MONETARY POLICY TRANSMISSION THROUGH HOUSING DURATION: EVIDENCE FROM REACHING-FOR-INCOME INVESTORS

ABSTRACT

Traditional theory posits that longer-duration assets are more sensitive to interest rate changes. Contrary to this, we document a puzzling phenomenon in housing markets: shorter-duration markets exhibit greater sensitivity to monetary policy shocks (MPS). We develop a novel zip-code-level measure of housing duration. The measure is largely associated with local rental yields, with higher yields corresponding to shorter durations. Empirically, a 100 basis-point increase in MPS leads to a 5.74% greater house price decline in markets one standard deviation shorter in duration. Utilizing detailed property-level transaction and rental listing data, we uncover "reaching-for-income" behavior by buy-to-rent (BTR) housing investors as the key mechanism. Lower interest rates disproportionately attract BTR investors toward higher-yield properties, intensifying price sensitivity in shorter-duration markets. Cross-sectional analyses show that this amplified price sensitivity is only pronounced in areas with substantial BTR investment activity. Our findings highlight a novel investor-driven transmission channel of monetary policy to housing markets, emphasizing housing duration as a critical factor in house price dynamics and revealing unintended consequences of investor behavior for housing market stability.

JEL classification: Monetary Policy Transmission, Real Estate, Reaching-for-Income.

I. Introduction

Traditional asset pricing theory suggests that assets with longer cash flow durations should exhibit greater sensitivity to interest rate changes. However, we reveal a puzzling divergence in real estate markets: properties with shorter cash flow durations show greater house price responses to monetary policy shocks compared to their longer-duration counterparts. Understanding this anomaly of monetary policy transmission to house prices is crucial, as housing constitutes a major component of household wealth (Kuhn, Schularick, and Steins, 2020) and directly influences consumption (Mian, Rao, and Sufi, 2013), investment decisions Cocco (2005); Flavin and Nakagawa (2008), innovation Bernstein, Mcquade, and Townsend (2021), and broader economic stability.

In this paper, we introduce a novel measure of housing cash flow duration at the zip code level. Similar in concept to Macaulay duration, this measure captures the weighted average timing of expected future rental cash flows that homeowners receive from housing markets. Using this innovative measurement, we thoroughly examine how monetary policy transmission to house prices varies across markets with different housing cash flow durations.

Contrary to conventional theory, our empirical findings indicate that housing markets with shorter durations are more sensitive to monetary policy changes than their longer-duration counterparts. We use the orthogonalized monetary policy surprise series developed by Bauer and Swanson (2023a) as our main measure of monetary policy changes. Our baseline specification reveals a significant heterogeneity: a 100 basis-point (bps) increase in monetary policy shock (MPS) results in an approximately 5.74% greater decline in house prices in markets with housing durations that are one standard deviation shorter. Additionally, regressions using duration percentile ranks show that a decrease in housing duration from the median to the bottom percentile is associated with an extra 8.5% decline in house prices for a 100 bps increase in MPS.

To construct the housing duration measure at the zip code level, we innovatively adapt the concept of Macaulay duration for real estate markets. Our housing duration is defined as the weighted average time to receive expected housing cash flows in future horizons, which come in the form of rental income or terminal house price. The weights are the present values of expected housing cash flows in relation to the current property price. Unlike bonds, real estate assets do not have a deterministic maturity, and future cash flows are uncertain. Therefore, expected cash flows are decomposed into finite forecasted rental incomes over a time horizon T and a terminal value calculated via the Gordon Growth Model (GGM) with an estimated long-term rent growth rate $\bar{g}_t$. This approach is similar to Weber (2018).

To estimate expected rents, we assume that rent growth is stationary and predict annual log rent growth for each future horizon. The predictor variables incorporate rental yield, lagged rent growth, and economic characteristics at the zip code level, including income, population demographics, and labor market conditions. The discount rate for each zip code and year is calculated by equating the present value of expected housing cash flows to the property market price, similar to the method described by Gonçalves (2021). Decomposing the housing duration measure, we find that rental yields alone account for over 92% of the variation in housing duration across zip codes, with higher rental yields significantly associated with shorter durations. The finding that housing duration can be largely represented by rental yield is consistent with Greenwald, Leombroni, Lustig, and Van Nieuwerburgh (2021).

To unravel the mechanism behind this phenomenon, we delve deeper into housing transactions and rental listings at the property level. Using a comprehensive dataset from ATTOM, which includes property transaction records and tax assessments, along with detailed rental listing data from Altos Research, we are able to estimate property-level rental yields for the entire universe of properties, including both owner- and renter-occupied houses. The estimated property-level rental yield could serve as an approximation for housing duration, as both our findings and prior studies have shown that housing duration can be largely explained by rental yield. By analyzing how transaction prices respond to MPS at the property level, we confirm our previous finding that properties with higher rental yields (shorter cash flow durations) are more sensitive to monetary policy changes.

Taking advantage of the granularity of the property-level data, our channel analysis reveals that "reaching-for-income" investment behavior leads to the increased sensitivity of house prices for high-rental-yield (i.e., short-housing-duration) properties. After a negative MPS, the likelihood of purchasing properties for rental purposes (known as buy-to-rent or BTR) tends to increase on average. However, properties with higher rental yields experience a higher probability increase than similar properties with lower rental yields. It provides evidence for the "reaching-for-income" investment behavior in housing markets, which aligns with Daniel, Garlappi, and Xiao (2021), suggesting that lower interest rates significantly increase demand for income-generating assets.

To investigate whether "reaching-for-income" behavior drives the heterogeneity in price sensitivity, we calculate the ratio of BTR transactions for each zip code and year. Our findings reveal that, for two comparable properties with the same rental yield, the property located in a zip code with a higher proportion of BTR transactions experiences a larger increase in transaction price following a negative MPS. Conversely, in areas without BTR transactions, the price responses align with theory predictions; that is, properties with lower rental yields (longer housing durations) become more sensitive to changes in monetary policy. It confirms that the "reaching-for-income" behavior exhibited by BTR investors drives the abnormally high sensitivity of short-duration markets to MPS.

In our zip-code-level analysis for the heterogeneity in house price sensitivity across housing durations, we use a preferred specification that includes the county-by-year and zip-code fixed effects. The fixed effect approach helps to mitigate estimation bias arising from time-varying economic characteristics at the county level and time-invariant characteristics at the zip code level. Additionally, we obtain consistent results from our regression analysis using housing duration percentile ranks as the primary variable of interest.

Additionally, our zip-code-level results remain robust even after controlling for various local economic factors and interacting these factors with MPS. Interestingly, there are cross-sectional heterogeneities in price sensitivity across other dimensions. For instance, higher-income areas have a greater sensitivity to the shock, while regions with high labor force participation tend to respond less strongly. Areas with higher rates of unemployment and homeownership show a stronger price reaction to MPS, which may indicate financial distress and mortgage constraints.

Our intertemporal analysis shows that the effects of MPS unfold gradually and persist over one- to three-year periods, peaking at the two-year period. Specifically, for a 100 basis point increase in MPS, a decrease in housing duration from the median to the bottom percentile results in additional house price decrease of approximately 2.2%, 8.5%, and 5.25% over one-, two-, and three-year horizons, respectively. This finding is consistent with the delayed pass-through of monetary policy effects documented in previous studies (Kuttner, 2013; Williams, 2015).

We conduct extensive robustness checks using alternative measurements of monetary policy shocks, such as changes in the federal funds rate, one-year Treasury yield surprises, and alternative monetary policy surprises derived from Jarociński and Karadi (2020) and Bauer and Swanson (2023a). Moreover, we examine the responses to long-term interest rates, such as 30-year mortgage rates, and find consistently higher sensitivity in shorter-duration housing markets. Across all alternative measures, we consistently observe that shorter-duration housing markets exhibit significantly greater price sensitivity to MPS.

In our channel analysis, we utilize property-level transaction data combined with rental listings to identify buy-to-rent (BTR) transactions. The BTR transactions are defined as those where properties are purchased and subsequently listed for rent within 24 months after the purchase. A negative MPS significantly increases the likelihood of BTR investments, especially for properties with high rental yields (shorter housing durations). Specifically, a negative 100 basis points of MPS increases the likelihood of BTR transactions by approximately 5.6 percentage points. This result indicates that investors are actively seeking properties that offer higher income streams in response to lower interest rates.

We categorize zip codes into high and low BTR intensity based on the median ratio of BTR transactions across zip codes. In zip codes with low BTR intensity, we find that both high- and low-rental-yield properties respond similarly to changes in monetary policy. However, in zip codes with high BTR intensity, we observe a significant divergence: properties with high rental yields (short-duration properties) experience a much larger price increase compared to similar properties with low rental yields (long-duration properties). These findings suggest that "reaching-for-income" behavior driven by BTR investors influences the transmission of monetary policy to housing markets, deviating from classical predictions associated with cash flow duration.

This paper contributes to the literature on monetary policy transmission and housing market dynamics by identifying a novel mechanism, "reaching-for-income" investment behavior by buy-to-rent investors, that amplifies the interest rate sensitivity in certain market segments. Prior work, such as Mian and Sufi (2009); Favara and Imbs (2015); Favilukis, Ludvigson, and Van Nieuwerburgh (2017), have established that expansions in credit supply amplify housing booms. Some other works also show how mortgage credit constraints, such as payment-to-income (PTI) and debt-to-income (DTI) limits, amplify monetary policy shocks (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. Our work introduces a novel perspective by demonstrating that shorter-duration (higher-rental-yield) housing markets exhibit significantly greater responsiveness 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 shifts. Our mechanism complements segmentation frameworks like Landvoigt, Piazzesi, and Schneider (2015), which link lower-tier market volatility to constrained buyers. However, our channel underscores the importance of investor behavior and housing market duration characteristics as important factors shaping monetary transmission to house markets.

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, we uncover a similar pattern in real estate markets. Specifically, our 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), our findings from housing markets provide robust and complementary evidence, similar to Giglio, Maggiori, and Stroebel (2015); Giglio, Maggiori, Rao, Stroebel, and Weber (2021). However, we push forward this area by exploring how duration influences monetary policy transmission to asset prices and highlight the amplified sensitivity of short-duration housing markets to interest rate changes.

Third, this paper contributes to the "reaching-for-income" literature by uncovering a granular, investor-driven transmission channel through which monetary policy shapes housing market dynamics. Prior studies document how investors reallocate toward higher-yielding assets in low-interest-rate environments, significantly influencing equity markets (Daniel et al. (2021); Jiang and Sun (2020)), bond markets (Hanson and Stein (2015); Becker and Ivashina (2015); Lian, Ma, and Wang (2019); Choi and Kronlund (2018)), historical housing markets (Korevaar (2023)), and across various asset classes due to behavioral biases and demographic differences (Lian et al. (2019); Gomes, Peng, Smirnova, and Zhu (2022)). Closest to our work, Gargano and Giacoletti (2022) show that interest rate decreases make older individuals substitute interest income with rental income and influence their participation in rental markets. However, those studies do not explicitly address how reaching-for-income investor behaviors influence the monetary policy transmission to asset prices. Our paper addresses this gap by providing micro-level evidence that properties with higher rental yields disproportionately attract buy-to-rent (BTR) investors who exhibit strong reaching-for-income behavior following monetary easing, thereby significantly amplifying the price sensitivity of short-duration markets. Our paper offers micro-level evidence that housing investment mediates monetary policy transmission, which will help to understand spatial disparities in housing market responses and highlight unintended consequences of monetary easing.

The remainder of this paper is organized as follows: Section II describes data and the construction of measurements. Section III shows the empirical results. Section IV concludes the paper.

II. Data and Measurement

A. Data Source

To construct the zip-code level housing duration, we implement the Zillow Home Value Index (ZHVI) and the Zillow Observed Rent Index (ZORI). ZHVI provides a measure of the house price levels and changes of the typical home in the 35th to 65th percentile range across zip codes. Similarly, ZORI provides a measure of the typical observed market rate rent across zip codes. It is a repeat-rent index that is weighted to the rental housing stock, not just those homes currently listed for rental, to ensure representativeness for the entire market. We use the same smoothed and seasonally adjusted version of the ZHVI and ZORI measured for all homes to reduce any discrepancies in the index construction or errors related to property type measurement. Since zip code-level ZHVI and ZORI data are available from as early as 2000 and 2015, respectively, our analysis of housing cash flow duration at the zip code level will start from 2016. However, for our property-level analysis, we can extend the measurement period back to 2011 due to the availability of detailed property-level rental listing data.

In our property-level analysis, we leverage ATTOM deed transaction record data to obtain property-level transaction information. ATTOM is a premier U.S. real estate data provider, and its data has been extensively used in literature. ATTOM has collected a nationwide panel of transaction records from all over the country, including more than 500 million real estate and loan transactions in over 2,690 counties.[1] From ATTOM, we are able to collect detailed deed transaction information, such as transaction date, property address, buyer and seller information, and sales prices. ATTOM deed transaction data

[1] As per the data description provided by ATTOM: https://https://www.attomdata.com/data/transactions-mortgage-data/recorder-data/

dates back as far as the early 1970s and has relatively better coverage since 1990.

We obtain the property characteristics from ATTOM Tax Assessment data, which covers more than 155 million properties in more than 3,000 counties nationwide. The data set includes publicly available information collected by county tax assessor offices, such as assessed land and property values, tax amount, and, most importantly, property characteristics. With the unique property ID across ATTOM data products, we could easily merge the transaction and property characteristics.

Before analysis, we clean the deed record data to identify valid transaction records and the transactions that are invalid but will end the property ownership of the prior homeowner. We follow some papers to form our cleaning algorithm, such as Baldauf, Favilukis, Garlappi, and Zheng (2022); Goldsmith-Pinkham and Shue (2023); Reher and Valkanov (2024). Our cleaning algorithm is discussed in detail in Appendix Section C. For example, some non-arm's length transactions are conducted among family members with very low transaction prices relative to comparable houses. Some deed records could even be added to include family members (e.g., offspring) as additional homeowners with zero recorded transaction prices. Those are deemed invalid transactions and are excluded from our rental and price estimation and final analysis. There could be some other examples that are invalid but end the property's prior owners' ownership. For example, some foreclosure transactions are made because of some payment defaults. Those foreclosure transactions will end the ownership of the prior owners, but the associated properties could be sold at a large discount. Some other deed record types, such as affidavits of death, also end ownership at very low prices for special situations. Overall, we do not want those abnormally low prices to bias our rent and price hedonic estimations and final analysis, so we clean the transactions before analysis.

Altos Rental Intel data covers the active rental market for single-family homes and apartments with a 98% national coverage rate. It tracks data points such as rental rate, property type, square footage, beds and baths, and amenities. Altos has historical rental data available back to 2011. The rental sources, which are independent from the MLS, do not include platforms like Craigslist. Instead, they consist of private proprietary sources that the company has contracted with. These sources cover most major metropolitan areas and states, essentially reaching every zip code in the US where there are houses or rental units available. The company refreshes data weekly to provide a true picture of the rental market and could provide the most timely rental listing information that satisfies our analysis needs.

B. Housing Duration at the Zip Code Level

Macaulay duration defines a bond duration as the weighted average time of receiving cash flows from the bond. Following the bond definition, we define the housing duration as the weighted average timing of receiving future cash flows (i.e., rental incomes) from housing markets. Specifically, the duration of a typical property in zip code z and year t is defined as the following:

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

where

$$w_{z,t+h} = \frac{\text{CF}_{z,t+h} \,/\, (1+r_{z,t})^h}{P_{z,t}} \tag{2}$$

and

$$\text{CF}_{z,t+h} = \begin{cases} \mathbb{E}_t\Big[\text{Rent}_{z,t+h}\Big], & \text{if } h < T \\ \mathbb{E}_t\Big[\text{Rent}_{z,t+T}\Big]\,(1+\bar{g}_t)/(r_{z,t}-\bar{g}_t)\,, & \text{if } h = T \end{cases} \tag{3}$$

In Equation 1, $w_{z,t+h}$ represents the value weight of the present value of expected cash flows received in year $t+h$ relative to the total market price of a typical property located in zip code z during year t. Here, h indicates the time horizon for when the cash flow is expected to be received. Intuitively, the housing duration is the weighted average of property cash flow maturities with the weights defined by the importance of present values of future cash flows relative to the current investment value.

Unlike bonds, real estate assets and stocks do not have a deterministic maturity year t+T, and the future cash flows are unknown ahead. For this reason, we follow Weber (2018) and divide the duration formula into two components: the duration of finite forecasting cash flow values before horizon T and the duration of the infinite terminal value at horizon T.

As shown in Equation 3, the expected cash flows have different formulas for the two periods. For the periods prior to the horizon T, the property cash flow is represented by $\mathbb{E}_t\Big[\text{Rent}_{z,t+h}\Big]$, which indicates the rental income that a landlord expects to receive from a typical property in zip code z at horizon h. For horizon T, the cash flow will be a terminal value from the property. We calculate this terminal value using the Gordon Growth Model (GGM), assuming a constant long-term rent growth rate, $\bar{g}_t$. This rate represents the average expected annual rent growth across all zip codes and forecast horizons in year t.

$P_{z,t}$ represents the current market price of a typical house at zip code z in year t and is measured by the Zillow Home Value Index (ZHVI). The rental income is measured from the Zillow Observed Rent Index (ZORI). We use the same smoothed and seasonally adjusted version of the market price index (ZHVI) and rent index (ZORI) measured for all homes to reduce any discrepancies in the index construction or errors related to property type measurement. In Section II.B.1, we will discuss in detail estimating the expected rents $\mathbb{E}_t\left[\text{Rent}_{z,t+h}\right]$.

Similar to Gonçalves (2021), we derive the discount rate for a zip code and year t by solving the value equation

$$P_{z,t} = \sum_{h=1}^{T} CF_{z,t+h} / (1 + r_{z,t})^h \tag{4}$$

The discount rate we calculate is equivalent to yield to maturity (YTM) or internal rate of return (IRR), which makes the current market price equal to the sum of the present values of all expected future cash flows from the asset.

For simplicity, we apply a constant discount rate to all expected cash flows over future horizons within a specific zip code and year. This simplified assumption does not change the ranking of housing duration across different zip codes. Therefore, our results, which focus on the cross-sectional heterogeneity in house price responses to monetary shocks, remain unaffected by this assumption.

B.1. Estimating Zip Code-level Expected Rent

The dividend growth is assumed to be stationary in previous literature (Shiller, 1981; Campbell and Shiller, 1988). We assume that rent growth is stationary, similar to dividend growth. As a result, we can turn the question of estimating the expected rent into predicting a sequence of future rent growth, as illustrated in the following equation.

$$\mathbb{E}_t\left[\ln(\text{rent})_{z,t+h}\right] = \ln(\text{rent})_{z,t} + \sum_{s=1}^{h} \mathbb{E}_t\left[\Delta \ln(\text{rent})_{z,[t+s-1,t+s]}\right] \tag{5}$$

where $\ln(\text{rent})_{z,t}$ is the natural logarithm of the rent value of a typical property in zip code z and observable in year t. $\mathbb{E}_t\left[\Delta \ln(\text{rent})_{z,[t+s-1,t+s]}\right]$ is the expected annual growth in the log rent in zip code z at horizon s.

