIP codes across the New York, Chicago, and Los Angeles CBSAs, classified by city-specific terciles of median household income and the home-price HCS (Figure 5a). The denial rate is the share of 1996 HMDA mortgage applications denied. Structure values are from Davis et al. (2021) (2012 vintage); the GMNS inverse elasticity is from Guren et al. (2021).

4.2 Factors Driving Heterogeneous HCSs

The distributional results show that mortgage-rate shocks transmit unevenly across neighborhoods. We now ask why. While traditional supply constraints are an important determinant of local price responses, they need not be the only one. In our setting, heterogeneity in

HCS may also reflect differences in housing-market liquidity, local demand amplification, and the extent to which land-price movements pass through into housing costs. The summary statistics for the proxies for these mechanisms are reported in Table 6 by group and full sample versions are provided in Table E.5.13 of appendix E.5. Table 7 reports the main cross-sectional associations between HCS and our ZIP-level mechanism variables. Table 8 complements these regressions with a Shapley-style decomposition of explained variation. We interpret the latter as a decomposition of predictive explanatory power, not as a causal variance decomposition. The within-CBSA specifications in columns (2) and (4) additionally require ZIP-level land and structure values from Davis et al. (2021), which cover a narrower set of ZIP codes than our other covariates. Those columns therefore cover 5,618 ZIP codes for home prices and 4,934 for rents, compared with 13,747 and 10,333 in the across-CBSA specifications. Appendix Table E.3.11 reports within-CBSA estimates that omit the land and structure measures and retain nearly the full sample, at 13,776 and 10,340 ZIP codes.

4.2.1 Determinants of HCS

Supply constraints. We begin with conventional supply measures. Areas with more inelastic housing supply exhibit larger home-price and rent HCS. A one-unit increase in the GMNS inverse elasticity is associated with a 0.74-unit increase in home-price HCS and a 0.46-unit increase in rent HCS, with both coefficients statistically significant. The home-price relationship survives the propagation of first-stage uncertainty, with a median coefficient of 0.591 and a 68% credible interval of [0.331, 0.801]. The rent coefficient attenuates considerably, to a median of 0.112 with an interval of [0.035, 0.217]. The strong relationship for home prices is notable. Despite differences in geography, horizon, and shock definition, our HCS estimates appear closely related to established measures of local supply responsiveness.

The decomposition points the same way. The GMNS elasticity is the largest single contributor to across-CBSA explained variation in the home-price HCS, at 50.2% point-wise and 57.0% across draws, with a 68% credible interval of [38.8%, 64.6%]. For rents its point-wise contribution is comparable, at 44.4%, but the median across draws falls to 14.2% with an interval of [4.6%, 33.2%]. The rent result therefore rests considerably more on the point-wise specification than the home-price result does.

Because the GMNS elasticity varies only across CBSAs, we cannot use it to study within-CBSA heterogeneity. Appendix B therefore considers the tract-level elasticities of Baum-Snow and Han (2024). Those measures provide weaker explanatory power for our HCS estimates, with developed-land elasticity emerging as the only consistently informative BSH measure. We interpret this pattern as consistent with, though not proving, the idea that our HCS object captures a shorter-run and somewhat different margin of adjustment than the BSH estimates.

We also use a downtown indicator as an alternative within-CBSA proxy for local scarcity. Consistent with greater short-run tightness near the urban core, downtown ZIP codes exhibit higher home-price pass-through, though the coefficient is small at 0.07 and only marginally significant. Its contribution to within-CBSA explained variation is correspondingly modest, at 1.5% point-wise and 3.7% across draws for home prices.

Housing-market liquidity. The liquidity variables matter most for owner-occupied housing. Home-price HCS tend to be lower in more liquid markets and higher in markets where turnover is likely to be limited. A one standard deviation increase in the homeownership rate is associated with a 0.09 to 0.10 reduction in home-price HCS, significant both across and within CBSAs, and the within-CBSA relationship survives propagation with an interval of [-0.070, -0.010]. A one log point increase in median resident age is associated with a 0.69 to 0.78 increase in home-price HCS, though both propagated intervals span zero. The decomposition ranks these variables in the same order. Homeownership accounts for 16.3% of within-CBSA explained variation in the home-price HCS point-wise and 18.1% across posterior draws in Table 8, the largest liquidity contribution in either specification. Resident age contributes 12.2% point-wise, but that share falls to 4.7% once VAR uncertainty is propagated, ranking it below homeownership. Among the liquidity variables the homeownership contribution carries the widest credible interval, at [7.2%, 29.1%], indicating that the importance ranking of individual controls is sensitive to the first-stage uncertainty. Taken together the liquidity factors account for 29.1% of within-CBSA explained variation in the home-price HCS, second only to the land-cost variables.

By contrast, the liquidity measures are less informative for rent HCS. This difference is not surprising, since resident age and home ownership rates primarily proxy for the supply of homes available for sale rather than the supply of rental units. One implication is that home-price and rent pass-through need not be governed by the same local frictions.

Demand amplification. Among the demand-side variables, natural amenities provide the clearest evidence of amplification. Across CBSAs, a one standard deviation increase in the natural amenity index is associated with a 0.13 increase in home-price HCS, and the relationship survives propagation with a median of 0.146 and an interval of [0.087, 0.210]. The amenity measure is also the second largest contributor to across-CBSA explained variation in the home-price HCS in both specifications, at 13.3% point-wise and 19.3% across draws, behind only the GMNS inverse elasticity. This pattern is consistent with the mechanism in Appendix C. When housing costs are a larger share of local expenditure, mortgage-rate declines generate larger outward shifts in housing demand.

The amenity index also carries a large share of across-CBSA variation in the rent HCS, at 33.8% point-wise and 41.7% across draws, where it becomes the single largest contributor once VAR uncertainty is propagated. The corresponding coefficient is 0.14 point-wise, although its propagated interval includes zero.

The evidence for crime is weaker. Within CBSAs, crime enters negatively for home prices, the sign anticipated in Table 2 if crime operates as a local disamenity, though the coefficient is statistically significant only in the specification that omits land and structure values (Table E.3.11). Across CBSAs, and for rents in both specifications, the point estimates are small and not distinguishable from zero, and the propagated credible intervals span zero throughout. We therefore view natural amenities as the sharper evidence for demand amplification and do not draw strong conclusions from the crime results, particularly given the measurement error induced by incomplete and non-random agency reporting in the underlying UCR data.

The credit-amplification channel receives more limited support. Pre-sample denial rates enter positively for home-price HCS within CBSAs and for rent HCS in both specifications, but none of these coefficients is statistically distinguishable from zero and every propagated interval includes zero. The decomposition assigns denial rates a small share of explained variation in the home-price HCS, at 0.8% across CBSAs and 6.4% within them point-wise. The rent shares are larger, at 6.9% and 8.2% point-wise and 11.0% and 24.3% across draws, but they rest on a much smaller base and carry very wide intervals, reaching [3.4%, 49.4%] within CBSAs. We therefore interpret the denial-rate results as suggestive rather than decisive. They are consistent with a role for mortgage-access margins, but for home prices they are much less central than the amenity and liquidity channels in explaining heterogeneity.

These modest denial-rate effects are not necessarily inconsistent with the broader credit literature. Mian and Sufi (2009) focus on the pre-crisis expansion of credit to constrained borrowers, while Bhutta and Ringo (2021) and Davis et al. (2020) study policy environments that differ from our full sample. More generally, recent survey evidence in Fuster and Zafar (2021) suggests that willingness to pay for housing may be less sensitive to mortgage-rate changes than to down-payment constraints. Indeed, the home-price HCS coefficients are lower in zip codes with higher land prices, which may proxy for down-payment constraints to the extent that more expensive areas require larger down payments. The ratio of median home values to renter income points in the same direction: in the point-wise specification, ZIP codes where homes are more expensive relative to the incomes of prospective first-time buyers exhibit modestly lower home-price HCS (Table 7), consistent with binding down-payment constraints muting the demand response to lower rates, although the propagated credible interval includes zero.

Housing Quality. Across CBSAs, ZIP codes with older housing stock exhibit larger home-price HCS, with a one log point increase in median housing age associated with a 0.16 increase and a propagated interval of [0.018, 0.244]. The corresponding coefficient for rents is small and not statistically distinguishable from zero. Within CBSAs, areas with higher structure values exhibit lower home-price and rent HCS, at -0.45 and -0.84 respectively, and both propagated intervals exclude zero. This is consistent with the mechanism in Murphy (2024). Pass-through is stronger where structures are cheaper, conditional on land values. The decomposition indicates that this channel dominates within-CBSA variation. Structure values alone account for 42.3% of within-CBSA explained variation in the home-price HCS point-wise and 36.5% across draws, the largest single contribution in either specification, and land values add a further 18.4% and 12.8%. Together the two land-cost variables account for 60.8% of within-CBSA explained variation in home-price HCS and 63.2% for rents.

Table 7: Determinants of Zip-Level Housing Cost Sensitivities Comparison

Dependent Variables:	Home Price HCS		Rental HCS	
Model:	(1)	(2)	(3)	(4)
Supply				
Traditional Supply Elasticity				
GMNS Inv Elas	0.74***		0.46***	
	0.591		*0.112*	
	[0.331, 0.801]		[0.035, 0.217]	
Near downtown		0.07*		0.17
		0.045		*0.102*
		[-0.001, 0.079]		[0.027, 0.176]
Housing Liquidity				
Median resident age (log)	0.78***	0.69***	-0.35	0.38
	0.089	*0.085*	*-0.077*	*0.202*
	[-0.207, 0.415]	[-0.058, 0.248]	[-0.360, 0.133]	[-0.074, 0.449]
Home ownership rate (std)	-0.10***	-0.09***	-0.008	-0.04
	-0.023	*-0.037*	*0.003*	*-0.004*
	[-0.046, 0.000]	[-0.070, -0.010]	[-0.022, 0.022]	[-0.029, 0.023]
Population (log)	-0.13***	-0.02	0.02	0.09**
	-0.017	*0.005*	*0.007*	*0.036*
	[-0.042, 0.000]	[-0.009, 0.020]	[-0.008, 0.025]	[-0.007, 0.087]
Demand Amplifiers				
Amenities				
Natural amenity index (std)	0.13**		0.14**	
	0.146		*0.076*	
	[0.087, 0.210]		[-0.012, 0.150]	
Crimes per 100k (log)	0.07	-0.06	0.08	0.17
	0.034	*0.018*	*0.010*	*0.031*
	[-0.008, 0.068]	[-0.036, 0.058]	[-0.051, 0.071]	[-0.062, 0.102]
Credit				
Denial rate (std)	0.02	0.10	0.08	0.08
	-0.036	*0.017*	*0.053*	*0.128*
	[-0.084, 0.010]	[-0.033, 0.063]	[-0.002, 0.097]	[-0.052, 0.255]
Median home price to renter inc	-0.06***		-0.04	
	-0.014		*-0.011*	
	[-0.039, 0.007]		[-0.036, 0.003]	
Land value (log)		-0.10*		-0.06
		-0.027		*0.021*
		[-0.077, 0.025]		[-0.086, 0.080]
Housing Quality				
Median age of home (log)	0.16***		0.05	
	0.130		*0.053*	
	[0.018, 0.244]		[0.005, 0.093]	
Structure value (log)		-0.45***		-0.84***
		-0.221		*-0.270*
		[-0.446, -0.008]		[-0.587, -0.072]
Fixed-effects				
cbsa		✓		✓
Fit statistics				
Observations	13,747	5,618	10,333	4,934
R^2 (Point-wise)	0.15	0.76	0.03	0.35
Median R^2	0.280	0.775	0.026	0.335
Posterior draws used	357	357	357	357

Notes: Coefficients and significance stars report the weighted least squares estimates using the point-wise median historical decompositions, with clustering at the CBSA level. Italicized entries report the median coefficient estimate across accepted narrative-restriction posterior draws that deliver a positive GMNS coefficient for both home values and rents. Bracketed entries report 68% credible intervals, formed from the 16th and 84th percentiles of the draw-by-draw coefficient distribution. The row labeled R^2 (Point-wise) reports the fit from the baseline point-wise specification, while the row labeled Median R^2 reports the median fit across propagated posterior draws. In the propagated specification, regressions are weighted by inverse first-stage variance $(1/\hat{\sigma}^2_{\beta_z})$ within each accepted draw.

