Monetary Policy and Housing Duration: Evidence from Reaching-for-Income Investors

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ABSTRACT

Fixed-income theory posits that longer-duration bonds are more sensitive to interest rate changes, and many assume this principle extends to other assets. Contrary to this view, I document a striking inversion in housing markets: shorter-duration properties exhibit greater sensitivity to monetary policy changes. I construct a novel zip-code–level measure of housing duration based on Macaulay duration, showing that shorter duration corresponds to higher rental yields. On average, a 100 basis-point cut in the federal funds rate raises house prices by 1.86 percent over two years, but markets with durations one standard deviation shorter experience an additional 0.71-percentage-point increase—about 38 percent of the average response. Using 30 million property transaction records combined with rental listings, I confirm the inverse duration–sensitivity relationship at the property level. The property-level evidence shows that the inversion is driven by the discount-rate channel through "reaching-for-income" investors. After rate cuts, income-seeking investors disproportionately target high-yield properties for rental purposes and prioritize near-term income over long-run returns. Their demand raises local prices and lowers discount rates more in short- than long-duration markets, generating a non-parallel shift in the housing term structure. Overall, the paper highlights an investor-driven channel in which rental-income preferences shape monetary policy transmission heterogeneity across housing markets.

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

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Duration is the benchmark measure of interest rate risk, relied upon by both financial institutions and academic researchers.[1] In fixed-income markets, Macaulay duration measures the value-weighted average timing of an asset's expected cash flows, with long-duration securities more sensitive to interest rate changes. Because the duration framework is so established, it has been extended beyond bonds to other asset classes. Pension funds, endowments, and other institutional investors rely on duration to manage portfolio risk exposures across asset classes, while central banks and scholars use it to study how monetary policy affects wealth redistribution (Auclert, 2019).[2]

In this framework, real estate is often assumed to be a long-duration asset with large interest rate sensitivity.[3] At the same time, institutional investors such as pension funds and insurers have increasingly tilted portfolios toward real estate, viewing it as a source of income-generating cash flows aligned with long-term liabilities.[4] If duration and sensitivity are mismatched, the consequences are serious: investors may underestimate the true interest rate risk embedded in real estate, leaving portfolios more exposed than recognized, and policymakers may misjudge how monetary policy transmits through one of the largest asset classes in the economy.

This paper asks whether duration measures the *true* interest rate sensitivity of house prices in housing markets. The answer is no. Contrary to the positive mapping between duration and sensitivity observed in bonds and equities, I document a striking inversion in housing markets: shorter-duration properties exhibit greater sensitivity to monetary policy changes. This reversal challenges the conventional duration view and motivates a new framework for understanding how monetary policy transmits to housing markets.

Figure 1 previews the main finding. Following a 100-basis-point cut in the federal funds rate (FFR), it reports the cumulative two-year house price response of duration quintiles 2–5 relative to the shortest-duration quintile (Quintile 1) for the real estate, bond, and equity markets. The figure indicates that shorter-duration housing markets rise more than longer-duration ones after rate cuts. By contrast, bonds and equities follow the conventional duration prediction: longer-duration assets

[1] See, e.g., Drechsler, Savov, and Schnabl (2021); DeMarzo, Krishnamurthy, and Nagel (2024).

[2] For example, many U.S. corporate pension plans are shifting portfolio allocations away from long-duration bonds toward intermediate-term or liquid assets as part of de-risking strategies, signaling active duration control. See the WSJ article.

[3] 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 long duration to real estate in household balance sheets to measure households' wealth exposure to interest rate risk.

[4] For instance, global pension funds are shifting toward real estate assets as those assets deliver steady income streams aligned with pension liabilities (see, e.g., Andonov, Kok, and Eichholtz (2013) and the article). Canadian pension funds are expanding their allocations to real estate based on the article.

exhibit greater sensitivity. The comparison highlights how sharply housing markets deviate from the standard duration principle.

Figure 1. Interest Rate Sensitivities of Asset Prices by Duration Quintiles

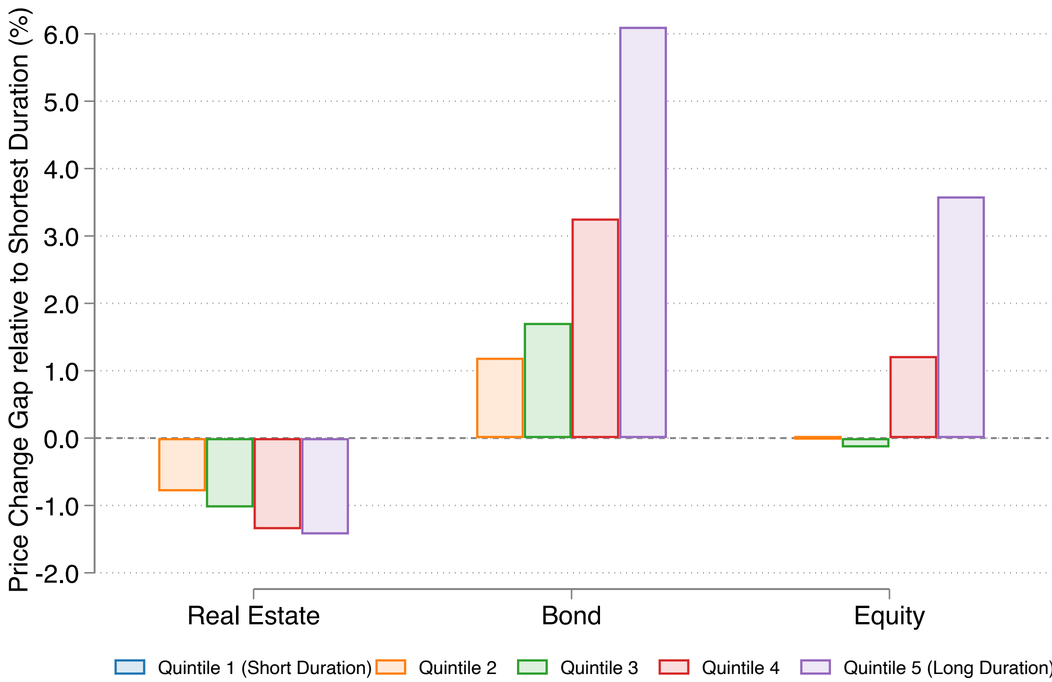

Figure 1 compares the sensitivities of asset prices to a 100-basis-point decrease in the federal funds rate (FFR) across duration quintiles in real estate, bond, and equity markets. The bars report the cumulative price increase gap of quintiles 2–5 relative to the shortest-duration quintile (Quintile 1) over a two-year horizon. Negative values indicate that shorter-duration assets have larger price increases and hence are more sensitive to interest rate changes than longer-duration assets, while positive values indicate the opposite. Each year, duration quintiles are assigned cross-sectionally within each asset class. Bond duration is Macaulay duration, and equity duration is constructed by Gonçalves (2021), who apply the Macaulay duration concept to equities. Estimation is performed at the zip-code–year level for real estate and at the individual asset-year level for bonds and equities. Standard errors are clustered at the zip code level for real estate and at the asset level for bonds and equities.

I start with a zip-code–level analysis and then move to the property level. Using American Community Survey (ACS) data from 2011 to 2023, I construct a novel measure of residential housing cash-flow duration at the zip code level. Unlike bonds, real estate has no fixed maturity or predefined payments. Following the concept of Macaulay duration, I define housing duration as the value-weighted average timing of expected housing cash flows, combining predicted rental incomes and a terminal house value over a five-year holding horizon. Intuitively, the measure captures how quickly a home-buyer realizes economic value from a property—either through rental income for landlords or through housing services for owner-occupants.

To construct the measure empirically, I predict rent growth at the zip-code level using local demographics, labor market conditions, and housing market characteristics, similar to the approach of Weber (2018) and Gonçalves (2021) for equities. Consistent with Greenwald et al. (2021), I find that shorter durations are strongly correlated with higher rental yields. At the property level, I exploit housing transaction and rental listing data to estimate property-level rental yields, which serve as proxies for the inverse of the property-level housing duration.[5] Section II.B provides further details of the measure construction.

With the housing duration measure, the first part of the paper examines how local house prices respond to interest rate changes at the zip-code–year level. The results reveal a striking reversal of the conventional duration prediction: shorter-duration housing markets respond more strongly to interest rate changes. On average, a 100-basis-point decline in the FFR increases house prices by about 1.86 percent over two years, but zip codes with durations one standard deviation shorter experience an additional 0.71-percentage-point increase, about 38 percent of the average effect. This pattern also holds at the one- and three-year horizons. Using 30 million property transaction records from ATTOM, I confirm that the inverse duration–sensitivity relationship still holds at the property level, and it is not driven by differences in mortgage and tax payments.

Why does duration fail to measure the interest rate sensitivity of house prices? A conceptual framework in Section I shows that price sensitivity equals modified duration only when cash flows are fixed and the term premium is either constant or shifts in parallel with policy rates. Two channels can overturn this benchmark: non-parallel, horizon-dependent shifts in the housing term structure (the discount-rate channel) and interest-rate-dependent housing cash flows (the cash-flow channel). This framework motivates the mechanism tests that follow.

In the second part of the paper, I examine the mechanism behind this duration-sensitivity inversion. I show that the discount-rate channel operating through reaching-for-income behavior drives the inverse duration-sensitivity pattern. After rate cuts, investors, particularly those living off income, develop stronger preferences for high-income-generating assets because lower rates reduce income from deposits and short-term bonds. Daniel, Garlappi, and Xiao (2021) define this behavior as reaching for income. In housing markets, I find clear evidence of this investment behavior. When interest rates fall, investors with strong preferences for near-term rental income are more likely to enter high-

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

yield, short-duration markets to purchase properties for rental purposes. Because of their preference for near-term income, these investors accept lower total returns from higher-yield properties. In zip codes with greater reaching-for-income activity, investor demand raises local house prices and lowers discount rates more for short- than for long-duration properties. This non-parallel shift in the housing term structure in response to interest rate cuts explains why shorter-duration markets exhibit larger price increases after the cuts.

By contrast, the cash-flow channel cannot explain the inverse duration-sensitivity pattern: rate cuts raise expected housing cash flows more in long-duration markets, contradicting what the cash-flow channel would require to explain the pattern. I exclude the "reaching-for-yield" mechanism, which emphasizes investors seeking risks rather than income.

Baseline Analysis. Using the zip-code-year-level sample from ACS data, I demonstrate the inverse relationship between housing duration and the sensitivity of house prices to interest rates. My preferred specification includes county-year and zip-code fixed effects to absorb time-varying county characteristics and time-invariant zip-code characteristics potentially correlated with duration. In addition, I perform a series of robustness checks and yield four findings. First, the reverse sensitivity is not driven by changes in demand from first-time homebuyers, demographic shifts, housing affordability, or household borrowing capacity correlated with duration, because I control for relevant local socioeconomic characteristics and their interactions with interest rate changes.[6] Second, the pattern is not caused by the choice of policy rate or by endogenous rate changes, because I use the 30-year mortgage rate in place of the FFR and also examine exogenous policy shocks using 1-year Treasury yield surprises and the monetary policy surprise (MPS) constructed by Bauer and Swanson (2023a) and Jarociński and Karadi (2020). Third, the inverse duration–sensitivity pattern is not an artifact of how the duration measure is constructed, because I reproduce the analysis using alternative measures, including rental yield as in Greenwald et al. (2021), a ten-year holding horizon measure, and one based on LASSO forecasts for rent growth. Finally, the pattern is not specific to the ACS data. I confirm the results using alternative data sources, including Zillow zip-code housing data and ATTOM transactions matched with Altos rental listings (see Internet Appendix). Overall, these results demonstrate

[6] Specifically, I control for income, population size, demographic composition (young and old ratios), labor force participation and unemployment, homeownership, rental vacancies, and a proxy for housing affordability. These controls capture demand-side channels that could otherwise explain the result. They do not fully capture supply-side credit conditions, such as local lender standards, which I address separately in the property-level analysis.

that the abnormal sensitivity of short-duration housing markets is statistically and economically significant and robust.

Using detailed 30 million transaction records from ATTOM combined with rental listings from Altos, I confirm the baseline zip-code findings at the property level: transaction prices of short-duration (high-rental-yield) properties respond more strongly to monetary policy shocks than long-duration (low-rental-yield) properties. The property-level evidence also yields two additional findings. First, the inverse duration–sensitivity pattern is not driven by housing cash outflows, such as mortgage payments and property tax liabilities: accounting for these outflows leaves the effect unchanged and, if anything, stronger. Second, after controlling for loan-to-value (LTV) ratios at purchase, the results are also not driven by leverage or credit access, ruling out the possibility that the higher price increases of shorter-duration markets simply reflect looser lending standards or easier financing after rate cuts.

"Reaching-for-Income" Mechanism. I find that the inverse duration–sensitivity pattern is driven by the discount-rate channel through reaching-for-income activity. First, I show that lower interest rates disproportionately increase the likelihood that high-rental-yield properties are purchased for rental purposes (buy-to-rent, BTR) by investors. Second, I demonstrate that these investors prioritize near-term rental income at the expense of long-run total returns, earning lower realized returns from shorter-duration, higher-yield properties after rates fall. Finally, I show that the excess sensitivity of short-duration markets is concentrated in areas with greater BTR activity but is absent in areas with low BTR activity.

I begin by identifying reaching-for-income activity in housing markets through buy-to-rent (BTR) transactions — investor purchases of properties intended for long-term rental rather than owner-occupancy. Using 30 million individual transaction records and historical tax assessments from ATTOM, I classify a purchase as BTR if the property is purchased, held for at least two years, and becomes (or remains) non-owner-occupied within that period, based on reported owner-occupancy status or mailing address in tax assessment. This definition captures long-term rental investments while excluding short-horizon house flippers and migrant buyers.

Then, I provide direct evidence that reaching-for-income activity exists in housing markets: investors disproportionately target high-yield properties after rate cuts. On average, properties with higher yields are more likely to be purchased for rent by investors. In particular, rate cuts raise the probability that high-rental-yield properties are purchased for rental purposes significantly more than low-yield properties. Instrumenting FFR changes with *exogenous* MPS reveals even stronger patterns, ruling out the concern that the results are driven by endogenous interest rate changes.

The higher BTR probability for high-yield properties is not explained by stronger local rental demand or demographic shifts, but instead reflects changes in investor demand for income-generating assets when rates decline. First, controlling for local rental vacancy rates, demographics, and other socioeconomic characteristics (as in the baseline robustness analysis) leaves the results intact. Second, I find that following rate cuts, high-yield properties are significantly more likely to transition from owner- to renter-occupied and less likely to shift from renter- to owner-occupied, compared with low-yield properties. These asymmetric dynamics also rule out the alternative explanation that the larger price increases in short-duration, high-yield markets are driven by stronger demand from first-time homebuyers after rates fall.

Using IRS Statistics of Income (SOI) zip-code tax data, I construct two proxies for homebuyers' demand for income-generating assets: the share of taxable IRA withdrawals (capturing older households) and the ratio of taxable interest income to adjusted gross income (AGI). Linking these proxies to homebuyers' mailing ZIP codes, I find that homebuyers with a stronger demand for near-term income are significantly more likely to purchase high-rental-yield properties for rent following interest rate cuts. This provides further evidence that BTR activity reflects reaching-for-income behavior in housing markets.

Reaching-for-income investors also sacrifice long-run total returns in exchange for short-term income. For BTR investors who purchase and later resell properties, I construct realized annualized returns by combining observed capital gains with imputed rental yields. I find that following rate cuts, BTR investors earn significantly lower realized returns from high-rental-yield properties relative to low-yield properties, with the return gap widening at longer holding horizons. This pattern is inconsistent with forward-looking rational investment motives and instead reflects investors' preference for near-term rental income at the expense of long-run returns.

Finally, I show that reaching-for-income investment activity explains the high sensitivity of short-duration markets. Exploiting cross-sectional variation in local BTR intensity, I find that the gap in interest rate sensitivity between short- and long-duration markets is negligible in low-BTR areas but becomes large and monotonically increasing in high-BTR areas. Once BTR activity is accounted for, short-duration markets no longer exhibit greater contemporaneous sensitivity to interest rate changes, and over a two-year horizon, their abnormal sensitivity to interest rates is cut nearly in half.

Turning to alternative mechanisms, the cash-flow channel cannot explain the inverse duration-sensitivity pattern. Specifically, I examine whether interest rate cuts raise expectations of rents and terminal housing values more in short-duration markets. If that were the case, this channel could explain the stronger price sensitivity of short-duration markets. Instead, I find the opposite: rate cuts increase expected cash flows more in long-duration markets. This pattern contradicts what the cash-flow channel would require to explain the inversion and instead reinforces the discount-rate channel operating through reaching-for-income investors. Moreover, controlling for local housing risks and their interactions with interest rate changes does not alter the relationship, ruling out a risk-based "reaching-for-yield" mechanism.

Together, these findings establish reaching-for-income behavior by BTR investors as the central mechanism behind the excess sensitivity of short-duration housing markets. When rates fall, high-yield, short-duration properties are more likely to be purchased for rent by housing investors. The BTR investors accept lower total returns from the higher-yield properties in exchange for near-term cash income. As a result, in areas with greater BTR activity, their demand pressure raises local house prices and lowers required returns, producing a larger decline in discount rates for short- relative to long-duration properties. Intuitively, if the aggregate market is dominated by representative investors with the "reaching-for-income" preference, rate cuts will reduce housing premia more for short- than long-duration properties because they accept a lower return 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 after rate cuts.