Our approach is close to Weber (2018) and Gonçalves (2021). They both estimate the expected firm payouts to investors by assuming clean surplus accounting. 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). On the other hand, Gonçalves (2021) extends this methodology by integrating twelve firm-level characteristics. He estimates expected firm payouts by predicting the ratio of clean surplus to book equity, as well as the growth in book equity.

For each forecasting horizon s, we estimate the expected log rent growth by first running the regression with the following specification.

$$\Delta \ln(\text{rent})_{z,[t+s-1,t+s]} = \alpha_s + \beta_{1,s} \ln(\text{rental yield})_{z,t} + \beta_{2,s} \Delta \ln(\text{rent})_{z,[t-1,t]} + \Gamma X_{z,t} + \epsilon_{z,t,s} \tag{6}$$

where the dependent variable is the natural logarithm of annual rent growth over horizon s in zip code z and year t. The variable $\ln(\text{rental yield})_{z,t}$ is the natural logarithm of the rental yield and $\Delta \ln(\text{rent})_{z,[t-1,t]}$ is the rent growth from year t-1 to t. $X_{z,t}$ represents a range of local economic characteristics of zip code z in year t, including income ratio (i.e., median household income in zip code z divided by the median national household income), income growth, population ratio (i.e., the population size in zip code z divided by total national population size), population growth, the ratio of young residents (under age 40) and its growth, the ratio of older residents (over age 60) and its growth, the level and growth of the labor force participation rate, the unemployment rate and the homeownership rate, as well as the vacancy rate.

Appendix Table A.1 presents the results of predictive regressions for future annual rent growth over the next one to five years. Columns 1 to 3 present the regression results for rent growth over the next year (from year t to year t+1) with various specifications. Among these, Column 3 is identified as the preferred specification. Using this same preferred specification, Columns 4 to 6 present the predictions for annual rent growth over the next two to five years.

With the estimated coefficients for the horizon h, we get the expected log rent growth via the following equation.

$$\mathbb{E}_t\left[\Delta \ln(\text{rent})_{z,[t+s-1,t+s]}\right] = \hat{\alpha}_s + \hat{\beta}_{1,s} \ln(\text{rental yield})_{z,t} + \hat{\beta}_{2,s} \Delta \ln(\text{rent})_{z,[t-1,t]} + \hat{\Gamma} X_{z,t} \tag{7}$$

C. Measuring Property-level Rental Yield

In our channel analysis, we exploit granular property-level housing transaction and rental listing data, which allows us to precisely identify the properties specifically purchased for rental investment, called "buy-to-rent" (BTR) properties. By concentrating on properties rented shortly after purchase (e.g., within 12 months), we can observe contemporaneous housing transaction prices and rents. It provides an ideal empirical setting to estimate rental yields for the universe of properties, such as owner-occupied houses, for which the rental yields are hard to observe. Employing the hedonic model, we rigorously establish the relationship among rents, property prices, and house characteristics. Our methodological innovation lies in applying these hedonic estimates, derived from the BTR subset, to the broader universe of properties—including owner-occupied houses—thereby generating comprehensive measures of property-level rental yields.

C.1. Estimating Property-level House Price with Hedonic Model

To estimate the expected house price of a property in one year, we first use the hedonic model to analyze the time-varying relationship between transaction prices and property characteristics based on all valid housing transactions. We then apply the estimated coefficients to other properties that do not have transaction data for the same period to predict their expected house prices.

Our house price estimation utilizes all valid housing transactions, which include actual transaction prices, property characteristics, and geographic identifiers. Appendix Section C describes the detailed process for cleaning the ATTOM housing transaction data. Using the valid housing transaction sample, we perform *year-by-year* regressions based on the following hedonic specification.

$$\ln(\text{price}_{i,z,t}) = \alpha_t + \Gamma_t X_{i,z,t} + \lambda_{z,p,t} + \epsilon_{i,z,t} \tag{8}$$

, where the dependent variable is the transaction price of property i in zip code z in year t.

$X_{i,z,t}$ represents the property characteristics applied in the hedonic model. They are selected by referring 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). The property characteristics include the log of the house age, the log of the property area in the square footage, the bedroom and bathroom numbers, a dummy variable that indicates the presence of a garage, the log of the garage area, dummy variables that indicate the presence of a pool, cooling facility, heating facility, a fireplace, a basement, a waterfront, a mountain view, recreational view, and good quality view.

$\lambda_{z,p,t}$ is the 5-digit zip code by property type fixed effects.[2] The property types include single-family residential houses, Condos/Townhouses/Co-Ops, Multi-family houses (2-4 units), Multi-family houses (5+ units), and others. We assume a heterogeneity in transaction prices across property types and zip codes in a year. Therefore, $\lambda_{z,p,t}$ captures the average transaction prices for each property type in each zip code during that year.

Next, we apply the estimated coefficients to all properties and calculate the expected house price for each property and year with the following equation.

$$\mathbb{E}[\ln(\text{price}_{i,z,t})] = \widehat{\alpha}_t^p + \widehat{\Gamma}_t^p X_{i,z,t} + \widehat{\lambda}_{z,p,t}^p \tag{9}$$

, where $\widehat{\alpha}_t^p$, $\widehat{\Gamma}_t^p$, and $\widehat{\lambda}_{z,p,t}^p$ are the estimated coefficients from Equation 8. The superscript "p" indicates that these coefficients are specific to house prices, differentiating them from the coefficients in the rent estimation in the following section.

Finally, we calculate the expected house price level and growth for each property in a year using the estimated log of house prices. The expected house price of property i in year t is defined as

$$\widehat{P}_{i,t} = \exp\left\{\mathbb{E}[\ln(\text{price}_{i,t})] + \frac{1}{2}\hat{\sigma}^2_{p,t}\right\} \tag{10}$$

, where $\mathbb{E}[\ln(\text{price}_{i,t})]$ is the expected log of house price of property i in year t from Equation 9 and $\hat{\sigma}^2_{p,t}$ denotes the estimated residual variance obtained from the price hedonic regressions.

The expected house price growth (i.e., capital gain) for property i in year t in horizon h takes the following form.

$$\widehat{\Delta P}_{i,[t-1,t+h]} = \widehat{P}_{i,t+h} / \widehat{P}_{i,t-1} - 1 \tag{11}$$

C.2. Estimating Property-level Expected Rental Yield from Hedonic Model

Our rent data is obtained from Altos Rental Intel. To obtain the joint distribution of rents and house prices, we first merge the rent and ATTOM data. The merging details are described in Ap-

[2] The zip code by property type fixed effects, $\lambda_{z,p,t}$, includes the subscript t due to our *year-by-year* regression analysis, resulting in estimated coefficients that vary each year.

pendix Section D. The merging process generates a sample of properties with both observed rental and transaction prices for the same property. Specifically, the rental listing data enables us to know when a property was listed for rent and the required rental price, while the housing transaction and tax assessment data allow us to determine when a property was transacted, how much the transaction price was, and its property characteristics.

Our rent estimation relies on the sample of "buy-to-rent" (BTR) properties. By merging rental listing data with housing transaction records, we can observe both rental prices and transaction prices for certain properties. When estimating rents, there may be aspects of property quality that are not captured by observable characteristics but are reflected in the transaction prices. The transaction price serves as a proxy for this unobserved property quality and helps explain the remaining components of rent that cannot be explained by the observable housing characteristics. Including housing transaction prices in the rent hedonic model could ultimately improve the rent estimation and better capture the variation in the rent-to-price ratio across areas over time.

However, there may be a time gap between the rent and transaction price if a landlord lists the property for rent a long time after its purchase. To mitigate bias in our rent estimation, we specifically focus on BTR properties. Those are defined as properties that are listed for rent within 12 months of the purchase transaction. Our defined BTR properties are similar to the "switcher" properties in American Housing Survey (AHS) data that transition from either owning to renting or renting to owning, as discussed by Diamond and Diamond (2024). This method ensures that we obtain a more accurate joint distribution of rental and transaction prices.

We estimate the rent hedonic model using the BTR property sample and then apply the estimated coefficients to all other owner-occupied houses. In the end, we obtain the expected rental yields for all properties over time. Specifically, we conduct *year-by-year* regressions according to the specified model.

$$\ln(\text{rent}_{i,z,t}) = \alpha_t + \beta_t \ln(\text{price}_{i,z,t}) + \Gamma_t X_{i,z,t} + \lambda_{z,p,t} + \epsilon_{i,z,t} \tag{12}$$

The dependent variable $\ln(\text{rent}_{i,z,t})$ is the log of the listed rent for property i in zip code z at year t. $X_{i,z,t}$ represents the same property characteristics used in the price hedonic model in Equation 8. The variable $\ln(\text{price}_{i,z,t})$ denotes the log of the transaction price for the same property. Furthermore, we include the 5-digit zip code by property type fixed effects, $\lambda_{z,p,t}$.

We will apply the estimated coefficients to all owner-occupied houses and get the expected value of the log rent with the following form.

$$\mathbb{E}\big[\ln(\text{rent}_{i,z,t})\big] = \widehat{\alpha}_t^r + \widehat{\beta}_t\,\mathbb{E}\big[\ln(\text{price}_{i,z,t})\big] + \widehat{\Gamma}_t^r X_{i,z,t} + \widehat{\lambda}_{z,p,t}^r \tag{13}$$

, where $\widehat{\alpha}_t^r$, $\widehat{\beta}_t$, $\widehat{\Gamma}_t^r$, and $\widehat{\lambda}_{z,p,t}^r$ are the estimated coefficients in the rent hedonic model from Equation 12 and $\mathbb{E}[\ln(\text{price}_{i,z,t})]$ is the expected log house price estimated from Equation 9.

Finally, we calculate the expected rental yield of a single property in a year with the following equation.

$$\mathbb{E}\Big[\text{rental yield}_{i,z,t}\Big] = \exp\left\{\mathbb{E}\big[\ln(\text{rent}_{i,z,t})\big] - \mathbb{E}\big[\ln(\text{price}_{i,z,t})\big] + \frac{1}{2}\big(\hat{\sigma}_{r,t}^2 + \hat{\sigma}_{p,t}^2 + 2\,\text{cov}_t(\hat{\epsilon}_r, \hat{\epsilon}_p)\big)\right\} \tag{14}$$

, where $\hat{\sigma}_{r,t}^2$ and $\hat{\sigma}_{p,t}^2$ represent the residual variance estimated by the rent and price hedonic models, respectively. $\text{cov}_t(\hat{\epsilon}_r, \hat{\epsilon}_p)$ denotes the covariance of the residuals from the two specifications.

D. Monetary Policy Shock Measure from Bauer and Swanson (2023a)

In our empirical analysis, we use the orthogonalized monetary policy surprise series (MPS_ORTH) developed by Bauer and Swanson (2023a) as our monetary policy shock measurement. For simplicity, we use "MPS" to represent their orthogonalized shocks (MPS_ORTH) in the paper.

To construct the MPS measure, Bauer and Swanson (2023a) use the first four quarterly Eurodollar futures contracts, ED1–ED4, and get 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. They also address the exogeneity issue by removing the component of the monetary policy surprises that are correlated with economic and financial data.

We prefer the MPS_ORTH measure for several reasons. First, it is designed to address critical issues of endogeneity associated with conventional monetary policy surprise measures, such as changes in the federal funds rate or surprises in the 1-year Treasury yield. Bauer and Swanson (2023a) demonstrate that conventional monetary policy surprises are systematically correlated ex-post with macroeconomic and financial data publicly available before the policy announcements, undermining the exogeneity and validity as instruments.

In contrast, the MPS_ORTH measure corrects for this issue by explicitly orthogonalizing high-frequency monetary policy surprises against macroeconomic and financial data publicly available before each policy announcement. Bauer and Swanson (2023a) document that this orthogonalization substantially reduces the correlation between policy surprises and publicly available economic data, significantly enhancing the exogeneity of the shocks. Consequently, MPS_ORTH avoids the attenuation biases and "puzzles" commonly observed in the literature, providing a cleaner identification of monetary policy effects.

Moreover, Bauer and Swanson (2023a) demonstrate that their refined monetary policy surprise series offers improved instrument relevance, capturing meaningful variations in monetary policy by including a broader set of events, such as Fed chair speeches and congressional testimonies, in addition to standard FOMC announcements.

In summary, we adopt the orthogonalized MPS measure from Bauer and Swanson (2023a) because it ensures exogeneity and relevance, which we think will provide more reliable and unbiased estimates of the house price sensitivity to monetary policy changes.

III. Empirical Results

A. Baseline Specification

To examine the heterogeneity in house price sensitivity to monetary policy shocks (MPS) across housing cash flow durations, we analyze a housing sample at the zip code-year level and perform regression analysis using the following specification.

$$\begin{aligned}\Delta HPI_{z,c,[t-1,t+h]} = \alpha_h &+ \beta_h\, MPS_t \times \text{Duration}_{z,t} \\ &+ \delta_h\, \text{Duration}_{z,t} + \zeta_c \times \theta_t + \lambda_z + \epsilon_{z,c,t,h}\end{aligned} \tag{15}$$

, 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, and h denotes the house price change horizon. The variable MPS_t is the aggregated annual orthogonalized monetary policy shock in year t constructed by Bauer and Swanson (2023a). Duration$_{z,t}$ is the zip code's duration value of zip code z in year t. In percentile regression analysis in Appendix Table A.2 in Section A, we use the expected duration *percentile ranks* across zip codes in a year as Duration$_{z,t}$ for robustness tests.

$MPS_t \times \text{Duration}_{z,t}$ is the interaction term between the zip-code expected duration values and the monetary policy shocks. The term $\zeta_c \times \theta_t$ represents the county-by-year fixed effects, where c and t denote county and year, respectively. 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 main interest of the coefficient β_h measures the heterogeneity in house price sensitivity to MPS across zip codes with varying housing duration. Suppose a negative relationship between house price growth and MPS. An estimated positive coefficient $\hat{\beta}_h$ (i.e., $\hat{\beta}_h > 0$) suggests that zip codes with longer expected housing durations are less sensitive to MPS, while those with shorter durations are more sensitive. In other words, a negative MPS will result in higher house price growth in zip codes with short housing durations compared to those with long durations. Conversely, if $\hat{\beta}_h$ is negative, it would indicate that zip codes with longer expected durations react more strongly to MPS.

B. What Explains Heterogeneity in Housing Cash Flow Duration

Table 1 investigates the relationships between estimated housing duration and various local economic characteristics. The findings suggest that local rental yield plays a significant role in explaining estimated housing duration. In particular, a higher rental yield in a given housing market correlates with shorter housing duration. It indicates that homeowners in areas with high rental yields will expect to receive cash flow sooner than those in other markets.

[INSERT TABLE 1 HERE]

In Table 1, we regress the estimated housing duration of zip code i in year t, on concurrent local economic characteristics. Column 1 includes only log rental yield as the explanatory variable. The estimated coefficient of -0.410 indicates that higher rental yields are associated with shorter housing durations. Additionally, the adjusted R^2 of 0.921 indicates that rental yield alone explains a substantial portion of the variation in housing duration across zip codes and years.

Column 2 includes the log of the rent level. The negative coefficient on the log of the rental yield remains unchanged, indicating that the rent level alone does not account for the negative relationship between housing duration and local rental yield. This finding suggests that both higher rental yields and higher current rent levels independently predict shorter housing durations.

Column 3 includes additional economic and demographic variables. The rental yield coefficient remains significantly negative at approximately -0.415. Higher local income negatively correlates with duration, possibly suggesting properties in high-income neighborhoods have higher housing consumption. In contrast, income growth is positively associated with housing duration, implying that higher income growth forecasts a greater value from cash flows received in the future.

Additionally, larger populations and higher population growth rates predict longer housing cash flow durations. Increased labor force participation is positively associated with housing durations, possibly reflecting expectations of stronger future economic conditions and higher future rental growth. On the other hand, higher unemployment rates and increased vacancy rates have a negative correlation with duration. It is likely due to increased financial distress, which can lead to forced sales, suppressed current house prices, and lower expectations of future rental growth.

Columns 4 to 6 introduce additional fixed effects to further control for unobserved heterogeneity. The rental yield coefficients remain significantly negative, ranging from -0.414 to -0.343. That reinforces the robustness of the negative relationship between rental yield and housing duration. Overall, the results highlight rental yields as critical determinants of housing cash flow durations.

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

C.1. Baseline Analysis

Figure 1 illustrates the impact of a 100 basis-point annual positive monetary policy shock (MPS) on annual house prices at the zip code level, separately for short- and long-duration housing markets. The MPS occurs at horizon 0 (i.e., from the end of year t-1 to t). The red and green lines indicate the response for long- and short-duration housing markets, respectively.

[INSERT FIGURE 1 HERE]

The figure clearly demonstrates that short-duration markets exhibit significantly greater sensitivity to MPS compared to long-duration markets. Specifically, at the contemporaneous horizon (year t), both markets experience significant price declines of approximately 10% following a 100 basis-point positive MPS. However, the magnitude of the decline is slightly but statistically significantly greater in short-duration markets. One year after the shock, house prices continue to decline in both markets, but the divergence between the two markets widens. It leads to approximately 5% larger house price decline in short-duration markets. By the second year following the shock, both markets start to recover gradually, though the price gap expands further, reaching approximately 10%. Finally, the impact of the monetary policy shock largely dissipates three years after the initial shock.

[INSERT TABLE 2 HERE]

Table 2 analyzes the differences in asset price sensitivity to monetary policy shocks (MPS) based on the cash flow durations of assets in the housing, bond, and stock markets. Panel A presents the results for zip-code housing markets. The findings indicate that, within the same county and year, zip codes with shorter housing durations tend to show greater sensitivity to MPS compared to those with longer durations.

In Column 1, we include only MPS and housing cash flow duration as explanatory variables. The results reveal a strong negative relationship between MPS and changes in house prices over a two-year horizon. Specifically, a 100 basis-point increase in MPS corresponds to an average decrease in house prices of approximately 46%. Additionally, the negative coefficient on housing duration suggests that zip codes with longer housing cash flow durations experience lower average growth in house prices.

In Column 2 of Panel A, we introduce an interaction term between MPS and housing duration to analyze how the impact of MPS on house prices varies across different housing durations. The positive coefficient for the interaction term suggests that a positive MPS has a larger negative impact on house prices in zip codes with shorter durations. Specifically, with a 100 basis-point increase in MPS, a one-standard-deviation decrease in housing duration (0.17 years) amplifies the negative MPS impact on house prices by approximately 3.68%[3]. In other words, zip codes with a 0.17-year shorter housing cash flow duration experience an additional house price decline by 3.68%.

Columns 3 and 4 include year and county-by-year fixed effects to account for overall time trends and time-varying characteristics within counties, respectively. Our preferred specification, shown in Column 5, incorporates both county-by-year and zip-code fixed effects. Including those fixed effects comprehensively controls for time-varying county characteristics and time-invariant zip-code characteristics.

In Column 5, the coefficient on the interaction term between MPS and housing duration remains significantly positive at 33.756. This finding indicates that zip codes with shorter housing durations experience significantly larger declines in house prices following monetary tightening. Specifically,

[3] $3.68\% = 21.66 \times 0.17 \times 0.01$

for a positive 100 basis-point MPS, a one-standard-deviation decrease in housing duration (0.17 years) leads to an approximate 5.74% larger house price decrease[4].