Table 8: Marginal R-Squared: Shapley-Owen-Shorrocks Decomposition with VAR Uncertainty

	Across	Within	Across	Within
Supply				
Traditional Supply Elasticity				
GMNS Inv Elas	50.17%		44.35%	
	57.03%		*14.23%*	
	[38.81%, 64.64%]		[4.58%, 33.24%]	
Near Downtown		1.48%		3.96%
		3.68%		*8.08%*
		[1.58%, 7.16%]		[1.38%, 20.12%]
Housing Liquidity				
Home ownership (std)	4.96%	16.26%	2.23%	4.69%
	2.49%	*18.10%*	*1.89%*	*2.17%*
	[1.09%, 5.56%]	[7.18%, 29.08%]	[1.07%, 4.72%]	[0.99%, 5.33%]
Population (log)	9.38%	0.61%	4.81%	11.06%
	0.74%	*3.91%*	*2.66%*	*7.75%*
	[0.31%, 2.65%]	[1.37%, 7.61%]	[1.10%, 5.63%]	[0.75%, 19.04%]
Median age of residents	11.57%	12.24%	1.76%	2.22%
	2.46%	*4.65%*	*1.96%*	*4.38%*
	[0.71%, 8.28%]	[2.60%, 12.26%]	[0.46%, 10.23%]	[1.70%, 12.85%]
Demand Amplifiers				
Amenities				
Natural Amenity Index	13.25%		33.84%	
	19.34%		*41.67%*	
	[10.47%, 29.22%]		[12.54%, 63.92%]	
(log) crime per 100k	0.51%	2.23%	1.92%	6.70%
	0.90%	*4.79%*	*2.34%*	*6.36%*
	[0.50%, 2.99%]	[0.81%, 14.16%]	[0.93%, 7.42%]	[1.90%, 15.21%]
Credit				
Denial Rate (std)	0.81%	6.42%	6.87%	8.20%
	2.41%	*4.60%*	*11.01%*	*24.28%*
	[1.03%, 6.16%]	[1.11%, 12.78%]	[2.76%, 21.05%]	[3.44%, 49.41%]
Median home price to renter inc	4.48%		3.82%	
	3.00%		*4.16%*	
	[1.69%, 7.35%]		[1.81%, 19.74%]	
Land Value (log)		18.42%		14.90%
		12.78%		*7.39%*
		[4.50%, 22.51%]		[2.84%, 20.87%]
Housing Quality				
Median Age of Home	4.87%		0.39%	
	5.21%		*2.67%*	
	[1.03%, 14.14%]		[0.73%, 7.35%]	
Structure Value (log)		42.34%		48.27%
		36.48%		*21.34%*
		[13.69%, 46.34%]		[4.09%, 45.50%]
R^2 (Point-wise)	0.154	0.063	0.034	0.029
Median R^2	0.280	0.063	0.026	0.026
	[0.120, 0.436]	[0.019, 0.155]	[0.012, 0.058]	[0.012, 0.048]
Posterior draws	357	357	357	357

Notes: Each cell shows the Shapley-Owen-Shorrocks marginal R^2 contribution expressed as a percentage of total R^2. The first line of each cell is the point-wise estimate using the median historical decompositions; the italicized line is the median across accepted narrative-restriction VAR draws; the bracketed line is the 68% credible interval (16th–84th percentiles). Across specifications use weighted OLS (weights = $1/\hat{\sigma}^2_{\beta_z}$) and decompose the total R^2. Within specifications residualize the outcome and all covariates on CBSA fixed effects (weighted demeaning, per the Frisch-Waugh-Lovell theorem) before the decomposition; the R^2 reported and decomposed in those columns is therefore the within-CBSA R^2. Accepted draws are restricted to those delivering a positive GMNS coefficient for both home values and rents.

Decomposition of explained variation. Table 8 allocates the explained variation in HCS across the individual characteristics. Two features of the table govern how its shares should be read. First, the across-CBSA and within-CBSA columns decompose different objects. The across columns decompose the total R^2 of a weighted regression without fixed effects, while the within columns residualize the outcome and all covariates on CBSA fixed effects and decompose the resulting within-CBSA R^2. Shares are therefore comparable within a column but not between the two column types. Second, the shares are percentages of a modest base. The point-wise R^2 is 0.154 across CBSAs and 0.063 within CBSAs for home prices, and 0.034 and 0.029 respectively for rents. The within-CBSA columns explain a small fraction of the residual variation in HCS, so the rankings they deliver should be read as the relative importance of the characteristics we observe rather than as evidence that observable characteristics account for most of the within-city dispersion in pass-through.

Aggregating the point-wise shares to the mechanism categories makes the contrast between the two margins clear. Across CBSAs, the supply elasticity accounts for 50.2% of explained variation in home-price HCS, housing liquidity for 25.9%, demand amplification through amenities and crime for 13.8%, the credit measures for 5.3%, and housing age for 4.9%. Within CBSAs the ordering changes substantially. Land-cost pass-through accounts for 60.8%, housing liquidity for 29.1%, crime and credit together for 8.7%, and the downtown indicator for 1.5%. The rent columns show a similar within-CBSA pattern, with land-cost pass-through at 63.2% and liquidity at 18.0%, but a different across-CBSA pattern in which natural amenities account for 33.8% against 44.4% for the supply elasticity. We aggregate only the point-wise column because the propagated entries are per-variable medians across draws and therefore need not sum to the column total.

4.2.2 Debt-to-Income Sensitivities

We complement the HCS analysis by estimating debt-to-income sensitivities (DS) at the ZIP-code level. Specifically, we re-estimate equation 2.11 using year-over-year growth in average ZIP-code debt-to-income ratios as the dependent variable and annualized versions of the right-hand-side variables. We construct debt-to-income ratios from Experian, which measures average debt and income levels across consumers in a zip code from 2007 to 2017. The resulting coefficient on the mortgage-rate decomposition measures how strongly local leverage responds when mortgage-rate shocks move national home prices. Table 9 reports the corresponding cross-sectional results.

We view the DS exercise as triangulation rather than a formal test of the mechanisms. If the same local characteristics that predict stronger housing-cost pass-through also predict stronger leverage responses, that strengthens the interpretation that the HCS relationships reflect economically meaningful channels rather than incidental correlations.

Supply constraints If home prices are more responsive in areas with an inelastic supply of housing, we should also expect buyers in these areas to take on more debt, implying a positive relationship between supply inelasticity and the DS. The estimates line up well with the supply-based interpretation of HCS. The GMNS coefficient is positive and significant in the model with the point-wise medians, and it has a 68% credible interval that excludes zero after propagating the posterior draws.

Housing-market liquidity. The housing liquidity hypothesis would predict the more liquid markets should exhibit lower (less sensitive) DS estimates based on lower home-price appreciation. We find mixed evidence to support this hypothesis. Homeownership rates remain the most consistent housing liquidity factor. The point-wise estimates are significant and the signs align with our predictions in both specifications. However, the propagated median coefficients are attenuated, and the credible intervals, while concentrated below zero, marginally include zero in both specifications. The relationship with resident age is more ambiguous. The across-CBSA estimates are negative in both the point-wise and propagated specifications, contrary to the predicted sign. Within CBSAs, the point-wise estimate is positive and significant, but the propagated median attenuates to near zero with a credible interval that spans both signs. Population shows mixed signs. Overall, the DS evidence is consistent with a role for housing liquidity, but the channel is less precisely estimated than the supply or land-cost channels.

Demand amplification. If mortgage-rate shocks have stronger demand shifts in high-amenity areas, one should observe a larger home-price HCS and stronger responses in leverage because more debt is typically needed to purchase more expensive homes. This implies a positive relationship between natural amenities and DS. The across-CBSA estimates are consistent with this prediction: the natural amenity index enters positively, though the magnitude is modest.

The crime variable carries no clear prediction. If higher-crime areas are lower-income, we could expect a stronger leverage response if the mortgage rate shocks expand access to credit on the extensive margin. However, higher crime may also dampen housing demand and mute both the price and leverage response. We find the crime variable has little systematic relationship with DS, which reinforces our view that the crime results are harder to interpret through a single demand-amplification mechanism.

Higher denial rates should predict stronger DS if mortgage rate reductions expand credit access. The point-wise estimates suggest this is relevant across CBSAs, but not within them, and the effects are strongly attenuated after accounting for the VAR uncertainty. Overall, the imprecise estimates for the role of credit denial rates from the DS exercise are consistent with the imprecision of its role in driving HCS.

The dependence of home-price HCS on land values (a proxy for down payment constraints) suggests that we should anticipate a stronger association between DS and land values. Indeed, the result indicate a strong negative dependence of DS on land values.

Structure quality pass-through. The stronger pass-through of housing demand shocks to housing costs in locations with low-quality structures suggests that debt is also more responsive when structure quality is low. This pass-through channel is strongly supported in the DS regressions. The within-CBSA estimates confirm this: both land values and structure values are negatively and significantly related to DS, and both 68% credible intervals exclude zero under propagation. This is the same pattern documented in the HCS regressions and is therefore one of the cleanest pieces of supporting evidence.

Overall, the DS exercise supports the main interpretation of the HCS results. The strongest and most consistent overlap appears for supply constraints, natural amenities across CBSAs, and the down-payment-constraint and pass-through channels within CBSAs.

Table 9: Determinants of Zip-Level Debt-to-Income Sensitivities: Draws Conditioned on Positive GMNS in the DTI Regression Only

Dependent Variable:		DTI DS		
Model:	Predicted	(1)	Predicted	(2)
Supply				
Traditional Supply Elasticity				
GMNS Inv Elas	+	0.66***	+	
		0.228		
		[0.077, 0.505]		
Near downtown	+		+	0.22
				0.067
				[-0.066, 0.250]
Housing Liquidity				
Median resident age (log)	+	-0.19	+	0.77*
		-0.289		*-0.251*
		[-0.953, 0.459]		[-0.917, 0.353]
Home ownership rate (std)	-	-0.23***	-	-0.23***
		-0.055		*-0.038*
		[-0.162, 0.050]		[-0.143, 0.059]
Population (log)	-	-0.17***	-	0.08
		-0.023		*0.069*
		[-0.122, 0.066]		[-0.016, 0.181]
Demand Amplifiers				
Amenities				
Natural amenity index	+	0.27***	+	
		0.074		
		[-0.006, 0.181]		
Crimes per 100k (log)	?	0.04	?	0.15*
		0.039		*0.006*
		[-0.096, 0.162]		[-0.161, 0.157]
Credit				
Denial Rate (std)	+	0.31***	+	0.24
		0.035		*0.023*
		[-0.084, 0.141]		[-0.163, 0.175]
Median home price to renter inc	-	-0.24***	-	
		-0.059		
		[-0.132, -0.005]		
Land value (log)	-		-	-0.82***
				-0.130
				[-0.360, 0.081]
Housing Quality				
Median age of home (log)	+	0.03	+	
		-0.071		
		[-0.240, 0.123]		
Structure Value (log)	-		-	-1.50***
				-0.380
				[-1.083, 0.107]
Fixed-effects				
cbsa				✓
Fit statistics				
Observations		14,065		5,656
R^2 (Point-wise)		0.05		0.21
Median R^2		0.028		0.280
Posterior draws used		312		312

Notes: Accepted draws are those delivering a positive GMNS coefficient in the debt-to-income regression, without any restriction on the home-value or rent regressions (312 draws). Because the draw set conditions on the sign of a coefficient the table reports, the GMNS row is positive by construction. Point-wise estimates are unaffected by the draw restriction and are identical across all three versions. Italicized entries report posterior medians and bracketed entries 68% credible intervals across accepted draws.

5 Conclusion

This paper estimates how national mortgage-rate shocks transmit into local housing costs. Using structural decompositions from Ben-David et al. (2024) and ZIP-code housing data, we construct neighborhood housing cost sensitivities (HCS) for both home prices and rents at a one-year horizon. This allows us to study not only how strongly mortgage-rate shocks pass through across geographic areas, but also whether that pass-through differs between owner-occupied and rental housing markets.