Contribution and Literature Review. This paper contributes to the literature on monetary policy transmission to housing market dynamics by documenting an intriguing pattern of house price responses to monetary policy changes and proposing a novel mechanism that amplifies the interest rate sensitivity in certain market segments. Prior work shows that expansions in credit supply amplify housing booms (Mian and Sufi, 2009; Favara and Imbs, 2015; Favilukis, Ludvigson, and Van Nieuwerburgh, 2017), and that mortgage credit constraints, such as payment-to-income (PTI) and debt-to-income (DTI) limits, amplify monetary policy effects (Greenwald, 2018; Bosshardt, Di Maggio, Kakhbod, and Kermani, 2024; Adelino, Schoar, and Severino, 2025). Through the deposits channel, Drechsler, Savov, and Schnabl (2017, 2022); Drechsler, Savov, Schnabl, and Supera (2024) have detailed how monetary tightening reshapes mortgage lending. Closest to my work, Hacamo (2024) documents heterogeneity in house price responses to mortgage rate changes by local price level. I introduce a novel perspective by showing that short-duration (high-rental-yield) housing markets exhibit significantly greater sensitivity to interest rate changes. The heightened sensitivity arises from the buy-to-rent housing investors who seek higher rental yields and adjust their investment strategies in response to monetary policy changes. My mechanism complements segmentation frameworks such as Landvoigt, Piazzesi, and Schneider (2015), which emphasize constrained buyers causing lower-tier market volatility, by highlighting instead the important role of investor behavior and reaching-for-income behavior in shaping monetary transmission.

Second, this paper advances the literature on the duration and term structure of equity returns by providing novel insights from the housing market, an important yet under-explored asset class. Building on the foundational work of Dechow, Sloan, and Soliman (2004) and Lettau and Wachter (2011), who established equity duration as a key determinant of asset risk, and the empirical findings of Binsbergen, Brandt, and Koijen (2012) and Van Binsbergen and Koijen (2017), who document higher returns for short-term equity claims, I uncover a similar pattern in real estate markets. Specifically, my study finds that short-duration housing markets, on average, experience higher future house price growth. This evidence aligns with the short-duration premium identified in equity markets by Weber (2018), Gonçalves (2021), and Gormsen and Lazarus (2023). Unlike equities with measurement controversies (Schulz, 2016; Boguth, Carlson, Fisher, and Simutin, 2023), my findings from housing markets provide robust and complementary evidence, similar to Giglio, Maggiori, and Stroebel (2015); Giglio, Maggiori, Rao, Stroebel, and Weber (2021). However, I advance this literature by exploring how duration influences monetary policy transmission to asset prices and highlight the amplified sensitivity of short-duration housing markets to monetary policy changes.

Third, this paper contributes to the "reaching-for-income" literature by documenting an investor-driven transmission channel through which monetary policy shapes housing markets. In particular, I show that preferences for rental income amplify the sensitivity of house prices to interest rate changes. The concept of reaching-for-income differs fundamentally from another similar term called "reaching-for-yield", which reflects changes in investors' risk appetite. Reaching-for-income emphasizes the *change* in interest rates, highlighting how rate declines induce income-dependent investors to shift toward assets that generate higher current income as traditional sources of interest income diminish

(Jiang and Sun, 2020; Daniel et al., 2021). By contrast, Campbell and Sigalov (2022) define reaching-for-yield as the tendency to take on more risk when real rates fall while risk premia remain constant, though most papers on this topic emphasize how the low *level* of interest rates triggers investors' reallocations into more-risky, higher-yielding assets.[7] Another distinction between the two terms lies in who is "reaching": Gomes et al. (2025) show that reaching-for-yield is more prevalent among younger and less-wealthy households, whereas reaching-for-income investors are typically older or retired. Closest to this paper, Gargano and Giacoletti (2022) document that lower rates lead older households to substitute interest income with rental income and to increase participation in rental markets. My paper contributes by highlighting how reaching-for-income behavior generates heterogeneity in monetary policy transmission across housing markets. I provide micro-level evidence that reaching-for-income amplifies the price sensitivity of short-duration, high-yield markets, shapes local house price responses to monetary policy changes, and produces spatial disparities in housing market dynamics.

The remainder of this paper is organized as follows: Section I is a conceptual framework that derives the relationship between the interest rate sensitivity of house prices and housing duration. Section II describes data and the construction of measurements. Section III shows the empirical baseline results. Section IV explores the reaching-for-income mechanism. Section VI concludes the paper.

I. 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 A.

[7] Evidence of reaching-for-yield has been 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).

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 $\{\mathbb{E}_t[C_{t+h}]\}_{h\geq 1}$ 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:

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

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 $\sum_{h\geq 1} w_t(h) = 1$. $\widetilde{D}_t$ 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 ex-*

pected 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.[8]

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 $\kappa_t > -1$.[9]

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

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

[8] 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 A.

[9] $\kappa_t \leq -1$ 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.

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 $D_{S,t} < D_{L,t}$, 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.

II. 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.[10] 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

[10]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.

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.[11]

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 II.B.

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:

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

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

While my primary analyses rely on ACS data, I also construct alternative measures of housing duration using Zillow data as a robustness check. To do so, I combine ZHVI with the Zillow Observed Rent Index (ZORI), which measures typical market rents in the 35th–65th percentile range within each

[11] 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.

zip code. ZORI is constructed using a repeat-rent methodology, weighted by the rental housing stock to ensure representativeness of the local rental market. I use the smoothed and seasonally adjusted versions of both ZHVI and ZORI to reduce measurement error from index construction and property-type heterogeneity. Because ZORI data at the zip code level are only available starting in 2015, later than the ACS series, I present results based on Zillow-constructed duration measures exclusively as robustness analyses in Internet Appendix Section F.

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 provide 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.[12] This approach yields a more reliable and representative sample for analysis and mitigates bias in subsequent estimates. A detailed discussion of my data cleaning procedure is provided in Internet Appendix Section B.

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

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

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 II.C.

To validate the primary findings from ACS data, I reproduce the baseline analysis using duration measures constructed from the ATTOM and Altos datasets. I compute average housing transaction prices and asking rents at the zip code–year level to proxy typical house and rental prices. Following methodologies similar to those used in constructing ZORI and ZHVI, I calculate mean prices and rents by averaging the middle 30% (35th–65th percentiles) of transaction prices and asking rents.[13] These measures allow me to estimate annual rent growth and rental yields at the zip code level and, subsequently, to construct housing cash-flow duration measures. The detailed results of these analyses are presented in the Internet Appendix Section E.

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 B.

[13]For methodology details, see `https://www.zillow.com/research/methodology-zori-repeat-rent-27092/` for ZORI and `https://www.zillow.com/research/zhvi-methodology-2019-deep-26226/` for ZHVI.

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

In our primary analysis, we measure interest rate changes using the annual change in the federal funds rate. Additionally, we evaluate house price sensitivity to the 30-year mortgage rate change. Data for both rates are obtained from the Federal Reserve Economic Data (FRED). Specifically, for each year t, we compute the annual change as the difference in interest rates between the end of year $t-1$ and the end of year t.

To capture the unexpected component of interest rate movements, we construct a 1-year Treasury yield surprise measure. This measure is derived by first obtaining the 1-year and 2-year Treasury yields from FRED. Using these yields, we calculate the implied forward 1-year Treasury yield. The yield surprise is then defined as the difference between the actual realized 1-year Treasury yield and the implied 1-year forward yield from last year. Detailed definitions and calculations of this measure are provided in the appendix table of variable definitions.

For robustness checks, we employ alternative monetary policy shocks developed by Bauer and Swanson (2023a) and Jarociński and Karadi (2020). The detailed descriptions and methodologies for these variables are included in the appendix table.

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 build on the definition of Macaulay duration and construct a new measure called *housing cash flow duration* (hereafter referred to as housing duration). This measure is defined as the value-weighted average time until future cash flows (i.e., rental income) are received from housing markets. Formally, the duration for properties located in zip code z at time t is defined as:

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

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

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

and expected cash flows $\mathrm{CF}_{z,t+h}$ is defined as:

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

In Equation 8, $w_{z,t+h}$ denotes the relative weight of the present value of expected cash flows $\mathrm{CF}_{z,t+h}$ 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 the weighted average maturity of housing cash flows, with the weights determined by the importance of the present values of expected future cash flows relative to the current investment value.

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 incomes 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.

In Equation 10, for periods before the terminal horizon H (i.e., $h < H$), the expected cash flow is the expected rental income $\mathbb{E}_t[\mathrm{Rent}_{z,t+h}]$, which represents the expected annual rents received from a typical rental property in zip code z at future horizon h.

At horizon H (i.e., $h = H$), the terminal cash flow is calculated via the Gordon Growth Model (GGM) with the estimated zip-code long-term rent growth rate $\bar{g}_{z,t}$. It assumes the homeowner will sell the property and obtain the house value in year $t+H$, which would be the claim for all expected future rental income from the property. $\bar{g}_{z,t}$ is the long-run rent growth expectation formed by a homeowner in zip code z and year t. The detailed estimation procedure for the long-term growth rate is provided in Section II.B.1.

Empirically, I use a 5-year horizon as the terminal horizon for constructing my duration measurement. However, changing the assumed terminal horizon is unlikely to alter my main conclusions. That is because it is the cross-sectional ranking of housing duration, rather than the duration value itself, that leads to the heterogeneity in interest rate sensitivity. Nonetheless, I have also constructed an alternative duration measurement using a 10-year horizon. The results are robust and are presented in Internet Appendix Section 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:

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

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). The zip-code rental incomes are measured by the median gross rents from the same ACS data. With the rental income values, I calculate the realized rent growth and conduct predictive regressions using local economic characteristics to estimate expected future rent growth and levels.

For robustness checks, I also create housing duration measures using alternative data sources from ATTOM, Altos, and Zillow. While my primary analyses are based on ACS data, I provide additional robustness analyses using the ATTOM and Altos datasets in Internet Appendix Section E, and those based on Zillow data are presented in Internet Appendix Section F.

In the next section, I will discuss in detail the estimation of the expected rents $\mathbb{E}_t\left[\text{Rent}_{z,t+h}\right]$.

B.1. 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:

$$\mathbb{E}_t\left[\ln(\text{rent})_{z,\,t+h}\right] = \ln(\text{rent})_{z,\,t} + \sum_{s=1}^{h} \mathbb{E}_t\left[\Delta\ln(\text{rent})_{z,\,[t+s-1,\,t+s]}\right], \tag{12}$$

where $\ln(\text{rent})_{z,t}$ is the log of the observed rental value for a typical property in zip code z at year t, 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 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:

$$\Delta \ln(\text{rent})_{z,[t+s-1,t+s]} = \alpha_s + \beta_{1,s} \ln(\text{rental yield})_{z,t} + \beta_{2,s} \Delta \ln(\text{rent})_{z,[t-1,t]} + \Gamma X_{z,t} + \epsilon_{z,t,s} , \tag{13}$$

where the dependent variable is the annual log rent growth at horizon s for zip code z in year t. The predictors include the log rental yield, $\ln(\text{rental yield})_{z,t}$, log rent growth in the last year, $\Delta \ln(\text{rent})_{z,[t-1,t]}$, and a comprehensive set of local economic characteristics denoted as $X_{z,t}$.

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 13 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.

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:

$$\mathbb{E}_t\left[\Delta \ln(\text{rent})_{z,[t+s-1,t+s]}\right] = \hat{\alpha}_s + \hat{\beta}_{1,s} \ln(\text{rental yield})_{z,t} + \hat{\beta}_{2,s} \Delta \ln(\text{rent})_{z,[t-1,t]} + \hat{\Gamma} X_{z,t} \tag{14}$$

C. Measuring Property-level Rental Yield

In my mechanism analysis, I exploit granular, property-level housing transaction and rental listing data to estimate rental yields for individual properties over time. As shown in Internet Appendix A.A.3, the housing duration measure simplifies to rental yield under the assumption of constant rent growth. Thus, in the property-level mechanism analysis, rental yield serves as a proxy for property-level housing duration, with higher rental yields indicating shorter durations.

Specifically, I merge housing transaction data with rental listings at the property level to construct a comprehensive dataset of historical transaction prices and listed rents for comparable properties. Leveraging this rich and detailed dataset, I implement hedonic models to estimate the expected transaction prices, rents, and rental yields for each individual property over time.

The underlying intuition of the hedonic estimation is that observed transaction prices and listed rents for properties with observable characteristics can be used to infer the market prices and rents for similar properties that lack recent market transactions or rental listings. By integrating transaction and rental listing data, this approach thus estimates the rental yields for the entire universe of properties, including owner-occupied houses for which direct rental yields are typically unobservable.

C.1. Estimating Property-level Prices, Rents, and Rental Yields Using Hedonic Models

I start by estimating the expected annual house price for each property using the hedonic model. First, I estimate the time-varying relationship between observed transaction prices and property characteristics through hedonic regressions. I then apply the estimated hedonic coefficients to the full sample of properties to derive property-level expected house prices.

The hedonic estimations use all valid transaction data that include realized transaction prices, property characteristics, and geographic identifiers. Internet Appendix Section B describes the detailed process for cleaning the ATTOM housing transaction data and identifying valid transactions.

To estimate expected house prices, I conduct hedonic regressions separately for each county-year combination. Specifically, *for each county and year*, I conduct a regression with the following specification.[14]

$$\ln(\text{price}_{i,k,z,c,t}) = \alpha_{c,t} + \Gamma'_{c,t} X_{i,k,z,c,t} + \lambda_{k,z,c,t} + \epsilon_{i,k,z,c,t}\,, \tag{15}$$

where the dependent variable is the log transaction price for property i of property type k in zip code z, county c, and year t.

$X_{i,k,z,c,t}$ encompasses a comprehensive set of property characteristics selected based on prior literature (Giglio et al., 2015; Giglio, Maggiori, and Stroebel, 2016; Gen Li, 2023; Goldsmith-Pinkham and Shue, 2023; Halket, Loewenstein, and Willen, 2023; Diamond and Diamond, 2024). These characteristics include the log of the house age, the log of the property area in square feet, and the number of bedrooms and bathrooms, along with their squared terms. Additionally, I include dummy variables indicating the presence of a garage, a pool, cooling and heating facilities, a fireplace, a basement, as well as views of waterfronts, mountains, recreational areas, and general quality views.

$\lambda_{k,z,c,t}$ represents zip-code-by-property-type fixed effects, accounting for unobserved heterogeneity across property types and zip codes over time.[15] Consequently, $\lambda_{k,z,c,t}$ captures the average transaction prices for each property type in each zip code in a year.

The estimated coefficients from Equation 15 are then applied to all properties with available characteristics to calculate the expected log price for each property in a year with the following equation.

$$\mathbb{E}[\ln(\text{price}_{i,k,z,c,t})] = \hat{\alpha}^{p}_{c,t} + \hat{\Gamma}^{p\prime}_{c,t} X_{i,k,z,c,t} + \hat{\lambda}^{p}_{k,z,c,t}\,, \tag{16}$$

where superscript p denotes coefficients specifically from hedonic estimations for house prices, distinguishing them from those obtained from rent hedonic estimations in the following.

Finally, given Jensen's inequality, the expected house price for property i in year t is defined as

$$\hat{P}_{i,t} \equiv \mathbb{E}[\text{price}_{i,t}] = \exp\left\{ \mathbb{E}[\ln(\text{price}_{i,t})] + \frac{1}{2}\,\widehat{u^2_{c,t}}^{\,p} \right\}, \tag{17}$$

[14]For robustness checks, I have also performed by-CBSA-year and by-MSA-year hedonic regression estimations. The alternative estimation approach yields very similar and consistent results.

[15]The zip-code-by-property-type fixed effects, $\lambda_{k,z,c,t}$, includes the subscripts c and t due to the *by-county-year* regression analysis, which results in estimated coefficients varying across counties and years. The reason also applies to $\alpha_{c,t}$ and $\Gamma_{c,t}$.

where $\widehat{u^2_{c,t}}^{p}$ is the estimated residual variance from by-county-year price hedonic regressions.

In parallel, I estimate property-level rents using analogous rent hedonic regressions. Using the ATTOM property sample with matched actual rental listing information, I first conduct *by-county-year* rent hedonic regressions with the following specification.

$$\ln(\text{rent}_{i,k,z,c,t}) = \alpha_{c,t} + \Gamma'_{c,t} X_{i,k,z,c,t} + \lambda_{k,z,c,t} + \epsilon_{i,k,z,c,t} , \tag{18}$$

where the dependent variable $\ln(\text{rent}_{i,k,z,c,t})$ is the log of listed rent for property i of property type k in zip code z, county c, and year t. $X_{i,k,z,c,t}$ represents the same property characteristics used in the price hedonic regression in Equation 15.

Applying the estimated rent coefficients yields the expected log rent for each property over time:

$$\mathbb{E}[\ln(\text{rent}_{i,k,z,c,t})] = \widehat{\alpha}^r_{c,t} + \widehat{\Gamma}^{r\prime}_{c,t} X_{i,k,z,c,t} + \widehat{\lambda}^r_{z,k,s,t} , \tag{19}$$

where the superscript r denotes the coefficients estimated from rent hedonic regressions.

Finally, the expected rent for individual property i in year t is defined as

$$\widehat{\text{Rent}}_{i,t} \equiv \mathbb{E}[\text{rent}_{i,t}] = \exp\left\{ \mathbb{E}[\ln(\text{rent}_{i,t})] + \frac{1}{2} \widehat{u^2_{c,t}}^{r} \right\} , \tag{20}$$

where $\widehat{u^2_{c,t}}^{r}$ denotes the estimated residual variance from rent hedonic regressions.

Finally, the expected annual rental yield for each property is computed as

$$\begin{aligned} \text{RY}_{i,t} \equiv \mathbb{E}\Big[\text{rental yield}_{i,t}\Big] = \exp\Big\{ & \mathbb{E}[\ln(\text{rent}_{i,t})] - \mathbb{E}[\ln(\text{price}_{i,t})] \\ & + \frac{1}{2} \big(\widehat{u^2_{c,t}}^{r} + \widehat{u^2_{c,t}}^{p} - 2\,\text{cov}(\widehat{u}^r_{c,t}, \widehat{u}^p_{c,t}) \big) \Big\} , \end{aligned} \tag{21}$$

where $\text{cov}(\widehat{u}^r_{c,t}, \widehat{u}^p_{c,t})$ represents the covariance of residuals from rent and price estimations.

D. Descriptive Statistics

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

To gain an intuitive understanding of regional differences in housing durations and rental yields, I calculate the average housing duration and rental yield across all zip codes and years within each county. Figure 2 illustrates county-level geographic heterogeneity in housing duration (Panel A) and rental yield (Panel B). Counties are classified into quintiles (Q1 to Q5), with darker shading corresponding to higher values of housing duration or rental yield.