Overall, Panel A demonstrates that the housing markets with shorter cash flow duration are substantially more sensitive to MPS than those with longer durations. This negative relationship between duration and price sensitivity to interest rate changes is puzzling, as it contrasts with the traditional view that longer-duration assets are typically more sensitive to interest rate fluctuations. In order to confirm it is a puzzling phenomenon that appears only in real estate markets, we perform the same annual analysis for bond and stock markets in Panels B and C.

Panels B and C conduct similar analyses on treasury bonds and stocks, respectively. To ensure the tests are comparable to those for housing markets, we examine the annual price change over a two-year period, which includes the year in which MPS occurs. The bond duration is calculated using the Macaulay duration formula and is sourced from the CRSP U.S. Treasury dataset. The equity duration at the stock-year level is developed by Gonçalves (2021).

Panels B and C both indicate that the prices of long-duration assets are more responsive to interest rate changes. In both panels, the negative coefficients on MPS suggest that a positive monetary policy shock leads to a negative price change (i.e., capital gains) on average. When we introduce the interaction term between MPS and duration, along with asset and year fixed effects, we observe negative coefficients on the interaction terms. It implies that the sensitivity of asset prices to MPS is indeed greater for long-duration assets. These findings for bond and equity markets align with standard duration theory, which states that long-duration assets are more affected by interest rate changes compared to short-duration assets.

In conclusion, Table 2 highlights an intriguing divergence: unlike bonds and equities, shorter-duration housing markets exhibit significantly higher sensitivity to MPS. Gaining a better understanding of the mechanism behind could offer valuable insights into the relationship between monetary policy and asset prices.

C.2. Diminishing House Price Sensitivity to MPS by Housing Duration Quintiles

To provide further evidence of a linearly decreasing relationship between housing cash flow duration and house price sensitivity to MPS, we categorize zip codes into five quintile groups based on

[4] 5.74% = 33.756 * 0.17 * 0.01

their estimated housing durations. Figure 2 illustrates the varying impact of MPS on house prices across the zip-code housing duration quintiles. Specifically, the figure shows the differences in house price changes following a negative 100 basis points of MPS, compared to quintile 5, which serves as the baseline group representing zip codes with the longest housing duration. Quintile 1 represents zip codes with the shortest housing durations.

[INSERT FIGURE 2 HERE]

The figure reveals that shorter-duration housing markets will react to MPS more strongly than longer-duration markets. For a negative 100 basis points of MPS, the shortest-duration group of zip code housing markets (quintile 1) will experience price increases approximately 11 percentage points larger than those in the longest-duration group (quintile 5) within two years following the shock. The second shortest-duration group (quintile 2) also shows a significant price increase, around 7%, compared to quintile 5 after the same shock. The third duration group (quintile 3) experiences a higher price increase than quintile 5, but this increase is not statistically significant. Overall, as we move from the shortest-duration group to the second longest, the price increases relative to the longest-duration group progressively diminish. These findings strongly indicate that there is a linearly decreasing relationship between housing cash flow duration and price sensitivity to MPS. The shorter-duration housing markets are significantly more responsive to MPS than longer-duration markets, reinforcing the results presented in Table 2.

C.3. Analysis Using Duration Percentiles

To mitigate potential biases stemming from outliers, Appendix Table A.2 presents robustness analyses using housing duration percentiles. Panel A provides the baseline results, consistently showing significantly positive interactions between MPS and housing duration percentiles. The coefficient on the interaction term in the preferred specification is 0.17, indicating that, for a 100 basis point increase in MPS, a decrease in housing duration from the median to the bottom percentile (i.e., from 50th to 0th percentile) corresponds to an additional 8.5% decrease in house prices.[5] Thus, zip codes in lower duration percentiles (i.e., shorter-duration housing markets) exhibit stronger sensitivity to monetary policy shocks.

[5] $0.085 = 0.170 \times 0.01 \times 50$.

Panel B conducts further heterogeneity analysis by incorporating controls for local economic characteristics and their interactions with MPS, consistent with Section III.C.4. The results confirm robustness, with the interaction terms between duration percentiles and MPS remaining positively significant across all specifications. These findings confirm our previous conclusion that the local housing market response to monetary policy shocks is substantially heterogeneous, driven independently by differences in housing cash flow duration and underlying economic fundamentals.

C.4. Heterogeneity in House Price Responses to Monetary Policy Shocks

Table 3 provides evidence on the cross-sectionally heterogeneous impacts of monetary policy shocks (MPS) on house price growth, emphasizing interactions between MPS and various economic characteristics in addition to local housing cash flow duration. The zip code-level economic characteristics include house price levels, median household income, population size, labor force participation, unemployment, homeownership, and vacancy rates. They are identified previously in Table 1 as potentially correlated with housing cash flow duration. Overall, the results demonstrate that the higher sensitivity of short-duration housing markets to MPS than long-duration markets is robust and not driven by local economic characteristics.

[INSERT TABLE 3 HERE]

Column 1 introduces additional control variables, including past one-year house price growth and local economic characteristics, compared to the baseline specification. The estimated coefficient on the interaction between MPS and housing cash flow duration remains significantly positive at around 30.386.

Columns 2 to 8 individually introduce interactions between MPS and specific economic characteristics while controlling for their direct effects. Across these specifications, the high price sensitivity in short-duration housing markets remains robust. The results confirm that zip codes with shorter housing cash flow duration exhibit greater house price sensitivity to MPS.

Additionally, interactions between MPS and local economic variables, such as house price levels, income, population size, labor force participation, unemployment, and homeownership rates, exhibit significant heterogeneity. Specifically, higher-income areas exhibit increased sensitivity to MPS, potentially reflecting greater leverage or reliance on credit among high-income homeowners. Areas with higher labor force participation demonstrate reduced sensitivity, possibly because stable incomes help homeowners better withstand interest rate fluctuations and mitigate forced sales caused by mortgage defaults, thus potentially sustaining housing demand during monetary tightening. In contrast, higher unemployment rates amplify negative house price responses, possibly reflecting increased financial distress and weakened housing demand. Similarly, higher homeownership rates intensify negative responses to MPS, likely due to increasing financial constraints faced by homeowners as interest rates increase. Overall, the findings underscore significant heterogeneity in local housing market responses to monetary policy changes.

C.5. House Price Responses Across Different Horizons

[INSERT TABLE 4 HERE]

Table 4 examines house price responses to monetary policy shocks (MPS) across one-, two-, and three-year horizons. Panel A presents results using duration values. The results consistently reveal significantly positive coefficients on the MPS-by-duration interaction terms across different horizons. The positive coefficients indicate a stronger sensitivity of house prices to MPS in shorter-duration housing markets. The pattern is still robust when controlling for time-varying zip code-level economic characteristics in Columns 2, 4, and 6.

Moreover, the heterogeneity of MPS responses is particularly pronounced at the two-year horizon, followed by the three-year horizon, suggesting the transmission of monetary policy shocks to house prices materializes gradually. Specifically, Columns 1, 3, and 5 in Panel A indicate that for a 100 basis point increase in MPS, a one standard deviation (0.17 years) increase in housing duration leads to additional house price decreases of approximately 1.7%, 5.7%, and 3.6% at the one-, two-, and three-year horizons, respectively. This slow response aligns with existing literature (Kuttner, 2013; Williams, 2015), indicating that house prices typically react gradually to interest rate changes over approximately two years.

Panel B confirms these findings using duration percentiles, consistently reporting significantly positive coefficients on the interaction terms across all horizons. The coefficients indicate higher house price sensitivity to MPS in shorter-duration zip codes. For example, baseline regression results in Columns 1, 3, and 5 imply that, for a 100 basis point increase in MPS, a decrease in housing duration from the median to the bottom percentile (50th to 0th percentile) results in additional house price decrease of approximately 2.2%, 8.5%, and 5.25% over one-, two-, and three-year horizons, respectively. Those findings robustly demonstrate that housing markets with shorter cash flow durations exhibit consistently greater sensitivity to MPS across various time horizons.

C.6. House Price Responses to Changes in 30-Year Mortgage Rates

People may be concerned that increases in short-term interest rates may not fully pass through to long-term mortgage rates, potentially explaining the observed high price sensitivity to MPS in short-duration housing markets. This concern is not entirely unfounded, as a key assumption underlying the definition of duration is the parallel shift of the yield curve. If short-term rate increases do not proportionally shift long-term rates, the relationship between interest rates and house prices may become distorted. This section explicitly examines the impact of changes in long-term rates, specifically the 30-year mortgage rate, on house prices across zip codes with varying housing durations.

Appendix Table A.3 examines how changes in the 30-year mortgage rate affect house price growth across zip codes with different housing cash flow durations. Panel A presents baseline results, consistently showing significantly positive coefficients on the interaction terms between mortgage rate changes and housing duration. It indicates that mortgage rate increases negatively impact house prices more strongly in shorter-duration markets. Specifically, the preferred specification in Column 5 reveals a highly significant positive interaction coefficient of 4.490, suggesting that shorter-duration zip codes experience significantly larger declines in house prices following mortgage rate increases.

Panel B further explores heterogeneity by incorporating various local economic characteristics and their interactions with mortgage rate changes. The positive coefficients on the main interaction terms remain robust across all specifications. Additionally, MPS interactions with other local economic characteristics reveal meaningful heterogeneity. For instance, higher local incomes amplify the sensitivity of house prices to mortgage rate changes, and higher unemployment significantly exacerbates negative price responses. These findings closely align with the results presented in Table 3 in Section III.C.4.

Appendix Table A.4 confirms that short-duration housing markets exhibit high price sensitivity consistently across one-, two-, and three-year horizons. It aligns well with earlier results using short-term MPS constructed by Bauer and Swanson (2023a). Specifically, Panel A presents results using duration values, demonstrating robust evidence that shorter-duration markets are consistently more sensitive to mortgage rate increases, even after controlling for zip code-level economic characteristics. Notably, the magnitude of interaction effects increases substantially from 1.577 contemporaneously to 7.216 at the three-year horizon. It implies that the impact of mortgage rate changes materializes in house prices gradually over time, as we discuss in Section III.C.5. Panel B further corroborates our findings using duration percentiles.

Overall, with the 30-year mortgage rate, our results robustly demonstrate that shorter-duration housing markets exhibit consistently higher price sensitivity across multiple horizons. It confirms that the observed house price sensitivity is not driven solely by the implementation of short-term rate shocks but also holds when analyzing long-term rate changes.

C.7. Alternative MPS Measurements

Table A.5 evaluates the robustness of our findings using alternative monetary policy shocks (MPS) and interest rate change measurements. These alternative measures include changes in the federal funds rate, surprises in the one-year Treasury yield, and other MPS measures constructed by Jarociński and Karadi (2020) (JK PM MPS and Median MPS) and Bauer and Swanson (2023a) (BS MPS). Panel A, which analyzes duration values, and Panel B, examining duration percentiles, consistently report significantly positive coefficients on interaction terms between these alternative monetary policy measures and housing duration. The interaction coefficients remain robustly positive across all alternative MPS measures, confirming that shorter-duration housing markets consistently exhibit greater price sensitivity. Thus, the robustness analysis strongly supports our conclusion that the higher sensitivity of shorter-duration housing markets is not driven by specific monetary policy shock measures but is broadly robust across different definitions of monetary policy changes.

C.8. Monetary Policy Transmission to House Prices by Zip-Code-Level Rental Yield

Considering that rental yield explains a substantial portion of the variation in housing duration, we repeat our analysis using rental yield rather than housing cash flow duration as the key explanatory variable. Appendix Tables A.6 through A.10 present the detailed results. Overall, the results using rental yields closely parallel our findings using duration. Zip codes with higher rental yields, corresponding to shorter-duration housing markets, consistently exhibit higher house price sensitivity to MPS.

Specifically, Appendix Tables A.6 and A.7 analyze rental yield values and percentiles, respectively. Both consistently report significantly negative coefficients on the interaction terms between MPS and rental yield across specifications. The results indicate that high-yield zip codes experience larger declines in house prices following monetary tightening. Our findings remain robust after controlling for local economic characteristics.

Furthermore, Appendix Table A.8 shows consistent results across various time horizons. It reveals that zip codes with higher rental yields exhibit a greater sensitivity to MPS over one-, two-, and three-year horizons. Similarly, Appendix Table A.9 extends this analysis using the 30-year mortgage rate instead of short-term MPS, reinforcing that markets with higher rental yields demonstrate heightened price sensitivity to MPS.

Finally, Appendix Table A.10 confirms that our conclusions hold broadly across alternative measures of MPS and interest rate changes, including changes in the federal funds rate, one-year yield surprises, and alternative MPS measurements from Jarociński and Karadi (2020) and Bauer and Swanson (2023a). Thus, our main conclusion—that shorter-duration (high rental yield) housing markets exhibit significantly higher sensitivity to MPS—is consistently supported by analyses using both housing cash flow duration and rental yield measures.

D. Evidence of Reaching-for-Income Behavior in Housing Markets

To investigate whether reaching-for-income or buy-to-rent (BTR) behavior contributes to the heterogeneity in house price sensitivity across various market segments, we will first analyze whether lower interest rates increase the likelihood of properties being purchased for rental purposes (i.e., BTR behavior). Once we establish evidence for BTR behavior, we will examine its impact on housing transaction payments and aggregate house prices under different monetary policy scenarios across various rental yield markets.

D.1. Higher Likelihood of Reaching-for-Income as Interest Rates Decrease

We define buy-to-rent (BTR) transactions as property purchases subsequently listed for rental within 24 months following the purchase transactions. The detailed identification strategy for those transactions is described in detail in Appendix Section D. Our empirical approach investigates the likelihood of BTR activity in different monetary policy environments across property rental yield by estimating the following regression specification:

$$\begin{aligned}\mathbb{P}(\text{Buy-to-Rent})_{i,z,c,t} = \alpha + \beta\, MPS_{i,t-1} \times \text{Rental yield}_{i,t-1} + \delta\, \text{Rental yield}_{i,t-1} \\ + \Gamma\, \mathbf{X}_i + \zeta_c \times \theta_t + \lambda_z + \epsilon_{i,z,c,t}\end{aligned} \tag{16}$$

where the dependent variable, $\mathbb{P}(\text{Buy-to-Rent})i,z,c,t$, is a dummy variable that equals to one if the property i in zip code z and county c is purchased in year t and subsequently listed for rental within 24 months after the transaction, and zero otherwise. The variable MPS_{t-1} captures the monetary policy shock occurring in year $t-1$. The variable Rental yield$_{i,t-1}$ measures the rental yield value or percentile rank at the property level. We include an interaction term between MPS and rental yield to investigate heterogeneity in homebuyer responses to MPS across different rental-yield properties.

$\mathbf{X}_i$ includes property-level characteristics detailed in Section II.C, capturing characteristics that may influence a property's likelihood of being purchased for rental purposes. $\zeta_c \times \theta_t$ is the county-by-year fixed effects to control for time-varying county-level economics characteristics. λ_z is the zip code fixed effects to control for the time-invariant zip code characteristics.

Our primary coefficient of interest, β, captures how MPS influences the probability for properties with varying rental yields to be purchased for rental purposes. Suppose that we observe a negative relationship between MPS and property rental yields (i.e., a negative main effect of MPS on BTR probability). A negative estimated coefficient, $\widehat{\beta}$ on the interaction term $MPS_{i,t-1} \times \text{Rental yield}_{i,t-1}$ would indicate that interest rate decreases disproportionately increase the probability of BTR activity for properties with higher rental yields more than those with lower rental yields. In other words, interest rate decreases would lead to an even higher likelihood of BTR for high rental yield properties compared to similar properties with lower rental yields.

Table 5 indicates that as interest rates decrease, the properties with high rental yields will have a greater probability of being purchased to rent compared to similar properties with low rental yields. The findings are confirmed by using rental yield values in Panel A and rental yield percentiles in Panel B. Rental yields, estimated at the property level discussed in Section II.C, serve as proxies for income-generating potential. The dependent variable is a dummy variable that equals one if a property purchased in a year is subsequently listed for rent within 24 months, and zero otherwise.

[INSERT TABLE 5 HERE]

Column 1 of Panel A shows a statistically significant negative relationship between MPS and BTR probability. Specifically, a negative 100 basis point MPS increases the likelihood of a property being purchased for rental purposes by 5.6 percentage points. Given the average BTR probability of approximately 5% in the sample, this effect is economically substantial, corresponding to a 112% increase relative to the mean. This result aligns with Daniel et al. (2021), suggesting that lower interest rates significantly increase demand for income-generating assets.

Column 2 introduces the interaction between MPS and rental yields (RY). The results indicate that properties with higher rental yields are significantly more likely to be purchased for rental purposes following a negative MPS. This finding implies that rental income potential strongly motivates investors to engage in buy-to-rent transactions during periods of monetary policy easing.

Columns 3 to 5 progressively introduce fixed effects to control for economic characteristics associated with rental yields. Column 3, which includes year fixed effects, shows a substantial increase in the magnitude of the interaction term. It suggests that high rental yield property having a higher sensitivity to MPS in the BTR likelihood comes from the variation in cross-sectional differences. Column 4 adds county-by-year fixed effects, slightly reducing the magnitude of the interaction coefficient but maintaining statistical significance. This implies that while local economic conditions partly influence buy-to-rent decisions, they do not entirely explain investors' decisions driven by rental yields. Finally, Column 5 includes zip-code fixed effects, confirming that within the same zip code, properties with higher rental yields remain significantly more likely to be purchased for rental purposes for buy-to-rent investors following negative MPS.

Analyzing rental yield percentiles, Panel B corroborates our findings from Panel A. In the preferred specification in Column 5, increasing the property rental yield from the bottom percentile to the median (0th to 50th percentile) raises the buy-to-rent likelihood by approximately 1.4%, representing a 24% increase relative to the mean response to MPS.

In summary, Table 5 demonstrates a negative relationship between MPS and the probability of buy-to-rent transactions. Lower interest rates increase the likelihood that properties are purchased for rental income, particularly among properties with higher rental yields. These findings provide initial evidence that rental-driven investment behavior may potentially influence local aggregate house prices as interest rates change. We will particularly explore this question in the next section.

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

To investigate whether reaching-for-income behavior drives the heterogeneity in house price sensitivity to monetary policy shocks (MPS), we analyze whether property-level price changes differ across local BTR intensity and property rental yield (RY) characteristics following MPS.

Figure 3 examines the heterogeneity in transaction price responses across property-level rental yields (RY) and local buy-to-rent (BTR) transaction intensity, following a negative 10 basis points monetary policy shock (MPS). Properties are classified into four groups based on median values of property-level RY and zip-code-level BTR ratios: "High RY High BTR," "Low RY High BTR," "High RY Low BTR," and "Low RY Low BTR." Transaction price changes are measured as the percentage change in a property's transaction price at year t relative to its expected price at year t-2, estimated via the hedonic model detailed in Section II.C.1. The MPS occurs between the end of year t-2 and t-1. The regression specification underlying the analysis controls for property-level characteristics and is provided in the figure's annotation. However, we will leave more constrained specifications in Table 6.