We document substantial heterogeneity in local housing-cost responses. Expansionary mortgage-rate shocks raise both home prices and rents more in lower-income ZIP codes, implying that declines in borrowing costs can have regressive effects on housing affordability. This conclusion is especially strong on the rental margin, which is economically important because low-income households are disproportionately exposed to rent increases. More broadly, our findings show that home-price and rent responses are not interchangeable: locations with strong home-price pass-through need not exhibit equally strong rent pass-through. Indeed, rents rise in a large share of ZIP codes in response to expansionary mortgage-rate shocks —a pattern that standard user-cost logic does not predict and that we conjecture reflects gentrification and in-migration pressures in appreciating neighborhoods. Assessing these mechanisms directly is an important avenue for future work.

To explain this heterogeneity, we consider mechanisms highlighted in the existing literature and propose a new mechanism through which natural amenities amplify housing demand shocks. Our cross-sectional results show that conventional supply constraints remain important, but they do not fully explain the geography of HCS. Natural amenities, housing-market liquidity, financing constraints, and differential pass-through from land costs into housing costs all help explain why otherwise similar mortgage-rate shocks generate different local outcomes. The response of household leverage to mortgage-rate shocks broadly supports these interpretations, although the evidence is more precise for some mechanisms than for others.

A limitation of the analysis is that the rental series is shorter and noisier than the home-price series, and our interpretation of the cross-sectional relationships relies on proxies that may reflect more than one underlying mechanism. In addition, the empirical design inherits the identifying assumptions of the aggregate structural decomposition. Longer rental panels and more direct measures of residential mobility, housing transactions, and mortgage originations would help distinguish the mechanisms underlying heterogeneous pass-through more sharply.

More broadly, our findings imply that a conventional housing-supply elasticity is not a sufficient statistic for the local incidence of mortgage-rate shocks. Short-run pass-through also depends on local demand amplification, housing-market liquidity, financing constraints, and structure quality, and these forces operate differently in owner-occupied and rental markets. Evaluating changes in borrowing costs—including those associated with monetary policy—therefore requires attention not only to the average national housing response, but also to where households live and whether they rent or own.

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Appendix

A Data Description

A.1 ZHVI and ZRI Construction

Zillow Home Value Index (ZHVI)
Loosely speaking, Zillow constructs the ZHVI in a three-step process. First, it estimates property values (Zestimates) using a neural network trained on a database of nearly 116 million homes, histories of transactions, listings, and property characteristics across the United States. Second, it uses the middle third of the distribution of Zestimates in a region to construct a weighted average. Third, it chains month-to-month changes in the trimmed mean into an index level. Because each Zestimate holds property attributes fixed, the resulting series is constructed to isolate market-driven value changes. Properties that undergo significant physical changes have their appreciation set to the median appreciation for that region[11]. In our work we use the *ZHVI All Homes (SFR, Condo/Co-op)* smoothed series, but Zillow provides a variety of options that calculate the ZHVI using different quantile ranges and property types.

Zillow Rental Index (ZRI)
The ZRI is calculated using a similar procedure, but with a different machine learning algorithm whose output is a predicted rental rate based on observed listings, home value Zestimates, property and geographic characteristics, and transaction histories. Similar to the ZHVI, every residential property in a given area—whether or not it has ever been rented—receives a monthly rental estimate. Zillow computes the ZRI using the median rental Zestimate for the target area, and applies a three-month moving average to smooth the data. Due to the relative sparsity of the rental data, additional quality-control rules require minimum thresholds for (1) the count of rent Zestimates, (2) the number of listings in the prior three months, and (3) the series' volatility. In cases where the geographic boundaries of a region change, the time series is recompiled to reflect the distribution of homes after the change. We use the *All Homes* market segment to align with our choice with the ZHVI. Zillow stopped publishing the ZRI in March 2020, and we rely on the archived dataset hosted on Kaggle (last updated 2017). A limitation of this approach is that the 2012-era quality adjustment of the ZRI is less robust than the current ZHVI's[12].

[11] The description of the quality adjustment follows from a 2019 methodology revision published by Zillow (ZHVI-1). Zillow published a more recent revision in 2023 (ZHVI-2), but the discussed changes are primarily related to the methodological changes to the home value Zestimates.

[12] The 2011 overview of the Zestimate methodology can be found (Rental Zestimate), and the post on the updated methodology here (ZRI-1).

A.2 ZIP-Code Characteristics and Local Controls

Local labor-market controls. Employment, firm counts, and average weekly earnings come from the Quarterly Census of Employment and Wages (QCEW) at the county level for 2000–2017. County values are assigned to ZIP codes using population-based crosswalk weights.

2000 Census (NHGIS) characteristics. Homeownership rates, total population, median resident age, median age of the housing stock, median housing values, and the median household income of renter-occupied households are drawn from 2000 Census summary files at the ZCTA level, queried from NHGIS (Schroeder et al., 2025). The homeownership rate is the share of occupied housing units that are owner-occupied. The home-value-to-renter-income ratio divides the ZCTA median housing value by the median household income of renter-occupied households (measured for 1999, per Census convention).

Natural amenities. The USDA Economic Research Service Natural Amenities Scale is a time-invariant county-level index constructed from climate, topography, and water-area measures. We assign county values to ZIP codes using county-to-ZIP crosswalks; because the index varies primarily across CBSAs, it enters only the across-CBSA specifications.

Crime. We construct county-level crime rates from the county files of the FBI Uniform Crime Reporting (UCR) program, retrieved from ICPSR, and from the compiled UCR panel of Kaplan (2024). The ICPSR files report total arrests in a county-year together with the population covered by the agencies that reported arrests; the Kaplan panel reports offenses known to police together with the corresponding covered population. Our baseline measure uses arrests, and the offenses series serves as an alternative.

For each county-year we compute a rate per 100,000 as the reported count divided by the population covered by reporting agencies, and we take the median of these annual rates over the pre-sample window 1991–2000.[13] We use the median rather than the mean because it is robust to a minority of years in which a county's counts are garbled or only a subset of its agencies report.

Two features of the UCR data warrant emphasis. First, because reporting is voluntary, the population covered by reporting agencies is frequently smaller than the county's total population; we therefore use covered population, rather than total county population, as the denominator, so that the rate reflects the population from which the reported counts are actually drawn. Second, coverage is uneven across counties and years. We treat county-years with zero reported counts as non-reporting and exclude them, and a county with no reporting year in the window is dropped from the sample. We do not require a balanced set of reporting years: doing so would drop counties non-randomly, since non-reporting is concentrated in particular states, and we prefer measurement error in a control variable to selection on the estimation sample. The cost is that counties are measured over somewhat different sets of years, and because the national crime rate fell over the 1990s, counties whose reporting years fall early in the window will have somewhat higher measured rates than counties measured later in it.

[13] The year 1993 is not available in the ICPSR extract.

The resulting rates are assigned to ZIP codes using population-weighted county-to-ZIP crosswalks and enter our specifications in logs. Given incomplete and non-random agency coverage, the crime variable is measured with error, and the coefficients associated with it should be interpreted conservatively.

Credit conditions. Mortgage denial rates are computed from the 1996 vintage of HMDA as the ratio of denied applications to accepted-plus-denied applications, after excluding preapprovals, purchased loans, withdrawn applications, incomplete applications, and approvals not accepted.

Land and structure values. ZIP-level land and structure values are from Davis et al. (2021), measured as of 2012 and entered in logs.

Debt-to-income. Average consumer debt and income levels by ZIP code are from Experian and cover 2007–2017; the debt-to-income ratio divides average debt by average income across consumers in the ZIP code.

Supply elasticities. The inverse supply elasticity of Guren et al. (2021) is measured at the CBSA level. The tract-level elasticities of Baum-Snow and Han (2024) are mapped to ZIP codes as described in Appendix B.

Table A.2.1: Data Sources

Variable	Source	Vintage / Years	Geography
Outcomes			
Home values (ZHVI, all homes)	Zillow	2000–2017 (Q)	ZIP (17,451)
Rents (ZRI, all homes)	Zillow	2010–2017 (Q)	ZIP (13,389)
Debt-to-income ratio	Experian	2007–2017	ZIP
Aggregate shocks			
Historical decompositions	Ben-David et al. (2024); narrative restrictions following Antolín-Díaz and Rubio-Ramírez (2018)	1974Q1–2018Q1	National
Local controls			
Employment, earnings, firm counts	QCEW (BLS)	2000–2017 (Q)	County → ZIP
Income			
AGI income classification	IRS Statistics of Income	2010	ZIP
Median household income	Census	2000	ZIP
Supply and liquidity			
Inverse supply elasticity	Guren et al. (2021)	—	CBSA → ZIP
Housing supply elasticities	Baum-Snow and Han (2024)	2001 estimates	Tract → ZIP
Near-downtown indicator	Constructed following Couture et al. (2024)	—	ZIP
Homeownership rate, population, median resident age	2000 Census (Schroeder et al., 2025)	2000	ZIP
Demand and credit			
Natural amenities scale	USDA ERS	1999	County → ZIP
Crime rates	FBI UCR, Kaplan (2024)	1995-2000 Average	County → ZIP
Mortgage denial rate	HMDA	1996	ZIP
Median home value to renter income	2000 Census (Schroeder et al., 2025)	2000	ZIP
Housing quality			
Median age of housing stock	2000 Census (Schroeder et al., 2025)	2000	ZIP
Land and structure values	Davis et al. (2021)	2012	ZIP

Notes: County-level variables are assigned to ZIP codes using population-weighted crosswalks; tract-level elasticities are mapped to ZIP codes using the HUD USPS crosswalk (see Appendix B). All ZIP-code characteristics are measured prior to the estimation sample.

B Baum-Snow Han Elasticities

Recent work by Baum-Snow and Han (2024) provides granular census tract estimates of the housing supply elasticity by various metrics including the responses of units, floor space, and developed land share to local housing demand (income) shocks. In this section we document the importance of BSH elasticities to explaining within CBSA variation of the HCS estimates. We find that the BSH elasticities are not strong predictors of within-CBSA variation in our HCS; nor does including BSH elasticities as additional controls substantially alter the estimated importance of other zip-level factors. We suspect that the limited influence of BSH supply elasticities can be attributed to the different time horizon in their study (5+ years compared to one year for the HCS estimates) and the different nature of the shock (income shocks in BSH compared to mortgage rate shocks in the HCS estimates). The lack of within-CBSA correlation between HCS and BSH suggests that our estimates may capture different aspects of housing market constraints.

The BSH elasticities cover 306 metropolitan areas using 2000-2010 data and provide nearly 64,000 census tract level estimates of housing elasticities. In the authors' replication files they provide multiple types of elasticities based on the measure of the housing supply (units, floor space, etc.) and the estimation procedure. We follow the authors' suggestion and use the 2001 estimates from the quadratic finite mixture model[14]. We map the tract estimates to zip codes using the HUD USPS Zip Code Crosswalk with 2000 Census geographies and construct zip-code-level measurements by taking a weighted average based on the share of residents within a census tract that falls within a zip code. We are ultimately able to map the BSH elasticities to 11,164 zip codes in our sample. CBSAs fixed effects explain between 30-40% of the variation in the elasticities, indicating that there is substantial within-CBSA variation that can be leveraged in our cross-sectional regressions.

To examine the relevance of the BSH elasticities in our cross sectional results we first regress our HCS estimates on the elasticities and CBSA fixed effects and report the results in Table (B.0.2) by measure of elasticity and HCS. In the home price specification, we find that there is little to no correlation between our home price sensitivity and the majority of the BSH elasticities. The one exception is with the developed land elasticity, where we find that, within CBSAs, zip codes with a more elastic supply of developed land exhibit less pass-through in home prices. This finding is similar in magnitude to the estimated coefficient on the GMNS inverse elasticity in Tables (7) and (E.3.11). In the rental specifications (columns (6)-(10)), we estimate negative coefficients on the unit, new unit, floor space, and new floor space elasticities, and a positive coefficient on the developed land elasticities. The standard errors in these models are large, particularly with the developed land elasticity, and none of the coefficients are significant at the 10% level, suggesting an ambiguous relationship between the rental sensitivities and supply elasticities within CBSAs.