The figure reveals substantial regional heterogeneity in housing durations and rental yields. For instance, coastal counties in California generally display longer housing durations than inland counties. Moreover, counties located in the central regions of the United States typically show shorter housing durations and higher rental yields. Regions with high house prices and high-income households, such as those surrounding New York City, Boston, and San Francisco, also have relatively longer housing durations. Although coastal areas in many parts of the U.S. generally correlate with longer durations, Florida seems to deviate from this pattern, with some coastal counties showing durations in the lower quintiles. This deviation suggests that other local factors beyond the house price level and coastal proximity may also influence housing durations and rental yields. Finally, comparing Panels A and B indicates a negative relationship between housing durations and rental yields.

D.2. Dominance Analysis for Housing Duration Variation

Figure 3 illustrates the proportion of housing duration variation attributed *uniquely* to each explanatory variable, estimated from a dominance analysis. The dominance analysis is a methodology designed to assess the relative importance of explanatory variables by decomposing the total variation explained in a regression model into unique contributions from each factor. Specifically, this analysis employs the Shapley value decomposition technique, derived from cooperative game theory, to allocate the explained variance among explanatory variables based on their average marginal contributions across all possible model combinations.

Rental yield emerges as the most influential factor, accounting for 47.1% of the explained variation in housing duration. Log(price) also demonstrates significant explanatory power, contributing 31.5%. Following that, Log(rent) and log(income) explain 7.4% and 7.0% of the variation, respectively. Other characteristics demonstrate a relatively smaller influence. Factors such as unemployment rate, labor force participation rate, and homeownership rate have relatively minor impacts. Population size, age demographics (% below 40 and % above 60), and rental vacancy rate show minimal explanatory power, each accounting for less than 1% of the total variation.

Overall, the analysis suggests that rental yield and property prices primarily explain the geographic heterogeneity in housing duration, while socioeconomic variables play secondary roles.

D.3. Description of Data

Table 1 presents descriptive statistics and a correlation matrix for the primary variables in the final sample analyzed in my baseline regressions in Tables 2 and 3. As I employ one-year-lagged housing market characteristics, Panels A, C, and D display statistics for these lagged variables, consistent with the regression analyses. The sample is limited 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.[16] The final sample with complete housing and local characteristics include 6,033 zip codes from 2011 to 2023.

Panel A provides statistics for housing duration measures and associated housing cash flow characteristics. The mean 5-year housing duration is approximately 4.467 years, with a standard deviation of 0.230. Rental yield averages 6.3%, with a standard deviation of 3.3%. Additionally, alternative duration measures, including Duration 5Y^{LASSO}, Duration 10Y, and Duration 10Y^{LASSO}, are presented. The suffixes "5Y" and "10Y" denote assumed holding horizons of 5 and 10 years, respectively. The primary duration measure assumes a 5-year horizon. The superscript "LASSO" indicates measures constructed using predicted rent growth from LASSO regressions.

Panel B summarizes the dependent variables, house price changes over three-year horizons. Annual average house price growth is approximately 7.8%, accumulates to 15.7% over two years, and reaches a cumulative 25.2% increase within three years.

Panel C describes local socioeconomic and housing market characteristics. The mean log household income is 11.01, approximately corresponding to $60,476, while the mean log population is 10.08, roughly equivalent to 23,861 individuals. On average, 53% of the population in zip codes is under 40, while about 20.5% is above 60 years old. The average homeownership rate is 57.5%, the average rental vacancy rate is 6.5%, and the mean income-to-price ratio stands at approximately 0.25.

Finally, Panel D presents pairwise correlations among the variables. Housing duration exhibits a strong negative correlation with rental yield, consistent with Greenwald et al. (2021). Given that the housing duration could be simplified to the price-to-rent ratio under the assumptions of constant rent growth and perpetual cash flows, the empirically observed negative relationship is intuitive. Addi-

[16] The criteria defined by the U.S. Census Bureau are detailed at https://www.census.gov/newsroom/blogs/random-samplings/2022/12/redefining-urban-areas-following-2020-census.html.

tionally, housing duration significantly correlates with economic and demographic factors, such as the log(income), log(income-to-price), unemployment rate, labor force rate, and age demographics.

III. Empirical Results

A. Baseline Specification

To examine heterogeneity in house price sensitivity to interest rate changes across zip codes with varying housing duration, I employ a regression analysis at the zip code-year level using the following baseline specification:

$$\begin{aligned} \Delta HPI_{z,c,[t-1,t+h]} = \alpha_h + \beta_h \, \Delta r_{[t-1,t]} \times \text{Duration}_{z,t} \\ + \delta_h \, \text{Duration}_{z,t} + \zeta_c \times \theta_t + \lambda_z + \epsilon_{z,c,t,h} \, , \end{aligned} \tag{22}$$

where $\Delta HPI_{z,c,[t-1,t+h]}$ is the percentage change in house prices of zip code z in county c from year $t-1$ to $t+h$, with h indicating the horizon over which the price change is measured. $\Delta r_{[t-1,t]}$ indicates the annual change in the federal funds rate (FFR) from the end of year $t-1$ to t, and $Duration_{z,t}$ denotes the housing duration level in zip code z in year t. The term $\zeta_c \times \theta_t$ represents the county-by-year fixed effects. λ_z denotes the zip code fixed effects. The fixed effects will help control for the time-varying county-level economic characteristics and time-invariant zip-code characteristics.

The primary explanatory variable of interest, $\Delta r_{[t-1,t]} \times Duration_{z,t-1}$, captures the heterogeneous house price sensitivity to FFR changes based on the zip-code housing duration. The coefficient of interest, β_h, measures how the sensitivity varies across zip codes with varying housing duration. Given a negative relationship between house price growth and interest rate changes, a positive estimated coefficient ($\hat{\beta}_h > 0$) indicates that zip codes with longer housing durations exhibit *lower sensitivity* to interest rate changes compared to those with shorter durations. In other words, a negative interest rate shock ($\Delta r < 0$) is associated with higher house price growth in areas with shorter housing durations. Conversely, a negative estimated coefficient ($\hat{\beta}_h < 0$) would imply greater sensitivity among zip codes with longer housing durations.

B. Monetary Policy Transmission to Zip-code House Prices by Housing Duration

B.1. Baseline Analysis

Figure 1 briefly illustrates the heterogeneous responses of asset prices to a 100 basis-point decrease in the federal funds rate (FFR), categorized by asset cash flow duration. Panels A, B, and C present price responses for real estate, bond, and equity markets, respectively. The interest rate shock occurs at horizon 0, representing the period from the end of year $t-1$ to year t. The x-axis indicates the response horizon h in years following the shock, while the y-axis shows cumulative percentage changes in asset prices. The red and green lines represent price changes for long-duration and short-duration assets, respectively.

Panel A of Figure 1 clearly demonstrates that short-duration housing markets exhibit significantly greater sensitivity to interest rate changes compared to long-duration markets. Specifically, at the contemporaneous year t (horizon 0), short-duration markets experience an immediate and statistically significant house price increase of approximately 1%, whereas long-duration markets show negligible immediate responses. This divergence widens significantly by the subsequent year (horizon 1), with short-duration markets cumulatively appreciating by around 4%, exceeding long-duration markets by approximately 1 percentage point. The gap remains stable until year three (horizon 2). By year four (horizon 3), the effect begins to dissipate. The price changes of the two markets converge at this point.

The pattern of interest rate sensitivity observed in housing markets contrasts sharply with that in bond and equity markets. Panels B and C reveal that long-duration bonds and equities demonstrate greater price sensitivity relative to their short-duration counterparts, consistent with theoretical predictions.

Specifically, Panel B shows that bond prices in both duration categories increase immediately following the decrease in rate; however, long-duration bonds appreciate approximately 2 percentage points more than short-duration bonds at the shock year (horizon 0). This divergence persists through year two (horizon 1) with a cumulative price increase difference of around 2 percentage points and remains stable even at year three (horizon 2).

Panel C presents similar patterns in equity markets compared to bond markets. Immediately after the interest rate decreases at horizon 0, equity prices for both duration categories increase significantly, but the magnitude is significantly greater for long-duration equities. The difference in cumulative price responses persists over the next two years, though narrowing slightly over time, and converges by year four (horizon 3).

In summary, the findings reveal an intriguing anomaly: Unlike bond and equity markets, housing markets exhibit greater price sensitivity to interest rate changes in short-duration markets rather than in long-duration markets. This phenomenon contradicts both theoretical predictions and empirical evidence from other asset classes.

Table 2 rigorously examines the heterogeneous sensitivity of asset prices to interest rate changes across asset duration for real estate (Panel A), bonds (Panel B), and equities (Panel C). Panel A provides compelling evidence that *shorter-duration housing markets* exhibit *significantly greater sensitivity* to changes in the federal funds rate (FFR), a stark contrast to the theoretically predicted positive relationship validated by bond and equity markets in Panels B and C.

In Column 1 of Panel A, I begin by including only the FFR change and housing duration. A 100 basis-point decrease in the FFR corresponds to an average two-year house price increase of approximately 1.86%. The negative coefficient on housing duration suggests higher price growth in shorter-duration zip codes on average.

Column 2 introduces an interaction term between FFR changes and housing duration. The significantly positive coefficient on this interaction term indicates greater sensitivity in short-duration housing markets. Specifically, a 100 basis-point FFR cut is associated with an additional price increase of roughly 0.4% in zip codes with durations shorter by one standard deviation (0.23 years), representing approximately 22% of the average price response to the FFR cut.[17] This result reveals the nontrivial influence of local market duration characteristics on both the direction and magnitude of house price responses.

Columns 3 and 4 progressively incorporate year and county-by-year fixed effects, respectively, controlling for nationwide house price trends and time-varying county characteristics. Column 5, my preferred specification, includes both county-year and zip-code fixed effects. The result confirms the higher sensitivity of shorter-duration housing markets. The interaction coefficient of 3.089 implies that a 100 basis-point decrease in the FFR yields an additional house price increase of approximately 0.71% in zip codes with durations shorter by one standard deviation.[18] The additional price increase represents approximately 37.6% of the average price response to the FFR cut.

[17] $0.4\% \approx 1.7 \times 0.23 \times 1\%$

[18] $0.71\% \approx 3.089 \times 0.23 \times 1\%$

In contrast, Panels B and C confirm the positive relationship between duration and price sensitivity to interest rate changes in bond and equity markets. To ensure comparability across asset classes, I consistently analyze the annual price changes over a two-year horizon. Specifically, a 100 basis-point decrease in the FFR is associated with average price increases of around 4.7% for treasury bonds and approximately 11% for equities. The significantly negative interaction coefficients in Columns 2 through 4 of Panels B and C confirm the expected duration-sensitivity relationship, which indicates that longer-duration bonds and equities experience significantly greater price increases following interest rate decreases.

Overall, Table 2 reveals a remarkable anomaly within housing markets: short-duration assets show substantially higher sensitivity to interest rate changes, opposite to theoretical predictions and also empirical evidence from bond and equity markets. Further investigation into the mechanisms underlying this anomaly could offer valuable insights into monetary policy transmission within real estate markets.

B.2. Diminishing Interest Rate Sensitivities by Duration Quintiles

To further substantiate the negative relationship between housing cash flow duration and sensitivity of house prices to interest rate changes, I classify zip codes into five quintiles based on their estimated housing durations. Figure 4 presents the heterogeneous responses of house prices across these duration quintiles following a 100 basis-point (bps) 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 quintile 5, which represents zip codes with the longest housing durations. Quintile 1, conversely, represents zip codes with the shortest housing durations.

The figure demonstrates a robustly stronger response of shorter-duration housing markets to interest rate shocks over the subsequent three years. In particular, following a 100 bps decrease in the FFR, the shortest-duration zip codes (quintile 1) experience price increases that are approximately 0.44, 1.5, and 1.6 percentage points larger than those in the longest-duration zip codes (quintile 5) at the one-, two-, and three-year horizons, respectively. Quintiles 2 and 3 similarly exhibit significantly larger price increases relative to quintile 5 following the interest rate decrease.

Importantly, the figure reveals a clear monotonic decline in house price sensitivity as the housing duration quintile increases. The results robustly confirm a negative relationship between housing duration and price sensitivity to interest rate changes. In other words, shorter-duration housing markets are significantly more responsive to interest rate changes than their longer-duration counterparts, a result that corroborates the findings presented in Table 2.

B.3. Heterogeneity by Local Characteristics

Table 3 presents robust evidence of heterogeneity in the two-year house price response to annual changes in the federal funds rate (FFR) by controlling for a comprehensive set of local characteristics. Specifically, the table investigates the robustness of the higher interest rate sensitivity of shorter-duration housing markets after controlling for a range of zip code-level demographic and economic characteristics, including median household income, population size, age distribution (proportions below 40 and above 60), labor force participation rate, unemployment rate, homeownership rate, rental vacancy rate, and income-to-price ratio.

Column 1 extends the baseline specification by adding the past one-year house price growth to control for the momentum effect. The estimated coefficient on the interaction term between the FFR change and housing cash flow duration remains significantly positive at around 3.021. Based on the specification, Column 2 further incorporates nine local economic and demographic characteristics to account for potential confounding factors from local market conditions. Column 3 introduces the interaction terms between FFR changes and each local characteristic to explicitly capture the heterogeneous impacts of interest rate changes across local characteristics. The results confirm that even after accounting for heterogeneous interest rate sensitivity across other local characteristics, the higher sensitivity of shorter-duration housing markets remains significant, and the estimated magnitude does not change much.

The results confirm my finding that shorter-duration housing markets respond more substantially to interest rate changes. The finding is robust to the inclusion of a wide array of local demographic and economic controls, as well as their interactions with monetary policy changes.

Figure 5 explores the heterogeneous house price response to interest rate changes across diverse zip-code demographic and economic characteristics. Specifically, it illustrates the additional two-year cumulative house price change associated with a one-standard-deviation (sd) increase in each characteristic following a 100-basis-point decrease in the federal funds rate (FFR). The heterogeneity is derived from the estimated coefficients on interaction terms in Table 3.

Several key patterns of heterogeneity emerge. First, zip codes with higher income levels exhibit a stronger sensitivity to monetary policy changes, probably caused by the higher leverage or reliance on credit among high-income homeowners. Conversely, zip codes with a higher share of residents below 40 or above 60 years old demonstrate lower sensitivity to interest rate changes. Younger residents typically dominate rental markets without much influence on the housing transaction markets. Old people usually have substantial cash savings and, hence, rely less on mortgages, which makes them less susceptible to interest rate changes.

Additionally, zip codes with higher labor force participation rates demonstrate less sensitivity to monetary policy changes, possibly because stable incomes from labor participation help homeowners better withstand interest rate fluctuations and mitigate forced sales caused by mortgage defaults during monetary tightening. Likewise, zip codes with higher income-to-price ratios, usually representing higher housing affordability, also show lower sensitivity.

Conversely, areas with higher unemployment rates or higher rental vacancy rates are more susceptible to interest rate changes. It could be driven by the increased vulnerability and reduced housing demand under deteriorating labor market conditions. A higher rental vacancy rate may exacerbate financial distress among property owners facing decreased rental revenues, which may force them to sell their properties at a fire sale during monetary tightening.

Overall, Figure 5 highlights substantial heterogeneity in the interest rate sensitivity across local characteristics following monetary policy changes. However, none of the characteristics I examined alter my primary finding that shorter-duration housing markets demonstrate greater interest rate sensitivity.

B.4. House Price Responses Across 1-, 2, and 3-year Horizons

Panel A of Table 4 analyzes house price responses to changes in the federal funds rate (FFR) over one-, two-, and three-year horizons. Columns 1, 3, and 5 implement the preferred baseline specification consistent with Column 5 in Panel A of Table 2. Columns 2, 4, and 6 further incorporate zip code-level economic characteristics and their interactions with FFR changes to control for potential confounding factors.

The results consistently demonstrate significantly positive coefficients on the interaction term between housing duration and FFR changes across all horizons. It suggests a greater sensitivity of house prices to interest rate changes in shorter-duration housing markets. Importantly, this relationship remains robust even after controlling for time-varying economic conditions at the zip-code level.

Additionally, the heterogeneity in interest rate sensitivity becomes particularly pronounced over the two-year horizon and remains substantial at the three-year horizon, suggesting a gradual transmission of monetary policy impacts to house prices. Specifically, Columns 1, 3, and 5 in Panel A indicate that, for a 100-basis-point reduction in the FFR, a one-standard-deviation (0.23 years) reduction in housing duration generates additional house price increases of approximately 0.25%, 0.71%, and 0.67% at the one-, two-, and three-year horizons, respectively. This gradual response aligns with existing literature (Kuttner, 2013; Williams, 2015), which identifies a gradual house price response to interest rate changes typically unfolding over a two- to three-year period.

B.5. House Price Responses to 30-Year Mortgage Rate Changes

People may be concerned that increases in short-term interest rates may not fully transmit to long-term mortgage rates. This concern arises due to the fundamental assumption underlying duration measures: a parallel shift of the yield curve. If an increase in short-term interest rate does not proportionately shift or negatively affect the long-term rate (Van Binsbergen and Grotteria, 2024), the relationship between interest rate sensitivity and duration measure may become distorted.

To directly address this potential issue, Panel B of Table 4 explicitly examines the impact of the 30-year mortgage rate on house prices across zip codes with varying housing durations. Similar to Panel A, Columns 1, 3, and 5 of Panel B present my preferred baseline specification, while Columns 2, 4, and 6 further incorporate zip-code economic characteristics and their interactions with changes in the 30-year mortgage rate.

Consistent with findings using the federal funds rate, the results robustly demonstrate greater sensitivity in shorter-duration housing markets across all time horizons analyzed. Specifically, Columns 1, 3, and 5 reveal significantly positive coefficients on the interaction terms, suggesting that a one-standard-deviation decrease in housing duration corresponds to additional house price increases of approximately 0.42%, 1.26%, and 1.56% at the one-, two-, and three-year horizons, respectively, following a 100-basis-point decrease in the 30-year mortgage rate. The findings remain robust when controlling for zip-code characteristics and their interactions with mortgage rate changes, as indicated in Columns 2, 4, and 6.

