# Housing Duration and Interest Rates: Evidence from Reaching-for-Income Investors

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**ABSTRACT**

In fixed-income markets, long-duration assets are more sensitive to interest rate changes, and this principle is commonly assumed to extend to other asset classes. I show that the opposite holds in housing markets: short-duration properties are more, not less, sensitive to interest rate changes. Using data from the American Community Survey, I find that a one-percentage-point cut in interest rates raises house prices by 1.86 percentage points over two years. However, housing markets with a duration one standard deviation below the mean experience an additional 0.71-percentage-point price increase. I argue that this inversion arises from a discount-rate channel driven by "reaching-for-income" investors. Short-duration properties offer higher rental yields. After rate cuts, income-seeking investors disproportionately target high-yield, short-duration properties for investment, prioritizing near-term income over long-term returns. This behavior pushes up prices and lowers discount rates in short-duration markets, generating a non-parallel shift in the term structure of housing discount rates. These findings highlight investor preferences as an important driver of heterogeneity in housing market responses to interest rate changes.

**Keywords:** Monetary Policy, Real Estate Finance, Reaching-for-Income.

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## I. Introduction

Originally developed for fixed-income securities, cash flow duration measures how soon investors receive cash flows from an asset. It is the benchmark measure of interest rate risk, relied upon by both financial institutions and academic researchers. When interest rates change, longer-duration bonds, whose cash flows arrive further in the future, exhibit larger price responses because a given change in discount rates has a larger effect on the present value of distant cash flows. The duration framework is so well established that it extends beyond bonds to other asset classes. Pension funds and other institutional investors rely on duration to manage portfolio exposure to interest rate risk, while central banks and researchers use it to study the redistributive effects of monetary policy (Auclert, 2019) and labor market dynamics (Meeuwis, Papanikolaou, Rothbaum, and Schmidt, 2025).[1]

Within this framework, real estate is often assumed to be a long-duration asset with high interest rate sensitivity.[2] At the same time, institutional investors have increasingly shifted portfolios toward real estate, viewing it as a long-duration asset whose cash-flow horizon matches their long-term liabilities.[3] This assumption naturally raises the question of whether duration accurately captures real estate's interest rate sensitivity. If duration and actual interest rate sensitivity diverge, investors may mismanage portfolio interest rate risk and incur substantial losses as rates change. Policymakers may likewise misjudge how monetary policy affects household wealth through housing.

This paper asks whether cash flow duration actually measures the interest rate sensitivity of house prices. The answer is no. Contrary to the positive duration–sensitivity relationship observed in bonds and equities, I document a striking inversion in housing markets: shorter-duration properties exhibit greater price sensitivity to interest rate changes. This inversion arises because, after rates fall, buy-to-rent (BTR) investors engage in "reaching-for-income" behavior, disproportionately purchasing short-duration, high-rental-yield properties and pushing up their prices. This inversion challenges the conventional duration view and introduces a new framework for understanding how interest rate changes pass through to housing markets.

[1] For instance, many U.S. corporate pension plans have shifted allocations from long-duration bonds toward intermediate-term or liquid assets as part of de-risking strategies, reflecting active duration management; see the Wall Street Journal.

[2] For example, Greenwald, Leombroni, Lustig, and Van Nieuwerburgh (2021) treat housing as a long-duration asset and attribute part of the rise in wealth inequality to capital gains on such assets when rates decline. Likewise, Catherine, Miller, Paron, and Sarin (2023) assign a long duration to real estate assets to measure households' exposure to interest rate risk.

[3] For instance, global pension funds have increased allocations to real estate because it provides long-term income streams that align with pension liabilities (see, e.g., Andonov, Kok, and Eichholtz (2013) and a recent report by Banking Exchange). Canadian pension funds are also expanding real estate holdings (see JLL Insights).

Figure 1 previews the main finding. It plots the cumulative two-year price increase across duration quintiles within the U.S. Treasury, residential real estate, and equity markets, relative to the benchmark quintile, after a one-percentage-point cut in the federal funds rate (FFR). The figure shows that shorter-duration housing markets rise more than longer-duration ones after rate cuts. In contrast, bonds and equities conform to the conventional duration pattern: longer-duration assets exhibit greater price sensitivity to interest rate changes. The pattern persists over one- to three-year horizons. This comparison underscores how strongly housing markets depart from the standard duration principle.

**Figure 1.** Price Responses to Interest Rate Cuts Across Duration Quintiles Within Each Asset Class

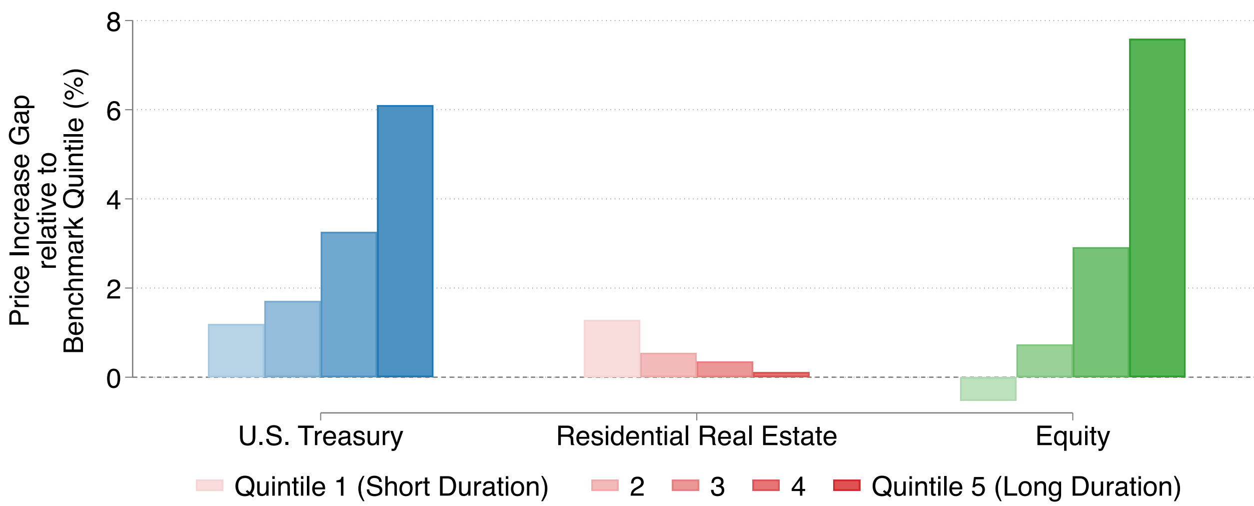


Figure 1 compares asset price responses to a one-percentage-point decrease in the federal funds rate (FFR) across duration quintiles within the U.S. Treasury, residential real estate, and equity markets. The bars show the two-year cumulative price increase gap relative to its benchmark for each duration quintile. For U.S. Treasuries and equities, the benchmark is the shortest-duration quintile (Quintile 1), whereas for residential real estate it is the longest-duration quintile (Quintile 5). A positive value indicates that a given quintile exhibits a larger price increase after rate cuts and is more sensitive to rate changes than the benchmark. Duration quintiles are assigned cross-sectionally within each asset class each year. Bond duration is measured using the Macaulay duration, and equity duration is constructed by Gonçalves (2021) by following the Macaulay duration concept. The housing duration measure is constructed similarly based on the same concept. Estimation is conducted at the asset-year level for Treasuries and equities and at the ZIP-code–year level for housing markets.

I construct a novel measure of residential housing cash flow duration (hereafter, housing duration) at the ZIP-code level, following the concept of Macaulay duration, using data from the American Community Survey (ACS) for 2011–2023. Intuitively, the measure captures how soon a homebuyer receives cash flows from a property, where cash flows are defined as either gross rent or net rent adjusted for rental vacancy, maintenance and insurance costs, and property taxes. Formally, housing duration is defined as the value-weighted average timing of expected cash flows for a typical property within a ZIP code. Section III.B describes the construction in detail.

What does housing duration capture? Intuitively, a short-duration house delivers its economic benefits, represented by rents, to the homeowner sooner than a long-duration house. For instance, a house with a high rental yield has a short duration because a greater portion of its total economic value is realized earlier through either housing services consumed by the owner or rental income received by the landlord. This intuition also explains why the measure, although constructed from rental cash flows, applies to all housing: owner-occupiers likewise receive economic benefits from the imputed rental value of the housing services they consume rather than renting comparable properties.

Empirically, shorter housing duration is strongly correlated with higher rental yields, consistent with Greenwald et al. (2021).[4] Shorter-duration markets exhibit higher implied discount rates, lower expected future rent growth, and lower house values. Local socioeconomic characteristics, except for household income, have relatively small explanatory power for the duration variation.

**Baseline Analysis.** In the first part of the paper, I examine how house prices respond to interest rate changes at the ZIP-code level. The analysis reveals a clear inversion of the conventional duration prediction: shorter-duration housing markets are more sensitive to interest rate changes. On average, a one-percentage-point decline in the FFR raises house prices by 1.86 percentage points over two years. Importantly, ZIP codes with durations one standard deviation shorter experience an additional 0.71-percentage-point increase, about 38 percent of the average response. This pattern holds for both gross- and net-rent-based duration measures and persists over one- to three-year horizons.

At the property level, I also confirm the pattern by linking 30 million ATTOM transactions to Altos rental listings. The transaction sample shows that differences in mortgage payments, property taxes, and credit constraints do not explain the inverse duration-sensitivity relationship.

A series of robustness tests reinforces the baseline findings. The findings are robust across alternative duration constructions, including measures based on gross and net rental yields following Greenwald et al. (2021), LASSO-based rent-growth forecasts, and actual ZIP-code holding horizons. Using the 30-year mortgage rate or plausibly exogenous shocks from Bauer and Swanson (2023) and Jarociński and Karadi (2020) as the policy rate measure produces the same pattern. Finally, alternative data sources from Zillow and ATTOM yield a consistent pattern. Overall, these analyses show that the inverse duration–sensitivity pattern is highly robust across measures and data sources.

[4] Rental yield is theoretically inversely related to housing duration under the assumption of constant rent growth and perpetual cash flows (see Internet Appendix F.3). Greenwald et al. (2021) directly use the price-to-rent ratio, the inverse of rental yield, as a proxy for housing duration.

**What Mechanisms Drive the Inverse Duration–Sensitivity Pattern?** The baseline specification controls for a rich set of time-varying ZIP-code socioeconomic characteristics, ruling out explanations based on shifts in first-time homebuyer demand, demographic composition, affordability, or borrowing capacity. The inverse duration–sensitivity pattern remains after further controlling for local housing supply elasticity, housing liquidity, housing market risk, and in-migration.

Using Home Mortgage Disclosure Act (HMDA) data, I additionally show that the larger house price increases following interest rate cuts in short-duration housing markets are not driven by a relaxation of borrowing constraints. Mortgage applications, approvals, and refinancing activity increase more in long-duration markets, not short-duration ones, after rate cuts. Controlling for these mortgage market responses leaves the heterogeneity in house price sensitivity across housing durations largely unchanged. These results rule out differential credit expansion as an explanation for the inversion.

Section II presents a conceptual framework that outlines two potential channels. The first is non-parallel shifts in the term structure of housing discount rates (the *discount-rate channel*), in which short-maturity premia decline more than long-maturity premia following a rate cut. The second is changes in expected housing cash flow growth (the *cash-flow channel*), whereby short-duration markets experience larger increases in expected rent growth when rates fall. This framework motivates the empirical mechanism tests that follow.

Empirically, the cash-flow channel does not explain the inverse duration–sensitivity pattern. Rate cuts raise expected rent growth more in long-duration markets, contradicting what the cash-flow channel would require to explain the inversion.

I therefore turn to the discount-rate channel. A short duration may reflect either more front-loaded expected cash flows, captured by lower expected rent growth, or greater housing market risks, captured by higher local discount rates. To disentangle these components, I construct two pseudo-duration measures that allow only expected rent growth or the local discount rate to vary across ZIP codes, holding the other fixed at its national annual average.

The results indicate that the inversion is primarily driven by differences in the *timing* of expected rental cash flows. Holding discount rates constant, short-duration markets with more front-loaded cash flows exhibit larger price increases following rate cuts, whereas holding cash-flow timing constant yields price responses consistent with the standard duration prediction. This evidence supports a preference-driven discount-rate mechanism in which rate cuts increase demand for assets delivering near-term rental cash flows and lower the required returns on such assets.

**"Reaching-for-Income" Mechanism.** In the second part of the paper, I show that the discount-rate channel through reaching-for-income behavior drives the inverse duration–sensitivity pattern. Following rate cuts, buy-to-rent (BTR) investors disproportionately purchase high-rental-yield, short-duration properties, pushing up their prices relative to long-duration ones.

As in Daniel, Garlappi, and Xiao (2021), reaching-for-income behavior refers to investors developing stronger preferences for income-generating assets when interest rates fall, because lower rates reduce income on deposits and short-term bonds. Using 30 million property-level transactions and historical tax assessments from ATTOM, I identify this reaching-for-income behavior through BTR transactions. I define a BTR purchase as a transaction in which a buyer acquires a property, subsequently converts it into a non-owner-occupied rental property, and holds it for a sustained period. This definition captures long-term rental investments while excluding short-horizon flippers.

BTR activity is predominantly driven by local, small-scale household investors rather than institutional buyers. BTR purchases are highly localized and concentrated among buyers holding only a small number of investment properties, with transactions more likely to be all-cash and less reliant on mortgage financing. Also, BTR investors disproportionately target high-rental-yield houses and tend to purchase smaller and older homes, and BTR buyers are, on average, older than non-BTR buyers.

The mechanism analysis reveals three main findings. First, after rates fall, high-yield, short-duration houses are more likely to be purchased for rental purposes. This pattern is more pronounced among buyers with a stronger preference for near-term income, such as older individuals or those with a high share of interest income in total income. Second, BTR investors accept lower realized total returns from high-yield properties after rate cuts, consistent with a preference for near-term rental income. Lastly, the greater rate sensitivity of short-duration properties becomes more pronounced as BTR activity increases and is negligible where BTR activity is low.

BTR investors' purchases exert price pressure that lowers short-maturity premia more than long-maturity premia after rate cuts. In ZIP codes with greater reaching-for-income activity, investor demand reduces discount rates and raises house prices more for short- than long-duration markets. This reaching-for-income behavior generates a non-parallel shift in the housing term structure of discount rates, which explains why shorter-duration markets exhibit larger price increases when rates fall.

Specifically, on average, high-rental-yield properties are more likely to be purchased for rent. After rate cuts, investors disproportionately target the high-yield properties for rental purposes, further increasing their likelihood of being bought to rent. Instrumenting FFR changes with plausibly exogenous monetary policy surprises yields even stronger results, ruling out concerns about endogenous rate movements. The pattern cannot be explained by stronger rental demand. Moreover, after rates fall, high-yield properties are more likely to transition from owner- to renter-occupied and less likely to revert, ruling out first-time-homebuyer demand as an alternative explanation.

Using IRS Statistics of Income (SOI) tax data, I construct two ZIP-code-level proxies for homebuyers' demand for near-term income: the share of taxable IRA withdrawals (capturing older households) and the ratio of taxable interest income to total income (capturing reliance on short-term investment income). Linking these proxies to homebuyers using their primary addresses, I find that buyers with stronger income demand are significantly more likely to purchase high-rental-yield properties for rent following rate cuts, confirming that BTR activity reflects reaching-for-income preferences.

Reaching-for-income investors are willing to accept lower long-run total returns in exchange for short-term rental income. Among BTR investors who subsequently resell the properties, the realized total returns, combining capital gains and imputed rental yields, are significantly lower for high-yield properties after rate cuts, and the return gap widens at longer holding horizons. This pattern is consistent with a preference for near-term cash flow at the expense of total returns.

Finally, reaching-for-income activity explains the higher rate sensitivity of short-duration markets. Exploiting geographic variation in local BTR intensity, I find that the sensitivity gap between short- and long-duration markets is negligible in low-BTR areas but rises monotonically with local BTR activity. Once BTR intensity is controlled for, short-duration markets no longer exhibit greater contemporaneous rate sensitivity, and their two-year excess sensitivity declines by nearly half.

Together, these findings establish reaching-for-income behavior by local BTR investors as one of the important mechanisms behind the inverse duration-sensitivity pattern in housing markets. When rates fall, investors seeking near-term income disproportionately purchase high-yield, short-duration properties, pushing up local prices and lowering required returns. Intuitively, if the aggregate market is dominated by investors with the reaching-for-income preference, rate cuts will reduce housing premia more for short- than long-duration properties because these investors accept lower returns in exchange for near-term income. This investor-driven, non-parallel shift in the housing term structure explains why shorter-duration markets exhibit larger price increases when rates fall.

**Contribution and Literature Review.** My paper contributes to understanding asset price dynamics, wealth inequality, and real-sector outcomes within the duration framework. The conventional view that longer-duration assets are more sensitive to interest rate changes is so entrenched in fixed-income theory that it is often assumed to hold across other asset classes. However, I document a striking reversal of this relationship in housing markets. Initially developed for bonds, the duration framework has been extended to equities, where duration is a key determinant of asset risk and expected returns (Cornell, 1999; Dechow, Sloan, and Soliman, 2004; Lettau and Wachter, 2007, 2011). Recent work shows downward-sloping equity and housing term structures and higher expected returns for short-duration stocks.[5] Importantly, emerging research demonstrates that duration has broad implications for asset price movements, wealth redistribution, and real-sector outcomes.[6] Greenwald et al. (2021) and Catherine et al. (2023) treat housing as a long-duration asset and attribute wealth inequality to the high interest rate exposure of these long-duration holdings. In contrast, I show that cash flow duration does not capture true interest rate sensitivity in residential housing markets, calling for caution when applying the duration framework to study the interest rate effect on house price dynamics.

Second, my paper contributes to the literature on monetary policy transmission to housing markets by documenting striking geographic heterogeneity in house price responses to monetary policy changes and proposing a novel mechanism that drives housing booms and busts in segmented markets. Only a limited body of work studies how monetary policy affects house prices (Kuttner, 2013; Williams, 2015; Aastveit and Anundsen, 2022; Gorea, Kryvtsov, and Kudlyak, 2025; Groiss and Syrichas, 2025) or rental markets.[7] Prior work shows that expansions in credit supply amplify housing booms (e.g., Mian and Sufi (2009); Favara and Imbs (2015); Landvoigt, Piazzesi, and Schneider (2015); Favilukis, Ludvigson, and Van Nieuwerburgh (2017)), while mortgage credit constraints also amplify

[5]For the downward-sloping equity term structure, see, e.g., Binsbergen, Brandt, and Koijen (2012); Van Binsbergen, Hueskes, Koijen, and Vrugt (2013); Schulz (2016); Van Binsbergen and Koijen (2017); Gonçalves (2021); Gormsen (2021); Bansal, Miller, Song, and Yaron (2021); Chen (2022); Boguth, Carlson, Fisher, and Simutin (2023); Cassella, Golez, Gulen, and Kelly (2023); Giglio, Kelly, and Kozak (2024). In real estate markets, Giglio, Maggiori, and Stroebel (2015); Giglio, Maggiori, Rao, Stroebel, and Weber (2021) document a downward-sloping housing term structure. For individual stock returns, see, e.g., Da (2009); Weber (2018); Li and Wang (2018); Gonçalves (2021); Gormsen and Lazarus (2023); Walter and Weber (2022).

[6]Golez and Koudijs (2025) and Gormsen and Lazarus (2025) link equity price movements to differences in cash flow duration. Auclert (2019) highlights duration as a key channel for wealth redistribution in monetary policy transmission. Meeuwis et al. (2025) develop a duration-based mechanism in labor markets, showing that matches with higher expected productivity growth have longer duration and are more sensitive to changes in risk premia. Kilic and Zhang (2025) demonstrate that duration shapes how interest rate changes affect production factor costs, such as commercial real estate, thereby dampening investment in high-duration areas when rates fall.

[7]For research on the effects of monetary policy on rents, see, e.g., Dias and Duarte (2019, 2022); Cloyne, Ferreira, and Surico (2020); Koeniger, Lennartz, and Ramelet (2022); Abramson, Han, and De Llanos (2025); Groiss and Syrichas (2025).

monetary policy effects on housing markets.[8] In addition, investor speculation and extrapolative expectations represent another important channel driving housing booms and busts (Chinco and Mayer, 2016; Gao, Sockin, and Xiong, 2020; Bayer, Mangum, and Roberts, 2021; Li, 2023). Hacamo (2024) shows that house price responses to mortgage rate changes differ across neighborhood price tiers, with middle-priced areas responding most strongly. I introduce a new perspective by showing that shorter-duration, higher-rental-yield markets exhibit stronger sensitivity to interest rate changes. This heightened sensitivity arises from buy-to-rent investors who target high-yield properties for near-term income, highlighting the crucial role of reaching-for-income behavior in housing booms and busts.

Third, my paper advances the reaching-for-income literature by clearly distinguishing it from the closely related concept of reaching-for-yield. Holding risk constant, I show that preferences for near-term cash flows, not greater risk-taking, influence how interest rate changes pass through to housing markets. When rates fall, income-seeking investors disproportionately purchase high-rent-yield properties, thereby amplifying the price responses of these short-duration markets to rate changes. This mechanism differs from reaching-for-yield, which reflects changes in investors' risk appetite. Reaching-for-income instead captures how *changes* in interest rates strengthen preferences for income-generating assets (Jiang and Sun, 2020; Daniel et al., 2021), whereas reaching-for-yield involves taking on more risk when real rates decline but risk premia remain unchanged (Campbell and Sigalov, 2022).[9] A further distinction concerns who exhibits these behaviors: younger, less wealthy households tend to reach for yield (Gomes et al., 2025), while older or retired investors substitute toward rental income when rates fall (Gargano and Giacoletti, 2022). I show that reaching-for-income behavior concentrates in high-yield markets, generating unexpected cross-sectional heterogeneity in house price responses to interest rate changes.

The remainder of the paper is organized as follows. Section II presents the conceptual framework linking housing duration to the interest rate sensitivity of house prices. Section III describes the data and measures. Section IV presents the baseline results. Section V examines the reaching-for-income mechanism, while Section VI evaluates alternative channels. Section VII concludes the paper.

[8] For literature on payment-to-income and debt-to-income limits, see, e.g., Greenwald (2018); Bosshardt, Di Maggio, Kakhbod, and Kermani (2024); Adelino, Schoar, and Severino (2025). For the deposits channel, see, e.g., Drechsler, Savov, and Schnabl (2017, 2022); Drechsler, Savov, Schnabl, and Supera (2024).

[9] Most papers in reaching-for-yield emphasize that low interest rate *levels*, not changes, trigger investors' reallocations into riskier, higher-yielding assets. Reaching-for-yield behavior is documented in bond markets (Hanson and Stein, 2015; Becker and Ivashina, 2015; Choi and Kronlund, 2018), historical housing markets (Korevaar, 2023), institutional portfolios (Di Maggio and Kacperczyk, 2017), and household decisions (Célérier and Vallée, 2017; Lian, Ma, and Wang, 2019; Gomes, Peng, Smirnova, and Zhu, 2025).

## II. Conceptual Framework

This section derives the theoretical relationship between the interest rate sensitivity of house prices and housing duration. I begin with a general case in which (i) expected rents may depend on the policy rate and (ii) the per-period discount rate applied to each cash flow may shift in parallel or non-parallel. I derive a general expression for the house-price semi-elasticity to the policy rate. I then focus on each of the following cases: (1) constant-premium or parallel shift in term structure, (2) non-parallel shift in term structure, and (3) interest-rate-dependent rents, each time closing the other channels. Full derivations are in Internet Appendix F.

### A. Setup and General Case for the Price Sensitivity to the Policy Rate

Consider a representative property that delivers an infinite stream of expected rental cash flows $\{\mathbb{E}_t[C_{t+h}]\}_{h\geq1}$ without operating costs, depreciation, and taxes. Let the per-period discount rate applied to the cash flow at $t+h$ be $y_t(h) = i_t + \phi_t(h)$, which equals the sum of the policy rate $i_t$ and a premium $\phi_t(h) > 0$. For simplicity, I assume a flat term structure at $t$, so $y_t(h) \equiv y_t$ for all $h$. I nevertheless allow both the discount rate and expected rents to co-move with the policy rate:

$$\kappa_t(h) \equiv \frac{\partial \phi_t(h)}{\partial i_t}, \qquad \frac{\partial y_t(h)}{\partial i_t} = 1 + \kappa_t(h), \qquad \Gamma_t(h) \equiv \frac{\partial \ln \mathbb{E}_t[C_{t+h}]}{\partial i_t}.$$

**House price.** The house price is the sum of the present values of future expected rental cash flows:

$$P_t = \sum_{h=1}^{\infty} \frac{\mathbb{E}_t[C_{t+h}]}{(1+y_t)^h}. \tag{1}$$

**Housing cash flow duration.** Define housing cash flow duration (or simply housing duration) and modified duration as:

$$D_t = \sum_{h=1}^{\infty} h \, \frac{\mathbb{E}_t[C_{t+h}](1+y_t)^{-h}}{P_t} \equiv \sum_{h=1}^{\infty} h \, w_t(h), \qquad \widetilde{D}_t \equiv \frac{D_t}{1+y_t}, \tag{2}$$

where $w_t(h) = \frac{\mathbb{E}_t[C_{t+h}](1+y_t)^{-h}}{P_t}$ and $\sum_{h\geq1} w_t(h) = 1$. $\widetilde{D}_t$ denotes modified duration. Housing duration is the value-weighted timing of expected rental cash flows, defined based on Macaulay duration from the fixed-income theory.

**Duration-weighted pass-through.** Not all horizons matter equally for price sensitivity. Define

$$\alpha_t(h) = \frac{h\, w_t(h)}{D_t}, \qquad \bar{\kappa}_t = \sum_{h \geq 1} \alpha_t(h)\kappa_t(h),$$

where $\alpha_t(h)$ are non-negative, sum-to-one duration weights, and $\bar{\kappa}_t$ is the *duration-weighted premium pass-through*, i.e., the average co-movement of the term premium with the policy rate across horizons. Because $y_t(h) = i_t + \phi_t(h)$, the discount-rate response is $\partial y_t(h)/\partial i_t = 1 + \kappa_t(h)$, so larger short-maturity premium moves (i.e., front-loaded $\kappa_t(h)$) raise $\bar{\kappa}_t$, especially for short-duration assets.