We augment the multivariate specification in columns (3) and (6) of Table (7) to include the BSH elasticities and report the estimates in Table (B.0.3). In the models with the home price sensitivity as the dependent variable (columns (1)-(5)), we find very similar results as before. The housing quality and land share variables (Near Downtown, structure and land values) remain significant at the 5% level and have virtually identical coefficients as in Table (7).

There is a similar degree of consistency in the rental specifications (columns (6)-(10)). The most notable difference is a slight increase in the magnitude of the crime rate coefficient across every specification. The sign, significance, and magnitude of the other coefficients are nearly identical to our previous results. The coefficients on the BSH elasticities exhibit mixed signs and large standard errors, making them too imprecise to draw any meaningful inferences about the relationship with the rental sensitivities. Overall, our main cross-sectional findings are robust to including the BSH elasticities. The primary exceptions are: (i) the denial rate variable loses significance in the home price specifications; (ii) the magnitude of the crime rate coefficient is larger and statistically significant in the rental price models when controlling for any of the BSH elasticities. In sum, the results suggest that the BSH elasticities provide some relevant information about supply constraints in our within-CBSA models, but they

[14] In the replication package the specific variables we use have a naming convention *gamma01b_ TYPE_ FMM*, where $TYPE \in$ {units, new units, floor space, new floor space, developed land}

Table B.0.2: HCS estimates and Baum-Snow Han elasticities

	Home price HCS					Rental HCS				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
BSH (Units)	0.003					-0.27				
	(0.10)					(0.23)				
BSH (New units)		0.05					-0.26			
		(0.10)					(0.26)			
BSH (Space)			0.01					-0.25		
			(0.09)					(0.18)		
BSH (New space)				0.08					-0.18	
				(0.13)					(0.36)	
BSH (Developed land)					-0.81*					0.14
					(0.46)					(1.3)
Fixed-effects										
cbsa	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics										
Observations	11,164	11,164	11,164	11,164	11,164	9,601	9,601	9,601	9,601	9,601
R^2	0.76	0.76	0.76	0.76	0.76	0.36	0.36	0.36	0.36	0.36

Clustered (cbsa) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

do not substantially alter our interpretation of the mechanisms we highlight.

Table B.0.3: Cross zip regressions with Baum-Snow Han elasticities

	Home price HCS					Rental HCS				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Demand Amplifiers										
Amenities										
Crimes per 100k (log)	-0.02	-0.02	-0.02	-0.02	-0.02	0.44*	0.44*	0.44*	0.44*	0.43*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
Credit										
Denial rate (std)	0.05	0.05	0.05	0.05	0.05	-0.20	-0.20	-0.21	-0.20	-0.20
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.16)	(0.15)	(0.16)	(0.15)	(0.15)
Land value (log)	-0.12***	-0.12**	-0.13***	-0.12**	-0.11**	-0.22	-0.21	-0.22	-0.20	-0.21
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Housing Quality										
Structure value (log)	-0.27**	-0.28**	-0.28**	-0.28**	-0.29***	-0.73**	-0.73**	-0.73**	-0.72**	-0.72**
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Supply										
Housing Liquidity										
Median resident age	0.48**	0.48**	0.48**	0.48**	0.44**	-0.03	-0.02	-0.03	-0.008	0.005
	(0.19)	(0.19)	(0.19)	(0.19)	(0.18)	(0.40)	(0.40)	(0.39)	(0.41)	(0.43)
Home ownership rate (std)	-0.09***	-0.09***	-0.08***	-0.09***	-0.08***	-0.02	-0.03	-0.02	-0.04	-0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Population (log)	-0.03	-0.02	-0.04	-0.02	-0.03	0.11	0.12*	0.10	0.13**	0.13**
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)
Traditional Supply Elasticity										
Near downtown	0.10**	0.10**	0.10**	0.10**	0.10**	0.13	0.13	0.13	0.13	0.12
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
BSH (Units)	-0.13					-0.05				
	(0.15)					(0.37)				
BSH (New units)		-0.10					0.07			
		(0.16)					(0.39)			
BSH (Space)			-0.16					-0.13		
			(0.12)					(0.27)		
BSH (New space)				-0.12					0.29	
				(0.18)					(0.44)	
BSH (Developed land)					-1.0**					0.92
					(0.51)					(1.4)
Fixed-effects										
cbsa	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics										
Observations	5,213	5,213	5,213	5,213	5,213	4,960	4,960	4,960	4,960	4,960
R^2	0.84	0.84	0.84	0.84	0.84	0.49	0.49	0.49	0.49	0.49

Clustered (cbsa) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C Amenities and Amplification of Housing Demand Shocks.

Here we present examples of how an initial shock to housing demand can have differential effects on the housing demand shift depending on the level of natural amenities. Our objective is not to take a stand on the precise mechanism driving demand amplification, but rather to demonstrate that demand-shock amplification can arise under reasonable conditions that (to the best of our knowledge) have previously been overlooked.

We begin by demonstrating heterogeneous amplification of interest-rate changes in a simple setting that features immobile households. We then extend the analysis to feature mobile households with heterogeneous location preferences.

C.1 Immobile Households

Here we demonstrate that interest rate reductions cause stronger increases in housing demand when households' cost of accessing amenities is lower. The simple intuition is based on the assumption that the cost of a bundle of housing and amenities depends both on the user cost of housing and the cost of accessing the amenities. In high-amenity areas, the cost of accessing amenities is low, so the user cost of housing accounts for the majority of the cost of the housing bundle. Interest rate reductions directly affect the user cost of housing but not the cost of amenities. Therefore, there is stronger pass-through from interest rates to housing (bundle) costs in high-amenity areas. This leads to stronger increases in housing demand, holding fixed households' nominal incomes.

Consider a representative household living in location ℓ that has utility over housing and amenities:

$$U_\ell = \left(A_\ell^{\frac{\sigma-1}{\sigma}} + H_\ell^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{C.1}$$

where A_ℓ is consumption of (natural) amenities and H_ℓ is housing. For simplicity, we abstract from consumption of non-housing, non-amenity goods.[15] We assume that housing and amenities are complements: $\sigma < 1$.[16] Location ℓ is characterized by the cost of enjoying amenities $c_{A\ell}$. In locations with high natural amenities, residents can enjoy nice weather and visiting the beach at very low cost, whereas residents of low-amenity areas must pay a much higher price (e.g., transportation for vacations) to access these amenities. Therefore, location ℓ has higher amenities than location ℓ' when $c_{A\ell} < c_{A\ell'}$.

[15] It is straightforward to derive the same results assuming that households have Cobb-Douglas utility over a general consumption good C and the bundle of housing and amenities.

[16] The complementarity assumption is not necessary for the sign of the comparative static with respect to amenity-access costs. For any $\sigma > 0$, $\sigma \neq 1$, the elasticity derived below satisfies $\partial \varepsilon_{H,r} / \partial c_A > 0$, so lower amenity-access costs make housing demand more responsive to interest-rate changes. The Cobb-Douglas case $\sigma = 1$ is the knife-edge case in which $\varepsilon_{H,r} = -1$ and the elasticity does not vary with c_A. However, the interpretation of this amplification depends on σ. When $0 < \sigma < 1$, lower amenity-access costs raise the housing expenditure share, so the result is consistent with a budget-share or pass-through interpretation: interest-rate declines matter more where housing costs are a larger share of the relevant bundle. When $\sigma > 1$, lower amenity-access costs still amplify the housing-demand response, but the mechanism is instead substitution between amenities and housing.

We specify housing costs following the user-cost model of Poterba (1984): $c_{H\ell} = rV_{H\ell}$, where r is the interest rate on a perpetual bond with face value V_ℓ equal to the value of the home.

The representative consumer maximizes utility such that the budget constraint holds:

$$c_A A + c_H H = I, \tag{C.2}$$

where we have dropped ℓ subscripts and will analyze how housing demand depends on c_A. Household optimization implies that housing demand can be written as

$$H^*(r) = \frac{I}{(rV)^\sigma c_A^{1-\sigma} + rV}. \tag{C.3}$$

The object of interest is the Marshallian elasticity of housing demand with respect to the interest rate:

$$\varepsilon_{H,r} \;=\; \frac{\partial \ln H}{\partial \ln r} \;=\; -1 - (\sigma - 1)\,\frac{V^{\sigma-1}\,c_A^{1-\sigma}\,r^{\sigma-1}}{V^{\sigma-1}\,c_A^{1-\sigma}\,r^{\sigma-1} + 1}\,, \tag{C.4}$$

which implies that a fall in interest rates causes an increase in housing demand. We are interested in how this elasticity depends on c_A. Define

$$B = V^{\sigma-1} c_A^{1-\sigma} r^{\sigma-1}, \qquad F(B) = \frac{B}{B+1} \in (0,1). \tag{C.5}$$

Equation C.4 becomes $\varepsilon_{H,r} = -1 - (\sigma-1)F(B)$. Taking a partial derivative with respect to c_A yields

$$\frac{\partial \varepsilon_{H,r}}{\partial c_A} = (\sigma - 1)^2\,\frac{B}{c_A\,(B+1)^2} > 0, \tag{C.6}$$

which states that $\varepsilon_{H,r}$ is more negative (stronger responsiveness) when c_A is low (stronger local amenities). In other words, interest-rate-reductions stimulate housing demand more in high-amenity areas.

C.2 Demand Amplification with Mobile Households

Next, we consider an alternative setting in which households can choose to live in a high-amenity location or a low-amenity location, $\ell \in H, L$. For simplicity, we assume that each household purchases a unit of housing in one of the locations, and they spend the rest of their income on a numeraire good. We abstract from transportation costs of enjoying amenities, to demonstrate that demand amplification does not rely on the assumption of transportation costs.

Households maximize indirect utility

$$U_\ell = A_\ell (Y - c_\ell)^{1-\alpha} e^{\epsilon_\ell}, \tag{C.7}$$

where ϵ_ℓ is an idiosyncratic preference shock associated with living in location ℓ. Under the assumption that ϵ has a Type-1 extreme value distribution, a household chooses a location with probability

$$P_H = \frac{A_H\,(Y - c_H)^{1-\alpha}}{A_H\,(Y - c_H)^{1-\alpha} + A_L\,(Y - c_L)^{1-\alpha}}, \quad P_L = 1 - P_H. \tag{C.8}$$

Demand for housing in location ℓ is the sum of households that choose that location: $Q_\ell = NP_\ell$. As before, we assume that home values are related to housing costs by $c_\ell = rV_\ell$.

We assume that supply exhibits identical elasticities across locations but potentially different intercepts:

$$Q^S_\ell = S_{0\ell}\, p_\ell^{\varepsilon_S}. \tag{C.9}$$

Equilibrium is defined by market-clearing in each location: $Q^S_\ell(p_\ell) = Q_\ell(p_H, p_L)$, where home values obey $c_\ell = r\,V_\ell$.

Since $A_H > A_L$ by assumption, it follows that $c_H > c_L$ if $S_{0H} \leq S_{0L}$ —that is, as long as there is more available space in the low-amenity location. This is easily satisfied in practice, since high-natural-amenity locations are sparse and concentrated on the coasts.

Proposition C1: A reduction in the interest rate increases housing demand more in the high-amenity area.

Proof: Write the relative probability that households choose location H as

$$\frac{P_H}{P_L} = \frac{A_H\,[Y - rV_H]^{1-\alpha}}{A_L\,[Y - rV_L]^{1-\alpha}} \equiv D(r). \tag{C.10}$$

Taking logs yields

$$\log D(r) = \log\left(\frac{A_H}{A_L}\right) + (1-\alpha)\left[\log(Y - rV_H) - \log(Y - rV_L)\right]. \tag{C.11}$$

Differentiating with respect to r yields

$$\frac{d}{dr}\log D(r) = -(1-\alpha)\left[\frac{V_H}{Y - rV_H} - \frac{V_L}{Y - rV_L}\right]. \tag{C.12}$$

Since $V_H > V_L$, the term in the bracket is positive such that $D(r)$ rises when r falls. ■

Intuitively, the interest rate reduction has a bigger effect on disposable income in the high-amenity city because housing costs are a larger share of expenditure there. The disproportionate increase in disposable income has a disproportionate effect on demand to live in the high-amenity area. Therefore, even though there are no explicit costs of accessing amenities, interest rates pass through to costs of living more in high-amenity areas than in low-amenity areas.