In summary, analyzing the impact of 30-year mortgage rates reinforces my central conclusion: shorter-duration housing markets consistently exhibit higher price sensitivity across multiple horizons, regardless of whether short-term or long-term interest rate changes are considered.

B.6. Robustness to Alternative Monetary Policy Shock (MPS) Measures

A potential concern is that changes in interest rates might correlate with unobserved confounding factors that also affect house price changes. Specifically, the observed higher sensitivity of house prices in shorter-duration housing markets could be driven by the unobserved confounding factors rather than interest rate shocks per se. Although including zip-code characteristics and their interactions with interest rate changes partially addresses this issue, I further strengthen my analysis by using alternative measures of monetary policy shocks (MPS) to measure the *exogenous* interest rate changes.

Table 5 illustrates the robustness of my findings across various MPS definitions. These alternative MPS measures, which are designed to capture the unexpected interest rate changes, include the one-year Treasury yield surprise, monetary policy surprises constructed by Jarociński and Karadi (2020) (JK PM MPS and Median MPS), and those developed by Bauer and Swanson (2023b) (BS MPS and BS MPS_ORTH).

Consistently, across all specifications presented in Table 5, I observe significantly positive coefficients on the interaction between housing duration and each alternative MPS measure. This persistent pattern reinforces the conclusion that shorter-duration housing markets exhibit higher sensitivity to interest rate changes, irrespective of the specific MPS measurement employed. This robustness strongly indicates that my primary finding is less likely to result from omitted confounding variables correlated simultaneously with interest rate changes and house price dynamics.

B.7. Alternative Housing Duration Measures

My primary results build on the duration measure constructed with the 5-year terminal horizon. However, the findings remain robust under alternative construction assumptions and methods. I construct two additional duration measures to validate the findings: one based on an extended 10-year holding period assumption and another derived from rent growth predictions obtained via LASSO regression with 10-fold cross-validation. By expanding the holding period to 10 years, I assume that homeowners expect to hold properties for 10 years, receive housing cash flow within the period, and finally obtain a terminal value from the house at the end of year 10. Section II.B provides a detailed description of constructing the alternative duration measures.

10-Year Holding Horizon for Duration Measure Construction

Using the 10-year duration measure, I replicate the heterogeneity analysis from my baseline specification (Table 4), presenting the results in Panel B of Internet Appendix Table IA.C3. Panel A reproduces the baseline 5-year measure results from Table 4 for direct comparison. I consistently find significantly positive coefficients on the interaction terms between housing duration and interest rate changes across all horizons. Further robustness checks using the 30-year mortgage rate changes, monetary policy surprise series from Bauer and Swanson (2023a), and other alternative monetary policy shocks (Internet Appendix Tables IA.C4, IA.C5, IA.C6, and IA.C7) reinforce my primary findings that shorter-duration housing markets exhibit greater price sensitivity to interest rate changes.

Duration from LASSO-predicted Rent Growth

Internet Appendix Table IA.C8 presents results employing a housing duration measure constructed using LASSO-selected predictors for rent growth. The detailed outcomes of the LASSO prediction regression are provided in Internet Appendix Table IA.C2. The significantly positive coefficients on the interaction terms are robust across horizons and even show a larger heterogeneity across housing duration compared to my primary baseline analysis using the duration constructed by all predictors. Additional regression details are documented in Internet Appendix Tables IA.C8 to IA.C13, further underscoring the robustness and consistency of my main findings regarding housing duration and interest rate sensitivity.

B.8. Monetary Policy Transmission to House Prices by Rental Yield

A potential concern arises from measurement errors associated with my housing duration measure, potentially driving the documented negative relationship between housing duration and interest rate sensitivity. To rigorously address the duration measurement concern, I employ an alternative proxy for duration: rental yield, defined as the ratio of rent to property price.

Under the assumption of constant rent growth and infinite future rental cash flows with the Gordon Growth Model, housing duration can be simplified to the price-to-rent ratio (the reciprocal of rental yield), as demonstrated in Greenwald et al. (2021). Empirically, I indeed find a large and negative correlation between rental yields and my primary duration measure. Theoretically, this negative relationship suggests that lower rental yield areas, equivalent to longer-duration markets, should exhibit greater price sensitivity to interest rate changes.

To validate my main findings, I reproduce the baseline analyses using rental yield as the primary explanatory variable. Internet Appendix Table IA.C17 presents heterogeneous house price responses to interest rate changes across zip codes with varying rental yields. The table consistently confirms my primary conclusions. Zip codes with higher rental yields, equivalent to shorter-duration housing markets, consistently demonstrate higher house price sensitivity to interest rate changes.

Specifically, in Panel A, Columns 1, 3, and 5 show that, following a 100-basis-point decrease in the FFR, zip codes with a one-standard-deviation (0.033) higher rental yield experience additional house price increases of approximately 0.23%, 0.65%, and 0.61%, over one-, two-, and three-year horizons, respectively. The additional price increases are economically nontrivial. For example, relative to an average two-year house price increase of approximately 1.77% after a 100-basis-point FFR cut, the additional increase of 0.65% accounts for 36.7% of the average price response. The findings are robust when controlling for local economic characteristics and their interactions with FFR changes.

Panel B investigates house price responses to changes in the 30-year mortgage rate over the same horizons. The results reinforce the main conclusion that housing markets with higher rental yields (shorter housing duration) are more sensitive to rate changes. Specifically, within two years of a 100-basis-point mortgage rate decrease, house prices increase on average by about 0.96%. A one-standard-deviation increase in rental yield (0.033), however, corresponds to an additional 1.03% price increase, which highlights substantial heterogeneity across housing markets by rental yields.

Figure 6 illustrates heterogeneity in interest rate sensitivity across zip-code rental yield quintiles. Zip codes are categorized annually into five rental yield quintiles, with quintile 1 corresponding to the lowest rental yields and quintile 5 the highest. The figure presents the differences in cumulative house price changes relative to the baseline (quintile 1) across horizons of one, two, and three years following a 100-basis-point (bps) decrease in the FFR.

The results consistently show that zip codes in higher rental yield quintiles exhibit substantially greater sensitivity to interest rate changes. For example, in the year of a 100-bps FFR cut, zip codes in the highest rental yield quintile experience a house price increase of approximately 0.41 percentage points greater than those in the lowest rental yield quintile. The response differences across rental yield quintiles magnify significantly over longer horizons, reaching about 1.31 percentage points at the two-year horizon and approximately 1.39 percentage points at the three-year horizon.

The observed monotonic increase in sensitivity across rental yield quintiles, consistent with findings in Figure 4 regarding housing duration, reinforces my primary results and mitigates concerns that outliers may be driving the identified relationship between housing duration and interest rate sensitivity.

Additional robustness analyses employing alternative monetary policy measures, such as monetary policy surprises from Bauer and Swanson (2023a), yield similar results. These analyses, detailed in Internet Appendix Tables IA.C16 through IA.C19, confirm the robustness of my primary findings.

Overall, all analyses using rental yield as the proxy for housing duration support my main conclusion: housing markets with higher rental yields, equivalent to shorter durations, exhibit significantly higher sensitivity to interest rate changes. Thus, the abnormal heterogeneity in monetary policy transmission documented by housing duration in my primary analysis remains robust, effectively mitigating potential measurement error concerns.

B.9. Robustness Checks Using Alternative Data Sources

The baseline analyses rely on the American Community Survey (ACS) data, as it provides extensive geographic and time-series coverage at the zip-code level. However, I also reproduce the analyses using alternative datasets to validate the robustness of my findings, including zip-code-level housing data from Zillow and property-level transaction data from ATTOM combined with rental listings from Altos.

In Internet Appendix F, I present robustness results based on the Zillow dataset.[19] The Zillow-based analyses produce results consistent with the baseline findings. Moreover, they indicate somewhat stronger heterogeneity in interest rate sensitivity compared with the ACS-based estimates, likely due to the more recent sample period. Consistently, I also observe stronger heterogeneity in the ACS data when restricting the analysis to more recent years.

In Internet Appendix E, analyses using combined property-level transaction data from ATTOM and rental listings from Altos further corroborate the main results. The sample spans from 2011 to

[19]Specifically, I construct the housing duration measure using the Zillow Home Value Index (ZHVI) and the Zillow Observed Rent Index (ZORI), following the methodology detailed in Section II.B. Because the ZORI data are only available from 2015 onward—later than the initial ACS coverage—the Zillow sample is primarily used for robustness tests.

2023, as the availability of Altos rental data began in 2011.[20] Results based on the ATTOM and Altos datasets closely align with the baseline results, yielding highly similar estimates and further confirming the robustness of the primary findings.

C. Property Transaction-level Heterogeneity in Monetary Policy Transmission

Exploiting the granularity of property-level transaction data, Table 6 corroborates the zip-code-level baseline results. It also addresses concerns that the observed heterogeneity in monetary policy transmission might be driven by mismeasurement of housing cash outflows from mortgage or tax-related cash flows.

Table 6 reports regressions of property-level transaction price sensitivity to FFR changes across properties with varying rental yields. The dependent variable is the cumulative two-year net price change, measured as the ratio of the actual transaction price in year t to the expected transaction price in year $t-2$ minus one. Expected prices are derived from price hedonic regressions using actual transaction prices of comparable properties, as described in Section II.C. Ex-ante property-level rental yield—negatively related to duration as documented in Internet Appendix A.A.3 and Greenwald et al. (2021)—serves as the property-level measure of housing duration.

Columns 1 and 2 reproduce the zip-code baseline analysis with the similar specifications. The estimates imply that following a 100 bps decline in the FFR, a property with a one-standard-deviation higher rental yield (≈ 0.072) have a higher transaction price increase by around 1.5 percentage points. This effect is both statistically and economically significant.

Columns 3 and 4 add mortgage-related controls: log annual mortgage payment and the loan-to-value (LTV) ratio, respectively, along with their interactions with FFR changes. Both specifications show that properties with larger mortgage payments or higher LTVs are themselves more sensitive to interest rate changes. Importantly, the coefficients on the FFR–rental-yield interaction become more negative, suggesting that mortgage obligations do not attenuate the heterogeneity. If anything, omitting mortgage outflows understates the degree to which short-duration properties are more sensitive

[20] To construct the housing duration measure at the zip-code level, I aggregate property-level transaction prices and listing rents following Zillow's published methodology. The Zillow methodology for rent indices is described at `https://www.zillow.com/research/methodology-zori-repeat-rent-27092/`, and for house price indices at `https://www.zillow.com/research/zhvi-methodology-2019-deep-26226/`. Specifically, I calculate the average of the middle 30% (35th–65th percentile) of asking rents and valid transaction prices to obtain representative mean rents and prices for each zip code and year. Realized rent growth, combined with mean house prices, is then used to construct the housing duration measure as detailed in Section II.B.

to monetary policy.

Columns 5 and 6 incorporate tax-related controls: log annual tax payment and the tax-to-value ratio, together with their interactions with FFR changes. The results again leave the main effect intact. The interaction between FFR changes and rental yield remains significantly negative, reinforcing that the higher interest rate sensitivity of shorter-duration (higher-yield) properties is not an artifact of ignoring tax-related outflows.

Overall, the property-level results confirm the main finding: short-duration properties exhibit higher price sensitivity to monetary policy changes, and this result cannot be attributed to mismeasurement of mortgage or tax-related cash flows.

IV. Discount-rate Channel: Reaching-for-Income Evidence in Housing Markets

To investigate whether reaching-for-income behavior contributes to the heterogeneity in house price sensitivity across various market segments, in this section, I will first examine whether lower interest rates increase the likelihood of properties being purchased for rental purposes, which I call "buy-to-rent" (BTR). Then, I will study the impact of this particular housing investment activity on the heterogeneity of monetary policy transmission to house prices across markets with varying housing duration.

A. Identifying Reaching-for-Income Housing Investment Activity

Using housing transaction records and historical tax assessment data from ATTOM, I identify buy-to-rent (BTR) transactions. The BTR investments are intended for long-term rental income rather than short-term capital gains. For this reason, I require a minimum *ex-post* property holding length of two years to be identified as a BTR transaction. This rule will help filter out those short-term investors, such as house flippers. Then, for each transaction, I verify whether the property is non-owner-occupied within two years of purchase. Owner-occupancy status is reported directly in the historical tax assessment data or, when missing, inferred by comparing the property and mailing addresses.[21]

A transaction is classified as BTR if the purchased property is non-owner-occupied in year $t+1$, regardless of its status in purchase year t. Thus, if a property is non-owner-occupied at purchase, it must

[21] If the property and mailing addresses differ in a given year, I classify the property in that year as non-owner-occupied. If both the occupancy status and mailing address are missing, I assume owner-occupancy. This rule biases against identifying BTR and thus will only underestimate the effect.

retain the non-owner-occupied status in the subsequent years.[22] Conversely, if the property is owner-occupied at purchase, it must switch to non-owner-occupied within two years after the purchase to be classified as BTR.[23]

While non-owner-occupied status may occasionally reflect vacation homes rather than rental properties, this concern is limited. First, only a small fraction of vacant homes are seasonal or vacation units.[24] Moreover, vacation homes do not typically require a separate mailing address for receiving tax documents, as the homeowners still have access to the property. To more rigorously validate the classification, I conduct robustness checks by linking transactions to Altos rental listing data and redefining BTR transactions as properties listed for rent within 24 months of purchase.[25] I obtain consistent results.

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

$$\begin{aligned} \mathbb{1}\{BTR\}_{i,z,c,t} = \alpha + \beta\, \Delta r_{[t-h-1,\, t-h]} \times \mathrm{RY}_{i,\, t-h-1} + \delta\, \mathrm{RY}_{i,\, t-h-1} \\ + \Gamma' X_{i,t} + \zeta_c \times \theta_t + \lambda_z + \epsilon_{i,z,c,t}, \end{aligned} \tag{23}$$

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 II.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, $\zeta_c \times \theta_t$, control for time-varying county characteristics, and zip code fixed effects, λ_z, absorb time-invariant zip-code characteristics. Identification thus arises from variation in rental yields across properties and zip codes over

[22] If a buyer lists a different mailing address in year t but moves into the property in year $t+1$, I classify the case as a migrant rather than a BTR investor.

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

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

[25] Rental listing records provide direct evidence that the property was purchased for rental purposes. Results using this alternative measure are consistent: when interest rates decline, high-rental-yield properties are disproportionately more likely to be purchased for rental use, corroborating the reaching-for-income hypothesis.

time.

With this specification, the coefficient of interest, β, measures the heterogeneity in the sensitivity of BTR activity to interest rate changes across properties with different ex-ante rental yields. A negative estimate of β implies that interest rate cuts disproportionately increase the probability of BTR activity for high-rental-yield properties, providing direct 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 indicates that as interest rates decrease, higher-rental-yield properties are more likely to be purchased for rent (BTR). Specifically, the table reports transaction-level regressions where the dependent variable equals one if a purchase is buy-to-rent (BTR). The key independent variable is the interaction between the property's *ex-ante* rental yield, $RY_{i,t-h-1}$, and the change in the FFR during the transaction year (Columns 1–2) or the prior year (Columns 3–4). All specifications include property characteristics, county-by-year fixed effects, and zip code fixed effects. Even-numbered columns additionally control for zip-level economic characteristics and their interactions with ΔFFR.

Two main patterns emerge. First, higher-yield properties are more likely to be purchased for rental on average. The coefficient on $RY_{i,t-h-1}$ is positive and significant across columns (e.g., 0.615 in Column 1), indicating that a one–standard-deviation increase in rental yield (≈ 0.075) is associated with a 4.6 percentage-point (pp) higher BTR probability. Second—and central to the reaching-for-income hypothesis—the interaction term $\Delta r_{[t-h-1,t-h]} \times RY_{i,t-h-1}$ is significantly negative in all specifications. It implies that BTR probability rises disproportionately for high-yield properties when interest rates fall. Specifically, Columns 2 and 4 show that a 100 bps FFR cut raises the likelihood that a one–standard-deviation higher-yield property is purchased for rent by about 0.95 pp (contemporaneous) and 0.9 pp (lagged), respectively. Relative to the average BTR probability of 4.6% for properties with rental yields one standard deviation above the mean, these effects represent an increase of about 21%. These effects are unlikely to be driven by stronger rental demand in high-yield markets, since the specifications already interact ΔFFR with zip-code demand proxies such as rental vacancy rates and local demographics.

Columns 5–8 instrument ΔFFR with orthogonalized monetary policy surprises (MPS) from Bauer and Swanson (2023a). The IV estimates on the interaction term remain significantly negative, confirming that the effect of rate cuts on BTR probability is concentrated in high-yield properties and is robust to using unanticipated monetary policy shocks.

Overall, Table 7 provides direct evidence of reaching-for-income behavior in housing markets. Lower interest rates make higher-yield properties more likely to be purchased for rental income than lower-yield properties. This pattern is not explained by local rental demand or other fundamentals, and is consistent with the broader evidence that declines in interest rates increase demand for income-generating assets (Daniel et al., 2021; Gargano and Giacoletti, 2022). Moreover, these results provide initial evidence that rental-income-driven investment behavior can shape local house price dynamics as interest rates change, which will be particularly examined in the next section.

B.1. Near-term Income Demand and BTR Probability

Table 9 examines whether preferences for near-term income shape the likelihood of BTR purchases across properties with different rental yields. The results provide further evidence of reaching-for-income behavior: homebuyers with stronger demand for immediate cash flows are more likely to purchase high-rental-yield properties for rent. Building on prior work showing that older or retired households disproportionately prefer assets delivering near-term income (Becker, Ivković, and Weisbenner, 2011; Jiang and Sun, 2020; Daniel et al., 2021), I construct two proxies for near-term income preference using IRS Statistics of Income (SOI) zip-code data: (i) the share of tax returns reporting taxable individual retirement arrangement (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 address zip code, which corresponds to the zip code of the homebuyer's primary residence. These proxies capture homebuyer demand for near-term investment income. For example, a buyer from a zip code with a high share of IRA withdrawals or a high taxable interest-income ratio is more likely to be older or to demand income-generating assets. Using these proxies, I then test how heterogeneity in BTR probabilities varies across homebuyers with different income preferences and across properties with different rental yields.