**Proposition** 1 (General sensitivity): *With horizon-dependent pass-through $\kappa_t(h)$ and interest-sensitive expected rental cash flows, the semi-elasticity of price to the policy rate equals*

$$-\frac{\partial \ln P_t}{\partial i_t} = \widetilde{D}_t(1 + \bar{\kappa}_t) - \overline{\Gamma}_t, \qquad \overline{\Gamma}_t = \sum_{h \geq 1} w_t(h)\Gamma_t(h). \tag{3}$$

Equation (3) decomposes the sensitivity into two components: (i) modified duration scaled by the duration-weighted pass-through of the term premium, and (ii) the value-weighted rent semi-elasticity.[10]

### B. Case 1: Constant Premium or Parallel Shift in Housing Term Structure

Shut down the cash-flow channel: $\Gamma_t(h) = 0$. Assume $\kappa_t \equiv \kappa_t(h) = \kappa_t(h')$ for all $h$. Then

$$-\frac{\partial \ln P_t}{\partial i_t} = \widetilde{D}_t(1 + \kappa_t). \tag{4}$$

When the premium is constant (i.e., $\kappa_t = 0$), interest rate sensitivity equals modified duration. With a parallel shift (i.e., $\kappa_t = c \ \forall\ h$, where $c$ is a constant), sensitivity equals modified duration scaled by a constant. Overall, under the constant premium or parallel shift in housing term structure, the positive duration-sensitivity mapping is preserved whenever $\kappa_t > -1$.[11]

[10] Allowing a non-flat curve leaves the structure unchanged and only replaces $(1 + y_t)^{-1}$ by horizon-specific $(1 + r_t(j))^{-1}$ inside an inner sum. Specifically, the general expression becomes $-\partial \ln P_t/\partial i_t = \sum_{h\geq 1} w_t(h)\big[\sum_{j=1}^{h} \beta_t(j)/(1 + r_t(j))\big] - \overline{\Gamma}_t$, with proof in Internet Appendix F.

[11] $\kappa_t \leq -1$ implies zero or negative total pass-through ($\beta_t \leq 0$), so, for example, an *exogenous* policy rate cut would not raise and even lower house prices. This is the opposite of the empirical baseline findings in the paper.

### C. Case 2: Non-Parallel Term-Structure Shift (Discount-rate Channel)

Hold rents fixed, $\Gamma_t(h) = 0$, but allow horizon-dependent pass-through $\kappa_t(h)$. From Proposition 1,

$$-\frac{\partial \ln P_t}{\partial i_t} = \widetilde{D}_t(1+\bar{\kappa}_t), \tag{5}$$

*Interpretation.* When pass-through is *front-loaded* (i.e., $\kappa_t(h)$ decreasing in $h$), short-maturity premia decrease more than long-maturity premia when $i_t$ falls. Then $\bar{\kappa}_t$ is larger for shorter-duration assets that place more weight on early cash flows, potentially inverting the duration ordering. For otherwise similar properties $S$ and $L$ with $D_{S,t} < D_{L,t}$, the short-duration property $S$ is more sensitive than $L$ iff

$$\frac{1+\bar{\kappa}_{S,t}}{1+\bar{\kappa}_{L,t}} > \frac{D_{L,t}}{D_{S,t}} > 1.$$

*In summary.* Under the discount-rate channel with a non-parallel term-structure, interest rate sensitivity is modified duration scaled by the duration-weighted premium pass-through. Cross-sectionally, front-loaded pass-through can overturn the duration ordering, making short-duration properties more sensitive than long-duration ones.

### D. Case 3: Interest-rate-dependent Rental Cash Flows (Cash-flow Channel)

Shut down the discount-rate channel by assuming the premium is constant with respect to $i_t$ (i.e., $\kappa_t(h) = 0$), but allow expected rents to depend on $i_t$. Proposition 1 yields

$$-\frac{\partial \ln P_t}{\partial i_t} = \widetilde{D}_t - \overline{\Gamma}_t \tag{6}$$

*Interpretation.* If $\overline{\Gamma}_t > 0$ (e.g., a rate cut lowers expected rents), the housing duration overstates true sensitivity. If $\overline{\Gamma}_t < 0$, the true sensitivity is *amplified*. For otherwise similar properties $S$ and $L$ with $D_{S,t} < D_{L,t}$, the short-duration property $S$ is more sensitive than $L$ iff

$$\overline{\Gamma}_{L,t} - \overline{\Gamma}_{S,t} > \widetilde{D}_{L,t} - \widetilde{D}_{S,t}.$$

*In summary.* Under the cash-flow channel, interest rate sensitivity equals modified duration net of the value-weighted rent semi-elasticity. Cross-sectionally, sufficiently negative rent responses can make short-duration properties more sensitive than long-duration ones.

## III. Data and Measurement

### A. Data Source

#### A.1. ZIP Code-Level Housing Data

**American Community Survey (ACS)** My baseline analysis relies on detailed housing market information at the ZIP code level from the American Community Survey (ACS) conducted by the U.S. Census Bureau.[12] The ACS is an ongoing survey administered annually, providing rich demographic, social, economic, and housing characteristics of the U.S. population across multiple geographic units, including the Zip Code Tabulation Area (ZCTA). To ensure reliable estimation at the ZIP code level, I use the 5-year ACS estimates, which aggregate data collected over a 60-month period. These estimates yield the largest sample size and the most precise measurements, thereby enhancing the reliability of my ZIP code-level analyses.[13]

The sample period spans from 2011 to 2023 because the ACS ZIP code tabulation area (ZCTA, hereafter referred to as ZIP code) data are available from 2011. For each ZIP code and year, I construct a panel of local demographic and economic characteristics, including population size, median household income, age distribution, labor force participation, and unemployment rates. Importantly, the dataset provides extensive housing market information, such as median gross rents, median property values, homeownership rates, vacancy rates, property type distributions (e.g., single- versus multi-family units), building vintages, and room counts.

In particular, the two variables, median rent and house value, measure typical rental and house prices within each ZIP code and year, which enables the construction of precise ZIP-code measures of rent growth and rental yield. With the rent growth and house price level of a ZIP code and year, I can predict future rent growth and construct the housing cash flow duration for local housing markets. The detailed duration construction procedure is described in Section III.B.

[12]The ACS is accessible via the U.S. Census Bureau at `https://data.census.gov/`. Stata users can efficiently download ACS data using the `getcensus` package.

[13]For details on differences across ACS 1-year, 3-year, and 5-year estimates, see `https://www.census.gov/programs-surveys/acs/guidance/estimates.html`.

**Zillow Home Value Index (ZHVI) and Zillow Observed Rent Index (ZORI)** To capture house price dynamics at the ZIP-code level, I use the Zillow Home Value Index (ZHVI). ZHVI measures the value of the typical home in the 35th–65th percentile of the price distribution within each ZIP code. I use the smoothed and seasonally adjusted ZHVI as the primary proxy for local house price levels and to compute annual price changes. ZHVI data are available as early as January 2000 for some ZIP codes, enabling the calculation of annual changes from 2001 onward. Specifically, the $h$-year cumulative house price change from year $t-1$ to $t+h$ for ZIP code $z$ is given by:

$$\Delta HPI_{z,[t-1,t+h]} = \frac{\text{HPI}_{z,t+h}}{\text{HPI}_{z,t-1}} - 1, \tag{7}$$

where $\text{HPI}_{z,t-1}$ denotes the ZHVI for ZIP code $z$ in year $t-1$.

### A.2. Property-Level Housing Data

**ATTOM Property Data** My property-level analysis relies on ATTOM Record data, a widely used source in finance and real estate research. ATTOM is a leading U.S. real estate data provider and maintains a nationwide panel of more than 500 million real estate and loan transaction records across over 2,690 counties. The deed transaction data provides detailed information such as transaction dates, property addresses, buyer and seller names, and sales prices. Coverage extends back to the early 1970s, with relatively comprehensive national coverage from 1990 onward.

To supplement transaction records, I obtain time-varying property characteristics from ATTOM Historical Tax Assessment data, which covers over 155 million properties across more than 3,000 counties. These assessment records report assessed land and property values, tax amounts, and a wide range of property characteristics. Although property characteristics are generally persistent, the historical records allow me to track changes in property characteristics over time.

To clean the deed transaction data, I first identify valid arms-length transactions, as well as transactions that, while technically invalid (e.g., foreclosures), still mark the termination of ownership for the prior homeowner. The data cleaning algorithm follows methodologies from prior studies.[14] This approach yields a more reliable and representative sample for analysis and mitigates bias in subsequent estimates. The detailed cleaning procedure is discussed in Internet Appendix Section A.

[14] See, e.g., Goldsmith-Pinkham and Shue (2023); Reher and Valkanov (2024); Baldauf, Favilukis, Garlappi, and Zheng (2025).

**Altos Rental Intel Data** My analysis also relies on the Altos Rental Intel dataset, which provides weekly updated rental listings for single-family homes and apartments. The dataset spans from 2011 to 2024, achieves roughly 98% national coverage, and includes detailed information such as asking rents, property types, square footage, bedrooms and bathrooms, and amenities. Unlike sources based on MLS feeds or platforms such as Craigslist, Altos compiles listings primarily from proprietary providers under private contracts, ensuring broad coverage of major metropolitan areas and states. This approach effectively captures nearly all U.S. ZIP codes with active rental markets. The weekly data refresh cycle ensures timely and accurate snapshots of local rental market conditions.

By combining ATTOM data with Altos rental listings, I obtain property characteristics for rental houses and perform a hedonic rent estimation to obtain the expected rents and rental yields for all ATTOM properties. The detailed estimation procedure is discussed in Section III.C.

### A.3. Bond and Equity Data

I conduct parallel heterogeneity analyses of interest rate sensitivity for Treasury bonds and equities. This comparison allows me to assess whether the duration–sensitivity patterns observed in real estate are consistent with those in other major asset classes. I obtain Treasury securities data from the CRSP Monthly Treasuries dataset, which reports Macaulay duration for each bond. For equities, I use the CRSP Monthly Stock dataset. Equity duration is constructed by Gonçalves (2021), who defines it as the value–weighted average time until a firm's expected future payouts are realized. This measure is constructed at the stock–fiscal year level. For example, the duration for fiscal year 2023 corresponds to the period from July 2023 to June 2024. To avoid look-ahead bias and to isolate the duration measure from ex-post monetary policy effects, I assign each firm's duration from fiscal year $t-1$ (released at the end of June in year $t-1$) to stock returns in calendar year $t$. In other words, the duration measure will be applied to a stock's returns starting 6 months after it becomes available. Details of the bond and equity data cleaning procedures are provided in Internet Appendix Section A.

### A.4. Interest Rate Changes and Monetary Policy Shock Measurement

In the baseline analysis, I measure interest rate changes using the annual change in the federal funds rate and, for robustness, the 30-year mortgage rate, both obtained from the Federal Reserve Economic Data (FRED). To isolate the unexpected component of policy changes, I construct a one-year

Treasury yield surprise, defined as the difference between the realized one-year yield and the implied one-year forward yield based on the actual one-year and two-year Treasury yields from FRED. For further robustness, I incorporate alternative exogenous monetary policy shock measures developed by Bauer and Swanson (2023) and Jarociński and Karadi (2020). Detailed definitions and construction steps for all rate and shock variables are provided in the appendix table of variable definitions.

### B. Construction of Housing Duration at the ZIP Code Level

Macaulay duration is defined as the value-weighted average time of receiving cash flows from the bond. Extending this concept from bond markets to equity markets, previous studies such as Weber (2018) and Gonçalves (2021) define equity duration accordingly. Similarly, I introduce a novel measure—*housing cash flow duration* (hereafter, housing duration)—which applies the Macaulay duration framework to housing markets. Specifically, housing duration is defined as the value-weighted average time of receiving future housing cash flows generated by a representative property in a particular housing market, with the weights determined by the importance of the present values of expected future cash flows relative to the current investment value. The housing cash flows are measured by either gross rent or net rent, accounting for costs, as discussed in detail in the following section. Formally, for properties located in ZIP code $z$ at year $t$, housing duration is given by:

$$\text{Duration}_{z,t} = \sum_{h=1}^{H} h \ w_{z,t+h} , \tag{8}$$

where the weight $w_{z,t+h}$ is calculated as:

$$w_{z,t+h} = \frac{\text{CF}_{z,t+h} / (1 + r_{z,t})^h}{P_{z,t}} , \tag{9}$$

In Equation 8, $w_{z,t+h}$ denotes the relative weight of the present value of expected housing cash flows $\text{CF}_{z,t+h}$ received in year $t+h$ relative to the total current house price $P_{z,t}$ in ZIP code $z$ at time $t$. Here, $h$ represents the time horizon when the cash flow is expected to be received. Intuitively, housing duration captures how soon a homebuyer expects to receive housing cash flows or realize economic benefits from the purchased property, with the shorter duration meaning the homebuyer can realize the benefits sooner from the property purchase rather than waiting for a longer time.

In the duration measure, the expected housing cash flows $\text{CF}_{z,t+h}$ are defined as:

$$\text{CF}_{z,t+h} = \begin{cases} \mathbb{E}_t\left[\text{Rent}_{z,t+h}\right], & \text{if } h < H \\ \mathbb{E}_t\left[\text{Rent}_{z,t+H}\right](1+\bar{g}_{z,t})/(r_{z,t}-\bar{g}_{z,t}), & \text{if } h = H, \end{cases} \tag{10}$$

where $\mathbb{E}_t\left[\text{Rent}_{z,t+h}\right]$ represents the expected gross or net rental cash flows generated by the typical house.

Unlike bonds, real estate assets (similar to equities) do not have deterministic maturity dates and predefined cash flows. Following Weber (2018), I address this issue by breaking down the cash flow equation into two components: the finite-horizon predicted rental cash flows occurring before the terminal year $t+H$, and the infinite-horizon terminal house value at year $t+H$, as shown in Equation 10. The combined duration calculated from the two components constitutes my final measure.

For periods before the terminal horizon $H$ (i.e., $h < H$), the expected cash flow is measured by the expected gross (or net) rental income, $\mathbb{E}_t[\text{Rent}_{z,t+h}]$, generated by a representative property in ZIP code $z$ at future horizon $h$. At the terminal horizon $H$ (i.e., $h = H$), the cash flow is calculated via the Gordon Growth Model (GGM), based on the estimated long-run rent growth rate for the ZIP code, $\bar{g}_{z,t}$.

Intuitively, these two components capture the cash flow stream received by a homeowner purchasing a house at time $t$. Until year $t+H$, the homeowner continuously receives the economic benefit represented by gross (or net) rental income. At the end of the holding period $t+H$, the homeowner sells the property and receives a lump-sum payment equal to the present value of all future housing cash flows beyond $H$, under the assumption that the rental income grows indefinitely at the constant long-term rate $\bar{g}_{z,t}$. The procedure for estimating this long-run rent growth rate is detailed in Section III.B.2.

I use a five-year terminal horizon when constructing the housing duration measure. The main conclusions, however, are not sensitive to this choice. The heterogeneity in interest rate sensitivity arises from the cross-sectional ranking of housing duration, rather than from its absolute level. To verify robustness, I also construct an alternative measure using a ten-year holding horizon. The results remain robust and are reported in Internet Appendix Tables IA.C3 and IA.C8.

Similar to Gonçalves (2021), I derive the discount rate for a ZIP code and year $t$ by solving the value equation in the following:

$$P_{z,t} = \sum_{h=1}^{H} CF_{z,t+h} \,/\, (1 + r_{z,t})^h \tag{11}$$

The implied discount rate is equivalent to yield to maturity (YTM) or internal rate of return (IRR), equating the current property value to the sum of discounted expected future cash flows.

Empirically, I measure current house prices, $P_{z,t}$, by using the median house values obtained from the American Community Survey (ACS) data. I also construct the ZIP-code gross and net rental cash flows, with construction details discussed in the next Section III.B.1. After obtaining realized local gross and net rents, I compute rent growth and forecast the expected future rental cash flows based on ZIP-code economic characteristics, with further details discussed in Section III.B.2.

Finally, based on the predicted streams of gross and net rental cash flows, I construct two housing duration measures: gross duration and net duration. Comparing the two duration measures allows me to verify that the results are not driven by the omission of ownership costs and to better understand the geographic heterogeneity in the timing of economic cash flows from housing purchases.

For robustness checks, I create housing duration measures using alternative data sources from ATTOM, Altos, and Zillow. While my primary analyses are based on ACS data, I perform additional robustness analyses using the ATTOM and Altos datasets, and based on Zillow data.

### B.1. Measuring Gross and Net Rental Cash Flows

I measure rental income in two ways. The first is *gross rent*, defined as the median rent at the ZIP-code level from the ACS, which captures the primary cash inflow component. The second is *net rent*, which adjusts gross rent for the vacancy rate—reflecting the possibility of unoccupied units—and for major ownership costs for a typical property in ZIP code $z$ and year $t$:[15]

$$\begin{aligned}\text{Net Rent}_{z,t} \;=\; & \text{Gross Rent}_{z,t} \times (1 - \text{Vacancy Rate}_{z,t}) \\ & - \text{Maintenance Cost}_{z,t} - \text{Insurance Cost}_{z,t} - \text{Property Tax}_{z,t}\,.\end{aligned} \tag{12}$$

Gross rents and vacancy rates are obtained directly from ACS. Maintenance and insurance costs are imputed using American Housing Survey (AHS) microdata, which provides detailed unit-level

[15] I leave mortgage payments to the property-level analysis, since they are tied to leverage purchases or investments.

information on property costs, values, and characteristics. Using this dataset, I perform hedonic regressions to estimate the cost functions that relate maintenance and insurance costs to property market value and characteristics such as age, size, and structure, and then apply the estimated coefficients to the ATTOM property-level sample. This procedure yields estimated maintenance and insurance costs and corresponding cost-to-value ratios at the property-year level, which I aggregate to the ZIP-code level.[16] Property taxes are measured from ATTOM tax assessment data, where I compute average tax-to-value ratios in each ZIP code and year. Finally, I obtain ZIP-code-level maintenance, insurance, and property tax amounts by multiplying the corresponding average cost and tax ratios by the median house value in the ACS sample. Full details of the hedonic specifications and variable construction are provided in Internet Appendix Section B.1.

These gross and net rent measures allow me to compute rental income growth and to construct housing cash-flow duration measures in the next section.

### B.2. Estimation of ZIP Code-level Expected Rent Growth and Level

Previous literature assumes that dividend growth is stationary (Shiller, 1981; Campbell and Shiller, 1988). Also, I assume that ZIP-code rent growth is stationary (An, Deng, Fisher, and Hu, 2016), similar to dividend growth. This assumption allows us to reframe the estimation of expected future rent levels as the prediction of a sequence of future rent growth rates. Formally, standing in year $t$, the expected log rent at horizon $h$ for ZIP code $z$ can be expressed as:

$$\mathbb{E}_t\left[\ln(\text{rent})_{z,\,t+h}\right] = \ln(\text{rent})_{z,\,t} + \sum_{s=1}^{h} \mathbb{E}_t\left[\Delta \ln(\text{rent})_{z,\,[t+s-1,\,t+s]}\right], \tag{13}$$

where $\ln(\text{rent})_{z,t}$ is the log of the gross or net rental income for a typical property in ZIP code $z$ at year $t$ estimated in the last section, and $\mathbb{E}_t[\Delta \ln(\text{rent})_{z,[t+s-1,t+s]}]$ denotes the expected annual log rent growth at horizon $s$.

My forecasting method is close to Weber (2018) and Gonçalves (2021), which predict expected firm payouts to investors under the clean surplus accounting assumption. Specifically, Weber (2018) forecasts future equity payouts by forecasting return on equity and growth in book equity, assuming

[16] Following Zillow's ZORI methodology, I use the mean of the middle quintile (35th–65th percentiles) within each ZIP code and year to mitigate bias caused by outliers while capturing the housing market changes. For methodology details, see https://www.zillow.com/research/methodology-zori-repeat-rent-27092/.

that the two ratios follow the autoregressive process based on Dechow et al. (2004). Extending this methodology, Gonçalves (2021) incorporates twelve firm-level characteristics to predict the ratio of clean surplus to book equity and the growth in book equity.

To predict expected log rent growth for each forecasting horizon $s$, I perform the *by-horizon* predictive regression estimation with the following specification:

$$\begin{aligned}\Delta \ln(\text{rent})_{z,[t+s-1,t+s]} = \alpha_s + \beta_{1,s}\,\Delta \ln(\text{rent})_{z,[t-1,t]} + \beta_{2,s}\,\Delta \ln(\text{price})_{z,[t-1,t]} + \beta_{3,s}\,\ln(\text{rental yield})_{z,t} \\ + \Gamma X_{z,t} + \epsilon_{z,t,s}\,,\end{aligned} \tag{14}$$

where the dependent variable is the annual log rent growth at horizon $s$ for ZIP code $z$ in year $t$. The predictors include the lagged log rent growth, the log house price growth, the log rental yield, and a comprehensive set of local economic characteristics denoted as $X_{z,t}$.[17]

The set $X_{z,t}$ captures various ZIP-code-year-level characteristics, including income ratio (i.e., ZIP-code median household income relative to national median household income), income growth, population ratio and growth, age distribution measures (shares of young and older residents and the growth), labor market indicators (i.e., labor force participation and unemployment rate and growth), housing market conditions (homeownership rate, rental vacancy rate, proportions of housing units by type, median room number growth), and renter-occupancy ratios and growth rates. The detailed list of predicting variables is presented in Internet Appendix Table IA.C1, and their definitions are explained in the Appendix.

To predict the long-term growth rate $\bar{g}_{z,t}$, I first calculate the average realized annual log rent growth from horizons 6 to 10 as Avg $\Delta\log(\text{rent})_{z,[t+6,t+7,t+8,t+9,t+10]}$. I then apply the same predictive regression framework as Equation 14 but replace the dependent variable with this average realized annual log rent growth, thereby obtaining the predicted long-term growth rate.

Internet Appendix Table IA.C1 presents predictive regression results for future rent growth over short- and long-term horizons. Columns 1 to 5 show the prediction for the log annual rent growth over horizons ranging from one to five years (i.e., $t+1$ to $t+5$). Column 6 focuses on longer-term predictions by using average annual rent growth from years $t+6$ to $t+10$ as the dependent variable.

[17] Excluding the rental yield from the predictive regression delivers nearly identical results. This alleviates the concern that the high correlation between housing duration and rental yield is mechanically induced by including the rental yield as a predictor of rent growth. It is because I have already incorporated a rich set of local economic characteristics as predictors, the inclusion of rental yield adds little incremental information: rental yield itself is an aggregate summary of local fundamentals that are already captured by $X_{z,t}$.

Additionally, I perform robustness checks using LASSO regressions with 10-fold cross-validation, which may help address potential concerns about overfitting due to the large number of predictors. Appendix Table IA.C2 reports the LASSO-selected predictors and estimation results. Notice that LASSO selection largely retains the original predictor set, with minimal variation in results compared to my baseline results. Consequently, the alternative duration measure using LASSO confirms robustness.

With the estimated coefficients, the expected log rent growth at horizon $s$ is calculated as:

$$\mathbb{E}_t\left[\Delta \ln(\text{rent})_{z,[t+s-1,t+s]}\right] = \widehat{\alpha}_s + \widehat{\beta}_{1,s}\,\Delta \ln(\text{rent})_{z,[t-1,t]} + \widehat{\beta}_{2,s}\,\Delta \ln(\text{price})_{z,[t-1,t]} + \widehat{\beta}_{3,s}\,\ln(\text{rental yield})_{z,t} + \widehat{\Gamma}' X_{z,t} \tag{15}$$

### C. Property-Level Rental Yield as a Proxy for Housing Duration

In my mechanism analysis, I exploit granular, property-level housing transaction and rental listing data to estimate rental yields for individual properties over time. Rental yield serves as an inverse proxy for housing duration, as shown in Internet Appendix F.3, where, under the assumption of constant rent growth, housing duration simplifies to the inverse of the rental yield (i.e., price-to-rent ratio). Hence, properties with higher rental yields correspond to shorter durations, consistent with Greenwald et al. (2021), who use the price-to-rent ratio as an empirical proxy for housing duration.

I combine granular transaction records and rental listings to construct a property-level panel containing both historical sale prices and listed rents for comparable homes. Using this dataset, I estimate expected prices and rents for the entire universe of properties, including those without recent transactions or rental listings, through hedonic models that relate observed prices and rents to detailed property characteristics and fixed effects. The hedonic estimates are obtained separately via by-county-year regressions, following standard approaches in the literature.[18] All model specifications and estimation details for constructing property-level expected prices, rents, and rental yields are provided in Internet Appendix Section B.2.

The intuition is straightforward: observed transactions and rental listings reveal the relationship between property characteristics and market values, allowing me to impute expected prices and rents

[18]See, e.g., Chambers, Spaenjers, and Steiner (2021); Eichholtz, Korevaar, Lindenthal, and Tallec (2021); Demers and Eisfeldt (2022); Halket, Loewenstein, and Willen (2023); Gilbukh, Haughwout, Landau, and Tracy (2023); Colonnello, Marfè, and Xiong (2024); Diamond and Diamond (2024).

for similar properties lacking direct observations. Integrating housing transaction and rental data in this way enables the estimation of rental yields for the full property universe, including owner-occupied homes for which rents are typically unobservable.

## D. Descriptive Statistics

### D.1. Geographic Distribution of Housing Duration and Rental Yield

Figure 2 illustrates county-level geographic heterogeneity in housing duration (Panel A) and rental yield (Panel B). I compute county-level averages of housing duration and rental yield across all ZIP codes and years within each county. Based on the average duration, I classify counties into quintiles, with darker colors corresponding to higher values of housing duration or rental yield.

The figure reveals substantial regional variation in housing durations and rental yields. Coastal and high-income metropolitan areas, such as California and the Northeast Corridor, tend to have longer housing durations. In contrast, central and southern regions of the United States exhibit shorter housing durations and higher rental yields. Although coastal areas generally correspond to longer durations, some parts of Florida deviate from this pattern, with most coastal counties appearing in lower duration quintiles. It suggests that a variety of local factors may influence housing durations and rental yields. Finally, comparing Panels A and B highlights that counties with shorter housing durations generally exhibit higher rental yields, consistent with Greenwald et al. (2021).

### D.2. Decomposition of Housing Duration Variation

Figure 3 decomposes the cross-sectional variation in housing duration into the shares *uniquely* explained by each local economic and housing market characteristic, using a dominance (Shapley value) analysis. Derived from cooperative game theory, this method evaluates the relative importance of explanatory variables by averaging each variable's marginal contribution to model fit across all possible combinations of covariates.

Panel A presents the results for *gross* housing duration. Gross rental yield emerges as the dominant factor, accounting for 47.1% of the explained variation. Property prices rank second (31.5%), followed by gross rent levels (7.4%) and local income (7.0%). In contrast, other local characteristics, such as unemployment, labor force participation, homeownership, and population composition, contribute minimally, together explaining less than 5% of the variation.