C.3 Interest Rates, Amenities, Land, Structures, and Financing Frictions

This section presents a parsimonious model in which interest-rate declines generate larger home-value appreciation in low-supply-elasticity and high-amenity locations, but smaller appreciation in locations with high land or structures values. The model combines three ingredients. First, housing costs are modeled using a standard user-cost formulation as in Poterba (1984). Second, homes are decomposed into land and structures, following the logic in Murphy (2024). Third, the interest-rate elasticity of housing demand is attenuated by financing frictions, especially down-payment constraints, as emphasized by Stein (1995), Ortalo-Magné and Rady (2006), Fuster and Zafar (2021), and Greenwald (2018).

Preferences and housing production. Locations are indexed by ℓ. Households in location ℓ have utility over amenities and housing,

$$U_\ell = \left(A_\ell^{\frac{\sigma-1}{\sigma}} + H_\ell^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{C.13}$$

where A_ℓ is amenity consumption and H_ℓ is housing consumption. The cost of accessing amenities is $c_{A\ell}$.

Housing is produced using land and structures according to a Leontief technology,

$$H_\ell = \min \left\{ L_\ell, \frac{S_\ell}{\gamma_\ell} \right\}. \tag{C.14}$$

Thus one unit of housing requires one unit of land and γ_ℓ units of structures. Let $V_{L\ell}$ denote the asset value of land per unit, and let $V_{S\ell}$ denote the exogenous asset value of one unit of structures. The total asset value of one unit of housing is

$$P_\ell = V_{L\ell} + \gamma_\ell V_{S\ell}. \tag{C.15}$$

Following the user-cost approach, the flow cost of one unit of housing is

$$c_{H\ell} = rP_\ell = rV_{L\ell} + \gamma_\ell r V_{S\ell}. \tag{C.16}$$

The first term is the flow cost of land, while the second term is the flow cost of structures.

Unconstrained housing demand. If the household is unconstrained by financing frictions, it solves

$$\max_{A_\ell, H_\ell} \left(A_\ell^{\frac{\sigma-1}{\sigma}} + H_\ell^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{C.17}$$

subject to

$$c_{A\ell} A_\ell + c_{H\ell} H_\ell = I_\ell. \tag{C.18}$$

The unconstrained housing demand is

$$H_\ell^u = \frac{I_\ell}{c_{H\ell}^\sigma c_{A\ell}^{1-\sigma} + c_{H\ell}}. \tag{C.19}$$

Define the unconstrained absolute user-cost elasticity of housing demand by

$$E_\ell \equiv -\frac{\partial \ln H_\ell^u}{\partial \ln c_{H\ell}}. \tag{C.20}$$

Using (C.19),

$$E_\ell = 1 + (\sigma - 1)F_\ell, \tag{C.21}$$

where

$$F_\ell = \frac{B_\ell}{1 + B_\ell}, \qquad B_\ell = \left(\frac{c_{H\ell}}{c_{A\ell}}\right)^{\sigma-1}. \tag{C.22}$$

Differentiating (C.21) with respect to the amenity-access cost gives

$$\frac{\partial E_\ell}{\partial \ln c_{A\ell}} = -(\sigma - 1)^2 F_\ell(1 - F_\ell) \leq 0. \tag{C.23}$$

Thus, except in the Cobb-Douglas knife-edge case $\sigma = 1$, lower amenity-access costs raise the unconstrained user-cost elasticity of housing demand.

Financing frictions. Households face a maximum loan-to-value ratio $\Lambda \in (0, 1)$. A household with liquid wealth M_i purchasing $H_{i\ell}$ units of housing in location ℓ must satisfy

$$(1 - \Lambda)P_\ell H_{i\ell} \leq M_i. \tag{C.24}$$

Let $H_{i\ell}^u$ denote the household's unconstrained housing demand. Actual demand is

$$H_{i\ell} = \min\left\{H_{i\ell}^u, \frac{M_i}{(1 - \Lambda)P_\ell}\right\}. \tag{C.25}$$

The key implication is that a decline in r relaxes the user-cost margin but does not directly relax the down-payment requirement in (C.24). Therefore, households whose housing demand is pinned down by liquid wealth have little or no direct response to r at a fixed home price.

Let $\mu_\ell \in [0, 1]$ denote the demand-weighted share of marginal buyers in location ℓ whose housing demand is constrained by (C.24). We assume

$$\mu_\ell = \mu\left(\frac{(1 - \Lambda)P_\ell}{M_\ell}\right), \qquad \mu'(\cdot) > 0, \tag{C.26}$$

where M_ℓ is a measure of liquid wealth for marginal buyers. Thus higher home values increase the down-payment burden and raise the constrained share unless liquid wealth rises proportionally.

To allow richer or less-levered marginal buyers to be less sensitive to financing conditions, we also introduce a rate-sensitivity shifter

$$\chi_\ell = \chi(Y_\ell, W_\ell) \in (0, 1], \qquad \frac{\partial \chi_\ell}{\partial Y_\ell} \leq 0, \qquad \frac{\partial \chi_\ell}{\partial W_\ell} \leq 0, \tag{C.27}$$

where Y_ℓ and W_ℓ denote income and wealth of marginal buyers. The term χ_ℓ captures the possibility that richer, less-levered, or cash-like buyers are less responsive to mortgage-rate changes.

A local log-linearization of aggregate housing demand around equilibrium can then be written as

$$d \ln H_\ell^d = -\eta_{r\ell} d \ln r - \eta_{P\ell} d \ln P_\ell, \tag{C.28}$$

where the effective interest-rate elasticity of housing demand is

$$\eta_{r\ell} = (1 - \mu_\ell)\chi_\ell E_\ell, \tag{C.29}$$

and the home-price elasticity of housing demand is

$$\eta_{P\ell} = (1 - \mu_\ell)\chi_\ell E_\ell + \mu_\ell. \tag{C.30}$$

The first term in (C.30) is the user-cost response of unconstrained households to a higher home price. The second term captures the fact that down-payment-constrained households can purchase less housing when P_ℓ rises. The normalization that constrained demand has unit price elasticity follows directly from the down-payment bound in (C.25). More general constrained price elasticities can be incorporated without changing the main economic logic.

Land supply and market clearing. Land supply in location ℓ is

$$L_\ell^s = \alpha_\ell V_{L\ell}^{\epsilon_\ell}, \qquad \epsilon_\ell \geq 0. \tag{C.31}$$

Because one unit of housing requires one unit of land, market clearing requires

$$H_\ell^d = L_\ell^s. \tag{C.32}$$

Let

$$\omega_\ell \equiv \frac{V_{L\ell}}{P_\ell} = \frac{V_{L\ell}}{V_{L\ell} + \gamma_\ell V_{S\ell}} \tag{C.33}$$

denote the land share of home value. Holding structures costs fixed, a change in P_ℓ maps into land values according to

$$d \ln V_{L\ell} = \frac{1}{\omega_\ell} d \ln P_\ell. \tag{C.34}$$

Therefore, the elasticity of housing supply with respect to the total home value is

$$\eta_\ell^s = \frac{\epsilon_\ell}{\omega_\ell}. \tag{C.35}$$

Interest-rate comparative statics. Combining demand and supply gives

$$-\eta_{r\ell} d \ln r - \eta_{P\ell} d \ln P_\ell = \frac{\epsilon_\ell}{\omega_\ell} d \ln P_\ell. \tag{C.36}$$

Solving for the response of home values to interest rates yields

$$\frac{\partial \ln P_\ell}{\partial \ln r} = -\frac{\eta_{r\ell}}{\eta_{P\ell} + \epsilon_\ell / \omega_\ell}. \tag{C.37}$$

Define the home-value appreciation elasticity with respect to an interest-rate decline as

$$\mathcal{A}_\ell \equiv -\frac{\partial \ln P_\ell}{\partial \ln r}. \tag{C.38}$$

Using (C.29) and (C.30),

$$\mathcal{A}_\ell = \frac{(1-\mu_\ell)\chi_\ell E_\ell}{(1-\mu_\ell)\chi_\ell E_\ell + \mu_\ell + \epsilon_\ell/\omega_\ell}. \tag{C.39}$$

This expression is the main result.

Implications for home-value appreciation. Let

$$N_\ell \equiv (1-\mu_\ell)\chi_\ell E_\ell, \qquad D_\ell \equiv N_\ell + \mu_\ell + \frac{\epsilon_\ell}{\omega_\ell}. \tag{C.40}$$

Then

$$\mathcal{A}_\ell = \frac{N_\ell}{D_\ell}. \tag{C.41}$$

First, appreciation is larger in low-supply-elasticity locations:

$$\frac{\partial \mathcal{A}_\ell}{\partial \epsilon_\ell} = -\frac{N_\ell}{\omega_\ell D_\ell^2} < 0. \tag{C.42}$$

Second, appreciation is larger in high-amenity locations. Holding μ_ℓ, χ_ℓ, and ω_ℓ fixed,

$$\frac{\partial \mathcal{A}_\ell}{\partial E_\ell} = \frac{(1-\mu_\ell)\chi_\ell\,(\mu_\ell + \epsilon_\ell/\omega_\ell)}{D_\ell^2} > 0. \tag{C.43}$$

Together with (C.23), this implies

$$\frac{\partial \mathcal{A}_\ell}{\partial \ln c_{A\ell}} = -\frac{(1-\mu_\ell)\chi_\ell\,(\mu_\ell + \epsilon_\ell/\omega_\ell)\,(\sigma-1)^2 F_\ell(1-F_\ell)}{D_\ell^2} \leq 0. \tag{C.44}$$

Thus lower amenity-access costs raise the appreciation response, except in the knife-edge Cobb-Douglas case $\sigma = 1$.

Third, appreciation is smaller when a larger share of marginal buyers is down-payment constrained:

$$\frac{\partial \mathcal{A}_\ell}{\partial \mu_\ell} = -\frac{\chi_\ell E_\ell\,(1 + \epsilon_\ell/\omega_\ell)}{D_\ell^2} < 0. \tag{C.45}$$

Since μ_ℓ is increasing in the down-payment burden $(1-\Lambda)P_\ell/M_\ell$, expensive locations have a lower effective rate elasticity of demand when high prices bind the down-payment constraint for more marginal buyers.

Fourth, appreciation is smaller when marginal buyers are less sensitive to financing conditions. Since

$$\frac{\partial \mathcal{A}_\ell}{\partial \chi_\ell} = \frac{(1-\mu_\ell)E_\ell\,(\mu_\ell + \epsilon_\ell/\omega_\ell)}{D_\ell^2} > 0, \tag{C.46}$$

locations populated by less-levered, wealthier, or otherwise less rate-sensitive marginal buyers have smaller home-value responses to interest-rate declines.

Land values and structures values. Let

$$K_\ell \equiv \gamma_\ell V_{S\ell}, \qquad P_\ell = V_{L\ell} + K_\ell, \qquad \theta_\ell \equiv \frac{K_\ell}{P_\ell} = 1 - \omega_\ell. \tag{C.47}$$

Holding μ_ℓ, χ_ℓ, and E_ℓ fixed, an increase in structures values lowers the land share ω_ℓ and raises the effective supply elasticity $\epsilon_\ell/\omega_\ell$. Therefore,

$$\frac{\partial \mathcal{A}_\ell}{\partial \ln K_\ell} = -\frac{N_\ell(\epsilon_\ell/\omega_\ell)\theta_\ell}{D_\ell^2} < 0. \tag{C.48}$$

Moreover, if higher structures values also raise the down-payment burden and increase μ_ℓ, the negative effect in (C.48) is reinforced.

The effect of high land values is more subtle. Holding μ_ℓ, χ_ℓ, and E_ℓ fixed, higher $V_{L\ell}$ raises the land share ω_ℓ, lowers the effective supply elasticity $\epsilon_\ell/\omega_\ell$, and mechanically raises appreciation:

$$\left.\frac{\partial \mathcal{A}_\ell}{\partial \ln V_{L\ell}}\right|_{\mu,\chi,E} = \frac{N_\ell(\epsilon_\ell/\omega_\ell)\theta_\ell}{D_\ell^2} > 0. \tag{C.49}$$

Thus, to obtain lower appreciation in high-land-value locations, the financing-friction channel must dominate this mechanical land-share channel.