[INSERT FIGURE 3 HERE]

The figure provides strong evidence that buy-to-rent (BTR) activity significantly influences the price sensitivity of high rental yield (short-duration) housing markets to MPS. Specifically, Properties with a high rental yield in high BTR areas ("High RY High BTR") experience a price increase of approximately 8% following the -10 bps MPS. In contrast, similarly high rental yield properties located in low BTR areas ("High RY Low BTR") exhibit a smaller price increase of around 5%. This striking difference suggests that buy-to-rent investment activity amplifies the price responsiveness of high rental yield (short-duration) markets to MPS.

Further evidence is obtained by comparing properties in markets with low BTR activity. In these areas, both high and low RY properties exhibit similarly moderate price increases following the negative MPS, with low RY properties even showing a slightly greater increase than high RY properties. This pattern aligns closely with standard theoretical predictions, indicating that, in the absence (or at low levels) of BTR investment, housing markets respond in line with the standard theory, which is lower rental yield (longer-duration) properties are more sensitive to MPS. Thus, the higher price sensitivity observed in higher rental yield markets appears predominantly driven by heightened BTR investment activity.

Within high BTR ratio areas, a stark contrast emerges between high and low RY properties. BTR activity appears to heighten the price sensitivity of high RY properties to MPS while reducing the sensitivity of low RY properties. The striking difference may reflect that BTR buyers, who are often experienced housing investors with strong bargaining power, tend to negotiate more aggressively in low RY markets where rental returns are less attractive. Consequently, a higher ratio of BTR transactions in an area may mitigate the MPS effect on house prices for low RY properties, dampening their sensitivity relative to high RY counterparts.

Overall, Figure 3 highlights that buy-to-rent investment behavior substantially contributes to the high sensitivity of house prices to MPS observed in high rental yield (short-duration) housing markets. Without significant BTR activity, price responses align closely with standard theoretical predictions. The figure further emphasizes the critical role of buy-to-rent investor behavior in shaping housing market dynamics following MPS.

D.3. Buy-to-Rent Activity Amplifies House Price Sensitivity in High Rental Yield Markets

In this section, we provide a rigorous analysis of whether buy-to-rent (BTR) investment activity amplifies the sensitivity of property prices to monetary policy shocks (MPS). Using the same property-level transaction dataset, we explore how changes in house prices following monetary policy shocks differ based on local concentrations of BTR investments and individual property rental yields (RY). Specifically, we estimate the following regression specification:

$$\begin{aligned}\Delta\text{Pay}_{i,z,c,[t-2,t]} = \alpha &+ \beta_1\, MPS_{t-1} \times \text{RY}_{i,t-1} \times \%\,\text{BTR}_{z,t} \\ &+ \beta_2\, MPS_t \times \text{RY}_{i,t-1} + \beta_3\, MPS_{t-1} \times \%\,\text{BTR}_{z,t} + \beta_4\, \text{RY}_{i,t-1} \times \%\,\text{BTR}_{z,t} \\ &+ \beta_5\, \text{RY}_{i,t-1} + \beta_6\, \%\,\text{BTR}_{z,t} + \Gamma X_i + \zeta_c \times \theta_t + \lambda_z + \epsilon_{i,z,c,t}\end{aligned} \tag{17}$$

, where the dependent variable, $\Delta\text{Pay}_{i,z,c,[t-2,t]}$, denotes the percentage change in the transaction price of property i, located in zip code z and county c, in year t relative to the expected price in year $t-2$. The method for estimating the expected property price is detailed in Section II.C.1. Our main explanatory variables include monetary policy shocks in year $t-1$ (MPS_{t-1}), property-level rental yields in year $t-1$ ($RY_{i,t-1}$), and the local buy-to-rent ratio in zip code z and year t ($\%BTR_{z,t}$). The interaction term $MPS_{t-1} \times RY_{i,t-1}$ assesses the heterogeneity in house price sensitivity to MPS across properties with different rental yields. Similarly, the interaction term $MPS_{t-1} \times \%BTR_{z,t}$ evaluates whether local BTR activity affects property price responses to MPS on average.

Importantly, our primary coefficient of interest, β_1, on the triple interaction term, $MPS_{t-1} \times RY_{i,t-1} \times \%BTR_{z,t}$, captures the joint effect of MPS, property-level RY, and the local concentration of BTR transactions on house price changes. An estimated negative coefficient, $\hat{\beta}_1 < 0$, would directly indicate that properties with higher rental yields located in areas with greater BTR activity exhibit an amplified sensitivity of prices to MPS. For example, following a negative MPS, a negative coefficient for $\hat{\beta}_1$ would suggest that the high-RY properties located in areas with a higher share of BTR activity would experience larger price increases compared to similar high-RY properties located in lower BTR concentrations.

Table 6 shows the regression results. Panel A reports results based on rental yield values, whereas Panel B utilizes rental yield percentiles. The dependent variable is the percentage change in transaction price for a property in year t relative to its expected price at year t-2, in which the expected price is estimated by the hedonic model detailed in Section II.C.1. The MPS occurs in the year before transactions (i.e., from the end of year t-2 to t-1). All specifications control for property characteristics to ensure comparability across similar-quality properties.

[INSERT TABLE 6 HERE]

In Column 1 of Panel A, we regress transaction price changes on the MPS, rental yield (RY), and zip-code-level buy-to-rent ratio (% BTR) without interaction terms. The coefficients indicate that higher rental yields and lower BTR ratios are associated with higher price growth on average. Specifically, a one standard deviation increase in rental yield (0.028) is associated with a 1.5% increase in price growth. A negative MPS of 10 basis points (bps) corresponds to a 5.7% increase in property transaction prices compared to expected prices in two years.

Column 2 introduces key interaction terms among MPS, property RY, and the local BTR ratio. The results demonstrate that for two properties with similar characteristics and high rental yields, the one located in an area with a higher proportion of BTR transactions exhibits greater price sensitivity to MPS. Specifically, following one standard deviation decrease in MPS (-12 bps), for a property with an average rental yield of 0.075, a one standard deviation increase in the BTR ratio (0.03) results in an additional 5.11% increase in price change compared to similar properties without the increase in BTR ratio.

Notably, in Column 2, the significantly positive coefficient on the MPS × RY interaction indicates that, in the absence of BTR activity, high rental yield properties are less sensitive to MPS than low rental yield comparables, consistent with standard theoretical predictions. This implies that BTR transactions play a critical role in amplifying the responsiveness of high rental yield properties to monetary policy.

Columns 3 through 5 progressively add fixed effects, including year (Column 3), county-by-year (Column 4), and zip-code fixed effects (Column 5), to control for local economic characteristics potentially correlated with rental yields. Despite including these comprehensive controls, the triple-interaction coefficient (MPS × Rental Yield × BTR ratio) remains significantly negative. Specifically, in Column 5, results suggest that for one standard deviation decrease in MPS (-12 bps), increasing the local BTR ratio by one standard deviation (0.03) increases the transaction price growth of a property with an average rental yield (approximately 0.075) by about 1.87%. It clearly emphasizes the importance of local buy-to-rent activity in amplifying price responses of high rental yield markets to monetary policy.

Panel B confirms our findings using percentile ranks of RY and BTR ratios, which ensures robustness against potential outliers or extreme values. Our results consistently show significant negative triple-interaction terms, which indicates again that high rental yield properties in high BTR areas experience significantly larger price responses than similar properties in low BTR areas following a monetary policy easing. Specifically, as indicated in Column 5, moving from the 0th to the 50th percentile in the BTR ratio corresponds to an additional 2.1% price increase for a median-percentile-RY property following a standard deviation decrease (-12 bps) MPS.

Moreover, the coefficients on interaction term, $\text{MPS}_{t-1}\times\ \text{RY}_{i,t-1}$, remains significantly positive across Columns 2 to 5. It provides robust evidence that, without BTR activity, high rental yield properties will exhibit less sensitivity to MPS than low rental yield ones, aligning with theory prediction.

Overall, Table 6 provides robust property-level evidence that the buy-to-rent investment activity significantly amplifies house price sensitivity to monetary policy shocks, particularly within high rental yield (short-duration) housing markets. The results highlight the crucial role of reaching-for-income investment behavior in shaping local housing market dynamics in response to changes in monetary policy.

IV. Conclusion

Our study uncovers a striking anomaly in the transmission of monetary policy to housing markets: properties characterized by shorter cash flow durations exhibit significantly greater sensitivity to monetary policy shocks compared to those with longer durations, a finding contrary to conventional financial theory. Leveraging a novel zip-code-level measure of housing duration, meticulously constructed from detailed property-level transaction and rental listing data, we provide compelling evidence supporting this divergence and elucidate its underlying mechanisms.

Specifically, we demonstrate that buy-to-rent (BTR) investors exhibit pronounced "reaching-for-income" behavior, preferentially targeting properties with high rental yields and shorter cash flow durations in response to monetary policy easing. This investor-driven demand significantly amplifies house price sensitivity in these markets, challenging traditional duration-based asset pricing models. In contrast, areas with low BTR investment activity display price sensitivities aligned with conventional theory, further emphasizing the role of investment behavior in shaping monetary policy transmission to real estate prices.

Our empirical findings hold robust across various monetary policy shock measures, alternative interest rate indicators, and extensive local economic controls, reinforcing the robustness of our conclusions. The analysis leverages granular, property-level transaction and rental data, providing compelling evidence that investor-driven dynamics, particularly "reaching-for-income" behavior, are critical determinants of monetary transmission to real estate markets.

Variable Definitions

Variable	Definition	Source
Monetary policy shock variables		
MPS	The orthogonalized monetary policy surprise series (MPS_ORTH) developed by Bauer and Swanson (2023a). For simplicity, we use "MPS" to represent their orthogonalized shocks (MPS_ORTH) in the paper.	Bauer and Swanson (2023a)
Δ FFR	The interest rate change: $\Delta r = r_t - r_{t-1}$, where r_t and r_{t-1} are the Fed Funds rates at the end of years t and $t-1$.	FRED St. Louis Fed
1-Year Yield Surprise	Interest rate 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 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 $t-1$. This captures the deviation between actual and expected yield.	FRED St. Louis Fed
Zip-code level variables		
$\Delta HPI_{z,[t-1,t+h]}$	House price growth in zip code i: $$\Delta HPI_{z,[t-1,t+h]} = \frac{\mathrm{HPI}_{z,\,t+h}}{\mathrm{HPI}_{z,\,t-1}} - 1$$, where $HPI_{z,t}$ is the Zillow Home Value Index (ZHVI) at zip z in year t.	Zillow
$\mathrm{Duration}_{z,t}$	Housing cash flow duration measurement (see Section II.B).	Estimation

Continued on next page

– *Continued from previous page*

Variable	Definition	Source
Rental yield$_{z,t}$	The rent yield in zip code i in year t is defined as the following. $$\text{Rental Yield}_{z,t} = \frac{\overline{\text{ZORI}_{z,t}} \times 12}{\text{ZHVI}_{z,t-1}}$$, where $\overline{\text{ZORI}_{z,t}}$ represents the average monthly rental income level at the zip code z at year t. We annualize it by multiplying 12. $\text{ZHVI}_{z,t-1}$ represents the house price level at the zip code z in December of year t-1.	Zillow
log(rental yield)$_{z,t}$	Natural logarithm of zip-code level rental yield	Zillow
log(rent)$_{z,t}$	Natural logarithm of ZORI	Zillow
log(income)$_{z,t}$	Natural logarithm of median household income (B19013_001)	U.S. Census
Income growth$_{z,t}$	The change of median household income (B19013_001) from year t-1 to t	U.S. Census
log(population)$_{z,t}$	Natural logarithm of the total population (B01003_001)	U.S. Census
Population growth$_{z,t}$	The change of total population (B01003_001) from year t-1 to t	U.S. Census
% below 40$_{z,t}$	The number of the population below 40 divided by the total population	U.S. Census
% below 40 growth$_{z,t}$	The change of % below 40 from year t-1 to t	U.S. Census
% above 60$_{z,t}$	The number of the population above 60 divided by the total population	U.S. Census
% above 60 growth$_{z,t}$	The change of % above 60 from year t-1 to t	U.S. Census
Labor force rate$_{z,t}$	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
Labor force rate growth$_{z,t}$	The change of labor force rate from year t-1 to t	U.S. Census
Unemployment rate$_{z,t}$	The number of unemployed people (b23025_005) as a percentage of the civilian labor force (b23025_003)	U.S. Census
Unemployment rate growth$_{z,t}$	The change of unemployment rate from year t-1 to t	U.S. Census

Continued on next page

– *Continued from previous page*

Variable	Definition	Source
Homeownership rate$_{z,t}$	The number of owner-occupied housing units (b25003_002) dividend by the total housing unit in the zip code (b25003_001)	U.S. Census
Homeownership rate growth$_{z,t}$	The change of homeownership rate from year t-1 to t	U.S. Census
Vacancy rate$_{z,t}$	The number of vacant housing units (b25002_003) dividend by the total housing unit (b25002_001)	U.S. Census
% BTR$_{z,t}$	The percentage of buy-to-rent (BTR) transactions in a zip code and year. The detailed identification procedure for BTR is discussed in Appendix Section D.	Estimation
Property level variables		
Rental yield (RY)	Property level rental yield estimated with the rent and price hedonic models. The detailed estimation procedure is discussed in detail in Section II.C	Estimation
$\Delta \text{Pay}_{i,z,[t-2,t]}$	Change in transaction price in year t relative to the expected property price at year t-2. The expected property prices are estimated with the hedonic model discussed in Section II.C.1.	Estimation

REFERENCES

Adelino, Manuel, Antoinette Schoar, and Felipe Severino, 2025, Credit supply and house prices: Evidence from mortgage market segmentation, *Journal of Financial Economics* 163, 103958.

Andrews, Spencer, and Andrei Gonçalves, 2020, The Bond, Equity, and Real Estate Term Structures, *SSRN Electronic Journal* Read_Status: In Progress Read_Status_Date: 2024-11-18T21:35:37.094Z.

Baldauf, Markus, Jack Y Favilukis, Lorenzo Garlappi, and Keling Zheng, 2022, Profiting from real estate: So easy a congressman can do it, *Available at SSRN 3801378* .

Bansal, Ravi, Shane Miller, Dongho Song, and Amir Yaron, 2021, The term structure of equity risk premia, *Journal of Financial Economics* 142, 1209–1228, Read_Status: New Read_Status_Date: 2023-10-13T01:21:10.539Z.

Bauer, Michael D, and Eric T Swanson, 2023a, A reassessment of monetary policy surprises and high-frequency identification, *NBER Macroeconomics Annual* 37, 87–155.

Bauer, Michael D., and Eric T. Swanson, 2023b, A Reassessment of Monetary Policy Surprises and High-Frequency Identification, *NBER Macroeconomics Annual* 37, 87–155, Read_Status: In Progress Read_Status_Date: 2024-11-14T03:55:10.285Z.

Becker, Bo, and Victoria Ivashina, 2015, Reaching for Yield in the Bond Market, *The Journal of Finance* 70, 1863–1902, Read_Status: In Progress Read_Status_Date: 2024-11-14T22:00:52.901Z.

Beraja, Martin, Andreas Fuster, Erik Hurst, and Joseph Vavra, 2019, Regional Heterogeneity and the Refinancing Channel of Monetary Policy*, *The Quarterly Journal of Economics* 134, 109–183, Read_Status: Read Read_Status_Date: 2024-10-14T04:09:41.430Z.

Berger, David, Konstantin Milbradt, Fabrice Tourre, and Joseph Vavra, 2021, Mortgage Prepayment and Path-Dependent Effects of Monetary Policy, *American Economic Review* 111, 2829–2878, Read_Status: New Read_Status_Date: 2024-10-28T04:13:15.127Z.

Bernstein, Shai, Timothy Mcquade, and Richard R. Townsend, 2021, Do Household Wealth Shocks Affect Productivity? Evidence from Innovative Workers During the Great Recession, *The Journal of Finance* 76, 57–111.

Binsbergen, Jules Van, Michael Brandt, and Ralph Koijen, 2012, On the Timing and Pricing of Dividends, *American Economic Review* 102, 1596–1618.

Boguth, Oliver, Murray Carlson, Adlai Fisher, and Mikhail Simutin, 2023, The Term Structure of Equity Risk Premia: Levered Noise and New Estimates, *Review of Finance* 27, 1155–1182, Read_Status: New Read_Status_Date: 2023-10-13T01:21:10.534Z.

Bosshardt, Joshua, Marco Di Maggio, Ali Kakhbod, and Amir Kermani, 2024, The credit supply channel of monetary policy tightening and its distributional impacts, *Journal of Financial Economics* 160, 103914.

Campbell, John Y., and Robert J. Shiller, 1988, The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors, *Review of Financial Studies* 1, 195–228.

Campbell, John Y., and Roman Sigalov, 2022, Portfolio choice with sustainable spending: A model of reaching for yield, *Journal of Financial Economics* 143, 188–206.

Chambers, David, Christophe Spaenjers, and Eva Steiner, 2021, The Rate of Return on Real Estate: Long-Run Micro-Level Evidence, *The Review of Financial Studies* 34, 3572–3607.

Choi, Jaewon, and Mathias Kronlund, 2018, Reaching for Yield in Corporate Bond Mutual Funds, *The Review of Financial Studies* 31, 1930–1965, Read_Status: New Read_Status_Date: 2024-05-29T14:58:32.864Z.

Cocco, João F., 2005, Portfolio Choice in the Presence of Housing, *Review of Financial Studies* 18, 535–567, Read_Status: Read Read_Status_Date: 2023-08-20T18:04:13.490Z.

Colonnello, Stefano, Roberto Marfè, and Qizhou Xiong, 2021, Housing Yields, *SSRN Electronic Journal* .

Damen, Sven, Matthijs Korevaar, and Stijn Van Nieuwerburgh, 2025, An Alpha in Affordable Housing?

Daniel, Kent, Lorenzo Garlappi, and Kairong Xiao, 2021, Monetary Policy and Reaching for Income, *The Journal of Finance* 76, 1145–1193, Read_Status: In Progress Read_Status_Date: 2024-09-23T20:52:42.888Z.

Dechow, Patricia M., Richard G. Sloan, and Mark T. Soliman, 2004, Implied Equity Duration: A New Measure of Equity Risk, *Review of Accounting Studies* 9, 197–228.

Di Maggio, Marco, and Amir Kermani, 2017, Credit-Induced Boom and Bust, *The Review of Financial Studies* 30, 3711–3758.

Di Maggio, Marco, Amir Kermani, Benjamin J. Keys, Tomasz Piskorski, Rodney Ramcharan, Amit Seru, and Vincent Yao, 2017, Interest Rate Pass-Through: Mortgage Rates, Household Consumption, and Voluntary Deleveraging, *American Economic Review* 107, 3550–3588, Read_Status: Read Read_Status_Date: 2024-07-09T11:12:45.799Z.

Di Maggio, Marco, Amir Kermani, and Christopher J Palmer, 2020, How Quantitative Easing Works: Evidence on the Refinancing Channel, *The Review of Economic Studies* 87, 1498–1528, Read_Status: New Read_Status_Date: 2024-10-14T02:57:21.139Z.