Panel B reports the decomposition for *net* housing duration, which adjusts for vacancy, maintenance, insurance, and property tax costs. Net rental yield remains the leading determinant, explaining 30.0% of the variation, though its contribution declines relative to the gross-duration case. Property prices, property taxes, and insurance and maintenance costs also account for substantial shares of the variation, while labor-market and demographic characteristics again play only minor roles.

Overall, rental yield and property prices emerge as the main determinants of cross-sectional differences in housing duration, whereas other socioeconomic factors have limited explanatory power.

### D.3. What Does Housing Duration Capture?

Figure 4 summarizes how housing duration correlates with key local economic and demographic characteristics. Shorter-duration markets are associated with higher rental yields, higher implied discount rates, and lower expected rent growth. The strong negative relationship between housing duration and rental yield is consistent with Greenwald et al. (2021), who use the price-to-rent ratio, the inverse of the rental yield, as a proxy for housing duration.

ZIP codes with shorter durations generally have younger residents, lower household incomes, higher unemployment rates, and slightly higher rental vacancy rates. Interestingly, the relationship between housing duration and homeownership rate is U-shaped, with both the shortest- and longest-duration markets exhibiting the lowest homeownership rates. Moreover, shorter-duration markets exhibit greater housing affordability, as reflected in higher income-to-price ratios. This pattern implies that the high interest rate sensitivity of short-duration housing prices is unlikely to be driven by differences in affordability; if affordability were the main channel, lower interest rates would have affected longer-duration, less-affordable markets more strongly instead.

### D.4. Descriptive Statistics of Data

Table 1 reports descriptive statistics and pairwise correlations for the main variables used in the baseline analyses. The sample is restricted to urban areas defined by the U.S. Census Bureau as those with at least 425 housing units per square mile, but results remain robust without this restriction.[19] The final sample covers 6,033 ZIP codes observed annually from 2011 to 2023.

Panel A summarizes housing duration measures and related market characteristics. The mean five-

[19]See Census Bureau (2022) for details.

year gross duration is 4.47 years, with a standard deviation of 0.23. The mean net duration adjusted for vacancy risk, maintenance, insurance, and property tax costs is 4.67 years. Average gross and net rental yields are 6.3 percent and 3.7 percent, respectively. The implied discount rates for gross and net cash flows ($r^{Gross}$ and $r^{Net}$) average 11.4 percent and 6.8 percent. Average log house prices equal 12.44, corresponding roughly to $253,000.

Panel B reports expected rent growth rates from the predictive model. The average one-year-ahead expected growth in gross rent is 3.6 percent, increasing gradually with longer forecast horizons to 4.9 percent in the long term. Panel C presents average cumulative house-price growth over three-year horizons. On average, house prices rise 7.8 percent in the first year, 15.7 percent over two years, and 25.2 percent over three years.

Panel D describes local socioeconomic and housing-market characteristics. The mean log household income is 11.05 (approximately $63,000) and the mean log population is 10.09 (about 24,000 residents). On average, 53 percent of residents are under 40, and 21 percent are above 60. The mean homeownership rate is 57 percent, the rental vacancy rate is 6 percent, and the mean income-to-price ratio is about 0.25.

Panel E reports pairwise correlations among the main variables. Housing duration is strongly negatively correlated with rental yields (–0.95 for gross and –0.90 for net), consistent with the inverse relationship between duration and yield predicted by valuation theory and documented by Greenwald et al. (2021). Duration is positively correlated with house prices and income, and negatively with unemployment and the share of young residents, suggesting that long-duration markets are typically wealthier, higher-priced, and more mature.

## IV. Empirical Results

### A. Baseline Specification

To examine how house price sensitivity to interest rate changes varies across housing markets with different durations, I estimate the following baseline specification using a ZIP-code–year panel sample:

$$\Delta HPI_{z,c,[t-1,\,t+h]} = \alpha_h + \beta_h \, \Delta r_{[t-1,\,t]} \times \text{Duration}_{z,t-1} + \delta_h \, \text{Duration}_{z,t-1} + \zeta_{c,t} + \lambda_z + \epsilon_{z,c,t,h} \,, \tag{16}$$

where $\Delta HPI_{z,c,[t-1,t+h]}$ denotes the percentage change in house prices in ZIP code $z$ within county $c$ from year $t-1$ to $t+h$, with $h$ indicating the horizon over which the price change is measured. $\Delta r_{[t-1,t]}$ is the annual change in the federal funds rate (FFR) from the end of year $t-1$ to $t$, and $\text{Duration}_{z,t-1}$ denotes the *ex ante* housing duration of ZIP code $z$ in year $t-1$. The term $\zeta_{c,t}$ represents county-by-year fixed effects, and $\lambda_z$ denotes ZIP-code fixed effects, which together absorb time-varying county characteristics and time-invariant ZIP-code characteristics. As a result, identification comes from comparing ZIP codes within the same county in the same year that differ in housing duration but experience the same interest rate shock.

The coefficient of interest, $\beta_h$, captures how the response of house prices to interest rate changes differs across markets with different housing durations. A negative relationship between house price growth and changes in the FFR implies that rate cuts ($\Delta r < 0$) are associated with higher average house price growth. ZIP codes that experience larger price increases following rate cuts would exhibit greater interest rate sensitivity of house prices. Therefore, a positive estimate of $\beta_h$ ($\hat{\beta}_h > 0$) would indicate that longer-duration markets experience smaller price increases after rate cuts and are thus *less sensitive* to monetary policy changes than shorter-duration markets. Conversely, a negative estimate ($\hat{\beta}_h < 0$) would imply greater sensitivity among longer-duration markets.

### B. ZIP-Code House Price Responses to Interest Rate Changes by Housing Duration

#### B.1. Baseline Analysis

Table 2 reports how asset price responses to changes in the federal funds rate (FFR) vary across asset durations within each of the three markets: residential real estate (Panel A), U.S. Treasuries (Panel B), and equities (Panel C). Housing duration is measured as the gross duration constructed from gross rental cash flows, as described in Section III.B. Bond duration follows the standard Macaulay duration measure, and equity duration is constructed by Gonçalves (2021) under the same Macaulay duration framework.

Panel A provides compelling evidence that shorter-duration housing markets exhibit significantly greater price sensitivity to monetary policy changes, in sharp contrast to the positive duration–sensitivity pattern observed for bonds and equities in Panels B and C.

Specifically, Column 1 of Panel A indicates that a 100-basis-point reduction in the FFR corresponds to an average two-year house price increase of about 1.86% across ZIP codes. Columns 2 to 5 progressively introduce the interaction between the FFR change and local housing duration, along with year and county-by-year fixed effects. The interaction term remains positive and highly significant across all specifications, indicating that house prices in shorter-duration markets respond more strongly to rate cuts. Column 5, the preferred specification including both county-by-year and ZIP-code fixed effects, yields an estimated interaction coefficient of 3.089. Given the cross-sectional standard deviation of housing duration of 0.23, this estimate implies that a ZIP code with a one-standard-deviation shorter duration experiences an additional house price increase of roughly 0.71% following a 100-basis-point rate cut, about 38% of the average price response, indicating economically meaningful heterogeneity in interest rate sensitivity across housing durations.

In contrast, Panels B and C reveal a positive relationship between duration and interest rate sensitivity for bonds and equities. A 100-basis-point FFR cut is associated with average two-year price increases of roughly 4.7% for U.S. Treasuries and about 11% for equities. The negative coefficients on the interaction term in Columns 2 to 4 confirm that longer-duration bonds and equities experience larger price increases following rate cuts, consistent with the conventional duration framework.

Overall, Table 2 highlights a striking divergence across asset classes: while bonds and equities conform to the positive duration–sensitivity relationship, housing markets exhibit the opposite pattern: short-duration housing markets are more sensitive to monetary policy changes.

### B.2. Gross and Net Duration Measures: Robustness to Local Characteristics

Table 3 confirms the inverse relationship between housing duration and interest rate sensitivity using duration measures that exclude and include operating costs, and by controlling for a comprehensive set of ZIP code-level demographic and economic characteristics, as listed in Figure 5. Panel A reports results based on the gross and net housing duration measures, while Panel B employs rental yield as a proxy for the inverse of housing duration, analogous to Greenwald et al. (2021), who use the price-to-rent ratio as a duration proxy.

Across all specifications, the coefficients on the interaction term between the FFR change and housing duration remain significantly positive, confirming the robustness of the higher interest rate sensitivity of shorter-duration housing markets. In both panels, the estimated coefficients on the interaction term in the baseline specifications (Columns 1 and 3) are similar in magnitude, suggesting that operating costs, such as vacancy, maintenance, insurance, and property taxes, are not the main drivers of the inverse duration–sensitivity relationship. After controlling for local characteristics and their interactions with FFR changes, the coefficients from the gross duration and rental yield regressions remain stable, whereas those from the net duration and rental-yield regressions decline modestly but stay significantly positive. This pattern implies that operating costs are correlated with local characteristics, influencing the overall interest rate sensitivity of local house prices, although the main cash inflow component, represented by gross rents, is much less affected.

Controlling for this extensive set of local fundamentals and their interaction terms helps rule out several competing explanations for the observed inverse duration–sensitivity relationship. These controls also capture both long-run and short-run housing demand fundamentals, including household income, employment, population size, affordability, and local market tightness. First, borrowing or income constraints, proxied by local household income levels, are unlikely to be the main driving factor. Second, the inclusion of homeownership and rental vacancy rates mitigates the concern that the result reflects differences in housing demand pressure across markets. Third, the inverse pattern is unlikely to be driven by first-time homebuyers. Because younger households are more likely to be first-time buyers and more sensitive to local housing affordability, controlling for the age distribution of the population and the income-to-price ratio as a proxy for affordability does not alter the main findings. Fourth, the pattern is not driven by local exposure to employment cycles, as the regressions already control for labor force participation and unemployment rates. Across all these specifications, the estimated coefficients on the main interaction term remain stable and significantly positive, reinforcing that the inverse duration–sensitivity pattern reflects differences in the timing of housing cash flows rather than demographic or economic composition effects.

### B.3. Heterogeneity by Local Characteristics

Figure 5 illustrates how the sensitivity of house prices to interest rate changes varies across ZIP-code demographic and economic characteristics. The estimates come from the coefficients on the interaction terms between FFR changes and local characteristics in Columns 2 and 4 of Panel A in Table 3. Each bar shows the additional two-year cumulative house-price change associated with a one-standard-deviation increase in the indicated characteristic following a 100-basis-point FFR decrease. Panel A uses the gross-duration measure, while Panel B uses the net-duration measure.

Four patterns stand out. First, higher-income areas respond more strongly to rate cuts, consistent with greater credit access and refinancing capacity. Second, markets with younger or older populations show weaker sensitivity: younger households are more likely to rent and less exposed to mortgage financing, while older homeowners rely less on debt. Third, areas with stronger labor markets (i.e., higher labor force participation and lower unemployment) exhibit smaller price responses, suggesting that stable employment and income allow households to smooth mortgage payments and avoid forced sales. Fourth, ZIP codes with higher housing affordability are less affected by interest rate changes, as rate changes shift borrowing capacity less when affordability is high. In contrast, areas with higher rental vacancy rates are more responsive, possibly because higher rental vacancies indicate weaker rental demand and more renters transitioning into homeownership when mortgage costs fall, amplifying price responses to rate cuts.

Overall, Figure 5 highlights substantial heterogeneity in house price responses to interest rate changes across local economic conditions, but these differences do not alter the main result that shorter-duration housing markets remain more sensitive to monetary policy changes.

### B.4. Diminishing Interest Rate Sensitivities by Duration Quintiles over 3-Year Horizons

Unlike bond and equity markets, housing markets respond to interest rate changes gradually, with price effects typically taking two to three years to materialize (Kuttner, 2013; Williams, 2015). To examine how price responses vary across local markets, I classify ZIP codes into five quintiles based on the estimated gross and net housing durations. Figure 6 plots the cumulative house price responses following a 100-basis-point decrease in the federal funds rate (FFR). Quintile 1 represents the shortest-duration markets, while Quintile 5 corresponds to the longest-duration markets and serves as the benchmark group. Each bar shows the cumulative price change relative to the benchmark at one-, two-, and three-year horizons, which are estimated with the baseline specification in Equation 16.

Panels A and B reveal a clear, monotonic decline in sensitivity as housing duration increases. In Panel A (gross duration), the shortest-duration markets (Quintile 1) experience cumulative price increases of approximately 0.45, 1.5, and 1.6 percentage points higher than those in the longest-duration quintile after one, two, and three years, respectively. Quintiles 2 and 3 also exhibit significantly stronger responses, while the response of Quintile 4 is only marginally above that of the longest-duration group and, in some cases, statistically insignificant. Panel B, which uses the net duration measure and adjusts for ownership costs and vacancy rates, shows a similar pattern, confirming that the results are not driven by these factors.

Overall, Figure 6 shows that house price sensitivity to interest rate changes declines systematically with housing duration. Short-duration markets, whose cash flows are realized sooner, react more strongly to rate cuts than long-duration markets. These results reinforce the inverse duration–sensitivity relationship documented in Table 2, which remains robust across both gross and net duration measures and persists over longer horizons.

### B.5. Alternative Policy Rate Measures

**30-Year Mortgage Rate Changes** A potential concern is that short-term policy rate changes may not fully transmit to long-term mortgage rates, which are more directly tied to housing finance and thus to house price dynamics (Van Binsbergen and Grotteria, 2024). Panel A of Table 4 addresses this issue by replacing the federal funds rate with the 30-year fixed mortgage rate as the monetary policy measure. The results closely mirror those based on the FFR. The interaction terms between mortgage rate changes and housing duration remain significantly positive across all specifications, indicating that shorter-duration markets continue to exhibit greater sensitivity to interest rate changes. Specifically, the interaction coefficients range from 5.49 to 4.58 for gross duration and from 5.59 to 2.30 for net duration. The magnitudes of these coefficients are somewhat larger than those estimated using the FFR, consistent with the notion that mortgage rates more directly affect borrowing costs and therefore have a more immediate impact on housing prices. Overall, using the 30-year mortgage rate as the policy measure reinforces the main finding that shorter-duration housing markets are more sensitive to interest rate changes, regardless of whether policy shifts are captured by short-term or long-term rates.

**Monetary Policy Shocks (MPS) as Instrumental Variables** Another potential concern is that changes in policy rates may correlate with unobserved macroeconomic conditions that also affect house prices, introducing omitted-variable bias. Although controlling for ZIP-code characteristics and their interactions with interest rate changes mitigates this issue, I further strengthen identification by instrumenting FFR changes with *plausibly exogenous* monetary policy shocks (MPS).[20] Panel B of Table 4 reports results using several established MPS measures, including the one-year Treasury yield surprise, the monetary policy shocks constructed by Bauer and Swanson (2023), and those from Jarociński and

[20] I also estimate the specifications directly using the MPS as the rate change measure and obtain nearly identical results.

Karadi (2020). Across all instruments, the interaction between monetary policy shocks and housing duration remains significantly positive, with coefficients ranging from roughly 2.8 to 4.6. This consistent pattern confirms that shorter-duration markets exhibit greater sensitivity to monetary shocks. The robustness of these estimates across alternative, plausibly exogenous instruments reinforces that the inverse duration–sensitivity relationship is not driven by endogeneity in policy rate changes.

### B.6. Alternative Housing Duration Measures

**Gross and Net Rental Yield as Proxies for Housing Duration** A potential concern is that measurement errors in my duration measure might drive the documented inverse relationship between housing duration and interest rate sensitivity. To address this concern, I employ gross and net rental yields, which are defined as the ratios of gross and net rents to property prices, as alternative proxies for the inverse of housing duration. Under the Gordon Growth Model (GGM) with constant rent growth and infinite rental cash flows, housing duration can be expressed as the price-to-rent ratio (i.e., the reciprocal of rental yield), as applied by Greenwald et al. (2021) and detailed in Internet Appendix F.3. Empirically, I also find a strong negative correlation between rental yields and housing durations, with higher rental yields corresponding to shorter durations.

As shown in Panel B of Table 3, using rental yield as an inverse duration measure yields results that align closely with my baseline analysis. Across all specifications, ZIP codes with higher rental yields, corresponding to shorter-duration markets, exhibit significantly greater house-price sensitivity to FFR changes. The monotonic increase in sensitivity across rental-yield quintiles, shown in Panels C and D of Figure 6, reveals a similar pattern observed using housing-duration quintiles in Panels A and B of the same figure. Additional analyses employing 30-year mortgage-rate changes and alternative MPS measures, reported in the Internet Appendix, confirm the robustness of these results. Overall, the consistent results using rental yields as the duration proxy reinforce that the observed inverse duration–sensitivity relationship is not driven by measurement error in the duration measure.

**Alternative Holding Horizon and LASSO-Based Rent Prediction** My primary results rely on a housing duration measure constructed with a 5-year terminal horizon. The findings remain robust when using alternative duration measures based on different construction assumptions and methods. Specifically, I construct (i) a 10-year duration measure assuming homeowners expect to hold properties for 10 years before realizing terminal values from selling the properties, (ii) duration measure using actual ZIP-code holding horizons, and (iii) duration measure derived from rent growth predictions using LASSO regression with 10-fold cross-validation. The results consistently show significantly positive interaction coefficients between housing duration and interest rate changes across all specifications and alternative measures. Detailed results are provided in the Internet Appendix C.

### B.7. Alternative Data Sources

To validate the robustness of the findings, I replicate the analyses using alternative data sources, including Zillow's housing indices and combined property-level transaction and rental data from ATTOM and Altos. Using the Zillow Home Value Index (ZHVI) and the Zillow Observed Rent Index (ZORI), I reconstruct the housing duration measure following the same methodology described in Section III.B.[21] The Zillow-based results are consistent with those from the ACS and indicate somewhat stronger heterogeneity in interest rate sensitivity, likely reflecting the more recent sample period. Consistent with this interpretation, restricting the ACS analysis to post-2015 years yields similar patterns. Analyses combining property-level transaction prices from ATTOM with rental listings from Altos further corroborate the main results. Overall, the consistency of the Zillow- and ATTOM–Altos–based results with the ACS analysis reinforces the robustness and external validity of my main findings.

## C. Property-Level Evidence: Controlling for Mortgage and Tax Cash Outflows

Using housing transaction data, I test whether the inverse duration–sensitivity relationship observed at the ZIP-code level holds at the property level. Table 5 confirms the baseline findings and addresses concerns that the relationship might be driven by mismeasurement of mortgage or tax-related cash outflows. Specifically, it reports how transaction prices respond over two years to interest rate changes across properties with different housing durations, proxied by ex-ante rental yields, while controlling for a comprehensive set of property characteristics and housing cash-flow variables.

Columns 1 and 2 replicate the baseline results and show that properties with higher rental yields (shorter durations) exhibit significantly stronger price responses to rate cuts. A one-standard-deviation higher rental yield ($\approx 0.072$) increases price sensitivity by about 1.5 percentage points following a 100-basis-point FFR decline. Columns 3 and 4 add controls for the log of annual mortgage payment and the

[21] Because ZORI data are available only from 2015 onward, later than the ACS coverage, the Zillow sample is primarily used for robustness tests.

loan-to-value (LTV) ratio, along with their interactions with rate changes. Properties with higher mortgage payments or LTV ratios exhibit greater price sensitivity. Columns 5 and 6 introduce tax-related controls, including the log of annual tax payment and the tax-to-value ratio. Importantly, accounting for mortgage and tax cash outflows, credit constraints, and tax burdens does not explain the stronger sensitivity of shorter-duration properties; if anything, it strengthens the relationship.

Overall, the property-level evidence reinforces the conclusion that short-duration (high-yield) properties are more sensitive to interest rate changes, and this relationship is not driven by differences in mortgage or tax cash outflows, credit constraints, or effective tax burdens.

### D. Duration Decomposition: Expected Cash Flow Growth versus Discount Rate

A shorter housing duration is empirically associated with a lower expected rent growth and a higher discount rate. Hence, the inverse relationship between duration and interest rate sensitivity may arise from heterogeneity either in the *timing* of expected rental cash flows, captured by rent growth expectations, or in local discount rates. To isolate these channels, Table 6 decomposes housing duration into two components: expected cash flow growth and discount rate components.

Following the same methodology in Section III.B, I construct two pseudo-duration measures, $Dur^{\bar{R}}$ and $Dur^{\bar{G}}$. $Dur^{\bar{R}}$ holds the discount rate fixed at the national average $\bar{R}$ while allowing heterogeneous local rent growth. This measure isolates the expected cash flow growth component of duration. Conversely, $Dur^{\bar{G}}$ holds rent growth fixed at the national average $\bar{G}$ while allowing heterogeneous local discount rates, thereby isolating the discount rate component. This decomposition parallels Walter and Weber (2022), who separate cash flow timing and discount-rate effects in equity duration.

Columns 1 to 4 of Table 6 show that when each pseudo-duration measure is considered separately, both yield a consistently strong inverse duration–sensitivity relationship. This consistency suggests that the inverse relationship is not mechanically driven by the estimation of local rent growth or discount rates. Eliminating heterogeneity in either local discount rates or expected rent growth individually does not alter the main finding.

When both pseudo-duration measures and their interactions are included in Columns 5 and 6, the coefficient on the cash-flow-growth-based interaction, $\Delta r_{[t-1,t]} \times Dur^{\bar{R}}_{z,t-1}$, remains large and significantly positive, whereas that on the discount-rate-based interaction, $\Delta r_{[t-1,t]} \times Dur^{\bar{G}}_{z,t-1}$, becomes significantly negative. This contrast implies that the inverse duration–sensitivity relationship is primarily driven by heterogeneity in expected rent growth, that is, the timing of expected cash flows, rather than by variation in local discount rates.

Overall, Table 6 suggests that short-duration, high-yield housing markets are more sensitive to interest rate changes, not because they have higher risks, but because their expected cash flows are front-loaded, as implied by lower future rent growth. The mechanism, therefore, reflects variation in the timing of expected cash flows rather than differences in local housing risks. This distinction clarifies that investors' behavior is best characterized as "reaching for income", a preference for assets delivering near-term cash payouts, rather than "reaching for yield," which involves greater risk-taking to achieve higher expected returns. The distinction between these two channels is discussed in detail in the Introduction and in Section VI. In summary, Table 6 demonstrates that geographic heterogeneity in the expected timing of rental cash flows, rather than in local discount rates, drives the stronger sensitivity of short-duration housing markets to interest rate changes.

## V. Discount-Rate Channel: Reaching-for-Income Evidence in Housing Markets

This section examines how the discount-rate channel through reaching-for-income behavior contributes to the heterogeneity in house-price sensitivity across markets. I first show that when interest rates decline, properties with higher rental yields are more likely to be purchased for rental purposes ("buy-to-rent," or BTR). These investors accept lower realized returns from high-yield houses following rate cuts. I then show that BTR activity amplifies price increases in short-duration markets, generating the observed inverse duration-sensitivity of housing prices to interest rate changes.

### A. Identifying Reaching-for-Income Housing Investment Activity

"Reaching for income" refers to the behavior whereby investors, particularly those who rely on cash flows, develop a stronger preference for income-generating assets such as dividend-paying stocks or high-yield bonds following interest rate declines. This behavior arises because lower interest rates reduce returns on savings accounts and short-term bonds (Daniel et al., 2021).

#### A.1. Identifying Buy-to-Rent Transactions

Using housing transaction records and historical tax assessment data from ATTOM, I identify buy-to-rent (BTR) transactions, which capture housing purchases intended for long-term rental income rather than short-term capital gains. Reaching-for-income behavior in housing markets is assessed by examining whether interest rate changes differentially affect the likelihood of BTR purchases for properties with higher ex-ante rental yields.

Formally, a transaction is classified as BTR if the property is purchased in year $t$, held for at least two years, and becomes or remains non-owner-occupied in year $t+1$. Properties that are non-owner-occupied at purchase must remain so in subsequent years, while properties that are owner-occupied at purchase must transition to non-owner-occupied status in the year following purchase.[22] Owner-occupancy status is observed directly in the tax assessment data or, when missing, inferred by comparing the property address with the mailing address.[23]

While non-owner-occupied status may occasionally reflect vacation homes rather than rental properties, this concern is limited. Only a small fraction of vacant homes are seasonal or vacation units,[24] and vacation homes typically do not require a separate mailing address for tax purposes. For additional validation, I link transactions to Altos rental listing data and redefine BTR transactions as properties listed for rent within 24 months of purchase. Results using this alternative definition are similar.

### A.2. Descriptive Evidence on Reaching-for-Income Housing Investors

Figure 7 shows that BTR purchases are predominantly conducted by local, small-scale housing investors. Nearly half occur within the same county as investors' primary addresses, more than 60 percent within the same core-based statistical area (CBSA), and roughly 80 percent within the same state. More than half of BTR properties are located within 25 miles of the buyer's primary address. BTR buyers are predominantly small-scale investors, with the distribution of investment property counts concentrated at low values at the time of purchase. Relative to non-BTR purchases, BTR transactions exhibit a higher likelihood of all-cash purchases and lower mortgage usage. Taken together, these patterns suggest that BTR activity is primarily conducted by small-scale individual investors active in local housing markets.

[22] Primary-residence mortgages typically require occupancy within 60 days of closing and restrict conversion to rental use within the first 12 months. This definition therefore captures buyers who initially claim owner-occupancy to obtain favorable mortgage terms but subsequently convert the property to rental use, as well as investors who temporarily occupy a property during renovations before renting it out.

[23] If the property and mailing addresses differ in a given year, the property is classified as non-owner-occupied. If both occupancy status and mailing address are missing, the property is assumed to be owner-occupied, which biases against identifying BTR transactions.

[24] Only ≈3.5% of vacant homes are seasonal or vacation homes based on U.S. Census data.

Figure 8 compares the distributions of property and buyer characteristics across buy-to-rent (BTR) and non-BTR transactions. BTR purchases are concentrated in properties with substantially higher rental yields relative to non-BTR purchases, even after controlling for county-by-year average rental yields through residualization using county-by-year fixed effects or by ranking properties within county and year. BTR properties also tend to be smaller and older than those in non-BTR transactions. In terms of buyer characteristics, BTR buyers are, on average, older than non-BTR buyers. These patterns indicate that BTR activity is disproportionately concentrated in the high-rental-yield segment of local housing markets among relatively older buyers.