A compact sufficient and necessary local condition can be written as follows. Let

$$R_\ell \equiv \mu_\ell + \frac{\epsilon_\ell}{\omega_\ell}. \tag{C.50}$$

Since $\mathcal{A}_\ell = N_\ell/(N_\ell + R_\ell)$, appreciation falls with $V_{L\ell}$ if and only if

$$\frac{\partial \ln N_\ell}{\partial \ln V_{L\ell}} < \frac{\partial \ln R_\ell}{\partial \ln V_{L\ell}}. \tag{C.51}$$

Using $N_\ell = (1-\mu_\ell)\chi_\ell E_\ell$, this condition becomes

$$-\frac{1}{1-\mu_\ell}\frac{\partial \mu_\ell}{\partial \ln V_{L\ell}} + \frac{\partial \ln \chi_\ell}{\partial \ln V_{L\ell}} + \frac{\partial \ln E_\ell}{\partial \ln V_{L\ell}} < \frac{\frac{\partial \mu_\ell}{\partial \ln V_{L\ell}} - (\epsilon_\ell/\omega_\ell)\,\theta_\ell}{\mu_\ell + \epsilon_\ell/\omega_\ell}. \tag{C.52}$$

The left-hand side captures the attenuation of effective rate-sensitive demand in high-land-value locations through down-payment constraints and lower financing sensitivity. The right-hand side captures the change in the denominator of the capitalization formula, including the mechanical land-share supply channel. Therefore, high land values reduce appreciation when their effect on constrained marginal buyers and financing sensitivity is sufficiently strong.

Flow housing costs. The flow housing cost is

$$c_{H\ell} = rP_\ell = rV_{L\ell} + \gamma_\ell r V_{S\ell}. \tag{C.53}$$

Since

$$\frac{\partial \ln P_\ell}{\partial \ln r} = -\mathcal{A}_\ell, \tag{C.54}$$

we have

$$\frac{\partial \ln c_{H\ell}}{\partial \ln r} = 1 - \mathcal{A}_\ell = \frac{\mu_\ell + \epsilon_\ell/\omega_\ell}{(1-\mu_\ell)\chi_\ell E_\ell + \mu_\ell + \epsilon_\ell/\omega_\ell}. \tag{C.55}$$

Thus an interest-rate decline lowers the flow cost of housing whenever $\mathcal{A}_\ell < 1$. The extent to which lower rates pass through into lower housing costs is smaller when more of the shock is capitalized into home values.

The flow land-cost component satisfies

$$c_{L\ell} = rV_{L\ell}, \tag{C.56}$$

so

$$\frac{\partial \ln c_{L\ell}}{\partial \ln r} = 1 - \frac{\mathcal{A}_\ell}{\omega_\ell}. \tag{C.57}$$

The structures-cost component satisfies

$$c_{S\ell} = \gamma_\ell r V_{S\ell}, \tag{C.58}$$

so

$$\frac{\partial \ln c_{S\ell}}{\partial \ln r} = 1. \tag{C.59}$$

Equations (C.55)–(C.59) show that the total flow cost of housing sums the land and structures components. Structures costs fall one-for-one with r, while land flow costs may fall or rise depending on the strength of land-value capitalization. In particular, $rV_{L\ell}$ rises after an interest-rate decline if $\mathcal{A}_\ell > \omega_\ell$.

Summary. The model predicts that the home-value appreciation response to a decline in interest rates is

$$\mathcal{A}_\ell = \frac{(1-\mu_\ell)\chi_\ell E_\ell}{(1-\mu_\ell)\chi_\ell E_\ell + \mu_\ell + \epsilon_\ell/\omega_\ell}. \tag{C.60}$$

Appreciation is larger when land supply is less elastic, when amenities make housing demand more sensitive to user costs, and when marginal buyers are less constrained. Appreciation is smaller in locations with high structures values because structures lower the land share and increase the effective supply elasticity with respect to home values. Appreciation is also smaller in high-land-value locations when high prices sufficiently increase the share of down-payment-constrained marginal buyers or reduce financing sensitivity among marginal buyers.

D Propagation of VAR Uncertainty

The main text reports results based both on the median historical decomposition and on estimates that propagate first-stage uncertainty from the structural VAR. This appendix explains why that propagation matters and how we implement it. The issue is that the historical decompositions entering the ZIP-level regressions are generated regressors, so treating them as fixed can understate uncertainty in both the HCS estimates and the downstream cross-sectional regressions (Pagan, 1984).

This concern is particularly relevant in set-identified SVARs. As emphasized by Fry and Pagan (2011) and Inoue and Kilian (2013, 2022), pointwise posterior summaries of impulse responses or historical decompositions need not correspond to any single admissible structural model. Using only those summaries in second-stage regressions can therefore mask economically meaningful first-stage uncertainty. Our solution is to sharpen the posterior using narrative restrictions and then propagate the accepted posterior draws through each stage of the empirical analysis.

We address these issues in two steps. First, we refine the posterior of the BTW model using the narrative restrictions described in Section 2.2. Second, we propagate the accepted posterior draws through the zip-level and cross-sectional regressions.

D.1 Implementing the Narrative Restrictions

We implement the narrative restrictions using Algorithm 1 of Antolín-Díaz and Rubio-Ramírez (2018). The procedure has three stages.

1. *Sign-restricted draws.* We draw from the posterior distribution of the reduced-form VAR parameters and random orthogonal rotations, retaining only those draws whose implied impulse responses satisfy the BTW sign restrictions.

2. *Narrative checks and importance weights.* For each sign-restricted draw, we check whether the shock-sign and historical-decomposition restrictions are satisfied at all three narrative episodes. For draws that pass, we compute the corresponding ADRR importance weights using simulated shock sequences.

3. *Resampling.* We resample from the narrative-passing draws with probabilities proportional to the resulting importance weights. The resampled draws form the posterior distribution used in the downstream analysis.

This procedure sharpens inference by discarding structurally admissible draws that imply implausible historical episodes. In our setting, the resulting posterior remains sufficiently large for inference while being materially more informative than the original sign-restricted set.

Table D.1.4 reports diagnostics for the narrative-restriction procedure.

Table D.1.4: Narrative Restriction Diagnostics

	Value
Sign-restricted draws	$N = 50{,}000$
Narrative-passing draws	$N_{\text{narr}} = 614$
Effective sample size (ESS)	329.5
Median importance weight	90.99
Max/Median importance weight	19.63

D.2 Propagation to Zip-Level Regressions

For each accepted admissible model $\Theta \in \boldsymbol{\Theta}$, we compute the year-over-year changes in the historical decompositions of national home prices associated with the mortgage-rate, housing-supply, expectation, and housing-consumption shocks: $\Delta M_t^{(\Theta)}$, $\Delta HS_t^{(\Theta)}$, $\Delta Exp_t^{(\Theta)}$, and $\Delta HC_t^{(\Theta)}$. We then estimate equation 2.11 separately for each draw, which yields a draw-specific HCS estimate $\hat{\beta}_{c,i}^{M,(\Theta)}$ for each zip code.

We next use these draw-specific HCS estimates in the cross-sectional regressions of equations 2.12 and 3.1. This produces a draw-by-draw distribution for every second-stage coefficient. In the main text, we report two complementary summaries: (i) estimates based on the median historical decomposition, and (ii) median coefficient estimates and 68% credible intervals obtained by propagating the accepted posterior draws through the zip-level and cross-sectional regressions.

This procedure preserves the uncertainty inherent in the first-stage structural decomposition. In particular, it allows the precision of the aggregate VAR estimates to influence both the estimated HCS measures and the cross-sectional relationships used to interpret them.

In the baseline propagated results, we additionally restrict attention to draws that imply a positive coefficient on the GMNS inverse elasticity in the across-CBSA regressions for *both* home prices and rents. We view this as a weak sign restriction motivated by the close conceptual relationship between our HCS object and established inverse supply-elasticity measures. Appendix E.1 report sensitivity to alternative restrictions.

D.3 Discussion

Our implementation is best viewed as quasi-Bayesian. We begin with posterior draws from the structural VAR, then propagate those draws through downstream regressions to obtain posterior distributions over the zip-level and cross-sectional coefficients. Alternative approaches are possible. A moving-block bootstrap could provide a frequentist analogue, while a fully hierarchical Bayesian model could jointly estimate the structural and microeconometric components. We leave a systematic comparison of these approaches to future work.

E Appendix Tables and Figures

E.1 Robustness to Alternative Restrictions

Our baseline propagated results in Section 4.2 restrict attention to the 357 of 614 narrative-passing draws that imply a positive across-CBSA GMNS coefficient. This restriction is motivated by the close conceptual relationship between our HCS and the GMNS inverse supply elasticity. Because our first-stage object is estimated in a manner similar to GMNS, differing mainly in that we specify the nature of the aggregate shock and in the estimation sample, we expect a positive relationship between the two and concentrate posterior weight on the draws consistent with it. In this appendix we assess how the estimated coefficients in the cross-sectional regressions respond when that restriction is relaxed, replaced by a screen on the precision of the first-stage estimates, or tightened. Tables E.1.5 through E.1.8 report the results.

Table E.1.5 uses all 614 narrative-passing draws. The home-price determinants are essentially unchanged from the baseline. The median GMNS coefficient is 0.571 with a 68% credible interval of $[0.298, 0.814]$, against 0.591 $[0.331, 0.801]$ in the baseline; the natural-amenity coefficient is 0.141 $[0.079, 0.204]$, against 0.146 $[0.087, 0.210]$; and the within-CBSA homeownership coefficient is -0.035 $[-0.067, -0.001]$, against -0.037 $[-0.070, -0.010]$. The three of the four central home-price relationships therefore do not depend on the restriction. Structure values are the exception. Once propagating the full-sample of satisfied draws the credible bands widen shift and now include zero, $[-0.406, 0.069]$ against $[-0.446, -0.008]$, though the medain coefficients remain comparable -0.187 versus -0.221. The rent GMNS relationship is less sharply identified in the unrestricted posterior, at 0.040 $[-0.087, 0.175]$, which is consistent with our motivation for concentrating on draws that imply the expected positive supply relationship. On the rent margin, the coefficients that remain distinguishable from zero without any restriction are pre-sample denial rates and, among the within-CBSA controls, the downtown indicator. Similar to the models with the home price HCS, we find the within-CBSA structure-value coefficient is less precisely estimated under full propagation, even though it remains the largest single contributor to within-CBSA explained variation in the decomposition of Table 8.

Table E.1.6 restricts the sample to the ZIP codes whose point-wise home and rent HCS are both estimated with $|t| > 1.645$, which reduces the sample from 13,747 to 2,945 ZIP codes in the no-FE specifications. Because the estimation sample changes, the point-wise estimates in this table are not directly comparable to those in the other tables. For example, the point-wise GMNS coefficient rises to 0.975 for home prices and 0.654 for rents. Given the reduction in the sample of ZIPs in this table we view the results as a validation check rather than a preferred specification. The main relationships survive on this restricted sample. The home GMNS coefficient is 0.646 $[0.350, 0.923]$, the within-CBSA homeownership coefficient remains negative and excludes zero, and the natural-amenity coefficient is distinguishable from zero for both home prices, at 0.128 $[0.047, 0.196]$, and rents, at 0.145 $[0.046, 0.239]$. The home-price amenity result is notable because it holds in the propagation even though its point-wise estimate on this small sample is not statistically significant. These patterns indicate that the relationship between the HCS, local supply inelasticity and natural amenities are not driven by imprecisely estimated sensitivities.

Tables E.1.7–E.1.8 progressively tighten the restriction on the draw-implied GMNS coefficients. Requiring a larger home GMNS coefficient raises the estimated home GMNS coefficient monotonically, from 0.571 in the unrestricted posterior to 0.699 and then 0.865 as the threshold moves from zero to 0.5 and 0.75, and the home natural-amenity coefficient rises in step, from 0.141 to 0.167 and 0.203. Tightening the rent threshold similarly raises the rent GMNS coefficient. This pattern is the expected consequence of concentrating posterior weight on draws that imply a stronger relationship between the HCS and the inverse supply elasticity. The number of retained draws falls quickly, from 614 to 223, 82, and 54, so the tightest cuts should be read as directional rather than as precisely estimated.