Table 9 shows that the BTR propensity is disproportionately higher for high-yield properties among homebuyers with stronger demand for near-term income. Columns 1 to 3 indicate that homebuyers from zip codes with a higher share of tax returns reporting taxable IRA distributions—areas more likely to contain older, income-seeking households—the responsiveness of BTR activity to rental yields is amplified following interest-rate declines. Put differently, for two otherwise similar high-yield properties, older (income-seeking) buyers are significantly more likely than younger buyers to buy to rent after a rate cut. This is reflected in the sharp decline of the coefficient on $\Delta r_{[t-2,t-1]} \times RY_{i,t-2}$ once the retirement-withdrawal proxy and its interactions are included (Columns 2–3), suggesting that the observed responsiveness of BTR to rate changes by property yields in Column 1 is primarily concentrated among income-seeking buyers. The negative and significant triple interaction term $\Delta r_{[t-2,t-1]} \times RY_{i,t-2} \times \%\text{Retirement Income File}_{i,t-2}$ confirms that near-term income demand makes the effect of rate cuts on the BTR probability of high-yield properties especially pronounced. Columns 4 to 6 reinforce this conclusion using the ratio of taxable interest income to AGI as an alternative proxy: if homebuyers from zip codes rely more on interest income, they could be more likely to purchase high-yield properties to rent after rates fall.

Overall, Table 9 provides compelling evidence of reaching-for-income behavior in housing markets. It shows that rate cuts disproportionately increase BTR activity in high-yield markets when homebuyers display stronger preferences for near-term income. This offers direct evidence of a reaching-for-income channel through which monetary easing amplifies investor demand for high-yield, short-duration housing assets, helping explain why monetary easing translates into greater price sensitivity in short-duration housing markets.

C. Realized Returns of BTR Investors

The "reaching-for-income" hypothesis posits that when interest rates fall, investors who live off income tilt toward income-generating assets, such as high-yield stocks or properties, because the income from savings accounts and short-term bonds falls with rates. If this behavior reflects a preference for short-term cash flows, these investors may accept lower realized total returns in exchange for higher near-term income when rates fall.

To test this implication, I examine realized total returns for BTR buyers who both purchase and subsequently sell a BTR property. Among all BTR transactions, I restrict the sample to two-way transactions with observed and valid resale records. The realized total return is defined as the sum of the realized capital gain and the rental income expected over the holding period. Capital gains are measured as the ratio of resale to purchase prices of the same property.[26] Specifically, for each property i

[26]By referring 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

purchased at year-month b and sold at year-month s, the realized gross return 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 $P_{i,s}$ are the observed actual purchase and sale prices, respectively, and $\widehat{\text{Rent}}_{i,\tau}$ denotes the expected monthly rental income the buyer would receive were the property rented, which is obtained from the rent hedonic estimations described in Section II.C. The rental-yield component aggregates these imputed rents over the realized holding period (excluding the purchase and sale transaction months) and scales by the observed purchase price. I then annualize the realized total returns using the holding length information.

Figure 8 illustrates how realized returns of BTR investors vary with rental yields following a 100-bp cut in the FFR one year prior to the purchase. It reveals that after the rate cut, BTR properties in higher rental yield deciles will have lower realized total returns. Specifically, properties are sorted into deciles by *ex-ante* rental yield measured prior to the rate change. For each decile, the y-axis reports the change in realized annual return (percentage points) associated with a 100-bps FFR cut. Panel A uses raw changes in FFR, while Panel B instruments FFR with the monetary policy surprises (MPS) constructed by Bauer and Swanson (2023a).

Panel A reveals a monotonic decline in realized returns as rental yields increase: following a 100 bps cut in the FFR, properties in the lowest rental-yield decile experience a reduction in realized returns of about 1.5%, while those in the highest decile experience a nearly 4.5% realized return decrease. Panel B shows a similar pattern when instrumenting FFR with MPS, but the magnitudes are substantially larger, ranging from a 6% decline for low-yield properties to nearly 12% for high-yield properties.[27] These results underscore that BTR investors in high-yield markets earn lower realized returns after rate cuts, consistent with a preference for near-term rental income even at the expense of total returns.

Table 8 presents the formal regression analysis of realized returns for BTR investors across proper-

transaction and retain the pair only if both purchase and resale are valid, as described in Internet Appendix Section B. 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.

[27] Raw FFR changes may reflect contemporaneous macro conditions—for example, rates may fall when aggregate rental yields are high—so the MPS instrument helps identify the causal effect of unexpected policy changes.

ties with varying rental yields purchased under different monetary policy environments. The results consistently indicate that when interest rates decline, investors purchasing higher-yield properties subsequently earn lower realized returns than those purchasing lower-yield properties.

Panel A uses changes in the FFR as the measure of monetary policy shocks. On average, declines in the FFR are associated with lower realized returns for BTR investors. More importantly, the interaction between FFR changes and rental yield is significantly positive across Columns 2 to 6, indicating that rate cuts are associated with disproportionately lower realized returns for properties with higher *ex-ante* rental yields relative to those with lower yields. Specifically, Column 2 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 bps prior to purchase. The results remain robust to the inclusion of controls for holding length, market-timing effects, and local economic characteristics, as well as their interactions with FFR changes in Columns 3 to 6.

Panel B instruments FFR changes with the MPS constructed by Bauer and Swanson (2023a) to address concerns about potential endogeneity. The findings are consistent with those in Panel A, but the magnitudes of the interaction terms are substantially larger. The results suggest that the effect of interest rate cuts on realized returns of high-yield properties is even more pronounced when focusing on plausibly exogenous monetary policy shocks.

Figure 9 shows how the realized returns of BTR investors respond to a 100 bps decline in the FFR across property holding horizons and *ex-ante* rental yields (RY). 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.[28]

Using raw FFR changes, Panel A indicates that at the one-year horizon, high-yield properties earn higher realized returns relative to low-yield properties following a rate cut. This finding echoes the baseline result that high-yield (short-duration) properties appreciate more strongly in the immediate aftermath of monetary easing. However, this advantage vanishes quickly: beyond two years of holding, high-yield properties underperform their low-yield counterparts, and the return gap widens monotonically with horizon length, leaving long-run realized returns substantially lower than for low-yield properties. Panel B instruments FFR changes with the MPS from Bauer and Swanson (2023a) and

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

produces even more negative estimates, suggesting that OLS coefficients may be attenuated by the endogeneity of monetary policy changes.

Overall, the figure demonstrates that investor tilts toward high-yield properties after rate cuts are unlikely to reflect forward-looking rational motives. If such motives dominated, high-yield properties should outperform relative to low-yield properties over longer horizons. Instead, the evidence is more consistent with a reaching-for-income mechanism: when rates fall, investors disproportionately chase income-generating assets that provide relatively high near-term rental income, even though this behavior entails lower total returns in the long run.

D. Reaching-for-Income Affect House Price Dynamics

The last section shows that the reaching-for-income investment activity does exist in the housing markets. That is, as the interest rates decrease, housing investors have a stronger preference for income-generating real estate assets and would be more likely to invest in properties with higher rental yield and rent them out. In this section, I further show that this housing investment motivation will have a price impact and, in the end, will drive the abnormal relationship of short duration and high house price sensitivity to interest rate changes documented in Section III.B.

D.1. Property Transition between Owner- and Renter-Occupied Status

A potential concern is that although high-rental-yield properties are more likely to be purchased for rental purposes when interest rates decline, this pattern may not necessarily generate broad price effects. In particular, the mechanism does not necessarily imply that short-duration (high-yield) markets will become more sensitive to interest rate changes. For instance, if BTR investors primarily target properties that are already renter-occupied, increased investor demand for rental houses would not put direct upward pressure on overall house prices.

Table 10 addresses this issue by examining property transitions between owner- and renter-occupied status. Panel A shows that high-rental-yield properties are, on average, significantly more likely to transition from owner to renter occupancy. Importantly, interest rate cuts amplify this tendency: following a decline in the FFR, high-yield properties exhibit an even higher probability of being converted to rental occupancy, with effects persisting up to two years after the shock. Using the MPS constructed by Bauer and Swanson (2023a) to instrument for FFR changes produces similar results, underscoring that the results are not driven by endogenous policy rate movements.

Panel B reports the reverse transition from renter to owner occupancy. First, properties with higher rental yields are less likely to transition into owner occupancy on average. Second, rate cuts further lower the likelihood: contemporaneous and lagged FFR cuts significantly reduce the probability that high-yield properties shift into owner use. Again, instrumenting with MPS corroborates the baseline findings.

In summary, the evidence in Table 10 indicates that declines in interest rates reshape the composition of the housing stock. High-rental-yield properties are increasingly likely to become renter-occupied and are less likely to become owner-occupied. These patterns are consistent with the reaching-for-income mechanism: investors facing lower interest rates disproportionately target short-duration, high-yield properties, exerting price pressure in the high-yield markets. Meanwhile, the results may rule out the alternative explanation that rising demand from first-time homebuyers drives the price pressure in high-yield markets. If that were the case, one would expect to observe greater transitions of such properties from renter to owner occupancy following interest rate cuts. The asymmetric transition dynamics thus provide direct evidence that investor-driven reaching-for-income behavior, rather than heightened owner demand, underlies the observed market dynamics in response to monetary policy.

D.2. House Price Sensitivity across Local Buy-to-Rent Activity

To test whether reaching-for-income activity drives the abnormal sensitivity of short-duration housing markets to interest rate changes, I exploit variation in local BTR intensity. Specifically, I sort zip codes into quintiles of *ex-ante* BTR transaction ratios and compare the house price response of short- and long-duration markets within each BTR quintile. This approach isolates the extent to which BTR activity amplifies the heterogeneity in price responses across housing duration.

Figure 10 shows that although shorter-duration housing markets, on average, respond more strongly to interest rate cuts than longer-duration markets, this difference is concentrated in areas with high BTR activity. In low-BTR areas, the short-versus-long gap largely disappears, and in some cases, longer-duration markets are slightly more responsive. By contrast, in the highest-BTR quintiles, short-duration markets exhibit substantially greater interest rate sensitivity, consistent with reaching-for-income activity amplifying local price reactions.

Panels A and B present results for a 100-basis-point cut in the FFR, while Panels C and D show responses to a 100-basis-point decline in the 30-year mortgage rate. At the contemporaneous horizon ($h = 0$, Panels A and C), short-duration markets unconditionally have higher price growth in response to rate cuts, but conditional on BTR intensity, this pattern only holds in high-BTR areas. At the two-year horizon ($h = 1$, Panels B and D), the findings are consistent: the high price response of short-duration markets is concentrated in high-BTR areas, and the short-versus-long-duration gap increases monotonically with BTR intensity.

Overall, these results indicate that reaching-for-income activity is an important mechanism behind the abnormal responsiveness of short-duration housing markets. Nonetheless, the persistence of higher sensitivity even after conditioning on BTR suggests that other forces could also contribute, providing a promising direction for future research.

Table 11 reports regression estimates of house price sensitivity to monetary policy changes across zip codes with varying housing duration and BTR intensity. Columns 1–4 use changes in the FFR as the interest rate measure, while Columns 5–8 use changes in the 30-year mortgage rate. Columns 1, 2, 5, and 6 present contemporaneous responses ($h = 0$), while Columns 3, 4, 7, and 8 report cumulative responses over a two-year horizon ($h = 1$).

The results suggest that reaching-for-income behavior by housing investors largely explains the high interest rate sensitivity in short-duration markets. In the baseline specification without controls for BTR intensity (Columns 1, 3, 5, and 7), shorter-duration markets consistently show stronger price responses to rate cuts, with magnitudes comparable to the baseline estimates in Table 4.

Once local BTR intensity is taken into account (Columns 2, 4, 6, and 8), the pattern changes substantially. In low-BTR areas, the sensitivity gap between short- and long-duration markets largely disappears. By contrast, in high-BTR areas, short-duration markets become disproportionately more sensitive to rate changes, as indicated by the significantly positive coefficients on the triple interaction term $\Delta r_{[t-1,t]} \times \text{Duration}_{z,t-1} \times \text{BTR\%}_{z,t-1}$.

Specifically, at the contemporaneous horizon ($h = 0$), the coefficients on $\Delta r_{[t-1,t]} \times \text{Duration}_{z,t-1}$ are insignificant in Columns 2 and 6, implying that once BTR activity is accounted for, short-duration markets no longer exhibit greater sensitivity to interest rate changes. In fact, Column 6 shows a negative (though insignificant) coefficient, suggesting that long-duration markets may even respond more strongly when BTR activity is minimal. At the two-year horizon ($h = 1$), the coefficients on

$\Delta r_{[t-1,t]}\times\text{Duration}_{z,t-1}$ are 47% to 68% smaller than in the baseline. The results again point to BTR intensity as an important driver of the abnormal heterogeneity in market responses to interest rate changes.

In summary, the results highlight reaching-for-income behavior as a key mechanism behind the heterogeneous transmission of monetary policy to local house prices. When rates fall, investors with strong preferences for rental income disproportionately enter high-yield, short-duration markets. Their inflows raise local prices and lower discount rates, particularly for high-yield, short-duration markets, which in turn generate the high interest rate sensitivity of short-duration markets documented in the baseline results.

V. Cash-flow Channel and Other Potential Mechanism

A. Cash-flow Channel

Table 12 evaluates whether the cash-flow channel can explain the stronger interest rate sensitivity of short-duration housing markets documented in the baseline results. As outlined in Section I.D, the cash-flow channel predicts that if rate cuts disproportionately raise expected cash flows in short-duration markets relative to long-duration ones, and the gap is sufficiently large, the conventional positive mapping between duration and sensitivity could be overturned. The regressions test this prediction by examining how changes in the federal funds rate (FFR) affect revisions in expected log rents at horizons $h = 1$ through $h = 5$ (Columns 1–10) and revisions in expected terminal house values (Columns 11–12) across markets with different durations.

The coefficient of interest is the interaction $\Delta r_{[t-1,t]} \times Duration_{z,t-1}$, which captures how interest rate changes affect revisions in expected cash flows differently by housing duration. Across horizons, this coefficient is consistently negative, indicating that longer-duration markets experience larger upward revisions in expected housing cash flows following rate cuts. The effect is statistically significant in specifications without county-by-year and zip-code fixed effects, and although it weakens once these fixed effects are added, the point estimates remain consistently negative. The findings are robust when examining the expectation revisions two years after (including) rate changes, as shown in the Internet Appendix. Thus, instead of boosting expected cash flows more in short-duration markets, monetary easing tends to raise expected housing cash flows more in long-duration markets.

This pattern is directly at odds with the duration-sensitivity inversion observed in the baseline results, where short-duration markets show larger price increases after rate cuts. If the cash-flow channel were the driver, one would expect larger upward revisions to expected housing cash flows in short-duration rather than long-duration markets, which is not the case. Instead, Table 12 shows that the cash-flow channel works in the opposite direction: it reinforces the conventional duration principle that long-duration assets should have a higher interest rate sensitivity.

Overall, these findings rule out the cash-flow channel as the driver of the stronger sensitivity in short-duration housing markets and instead reinforce the role of the discount-rate channel operating through investor "reaching-for-income" behavior.

B. "Reaching-for-Yield" Mechanism

The concept of "reaching-for-yield" differs fundamentally from "reaching-for-income" in that "reaching-for-yield" reflects investors' risk appetite. Formally, Campbell and Sigalov (2022) defines reaching for yield as a tendency to take more risk when the real interest rate declines while the risk premium remains constant, though most previous papers emphasize the low *level* of interest rate rather than the *change* of interest rate in their definition.[29] By contrast, "reaching-for-income" primarily focuses on *change* of interest rate and emphasizes how declines in interest rates induce investors to tilt toward higher current-income assets (Jiang and Sun, 2020; Daniel et al., 2021).

Internet Appendix Table IA.C15 evaluates whether the inverse duration–sensitivity relationship can be explained by differences in local housing market risk and, in particular, a reaching-for-yield channel. Using five years of monthly house price data, I construct (i) a zip-code housing market beta, defined as the correlation between local and national price growth scaled by their volatilities, following Frazzini and Pedersen (2014),[30] and (ii) the volatility of local price growth relative to national volatility. Second, I calculate the volatility of local house price growth, scaled by national volatility, as an alternative proxy for local housing market risk. The results show that the inverse duration-sensitivity relationship persists after controlling for local housing market risk measures, as well as their interactions with interest rate changes. Controlling for local housing risk does not materially alter the estimated duration effect. This evidence rules out differences in local housing risk and a risk-

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

[30] This estimated beta is the same as the one estimated by regressing local price change on aggregate market price change. Empirically, I do find that the results yielded by the two methods are very close.

based reaching-for-yield channel as explanations for the high sensitivity of short-duration housing markets to monetary policy changes.

VI. Conclusion

This paper asks whether duration measures the *true* interest-rate sensitivity of house prices. It does not. Contrary to the positive mapping between duration and sensitivity observed in bonds and equities, I document an inversion in housing markets: shorter-duration (high-rental-yield) markets respond more strongly to monetary policy. I establish this fact with a new zip-code–level measure of housing duration based on Macaulay duration and confirm it at the property level using 30 million transactions combined with rental listings. The effect is robust across horizons, specifications, alternative duration constructions, and data sources.

The property-level evidence points to the discount-rate channel as the driver: after rate cuts, buy-to-rent investors "reach for income," reallocating toward high-yield, short-duration properties, bidding up prices, and lowering discount rates disproportionately more in short- than in long-duration markets. This investor-driven, non-parallel shift in the housing term structure explains the inversion.

These findings have practical 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.

The results also bear on monetary policy. Transmission to housing is not uniform: rate cuts stimulate short-duration markets more strongly and reallocate housing stock from owner- to renter-occupancy in high-yield areas. Accounting for investor preferences for near-term income can improve quantitative models of monetary policy transmission.