### A.3. Empirical Specification

To formally examine the reaching-for-income behavior, I estimate the following specification:

$$\mathbb{1}\{BTR\}_{i,z,c,t} = \alpha + \beta\, \Delta r_{[t-h-1,\, t-h]} \times \mathrm{RY}_{i,\, t-h-1} + \delta\, \mathrm{RY}_{i,\, t-h-1} + \Gamma' X_{i,t} + \zeta_{c,t} + \lambda_z + \epsilon_{i,z,c,t}, \tag{17}$$

where the dependent variable $\mathbb{1}\{BTR\}_{i,z,c,t}$ equals one if property $i$ in ZIP code $z$, county $c$, and year $t$ is classified as buy-to-rent, and zero otherwise. $\Delta r_{[t-h-1,\, t-h]}$ measures the change in interest rates $h$ years prior to transaction $t$. The baseline analyses use the FFR as the interest rate measure, with robustness checks based on changes in the 30-year mortgage rate (see Internet Appendix). $\mathrm{RY}_{i,\, t-h-1}$ denotes the ex-ante rental yield for property $i$, estimated via hedonic regression approach detailed in Section III.C.

The vector $X_{i,t}$ includes property characteristics used in the rental yield estimation, which capture attributes correlated with BTR probability. The county-by-year fixed effects, $\zeta_{c,t}$, control for time-varying county characteristics, and ZIP code fixed effects, $\lambda_z$, absorb time-invariant ZIP-code characteristics. Identification thus arises from variation in rental yields across properties and ZIP codes over time.

With this specification, the coefficient of interest, $\beta$, captures the heterogeneity in the sensitivity of BTR probability to interest rate changes across houses with different *ex-ante* rental yields. A negative estimate of $\beta$ would thus imply that interest rate cuts disproportionately increase the probability of BTR activity for high-rental-yield houses, providing evidence of reaching-for-income behavior in housing markets.

### B. High Buy-to-Rent Probability for High Rental Yield Properties as Interest Rates Decrease

Table 7 presents evidence that lower interest rates make high-rental-yield properties more likely to be purchased for rental purposes ("buy-to-rent," or BTR). The table reports transaction-level regressions in which the dependent variable equals one if the property is purchased for rental purposes (BTR). The main variable of interest is the interaction between a property's *ex-ante* rental yield, $RY_{i,t-h-1}$, and the change in the federal funds rate (FFR) during or before the transaction year.

Two clear patterns emerge. First, properties with higher rental yields are more likely to be BTR on average. A one-standard-deviation increase in rental yield (about 0.075) raises the probability of a BTR purchase by roughly 4.6 percentage points. Second, the interaction between interest rate changes and rental yields is significantly negative, indicating that rate cuts disproportionately increase BTR purchases among high-yield properties. A 100-basis-point decline in the FFR raises the probability that a high-yield property is purchased for rent by about one percentage point, or roughly 21% relative to the baseline BTR probability. Columns 5–8 use orthogonalized monetary policy surprises (MPS) from Bauer and Swanson (2023) as an instrument for FFR changes, confirming the robustness of the findings. These regressions also control for local rental market conditions (e.g., rental vacancy rates) and demographic characteristics, ensuring that the results are not driven by changes in local rental demand.

Overall, the results provide direct evidence of reaching-for-income behavior in housing markets. Declines in interest rates increase demand for income-generating assets (Daniel et al., 2021; Gargano and Giacoletti, 2022), making high-yield properties more likely to be purchased for rental purposes. Moreover, this rental-income-driven investment behavior may affect local house price dynamics as interest rates change, which will be examined in the next section.

#### B.1. Near-Term Income Demand and Reaching-for-Income Behavior

Table 8 links preferences for near-term cash income to BTR purchases. The results provide additional evidence of reaching-for-income behavior: homebuyers with a stronger demand for immediate cash income are more likely to purchase high-rental-yield properties for rental purposes.

Building on prior work showing that older or retired households prefer assets delivering cash income (Becker, Ivković, and Weisbenner, 2011; Jiang and Sun, 2020; Daniel et al., 2021), I construct two proxies for cash income preference using IRS Statistics of Income (SOI) ZIP-code-level data: (i) the share of tax returns reporting taxable individual retirement account (IRA) distributions, and (ii) the ratio of taxable interest income to adjusted gross income (AGI). Each buyer is linked to these measures via the mailing ZIP code corresponding to their primary residence. A higher share of IRA withdrawals or a higher interest-income ratio indicates a greater demand for income-generating assets. A higher interest-income ratio also represents a stronger exposure to interest rate changes.

Columns 1 to 3 use the *ex-ante* IRA-withdrawal share as a proxy and show that following rate declines, homebuyers from areas with more retirement withdrawals are more likely to buy high-rental-yield houses for rental purposes, as indicated by the negative coefficient on the triple interaction term $\Delta r_{[t-2,t-1]} \times RY_{i,t-2} \times \%\text{Retirement Income File}_{i,t-2}$. This conclusion is reinforced by the sharp decline in the coefficient on $\Delta r_{[t-2,t-1]} \times RY_{i,t-2}$ once the triple interactions are included in Columns 2 and 3, suggesting that the observed responsiveness of BTR to rate changes in Column 1 is primarily concentrated among older, income-seeking homebuyers. Columns 4 to 6 reinforce this result using the *ex-ante* interest-income ratio as an alternative proxy: homebuyers from ZIP codes with higher interest income exposure are also more likely to purchase high-yield properties for rent when interest rates fall.

Overall, Table 8 provides compelling evidence of reaching-for-income behavior in housing markets. It suggests that after rate cuts, the higher BTR probability for properties with higher rental yields is more likely to be driven by preferences for near-term cash income rather than capital gains.

### C. Realized Returns of BTR Investors

If reaching-for-income behavior reflects a preference for short-term cash income, then BTR investors should be willing to accept lower realized total returns in exchange for higher near-term income when interest rates fall. To test this implication, I examine realized total returns for BTR investors who both purchase and subsequently sell a rental property. Among all BTR transactions, I restrict the sample to two-way transactions with valid resale records. The realized total return is defined as the sum of the realized capital gain and the imputed rental income over the holding period. Capital gains are measured as the ratio of resale to purchase prices for the same property.[25] Formally, the realized

[25]Following Goldsmith-Pinkham and Shue (2023); Kermani and Wong (2024); Baldauf et al. (2025), I construct realized capital gains from the two-way transactions. First, for each purchase transaction, I identify its subsequent ownership-end transaction and retain the pair only if both purchase and resale are valid, as described in Internet Appendix Section A. Second, I require a minimum holding period of six months. Third, I verify buyer-seller identity consistency by fuzzy-matching names across purchase and resale records, requiring at least one match above a 60 similarity score using the `partial_token_sort_ratio` algorithm in the `thefuzz` Python package.

total return of property $i$ purchased and sold at year-month $b$ and $s$, respectively, is

$$\text{Ret}_{i,b,s} = \underbrace{\frac{P_{i,s}}{P_{i,b}}}_{\text{realized capital gain}} + \underbrace{\frac{\sum_{\tau=b+1}^{s-1} \widehat{\text{Rent}}_{i,\tau}}{P_{i,b}}}_{\text{imputed rental yield over holding period}},$$

where $P_{i,b}$ and $P_{i,s}$ denote the observed purchase and sale prices, respectively. $\widehat{\text{Rent}}_{i,\tau}$ represents the expected monthly rent derived from the hedonic rent estimation described in Section III.C. The rental-yield component aggregates imputed rents over the holding period (excluding the purchase and sale months). Realized total returns are then annualized based on the actual holding length.

### C.1. Lower Realized Returns for High-Yield, Short-Duration Properties after Rate Cuts

Figure 9 shows that realized returns of BTR investors decline monotonically with rental yield following a 100-basis-point cut in the FFR one year prior to purchase. Properties are sorted into deciles by *ex-ante* rental yield, and the figure plots the estimated change in realized annual return per 100-bps FFR cut. Panel A, using raw FFR changes, indicates that realized returns fall by about 1.5 percentage points for the lowest-yield decile and nearly 4.5 points for the highest-yield decile. Panel B, which instruments the FFR with the monetary policy surprise (MPS) measure from Bauer and Swanson (2023), yields a similar monotonic pattern with larger magnitudes, ranging from roughly 6 to 12 percentage points.

Table 9 formally confirms these results. Across specifications, declines in the FFR are associated with lower realized returns for BTR investors, particularly among high-yield properties. The interaction between FFR changes and rental yield is significantly positive across Columns 2 through 6 in both panels, indicating that rate cuts are followed by disproportionately lower realized returns for properties with higher *ex-ante* rental yields. Column 2 of Panel A shows that, with county-by-year and ZIP-code fixed effects, a one-standard-deviation increase in rental yield (≈0.082) corresponds to about a 0.4-percentage-point reduction in realized returns when the FFR decreases by 100 basis points prior to purchase. These results remain robust after including controls for holding length, market timing, and local economic characteristics, as well as their interactions with FFR changes. Panel B, which instruments the FFR with the MPS measure, produces similar but larger effects.

Overall, Figure 9 and Table 9 demonstrate that rate cuts lead to lower realized returns for high-yield properties, consistent with a reaching-for-income motive in which BTR investors favor near-term rental cash flows at the expense of total returns. If investor behavior were instead dominated by a reaching-for-yield motive, pursuing higher expected returns from riskier assets, we would expect high-yield properties to outperform low-yield ones following rate cuts. The observed pattern of lower realized returns for high-yield investments suggests that lower interest rates induce income-oriented investors to bid up high-yield, short-duration properties, reducing their subsequent realized returns.

### C.2. High-Yield Properties Underperform over Longer Holding Horizons

Figure 10 shows how realized returns of BTR investors respond to a 100-basis-point decline in the federal funds rate (FFR) across property holding horizons and *ex-ante* rental yields. Although the baseline definition of BTR investors requires a minimum holding period of two years, I relax this restriction here to illustrate the dynamics for very short-horizon investors, such as house flippers.[26]

Panel A, using raw FFR changes, shows that at the one-year horizon, high-yield properties earn higher realized returns than low-yield properties following a rate cut. This pattern is consistent with the baseline result that high-yield, short-duration properties appreciate more strongly in the immediate aftermath of monetary easing. However, this advantage fades quickly: beyond two years of holding, high-yield properties underperform their low-yield counterparts, and the return gap widens monotonically with the holding horizon, leaving long-run realized returns substantially lower for high-yield properties. Panel B, which instruments FFR changes with the MPS measure from Bauer and Swanson (2023), produces even larger negative estimates.

Overall, the figure demonstrates that investors' tilt toward high-yield properties after rate cuts is unlikely to reflect forward-looking rational motives. If investors were responding to expectations of higher future returns, high-yield properties would outperform low-yield ones over longer horizons. The evidence also suggests that this behavior is unlikely to reflect a "*reaching-for-yield*" motive, in which investors deliberately seek higher expected returns from riskier assets. Instead, the evidence supports a reaching-for-income mechanism: when rates fall, investors disproportionately chase income-generating assets that deliver relatively high near-term rental income, even though this behavior leads to lower total returns in the long run.

[26] This relaxation is purely illustrative; all other analyses maintain the two-year definition. One-year holders are not classified as BTR investors because their strategies are more plausibly driven by capital gains than by rental income.

### D. Property Transition between Owner- and Renter-Occupied Status

Although high-rental-yield properties are more likely to be purchased for rental purposes when interest rates decline, such activity may not necessarily make short-duration, high-yield markets more sensitive to rate changes. If BTR investors primarily target properties that are already renter-occupied, increased investor demand would not raise aggregate house prices.

Table 10 examines how interest rate changes affect transitions between owner- and renter-occupied status. Panel A shows that properties with higher rental yields are significantly more likely to transition from owner to renter occupancy on average. This tendency strengthens following FFR cuts. The interaction between rental yield and the FFR change is consistently negative, indicating that rate declines disproportionately increase the likelihood of owner-to-renter occupancy conversions among high-yield properties. The effect persists for up to two years after the shock. Using the MPS measure from Bauer and Swanson (2023) as an instrument for FFR changes yields similar estimates, confirming that the effect is not driven by endogenous interest rate changes.

Panel B reports the reverse transition from renter to owner occupancy. On average, high-rental-yield properties are less likely to revert to owner occupancy, and this probability declines further following rate cuts. Both contemporaneous and lagged FFR cuts significantly decrease renter-to-owner transitions, and the MPS-instrumented estimates corroborate these findings.

Overall, the evidence in Table 10 shows that lower interest rates reallocate housing stock toward the rental sector. High-rental-yield properties are increasingly likely to transition to rental occupancy and less likely to transition to owner occupancy. These asymmetric transition dynamics are consistent with a reaching-for-income mechanism: when rates fall, income-oriented investors disproportionately purchase short-duration, high-yield properties for rental purposes, turning owner-occupied houses into renter-occupied ones and exerting price pressure in those segments. The results also help rule out the alternative explanation that stronger demand from first-time homebuyers or housing consumers drives the observed sensitivity. If that were the case, rate cuts would instead increase transitions from renter to owner occupancy, especially for high-yield houses. Instead, the evidence supports the view that investor-driven reaching-for-income behavior, rather than rising homeowner demand, therefore drives the heterogeneous house price responses to monetary policy.

### E. Reaching-for-Income Affects House Price Dynamics

This section examines whether the reaching-for-income activity drives the greater price sensitivity of short-duration housing markets to interest rate changes documented in Section IV.B.

#### E.1. House Price Sensitivity across Local Buy-to-Rent Activity

To test whether reaching-for-income behavior amplifies price sensitivity, I exploit variation in local BTR intensity. ZIP codes are sorted into quintiles based on *ex-ante* BTR transaction ratios, and within each quintile, I compare the house price responses of short- and long-duration markets to interest rate changes. This design isolates the extent to which BTR activity amplifies differential price responses between short- and long-duration markets.

Figure 11 shows that although short-duration markets, on average, respond more strongly to rate cuts, this difference is concentrated in areas with high BTR activity. In low-BTR areas, the short-versus-long gap nearly disappears, and in some cases reverses. By contrast, in the highest-BTR quintiles, short-duration markets display substantially greater sensitivity to rate cuts, consistent with BTR activity amplifying short-duration price responses.

In the figure, each bar shows, following a 100-basis-point interest rate cut, the additional price increase associated with a one-standard-deviation increase in housing duration within a given BTR quintile. To measure interest rate changes, Panels A and B use the FFR, while Panels C and D apply the 30-year mortgage rate. At the contemporaneous horizon ($h = 0$), short-duration markets do not exhibit higher price growth than long-duration ones following rate cuts in low-BTR areas. As BTR intensity increases, the short-minus-long gap widens and becomes significant. At the two-year horizon ($h = 1$), the pattern persists, though even low-BTR areas begin to show greater short-duration sensitivity.

Overall, these results indicate that reaching-for-income investment activity plays a key role in explaining the heightened responsiveness of short-duration housing markets to interest rate cuts. However, the inverse duration–sensitivity pattern at the two-year horizon, even in low-BTR areas, suggests that additional forces may also contribute, pointing to further mechanisms for future research.

Table 11 reports formal regressions estimating the interest rate sensitivity of house prices across ZIP codes with varying housing duration and BTR intensity. In the baseline specification without BTR intensity controls in Columns 1, 3, 5, and 7, short-duration markets exhibit significantly stronger price responses to rate cuts, consistent with the inverse duration–sensitivity pattern in Table 4.

Controlling for BTR intensity in Columns 2, 4, 6, and 8 substantially weakens this inverse relationship. The triple interaction term, $\Delta r_{[t-1,t]} \times \text{Duration}_{z,t-1} \times \text{BTR\%}_{z,t-1}$, is positive and significant, indicating that the heightened sensitivity of short-duration markets is concentrated in areas with strong BTR activity. In low-BTR areas, the higher interest rate sensitivity of shorter-duration markets largely disappears, and in some cases even reverses. At the contemporaneous horizon ($h = 0$), the coefficients on $\Delta r_{[t-1,t]} \times \text{Duration}_{z,t-1}$ become insignificant once BTR is included, while at the two-year horizon ($h = 1$) the baseline effect declines by roughly 50 to 70 percent, reinforcing that the observed inverse duration-sensitivity relationship is primarily driven by the reaching-for-income behavior.

Overall, the results underscore that reaching-for-income investment activity amplifies the transmission of monetary policy to local housing markets. When rates fall, investors seeking rental income disproportionately enter high-yield, short-duration markets. Their inflows bid up local house prices and lower discount rates, particularly in high-BTR markets. As a result, the reaching-for-income behavior leads to a stronger price sensitivity observed in short-duration markets.

## VI. Alternative Channels

This section evaluates alternative explanations for the inverse relationship between housing duration and interest rate sensitivity in house prices. It shows that none account for the stronger price responses in short-duration markets.

### A. Cash-Flow Channel

Table 12 examines whether the cash-flow channel can explain the stronger interest rate sensitivity of short-duration housing markets. Specifically, it estimates how interest rate changes affect revisions in expected rental cash flows and terminal house values across markets with different durations. As discussed in Section II.D, the cash-flow channel predicts that if rate cuts disproportionately increase expected cash flows in short-duration markets relative to long-duration ones, and the gap is sufficiently large, the conventional positive relationship between duration and sensitivity could be overturned.

The results show that longer-duration markets experience larger upward revisions in expected housing cash flows following rate cuts. The coefficients of interest, $\Delta r_{[t-1,t]} \times Duration_{z,t-1}$, are consistently negative across horizons, although they weaken once county-by-year and ZIP-code fixed effects are included. Thus, instead of boosting expected cash flows more in short-duration markets, lower interest rates raise expected cash flows more in long-duration markets.

This pattern runs counter to the inverse duration–sensitivity relationship documented in the baseline results. If the cash-flow channel drove the inversion, one would expect larger upward revisions in expected cash flows in short-duration rather than long-duration markets. Instead, Table 12 shows that the cash-flow channel operates in the opposite direction. Overall, these findings rule out the cash-flow channel as the source of the inverse duration–sensitivity relationship. Instead, they reinforce the role of the discount-rate channel through investor "reaching-for-income" behavior.

### B. Credit Channel

A potential alternative mechanism is a credit channel. When interest rates decline, potential first-time homebuyers in short-duration housing markets, who may be relatively more credit-constrained, could experience a larger relaxation of borrowing constraints, leading to larger increases in housing demand for owner occupancy and house price growth in those markets.

Although the transition evidence in Section V.D shows that short-duration, high-rental-yield properties are more likely to transition from owner-occupied to renter-occupied status and less likely to transition into owner occupancy, which does not support a credit-constraint-based explanation, I further test this mechanism directly by examining mortgage application, approval, and refinancing responses to interest rate changes using the Home Mortgage Disclosure Act (HMDA) data.

**Purchase Mortgage Applications and Approvals** Panel A of Internet Appendix Table IA.C18 shows that declines in interest rates lead to larger increases in mortgage application activity in long-duration housing markets than in short-duration markets. This pattern holds for both the full sample of mortgage applications and the subsample of owner-occupied primary residence mortgages. Although short-duration markets exhibit higher average application growth over time, the negative interaction coefficients indicate that, following a one-percentage-point decline in interest rates, housing markets with one standard deviation *longer* housing duration experience approximately 1.6 percentage points larger increases in mortgage applications relative to short-duration markets.

Panels B and C report corresponding results for approved mortgage growth and approval rates. Consistent with the application results, approved mortgage growth is significantly stronger in long-duration markets following interest rate declines, and approval rates are also higher in long-duration markets over one- and two-year horizons.

Overall, Internet Appendix Table IA.C18 shows that interest rate declines generate stronger mortgage demand and approval responses in long-duration housing markets, not in short-duration markets. These findings suggest that a relaxation of credit constraints is unlikely to explain the disproportionately larger house price responses observed in short-duration markets following interest rate cuts.

Linking these mortgage market responses to the baseline house price results, Internet Appendix Tables IA.C19 and IA.C20 show that controlling for changes in mortgage applications, approvals, and approval rates has little effect on the estimated interaction between interest rate changes and housing duration. The coefficients on the main interaction term remain stable across specifications and horizons, indicating that differences in mortgage demand and approval activity do not account for the inverse duration–interest rate sensitivity pattern in housing prices.

**Refinancing** Local heterogeneity in mortgage refinancing activity does not explain the observed inverse duration-rate sensitivity in house prices. Using HMDA data, I construct ZIP-code–year measures of refinancing activity, including changes in the number of refinancing mortgages. Panel A of Internet Appendix Table IA.C21 shows that following interest rate cuts, long-duration markets experience larger increases in refinancing activity than short-duration markets. This pattern implies that, if refinancing were the relevant channel, interest rate cuts should generate stronger house price responses in long-duration markets rather than the opposite. Panel B re-estimates the baseline specification while controlling for changes in local refinancing activity and continues to yield a robust inverse duration-rate sensitivity relationship. Overall, these results indicate that heterogeneity in mortgage refinancing activity does not drive the observed inversion.

### C. "Reaching-for-Yield" Channel

The concept of "reaching for yield" differs fundamentally from "reaching for income" in that "reaching for yield" reflects investors' risk-taking behavior. Formally, Campbell and Sigalov (2022) define reaching for yield as the tendency to take more risk when the real interest rate declines while the risk premium remains constant, although most previous papers emphasize the low *level* of interest rates rather than changes in rates in their definition.[27] By contrast, "reaching for income" focuses on

[27] See, e.g., Becker and Ivashina (2015), Hanson and Stein (2015), Di Maggio and Kacperczyk (2017), Célérier and Vallée (2017), and Lian et al. (2019).

*changes* in interest rates and emphasizes how declines in rates induce investors to tilt toward higher current-income assets (Jiang and Sun, 2020; Daniel et al., 2021; Gargano and Giacoletti, 2022).

Internet Appendix Table IA.C17 examines whether the inverse duration–sensitivity relationship can be explained by differences in local housing market risk, particularly through a reaching-for-yield mechanism. Using five years of monthly house price data, I construct (i) a ZIP-code-level housing market beta, defined as the correlation between local and national price growth scaled by their volatilities, following Frazzini and Pedersen (2014), and (ii) the volatility of local price growth relative to national volatility.[28] The results show that the inverse duration–sensitivity relationship persists after controlling for local housing market risk. Overall, differences in local housing risk and a risk-based reaching-for-yield channel do not explain the stronger rate sensitivity of short-duration markets.

### D. Other Potential Mechanism

**Housing Supply Elasticity** Local housing supply elasticities affect house price dynamics.[29] However, the inverse duration–sensitivity pattern cannot be attributed to differences in local supply elasticities. Using tract-level measures from Baum-Snow and Han (2024), such as elasticities for total housing units, new construction, and land development, aggregated to the ZIP-code level, I re-estimate the baseline regressions in Internet Appendix Tables IA.C22 and IA.C23. The duration–rate-change interaction coefficients remain nearly unchanged, controlling for housing supply elasticities. Hence, cross-sectional variation in local supply elasticities does not explain the main finding.

**Migration** Local population inflows do not explain why shorter-duration markets are more sensitive to interest rate changes. Using annual ZIP-code–level in-migration data from the U.S. Census Bureau, I find that neither the level nor the growth of the in-migration rate explains the inverse duration–sensitivity pattern (Internet Appendix Table IA.C24). After controlling for ZIP-code economic characteristics, house price responses remain similar. The results suggest that the baseline controls already capture the relevant local fundamentals driving migration dynamics.

**Housing Liquidity** Local housing liquidity does not drive the inverse duration–sensitivity pattern. Using ATTOM transaction and tax assessment data, I construct a ZIP-code–level measure of housing liquidity, defined as the ratio of actual transactions to total available properties in a given year. Internet

[28]This beta estimate is equivalent to the coefficient from a regression of local price growth on aggregate price growth; empirically, both methods yield nearly identical results.

[29]See, e.g., Saiz (2010); Davidoff (2015); Aastveit and Anundsen (2022).

Appendix Table IA.C25 shows that controlling for ex-ante housing liquidity and its interaction with the rate changes leaves the duration–sensitivity relationship unchanged. Moreover, while high-liquidity markets exhibit stronger price responses to interest rate changes, this effect is independent of housing duration. Overall, local market liquidity does not drive the inverse duration–sensitivity relationship.

## VII. Conclusion

This paper asks whether duration captures the *true* interest rate sensitivity of house prices. The answer is no. In contrast to the positive relation between duration and sensitivity observed in bonds and equities, housing markets exhibit an inversion: shorter-duration, high-rental-yield markets respond more strongly to interest rate changes. I document this fact using a new ZIP-code–level measure of housing duration based on Macaulay duration and confirm it at the property level with 30 million transaction records matched to rental listings. The result is robust across horizons, specifications, alternative duration constructions, and data sources.

Property-level evidence points to the discount-rate channel as the key mechanism. Following rate cuts, buy-to-rent investors "reach for income," reallocating toward high-yield, short-duration properties, pushing up prices, and reducing discount rates more in these markets than in long-duration ones. This investor-driven, non-parallel shift in the housing term structure explains the inversion.

These findings have important implications for portfolio construction and risk management. Because real estate is often treated as a long-duration asset, duration-based hedges may understate actual exposure if they ignore this cross-sectional inversion. Portfolios tilted toward long-duration housing markets may deliver less exposure to interest rate risk, while portfolios tilted toward short-duration markets may be more exposed than anticipated. Investors should recognize that high-yield, short-duration real estate assets can amplify sensitivity to interest rate changes.

In sum, duration remains the benchmark for understanding interest rate risk, yet housing markets deviate from the conventional duration pattern. Exploring this inverse duration–sensitivity relationship in housing markets refines risk measurement and deepens our understanding of how monetary policy transmits to one of the economy's largest asset classes.