Table E.1.5: Determinants of Zip-Level Housing Cost Sensitivities — All draws

Dependent Variables:	Home Price HCS		Rental HCS	
Model:	(1)	(2)	(3)	(4)
Supply				
Traditional Supply Elasticity				
GMNS Inv Elas	0.74*** *0.571* [0.298, 0.814]		0.46*** *0.040* [-0.087, 0.175]	
Near downtown		0.07* *0.041* [-0.010, 0.076]		0.17 *0.117* [0.037, 0.191]
Housing Liquidity				
Median resident age (log)	0.78*** *0.089* [-0.218, 0.440]	0.69*** *0.081* [-0.070, 0.248]	-0.35 *0.019* [-0.277, 0.337]	0.38 *0.188* [-0.124, 0.440]
Home ownership rate (std)	-0.10*** *-0.021* [-0.047, 0.005]	-0.09*** *-0.035* [-0.067, -0.001]	-0.008 *-0.005* [-0.038, 0.019]	-0.04 *0.002* [-0.025, 0.030]
Population (log)	-0.13*** *-0.018* [-0.046, -0.001]	-0.02 *0.004* [-0.012, 0.019]	0.02 *0.006* [-0.010, 0.023]	0.09** *0.019* [-0.020, 0.071]
Demand Amplifiers				
Amenities				
Natural amenity index (std)	0.13** *0.141* [0.079, 0.204]		0.14** *0.092* [-0.006, 0.178]	
Crimes per 100k (log)	0.07 *0.029* [-0.022, 0.065]	-0.06 *0.015* [-0.043, 0.058]	0.08 *-0.013* [-0.083, 0.049]	0.17 *0.001* [-0.103, 0.076]
Credit				
Denial rate (std)	0.02 *-0.029* [-0.080, 0.024]	0.10 *0.014* [-0.034, 0.064]	0.08 *0.057* [0.001, 0.100]	0.08 *0.150* [-0.024, 0.283]
Median home price to renter inc	-0.06*** *-0.012* [-0.039, 0.014]		-0.04 *-0.002* [-0.027, 0.014]	
Land value (log)		-0.10* *-0.027* [-0.081, 0.029]		-0.06 *0.042* [-0.062, 0.106]
Housing Quality				
Median age of home (log)	0.16*** *0.124* [0.004, 0.240]		0.05 *0.052* [-0.011, 0.095]	
Structure value (log)		-0.45*** *-0.187* [-0.406, 0.069]		-0.84*** *-0.156* [-0.457, 0.121]
Observations	13,747	5,618	10,333	4,934
Median R^2	0.273	0.768	0.030	0.332
Posterior draws used	614	614	614	614

Notes: Restriction: All draws. First line of each cell is the point-wise WLS estimate (median historical decomposition) with significance stars; italic line is the posterior median across the restricted draw set; bracketed line is the 68% credible interval. Observations are point-wise; posterior draws are the size of the restricted set. Columns (1) and (3) are no-FE; (2) and (4) add CBSA fixed effects with land and structure values.

Table E.1.6: Determinants of Zip-Level Housing Cost Sensitivities — Precise HCS ($|t| > 1.645$, both margins)

Dependent Variables:	Home Price HCS		Rental HCS	
Model:	(1)	(2)	(3)	(4)
Supply				
Traditional Supply Elasticity				
GMNS Inv Elas	0.975*** *0.646* [0.350, 0.923]		0.654** *0.111* [-0.003, 0.260]	
Near downtown		0.036 *0.031* [-0.053, 0.094]		0.083 *0.053* [-0.030, 0.135]
Housing Liquidity				
Median resident age (log)	0.226 *-0.011* [-0.203, 0.173]	0.741*** *0.088* [-0.071, 0.266]	0.158 *0.199* [-0.182, 0.514]	0.134 *0.334* [0.064, 0.601]
Home ownership rate (std)	-0.100** *-0.032* [-0.063, -0.001]	-0.083*** *-0.043* [-0.077, -0.008]	-0.105 *-0.035* [-0.079, -0.002]	-0.053 *-0.001* [-0.042, 0.032]
Population (log)	-0.231*** *-0.051* [-0.100, -0.015]	-0.035 *-0.007* [-0.027, 0.007]	0.037 *0.016* [-0.014, 0.049]	0.142 *0.043* [-0.014, 0.125]
Demand Amplifiers				
Amenities				
Natural amenity index (std)	0.068 *0.128* [0.047, 0.196]		0.285*** *0.145* [0.046, 0.239]	
Crimes per 100k (log)	0.188* *0.082* [0.029, 0.132]	-0.015 *0.068* [0.000, 0.127]	-0.096 *-0.057* [-0.128, 0.046]	0.066 *-0.025* [-0.160, 0.106]
Credit				
Denial rate (std)	0.080 *-0.023* [-0.098, 0.047]	0.130 *0.017* [-0.068, 0.092]	0.125 *0.084* [-0.021, 0.152]	-0.282 *0.008* [-0.245, 0.202]
Median home price to renter inc	-0.089*** *-0.022* [-0.056, 0.006]		-0.104* *-0.024* [-0.061, 0.010]	
Land value (log)		-0.233*** *-0.086* [-0.165, -0.002]		-0.099 *0.041* [-0.149, 0.171]
Housing Quality				
Median age of home (log)	0.169** *0.146* [0.027, 0.262]		-0.003 *0.047* [-0.056, 0.136]	
Structure value (log)		-0.501*** *-0.107* [-0.351, 0.204]		-1.382*** *-0.442* [-0.743, -0.115]
Observations	2,945	1,455	2,945	1,455
Median R^2	0.327	0.804	0.050	0.435
Posterior draws used	614	614	614	614

Notes: Restriction: Precise HCS ($|t| > 1.645$, both margins). First line of each cell is the point-wise WLS estimate (median historical decomposition) with significance stars; italic line is the posterior median across the restricted draw set; bracketed line is the 68% credible interval. Observations are point-wise; posterior draws are the size of the restricted set. Columns (1) and (3) are no-FE; (2) and (4) add CBSA fixed effects with land and structure values.

Table E.1.7: Determinants of Zip-Level Housing Cost Sensitivities — HP GMNS > 0.5, Rent GMNS > 0

Dependent Variables:	Home Price HCS		Rental HCS	
Model:	(1)	(2)	(3)	(4)
Supply				
Traditional Supply Elasticity				
GMNS Inv Elas	0.74*** *0.699* [0.576, 0.894]		0.46*** *0.121* [0.036, 0.218]	
Near downtown		0.07* *0.045* [0.002, 0.082]		0.17 *0.100* [0.028, 0.178]
Housing Liquidity				
Median resident age (log)	0.78*** *0.116* [-0.179, 0.421]	0.69*** *0.070* [-0.076, 0.220]	-0.35 *-0.061* [-0.347, 0.167]	0.38 *0.243* [-0.050, 0.496]
Home ownership rate (std)	-0.10*** *-0.017* [-0.037, 0.005]	-0.09*** *-0.037* [-0.068, -0.013]	-0.008 *0.000* [-0.023, 0.021]	-0.04 *-0.006* [-0.034, 0.020]
Population (log)	-0.13*** *-0.017* [-0.043, -0.000]	-0.02 *0.003* [-0.009, 0.017]	0.02 *0.010* [-0.006, 0.027]	0.09** *0.032* [-0.009, 0.085]
Demand Amplifiers				
Amenities				
Natural amenity index (std)	0.13** *0.167* [0.122, 0.225]		0.14** *0.075* [-0.007, 0.153]	
Crimes per 100k (log)	0.07 *0.030* [-0.015, 0.063]	-0.06 *0.027* [-0.029, 0.061]	0.08 *0.003* [-0.053, 0.053]	0.17 *0.036* [-0.062, 0.119]
Credit				
Denial rate (std)	0.02 *-0.046* [-0.088, -0.004]	0.10 *0.015* [-0.029, 0.056]	0.08 *0.056* [0.009, 0.101]	0.08 *0.126* [-0.046, 0.265]
Median home price to renter inc	-0.06*** *-0.006* [-0.026, 0.012]		-0.04 *-0.010* [-0.035, 0.003]	
Land value (log)		-0.10* *-0.023* [-0.063, 0.028]		-0.06 *0.032* [-0.078, 0.088]
Housing Quality				
Median age of home (log)	0.16*** *0.168* [0.087, 0.263]		0.05 *0.055* [0.007, 0.102]	
Structure value (log)		-0.45*** *-0.212* [-0.418, -0.004]		-0.84*** *-0.269* [-0.562, -0.055]
Observations	13,747	5,618	10,333	4,934
Median R^2	0.351	0.806	0.024	0.333
Posterior draws used	223	223	223	223

Notes: Restriction: HP GMNS > 0.5, Rent GMNS > 0. First line of each cell is the point-wise WLS estimate (median historical decomposition) with significance stars; italic line is the posterior median across the restricted draw set; bracketed line is the 68% credible interval. Observations are point-wise; posterior draws are the size of the restricted set. Columns (1) and (3) are no-FE; (2) and (4) add CBSA fixed effects with land and structure values.

Table E.1.8: Determinants of Zip-Level Housing Cost Sensitivities — HP GMNS > 0.5, Rent GMNS > 0.2

Dependent Variables:	Home Price HCS		Rental HCS	
Model:	(1)	(2)	(3)	(4)
Supply				
Traditional Supply Elasticity				
GMNS Inv Elas	0.74***		0.46***	
	0.777		*0.237*	
	[0.594, 1.068]		[0.195, 0.384]	
Near downtown		0.07*		0.17
		0.037		*0.072*
		[0.001, 0.092]		[-0.026, 0.171]
Housing Liquidity				
Median resident age (log)	0.78***	0.69***	-0.35	0.38
	0.257	*0.147*	*-0.333*	*0.270*
	[-0.117, 0.545]	[0.023, 0.361]	[-0.572, -0.032]	[-0.108, 0.779]
Home ownership rate (std)	-0.10***	-0.09***	-0.008	-0.04
	-0.019	*-0.044*	*0.003*	*-0.023*
	[-0.051, 0.001]	[-0.088, -0.013]	[-0.023, 0.024]	[-0.059, 0.018]
Population (log)	-0.13***	-0.02	0.02	0.09**
	-0.024	*0.004*	*0.016*	*0.062*
	[-0.049, 0.008]	[-0.008, 0.020]	[-0.009, 0.034]	[-0.000, 0.148]
Demand Amplifiers				
Amenities				
Natural amenity index (std)	0.13**		0.14**	
	0.189		*0.063*	
	[0.139, 0.283]		[-0.067, 0.142]	
Crimes per 100k (log)	0.07	-0.06	0.08	0.17
	0.038	*0.010*	*0.031*	*0.088*
	[-0.014, 0.079]	[-0.043, 0.066]	[-0.036, 0.126]	[-0.057, 0.221]
Credit				
Denial rate (std)	0.02	0.10	0.08	0.08
	-0.056	*0.020*	*0.043*	*0.024*
	[-0.099, -0.018]	[-0.036, 0.062]	[-0.020, 0.098]	[-0.184, 0.175]
Median home price to renter inc	-0.06***		-0.04	
	-0.017		*-0.035*	
	[-0.042, 0.007]		[-0.065, -0.012]	
Land value (log)		-0.10*		-0.06
		-0.019		*-0.008*
		[-0.067, 0.035]		[-0.171, 0.051]
Housing Quality				
Median age of home (log)	0.16***		0.05	
	0.218		*0.059*	
	[0.107, 0.336]		[0.003, 0.112]	
Structure value (log)		-0.45***		-0.84***
		-0.243		*-0.556*
		[-0.474, -0.028]		[-0.877, -0.341]
Observations	13,747	5,618	10,333	4,934
Median R^2	0.311	0.815	0.026	0.335
Posterior draws used	54	54	54	54

Notes: Restriction: HP GMNS > 0.5, Rent GMNS > 0.2. First line of each cell is the point-wise WLS estimate (median historical decomposition) with significance stars; italic line is the posterior median across the restricted draw set; bracketed line is the 68% credible interval. Observations are point-wise; posterior draws are the size of the restricted set. Columns (1) and (3) are no-FE; (2) and (4) add CBSA fixed effects with land and structure values.