Several limitations point to avenues for future work. First, while the reaching-for-income mechanism explains much of the inversion, it is unlikely to be the only force at play. Residual excess sensitivity of short-duration markets suggests that other channels may matter and deserve closer study. Second, the micro-foundations of reaching-for-income remain unresolved: does it reflect rational motives such as income-smoothing under borrowing constraints and liability matching, or behavioral forces such as yield-chasing heuristics, money illusion, or heterogeneous beliefs? Distinguishing these explanations would sharpen our understanding of investor behavior. Third, the broader social consequences of reaching-for-income investment remain underexplored. By reallocating housing stock toward rental use and amplifying price sensitivity in high-yield markets, this behavior may affect affordability, tenure choices, and distributional outcomes. Future research should link the financial mechanisms identified here to welfare and policy design.

In sum, duration remains foundational for thinking about interest rate risk, but the housing cross-section defies the bond intuition: shorter-duration markets are more policy-sensitive. Recognizing and modeling the investor-driven discount-rate channel that produces this inversion helps reconcile the facts, improves risk measurement, and sharpens our understanding of how monetary policy transmits to one of the largest asset classes in the economy.

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 (2023b). To construct the raw MPS measurement, Bauer and Swanson (2023b) 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 (2023b)

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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 z in year t.	Zillow
$\text{Duration}_{z,t}$	Housing cash flow duration measurement constructed with the assumed holding horizon of five years. We 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 II.B for construction details.	Estimation
$\text{RY}_{z,t}$	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: $$\text{RY}_{z,t} = \frac{\text{Median Gross Rent}_{z,t} \times 12}{\text{Median Home Value}_{z,t}},$$ 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

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Variable	Definition	Source
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
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

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Variable	Definition	Source
% $\text{BTR}_{z,t}$	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 I.	Altos and ATTOM

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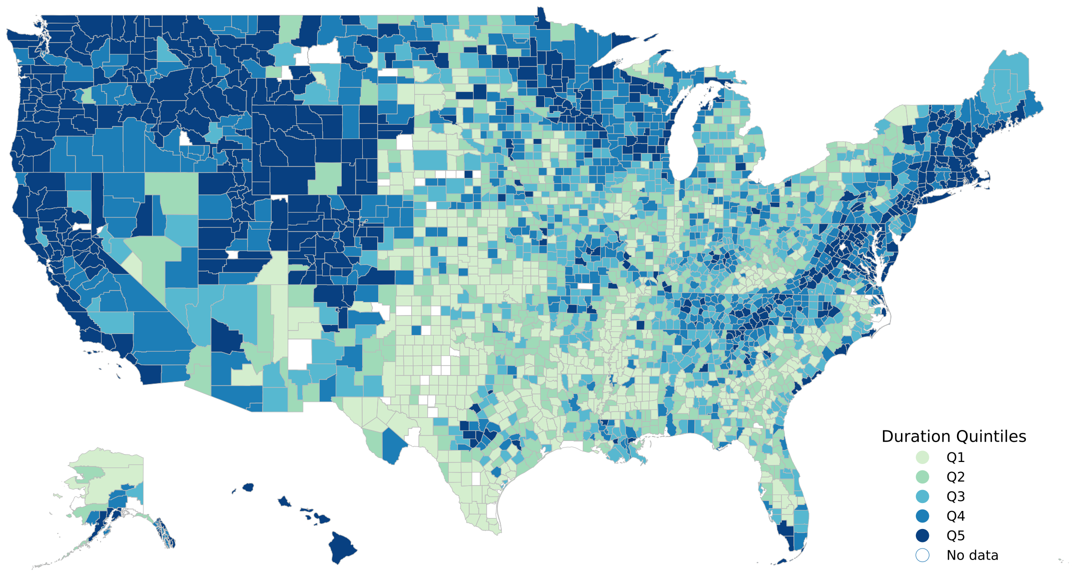
Figure 2. County-level Geographic Heterogeneity in Housing Duration

Panel A: Duration



Panel B: Rental Yield

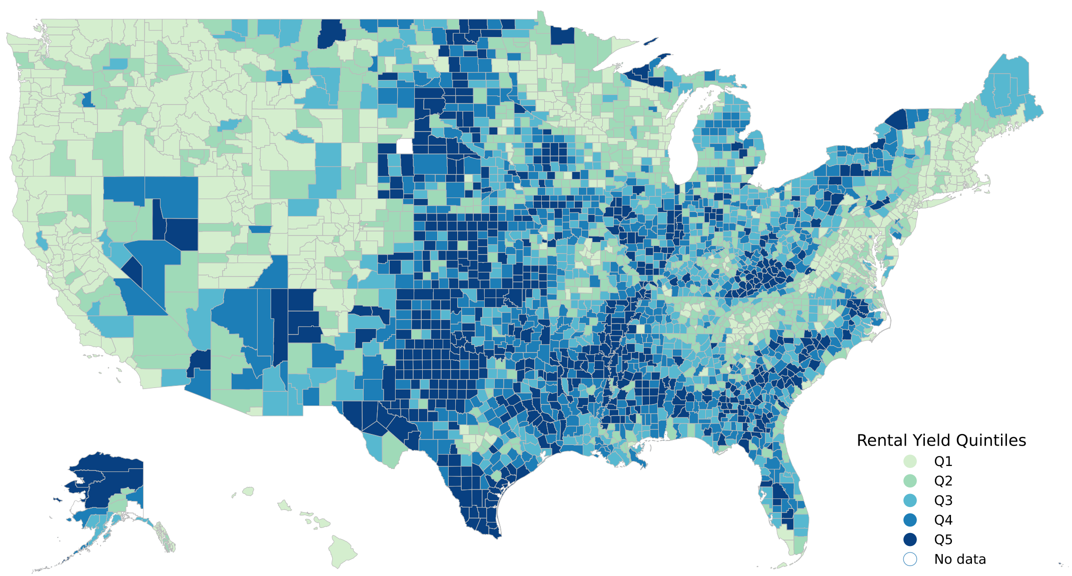


Figure 2 presents county-level geographic heterogeneity in housing duration (Panel A) and rental yield (Panel B). Both panels categorize counties into quintiles (Q1 to Q5), with darker shading indicating higher quintile values. Panel A illustrates the geographic distribution of housing durations. The detailed estimation procedures for housing duration at the zip-code level are provided in Section II.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. Percentage of Explained Housing Duration Variation

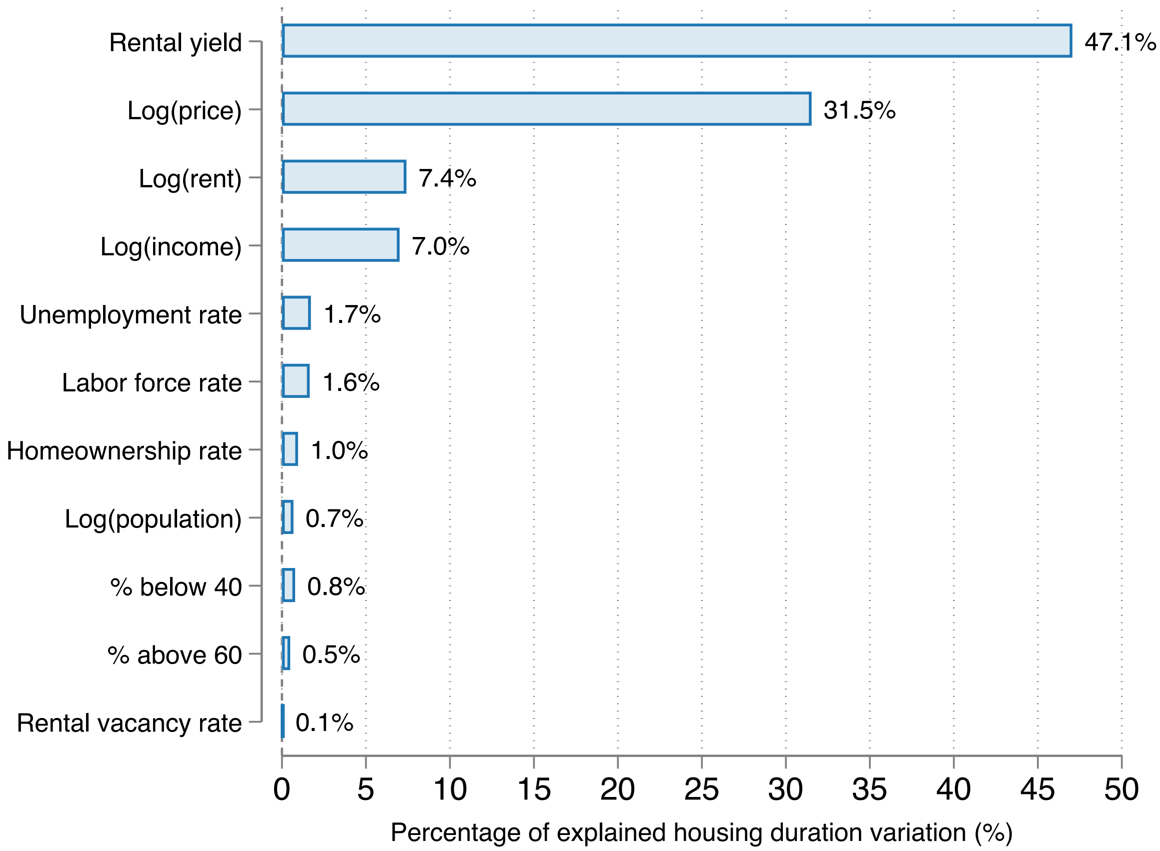


Figure 3 illustrates the proportion of housing duration variation attributed *uniquely* to each explanatory variable, estimated from a dominance analysis. The dominance analysis is a methodology designed to assess the relative importance of explanatory variables by decomposing the total variation explained in a regression model into unique contributions from each factor. Specifically, this analysis employs the Shapley value decomposition technique, derived from cooperative game theory, to allocate the explained variance among explanatory variables based on their average marginal contributions across all possible model combinations. The x-axis shows the percentage of explained housing duration variation, while the y-axis lists the examined local characteristics.

Figure 4. Heterogeneity in House Price Sensitivity across Housing Duration Quintiles

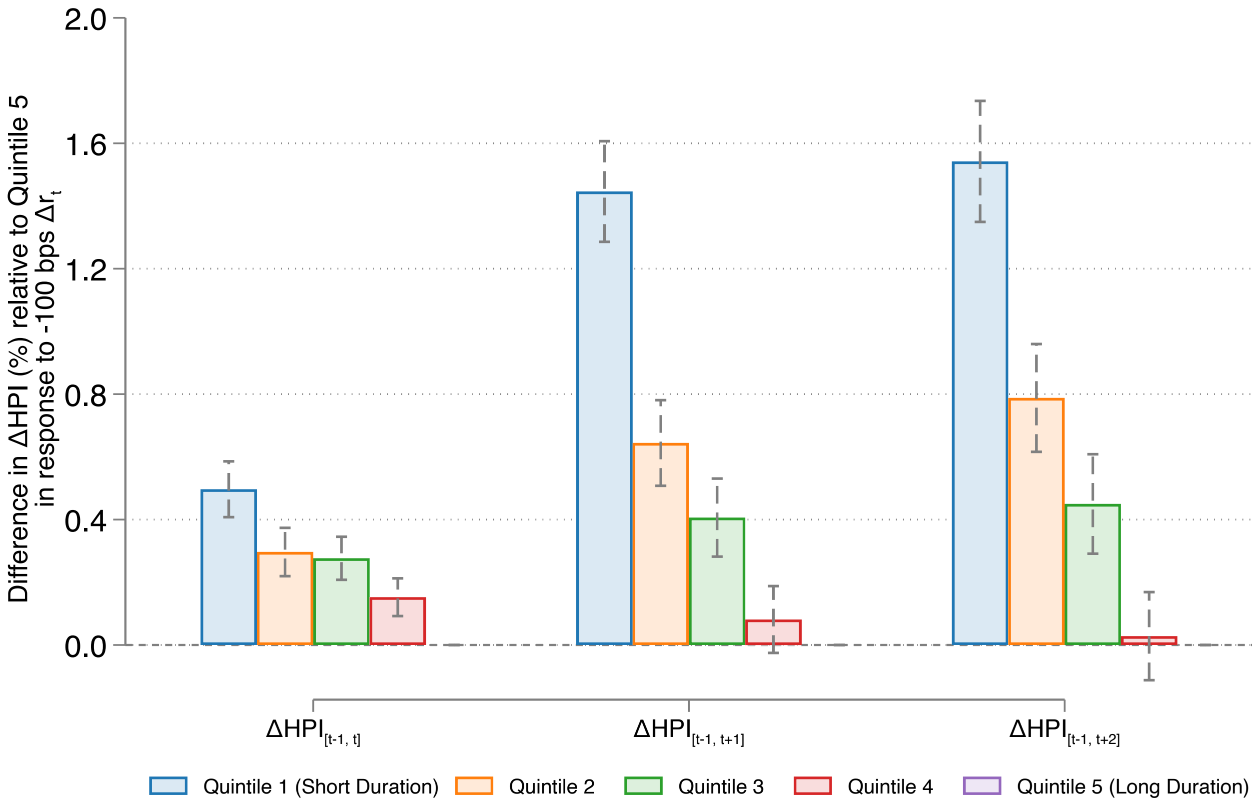


Figure 4 presents the heterogeneous responses of house prices across these duration quintiles following a 100 basis-point (bps) reduction in the federal funds rate (FFR). Specifically, the figure highlights the relative differences in house price changes over horizons of 1, 2, and 3 years for each duration quintile compared to quintile 5 (baseline group). Each year, zip codes are categorized into five housing duration quintiles, which are represented by five bars respectively. Quintile 1 represents zip codes with the shortest housing cash flow durations, while quintile 5 includes those with the longest housing durations. The interest rate shock is introduced at horizon 0, representing the period from 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 quintile 5 (long duration) group. The analysis employs the same regression specification as Column 5 of Table 2 Panel A for each horizon, as presented in the following:

$$\Delta HPI_{z,c,[t-1,t+h]} = \alpha_h + \beta_{1,h}\,\Delta r_{[t-1,t]} \times \text{Duration Quintile}_{z,t-1} + \beta_{2,h}\,\text{Duration Quintile}_{z,t-1} + \zeta_c \times \theta_t + \lambda_z + \epsilon_{z,c,t,h},$$

where $\Delta HPI_{z,c,[t-1,t+h]}$ is the cumulative house price change of zip code z in county c from year $t-1$ to $t+h$. $\Delta r_{[t-1,t]}$ indicates the annual change in the federal funds rate from year $t-1$ to t. Duration $\text{Quintile}_{z,t-1}$ is a categorical variable ranging from 1 to 5, indicating the quintile ranking of housing cash flow duration for zip code z in year $t-1$. The term $\zeta_c \times \theta_t$ represents the county-year fixed effects, and λ_z denotes the zip code fixed effects. The gray-capped error bars indicate 95% confidence intervals. Standard errors are clustered at the zip code level.

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

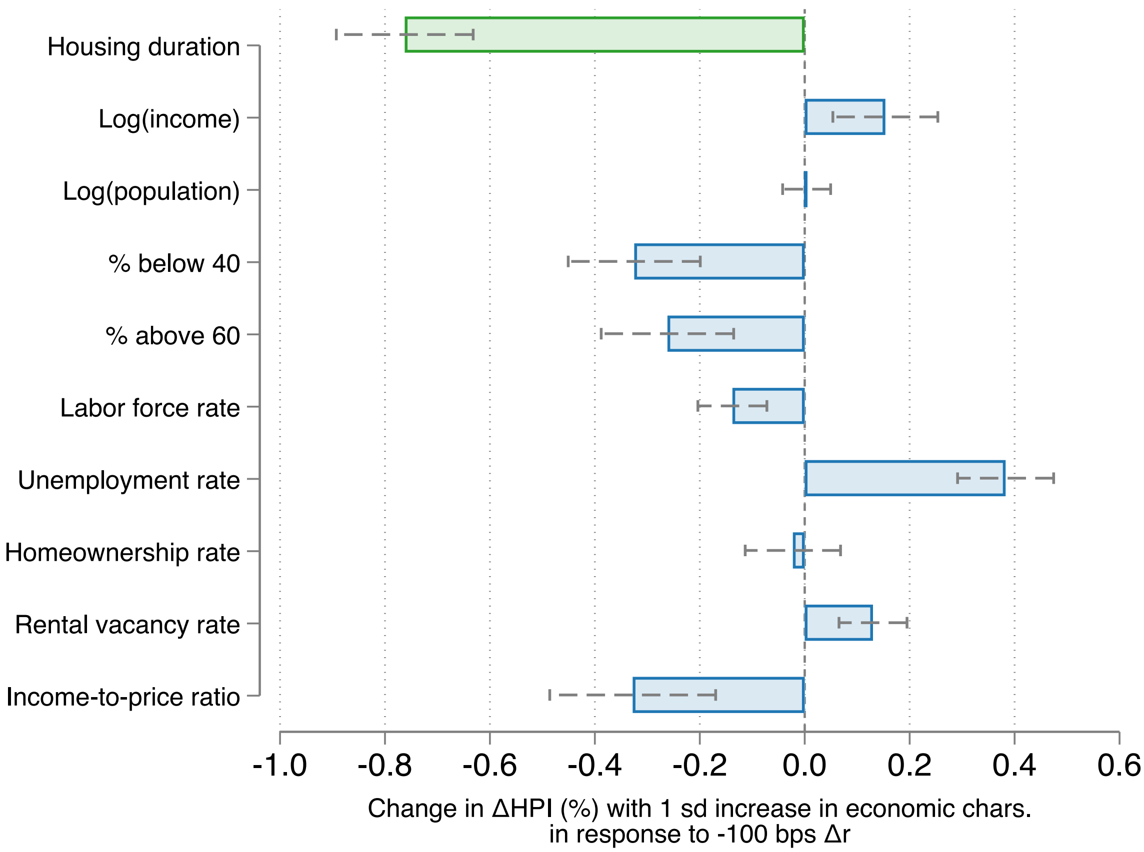


Figure 5 explores the heterogeneous house price response to interest rate changes across diverse zip-code demographic and economic characteristics. Specifically, it illustrates the additional two-year cumulative house price change associated with a one-standard-deviation (sd) increase in each characteristic following a 100-basis-point decrease in the federal funds rate (FFR). The interest rate shock is introduced at horizon 0, representing the period from year $t-1$ to t. The x-axis indicates the additional two-year cumulative house price change, $\Delta HPI_{z,c,[t-1,t+1]}$, associated with a one standard deviation (sd) increase in a specific characteristic following the negative interest rate shock. The y-axis lists the economic characteristics examined. The heterogeneity is estimated using the regression specification employed in Column 3 of Table 3, as indicated in the following:

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

where $\Delta HPI_{z,c,[t-1,t+1]}$ denotes the two-year cumulative house price change in zip code z, county c, from year $t-1$ to $t+1$, and $\Delta r_{[t-1,t]}$ represents the annual change in the FFR from year $t-1$ to t. The variable $\text{Duration}_{z,t}$ captures housing duration at the zip-code-year level. The term $\zeta_c \times \theta_t$ represents the county-year fixed effects, and λ_z denotes the zip code fixed effects. 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 House Price Sensitivity across Rental Yield Quintiles

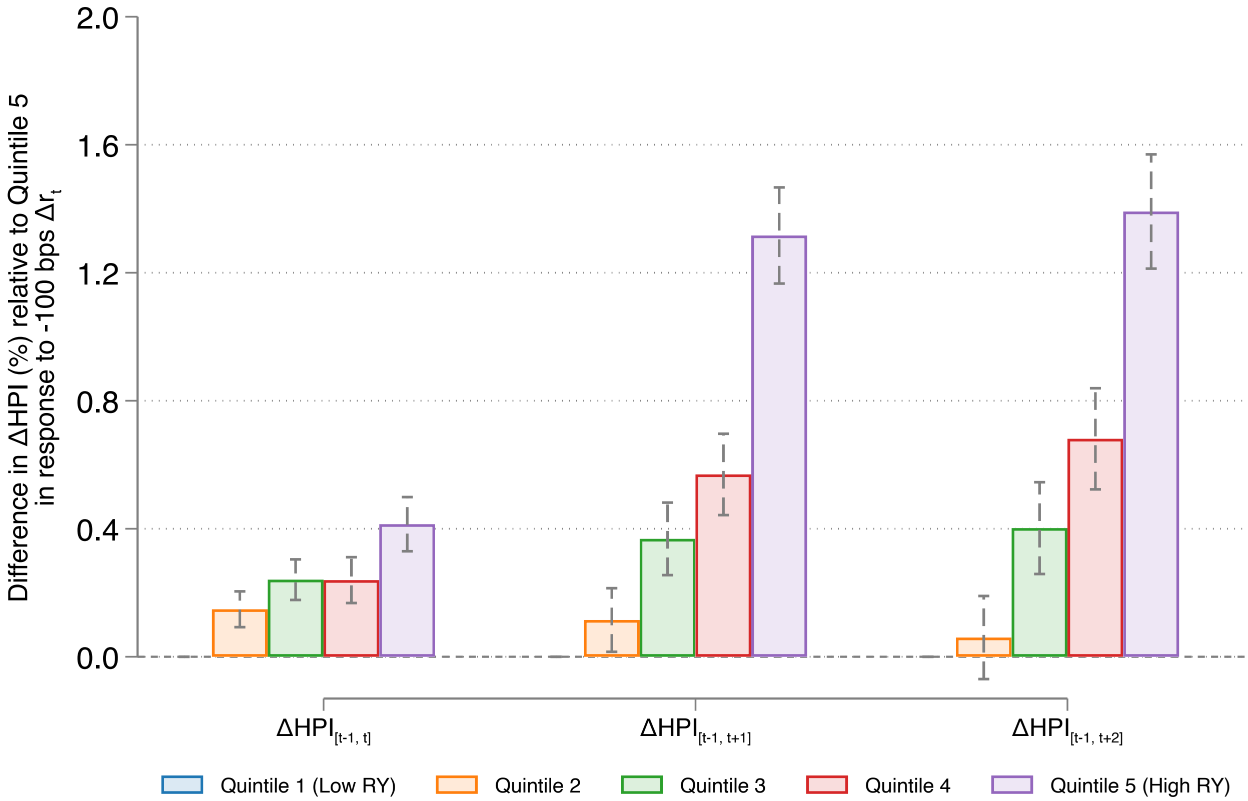


Figure 6 illustrates the differences in house price responses across zip-code rental yield quintiles following a 100 basis-point (bps) decrease in the federal funds rate (FFR), compared to quintile 1 (baseline group). Each year, zip codes are categorized into five rental yield quintiles, which are represented by five bars respectively. Quintile 1 represents zip codes with the lowest rental yield, while quintile 5 includes those with the highest rental yield. The interest rate shock is introduced at horizon 0, representing the period from 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 quintile 5 (long duration) group. The analysis employs the same regression specification as Column 5 of Table 2 Panel A for each horizon, as presented in the following:

$$\Delta HPI_{z,c,[t-1,t+h]} = \alpha_h + \beta_{1,h}\, \Delta r_{[t-1,t]} \times \mathrm{RY}_{z,t-1} + \beta_{2,h}\, \mathrm{RY}_{z,t-1} + \zeta_c \times \theta_t + \lambda_z + \epsilon_{z,c,t},$$

where $\Delta HPI_{z,c,[t-1,t+h]}$ is the cumulative house price change of zip code z in county c from year $t-1$ to $t+h$. $\Delta r_{[t-1,t]}$ indicates the annual change in the federal funds rate from year $t-1$ to t. $\mathrm{RY}_{z,t-1}$ is a categorical variable ranging from 1 to 5, indicating the quintile ranking of rental yield for zip code z in year $t-1$. The term $\zeta_c \times \theta_t$ represents the county-year fixed effects, and λ_z denotes the zip code fixed effects. The gray-capped error bars indicate 95% confidence intervals. Standard errors are clustered at the zip code level.

Figure 7. Average Estimated Rental Yield of Transacted Properties

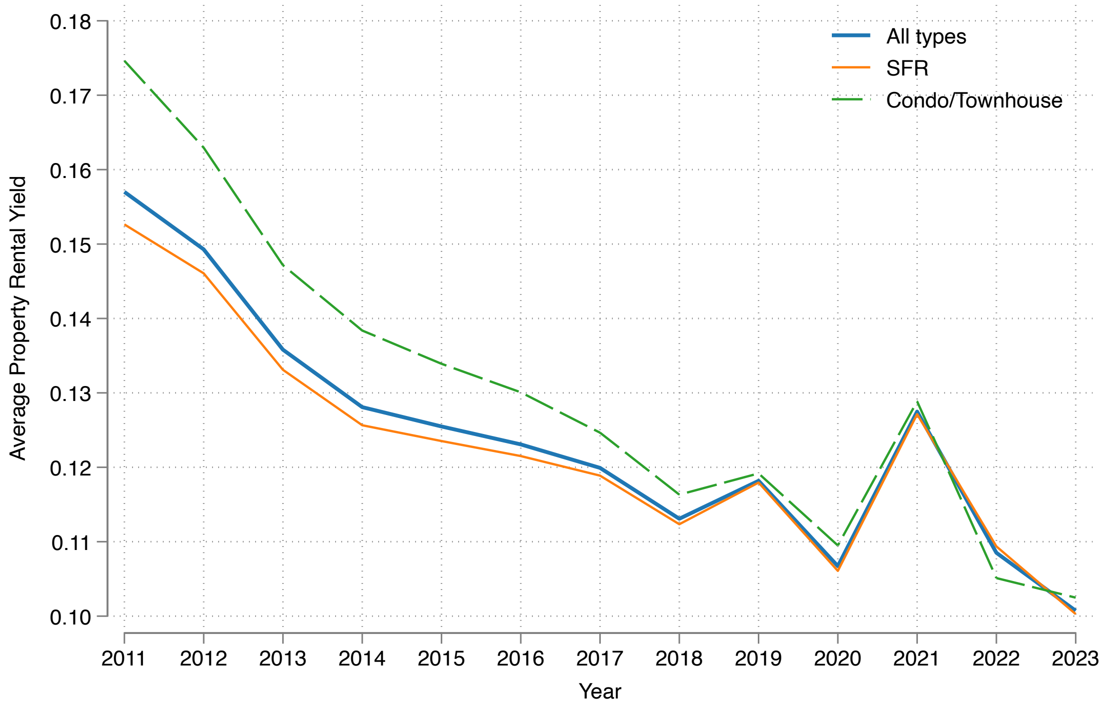
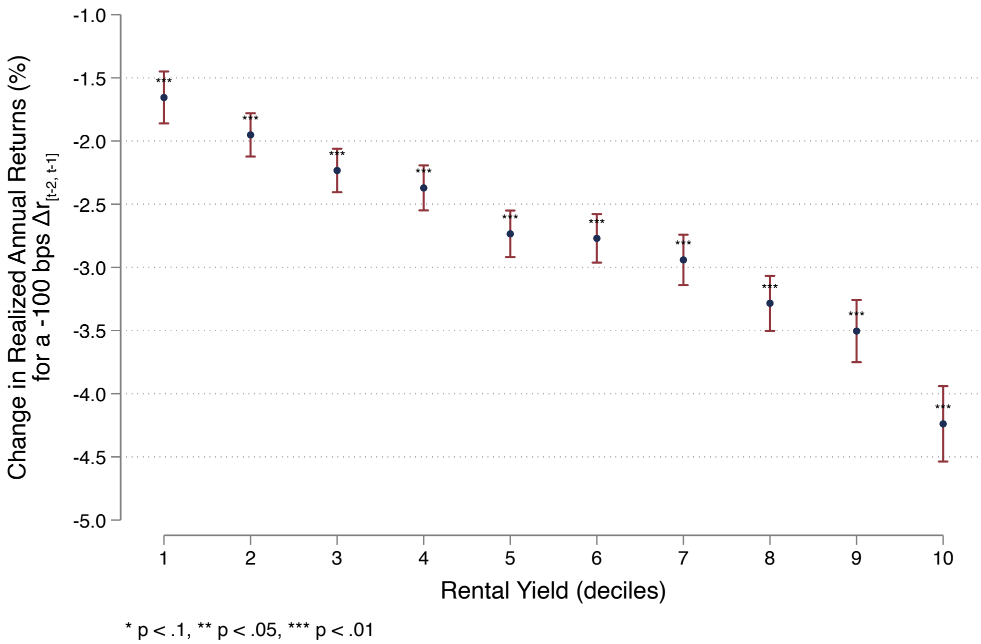


Figure 7 illustrates the annual average estimated rental yields of transacted properties from 2011 to 2023, categorized by property type. For each year and for all properties with characteristics available, I estimate property-level rental yields using hedonic models. The details of the estimation methodology are provided in Section II.C. Using the estimated rental yields, the figure presents the annual averages of transacted properties across different property types, as indicated in the legend.

Figure 8. 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

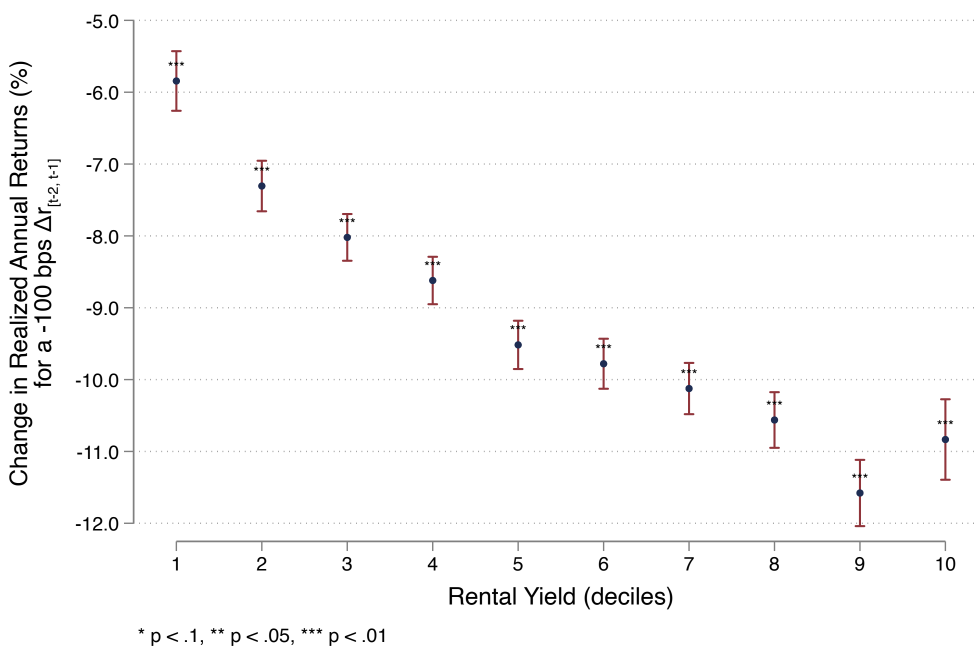
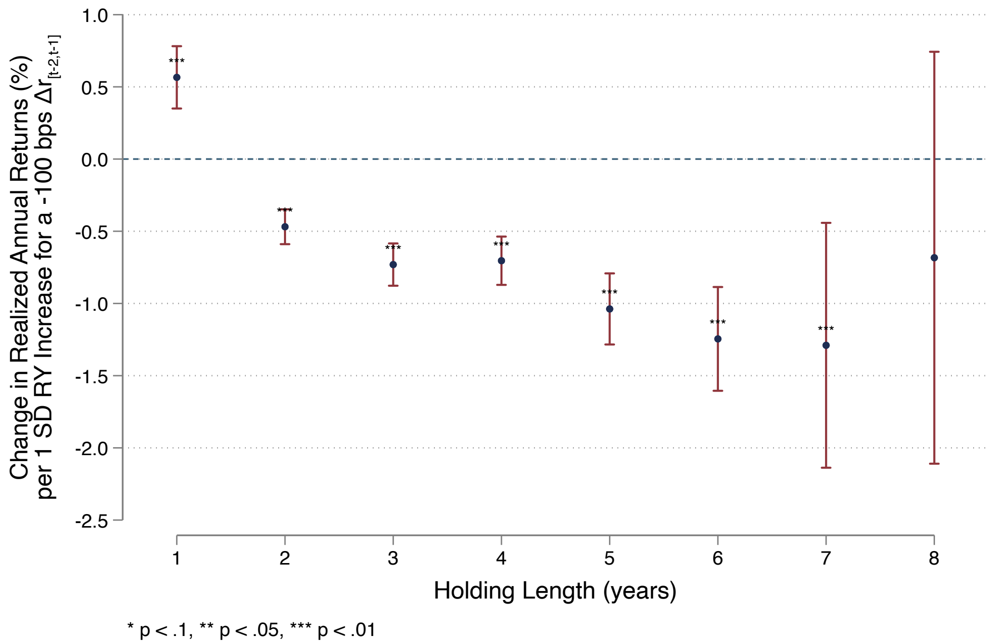


Figure 8 illustrates the heterogeneous effects of changes in the Federal Funds Rate (FFR) on the realized annual returns of Buy-to-Rent (BTR) investors across property rental yield and the length of the property holding period. Each point represents the estimated change in realized annual return (in 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 use the orthogonalized monetary policy surprise (MPS) measure of Bauer and Swanson (2023a) 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 9. Change in Realized Returns of BTR Investors by Holding Length

Panel A: Raw FFR Changes



Panel B: FFR Changes Instrumented by MPS

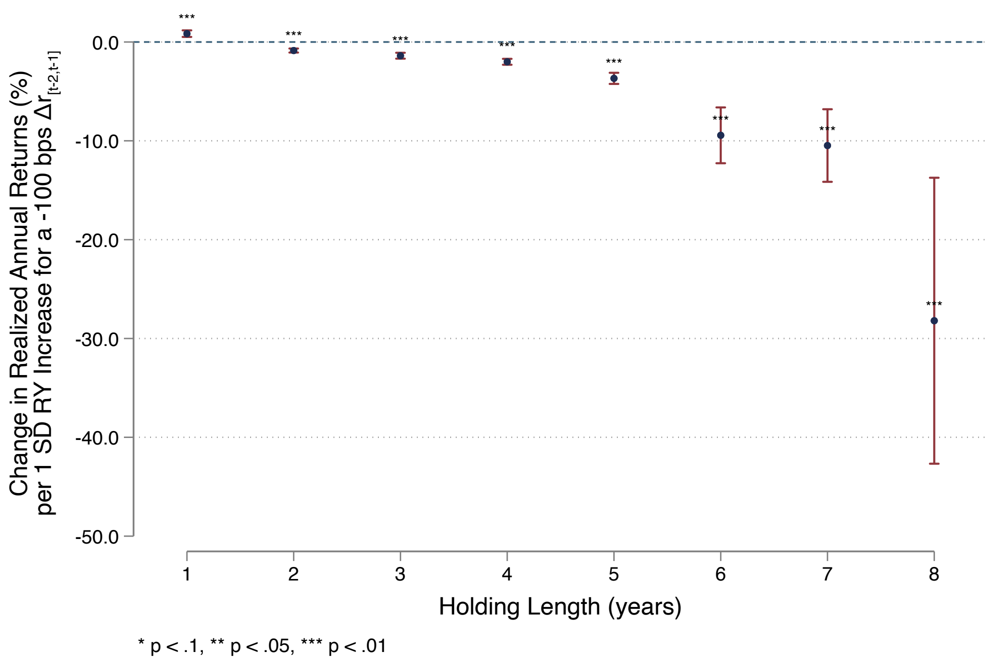


Figure 9 illustrates the heterogeneous effects of changes in the Federal Funds Rate (FFR) on the realized annual returns of Buy-to-Rent (BTR) investors across property rental yield and the length of the property holding period. Each point represents the estimated change in realized annual return (in 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 use the orthogonalized monetary policy surprise (MPS) measure of Bauer and Swanson (2023a) 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. Heterogeneity in House Price Sensitivity to Interest Rates across Buy-to-Rent Ratio Quintiles and Housing Duration