**Appendix: Variable Definitions**

| Variable | Definition | Source |
|---|---|---|
| *Interest rate change and monetary policy shock variables* | | |
| $\Delta r_{[t-1,t]}$ | The annual change in the federal funds rates (FEDFUNDS) from the end of year $t-1$ to $t$. | FRED St. Louis Fed |
| $\Delta r^{30Y}_{[t-1,t]}$ | The annual change in the 30-year mortgage rates (MORTGAGE30US) from the end of year $t-1$ to $t$. | FRED St. Louis Fed |
| 1-Year Yield Surprise | $$Surprise_t = y_{t,1} - f_{t-1,1}\,,$$ where $y_{t,1}$ is the 1-year Treasury yield at year $t$, and $f_{t-1,1}$ is the 1-year forward rate: $$f_{t-1,1} = \frac{(1+y_{t-1,2})^2}{(1+y_{t-1,1})} - 1\,,$$ where $y_{t-1,2}$ is the 2-year Treasury yield at $t-1$. The measure captures the deviation between actual and expected yield. | FRED St. Louis Fed |
| BS MPS, BS MPS_ORTH | The raw (MPS) and orthogonalized monetary policy surprise series (MPS_ORTH) developed by Bauer and Swanson (2023). To construct the raw MPS measure, Bauer and Swanson (2023) uses the first four quarterly Eurodollar futures contracts, ED1-ED4, and gets the first principal component of the changes in these four futures rates around the windows of monetary policy announcement events. They expand the set of monetary policy announcement events to include press conferences, speeches, and testimony by the Federal Reserve chair, in addition to the FOMC announcements. The orthogonalized monetary policy surprise (MPS_ORTH) measure is computed as the residuals from regressing raw MPS on the six macro and financial variables. | Bauer and Swanson (2023) |

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| **Variable** | **Definition** | **Source** |
|---|---|---|
| JK PM MPS | Monetary Policy and Central Bank Information shocks obtained with simple ("Poor Man's") sign restrictions | Jarociński and Karadi (2020) |
| JK Median MPS | Monetary Policy and Central Bank Information shocks obtained with the median rotation that implements the sign restrictions | Jarociński and Karadi (2020) |
| *ZIP-code level variables* | | |
| $\Delta HPI_{z,[t-1,t+h]}$ | House price growth in ZIP code $z$: $$\Delta HPI_{z,[t-1,t+h]} = \frac{\mathrm{HPI}_{z,t+h}}{\mathrm{HPI}_{z,t-1}} - 1,$$ where $HPI_{z,t}$ is the Zillow Home Value Index (ZHVI) at ZIP code $z$ in year $t$. | Zillow |
| Duration$_{z,t}$ | Housing cash flow duration measure constructed with the assumed holding horizon of five years. I also constructed alternative duration measures using a 10-year horizon (Duration 10Y) and using the LASSO regression (Duration 5Y$^{LASSO}$ and Duration 10Y$^{LASSO}$). See Section III.B for construction details. | Estimation |
| $Dur^{\bar{R}}_{z,t-1}$ | Pseudo housing duration constructed using the same methodology described in Section III.B, except that it applies the same national average discount rate, $\bar{R}$, for all ZIP codes while allowing heterogeneous local rent growth rates. | Estimation |
| $Dur^{\bar{G}}_{z,t-1}$ | Pseudo housing duration constructed using the same methodology described in Section III.B, except that it applies the same national rent growth rate, $\bar{G}$, for all ZIP codes while allowing heterogeneous ZIP-code discount rates. | Estimation |

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| Variable | Definition | Source |
| --- | --- | --- |
| $\mathrm{RY}_{z,t}$ | Gross rental yield in ZIP code $z$ in year $t$ defined as the median rent in that ZIP code divided by the median home price, calculated as follows: $$\mathrm{RY}_{z,t} = \frac{\text{Median Gross Rent}_{z,t} \times 12}{\text{Median Home Value}_{z,t}},$$ where Median Gross $\text{Rent}_{z,t}$ and Median Home $\text{Value}_{z,t}$ are the median gross rent and the median home value in ZIP code $z$ for the year $t$, respectively. Both variables are obtained from the DP04 table in the American Community Survey data conducted by the U.S. Census Bureau. | U.S. Census Bureau |
| Log(rental yield) | Natural logarithm of the rental yield at the ZIP-code-year level | U.S. Census Bureau |
| Log(rent) | Natural logarithm of gross median rent | U.S. Census Bureau |
| Log(income) | Natural logarithm of median household income (B19013_001) | U.S. Census Bureau |
| Income growth | The annual change of median household income (B19013_001) | U.S. Census Bureau |
| Log(population) | Natural logarithm of the total population (B01003_001) | U.S. Census Bureau |
| Population growth | The annual change of total population (B01003_001) | U.S. Census Bureau |
| % below 40 | The number of the population below 40 divided by the total population | U.S. Census Bureau |
| % below 40 growth | The annual change of % below 40 | U.S. Census Bureau |
| % above 60 | The number of the population above 60 divided by the total population | U.S. Census Bureau |
| % above 60 growth | The annual change of % above 60 | U.S. Census Bureau |
| Labor force rate | The number of population in the civilian labor force (b23025_003) divided by the total number of the population 16 years and over (b23025_001) | U.S. Census Bureau |
| Labor force rate growth | The annual change of labor force rate | U.S. Census Bureau |

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| Variable | Definition | Source |
|---|---|---|
| Unemployment rate | The number of unemployed people (b23025_005) as a percentage of the civilian labor force (b23025_003) | U.S. Census Bureau |
| Unemployment rate growth | The annual change of unemployment rate | U.S. Census Bureau |
| Homeownership rate | The number of owner-occupied housing units (b25003_002) divided by the total housing units in the ZIP code (b25003_001) | U.S. Census Bureau |
| Homeownership rate growth | The annual change of homeownership rate | U.S. Census Bureau |
| Rental vacancy rate | The percentage of vacant housing units in rental houses (DP04_0005) | U.S. Census Bureau |
| Log(income-to-price ratio) | The natural log of the ratio of median household income (B19013_001) to median home value from DP04 table in the American Community Survey data | U.S. Census Bureau |
| % $BTR_{z,t}$ | The percentage of buy-to-rent (BTR) transactions in a ZIP code and year. The detailed identification procedure for BTR is discussed in Appendix Section D. | Altos and ATTOM |

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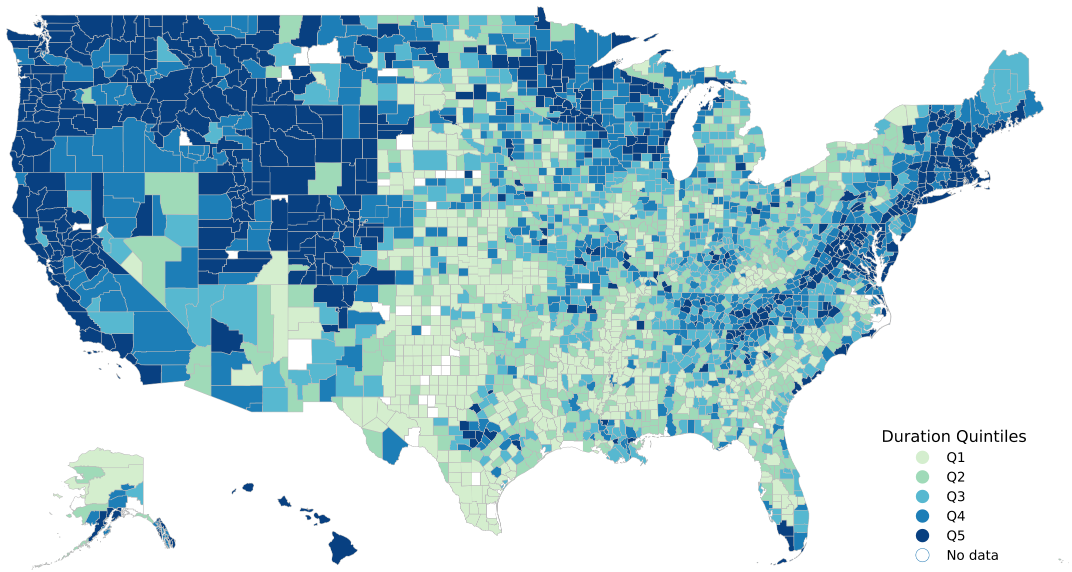
**Figure 2.** County-level Geographic Heterogeneity in Housing Duration

Panel A: Duration




Panel B: Rental Yield

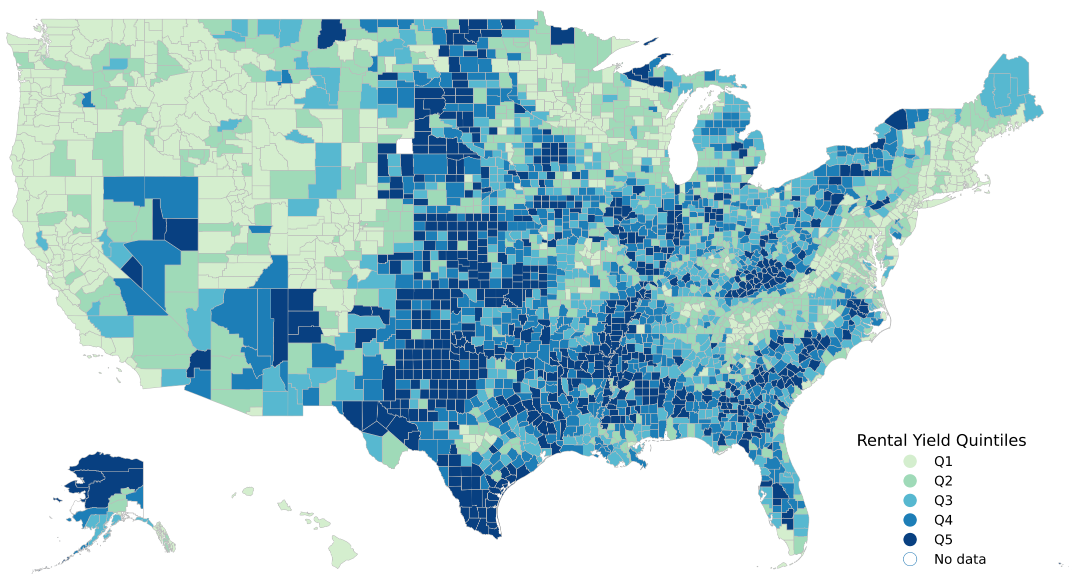



Figure 2 presents county-level geographic heterogeneity in gross housing duration (Panel A) and gross rental yield (Panel B). Both panels categorize counties into quintiles (Q1 to Q5), with darker colors indicating higher quintile values. Panel A illustrates the geographic distribution of housing durations. The detailed estimation procedures for housing duration at the ZIP-code level are provided in Section III.B. Panel B shows the distribution of rental yields, defined as the ratio of annualized median rent to property values, calculated from the American Community Survey (ACS) data. County-level measures for both housing duration and rental yield are computed by averaging across all available ZIP codes and years within each county. Counties without sufficient data are shown in white.

**Figure 3.** Decomposition of Housing Duration Variation

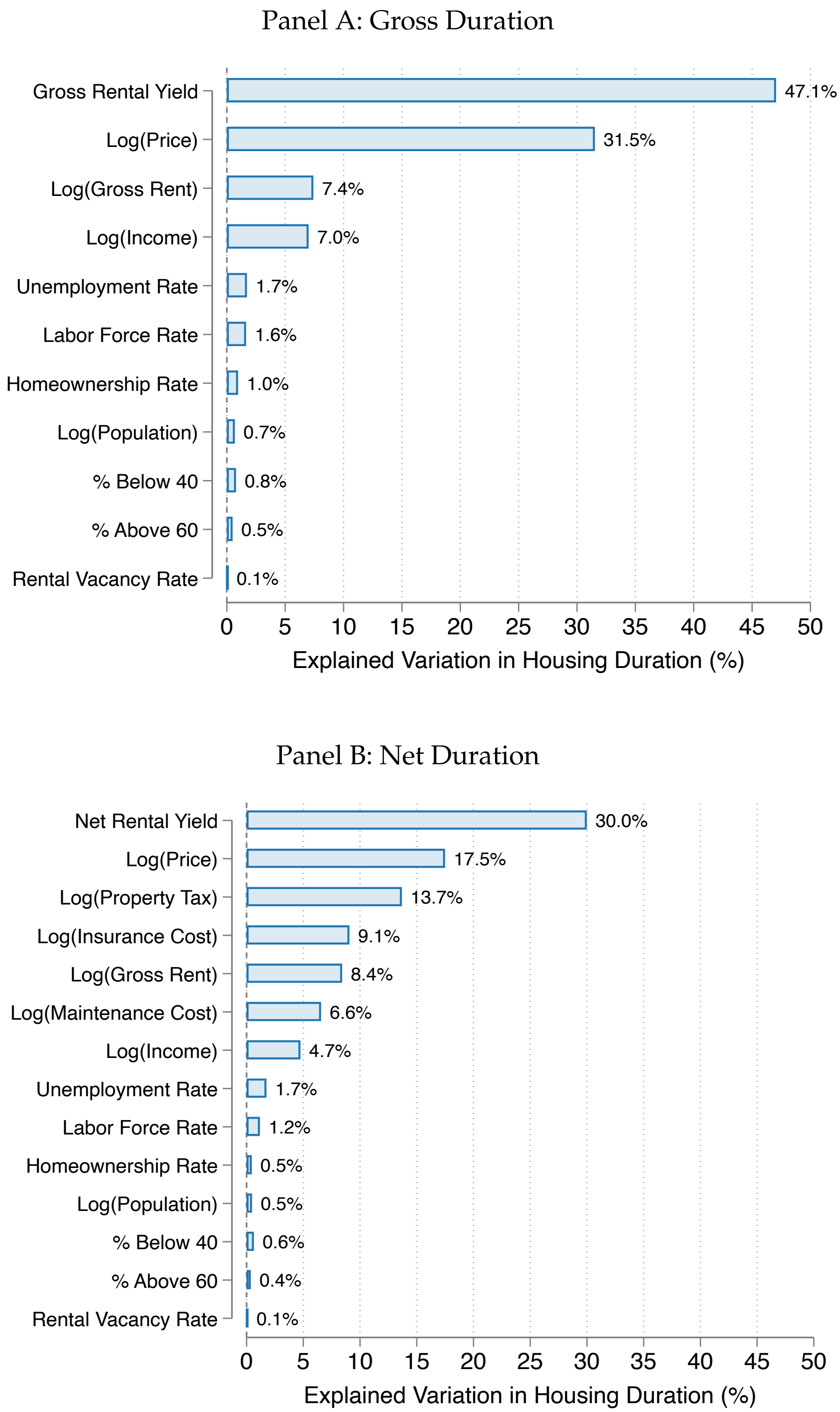



Figure 3 illustrates the proportion of housing duration variation attributed *uniquely* to each local economic and housing characteristic, using a dominance analysis framework. This method, based on the Shapley value decomposition from cooperative game theory, attributes the explained variance to each explanatory variable by averaging its marginal contribution across all possible model permutations. Panel A reports results for gross duration, while Panel B reports results for net duration. The x-axis shows the share of housing duration variation explained, while the y-axis lists the examined local characteristics.

**Figure 4.** Cross-Sectional Relationship Between Housing Duration and Local Characteristics

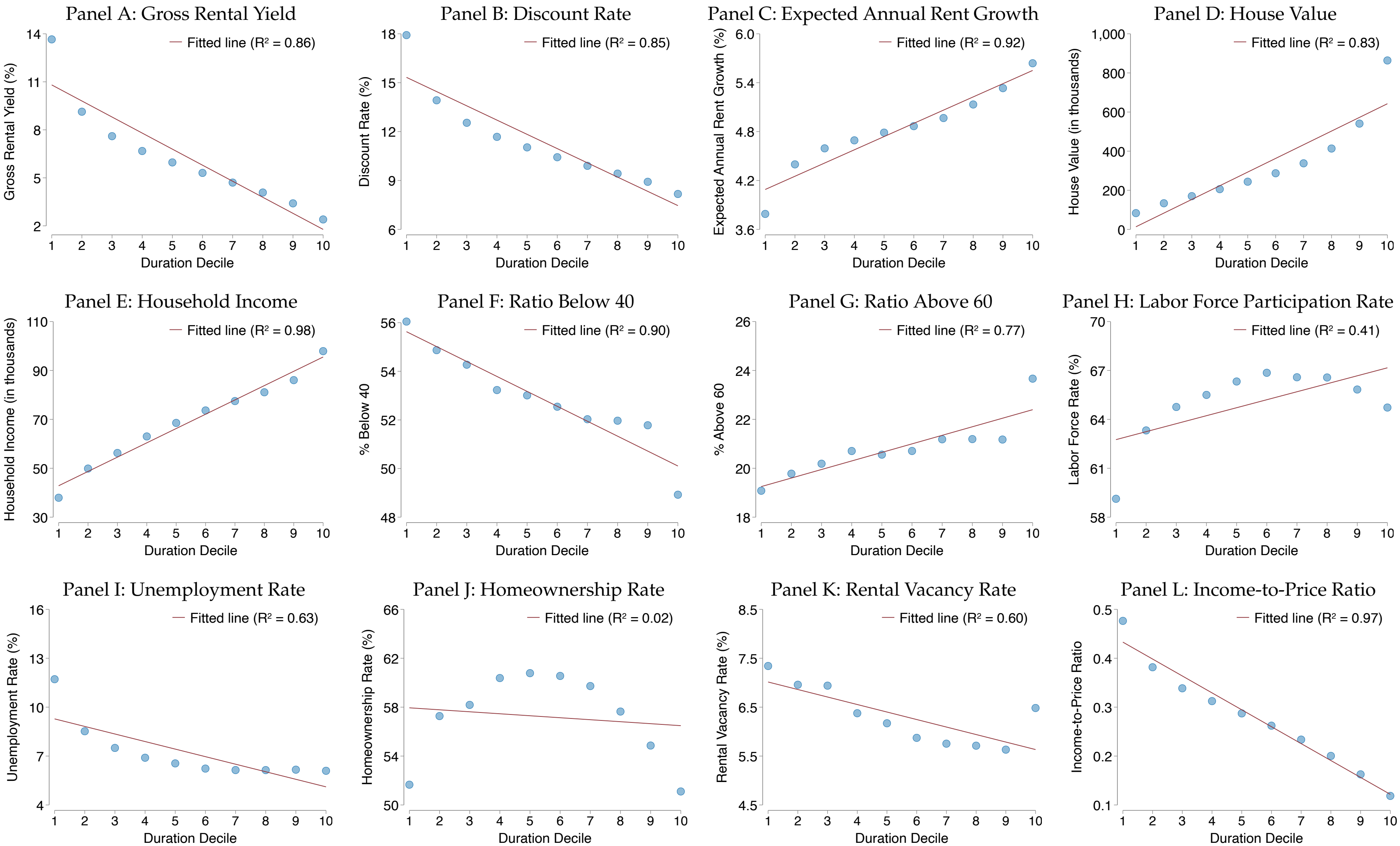



Figure 4 illustrates the cross-sectional relationship between gross housing duration and various ZIP-code characteristics. Each panel plots the mean of a given characteristic within each duration decile against the duration decile, along with the fitted least-squares line. The $R^2$ reported in the upper-right corner corresponds to the univariate regression of the mean characteristic on duration deciles. Duration deciles are assigned each year based on the ZIP-code–level housing duration measure described in Section III.B, where lower deciles correspond to shorter-duration housing markets and higher deciles correspond to longer-duration markets.

**Figure 5.** Heterogeneity in House Price Sensitivity across Local Economic Characteristics

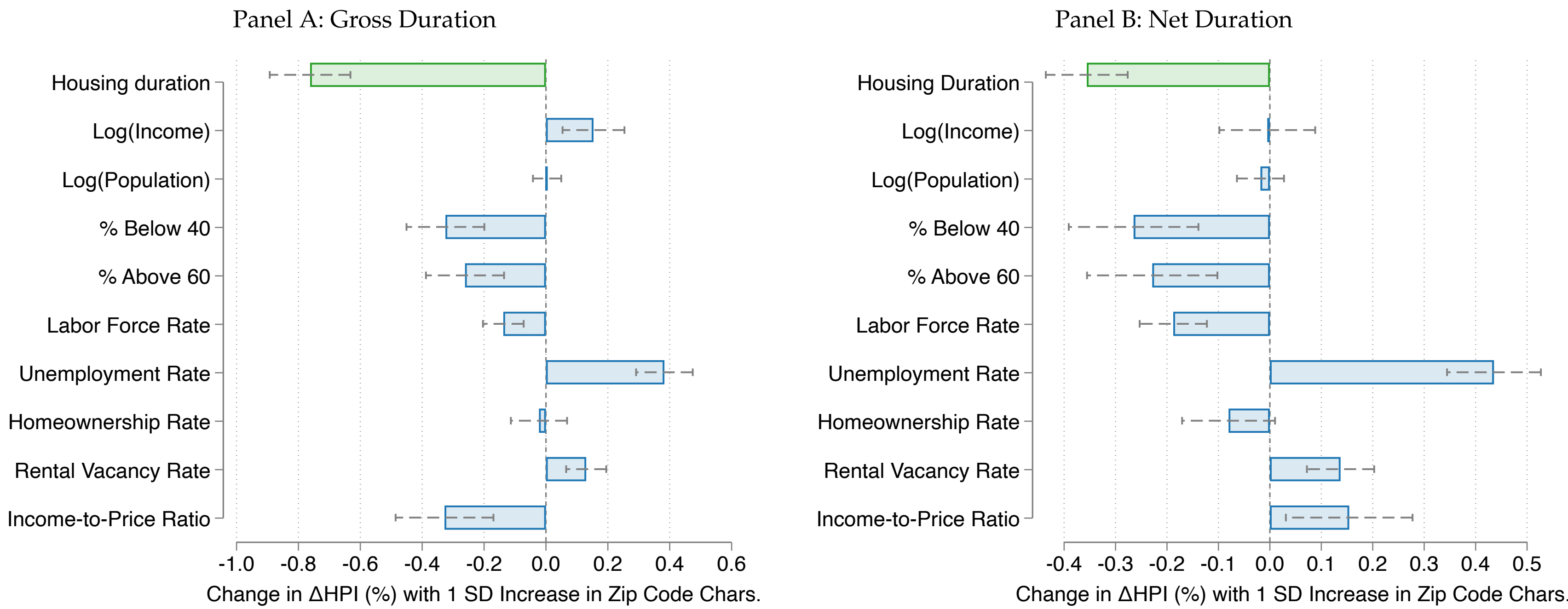



Figure 5 examines heterogeneity in house price sensitivity to interest rate changes across ZIP-code demographic and economic characteristics. The figure reports the additional two-year cumulative house price change associated with a one–standard deviation (sd) increase in each ZIP-code characteristic following a 100–basis-point decrease in the federal funds rate (FFR). The interest rate shock occurs at horizon 0 from the end of year $t-1$ to $t$. Panel A plots results based on gross housing duration, which are obtained from the regression in Column 2 of Panel A in Table 3. Panel B uses the net housing duration measure and is obtained from the regression in Column 4 of Panel A in Table 3. In both panels, the x-axis shows the incremental two-year cumulative house price change, $\Delta HPI_{z,c,[t-1,t+1]}$, attributable to a one–sd increase in the indicated characteristic following the negative interest rate shock. The y-axis lists the demographic and economic characteristics. The estimates are obtained from the following regression specification:

$$\Delta HPI_{z,c,[t-1,t+1]} = \alpha + \beta_1 \, \Delta r_{[t-1,t]} \times \text{Duration}_{z,t-1} + B' \, \Delta r_{[t-1,t]} \times \text{Economic Chars}_{z,t-1} + \delta \, \text{Duration}_{z,t-1} + \gamma \, \text{Economic Chars}_{z,t-1} + \zeta_{c,t} + \lambda_z + \epsilon_{z,c,t},$$

where $\Delta HPI_{z,c,[t-1,t+1]}$ is the two-year cumulative house price change in ZIP code $z$, county $c$, from year $t-1$ to $t+1$, and $\Delta r_{[t-1,t]}$ denotes the annual change in the FFR from $t-1$ to $t$. The variable $\text{Duration}_{z,t-1}$ captures ex-ante housing duration (gross or net, depending on the panel), while $\zeta_{c,t}$ and $\lambda_z$ denote county-year and ZIP-code fixed effects, respectively. With the estimated coefficients, the bar value equals $\hat{\beta} \times 1$ sd of Economic Chars. $\times -1\%$. The gray-capped error bars indicate 95% confidence intervals. Standard errors are clustered at the ZIP code level.

**Figure 6.** Heterogeneity in 1-, 2-, and 3-Year Horizon House Price Sensitivity across Housing Duration and Rental Yield Quintiles

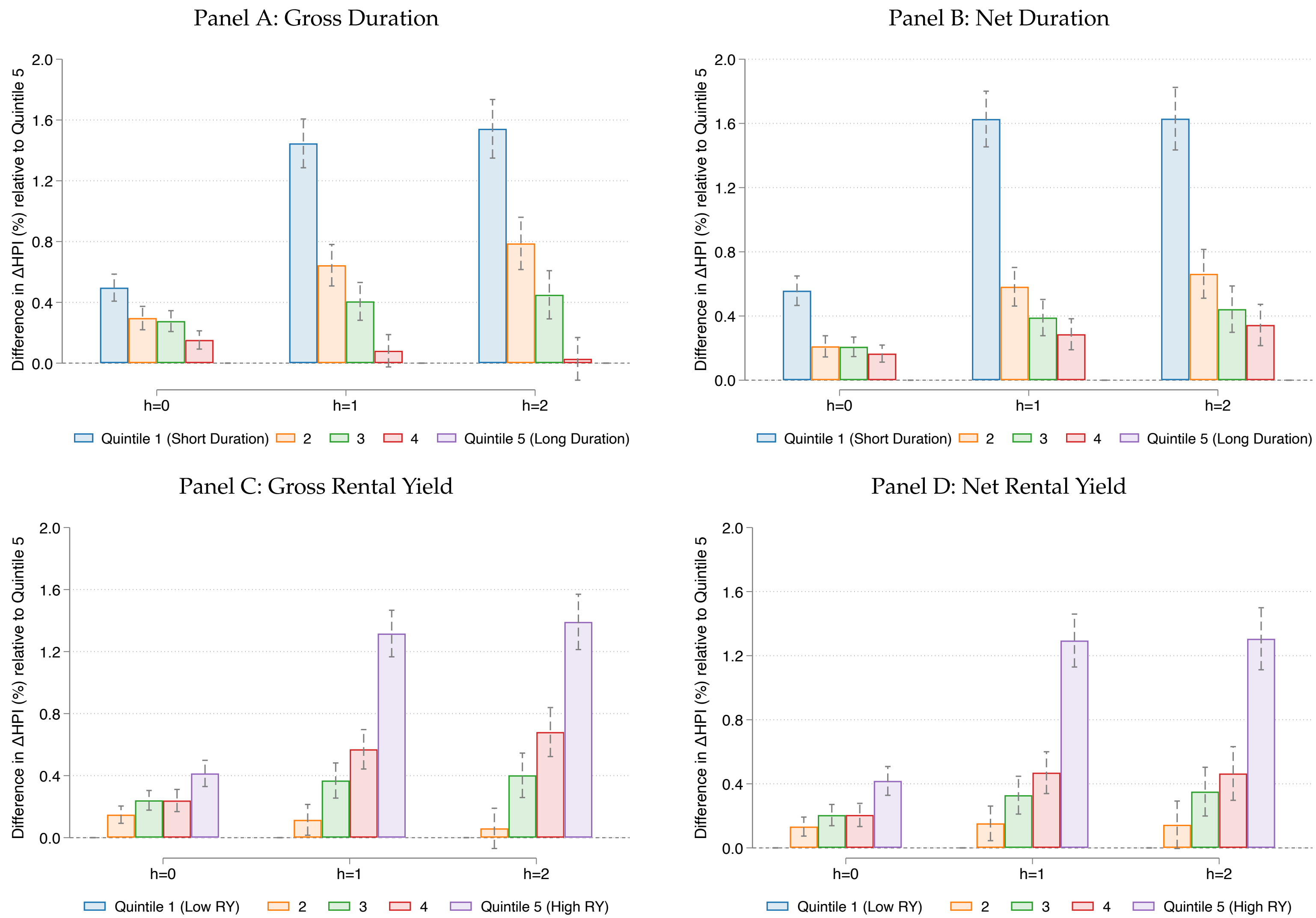



Figure 6 presents the heterogeneous responses of house prices across housing duration quintiles following a 100-basis-point reduction in the federal funds rate (FFR). Specifically, the figure highlights the relative differences in house price changes over horizons of 1, 2, and 3 years for each duration quintile compared to the benchmark group, which is quintile 5 for Panels A and B and quintile 1 for Panels C and D. Panels A and B present results by gross and net housing duration, while Panels C and D use gross and net rental yields as inverse-duration measures. Each year, ZIP codes are sorted into quintiles, with quintile 1 corresponding to the shortest duration (or lowest rental yield) and quintile 5 to the longest duration (or highest rental yield). The interest rate shock occurs at horizon 0 from the end of year $t-1$ to $t$. The x-axis represents the response horizon $h$ in years following the interest rate change, while the y-axis shows the difference in the cumulative percentage change in house prices over 1-, 2-, and 3-year horizons relative to the benchmark group. The analysis employs the same regression specification as Column 5 of Table 2 Panel A for each horizon. The gray-capped error bars indicate 95% confidence intervals. Standard errors are clustered at the ZIP code level.