Diamond, Rebecca, and William Diamond, 2024, Racial Differences in the Total Rate of Return on Owner-Occupied Housing, Technical Report w32916, National Bureau of Economic Research, Cambridge, MA.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2017, The Deposits Channel of Monetary Policy*, *The Quarterly Journal of Economics* 132, 1819–1876, Read_Status: New Read_Status_Date: 2024-09-18T04:02:47.484Z.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2022, How monetary policy shaped the housing boom, *Journal of Financial Economics* 144, 992–1021.

Drechsler, Itamar, Alexi Savov, Philipp Schnabl, and Dominik Supera, 2024, Monetary policy and the mortgage market, Working Paper, presented at Jackson Hole Economic Policy Symposium.

Eichenbaum, Martin, Sergio Rebelo, and Arlene Wong, 2022, State-Dependent Effects of Monetary Policy: The Refinancing Channel, *American Economic Review* 112, 721–761, Read_Status: New Read_Status_Date: 2023-10-16T22:40:49.042Z.

Eichholtz, Piet, Matthijs Korevaar, Thies Lindenthal, and Ronan Tallec, 2021, The Total Return and Risk to Residential Real Estate, *The Review of Financial Studies* 34, 3608–3646.

Fama, Eugene F, and Kenneth R French, 2025, House Prices and Rents, *The Review of Financial Studies* 38, 547–563.

Favara, Giovanni, and Jean Imbs, 2015, Credit Supply and the Price of Housing, *American Economic Review* 105, 958–992, Read_Status: New Read_Status_Date: 2024-12-28T00:17:21.508Z.

Favilukis, Jack, Sydney C. Ludvigson, and Stijn Van Nieuwerburgh, 2017, The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk Sharing in General Equilibrium, *Journal of Political Economy* 125, 140–223, Publisher: The University of Chicago Press.

Flavin, Marjorie, and Shinobu Nakagawa, 2008, A Model of Housing in the Presence of Adjustment Costs: A Structural Interpretation of Habit Persistence, *American Economic Review* 98, 474–495, Read_Status: New Read_Status_Date: 2023-08-08T02:47:30.820Z.

Gargano, Antonio, and Marco Giacoletti, 2022, Individual Investors' Housing Income and Interest Rates Fluctuations, *SSRN Electronic Journal* .

Gen Li, Gen, 2023, Spatial Extrapolation in Housing Markets, *SSRN Electronic Journal* .

Giglio, Stefano, Bryan Kelly, and Serhiy Kozak, 2024, Equity Term Structures without Dividend Strips Data, *The Journal of Finance* 79, 4143–4196.

Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber, 2021, Climate Change and Long-Run Discount Rates: Evidence from Real Estate, *The Review of Financial Studies* 34, 3527–3571, Read_Status: In Progress Read_Status_Date: 2025-01-25T23:05:44.711Z.

Giglio, Stefano, Matteo Maggiori, and Johannes Stroebel, 2015, Very Long-Run Discount Rates, *The Quarterly Journal of Economics* 130, 1–53.

Giglio, Stefano, Matteo Maggiori, and Johannes Stroebel, 2016, No-Bubble Condition: Model-Free Tests in Housing Markets, *Econometrica* 84, 1047–1091.

Gilbukh, Sonia, Andrew Haughwout, Rebecca J. Landau, and Joseph Tracy, 2023, The price-to-rent ratio: A macroprudential application, *Real Estate Economics* 51, 503–532.

Goldsmith-Pinkham, Paul, and Kelly Shue, 2023, The gender gap in housing returns, *The Journal of Finance* 78, 1097–1145.

Gomes, Francisco, Cameron Peng, Oksana Smirnova, and Ning Zhu, 2022, Reaching for Yield: Evidence from Households, *SSRN Electronic Journal* .

Gonçalves, Andrei S, 2021, The short duration premium, *Journal of Financial economics* 141, 919–945.

Gormsen, Niels Joachim, and Eben Lazarus, 2023, Duration-Driven Returns, *The Journal of Finance* 78, 1393–1447, Read_Status: In Progress Read_Status_Date: 2024-11-17T21:42:06.202Z.

Gorodnichenko, Yuriy, and Michael Weber, 2016, Are Sticky Prices Costly? Evidence from the Stock Market, *American Economic Review* 106, 165–199.

Greenwald, Daniel, Matteo Leombroni, Hanno N. Lustig, and Stijn Van Nieuwerburgh, 2021, Financial and Total Wealth Inequality with Declining Interest Rates, *SSRN Electronic Journal* .

Greenwald, Daniel L., 2018, The Mortgage Credit Channel of Macroeconomic Transmission, *SSRN Electronic Journal* .

Gurkaynak, Refet S, Brian Sack, and Eric T Swanson, 2005, Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements .

Halket, Jonathan, Lara Loewenstein, and Paul S Willen, 2023, The cross-section of housing returns .

Hanson, Samuel G., and Jeremy C. Stein, 2015, Monetary policy and long-term real rates, *Journal of Financial Economics* 115, 429–448, Read_Status: New Read_Status_Date: 2024-05-29T14:58:32.542Z.

Jarociński, Marek, and Peter Karadi, 2020, Deconstructing Monetary Policy Surprises— The Role of Information Shocks, *American Economic Journal: Macroeconomics* 12, 1–43.

Jiang, Hao, and Zheng Sun, 2020, Reaching for dividends, *Journal of Monetary Economics* 115, 321–338, Read_Status: New Read_Status_Date: 2024-05-23T17:57:35.516Z.

Kermani, Amir, and Francis Wong, 2024, Racial Disparities in Housing Returns, *SSRN Electronic Journal* .

Korevaar, Matthijs, 2023, Reaching for yield and the housing market: Evidence from 18th-century Amsterdam, *Journal of Financial Economics* 148, 273–296, Read_Status: New Read_Status_Date: 2023-08-09T00:32:28.671Z.

Kroen, Thomas, Ernest Liu, Atif R. Mian, and Amir Sufi, 2021, Falling Rates and Rising Superstars, *SSRN Electronic Journal* .

Kuhn, Moritz, Moritz Schularick, and Ulrike I. Steins, 2020, Income and Wealth Inequality in America, 1949–2016, *Journal of Political Economy* 128, 3469–3519.

Kuttner, Kenneth N., 2013, Low Interest Rates and Housing Bubbles: Still No Smoking Gun, in *World Scientific Studies in International Economics*, volume 30, 159–185 (WORLD SCIENTIFIC), Read_Status: New Read_Status_Date: 2024-12-27T18:13:07.145Z.

Landvoigt, Tim, Monika Piazzesi, and Martin Schneider, 2015, The Housing Market(s) of San Diego, *American Economic Review* 105, 1371–1407, Read_Status: In Progress Read_Status_Date: 2025-01-05T05:55:54.595Z.

Lettau, Martin, and Jessica A. Wachter, 2011, The term structures of equity and interest rates, *Journal of Financial Economics* 101, 90–113.

Lian, Chen, Yueran Ma, and Carmen Wang, 2019, Low Interest Rates and Risk-Taking: Evidence from Individual Investment Decisions, *The Review of Financial Studies* 32, 2107–2148, Read_Status: New Read_Status_Date: 2024-05-23T17:57:48.605Z.

Loutskina, Elena, and Philip E. Strahan, 2015, Financial integration, housing, and economic volatility, *Journal of Financial Economics* 115, 25–41.

Mian, Atif, Kamalesh Rao, and Amir Sufi, 2013, Household Balance Sheets, Consumption, and the Economic Slump, *The Quarterly Journal of Economics* 128, 1687–1726.

Mian, Atif, and Amir Sufi, 2009, The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis*, *Quarterly Journal of Economics* 124, 1449–1496.

Mian, Atif, and Amir Sufi, 2022, Credit Supply and Housing Speculation, *The Review of Financial Studies* 35, 680–719, Read_Status: In Progress Read_Status_Date: 2024-10-28T04:14:02.644Z.

Nakamura, Emi, and Jón Steinsson, 2018, High-Frequency Identification of Monetary Non-Neutrality: The Information Effect*, *The Quarterly Journal of Economics* 133, 1283–1330.

Reher, Michael, and Rossen Valkanov, 2024, The Mortgage-Cash Premium Puzzle, *The Journal of Finance* jofi.13373, Read_Status: New Read_Status_Date: 2024-09-03T17:34:25.065Z.

Schulz, Florian, 2016, On the Timing and Pricing of Dividends: Comment, *American Economic Review* 106, 3185–3223.

Shiller, Robert J, 1981, Do stock prices move too much to be justified by subsequent changes in dividends?, *American Economic Review* 71, 421–436.

Van Binsbergen, Jules H., and Ralph S.J. Koijen, 2017, The term structure of returns: Facts and theory, *Journal of Financial Economics* 124, 1–21.

Weber, Michael, 2018, Cash flow duration and the term structure of equity returns, *Journal of Financial Economics* 128, 486–503.

Williams, John C, 2015, Measuring Monetary Policy's Effect on House Prices .

Figure 1. House Price Responses to Monetary Policy Shock by Duration of Housing Markets

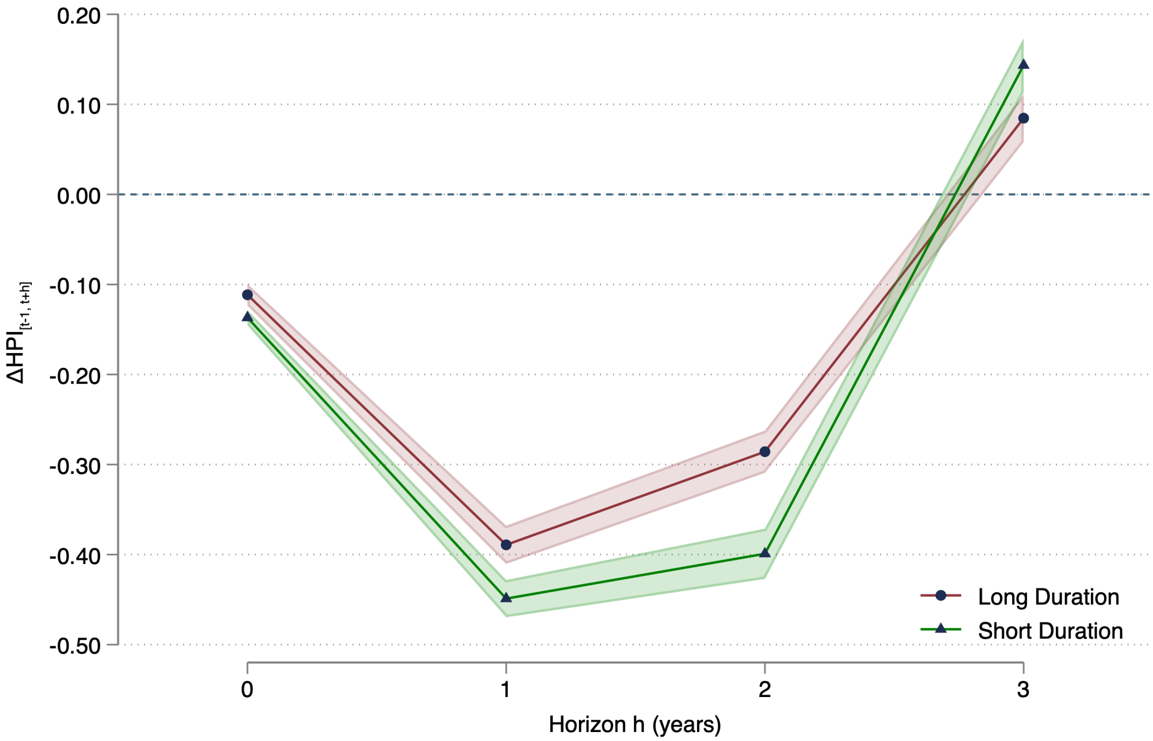

Figure 1 illustrates the impact of a 100 basis points annual positive monetary policy shock (MPS) on annual house prices in both short- and long-duration housing markets at the zip code level. The MPS occurs at horizon 0 (i.e., from year t-1 to t). The x-axis represents the response horizon (h) in years, while the y-axis shows the percentage change in house prices within the horizon since the shock. The red and green lines indicate the price response for long- and short-duration housing markets, respectively. The house price responses are estimated separately for each horizon h via regression with the specification

$$\Delta HPI_{i,[t-1,t+h]} = \alpha_h + \beta_{1,h}\, MPS_t \times \mathbb{1}\{\text{Long Duration}\}_{i,t} + \beta_{2,h}\, MPS_t + \beta_{3,h}\, \mathbb{1}\{\text{Long Duration}\}_{i,t} + \epsilon_{i,t,h}$$

, where $\Delta HPI_{i,[t-1,t+h]}$ is the house price percentage change of zip code i from year t-1 to t+h. The variable MPS_t denotes the annual monetary policy shocks in year t, as estimated by Bauer and Swanson (2023a). Additionally, $\mathbb{1}\{\text{Long Duration}\}_{i,t}$ is an indicator variable that equals one if zip code i has a housing duration above the 50th percentile across all zip codes in year t; otherwise, it equals zero. With the estimated coefficients from regressions, the values of the green line (i.e., short duration) equal $0.0100 \times \hat{\beta}_{2,h}$, while the values of the red line (i.e., long duration) equal $0.0100 \times (\hat{\beta}_{1,h} + \hat{\beta}_{2,h})$. The shaded area in the plot represents the 95% confidence interval. Standard errors are clustered at the zip code level.

Figure 2. Difference in House Price Change across Housing Duration after Monetary Policy Shock

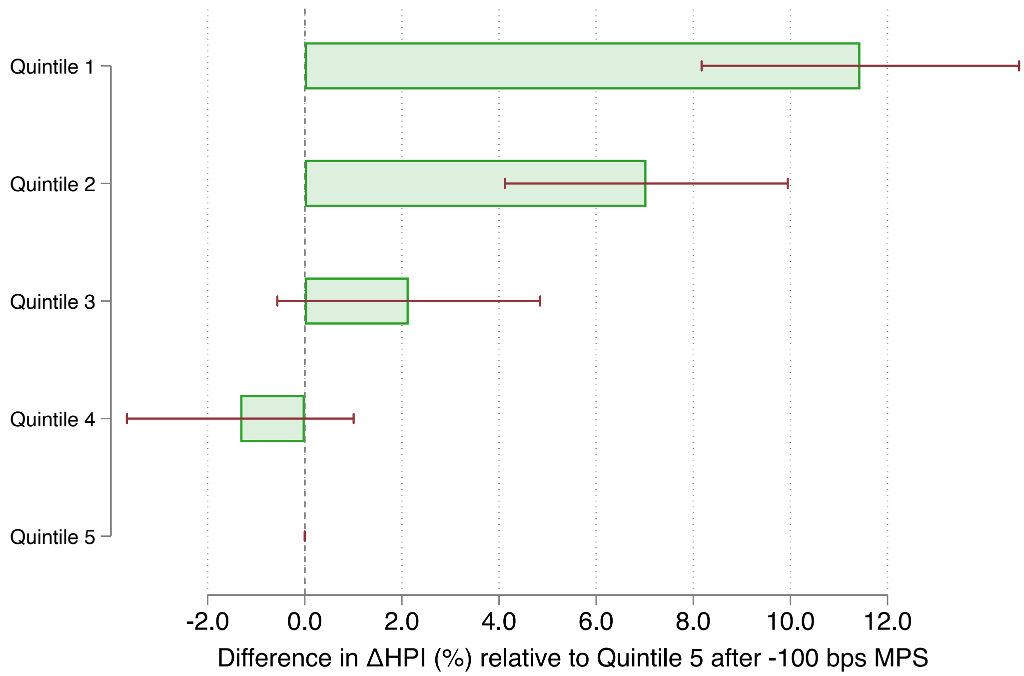

Figure 2 presents the differences in house price changes across zip codes categorized by housing cash flow duration quintiles, following a -100 basis points (bps) monetary policy shock (MPS), relative to quintile 5 (the baseline group). Zip codes are assigned into five duration-based quintiles, with quintile 1 (quintile 5) representing zip codes with the shortest (longest) housing cash flow duration. The x-axis indicates the difference in house price changes in percentage relative to quintile 5 within two years following the MPS. To estimate the different price changes, we use our preferred baseline specification analogous to Column 5 of Table 2 Panel A:

$$\Delta HPI_{z,c,[t-1,t+1]} = \alpha + \beta MPS_t \times \text{Duration Quintile}_{z,t} + \text{Duration Quintile}_{z,t} + \zeta_c \times \theta_t + \lambda_z + \epsilon_{z,c,t}$$

, where $\Delta HPI_{z,c,[t-1,t+1]}$ is the house price percentage change of zip code z in county c from year t-1 to t+1. The variable MPS_t is the aggregated annual monetary policy shock in year t constructed by Bauer and Swanson (2023a). Duration Quintile$_{z,t}$ is a categorical indicator from 1 to 5 that captures the quintile of housing cash flow duration for zip code z at year t. The term $\zeta_c \times \theta_t$ represents the county-by-year fixed effects, and λ_z denotes the zip code fixed effects. The red-capped error bars indicate 95% confidence intervals. Standard errors are clustered at the zip code level.