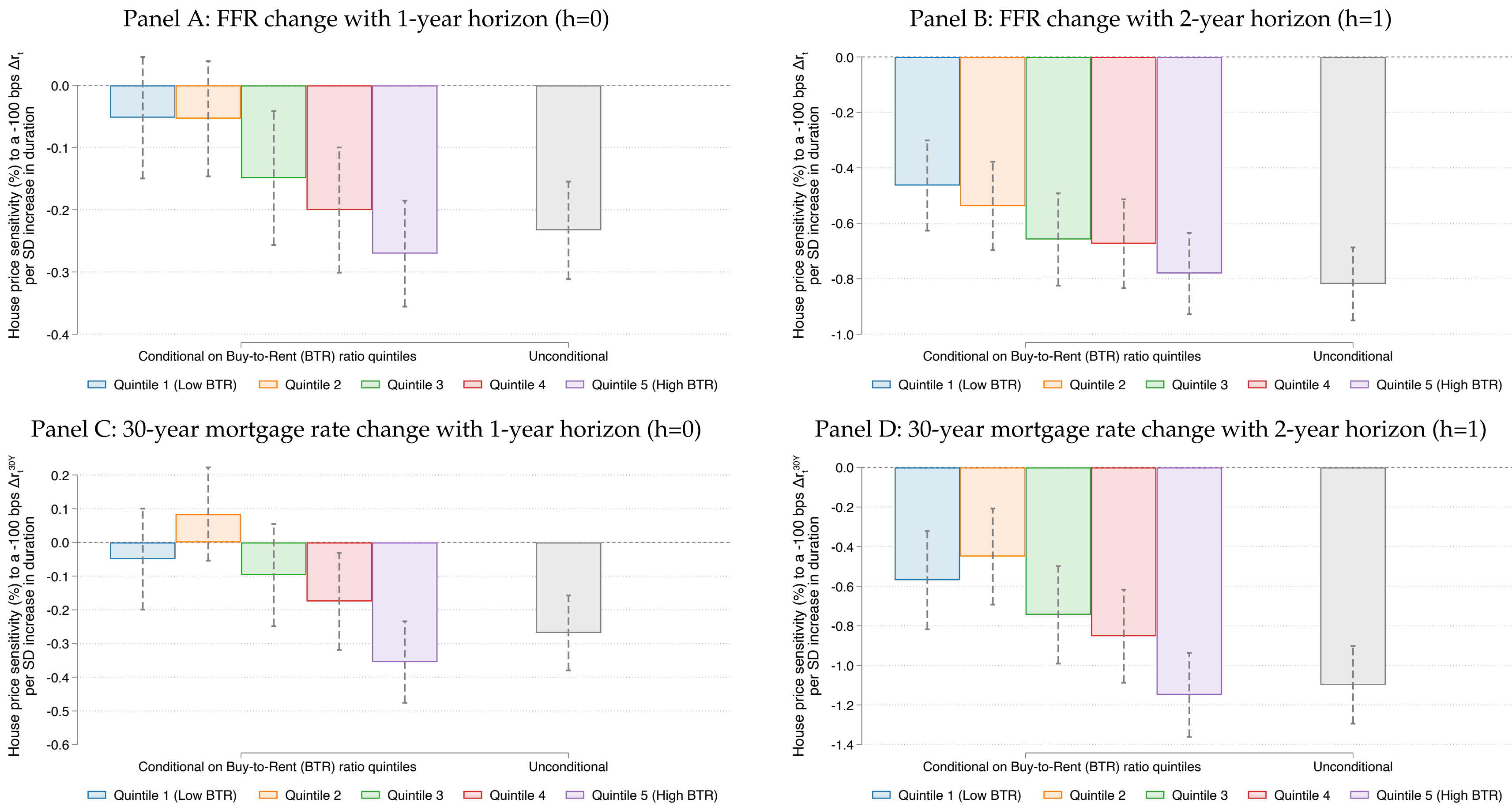


Figure 10 illustrates the heterogeneous sensitivity of house prices to interest rate reductions across zip-code Buy-to-Rent (BTR) ratio quintiles. Panels A and B present the additional increase in house prices associated with a one-standard-deviation (SD) increase in zip-code housing duration following 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:

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

The rightmost gray bar represents the unconditional house price sensitivity across all zip codes, estimated via Equation 22. 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. Sumary Statistics

	Mean	SD	P5	P25	Median	P75	P95
Panel A: Housing Duration and Cash Flow Characteristics							
Duration	4.467	0.230	4.026	4.356	4.504	4.628	4.766
Duration 5Y^{LASSO}	4.468	0.229	4.029	4.358	4.505	4.628	4.766
Duration 10Y	7.861	0.807	6.342	7.426	7.961	8.434	8.990
Duration 10Y^{LASSO}	7.865	0.803	6.352	7.433	7.965	8.435	8.988
Rental yield	0.063	0.033	0.025	0.041	0.056	0.076	0.126
Log(rent growth)	0.038	0.046	-0.023	0.012	0.034	0.061	0.110
Log(price)	12.44	0.73	11.24	11.94	12.43	12.93	13.65
Panel B: House Price Changes over 3-year Horizons							
Δ HPI$_{z,[t-1,t]}$	0.078	0.066	-0.009	0.036	0.069	0.110	0.198
Δ HPI$_{z,[t-1,t+1]}$	0.157	0.116	0.000	0.079	0.141	0.219	0.371
Δ HPI$_{z,[t-1,t+2]}$	0.252	0.159	0.037	0.143	0.233	0.339	0.541
Panel C: Local Characteristics							
Log(income)$_{z,t-1}$	11.01	0.45	10.25	10.72	11.02	11.32	11.72
Log(population)$_{z,t-1}$	10.08	0.74	8.70	9.73	10.21	10.57	11.05
% below 40$_{z,t-1}$	0.530	0.092	0.391	0.478	0.531	0.585	0.665
% above 60$_{z,t-1}$	0.205	0.079	0.108	0.156	0.195	0.236	0.326
Labor force rate$_{z,t-1}$	0.650	0.076	0.515	0.614	0.659	0.698	0.757
Unemployment rate$_{z,t-1}$	0.076	0.042	0.029	0.047	0.065	0.093	0.158
Homeownership rate$_{z,t-1}$	0.575	0.184	0.234	0.459	0.593	0.714	0.844
Rental vacancy rate$_{z,t-1}$	0.065	0.056	0.014	0.034	0.055	0.082	0.141
Log(income-to-price)$_{z,t-1}$	-1.380	0.482	-2.256	-1.675	-1.318	-1.028	-0.709

Panel D: Correlation of Housing Duration and Local Characteristics

		1	2	3	4	5	6	7	8	9	10	11
1	Duration	1.000										
2	Rental yield	-0.991***	1.000									
3	Log(income)	0.573***	-0.564***	1.000								
4	Log(population)	0.076***	-0.086***	0.095***	1.000							
5	% below 40	-0.192***	0.180***	-0.332***	0.235***	1.000						
6	% above 60	0.130***	-0.127***	0.189***	-0.269***	-0.892***	1.000					
7	Labor force rate	0.243***	-0.254***	0.408***	0.180***	0.347***	-0.522***	1.000				
8	Unemployment rate	-0.423***	0.456***	-0.664***	-0.020***	0.219***	-0.190***	-0.340***	1.000			
9	Homeownership rate	0.022***	-0.036***	0.558***	0.004	-0.557***	0.414***	0.002	-0.319***	1.000		
10	Rental vacancy rate	-0.089***	0.094***	-0.132***	-0.251***	-0.185***	0.246***	-0.242***	0.112***	0.054***	1.000	
11	Log(income-to-price)	-0.789***	0.749***	-0.189***	-0.074***	0.021***	-0.054***	0.018***	0.090***	0.382***	0.067***	1.000

Table 1 presents summary statistics of key variables in the analysis. Panel A reports housing duration and associated cash flow characteristics. Panel B describes house price changes over one-, two-, and three-year horizons. Panel C provides descriptive statistics for zip-code socioeconomic and housing market characteristics. Panel D 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

	Δ 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

	Δ 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

	Δ 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 II.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 Housing Duration, Controlling for Local Economic Characteristics

	Δ HPI$_{z,[t-1,t+1]}$		
	(1)	(2)	(3)
$\Delta r_{[t-1,t]} \times$ Duration$_{z,t-1}$	3.021***	2.957***	3.314***
	(0.158)	(0.158)	(0.289)
Duration$_{z,t-1}$	-0.278***	-0.052**	-0.056***
	(0.017)	(0.022)	(0.022)
Δ HPI$_{z,[t-2,t-1]}$	0.180***	0.124***	0.129***
	(0.014)	(0.013)	(0.013)
$\Delta r_{[t-1,t]} \times$ log(income)$_{z,t-1}$			-0.342***
			(0.114)
$\Delta r_{[t-1,t]} \times$ log(population)$_{z,t-1}$			-0.005
			(0.031)
$\Delta r_{[t-1,t]} \times$ % below 40$_{z,t-1}$			3.547***
			(0.701)
$\Delta r_{[t-1,t]} \times$ % above 60$_{z,t-1}$			3.316***
			(0.816)
$\Delta r_{[t-1,t]} \times$ labor force rate$_{z,t-1}$			1.809***
			(0.440)
$\Delta r_{[t-1,t]} \times$ unemployment rate$_{z,t-1}$			-9.115***
			(1.112)
$\Delta r_{[t-1,t]} \times$ homeownership rate$_{z,t-1}$			0.123
			(0.252)
$\Delta r_{[t-1,t]} \times$ rental vacancy rate$_{z,t-1}$			-2.307***
			(0.586)
$\Delta r_{[t-1,t]} \times$ income-to-price ratio$_{z,t-1}$			0.680***
			(0.167)
Adjusted R^2	0.807	0.818	0.820
Observations	60,920	60,920	60,920
County × Year FE	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes
Zip Economic Chars		Yes	Yes

Table 3 presents heterogeneous impacts of annual changes in the federal funds rate (FFR) on two-year house price growth across zip codes with varying housing duration levels, controlling for local economic characteristics. The dependent variable, $\Delta HPI_{z,[t-1,t+1]}$, represents the house price growth 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. The key explanatory variable, $\Delta r_{[t-1,t]} \times Duration_{z,t-1}$, captures the heterogeneous house price sensitivity to FFR changes based on the zip-code housing duration. Section II.B provides details on the estimation of housing duration. All specifications include county-year and zip-code fixed effects. Column 1 incorporates the lagged house price growth to control for momentum effects. Column 2 additionally controls for a comprehensive set of lagged local economic characteristics, such as log median income, population size, young and old ratios, labor force participation rate, unemployment rate, homeownership rate, rental vacancy rate, and the income-to-price ratio. Column 3 further introduces interaction terms between changes in FFR and the local economic 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. Housing Duration and Heterogeneous House Price Responses to Interest Rate Changes over 1-, 2-, and 3-Year Horizons

Panel A: Federal Funds Rate Changes

	Δ HPI$_{z,[t-1,t]}$		Δ HPI$_{z,[t-1,t+1]}$		Δ HPI$_{z,[t-1,t+2]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta r_{[t-1,t]} \times$ Duration$_{z,t-1}$	1.073***	0.939***	3.089***	3.314***	2.897***	3.084***
	(0.084)	(0.170)	(0.152)	(0.289)	(0.164)	(0.340)
Duration$_{z,t-1}$	-0.152***	-0.012	-0.308***	-0.056***	-0.426***	-0.101***
	(0.009)	(0.010)	(0.018)	(0.022)	(0.029)	(0.035)
Δ HPI$_{z,[t-2,t-1]}$		0.127***		0.129***		0.075***
		(0.008)		(0.013)		(0.017)
Adjusted R^2	0.773	0.787	0.805	0.820	0.805	0.821
Observations	60,947	60,947	60,920	60,920	55,292	55,292
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

Panel B: 30-Year Mortgage Rate Changes

	Δ HPI$_{z,[t-1,t]}$		Δ HPI$_{z,[t-1,t+1]}$		Δ HPI$_{z,[t-1,t+2]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta r^{30Y}_{[t-1,t]} \times$ Duration$_{z,t-1}$	1.830***	1.127***	5.488***	4.584***	6.769***	5.679***
	(0.120)	(0.240)	(0.225)	(0.422)	(0.275)	(0.553)
Duration$_{z,t-1}$	-0.149***	-0.009	-0.302***	-0.048**	-0.423***	-0.094***
	(0.009)	(0.010)	(0.018)	(0.021)	(0.028)	(0.034)
Δ HPI$_{z,[t-2,t-1]}$		0.119***		0.110***		0.053***
		(0.008)		(0.013)		(0.017)
Adjusted R^2	0.773	0.788	0.806	0.822	0.808	0.824
Observations	60,947	60,947	60,920	60,920	55,292	55,292
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Economic Chars		Yes		Yes		Yes
$\Delta r^{30Y}_{[t-1,t]} \times$ Zip Economic Chars		Yes		Yes		Yes

Table 4 presents the heterogeneous effects of interest rate changes on house price growth over 1-, 2-, and 3-year horizons across zip codes with varying housing duration levels. Panel A uses the federal funds rate (FFR) as the interest rate measure, while Panel B employs the 30-year mortgage rate. The dependent variable in each column is the cumulative change in house prices, $\Delta HPI_{z,[t-1,t+h]}$, from the end of year $t-1$ to $t+h$, where $h \in \{0,1,2\}$ denotes the ex-post horizon in years. The key explanatory variable, $\Delta r_{[t-1,t]} \times Duration_{z,t-1}$, captures the heterogeneous house price sensitivity to FFR changes based on the zip-code housing duration. $\Delta r_{[t-1,t]}$ measures the annual change in the FFR (Panel A) or 30-year mortgage rate (Panel B) from the end of year $t-1$ to t. Section II.B provides details on the estimation of housing duration. All specifications include county-year and zip-code fixed effects. Columns 2, 4, and 6 additionally control for time-varying zip-code economic characteristics and their interactions with the interest rate change, 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. Monetary Policy Shocks, Housing Duration, and House Price Growth

	Δ HPI$_{i,[t-1,t+1]}$									
	1-Year Yield Surprise$_t$		BS MPS$_t$		BS MPS_ORTH $_t$		JK PM MPS$_t$		JK Median MPS$_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MPS$_t$ × Duration$_{z,t-1}$	3.872***	3.425***	27.539***	25.053***	15.373***	33.825***	0.324***	0.260***	0.304***	0.260***
	(0.166)	(0.313)	(1.240)	(2.412)	(1.631)	(3.252)	(0.013)	(0.025)	(0.013)	(0.025)
Duration$_{z,t-1}$	-0.298***	-0.043**	-0.293***	-0.039*	-0.304***	-0.063***	-0.289***	-0.034	-0.285***	-0.031
	(0.018)	(0.021)	(0.017)	(0.021)	(0.018)	(0.022)	(0.017)	(0.021)	(0.018)	(0.021)
Δ HPI$_{z,[t-2,t-1]}$		0.125***		0.129***		0.142***		0.120***		0.126***
		(0.013)		(0.013)		(0.013)		(0.013)		(0.013)
Adjusted R^2	0.806	0.821	0.806	0.821	0.801	0.816	0.806	0.821	0.805	0.820
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
MPS$_t$ × Zip Economic Chars		Yes		Yes		Yes		Yes		Yes

Table 5 examines how alternative measurements of monetary policy shocks (MPS) affect house price growth differently across zip codes with varying housing durations. The specific MPS measure used in each column is indicated at the top. The dependent variable, $\Delta HPI_{z,[t-1,t+1]}$, is the cumulative house price growth from the end of year $t-1$ to $t+1$. The primary explanatory variable, $MPS_t \times Duration_{z,t-1}$, captures the heterogeneous house price sensitivity to MPS based on the zip-code housing duration. Section II.B provides details on the estimation of housing duration. The MPS variable, MPS_t, aggregates monetary policy shocks occurring between the end of year $t-1$ and t. Columns 1 and 2 employ the 1-year treasury yield surprise as the MPS measure. Columns 3 and 4 utilize the standard MPS measure developed by Bauer and Swanson (2023a), while columns 5 and 6 apply the orthogonalized version from Bauer and Swanson (2023a). Columns 7 and 8 incorporate the PM MPS measure from Jarociński and Karadi (2020), and columns 9 and 10 use their median MPS measure. All specifications include county-year and zip-code fixed effects. Columns 2, 4, 6, 8, and 10 additionally control for time-varying zip-code economic characteristics and their interactions with MPS, 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 6. Property Price Sensitivity to Interest Rate Changes: Controlling for Mortgage and Tax Payments

	Δ 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)
Δ 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 6 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 3–6 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 7. Impact of Interest Rate Changes on Buy-to-Rent (BTR) Probability

	$\mathbb{1}\{\text{BTR}\}_{i,t}$							
	ΔFFR				ΔFFR 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)
$\Delta r_{[t-h-1,t-h]} \times$ % Below $40_{z,t-h-1}$		-0.609***		-2.401***		-4.238***		-6.249***
		(0.218)		(0.271)		(0.341)		(0.431)
$\Delta r_{[t-h-1,t-h]} \times$ % 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, $\Delta r_{[t-h-1,\,h-h]}$, 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 II.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 (2023a) 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 II.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. 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)
$\Delta r_{[t-2,t-1]} \times$ 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)					
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)		
Δ 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)
$\widehat{\Delta r}_{[t-2,t-1]} \times$ 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)					
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)		
Δ 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 8 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 use the orthogonalized monetary policy surprise (MPS) measure of Bauer and Swanson (2023a) 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 9. Near-Term Income Demand and the Likelihood of BTR Purchases

	$\mathbb{1}\{\text{BTR}\}_{i,t}$					
	%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)
Δ 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 9 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 10. Interest Rate Changes and Property Transitions Between Owner- and Renter-Occupied Property Status

Panel A: Owner to Renter (OTR)

	$\mathbb{1}\{\text{OTR}\}_{i,t}$							
	ΔFFR				ΔFFR 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)

	$\mathbb{1}\{\text{RTO}\}_{i,t}$							
	ΔFFR				ΔFFR 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 (2023a) 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

	Δ 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)
Δ 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.