**Figure 7.** Geographic, Buyer, and Transaction Characteristics of Buy-to-Rent (BTR) Transactions

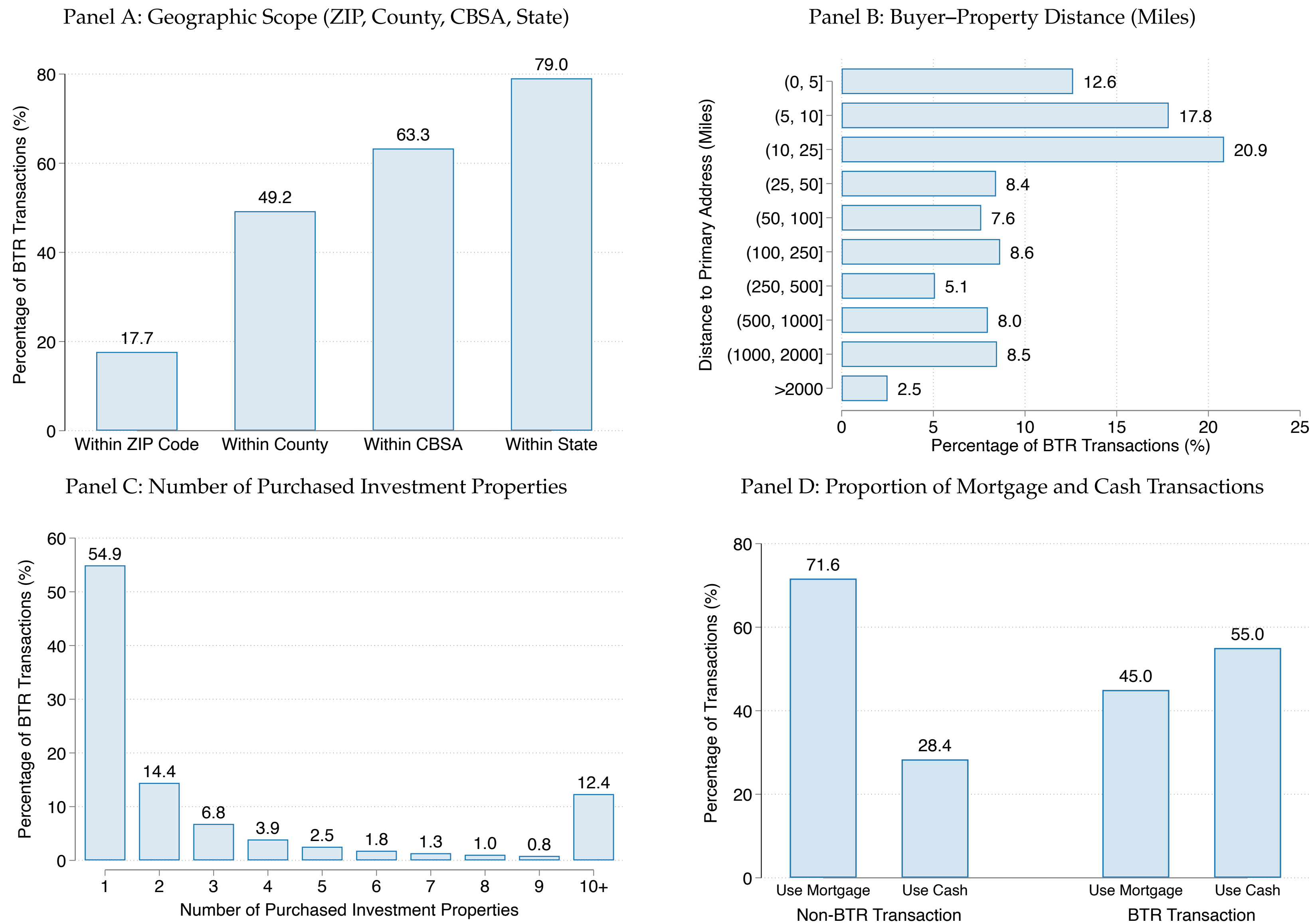



Figure 7 summarizes the geographic proximity, buyer investment scale, and mortgage usage characteristics of buy-to-rent (BTR) housing transactions. Panel A reports the share of BTR purchases in which the purchased property and the buyer's primary address are located within the same ZIP code, county, core-based statistical area (CBSA), or state. Panel B shows the distribution of BTR transactions by buyer–property distance (in miles), measured as the centroid distance between the buyer's mailing ZIP code and the property ZIP code, using the NBER ZIP Code Distance Database. Panel C presents the distribution of BTR transactions by the total number of investment properties purchased by the buyer up to the transaction. Panel D reports the proportions of mortgage-financed and all-cash purchases separately for BTR and non-BTR transactions.

**Figure 8.** Distributions of Property and Buyer Characteristics

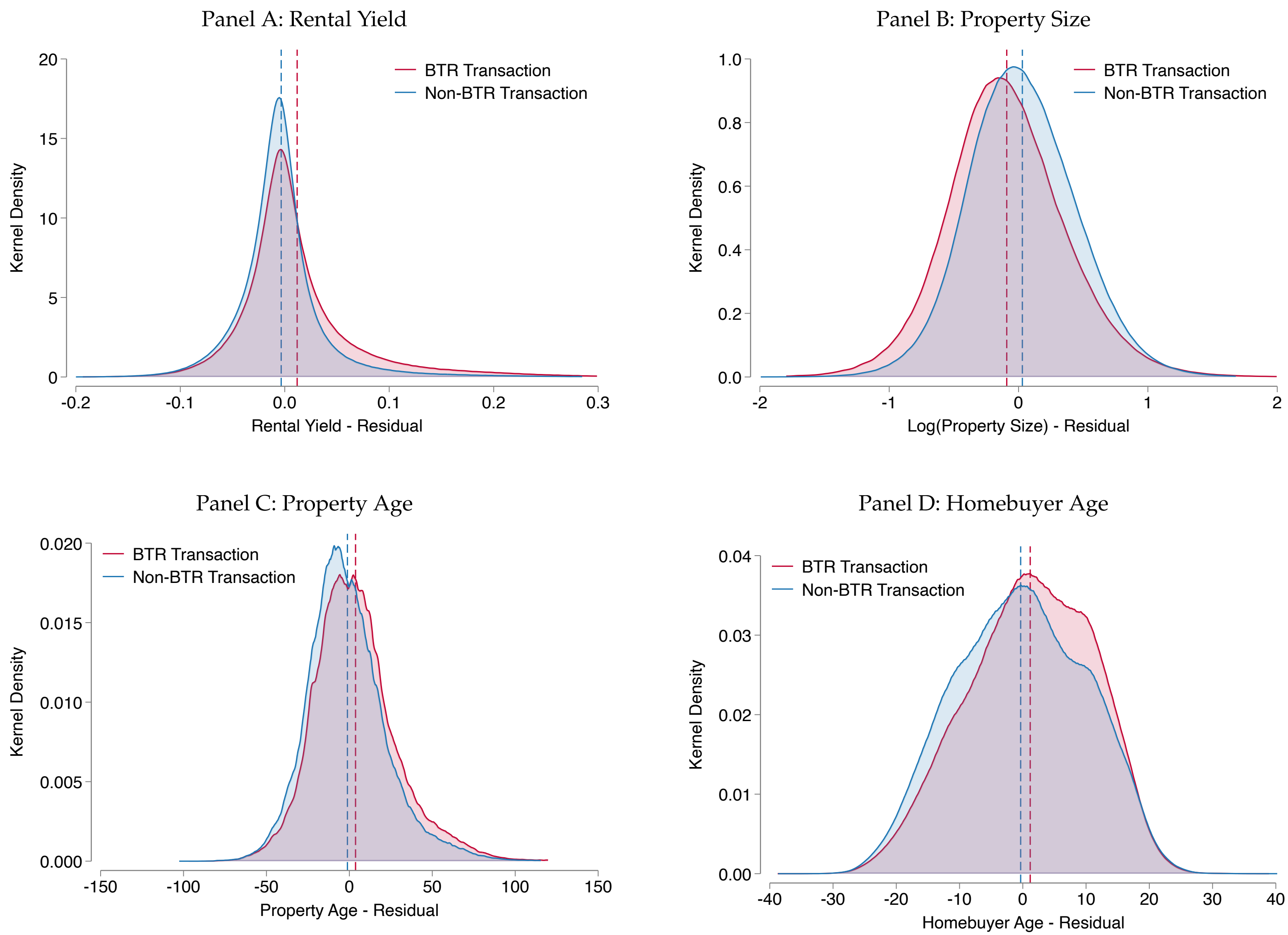



*Figure continues on the next page.*

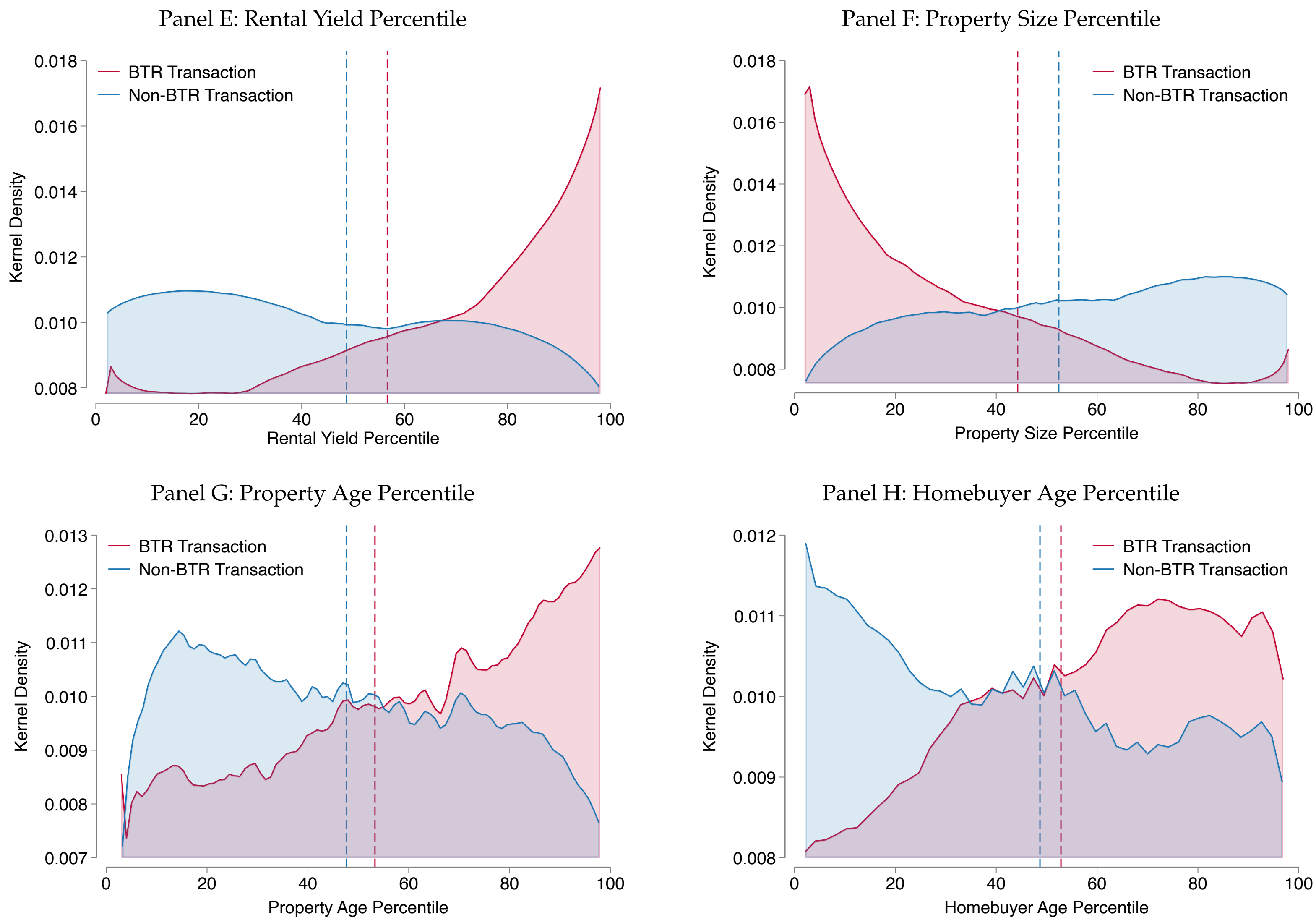
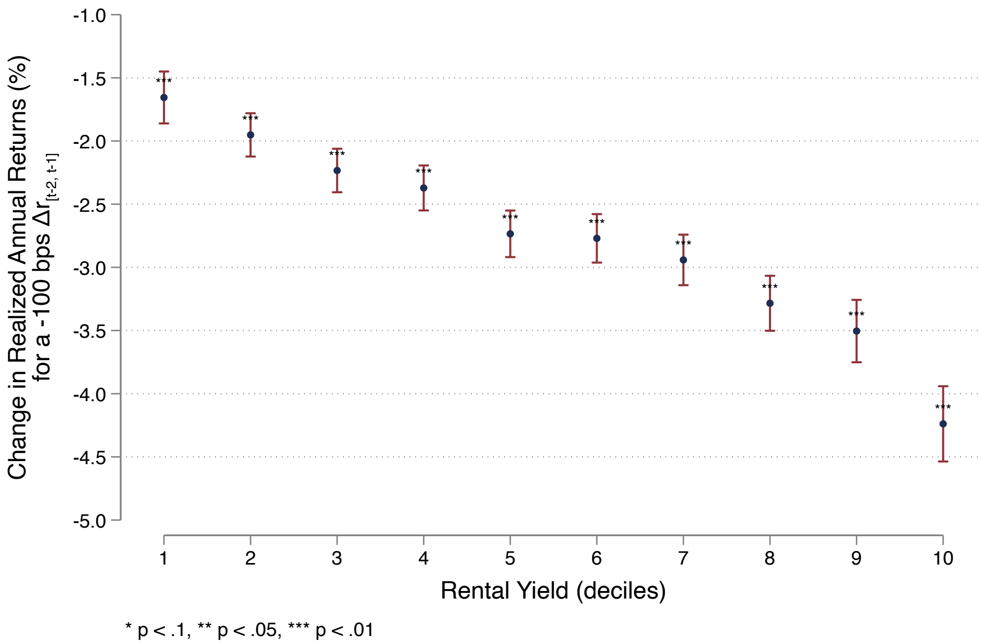



Figure 8 presents kernel density estimates of property and buyer characteristics for buy-to-rent (BTR) and non-BTR transactions. Panels A–D report kernel densities of residualized rental yield, log property size, property age, and homebuyer age, respectively. Residuals are obtained from regressions of property characteristics on county–year fixed effects. Panels E–H report the corresponding distributions expressed as percentile ranks within a county and year. In all panels, dashed vertical lines indicate group averages for BTR and non-BTR transactions.

**Figure 9.** Change in Realized Returns of BTR Investors for a Federal Funds Rate (FFR) Cut

Panel A: Raw FFR Changes




Panel B: FFR Changes Instrumented by MPS

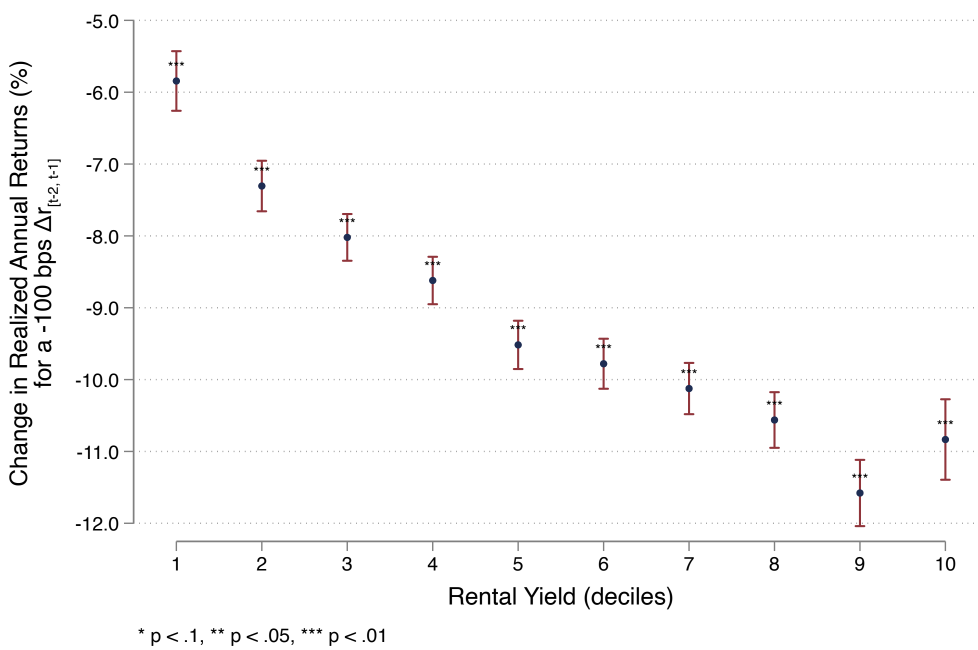
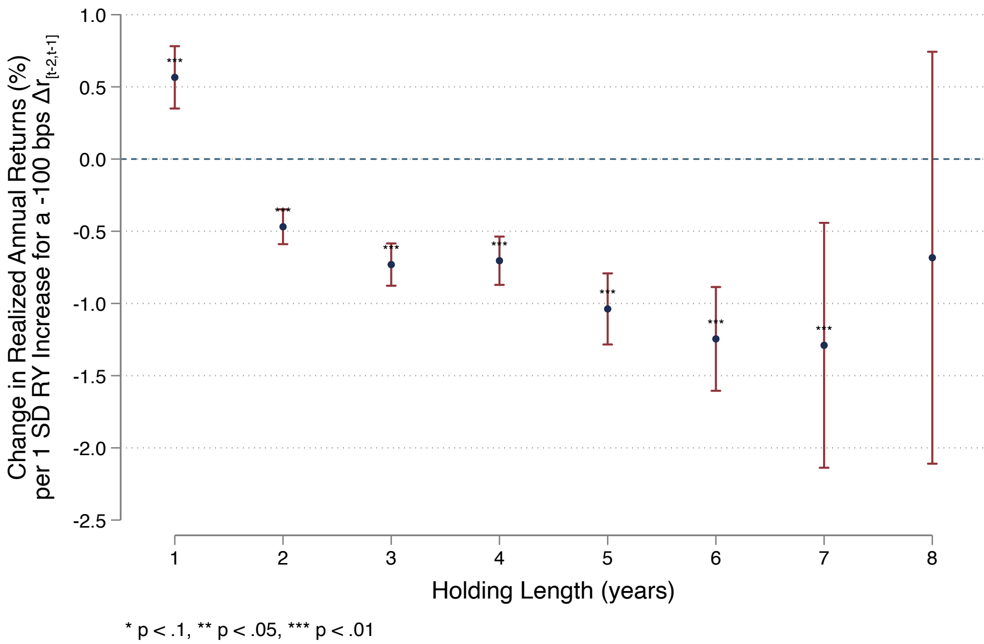



Figure 9 illustrates the heterogeneous effects of changes in the Federal Funds Rate (FFR) on the realized annual returns of Buy-to-Rent (BTR) investors across property rental yield and the length of the property holding period. Each point represents the estimated change in realized annual return (in percentage points) per one standard deviation (SD) increase in rental yield (RY) in response to a -100 basis points (bps) of FFR change. Panel A reports the results for 1-year-lagged changes in the FFR, measured from the end of year $t-2$ to the end of year $t-1$, one year prior to the purchase year $t$. Panel B uses the orthogonalized monetary policy surprise (MPS) measure of Bauer and Swanson (2023) as an instrument for FFR changes. Red-capped error bars represent the 95% confidence intervals. Standard errors are clustered at the property level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

**Figure 10.** Change in Realized Returns of BTR Investors by Holding Length

Panel A: Raw FFR Changes




Panel B: FFR Changes Instrumented by MPS

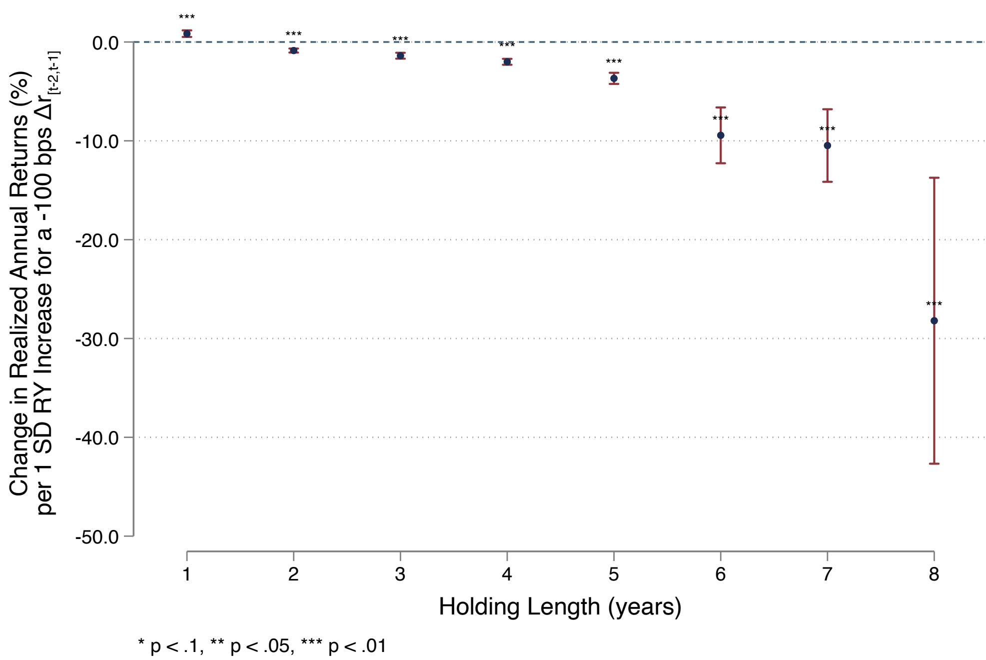



Figure 10 illustrates the heterogeneous effects of changes in the Federal Funds Rate (FFR) on the realized annual returns of Buy-to-Rent (BTR) investors across property rental yield and the length of the property holding period. Each point represents the estimated change in realized annual return (in percentage points) per one standard deviation (SD) increase in rental yield (RY) in response to a -100 basis points (bps) of FFR change. Panel A reports the results for 1-year-lagged changes in the FFR, measured from the end of year $t-2$ to the end of year $t-1$, one year prior to the purchase year $t$. Panel B uses the orthogonalized monetary policy surprise (MPS) measure of Bauer and Swanson (2023) as an instrument for FFR changes. Red-capped error bars represent the 95% confidence intervals. Standard errors are clustered at the property level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

**Figure 11.** Heterogeneity in House Price Sensitivity to Interest Rates across Buy-to-Rent Ratio Quintiles and Housing Duration

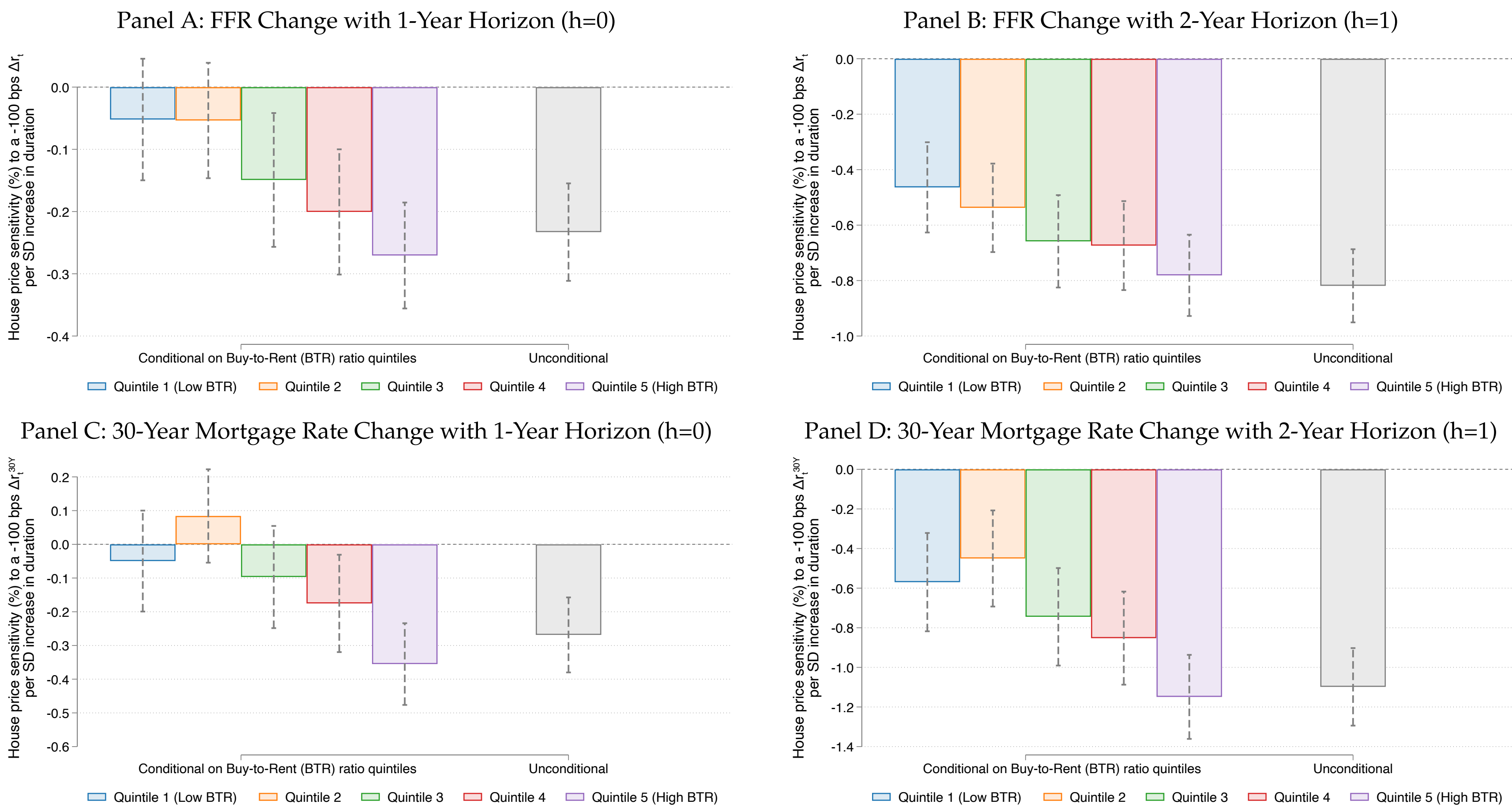



Figure 11 illustrates the heterogeneous sensitivity of house prices to interest rate reductions across ZIP-code Buy-to-Rent (BTR) ratio quintiles. Panels A and B present the additional increase in house prices associated with a one-standard-deviation (SD) increase in ZIP-code housing duration following a 100 basis point (bps) cut in the Federal Funds Rate (FFR), while Panel C illustrates this response to a 100 bps decrease in the 30-year mortgage rate. Each bar quantifies the additional change in house price sensitivity attributed to a one-SD increase in housing duration, segmented by BTR ratio quintiles. The estimations rely on the following regression specification:

$$\Delta HPI_{z,c,[t-1,t+h]} = \alpha_h + \sum_{q=2}^{5} \beta_{0,h,q}\ \Delta r_{[t-1,t]} \times \text{Duration}_{z,t-1} \times \mathbb{1}\{\text{BTR Quintile } q\}_{z,t-1} + \beta_{1,h}\ \Delta r_{[t-1,t]} \times \text{Duration}_{z,t-1} + \sum_{q=2}^{5} \beta_{2,h,q}\ \Delta r_{[t-1,t]} \times \mathbb{1}\{\text{BTR Quintile } q\}_{z,t-1}$$
$$+ \sum_{q=2}^{5} \beta_{3,h,q}\ \text{Duration}_{z,t-1} \times \mathbb{1}\{\text{BTR Quintile } q\}_{z,t-1} + \sum_{q=2}^{5} \mathbb{1}\{\text{BTR Quintile } q\}_{z,t-1} + \beta_{5,h}\ \text{Duration}_{z,t-1} + \zeta_{c,t} + \lambda_z + X_{z,t} + \epsilon_{z,c,t,h}.$$

The rightmost gray bar represents the unconditional house price sensitivity across all ZIP codes, estimated via Equation 16. Panels A and C illustrate price responses within the same year of interest rate change ($h = 0$), while Panels B and D depict the responses within two years following the rate change ($h = 1$). Gray-capped error bars represent the 95% confidence intervals, with standard errors clustered at the ZIP-code level.