Table E.1.9: Determinants of Zip-Level Housing Cost Sensitivities — HP GMNS > 0.75, Rent GMNS > 0

Dependent Variables:	Home Price HCS		Rental HCS	
Model:	(1)	(2)	(3)	(4)
Supply				
Traditional Supply Elasticity				
GMNS Inv Elas	0.74***		0.46***	
	0.865		*0.147*	
	[0.777, 1.089]		[0.039, 0.305]	
Near downtown		0.07*		0.17
		0.045		*0.115*
		[0.004, 0.086]		[0.024, 0.195]
Housing Liquidity				
Median resident age (log)	0.78***	0.69***	-0.35	0.38
	0.143	*0.057*	*-0.107*	*0.253*
	[-0.143, 0.498]	[-0.090, 0.228]	[-0.386, 0.199]	[-0.066, 0.536]
Home ownership rate (std)	-0.10***	-0.09***	-0.008	-0.04
	-0.015	*-0.038*	*-0.003*	*-0.010*
	[-0.039, 0.010]	[-0.070, -0.013]	[-0.034, 0.020]	[-0.042, 0.020]
Population (log)	-0.13***	-0.02	0.02	0.09**
	-0.020	*0.003*	*0.010*	*0.038*
	[-0.048, -0.004]	[-0.010, 0.021]	[-0.010, 0.035]	[-0.015, 0.103]
Demand Amplifiers				
Amenities				
Natural amenity index (std)	0.13**		0.14**	
	0.203		*0.082*	
	[0.157, 0.289]		[-0.019, 0.160]	
Crimes per 100k (log)	0.07	-0.06	0.08	0.17
	0.026	*0.034*	*-0.009*	*0.041*
	[-0.017, 0.067]	[-0.044, 0.065]	[-0.076, 0.073]	[-0.086, 0.138]
Credit				
Denial rate (std)	0.02	0.10	0.08	0.08
	-0.055	*0.018*	*0.054*	*0.132*
	[-0.096, -0.012]	[-0.029, 0.066]	[0.000, 0.107]	[-0.086, 0.267]
Median home price to renter inc	-0.06***		-0.04	
	-0.002		*-0.017*	
	[-0.026, 0.018]		[-0.053, 0.006]	
Land value (log)		-0.10*		-0.06
		-0.009		*0.037*
		[-0.068, 0.030]		[-0.092, 0.089]
Housing Quality				
Median age of home (log)	0.16***		0.05	
	0.204		*0.063*	
	[0.119, 0.348]		[0.011, 0.121]	
Structure value (log)		-0.45***		-0.84***
		-0.208		*-0.347*
		[-0.429, 0.001]		[-0.765, -0.024]
Observations	13,747	5,618	10,333	4,934
Median R^2	0.369	0.823	0.022	0.311
Posterior draws used	82	82	82	82

Notes: Restriction: HP GMNS > 0.75, Rent GMNS > 0. First line of each cell is the point-wise WLS estimate (median historical decomposition) with significance stars; italic line is the posterior median across the restricted draw set; bracketed line is the 68% credible interval. Observations are point-wise; posterior draws are the size of the restricted set. Columns (1) and (3) are no-FE; (2) and (4) add CBSA fixed effects with land and structure values.

E.2 Alternative Distributional Effects Tables

Table E.2.10: Distributional Effects (Income)

Dependent Variables:	Home Price HCS		Rental HCS	
Model:	(1)	(2)	(3)	(4)
Median HH income (2000)	-0.33**	-0.43***	-0.42***	-0.59***
	0.105	*-0.176*	*-0.114*	*-0.199*
	[-0.082, 0.277]	[-0.344, 0.015]	[-0.205, -0.049]	[-0.378, -0.094]
Fixed-effects				
cbsa		✓		✓
Observations	13,775	13,775	10,346	10,341
Posterior draws used	357	357	357	357

Notes: Coefficients and significance stars report the original weighted least squares estimates using the point-wise median historical decompositions, with clustering at the CBSA level. Italicized entries report the median coefficient estimate across accepted narrative-restriction posterior draws from the VAR-uncertainty propagation exercise. Bracketed entries report 68% credible intervals, formed from the 16th and 84th percentiles of the draw-by-draw coefficient distribution. In the propagated specification, regressions are weighted by inverse first-stage variance ($1/\hat{\sigma}^2_{\beta_z}$) within each accepted narrative-restriction VAR draw.

E.3 Alternative within CBSA Models

Table E.3.11: Determinants of Zip-Level Housing Cost Sensitivities: CBSA Fixed Effects

Dependent Variables:	Home Price HCS	Rental HCS
Model:	(1)	(2)
Supply		
Housing Liquidity		
Median resident age (log)	0.30***	-0.31
	-0.074	*-0.031*
	[-0.235, 0.102]	[-0.406, 0.252]
Home ownership rate (std)	-0.06***	0.002
	-0.021	*0.006*
	[-0.036, -0.003]	[-0.019, 0.029]
Population (log)	-0.06***	0.002
	-0.004	*0.010*
	[-0.016, 0.007]	[-0.009, 0.035]
Demand Amplifiers		
Amenities		
Crimes per 100k (log)	-0.08*	-0.02
	0.010	*-0.029*
	[-0.039, 0.048]	[-0.117, 0.026]
Credit		
Denial rate (std)	0.12***	0.18
	0.030	*0.107*
	[-0.020, 0.065]	[0.051, 0.175]
Housing Quality		
Median age of home (log)	0.05*	0.21***
	0.052	*0.101*
	[-0.016, 0.103]	[0.054, 0.159]
Fixed-effects		
cbsa	✓	✓
Fit statistics		
Observations	13,776	10,340
R^2 (Point-wise)	0.60	0.27
Median R^2	0.637	0.272
Posterior draws used	357	357

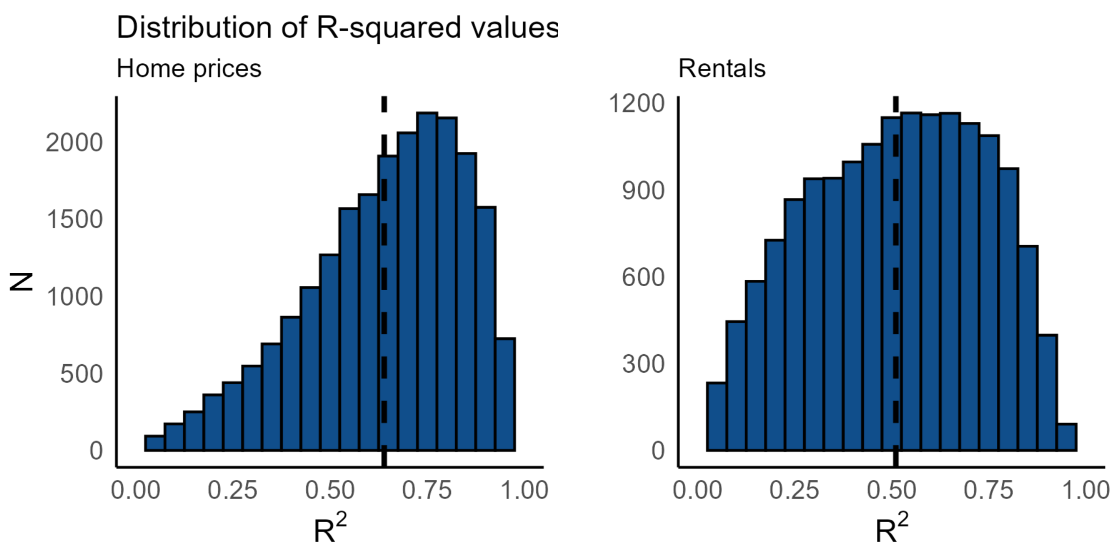
Notes: Coefficients and significance stars report the weighted least squares estimates using the point-wise median historical decompositions, with clustering at the CBSA level. Italicized entries report the median coefficient estimate across accepted narrative-restriction posterior draws that deliver a positive GMNS coefficient for both home values and rents. Bracketed entries report 68% credible intervals, formed from the 16th and 84th percentiles of the draw-by-draw coefficient distribution. These specifications include CBSA fixed effects but omit land and structure values. The row labeled R^2 (Point-wise) reports the fit from the baseline point-wise specification, while the row labeled Median R^2 reports the median fit across propagated posterior draws. In the propagated specification, regressions are weighted by inverse first-stage variance $(1/\hat{\sigma}^2_{\beta_z})$ within each accepted draw. The denial rate is defined as the share of mortgage applications denied from the 1996 vintage of HMDA. Crime is the median annual county arrest rate per 100,000 over 1991–2000.

E.4 Summaries with the point-wise median model

Table E.4.12: R-squared of the Mortgage Rate Decomposition and MP Shock Regressions

	4 Lags	8 Lags	12 Lags	16 Lags
BRW	0.16	0.27	0.28	0.38
NS-News	0.06	0.08	0.10	0.10
NS-FF	0.13	0.29	0.48	0.61
Romer and Romer	0.07	0.32	0.52	0.64
GSS-Target	0.12	0.24	0.37	0.48
GSS-Path	0.01	0.02	0.04	0.08

This table reports the R^2 values of regressing the mortgage rate historical decomposition on various monetary policy instruments. BRW are the shocks from Bu et al. (2019), NS-News is the news shock from Nakamura and Steinsson (2018), NS-FF is the first principal component of the news shock measured in the 30-minute interval around FOMC announcements. The GSS Path and Target shocks are the respective shocks from Gürkaynak et al. (2005). Each variable was graciously provided and retrieved from Miguel Acosta's website.



(a) Housing prices

(b) Rental prices

Figure E.4.1: This figure reports the distribution of R^2 values from estimating equation (2.11) using only the historical decompositions and quarter FEs as controls.

E.5 Summary Stats

Table E.5.13: Summary Statistics for Cross-Sectional Regressors

	N	Mean	St. Dev.	P25	Median	P75	In regression
Dependent variables							
Home-price HCS	14,159	1.01	1.32	0.20	0.96	1.83	–
Rent HCS	10,503	-0.31	2.73	-1.86	-0.23	1.20	–
Supply							
GMNS inverse elasticity	14,159	0.93	0.43	0.62	0.90	1.17	Level
Near downtown (indicator)	11,051	0.13	0.34	0.00	0.00	0.00	Level
Housing liquidity							
Median resident age (years)	14,159	41.41	6.59	37.10	41.00	45.00	Log
Home ownership rate (%)	13,778	65.71	17.49	56.77	69.39	77.95	Standardized
Population (2000)	14,159	15,787	15,092	3,723.6	11,033	24,217	Log
Demand amplifiers							
Natural amenity index	14,159	0.98	2.99	-0.85	0.26	2.06	Standardized
Arrests per 100k	14,159	4,815.8	2,228.7	3,305.2	4,594.0	5,964.0	Log
Credit							
Denial rate, 1996 (%)	14,159	26.31	8.29	20.81	25.21	30.58	Standardized
Median home price to renter inc	13,747	4.55	2.42	3.24	3.99	5.09	Level
Land value, 2012	7,020	112,932	140,107	39,076	62,303	125,758	Log
Housing quality							
Median age of home (years)	13,777	30.69	13.53	21.00	28.00	40.00	Log
Structure value, 2012	7,020	176,341	71,910	129,547	157,548	201,858	Log

Notes: Statistics are computed over ZIP codes with a non-missing point-wise home-price HCS and are unweighted; the cross-sectional regressions are weighted by inverse first-stage variance. Variables are reported in levels, while the final column records the transformation used in the regressions of Table 7. Standardized variables are demeaned and scaled by their standard deviation and therefore enter with mean zero and unit variance. Land and structure values are from Davis et al. (2021) and cover substantially fewer ZIP codes than the other covariates, which accounts for the smaller samples in the within-CBSA specifications. The GMNS inverse elasticity is from Guren et al. (2021) and varies only across CBSAs.