Figure 3. Transcation Price Changes by Property Rental Yield and Local Buy-to-Rent Ratio

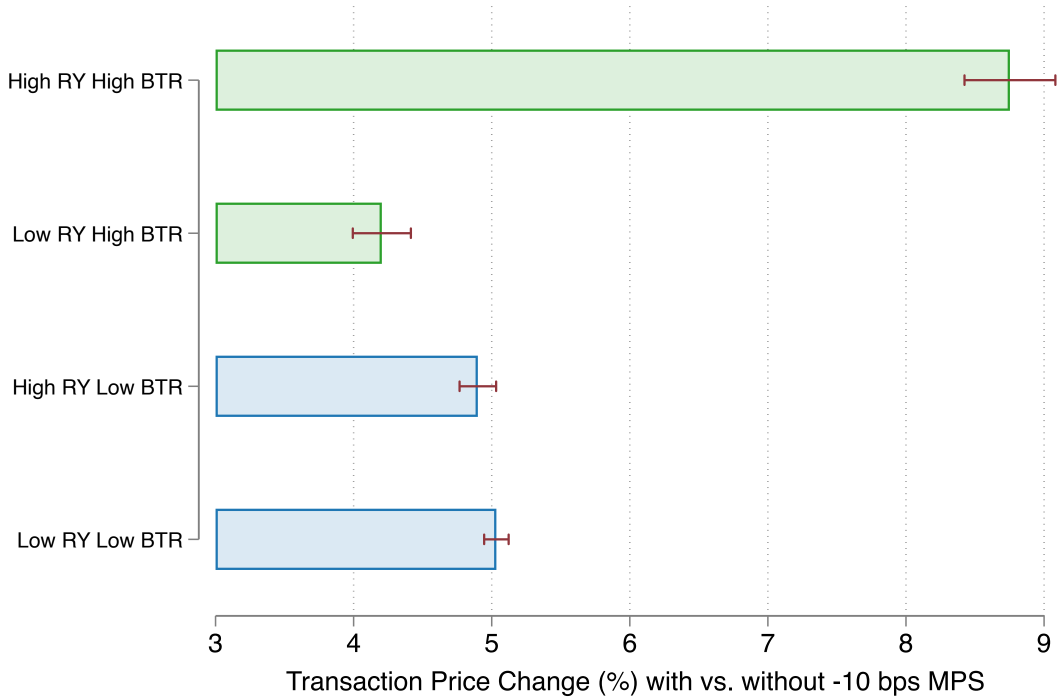

Figure 3 illustrates the transaction price changes across properties categorized by rent yield (RY) and buy-to-rent (BTR) ratio, following a -100 basis points (bps) monetary policy shock (MPS). Transacted properties in the sample are classified into four categories based on sample medians of property RY and zip-code BTR ratios: "High RY High BTR," "High RY Low BTR," "Low RY High BTR," and "Low RY Low BTR." The y-axis represents the four categories. The x-axis represents the change in transaction price in year t relative to the expected property price at year t-2, following a -100 bps MPS that occurs in year $t-1$ (i.e., from the end of year $t-2$ to $t-1$). The expected property prices are estimated with the hedonic model discussed in Section II.C.1. The figure is created based on the estimates derived from the following regression:

$$\begin{aligned}\Delta\text{Pay}_{i,z,c,[t-2,t]} = \alpha &+ \beta_1 \, \boldsymbol{MPS}_{t-1} \times \text{High RY}_{i,t-1} \times \text{High BTR}_{z,t} \\ &+ \beta_2 \, \boldsymbol{MPS}_t \times \text{High RY}_{i,t-1} + \beta_3 \, \boldsymbol{MPS}_{t-1} \times \text{High BTR}_{z,t} + \beta_4 \, \text{High RY}_{i,t-1} \times \text{High BTR}_{z,t} \\ &+ \beta_5 \, \boldsymbol{MPS}_{t-1} + \beta_6 \, \text{High RY}_{i,t-1} + \beta_7 \, \text{High BTR}_{z,t} + \Gamma X_i + \epsilon_{i,z,c,t}\end{aligned}$$

, where $\text{Pay}_{i,z,c,[t-2,t]}$ represents the percentage change in the transaction price of property i in year t relative to the expected property price at year t-2, and MPS is the monetary policy shock constructed by Bauer and Swanson (2023a). The variable $\text{High RY}_{i,t-1}$ is a dummy variable that equals one if property i has a rental yield above the median in year $t-1$. Similarly, $\text{High BTR}_{z,t}$ is a dummy variable that equals one if the zip code z of property i has a buy-to-rent transaction ratio that is above the median in year t. The error bars in the plot represent the 95% confidence interval. Standard errors are clustered at the property level.

Table 1. Relationships between Housing Duration, Rental Yield, and Local Characteristics

	Duration$_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
log(rental yield)$_{i,t}$	-0.410***	-0.420***	-0.415***	-0.414***	-0.401***	-0.343***
	(0.005)	(0.007)	(0.006)	(0.006)	(0.007)	(0.010)
log(rent)$_{i,t}$		-0.022***	-0.010	-0.007	-0.007	0.026***
		(0.008)	(0.011)	(0.011)	(0.009)	(0.009)
log(income)$_{i,t}$			-0.030***	-0.027***	-0.003	-0.009*
			(0.008)	(0.008)	(0.007)	(0.005)
Income growth$_{i,t}$			0.123***	0.088***	0.084***	0.075***
			(0.010)	(0.010)	(0.009)	(0.005)
log(population)$_{i,t}$			0.006***	0.006***	0.006***	0.012***
			(0.002)	(0.002)	(0.002)	(0.003)
Population growth$_{i,t}$			0.201***	0.122***	0.086***	0.032***
			(0.018)	(0.021)	(0.018)	(0.008)
% below 40$_{i,t}$			-0.033*	0.001	0.047*	-0.076***
			(0.019)	(0.023)	(0.025)	(0.017)
% below 40 growth$_{i,t}$			-0.051***	-0.026**	-0.025**	0.004
			(0.007)	(0.013)	(0.012)	(0.006)
% above 60$_{i,t}$			-0.019	0.027	0.083***	0.003
			(0.024)	(0.029)	(0.030)	(0.025)
% above 60 growth$_{i,t}$			-0.056***	-0.004	-0.014**	-0.015***
			(0.006)	(0.008)	(0.006)	(0.003)
Labor force rate$_{i,t}$			0.086***	0.083***	0.107***	0.066***
			(0.023)	(0.023)	(0.020)	(0.016)
Labor force rate growth$_{i,t}$			-0.108***	-0.068***	-0.076***	-0.097***
			(0.024)	(0.024)	(0.019)	(0.010)
Unemployment rate$_{i,t}$			-0.449***	-0.454***	-0.346***	0.005
			(0.055)	(0.056)	(0.049)	(0.034)
Unemployment rate growth$_{i,t}$			-0.003	-0.014***	-0.009***	-0.016***
			(0.002)	(0.002)	(0.002)	(0.001)
Homeownership rate$_{i,t}$			0.020*	0.020*	-0.021**	-0.040***
			(0.012)	(0.012)	(0.009)	(0.012)
Homeownership rate growth$_{i,t}$			-0.021*	-0.029**	-0.029***	-0.032***
			(0.012)	(0.012)	(0.010)	(0.004)
Vacancy rate$_{i,t}$			-0.166***	-0.172***	-0.178***	-0.051***
			(0.027)	(0.026)	(0.023)	(0.015)
Adjusted R^2	0.921	0.922	0.933	0.939	0.961	0.995
Observations	16,913	16,913	16,913	16,913	16,913	16,913
Year FE				Yes		
County × Year FE					Yes	Yes
Zip FE						Yes

Table 1 illustrates the relationships between estimated housing duration and local economic characteristics. The dependent variable is the estimated housing duration of zip code i in year t. Section II.B provides details on the estimation of housing duration. Column 1 analyzes the correlation between duration and rental yield and highlights rental yields as critical determinants of housing cash flow durations. Column 2 incorporates the log of rent levels as an additional explanatory variable. Column 3 includes a broader range of local economic characteristics. Columns 4 to 6 present results with different combinations of fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2. Duration and Monetary Policy Transmission to Asset Prices

Panel A: Real estate

	Δ HPI$_{i,[t-1,t+1]}$				
	(1)	(2)	(3)	(4)	(5)
MPS$_t$ × Duration$_{i,t}$		21.660***	31.233***	45.542***	33.756***
		(3.807)	(3.900)	(4.319)	(4.152)
MPS$_t$	-46.430***	-144.633***			
	(0.607)	(17.263)			
Duration$_{i,t}$	-0.132***	-0.152***	-0.176***	-0.165***	-0.517***
	(0.009)	(0.011)	(0.011)	(0.012)	(0.054)
Adjusted R^2	0.299	0.301	0.403	0.815	0.881
Observations	16,883	16,883	16,883	16,883	16,883
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)
MPS$_t$ × Duration$_{i,t}$		-2.187***	-1.780***	-1.309***
		(0.229)	(0.258)	(0.171)
MPS$_t$	-19.618***	-5.597***	-7.303***	
	(0.680)	(1.330)	(1.525)	
Duration$_{i,t}$	0.004***	0.004***	0.015***	0.012***
	(0.000)	(0.000)	(0.000)	(0.001)
Adjusted R^2	0.148	0.175	0.139	0.754
Observations	3,886	3,886	3,886	3,886
Bond FE			Yes	Yes
Year FE				Yes

Panel C: Equity

	Δ P$_{i,[t-1,t+1]}$			
	(1)	(2)	(3)	(4)
MPS$_t$ × Duration$_{i,t}$		-0.117**	-0.117**	-0.095
		(0.055)	(0.059)	(0.059)
MPS$_t$	-64.524***	-56.891***	-65.191***	
	(3.129)	(4.291)	(4.452)	
Duration$_{i,t}$	-0.000***	-0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.006	0.006	0.067	0.109
Observations	83,409	83,409	83,409	83,409
Stock FE			Yes	Yes
Year FE				Yes

Table 2 illustrates the price responses to monetary policy shocks (MPS) across different asset duration levels in the housing, bond, and stock markets. Panel A presents the baseline analysis for heterogeneous impacts of MPS on house prices by duration levels of zip-code housing markets. This analysis is conducted at the zip code and year level. Panels B and C show the responses of asset prices to MPS in the bond and equity markets, respectively. To ensure comparability with the housing analysis, each observation in Panels B and C corresponds to a year and respective bond or stock. The dependent variable in Panel A, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t+1, where t is the year when MPS occurs. In Panels B and C, the dependent variables are the price changes of bonds and stocks, respectively, over the same horizon after MPS for comparison purposes. The variable MPS_t captures the annual monetary policy shocks that occur in year t, as estimated by Bauer and Swanson (2023a). The variable $Duration_{i,t}$ indicates the duration level of asset i in year t. Section II.B provides details on the estimation of housing duration. For bonds, duration is defined as the Macaulay duration in years, calculated by the CRSP U.S. Treasury dataset, while equity duration is estimated by Gonçalves (2021). We include different combinations of fixed effects indicated at the bottom of the table. Standard errors are clustered at the individual asset level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. House Price Sensitivities to Monetary Policy Shocks, Control for Local Characteristics

	Δ HPI$_{i,[t-1,t+1]}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MPS$_t$ × Duration$_{i,t}$	30.386***	31.135***	44.670***	26.991***	28.925***	23.876***	33.551***	30.379***
	(4.197)	(4.835)	(4.725)	(4.248)	(4.101)	(4.352)	(4.049)	(4.184)
Duration$_{i,t}$	-0.521***	0.612***	-0.531***	-0.508***	-0.520***	-0.513***	-0.504***	-0.521***
	(0.055)	(0.041)	(0.055)	(0.056)	(0.055)	(0.055)	(0.056)	(0.055)
Δ HPI$_{i,[t-2,t-1]}$	0.053	0.175***	0.069**	0.054*	0.055*	0.053	0.074**	0.054
	(0.033)	(0.024)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
log(HPI)$_{i,t}$		-0.726***						
		(0.022)						
MPS$_t$ × log(HPI)$_{i,t}$		-4.776***						
		(1.562)						
MPS$_t$ × log(income)$_{i,t}$			-9.656***					
			(1.608)					
MPS$_t$ × log(population)$_{i,t}$				-4.504***				
				(0.722)				
MPS$_t$ × labor force rate$_{i,t}$					15.538**			
					(7.377)			
MPS$_t$ × unemployment rate$_{i,t}$						-75.088***		
						(25.545)		
MPS$_t$ × homeownership rate$_{i,t}$							-27.502***	
							(2.175)	
MPS$_t$ × vacancy rate$_{i,t}$								-0.646
								(8.304)
Adjusted R^2	0.887	0.931	0.888	0.888	0.887	0.887	0.890	0.887
Observations	16,883	16,883	16,883	16,883	16,883	16,883	16,883	16,883
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

Table 3 shows the heterogeneous impacts of monetary policy shocks (MPS) on house prices by duration levels of zip-code housing markets, controlling for local economic characteristics. The dependent variable, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t+1, where t is the year when MPS occurs. The variable MPS_t captures the annual monetary policy shocks that occur in year t, as estimated by Bauer and Swanson (2023a). The variable $Duration_{i,t}$ indicates the duration level of zip code i in year t. Section II.B provides details on the estimation of housing duration. Each observation in the sample represents a zip code in a year. We control for a range of time-varying economic characteristics at the zip-code level, including the logarithm of median household income, income growth, the logarithm of population size, population growth, the ratio of young residents (under age 40) and its growth, the ratio of older residents (over age 60) and its growth, the level and growth of the labor force participation rate, the unemployment rate, and the homeownership rate, as well as the vacancy rate. Additionally, we include county-year and zip-code fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Housing Duration and Monetary Policy Transmission to House Prices in 1, 2 and 3-year Horizons

Panel A: Duration values

	Δ HPI$_{i,[t-1,t]}$		Δ HPI$_{i,[t-1,t+1]}$		Δ HPI$_{i,[t-1,t+2]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
MPS$_t\times$ Duration$_{i,t}$	10.008***	7.373***	33.756***	30.386***	21.155***	19.273***
	(1.934)	(1.884)	(4.152)	(4.197)	(3.938)	(3.966)
Duration$_{i,t}$	0.099***	0.117***	-0.517***	-0.521***	-1.362***	-1.372***
	(0.033)	(0.034)	(0.054)	(0.055)	(0.086)	(0.086)
Δ HPI$_{i,[t-2,t-1]}$		0.073***		0.053		0.023
		(0.019)		(0.033)		(0.040)
Adjusted R^2	0.848	0.855	0.881	0.887	0.901	0.908
Observations	16,893	16,893	16,883	16,883	12,886	12,886
County $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Economic Chars		Yes		Yes		Yes

Panel B: Duration percentiles

	Δ HPI$_{i,[t-1,t]}$		Δ HPI$_{i,[t-1,t+1]}$		Δ HPI$_{i,[t-1,t+2]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
MPS$_t\times$ Duration$_{i,t}$	0.044***	0.030***	0.170***	0.152***	0.105***	0.095***
	(0.010)	(0.010)	(0.021)	(0.021)	(0.020)	(0.020)
Duration$_{i,t}$	0.001***	0.001***	-0.002***	-0.002***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ HPI$_{i,[t-2,t-1]}$		0.068***		0.023		-0.019
		(0.018)		(0.032)		(0.040)
Adjusted R^2	0.848	0.855	0.876	0.883	0.888	0.896
Observations	16,893	16,893	16,883	16,883	12,886	12,886
County $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Economic Chars		Yes		Yes		Yes

Table 4 examines the house price responses to monetary policy shocks (MPS) over one-, two-, and three-year horizons. Panel A presents the results using duration values, while Panel B implements duration percentiles. Each year, a zip code is assigned a percentile based on its estimated housing duration value relative to all other zip codes for that year. The dependent variable, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t in Columns 1 and 2, from year t-1 to t+1 in Columns 3 and 4, and from year t-1 to t+2, where t is the year when MPS occurs. The variable MPS_t captures the annual monetary policy shocks that occur in year t, as estimated by Bauer and Swanson (2023a). The variable $Duration_{i,t}$ indicates the duration level or percentiles of zip code i in year t. Section II.B provides details on the estimation of housing duration. Each observation in the sample represents a zip code in a year. In Columns 2, 4, and 6, we control for the same time-varying economic characteristics at the zip-code level as Table 3. We also include county-year and zip-code fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Property-level Buy-to-Rent Probability and Monetary Policy Shocks by Rental Yield

Panel A: Value regression

	$\mathbb{P}$ (Buy-to-Rent)$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
MPS$_{t-1}$ × Rental yield$_{i,t-1}$		-16.845***	-49.970***	-36.959***	-43.889***
		(3.991)	(4.184)	(5.430)	(5.561)
MPS$_{t-1}$	-5.632***	-4.448***			
	(0.079)	(0.287)			
Rental yield$_{i,t-1}$	0.279***	0.280***	0.051***	-0.224***	-0.250***
	(0.005)	(0.005)	(0.006)	(0.008)	(0.011)
Adjusted R^2	0.005	0.005	0.009	0.015	0.022
Observations	3,991,954	3,991,954	3,991,954	3,991,954	3,991,954
Property Chars	Yes	Yes	Yes	Yes	Yes
Year FE			Yes		
County × Year FE				Yes	Yes
Zip FE					Yes

Panel B: Percentile regression

	$\mathbb{P}$ (Buy-to-Rent)$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
MPS$_{t-1}$ × Rental yield$_{i,t-1}$		-0.026***	-0.039***	-0.018***	-0.028***
		(0.003)	(0.003)	(0.004)	(0.004)
MPS$_{t-1}$	-5.954***	-4.761***			
	(0.079)	(0.164)			
Rental yield$_{i,t-1}$	0.000***	0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.005	0.005	0.009	0.016	0.023
Observations	3,991,954	3,991,954	3,991,954	3,991,954	3,991,954
Property Chars	Yes	Yes	Yes	Yes	Yes
Year FE			Yes		
County × Year FE				Yes	Yes
Zip FE					Yes

Table 5 examines how monetary policy shocks (MPS) affect the probability that properties are purchased for rental purposes ("Buy-to-Rent") across properties with varying rental yields. Panel A reports results using rental yield values, while Panel B employs rental yield percentiles. The analysis employs the following specification at the transaction level:

$$\begin{aligned}\mathbb{P}(\text{Buy-to-Rent})_{i,z,c,t} &= \alpha + \beta\, MPS_{i,t-1} \times \text{Rental yield}_{i,t-1} + \delta\, \text{Rental yield}_{i,t-1} \\ &+ \Gamma \mathbf{X}_i + \zeta_c \times \theta_t + \lambda_z + \epsilon_{i,z,c,t}\end{aligned} \tag{18}$$

where the dependent variable, $\mathbb{P}$(Buy-to-Rent)i, z, c, t, is a dummy variable that equals to one if the property i in zip code z and county c is purchased in year t and subsequently listed for rental within 24 months after the transaction, and zero otherwise. The variable MPS_{t-1} captures the monetary policy shock occurring in year $t-1$, which is developed by Bauer and Swanson (2023a). The variable Rental yield$_{i,t-1}$ measures the rental yield value or percentile rank at the property level. In all columns, we control for the property characteristics, $\mathbf{X}_i$, to compare properties with similar quality detailed in Section II.C. $\zeta_c \times \theta_t$ is the county-by-year fixed effects to control for time-varying county-level economics characteristics. λ_z is the zip code fixed effects to control for the time-invariant zip code characteristics. We progressively introduce year, county-by-year, and zip-code fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the property level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Property-level Payment Change and Monetary Policy Shocks by Rental Yield

Panel A: Value regression

	Δ Pay $_{i,z,[t-2,t]}$				
	(1)	(2)	(3)	(4)	(5)
$\text{MPS}_{t-1} \times \text{RY}_{i,t-1} \times \%\ \text{BTR}_{z,t}$		-18925.15***	-9754.40***	-7356.80***	-6908.01***
		(1153.37)	(1217.79)	(1417.74)	(1460.71)
$\text{MPS}_{t-1} \times \text{RY}_{i,t-1}$		116.29**	77.64	8.56	-52.36
		(56.12)	(55.10)	(65.66)	(68.57)
$\text{MPS}_{t-1} \times \%\ \text{BTR}_{z,t}$		1126.60***	637.18***	508.42***	443.47***
		(79.57)	(81.23)	(98.15)	(101.62)
$\text{RY}_{i,t-1} \times \%\ \text{BTR}_{z,t}$		-10.37***	-4.79***	-4.83***	-3.08**
		(1.00)	(1.05)	(1.18)	(1.28)
MPS_{t-1}	-57.13***	-54.46***			
	(0.42)	(3.67)			
$\text{RY}_{i,t-1}$	0.53***	1.16***	1.73***	1.57***	0.88***
	(0.05)	(0.07)	(0.07)	(0.10)	(0.16)
$\%\ \text{BTR}_{z,t}$	-0.27***	0.61***	0.30***	0.59***	0.15
	(0.03)	(0.08)	(0.09)	(0.11)	(0.13)
Adjusted R^2	0.004	0.004	0.007	0.009	0.010
Observations	3,944,012	3,944,012	3,944,012	3,944,012	3,944,012
Property Chars	Yes	Yes	Yes	Yes	Yes
Year FE			Yes		
County × Year FE				Yes	Yes
Zip FE					Yes