**Table 1**. Summary Statistics

| | Mean | SD | P5 | P25 | Median | P75 | P95 |
|---|---|---|---|---|---|---|---|
| **Panel A: Housing Duration, Implied Discount Rate, and House Price** | | | | | | | |
| Gross Duration | 4.467 | 0.230 | 4.026 | 4.356 | 4.504 | 4.628 | 4.766 |
| Net Duration | 4.669 | 0.203 | 4.262 | 4.557 | 4.704 | 4.821 | 4.940 |
| Gross Duration (10Y) | 7.861 | 0.807 | 6.342 | 7.426 | 7.961 | 8.434 | 8.990 |
| Net Duration (10Y) | 8.634 | 0.791 | 7.082 | 8.162 | 8.743 | 9.231 | 9.742 |
| Gross Rental Yield | 0.063 | 0.033 | 0.025 | 0.041 | 0.056 | 0.076 | 0.126 |
| Net Rental Yield | 0.037 | 0.028 | 0.006 | 0.018 | 0.032 | 0.049 | 0.089 |
| $r^{Gross}$ | 0.114 | 0.030 | 0.080 | 0.094 | 0.108 | 0.126 | 0.171 |
| $r^{Net}$ | 0.068 | 0.052 | -0.019 | 0.036 | 0.069 | 0.099 | 0.148 |
| Log(Price) | 12.44 | 0.73 | 11.24 | 11.94 | 12.43 | 12.93 | 13.65 |
| **Panel B: Expected Rent Growth** | | | | | | | |
| $\mathbb{E}_t[\Delta\text{Log(Gross Rent)}_{z,[t,t+1]}]$ | 0.036 | 0.014 | 0.012 | 0.027 | 0.036 | 0.045 | 0.058 |
| $\mathbb{E}_t[\Delta\text{Log(Gross Rent)}_{z,[t+1,t+2]}]$ | 0.040 | 0.014 | 0.017 | 0.031 | 0.041 | 0.049 | 0.061 |
| $\mathbb{E}_t[\Delta\text{Log(Gross Rent)}_{z,[t+2,t+3]}]$ | 0.043 | 0.013 | 0.021 | 0.034 | 0.043 | 0.052 | 0.064 |
| $\mathbb{E}_t[\Delta\text{Log(Gross Rent)}_{z,[t+3,t+4]}]$ | 0.047 | 0.014 | 0.026 | 0.038 | 0.046 | 0.055 | 0.069 |
| $\mathbb{E}_t[\Delta\text{Log(Gross Rent)}_{z,[t+4,t+5]}]$ | 0.047 | 0.014 | 0.025 | 0.039 | 0.047 | 0.055 | 0.068 |
| $\mathbb{E}_t[\Delta\text{Log(Gross Rent)}_{z,LT}]$ | 0.049 | 0.006 | 0.040 | 0.045 | 0.049 | 0.053 | 0.060 |
| **Panel C: House Price Changes over 3-year Horizons** | | | | | | | |
| $\Delta\ \text{HPI}_{z,[t-1,t]}$ | 0.078 | 0.066 | -0.009 | 0.036 | 0.069 | 0.110 | 0.198 |
| $\Delta\ \text{HPI}_{z,[t-1,t+1]}$ | 0.157 | 0.116 | 0.000 | 0.079 | 0.141 | 0.219 | 0.371 |
| $\Delta\ \text{HPI}_{z,[t-1,t+2]}$ | 0.252 | 0.159 | 0.037 | 0.143 | 0.233 | 0.339 | 0.541 |
| **Panel D: Local Characteristics** | | | | | | | |
| Log(Income) | 11.05 | 0.45 | 10.28 | 10.75 | 11.06 | 11.36 | 11.77 |
| Log(Population) | 10.09 | 0.74 | 8.70 | 9.74 | 10.22 | 10.58 | 11.05 |
| % Below 40 | 0.528 | 0.091 | 0.390 | 0.477 | 0.529 | 0.583 | 0.663 |
| % Above 60 | 0.209 | 0.079 | 0.111 | 0.160 | 0.199 | 0.241 | 0.331 |
| Labor Force Rate | 0.650 | 0.076 | 0.515 | 0.613 | 0.658 | 0.697 | 0.756 |
| Unemployment Rate | 0.072 | 0.040 | 0.028 | 0.045 | 0.062 | 0.088 | 0.151 |
| Homeownership Rate | 0.574 | 0.184 | 0.233 | 0.458 | 0.591 | 0.713 | 0.844 |
| Rental Vacancy Rate | 0.063 | 0.056 | 0.011 | 0.032 | 0.052 | 0.080 | 0.136 |
| Log(Income-to-Price) | -1.389 | 0.483 | -2.264 | -1.686 | -1.327 | -1.038 | -0.710 |

Panel E: Correlation of Housing Duration and Local Characteristics

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Gross Duration | 1.000 | | | | | | | | | | | | |
| 2 | Net Duration | 0.922*** | 1.000 | | | | | | | | | | | |
| 3 | Gross Rental yield | -0.991*** | -0.901*** | 1.000 | | | | | | | | | | |
| 4 | Net Rental yield | -0.929*** | -0.963*** | 0.940*** | 1.000 | | | | | | | | | |
| 5 | Log(Income) | 0.584*** | 0.540*** | -0.573*** | -0.516*** | 1.000 | | | | | | | | |
| 6 | Log(Population) | 0.092*** | 0.058*** | -0.098*** | -0.073*** | 0.097*** | 1.000 | | | | | | | |
| 7 | % Below 40 | -0.189*** | -0.164*** | 0.179*** | 0.146*** | -0.326*** | 0.232*** | 1.000 | | | | | | |
| 8 | % Above 60 | 0.133*** | 0.099*** | -0.131*** | -0.085*** | 0.194*** | -0.270*** | -0.892*** | 1.000 | | | | | |
| 9 | Labor Force Rate | 0.246*** | 0.246*** | -0.253*** | -0.257*** | 0.400*** | 0.182*** | 0.357*** | -0.526*** | 1.000 | | | | |
| 10 | Unemployment Rate | -0.432*** | -0.391*** | 0.464*** | 0.404*** | -0.656*** | -0.019*** | 0.214*** | -0.189*** | -0.336*** | 1.000 | | | |
| 11 | Homeownership Rate | 0.022*** | 0.038*** | -0.039*** | -0.049*** | 0.547*** | 0.004 | -0.562*** | 0.425*** | -0.017*** | -0.325*** | 1.000 | | |
| 12 | Rental Vacancy Rate | -0.079*** | -0.108*** | 0.085*** | 0.103*** | -0.119*** | -0.237*** | -0.190*** | 0.253*** | -0.242*** | 0.091*** | 0.048*** | 1.000 | |
| 13 | Log(Income-to-Price) | -0.793*** | -0.701*** | 0.752*** | 0.668*** | -0.212*** | -0.086*** | 0.024*** | -0.056*** | 0.008* | 0.101*** | 0.373*** | 0.054*** | 1.000 |

Table 1 presents summary statistics of key variables in the ZIP-code-level analysis. Panel A reports results for housing duration, rental yield, implied discount rates, and house prices. Panel B describes the expected gross rent growth from predictive regressions. Panel C describes house price changes over one-, two-, and three-year horizons. Panel D provides descriptive statistics for ZIP-code socioeconomic and housing market characteristics. Panel E presents pairwise correlations between housing duration and local characteristics. Definitions of the variables are provided in the Appendix. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 2**. Heterogeneous Interest Rate Sensitivity of Asset Prices by Duration

Panel A: Real estate

| | $\Delta$ HPI$_{z,[t-1,t+1]}$ | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $\Delta r_{[t-1,t]} \times$ Duration$_{z,t-1}$ | | 1.707*** | 1.752*** | 3.396*** | 3.089*** |
| | | (0.154) | (0.154) | (0.148) | (0.152) |
| $\Delta r_{[t-1,t]}$ | -1.862*** | -9.490*** | | | |
| | (0.027) | (0.695) | | | |
| Duration$_{z,t-1}$ | -0.120*** | -0.128*** | -0.128*** | -0.176*** | -0.308*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.018) |
| Adjusted $R^2$ | 0.108 | 0.111 | 0.251 | 0.746 | 0.805 |
| Observations | 60,920 | 60,920 | 60,920 | 60,920 | 60,920 |
| Year FE | | | Yes | | |
| County × Year FE | | | | Yes | Yes |
| ZIP FE | | | | | Yes |

Panel B: Bond

| | $\Delta$ P$_{i,[t-1,t+1]}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta r_{[t-1,t]} \times$ Duration$_{i,t-1}$ | | -0.479*** | -0.416*** | -0.372*** |
| | | (0.013) | (0.020) | (0.014) |
| $\Delta r_{[t-1,t]}$ | -4.679*** | -1.168*** | -1.081*** | |
| | (0.191) | (0.084) | (0.118) | |
| Duration$_{i,t-1}$ | 0.001*** | 0.004*** | 0.024*** | -0.015*** |
| | (0.000) | (0.000) | (0.001) | (0.002) |
| Adjusted $R^2$ | 0.370 | 0.515 | 0.560 | 0.813 |
| Observations | 2,307 | 2,307 | 2,307 | 2,307 |
| Bond FE | | | Yes | Yes |
| Year FE | | | | Yes |

Panel C: Equity

| | $\Delta$ P$_{i,[t-1,t+1]}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta r_{[t-1,t]} \times$ Duration$_{i,t-1}$ | | -0.071*** | -0.057** | -0.055** |
| | | (0.025) | (0.026) | (0.026) |
| $\Delta r_{[t-1,t]}$ | -11.152*** | -7.675*** | -8.876*** | |
| | (0.584) | (1.119) | (1.174) | |
| Duration$_{i,t-1}$ | -0.001** | -0.000 | -0.001 | -0.001 |
| | (0.000) | (0.000) | (0.001) | (0.001) |
| Adjusted $R^2$ | 0.019 | 0.020 | 0.119 | 0.170 |
| Observations | 22,011 | 22,011 | 22,011 | 22,011 |
| Stock FE | | | Yes | Yes |
| Year FE | | | | Yes |

Table 2 illustrates the heterogeneous asset price responses to changes in the federal funds rate (FFR) across varying asset duration levels within the real estate (Panel A), bond (Panel B), and equity markets (Panel C). Panel A performs analysis at the ZIP code-year level for housing markets, while Panels B and C analyze individual asset-year observations for bonds and equities, respectively. The interest rate shock occurs at horizon 0 (i.e., year $t$), corresponding to the period from the end of year $t-1$ to $t$. To compare across asset classes, the table examines price responses within a two-year horizon following the shock. In Panel A, the dependent variable, $\Delta HPI_{z,[t-1,t+1]}$, denotes cumulative house price growth in ZIP code $z$ from the end of year $t-1$ to $t+1$. Panels B and C examine the price changes for bonds and equities over the same horizon, respectively. The key explanatory variable, $\Delta r_{[t-1,t]} \times Duration_{i,t-1}$, captures the heterogeneous sensitivity of asset prices to the FFR changes based on the asset duration level. Section III.B provides details on the estimation of housing duration. Bond duration is defined by the Macaulay duration in years, calculated by the CRSP U.S. Treasury dataset, while equity duration is estimated by Gonçalves (2021). The combinations of fixed effects are indicated at the bottom of the table. Standard errors are clustered at the ZIP code (Panel A) or individual asset level (Panels B and C). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 3**. Heterogeneity in House Price Sensitivity to Interest Rate Changes by Different Housing Duration Measures, Controlling for Local Economic Characteristics

Panel A: Duration

| | $\Delta$ HPI$_{z,[t-1,t+1]}$ | | | |
|---|---|---|---|---|
| | Gross Duration | | Net Duration | |
| | (1) | (2) | (3) | (4) |
| $\Delta r_{[t-1,t]} \times$ Duration$_{z,t-1}$ | 3.089*** | 3.314*** | 3.111*** | 1.695*** |
| | (0.152) | (0.289) | (0.160) | (0.193) |
| Duration$_{z,t-1}$ | -0.308*** | -0.056*** | -0.133*** | -0.010 |
| | (0.018) | (0.022) | (0.009) | (0.008) |
| $\Delta$ HPI$_{z,[t-2,t-1]}$ | | 0.129*** | | 0.126*** |
| | | (0.013) | | (0.013) |
| Adjusted $R^2$ | 0.805 | 0.820 | 0.798 | 0.819 |
| Observations | 60,920 | 60,920 | 60,920 | 60,920 |
| County × Year FE | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | | Yes | | Yes |
| $\Delta r_{[t-1,t]} \times$ ZIP Economic Chars | | Yes | | Yes |

Panel B: Rental Yield

| | Gross Rental Yield | | Net Rental Yield | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta r_{[t-1,t]} \times$ RY$_{z,t-1}$ | -19.826*** | -20.063*** | -22.495*** | -15.148*** |
| | (0.936) | (1.625) | (1.145) | (1.899) |
| RY$_{z,t-1}$ | 1.724*** | 0.439*** | 1.295*** | -0.358*** |
| | (0.107) | (0.115) | (0.093) | (0.111) |
| $\Delta$ HPI$_{z,[t-2,t-1]}$ | | 0.158*** | | 0.130*** |
| | | (0.013) | | (0.014) |
| Adjusted $R^2$ | 0.795 | 0.810 | 0.795 | 0.814 |
| Observations | 72,334 | 72,334 | 62,415 | 62,415 |
| County × Year FE | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | | Yes | | Yes |
| $\Delta r_{[t-1,t]} \times$ ZIP Economic Chars | | Yes | | Yes |

Table 3 presents the different two-year house price responses to the federal funds rate (FFR) changes across ZIP codes with different housing durations, controlling for ZIP-code economic characteristics and their interaction terms with FFR changes. The ZIP-code characteristics are listed in Figure 5, which include median household income, population size, age distribution (shares below 40 and above 60), labor force participation rate, unemployment rate, homeownership rate, rental vacancy rate, and the income-to-price ratio. The dependent variable, $\Delta HPI_{z,[t-1,t+1]}$, is the house price change from year $t-1$ to year $t+1$ in ZIP code $z$, where year $t$ corresponds to the year of the FFR change. $\Delta r_{[t-1,t]}$ indicates the annual change in the federal funds rate from year $t-1$ to $t$, and $Duration_{z,t}$ denotes the housing duration level in ZIP code $z$ in year $t$. Section III.B provides details on the estimation of housing duration. All specifications include county-year and ZIP-code fixed effects. Columns 2 and 4 further introduce interaction terms between FFR changes and the local characteristics. Definitions of the variables are provided in the Appendix. Standard errors are clustered at the ZIP code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 4**. House Price Sensitivities to 30-Year Mortgage Rate Changes and Monetary Policy Shocks

Panel A: 30-Year Mortgage Rate Changes

| | $\Delta$ HPI$_{z,[t-1,t+1]}$ | | | |
|---|---|---|---|---|
| | Gross Duration | | Net Duration | |
| | (1) | (2) | (3) | (4) |
| $\Delta r^{30Y}_{[t-1,t]} \times$ Duration$_{z,t-1}$ | 5.488*** | 4.584*** | 5.593*** | 2.298*** |
| | (0.225) | (0.422) | (0.237) | (0.288) |
| Duration$_{z,t-1}$ | -0.302*** | -0.048** | -0.134*** | -0.010 |
| | (0.018) | (0.021) | (0.009) | (0.008) |
| $\Delta$ HPI$_{z,[t-2,t-1]}$ | | 0.110*** | | 0.107*** |
| | | (0.013) | | (0.013) |
| Adjusted $R^2$ | 0.806 | 0.822 | 0.799 | 0.821 |
| Observations | 60,920 | 60,920 | 60,920 | 60,920 |
| County × Year FE | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | | Yes | | Yes |
| $\Delta r^{30Y}_{[t-1,t]} \times$ ZIP Economic Chars | | Yes | | Yes |

Panel B: Monetary Policy Shocks as Instrumental Variables

| | $\Delta$ HPI$_{z,[t-1,t+1]}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1-Year Yield Surprise | | BS MPS | | BS MPS_ORTH | | JK PM MPS | | JK Median MPS | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| $\widehat{\Delta r}_{[t-1,t]} \times$ Duration$_{z,t-1}$ | 3.591*** | 3.124*** | 4.054*** | 3.589*** | 2.154*** | 4.591*** | 3.742*** | 2.892*** | 3.368*** | 2.801*** |
| | (0.154) | (0.289) | (0.179) | (0.350) | (0.225) | (0.458) | (0.150) | (0.284) | (0.146) | (0.274) |
| Duration$_{z,t-1}$ | -0.310*** | -0.056*** | -0.313*** | -0.056*** | -0.303*** | -0.062*** | -0.311*** | -0.055** | -0.309*** | -0.054** |
| | (0.018) | (0.022) | (0.018) | (0.022) | (0.018) | (0.022) | (0.018) | (0.022) | (0.018) | (0.022) |
| $\Delta$ HPI$_{z,[t-2,t-1]}$ | | 0.121*** | | 0.129*** | | 0.145*** | | 0.119*** | | 0.120*** |
| | | (0.013) | | (0.013) | | (0.014) | | (0.013) | | (0.013) |
| Adjusted $R^2$ | -0.010 | 0.065 | -0.012 | 0.063 | -0.012 | 0.059 | -0.011 | 0.064 | -0.010 | 0.066 |
| Observations | 60,920 | 60,920 | 60,920 | 60,920 | 60,920 | 60,920 | 60,920 | 60,920 | 60,920 | 60,920 |
| County × Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | | Yes | | Yes | | Yes | | Yes | | Yes |
| $\widehat{\Delta r}_{[t-1,t]} \times$ ZIP Economic Chars | | Yes | | Yes | | Yes | | Yes | | Yes |

Table 4 reports the heterogeneity in house price responses to monetary policy changes across ZIP codes with different housing durations. The dependent variable, $\Delta HPI_{z,[t-1,t+1]}$, is the cumulative house price growth between the end of year $t-1$ and $t+1$. The main explanatory variable of interest, $\widehat{\Delta r}_{[t-1,t]} \times Duration_{z,t-1}$, captures how the sensitivity of house prices to changes in the monetary policy rate varies with local housing duration. Panel A uses the 30-year mortgage rate as the policy rate. Panel B uses exogenous monetary policy shocks to instrument for the federal funds rate changes, where the implemented shock is indicated at the top of each column: Columns 1 and 2 employ the one-year Treasury yield surprise; Columns 3 and 4 use the monetary policy surprise (MPS) series from Bauer and Swanson (2023); Columns 5 and 6 employ the orthogonalized MPS from Bauer and Swanson (2023); Columns 7 and 8 adopt the PM MPS constructed by Jarociński and Karadi (2020); and Columns 9 and 10 use their median shock measure. Panel A employs both gross and net duration measures in the analysis, while Panel B presents results using gross duration; results with net duration are presented in Internet Appendix Table IA.C12. Section III.B provides details on the estimation of housing duration. All regressions include county-by-year and ZIP-code fixed effects. Specifications in even-numbered columns additionally control for time-varying ZIP-code economic characteristics and their interactions with rate changes, consistent with Column 3 of Table 3. Standard errors are clustered at the ZIP-code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 5**. Property Price Sensitivity to Interest Rate Changes: Controlling for Mortgage and Tax Payments

| | $\Delta$ P$_{i,[t-2,t]}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta r_{[t-2,t-1]}\times$ RY$_{i,t-2}$ | -19.875*** | -22.043*** | -25.404*** | -25.072*** | -35.933*** | -32.583*** |
| | (0.107) | (0.110) | (0.109) | (0.110) | (0.113) | (0.109) |
| RY$_{i,t-2}$ | 1.042*** | 1.123*** | 1.289*** | 1.277*** | 1.763*** | 1.674*** |
| | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.003) |
| $\Delta$ HPI$_{z,[t-3,t-2]}$ | | 0.315*** | 0.306*** | 0.311*** | 0.350*** | 0.052*** |
| | | (0.004) | (0.004) | (0.004) | (0.003) | (0.003) |
| Log(Mortgage Payment)$_{i,t}$ | | | 0.017*** | | | |
| | | | (0.000) | | | |
| $\Delta r_{[t-2,t-1]}\times$ Log(Mortgage Payment)$_{i,t}$ | | | -0.064*** | | | |
| | | | (0.001) | | | |
| LTV$_{i,t}$ | | | | 0.152*** | | |
| | | | | (0.000) | | |
| $\Delta r_{[t-2,t-1]}\times$ LTV$_{i,t}$ | | | | -0.178*** | | |
| | | | | (0.015) | | |
| Log(Tax Payment)$_{i,t}$ | | | | | 0.297*** | |
| | | | | | (0.000) | |
| $\Delta r_{[t-2,t-1]}\times$ Log(Tax Payment)$_{i,t}$ | | | | | -1.688*** | |
| | | | | | (0.012) | |
| Tax-to-Value Ratio$_{i,t}$ | | | | | | -25.086*** |
| | | | | | | (0.015) |
| $\Delta r_{[t-2,t-1]}\times$ Tax-to-Value Ratio$_{i,t}$ | | | | | | 64.490*** |
| | | | | | | (1.180) |
| Adjusted $R^2$ | 0.136 | 0.138 | 0.172 | 0.164 | 0.225 | 0.325 |
| Observations | 28,399,832 | 28,399,832 | 28,399,832 | 28,399,832 | 28,399,832 | 28,399,832 |
| Property Chars | Yes | Yes | Yes | Yes | Yes | Yes |
| County × Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | | Yes | Yes | Yes | Yes | Yes |
| $\Delta r_{[t-2,t-1]}\times$ ZIP Economic Chars | | Yes | Yes | Yes | Yes | Yes |

Table 5 reports transaction-level regressions of property price changes, $\Delta P_{i,[t-2,t]}$, on the interaction between the change in the FFR one year before the transaction, $\Delta r_{[t-2,t-1]}$, and the property's ex-ante rental yield measured at $t-2$, $RY_{i,t-2}$. The transaction occurs at year $t$. Columns 1 and 2 use the baseline controls and fixed effects from Table 3 and show how the sensitivity of transaction-level price changes to interest rate changes varies with ex-ante rental yields. Columns 3 to 6 sequentially control for log mortgage payment, loan-to-value ratio (LTV), log property tax payment, and tax-to-value ratio, along with their interactions with interest rate changes. All regressions include property characteristics, county-by-year fixed effects, ZIP code fixed effects, ZIP code economic characteristics, and their interactions with interest rate changes. Standard errors are clustered at the property level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 6.** Duration Decomposition: Expected Cash Flow Growth and Discount Rate Components

| | $\Delta$ HPI$_{z,[t-1,t+1]}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta r_{[t-1,t]} \times$ Dur$^{\bar{R}}_{z,t-1}$ | 2.584*** | 2.534*** | | | 7.802*** | 5.402*** |
| | (0.135) | (0.244) | | | (1.456) | (1.675) |
| $\Delta r_{[t-1,t]} \times$ Dur$^{\bar{G}}_{z,t-1}$ | | | 2.936*** | 3.121*** | -6.367*** | -3.755* |
| | | | (0.156) | (0.293) | (1.674) | (2.044) |
| Dur$^{\bar{R}}_{z,t-1}$ | -0.246*** | -0.059*** | | | 0.159*** | -0.144** |
| | (0.015) | (0.018) | | | (0.060) | (0.059) |
| Dur$^{\bar{G}}_{z,t-1}$ | | | -0.308*** | -0.066*** | -0.497*** | 0.110 |
| | | | (0.018) | (0.022) | (0.071) | (0.070) |
| $\Delta$ HPI$_{z,[t-2,t-1]}$ | | 0.129*** | | 0.130*** | | 0.128*** |
| | | (0.013) | | (0.013) | | (0.014) |
| Adjusted $R^2$ | 0.805 | 0.820 | 0.806 | 0.820 | 0.806 | 0.820 |
| Observations | 60,836 | 60,836 | 60,836 | 60,836 | 60,836 | 60,836 |
| County × Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | | Yes | | Yes | | Yes |
| $\Delta r_{[t-1,t]} \times$ ZIP Economic Chars | | Yes | | Yes | | Yes |