Panel B: Percentile regression

	Δ Pay $_{i,z,[t-2,t]}$				
	(1)	(2)	(3)	(4)	(5)
$\text{MPS}_{t-1} \times \text{RY}_{i,t-1} \times \%\ \text{BTR}_{z,t}$		-0.022***	-0.012***	-0.007***	-0.007***
		(0.001)	(0.001)	(0.001)	(0.001)
$\text{MPS}_{t-1} \times \text{RY}_{i,t-1}$		0.601***	0.336***	0.163***	0.152***
		(0.029)	(0.029)	(0.037)	(0.039)
$\text{MPS}_{t-1} \times \%\ \text{BTR}_{z,t}$		0.766***	0.467***	0.293***	0.287***
		(0.028)	(0.027)	(0.036)	(0.041)
$\text{RY}_{i,t-1} \times \%\ \text{BTR}_{z,t}$		-0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
MPS_{t-1}	-56.916***	-69.904***			
	(0.432)	(1.303)			
$\text{RY}_{i,t-1}$	0.001***	0.001***	0.001***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\%\ \text{BTR}_{z,t}$	-0.000***	0.000**	-0.000**	0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.004	0.004	0.007	0.009	0.010
Observations	3,944,012	3,944,012	3,944,012	3,944,012	3,944,012
Property Chars	Yes	Yes	Yes	Yes	Yes
Year FE			Yes		
County × Year FE				Yes	Yes
Zip FE					Yes

Table 6 examines the impact of monetary policy shocks (MPS) on property-level transaction price changes across properties categorized by rent yield (RY) and buy-to-rent (BTR) ratio. Panel A presents regression results using values of RY and BTR, while Panel B performs percentile regressions. The dependent variable, $\Delta\text{Pay}_{i,z,c,[t-2,t]}$, represents the change in transaction price at year t of property i relative to its expected property price at year t-2, which is estimated with the hedonic model discussed in Section II.C.1. MPS occurs in year $t-1$ (i.e., from the end of year $t-2$ to $t-1$). The variable Rental yield$_{i,t-1}$ is the estimated property-level rental yield discussed in detail in Section II.C. The variable % $\text{BTR}_{z,t}$ is the percentage of BTR transactions in zip code z at year t. The specifications take the form as Equation 17. Standard errors are clustered at the property level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A. Results

Figure A.1. Monetary Policy Transmission to House Prices by Rental Yields of Housing Markets

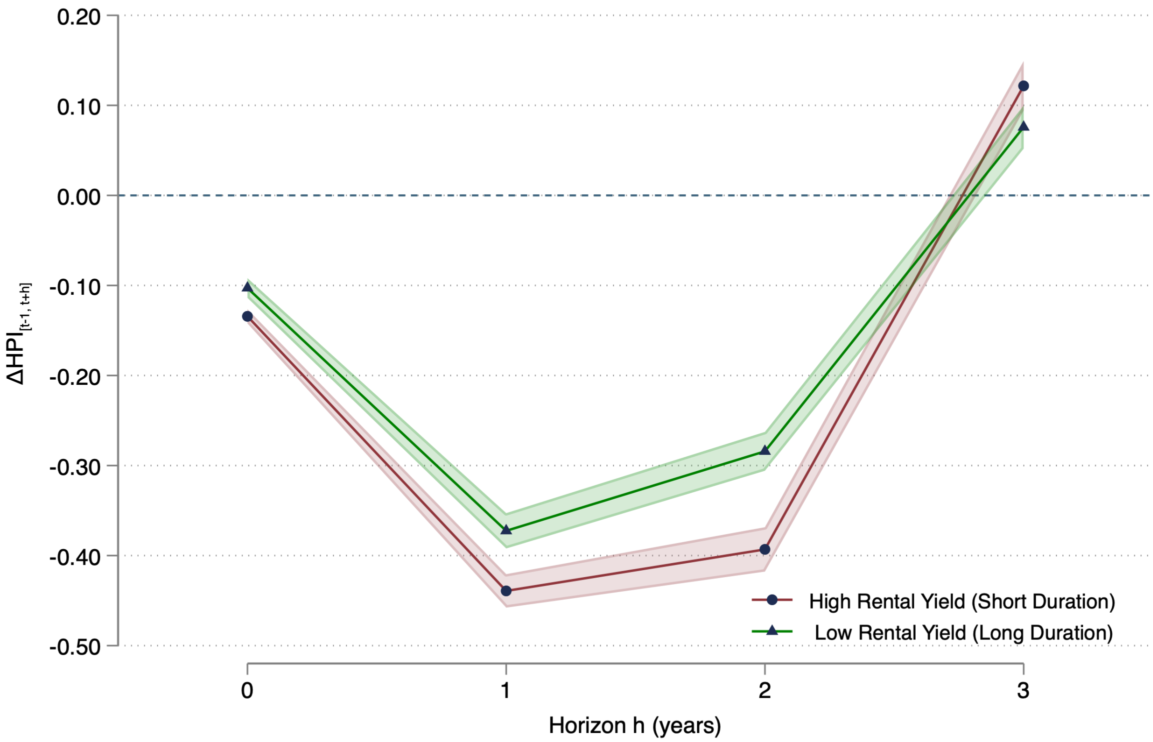

Figure A.1 illustrates the impact of a 100 basis points annual positive monetary policy shock (MPS) on annual house prices in both short- and long-rental-yield housing markets at the zip code level. The shock is applied at horizon 0 (i.e., year t). The x-axis represents the response horizon (h) in years, while the y-axis shows the percentage change in house prices within the horizon since the shock. The red line indicates the response for high-rental-yield housing markets, whereas the green line reflects the response for low-rental-yield markets. The house price responses are estimated separately for each horizon h via regression with the specification

$$\Delta HPI_{i,[t-1,t+h]} = \alpha_h + \beta_{1,h}\, MPS_t \times \mathbb{1}\{\text{High Rental Yield}\}_{i,t} + \beta_{2,h}\, MPS_t + \beta_{3,h}\, \mathbb{1}\{\text{High Rental Yield}\}_{i,t} + \epsilon_{i,t,h}$$

, where $\Delta HPI_{i,[t-1,t+h]}$ is the house price percentage change of zip code i from year t-1 to t+h. The variable MPS_t denotes the annual monetary policy shocks in year t, as estimated by Bauer and Swanson (2023a). Additionally, $\mathbb{1}\{\text{High Rental Yield}_{i,t}\}$ is an indicator variable that equals one if zip code i has a rental yield above the 50th percentile across all zip codes in year t; otherwise, it equals zero. With the estimated coefficients from regressions, the values of the green line (i.e., low rental yield) equal $0.0100 \times \hat{\beta}_{2,h}$, while the values of the red line (i.e., high rental yield) equal $0.0100 \times (\hat{\beta}_{1,h} + \hat{\beta}_{2,h})$. The shaded area in the plot represents the 95% confidence interval. Standard errors are clustered at the zip code level.

Table A.1. Future Rent Growth Prediction with Rental Yield, and Local Characteristics

	Δ log(rent)$_{i,[t+h-1,t+h]}$						
	h=1			h=2	h=3	h=4	h=5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(rental yield)$_{i,t}$	0.019***	0.014***	0.005***	-0.004**	-0.009***	0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Δ log(rent)$_{i,[t-1,t]}$		0.289***	0.301***	-0.310***	-0.178***	0.129***	-0.094***
		(0.005)	(0.006)	(0.008)	(0.011)	(0.022)	(0.032)
Income ratio$_{i,t}$			-0.007***	-0.028***	-0.029***	-0.016***	-0.005**
			(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Income growth$_{i,t}$			-0.117***	-0.094***	0.038***	0.067***	-0.076***
			(0.009)	(0.010)	(0.011)	(0.013)	(0.018)
Population ratio$_{i,t}$			5.265	0.149	-7.869	-34.732***	-25.823***
			(4.432)	(8.034)	(7.966)	(9.349)	(9.823)
Population growth$_{i,t}$			0.058***	-0.014	-0.561***	-0.231***	0.595***
			(0.014)	(0.016)	(0.020)	(0.027)	(0.032)
% below 40$_{i,t}$			-0.003	0.077***	-0.079***	-0.390***	-0.097***
			(0.007)	(0.013)	(0.015)	(0.019)	(0.017)
% below 40 growth$_{i,t}$			-0.026***	-0.075***	0.324***	0.213***	-0.403***
			(0.005)	(0.007)	(0.013)	(0.010)	(0.012)
% above 60$_{i,t}$			-0.021**	0.087***	-0.136***	-0.523***	-0.123***
			(0.010)	(0.017)	(0.020)	(0.026)	(0.024)
% above 60 growth$_{i,t}$			-0.062***	0.088***	0.208***	-0.118***	-0.213***
			(0.007)	(0.010)	(0.018)	(0.010)	(0.013)
Labor force rate$_{i,t}$			-0.028***	-0.034***	-0.067***	-0.109***	0.021*
			(0.006)	(0.010)	(0.012)	(0.014)	(0.012)
Labor force rate growth$_{i,t}$			0.091***	0.147***	0.068*	-0.241***	-0.172***
			(0.018)	(0.025)	(0.040)	(0.031)	(0.036)
Unemployment rate$_{i,t}$			0.034**	-0.068***	-0.020	0.087***	0.496***
			(0.014)	(0.023)	(0.025)	(0.031)	(0.041)
Unemployment rate growth$_{i,t}$			0.030***	0.022***	-0.030***	-0.033***	-0.037***
			(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
Homeownership rate$_{i,t}$			0.023***	0.073***	0.076***	0.036***	0.045***
			(0.002)	(0.004)	(0.005)	(0.005)	(0.005)
Homeownership rate growth$_{i,t}$			0.089***	0.033**	-0.064***	-0.004	-0.025
			(0.010)	(0.014)	(0.023)	(0.016)	(0.020)
Vacancy rate$_{i,t}$			0.031***	0.071***	0.109***	0.107***	0.105***
			(0.005)	(0.009)	(0.011)	(0.014)	(0.013)
Adjusted R^2	0.031	0.113	0.164	0.206	0.233	0.264	0.395
Observations	18,834	18,834	18,834	14,437	11,095	8,566	6,307

Table A.1 presents the results of predictive regressions for future annual rent growth over the next one to five years. The dependent variable is the logarithm of annual rent growth from year $t+h-1$ to year $t+h$, where h represents the forecast horizon indicated at the top of the column numbers. Columns 1 to 3 present the predictive regressions for rent growth over the next year (from year t to year t+1) using various specifications. Among these, Column 3 is identified as the preferred specification. Using this same preferred specification, Columns 4 to 6 present the predictions for annual rent growth over the next two to five years. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.2. Housing Duration Percentiles and Monetary Policy Transmission to House Prices

Panel A: Baseline

	Δ HPI$_{i,[t-1,t+1]}$				
	(1)	(2)	(3)	(4)	(5)
MPS$_t$ × Duration$_{i,t}$		0.146***	0.164***	0.223***	0.170***
		(0.020)	(0.020)	(0.022)	(0.021)
MPS$_t$	-45.742***	-53.218***			
	(0.605)	(1.188)			
Duration$_{i,t}$	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.310	0.312	0.403	0.811	0.876
Observations	16,883	16,883	16,883	16,883	16,883
Year FE			Yes		
County × Year FE				Yes	Yes
Zip FE					Yes

Panel B: Control for local characteristics

	Δ HPI$_{i,[t-1,t+1]}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MPS$_t$ × Duration$_{i,t}$	0.152***	0.109***	0.217***	0.128***	0.145***	0.113***	0.162***	0.152***
	(0.021)	(0.027)	(0.024)	(0.021)	(0.021)	(0.023)	(0.020)	(0.021)
Duration$_{i,t}$	-0.002***	0.003***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ HPI$_{i,[t-2,t-1]}$	0.023	0.165***	0.037	0.023	0.024	0.021	0.043	0.023
	(0.032)	(0.024)	(0.033)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
log(HPI)$_{i,t}$		-0.658***						
		(0.020)						
MPS$_t$ × log(HPI)$_{i,t}$		-0.439						
		(1.739)						
MPS$_t$ × log(income)$_{i,t}$			-8.324***					
			(1.648)					
MPS$_t$ × log(population)$_{i,t}$				-4.792***				
				(0.717)				
MPS$_t$ × labor force rate$_{i,t}$					17.109**			
					(7.448)			
MPS$_t$ × unemployment rate$_{i,t}$						-89.717***		
						(25.224)		
MPS$_t$ × homeownership rate$_{i,t}$							-27.607***	
							(2.183)	
MPS$_t$ × vacancy rate$_{i,t}$								1.747
								(8.364)
Adjusted R^2	0.883	0.929	0.884	0.884	0.883	0.883	0.886	0.883
Observations	16,883	16,883	16,883	16,883	16,883	16,883	16,883	16,883
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

Table A.2 shows the heterogeneous impacts of monetary policy shocks (MPS) on house prices across different housing duration percentiles of the zip-code markets. Each year, a zip code is assigned a percentile based on its estimated housing duration value relative to all other zip codes for that year. Panel A presents the results obtained using the baseline specification, while Panel B displays the results after controlling for local economic characteristics. The dependent variable, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t+1, where t is the year when MPS occurs. The variable MPS_t captures the annual monetary policy shocks that occur in year t, as estimated by Bauer and Swanson (2023a). The variable $Duration_{i,t}$ indicates the duration percentiles of zip code i in year t. Section II.B provides details on the estimation of housing duration. Each observation in the sample represents a zip code in a year. In Panel B, we control for the same time-varying economic characteristics at the zip-code level as Table 3. We also include different combinations of fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.3. Duration, 30-Year Mortgage Rate Change, and House Price Growth

Panel A: Baseline

	Δ HPI$_{i,[t-1,t+1]}$				
	(1)	(2)	(3)	(4)	(5)
Δ 30-year Mortgage Rate$_t$ × Duration$_{i,t}$		1.042**	1.357***	7.786***	4.490***
		(0.500)	(0.494)	(0.488)	(0.493)
Δ 30-year Mortgage Rate$_t$	-1.784***	-6.506***			
	(0.065)	(2.274)			
Duration$_{i,t}$	-0.118***	-0.123***	-0.154***	-0.164***	-0.452***
	(0.009)	(0.010)	(0.010)	(0.011)	(0.056)
Adjusted R^2	0.050	0.051	0.400	0.818	0.881
Observations	16,883	16,883	16,883	16,883	16,883
Year FE			Yes		
County × Year FE				Yes	Yes
Zip FE					Yes

Panel B: Robustness

	Δ HPI$_{i,[t-1,t+1]}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ 30-year Mortgage Rate$_t$ × Duration$_{i,t}$	3.914***	2.331***	2.708***	3.713***	3.722***	2.181***	3.961***	3.891***
	(0.505)	(0.518)	(0.527)	(0.505)	(0.482)	(0.475)	(0.506)	(0.499)
Duration$_{i,t}$	-0.454***	0.673***	-0.446***	-0.444***	-0.451***	-0.428***	-0.452***	-0.456***
	(0.059)	(0.041)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
Δ HPI$_{i,[t-2,t-1]}$	0.036	0.153***	0.014	0.039	0.036	0.022	0.041	0.035
	(0.033)	(0.024)	(0.034)	(0.033)	(0.033)	(0.033)	(0.034)	(0.033)
log(HPI)$_{i,t}$		-0.732***						
		(0.022)						
Δ 30-year Mortgage Rate$_t$ × log(HPI)$_{i,t}$		0.206						
		(0.182)						
Δ 30-year Mortgage Rate$_t$ × log(income)$_{i,t}$			0.830***					
			(0.174)					
Δ 30-year Mortgage Rate$_t$ × log(population)$_{i,t}$				-0.348***				
				(0.084)				
Δ 30-year Mortgage Rate$_t$ × labor force rate$_{i,t}$					2.049**			
					(0.810)			
Δ 30-year Mortgage Rate$_t$ × unemployment rate$_{i,t}$						-21.331***		
						(2.824)		
Δ 30-year Mortgage Rate$_t$ × homeownership rate$_{i,t}$							-0.359	
							(0.264)	
Δ 30-year Mortgage Rate$_t$ × vacancy rate$_{i,t}$								-0.800
								(0.909)
Adjusted R^2	0.887	0.931	0.887	0.887	0.887	0.888	0.887	0.887
Observations	16,883	16,883	16,883	16,883	16,883	16,883	16,883	16,883
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

Table A.3 illustrates the price responses to 30-year mortgage rate changes across different asset duration levels in the housing markets. Panel A presents the baseline analysis. Panel B shows the heterogeneity in house price responses, controlling for local economic characteristics. The dependent variable in Panel A, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t+1, where t is the year when the mortgage rate change applies. Δ 30-year Mortgage Rate$_t$ is the annual 30-year mortgage rate change from year t-1 to t. The variable $Duration_{i,t}$ indicates the housing duration of zip code i in year t. Section II.B provides details on the estimation of housing duration. We include different combinations of fixed effects indicated at the bottom of the table. Standard errors are clustered at the individual asset level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.4. Housing Duration, 30-year Mortgage Rate Change, and House Price Growth in 1, 2 and 3-year Horizons

Panel A: Duration values

	Δ HPI$_{i,[t-1,t]}$		Δ HPI$_{i,[t-1,t+1]}$		Δ HPI$_{i,[t-1,t+2]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ 30-year Mortgage Rate$_t \times$ Duration$_{i,t}$	1.577***	1.171***	4.490***	3.914***	7.216***	6.612***
	(0.250)	(0.243)	(0.493)	(0.505)	(0.621)	(0.670)
Duration$_{i,t}$	0.119***	0.135***	-0.452***	-0.454***	-1.300***	-1.303***
	(0.033)	(0.035)	(0.056)	(0.059)	(0.087)	(0.089)
Δ HPI$_{i,[t-2,t-1]}$		0.067***		0.036		-0.026
		(0.019)		(0.033)		(0.041)
Adjusted R^2	0.848	0.855	0.881	0.887	0.904	0.910
Observations	16,893	16,893	16,883	16,883	12,886	12,886
County $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Economic Chars		Yes		Yes		Yes

Panel B: Duration percentiles

	Δ HPI$_{i,[t-1,t]}$		Δ HPI$_{i,[t-1,t+1]}$		Δ HPI$_{i,[t-1,t+2]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ 30-year Mortgage Rate$_t \times$ Duration$_{i,t}$	0.007***	0.005***	0.027***	0.024***	0.050***	0.047***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Duration$_{i,t}$	0.001***	0.001***	-0.002***	-0.002***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ HPI$_{i,[t-2,t-1]}$		0.065***		0.007		-0.069*
		(0.018)		(0.032)		(0.040)
Adjusted R^2	0.849	0.855	0.877	0.884	0.892	0.900
Observations	16,893	16,893	16,883	16,883	12,886	12,886
County $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Economic Chars		Yes		Yes		Yes