Table 6 decomposes the sensitivity of house prices to interest rate changes into two components of housing duration: the expected cash flow growth component and the discount rate component. I construct two pseudo housing duration measures, $Dur^{\bar{R}}_{z,t-1}$ and $Dur^{\bar{G}}_{z,t-1}$. $Dur^{\bar{R}}_{z,t-1}$ is constructed using the same methodology described in Section III.B, except that it applies the same national average discount rate $\bar{R}$ for all ZIP codes while allowing heterogeneous local rent growth rates. Conversely, $Dur^{\bar{G}}_{z,t-1}$ applies the national average rent growth rate $\bar{G}$ across all ZIP codes while allowing heterogeneous local discount rates. Columns 1 and 2 include only $Dur^{\bar{R}}_{z,t-1}$ and its interaction with interest rate changes, while columns 3 and 4 include only $Dur^{\bar{G}}_{z,t-1}$ and its interaction with rate changes. Columns 5 and 6 incorporate both pseudo-duration measures and their respective interactions with rate changes. The dependent variable, $\Delta HPI_{z,[t-1,t+1]}$, denotes cumulative house price growth between the end of years $t-1$ and $t+1$. All regressions include county-by-year and ZIP-code fixed effects. Even-numbered columns additionally control for time-varying ZIP-code economic characteristics and their interactions with interest rate changes. Standard errors are clustered at the ZIP-code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 7**. Impact of Interest Rate Changes on Buy-to-Rent (BTR) Probability

| | $\mathbb{1}\{\text{BTR}\}_{i,t}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $\Delta$FFR | | | | $\Delta$FFR Instrumented by MPS | | | |
| | $h=0$ | | $h=1$ | | $h=0$ | | $h=1$ | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\Delta r_{[t-h-1,t-h]} \times \text{RY}_{i,t-h-1}$ | -11.772*** | -12.645*** | -11.263*** | -11.752*** | -10.984*** | -11.118*** | -9.306*** | -9.402*** |
| | (0.087) | (0.092) | (0.094) | (0.098) | (0.112) | (0.117) | (0.120) | (0.123) |
| $\text{RY}_{i,t-h-1}$ | 0.615*** | 0.635*** | 0.590*** | 0.594*** | 0.601*** | 0.602*** | 0.557*** | 0.553*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| $\Delta r_{[t-h-1,t-h]} \times \text{Log(Income)}_{z,t-h-1}$ | | -0.387*** | | -0.253*** | | -0.163*** | | -0.120* |
| | | (0.034) | | (0.043) | | (0.051) | | (0.064) |
| $\Delta r_{[t-h-1,t-h]} \times \text{Log(Population)}_{z,t-h-1}$ | | -0.036*** | | -0.154*** | | -0.070*** | | -0.178*** |
| | | (0.010) | | (0.012) | | (0.015) | | (0.019) |
| $\Delta r_{[t-h-1,t-h]} \times \text{\% Below } 40_{z,t-h-1}$ | | -0.609*** | | -2.401*** | | -4.238*** | | -6.249*** |
| | | (0.218) | | (0.271) | | (0.341) | | (0.431) |
| $\Delta r_{[t-h-1,t-h]} \times \text{\% Above } 60_{z,t-h-1}$ | | -1.052*** | | -0.955*** | | -2.597*** | | -2.975*** |
| | | (0.230) | | (0.287) | | (0.351) | | (0.440) |
| $\Delta r_{[t-h-1,t-h]} \times \text{Labor Force Rate}_{z,t-h-1}$ | | 0.346** | | -0.805*** | | 0.549** | | -1.882*** |
| | | (0.144) | | (0.181) | | (0.221) | | (0.278) |
| $\Delta r_{[t-h-1,t-h]} \times \text{Unemployment Rate}_{z,t-h-1}$ | | 5.107*** | | 2.085*** | | 2.856*** | | 1.516** |
| | | (0.345) | | (0.425) | | (0.571) | | (0.703) |
| $\Delta r_{[t-h-1,t-h]} \times \text{Homeownership Rate}_{z,t-h-1}$ | | 0.163** | | -1.025*** | | -0.616*** | | -2.008*** |
| | | (0.078) | | (0.098) | | (0.116) | | (0.145) |
| $\Delta r_{[t-h-1,t-h]} \times \text{Rental Vacancy Rate}_{z,t-h-1}$ | | 0.085 | | -0.353** | | -0.393** | | -1.108*** |
| | | (0.117) | | (0.148) | | (0.170) | | (0.232) |
| $\Delta r_{[t-h-1,t-h]} \times \text{Income-to-Price Ratio}_{z,t-h-1}$ | | 0.490*** | | 0.214*** | | -0.416*** | | -0.538*** |
| | | (0.035) | | (0.043) | | (0.054) | | (0.066) |
| $\Delta\ \text{HPI}_{z,[t-h-2,t-h-1]}$ | | 0.047*** | | -0.014*** | | 0.041*** | | -0.018*** |
| | | (0.003) | | (0.003) | | (0.003) | | (0.003) |
| Adjusted $R^2$ | 0.138 | 0.138 | 0.138 | 0.138 | 0.022 | 0.022 | 0.022 | 0.022 |
| Observations | 31,906,343 | 31,906,343 | 29,369,961 | 29,369,961 | 31,906,343 | 31,906,343 | 29,369,961 | 29,369,961 |
| Property Chars | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| County × Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | | Yes | | Yes | | Yes | | Yes |

Table 7 presents the impact of interest rate changes on the probability that a property is purchased for rental purposes (buy-to-rent, BTR) across properties with varying rental yields (RY). The dependent variable is an indicator that equals one if the property is purchased for rental purposes, and zero otherwise. The variable, $\Delta r_{[t-h-1,\,t-h]}$, measures the interest rate changes that occurred $h$ years before the transaction. The variable, $\text{RY}_{i,\,t-h-1}$, is the ex-ante property rental yield value estimated through hedonic estimations described in Section III.C. The coefficient on the interaction term, $\Delta r_{[t-h-1,t-h]} \times \text{RY}_{i,t-h-1}$, captures the heterogeneous effects of interest rate changes on the BTR probability across varying property rental yields. Columns 1 to 4 present estimates using changes in the federal funds rate (FFR), while Columns 5–8 use the orthogonalized monetary policy surprise (MPS) measure of Bauer and Swanson (2023) as an instrument for FFR changes. Columns 1, 2, 5, and 6 report contemporaneous effects ($h=0$), and Columns 3, 4, 7, and 8 report effects of one-year-lagged interest rate changes ($h=1$). All columns control for the same property characteristics used in the hedonic estimation of rental yields described in Section III.C and incorporate county-by-year and ZIP-code fixed effects. Additionally, Columns 2, 4, 6, and 8 further control for ZIP-code-level economic characteristics and their interactions with interest rate changes. Standard errors are clustered at the property level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 8**. Near-Term Income Demand and Reaching-for-Income Behavior

| | $\mathbb{1}\{\text{BTR}\}_{i,t}$ | | | | | |
|---|---|---|---|---|---|---|
| | %Retirement Income File | | | Interest Income Ratio | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta r_{[t-2,t-1]} \times$ RY$_{i,t-2}$ | -10.885*** | -0.554** | -1.062*** | -10.532*** | -7.678*** | -8.682*** |
| | (0.098) | (0.231) | (0.235) | (0.098) | (0.135) | (0.138) |
| $\Delta r_{[t-2,t-1]} \times$ RY$_{i,t-2} \times$ %Retirement Income File$_{i,t-2}$ | | -55.621*** | -55.226*** | | | |
| | | (1.109) | (1.111) | | | |
| $\Delta r_{[t-2,t-1]} \times$ %Retirement Income File$_{i,t-2}$ | | 3.199*** | 3.485*** | | | |
| | | (0.191) | (0.236) | | | |
| RY$_{i,t-2} \times$ %Retirement Income File$_{i,t-2}$ | | 3.025*** | 3.060*** | | | |
| | | (0.030) | (0.030) | | | |
| %Retirement Income File$_{i,t-2}$ | | -0.819*** | -0.828*** | | | |
| | | (0.005) | (0.005) | | | |
| $\Delta r_{[t-2,t-1]} \times$ RY$_{i,t-2} \times$ Interest Income Ratio$_{i,t-2}$ | | | | | -317.947*** | -325.877*** |
| | | | | | (16.307) | (16.352) |
| $\Delta r_{[t-2,t-1]} \times$ Interest Income Ratio$_{i,t-2}$ | | | | | 50.939*** | 65.473*** |
| | | | | | (2.568) | (2.925) |
| RY$_{i,t-2} \times$ Interest Income Ratio$_{i,t-2}$ | | | | | 15.800*** | 15.836*** |
| | | | | | (0.293) | (0.294) |
| Interest Income Ratio$_{i,t-2}$ | | | | | 0.916*** | 0.885*** |
| | | | | | (0.048) | (0.048) |
| RY$_{i,t-2}$ | 0.589*** | 0.020*** | 0.012* | 0.564*** | 0.429*** | 0.449*** |
| | (0.003) | (0.006) | (0.006) | (0.003) | (0.004) | (0.004) |
| $\Delta$ HPI$_{z,[t-3,t-2]}$ | | | -0.034*** | | | 0.008** |
| | | | (0.003) | | | (0.004) |
| Adjusted $R^2$ | 0.143 | 0.145 | 0.145 | 0.140 | 0.141 | 0.141 |
| Observations | 26,988,128 | 26,988,128 | 26,988,128 | 27,075,645 | 27,075,645 | 27,075,645 |
| Property Chars | Yes | Yes | Yes | Yes | Yes | Yes |
| County × Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | | | Yes | | | Yes |
| $\Delta r_{[t-h-1,t-h]} \times$ ZIP Economic Chars | | | Yes | | | Yes |

Table 8 reports regression results on heterogeneity in buy-to-rent (BTR) probabilities across homebuyers with different preferences for near-term income and across properties with different rental yields. The dependent variable is an indicator that equals one if a property is purchased for rental purposes, and zero otherwise. Columns 1 to 3 use the share of tax filers reporting taxable individual retirement account (IRA) distributions in the mailing address ZIP code as a proxy for homebuyer demand for near-term income, while Columns 4 to 6 use the ratio of interest income amount to total income reported on tax returns in the ZIP code. The main variables of interest are $\Delta r_{[t-2,t-1]} \times RY_{i,t-2}$ and its interactions with the retirement- and interest-income proxies, which capture whether income-seeking homebuyers are more likely to purchase high-yield properties for rent after interest rate declines. All regressions include property characteristics, county-by-year fixed effects, and ZIP-code fixed effects. Columns 3 and 6 additionally control for ZIP-code-level economic characteristics and their interactions with interest rate changes. Standard errors are clustered at the property level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 9**. Realized Returns of BTR Investors, Rental Yield, and Federal Funds Rate (FFR) Changes

Panel A: ΔFFR

| | Realized Ann Return$_{i,t}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta r_{[t-2,t-1]} \times \text{RY}_{i,t-2}$ | | 4.852*** | 5.084*** | 4.529*** | 4.538*** | 3.715*** |
| | | (0.572) | (0.568) | (0.566) | (0.568) | (0.648) |
| $\Delta r_{[t-2,t-1]}$ | 0.321*** | | | | | |
| | (0.028) | | | | | |
| $\text{RY}_{i,t-2}$ | 0.508*** | 0.460*** | 0.468*** | 0.467*** | 0.468*** | 0.474*** |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Holding Length | | | -0.012*** | -0.019*** | | |
| | | | (0.000) | (0.000) | | |
| $\Delta\ \text{HPI}_{z,[t-3,t-2]}$ | | | | | | 0.041*** |
| | | | | | | (0.004) |
| Adjusted $R^2$ | 0.101 | 0.225 | 0.252 | 0.269 | 0.267 | 0.267 |
| Observations | 1,214,961 | 1,214,961 | 1,214,961 | 1,214,961 | 1,214,961 | 1,214,961 |
| County × Buy Year FE | | Yes | Yes | Yes | Yes | Yes |
| ZIP FE | | Yes | Yes | Yes | Yes | Yes |
| County × Sell Year FE | | | | Yes | Yes | Yes |
| Buy Year × Sell Year FE | | | | | Yes | Yes |
| ZIP Economic Chars | | | | | | Yes |
| $\Delta r_{[t-2,t-1]} \times$ ZIP Economic Chars | | | | | | Yes |

Panel B: ΔFFR Instrumented by MPS

| | Realized Ann Return$_{i,t}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\widehat{\Delta r}_{[t-2,t-1]} \times \text{RY}_{i,t-2}$ | | 21.373*** | 21.859*** | 21.021*** | 21.471*** | 18.487*** |
| | | (1.060) | (1.042) | (1.037) | (1.041) | (1.177) |
| $\widehat{\Delta r}_{[t-2,t-1]}$ | 7.310*** | | | | | |
| | (0.051) | | | | | |
| $\text{RY}_{i,t-2}$ | 0.527*** | 0.441*** | 0.449*** | 0.448*** | 0.449*** | 0.456*** |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Holding Length | | | -0.012*** | -0.019*** | | |
| | | | (0.000) | (0.000) | | |
| $\Delta\ \text{HPI}_{z,[t-3,t-2]}$ | | | | | | 0.030*** |
| | | | | | | (0.004) |
| Adjusted $R^2$ | 0.032 | 0.022 | 0.056 | 0.027 | 0.021 | 0.021 |
| Observations | 1,214,961 | 1,214,961 | 1,214,961 | 1,214,961 | 1,214,961 | 1,214,961 |
| Cragg-Donald F Statistics | 378,334 | 362,547 | 362,539 | 361,344 | 361,190 | 21,121 |
| County × Buy Year FE | | Yes | Yes | Yes | Yes | Yes |
| ZIP FE | | Yes | Yes | Yes | Yes | Yes |
| County × Sell Year FE | | | | Yes | Yes | Yes |
| Buy Year × Sell Year FE | | | | | Yes | Yes |
| ZIP Economic Chars | | | | | | Yes |
| $\widehat{\Delta r}_{[t-2,t-1]} \times$ ZIP Economic Chars | | | | | | Yes |

Table 9 presents the regression results for individual property-level realized annual returns on changes in the Federal Funds Rate (FFR) and their interaction with the property's *ex-ante* rental yield (RY). The dependent variable is the realized annual returns for Buy-to-Rent (BTR) investors, which include the estimated rental yield during the holding periods as well as capital gains from buying and selling the same property. Panel A analyzes the impact of the FFR change that occurred from the end of year $t-2$ to the end of year $t-1$, which is one year prior to the purchase transaction year $t$. In contrast, Panel B uses the orthogonalized monetary policy surprise (MPS) measure of Bauer and Swanson (2023) as an instrument for FFR changes. The fixed effects included in the analysis are noted at the bottom of the table. Standard errors are clustered at the property level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 10**. Interest Rate Changes and Property Transitions Between Owner- and Renter-Occupied Property Status

Panel A: Owner to Renter (OTR)

| | $\mathbb{1}\{\text{OTR}\}_{i,t}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $\Delta$FFR | | | | $\Delta$FFR Instrumented by MPS | | | |
| | $h=0$ | | $h=1$ | | $h=0$ | | $h=1$ | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\Delta r_{[t-h-1,t-h]} \times \text{RY}_{i,t-h-1}$ | -2.957*** | -2.875*** | -2.691*** | -2.256*** | -4.774*** | -3.660*** | -4.612*** | -3.323*** |
| | (0.077) | (0.082) | (0.083) | (0.088) | (0.101) | (0.105) | (0.106) | (0.108) |
| $\text{RY}_{i,t-h-1}$ | 0.140*** | 0.130*** | 0.123*** | 0.107*** | 0.172*** | 0.139*** | 0.156*** | 0.123*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| $\Delta\ \text{HPI}_{z,[t-h-2,t-h-1]}$ | | -0.035*** | | -0.039*** | | -0.035*** | | -0.037*** |
| | | (0.003) | | (0.003) | | (0.003) | | (0.003) |
| Adjusted $R^2$ | 0.059 | 0.060 | 0.058 | 0.058 | 0.001 | 0.001 | 0.000 | 0.000 |
| Observations | 31,906,343 | 31,906,343 | 29,369,961 | 29,369,961 | 31,906,343 | 31,906,343 | 29,369,961 | 29,369,961 |
| Cragg-Donald F Statistics | | | | | 48,002,310 | 1,804,414 | 43,648,238 | 1,436,506 |
| Property Chars | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| County × Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | | Yes | | Yes | | Yes | | Yes |
| $\Delta r_{[t-h-1,t-h]} \times$ ZIP Economic Chars | | Yes | | Yes | | Yes | | Yes |

Panel B: Renter to Owner (RTO)

| | $\mathbb{1}\{\text{RTO}\}_{i,t}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $\Delta$FFR | | | | $\Delta$FFR Instrumented by MPS | | | |
| | $h=0$ | | $h=1$ | | $h=0$ | | $h=1$ | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\Delta r_{[t-h-1,t-h]} \times \text{RY}_{i,t-h-1}$ | 2.810*** | 2.517*** | 1.742*** | 0.890*** | 5.520*** | 4.506*** | 4.703*** | 3.019*** |
| | (0.079) | (0.084) | (0.079) | (0.083) | (0.101) | (0.105) | (0.105) | (0.108) |
| $\text{RY}_{i,t-h-1}$ | -0.087*** | -0.071*** | -0.054*** | -0.026*** | -0.136*** | -0.105*** | -0.104*** | -0.062*** |
| | (0.002) | (0.003) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| $\Delta\ \text{HPI}_{z,[t-h-2,t-h-1]}$ | | 0.056*** | | 0.064*** | | 0.057*** | | 0.061*** |
| | | (0.003) | | (0.003) | | (0.003) | | (0.003) |
| Adjusted $R^2$ | 0.039 | 0.039 | 0.040 | 0.040 | 0.004 | 0.005 | 0.005 | 0.005 |
| Observations | 31,906,343 | 31,906,343 | 29,369,961 | 29,369,961 | 31,906,343 | 31,906,343 | 29,369,961 | 29,369,961 |
| Cragg-Donald F Statistics | | | | | 48,002,310 | 1,804,414.2 | 43,648,238 | 1,436,506.2 |
| Property Chars | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| County × Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | | Yes | | Yes | | Yes | | Yes |
| $\Delta r_{[t-h-1,t-h]} \times$ ZIP Economic Chars | | Yes | | Yes | | Yes | | Yes |

Table 10 presents the effects of interest rate changes on the probability of transitions between owner-occupied and renter-occupied property statuses. The dependent variable is an indicator denoting whether a property transitions from owner- to renter-occupied (OTR, Panel A) or from renter- to owner-occupied (RTO, Panel B). The key interaction term, $\Delta r_{[t-h-1,t-h]} \times \text{RY}_{i,t-h-1}$, captures heterogeneous effects across properties with varying rental yields. Columns 1 to 4 illustrate responses to changes in the Federal Funds Rate (FFR), while Columns 5 to 8 use the orthogonalized monetary policy surprise (MPS) measure of Bauer and Swanson (2023) as an instrument for FFR changes. The table presents the effect within 2 years after a rate change. Specifically, Columns 1, 2, 5, and 6 capture transitions within the year of the interest rate change ($h=0$), whereas Columns 3, 4, 7, and 8 report the effect of the rate change from two years ago ($h=1$). All columns control for property-level characteristics and incorporate county-by-year and ZIP-code fixed effects. Additionally, Columns 2, 4, 6, and 8 further control for ZIP-code-level economic characteristics and their interactions with interest rate changes. Standard errors are clustered at the property level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 11**. Heterogeneity in House Price Sensitivity to Interest Rates across Buy-to-Rent Intensity and Housing Duration

| | $\Delta$ HPI$_{z,[t-1,t+h]}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | FFR | | | | 30-Year Mortgage Rate | | | |
| | $h=0$ | | $h=1$ | | $h=0$ | | $h=1$ | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\Delta r_{[t-1,t]} \times$ Duration$_{z,t-1}$ | 1.020*** | 0.069 | 3.585*** | 1.908*** | 1.177*** | -0.402 | 4.809*** | 1.519*** |
| | (0.175) | (0.213) | (0.295) | (0.360) | (0.248) | (0.321) | (0.437) | (0.549) |
| $\Delta r_{[t-1,t]} \times$ Duration$_{z,t-1} \times$ BTR%$_{z,t-1}$ | | 0.012*** | | 0.017*** | | 0.021*** | | 0.039*** |
| | | (0.002) | | (0.004) | | (0.003) | | (0.006) |
| $\Delta r_{[t-1,t]} \times$ BTR%$_{z,t-1}$ | | -0.055*** | | -0.085*** | | -0.094*** | | -0.180*** |
| | | (0.010) | | (0.017) | | (0.016) | | (0.026) |
| Duration$_{z,t-1} \times$ BTR%$_{z,t-1}$ | | -0.000 | | -0.000** | | -0.000 | | -0.000** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| BTR%$_{z,t-1}$ | | 0.000 | | 0.001*** | | 0.000 | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Duration$_{z,t-1}$ | -0.024** | -0.021* | -0.078*** | -0.058*** | -0.021** | -0.019* | -0.069*** | -0.048** |
| | (0.011) | (0.011) | (0.022) | (0.022) | (0.010) | (0.011) | (0.022) | (0.022) |
| $\Delta$ HPI$_{z,[t-2,t-1]}$ | 0.113*** | 0.112*** | 0.114*** | 0.114*** | 0.105*** | 0.106*** | 0.097*** | 0.097*** |
| | (0.009) | (0.009) | (0.014) | (0.014) | (0.009) | (0.009) | (0.014) | (0.014) |
| Adjusted $R^2$ | 0.793 | 0.794 | 0.826 | 0.826 | 0.794 | 0.795 | 0.828 | 0.828 |
| Observations | 56,684 | 56,684 | 56,658 | 56,658 | 56,684 | 56,684 | 56,658 | 56,658 |
| County × Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP Economic Chars | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $\Delta r_{[t-1,t]} \times$ ZIP Economic Chars | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Table 11 presents regression results examining the heterogeneous sensitivity of house prices at the ZIP-code level to changes in the Federal Funds Rate (FFR) and the 30-year mortgage rate, conditional on ZIP-code housing duration and Buy-to-Rent (BTR) investment intensity. Columns 1 to 4 report results for house price sensitivity to the FFR changes, while Columns 5 to 8 document the response to the 30-year mortgage rate changes. The table presents the effect within 2 years after a rate change. Specifically, Columns 1, 2, 5, and 6 illustrate house price responses within the year of the interest rate change ($h = 0$), whereas Columns 3, 4, 7, and 8 show cumulative responses observed two years after the rate change ($h = 1$). The key interaction terms, $\Delta r_{[t-1,t]} \times \text{Duration}_{z,t-1}$ and $\Delta r_{[t-1,t]} \times \text{Duration}_{z,t-1} \times \text{BTR\%}_{z,t-1}$, capture variations in house price sensitivity associated with differences in housing duration and the intensity of buy-to-rent investment across ZIP codes. The variable BTR% denotes percentiles of BTR transaction ratios across all ZIP codes in a given year, measuring the intensity of buy-to-rent investment activity. All columns include county-by-year fixed effects, ZIP-code fixed effects, ZIP-code economic characteristics, and their interactions with interest rate changes. Standard errors are clustered at the ZIP code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 12**. Cash-Flow Channel: Interest Rate Effects on Expected Housing Cash Flows

| | $\mathbb{E}_t[\ln(\text{Rent}_{t+h})] - \mathbb{E}_{t-1}[\ln(\text{Rent}_{t+h})]$ | | | | | | | | | | $\mathbb{E}_t[\ln(\text{P}_T)] - \mathbb{E}_{t-1}[\ln(\text{P}_T)]$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $h = 1$ | | $h = 2$ | | $h = 3$ | | $h = 4$ | | $h = 5$ | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $\Delta r_{[t-1,t]} \times$ Duration$_{z,t-1}$ | -0.190*** | -0.040 | -0.195*** | -0.047 | -0.189*** | -0.028 | -0.243*** | -0.101 | -0.239*** | -0.169 | -0.671*** | -1.178*** |
| | (0.055) | (0.082) | (0.056) | (0.085) | (0.060) | (0.090) | (0.071) | (0.100) | (0.081) | (0.104) | (0.116) | (0.142) |
| $\Delta r_{[t-1,t]}$ | 1.910*** | | 2.140*** | | 2.256*** | | 2.704*** | | 2.662*** | | 4.977*** | |
| | (0.242) | | (0.249) | | (0.268) | | (0.318) | | (0.363) | | (0.524) | |
| Duration$_{z,t-1}$ | -0.015*** | 0.081*** | -0.016*** | 0.036*** | -0.016*** | -0.004 | -0.010*** | -0.076*** | -0.007*** | -0.141*** | 0.006*** | -0.284*** |
| | (0.001) | (0.010) | (0.001) | (0.012) | (0.001) | (0.014) | (0.001) | (0.016) | (0.001) | (0.018) | (0.002) | (0.020) |
| Adjusted $R^2$ | 0.134 | 0.243 | 0.169 | 0.269 | 0.179 | 0.282 | 0.182 | 0.302 | 0.198 | 0.307 | 0.169 | 0.588 |
| Observations | 60,420 | 60,420 | 60,420 | 60,420 | 60,420 | 60,420 | 60,420 | 60,420 | 60,420 | 60,420 | 60,420 | 60,420 |
| County × Year FE | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes |
| ZIP FE | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes |

Table 12 reports regression results testing the cash-flow channel by examining how interest rate changes affect expected rents and terminal house values differently across housing durations. Columns 1–10 present the impact of changes in the federal funds rate (FFR) on changes in expected log rent, measured as the update from $t-1$ to $t$ for horizons $h = 1$ through $h = 5$. Columns 11–12 focus on changes in the expected log terminal house values. The key variable of interest is the interaction term, $\Delta r_{[t-1,t]} \times \text{Duration}_{z,t-1}$, which captures how revisions in expected rents and terminal values in response to interest rate changes differ by housing duration. Even-numbered columns include county-by-year fixed effects and ZIP-code fixed effects to account for local heterogeneity, and standard errors are clustered at the ZIP-code level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.