Table A.4 examines the house price responses to 30-year mortgage rate changes over one-, two-, and three-year horizons. Panel A analyzes duration values, while Panel B uses duration percentile rank as the independent variable. Each year, a zip code is assigned a percentile based on its estimated housing duration value relative to all other zip codes for that year. The dependent variable, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t in Columns 1 and 2, from year t-1 to t+1 in Columns 3 and 4, and from year t-1 to t+2, where t is the year when the mortgage rate change applies. Δ 30-year Mortgage Rate$_t$ is the annual 30-year mortgage rate change from year t-1 to t. The variable $Duration_{i,t}$ indicates the duration level or percentiles of zip code i in year t. Section II.B provides details on the estimation of housing duration. Each observation in the sample represents a zip code in a year. In Columns 2, 4, and 6, we control for the same time-varying economic characteristics at the zip-code level as Table 3. We also include county-year and zip-code fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.5. Alternative Monetary Policy Shocks and Interest Rate Change Measurement, Housing Duration, and House Price Growth

Panel A: Duration values

	Δ FFR$_t$		1-Year Yield Surprise$_t$		JK PM MPS$_t$		JK Median MPS$_t$		BS MPS$_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MPS$_t$ × Duration$_{i,t}$	2.498***	2.198***	3.220***	2.812***	0.213***	0.183***	0.215***	0.186***	23.506***	20.634***
	(0.296)	(0.306)	(0.350)	(0.357)	(0.027)	(0.027)	(0.027)	(0.028)	(2.578)	(2.599)
Duration$_{i,t}$	-0.476***	-0.478***	-0.447***	-0.450***	-0.442***	-0.448***	-0.443***	-0.449***	-0.462***	-0.466***
	(0.055)	(0.057)	(0.055)	(0.058)	(0.056)	(0.059)	(0.056)	(0.059)	(0.055)	(0.057)
Δ HPI$_{i,[t-2,t-1]}$		0.042		0.038		0.042		0.043		0.044
		(0.033)		(0.033)		(0.033)		(0.033)		(0.033)
Adjusted R^2	0.881	0.887	0.881	0.887	0.880	0.886	0.880	0.886	0.881	0.887
Observations	16,883	16,883	16,883	16,883	16,883	16,883	16,883	16,883	16,883	16,883
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

Panel B: Duration percentiles

	Δ FFR$_t$		1-Year Yield Surprise$_t$		JK PM MPS$_t$		JK Median MPS$_t$		BS MPS$_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MPS$_t$ × Duration$_{i,t}$	0.014***	0.013***	0.019***	0.017***	0.001***	0.001***	0.001***	0.001***	0.130***	0.116***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)	(0.011)
Duration$_{i,t}$	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ HPI$_{i,[t-2,t-1]}$		0.013		0.010		0.012		0.013		0.014
		(0.032)		(0.032)		(0.032)		(0.032)		(0.032)
Adjusted R^2	0.877	0.883	0.877	0.884	0.877	0.883	0.876	0.883	0.877	0.883
Observations	16,883	16,883	16,883	16,883	16,883	16,883	16,883	16,883	16,883	16,883
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

Table A.5 examines the house price responses to alternative measurements for monetary policy shock (MPS). The MPS measurement is indicated on the top of each column. Panel A analyzes duration values, while Panel B uses duration percentile rank as the independent variable. Each year, a zip code is assigned a percentile based on its estimated housing duration value relative to all other zip codes for that year. The dependent variable, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t+1, where t is the year when the MPS applies. The variable $Duration_{i,t}$ indicates the duration level or percentiles of zip code i in year t. Section II.B provides details on the estimation of housing duration. Each observation in the sample represents a zip code in a year. In Columns 2, 4, and 6, we control for the same time-varying economic characteristics at the zip-code level as Table 3. We also include county-year and zip-code fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.6. Monetary Policy Transmission to House Prices by Rental Yield Values

Panel A: Baseline

	Δ HPI$_{i,[t-1,t+1]}$				
	(1)	(2)	(3)	(4)	(5)
MPS$_t$ × rental yield$_{i,t}$		-183.836***	-229.201***	-348.113***	-169.827***
		(24.711)	(24.428)	(25.196)	(24.796)
MPS$_t$	-45.048***	-34.325***			
	(0.534)	(1.520)			
Rental yield$_{i,t}$	1.352***	1.520***	1.525***	1.454***	5.952***
	(0.058)	(0.069)	(0.069)	(0.074)	(0.246)
Adjusted R^2	0.322	0.324	0.425	0.824	0.901
Observations	22,086	22,086	22,086	22,086	22,086
Year FE			Yes		
County × Year FE				Yes	Yes
Zip FE					Yes

Panel B: Control for local characteristics

	Δ HPI$_{i,[t-1,t+1]}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MPS$_t$ × rental yield$_{i,t}$	-152.810***	-286.832***	-244.333***	-144.134***	-141.537***	-124.712***	-174.141***	-146.787***
	(25.599)	(30.449)	(28.649)	(25.884)	(24.897)	(27.447)	(25.521)	(24.730)
Rental yield$_{i,t}$	5.812***	1.678***	5.866***	5.787***	5.801***	5.780***	5.730***	5.841***
	(0.241)	(0.333)	(0.241)	(0.242)	(0.242)	(0.243)	(0.241)	(0.240)
Δ HPI$_{i,[t-2,t-1]}$	0.093***	0.204***	0.109***	0.094***	0.094***	0.092***	0.109***	0.095***
	(0.024)	(0.022)	(0.024)	(0.024)	(0.023)	(0.024)	(0.024)	(0.023)
log(HPI)$_{i,t}$		-0.423***						
		(0.025)						
MPS$_t$ × log(HPI)$_{i,t}$		-7.670***						
		(1.407)						
MPS$_t$ × log(income)$_{i,t}$			-9.111***					
			(1.255)					
MPS$_t$ × log(population)$_{i,t}$				-2.295***				
				(0.550)				
MPS$_t$ × labor force rate$_{i,t}$					16.334***			
					(5.853)			
MPS$_t$ × unemployment rate$_{i,t}$						-43.443**		
						(18.989)		
MPS$_t$ × homeownership rate$_{i,t}$							-20.461***	
							(1.757)	
MPS$_t$ × vacancy rate$_{i,t}$								-24.473***
								(6.957)
Adjusted R^2	0.905	0.918	0.906	0.905	0.905	0.905	0.906	0.905
Observations	22,086	22,086	22,086	22,086	22,086	22,086	22,086	22,086
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

Table A.6 shows the heterogeneous impacts of monetary policy shocks (MPS) on house prices across different rental yield values of the zip-code markets. Panel A presents the results obtained using the baseline specification, while Panel B displays the results after controlling for local economic characteristics. The dependent variable, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t+1, where t is the year when MPS occurs. The variable MPS_t captures the annual monetary policy shocks that occur in year t, as estimated by Bauer and Swanson (2023a). The variable Rental yield$_{i,t}$ indicates the rental yield level of zip code i in year t. Each observation in the sample represents a zip code in a year. In Panel B, we control for the same time-varying economic characteristics at the zip-code level as Table 3. We also include different combinations of fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.7. Monetary Policy Transmission to House Prices by Rent Yield Percentiles

Panel A: Baseline

	Δ HPI$_{i,[t-1,t+1]}$				
	(1)	(2)	(3)	(4)	(5)
MPS$_t$ × rental yield$_{i,t}$		-0.170***	-0.179***	-0.234***	-0.160***
		(0.018)	(0.018)	(0.018)	(0.016)
MPS$_t$	-44.765***	-36.311***			
	(0.531)	(1.051)			
Rental yield$_{i,t}$	0.001***	0.001***	0.001***	0.001***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.317	0.320	0.423	0.814	0.890
Observations	22,086	22,086	22,086	22,086	22,086
Year FE			Yes		
County × Year FE				Yes	Yes
Zip FE					Yes

Panel B: Control for local characteristics

	Δ HPI$_{i,[t-1,t+1]}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MPS$_t$ × rental yield$_{i,t}$	-0.144***	-0.174***	-0.194***	-0.138***	-0.136***	-0.108***	-0.153***	-0.147***
	(0.017)	(0.024)	(0.018)	(0.017)	(0.016)	(0.017)	(0.016)	(0.016)
Rental yield$_{i,t}$	0.005***	0.002***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ HPI$_{i,[t-2,t-1]}$	0.043*	0.201***	0.055**	0.044*	0.044*	0.041*	0.057**	0.045**
	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
log(HPI)$_{i,t}$		-0.458***						
		(0.019)						
MPS$_t$ × log(HPI)$_{i,t}$		-3.849**						
		(1.616)						
MPS$_t$ × log(income)$_{i,t}$			-6.289***					
			(1.284)					
MPS$_t$ × log(population)$_{i,t}$				-1.460**				
				(0.577)				
MPS$_t$ × labor force rate$_{i,t}$					21.042***			
					(6.089)			
MPS$_t$ × unemployment rate$_{i,t}$						-79.070***		
						(19.132)		
MPS$_t$ × homeownership rate$_{i,t}$							-17.760***	
							(1.785)	
MPS$_t$ × vacancy rate$_{i,t}$								-33.038***
								(6.879)
Adjusted R^2	0.895	0.917	0.895	0.895	0.895	0.895	0.896	0.895
Observations	22,086	22,086	22,086	22,086	22,086	22,086	22,086	22,086
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

Table A.7 shows the heterogeneous impacts of monetary policy shocks (MPS) on house prices across different housing rental yield percentiles of the zip-code markets. Each year, a zip code is assigned a percentile based on its rental yield value relative to all other zip codes for that year. Panel A presents the results obtained using the baseline specification, while Panel B displays the results after controlling for local economic characteristics. The dependent variable, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t+1, where t is the year when MPS occurs. The variable MPS_t captures the annual monetary policy shocks that occur in year t, as estimated by Bauer and Swanson (2023a). The variable Rental yield$_{i,t}$ indicates the rental yield percentiles of zip code i in year t. Each observation in the sample represents a zip code in a year. In Panel B, we control for the same time-varying economic characteristics at the zip-code level as Table 3. We also include different combinations of fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.8. Rental Yield and Monetary Policy Transmission to House Prices in 1, 2 and 3-year Horizons

Panel A: Rental yield values

	Δ HPI$_{i,[t-1,t]}$		Δ HPI$_{i,[t-1,t+1]}$		Δ HPI$_{i,[t-1,t+2]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
MPS$_t$ × rental yield$_{i,t}$	-48.853***	-33.950**	-169.827***	-152.810***	-90.395***	-77.547***
	(14.375)	(14.345)	(24.796)	(25.599)	(24.019)	(24.534)
Rental yield$_{i,t}$	2.619***	2.637***	5.952***	5.812***	8.844***	8.461***
	(0.118)	(0.120)	(0.246)	(0.241)	(0.466)	(0.451)
Δ HPI$_{i,[t-2,t-1]}$		0.138***		0.093***		0.044
		(0.013)		(0.024)		(0.032)
Adjusted R^2	0.860	0.866	0.901	0.905	0.906	0.911
Observations	22,097	22,097	22,086	22,086	16,849	16,849
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Economic Chars		Yes		Yes		Yes

Panel B: Rental yield percentiles

	Δ HPI$_{i,[t-1,t]}$		Δ HPI$_{i,[t-1,t+1]}$		Δ HPI$_{i,[t-1,t+2]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
MPS$_t$ × rental yield$_{i,t}$	-0.052***	-0.039***	-0.160***	-0.144***	-0.068***	-0.061***
	(0.008)	(0.008)	(0.016)	(0.017)	(0.017)	(0.017)
Rental yield$_{i,t}$	0.003***	0.003***	0.006***	0.005***	0.009***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ HPI$_{i,[t-2,t-1]}$		0.119***		0.043*		-0.023
		(0.014)		(0.023)		(0.029)
Adjusted R^2	0.857	0.863	0.890	0.895	0.891	0.898
Observations	22,097	22,097	22,086	22,086	16,849	16,849
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Economic Chars		Yes		Yes		Yes

Table A.8 examines the house price responses to monetary policy shocks (MPS) over one-, two-, and three-year horizons. Panel A focuses on the differences in house price responses across various rental yield values of zip-code housing markets, while Panel B explores the variations in responses across different rental yield percentiles. Each year, a zip code is assigned a percentile based on its rental yield value relative to all other zip codes for that year. The dependent variable, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t in Columns 1 and 2, from year t-1 to t+1 in Columns 3 and 4, and from year t-1 to t+2, where t is the year when MPS occurs. The variable MPS_t captures the annual monetary policy shocks that occur in year t, as estimated by Bauer and Swanson (2023a). The variable Rental yield$_{i,t}$ indicates the rental yield level or percentiles of zip code i in year t. Each observation in the sample represents a zip code in a year. In Columns 2, 4, and 6, we control for the same time-varying economic characteristics at the zip-code level as Table 3. We also include county-year and zip-code fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.9. 30-Year Mortgage Rate and House Price Changes by Rental Yield Values

Panel A: Baseline

	Δ HPI$_{i,[t-1,t+1]}$				
	(1)	(2)	(3)	(4)	(5)
Δ 30-year Mortgage Rate$_t$ $\times$ rental yield$_{i,t}$		-6.476**	-8.821***	-56.860***	-28.726***
		(3.130)	(3.120)	(3.230)	(3.171)
Δ 30-year Mortgage Rate$_t$	-1.656***	-1.276***			
	(0.058)	(0.181)			
Rental yield$_{i,t}$	1.368***	1.409***	1.370***	1.496***	5.936***
	(0.059)	(0.064)	(0.063)	(0.073)	(0.247)
Adjusted R^2	0.090	0.090	0.422	0.827	0.902
Observations	22,086	22,086	22,086	22,086	22,086
Year FE			Yes		
County $\times$ Year FE				Yes	Yes
Zip FE					Yes

Panel B: Control for local characteristics

	Δ HPI$_{i,[t-1,t+1]}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ 30-year Mortgage Rate$_t$ $\times$ rental yield$_{i,t}$	-26.240***	-6.568*	-20.845***	-25.682***	-25.110***	-16.780***	-26.521***	-25.519***
	(3.216)	(3.361)	(3.303)	(3.227)	(3.038)	(2.962)	(3.242)	(3.102)
Rental yield$_{i,t}$	5.797***	1.605***	5.751***	5.779***	5.788***	5.691***	5.796***	5.817***
	(0.242)	(0.332)	(0.243)	(0.242)	(0.242)	(0.245)	(0.241)	(0.241)
Δ HPI$_{i,[t-2,t-1]}$	0.083***	0.182***	0.070***	0.085***	0.083***	0.075***	0.086***	0.082***
	(0.023)	(0.022)	(0.024)	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)
log(HPI)$_{i,t}$		-0.418***						
		(0.025)						
Δ 30-year Mortgage Rate$_t$ $\times$ log(HPI)$_{i,t}$		0.465***						
		(0.163)						
Δ 30-year Mortgage Rate$_t$ $\times$ log(income)$_{i,t}$			0.545***					
			(0.132)					
Δ 30-year Mortgage Rate$_t$ $\times$ log(population)$_{i,t}$				-0.185***				
				(0.062)				
Δ 30-year Mortgage Rate$_t$ $\times$ labor force rate$_{i,t}$					1.653**			
					(0.658)			
Δ 30-year Mortgage Rate$_t$ $\times$ unemployment rate$_{i,t}$						-15.549***		
						(2.215)		
Δ 30-year Mortgage Rate$_t$ $\times$ homeownership rate$_{i,t}$							-0.250	
							(0.207)	
Δ 30-year Mortgage Rate$_t$ $\times$ vacancy rate$_{i,t}$								-2.304***
								(0.720)
Adjusted R^2	0.905	0.917	0.906	0.906	0.906	0.906	0.905	0.906
Observations	22,086	22,086	22,086	22,086	22,086	22,086	22,086	22,086
County $\times$ 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

Table A.9 shows the heterogeneous impacts of 30-year mortgage rate changes on house prices across different rental yield values of the zip-code markets. Panel A presents the results obtained using the baseline specification, while Panel B displays the results after controlling for local economic characteristics. The dependent variable, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t+1, where t is the year when MPS occurs. Δ 30-year Mortgage Rate$_t$ is the annual 30-year mortgage rate change from year t-1 to t. The variable Rental yield$_{i,t}$ indicates the rental yield level of zip code i in year t. Each observation in the sample represents a zip code in a year. In Panel B, we control for the same time-varying economic characteristics at the zip-code level as Table 3. We also include different combinations of fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.10. Alternative Monetary Policy Shocks and Interest Rate Change Measurement, Rental Yield, and House Price Growth

Panel A: Rental yield values

	Δ FFR$_t$		1-Year Yield Surprise$_t$		JK PM MPS$_t$		JK Median MPS$_t$		BS MPS$_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MPS$_t$ × rental yield$_{i,t}$	-16.648***	-15.166***	-15.609***	-14.100***	-0.915***	-0.820***	-1.030***	-0.926***	-115.101***	-103.992***
	(1.801)	(1.864)	(2.150)	(2.225)	(0.163)	(0.169)	(0.162)	(0.168)	(18.283)	(18.679)
Rental yield$_{i,t}$	5.960***	5.818***	5.805***	5.683***	5.786***	5.667***	5.774***	5.655***	5.831***	5.708***
	(0.245)	(0.240)	(0.254)	(0.249)	(0.258)	(0.254)	(0.257)	(0.253)	(0.253)	(0.247)
Δ HPI$_{i,[t-2,t-1]}$		0.085***		0.088***		0.092***		0.091***		0.093***
		(0.023)		(0.024)		(0.024)		(0.024)		(0.023)
Adjusted R^2	0.902	0.905	0.901	0.905	0.901	0.905	0.901	0.905	0.901	0.905
Observations	22,086	22,086	22,086	22,086	22,086	22,086	22,086	22,086	22,086	22,086
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

Panel B: Rental yield percentiles

	Δ FFR$_t$		1-Year Yield Surprise$_t$		JK PM MPS$_t$		JK Median MPS$_t$		BS MPS$_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MPS$_t$ × rental yield$_{i,t}$	-0.010***	-0.009***	-0.013***	-0.011***	-0.001***	-0.001***	-0.001***	-0.001***	-0.084***	-0.073***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.010)
Rental yield$_{i,t}$	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ HPI$_{i,[t-2,t-1]}$		0.039*		0.038*		0.042*		0.042*		0.043*
		(0.023)		(0.023)		(0.023)		(0.023)		(0.023)
Adjusted R^2	0.890	0.894	0.890	0.895	0.889	0.894	0.889	0.894	0.889	0.894
Observations	22,086	22,086	22,086	22,086	22,086	22,086	22,086	22,086	22,086	22,086
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

Table A.10 examines the house price responses to alternative measurements for monetary policy shock (MPS). The MPS measurement is indicated on the top of each column. Panel A analyzes duration values, while Panel B uses duration percentile rank as the independent variable. Each year, a zip code is assigned a percentile based on its estimated housing duration value relative to all other zip codes for that year. The dependent variable, $\Delta HPI_{i,[t-1,t+1]}$, is the house price growth of zip code i from the end of year t-1 to t+1, where t is the year when the MPS applies. The variable $Duration_{i,t}$ indicates the duration level or percentiles of zip code i in year t. Section II.B provides details on the estimation of housing duration. Each observation in the sample represents a zip code in a year. In Columns 2, 4, and 6, we control for the same time-varying economic characteristics at the zip-code level as Table 3. We also include county-year and zip-code fixed effects, as indicated at the bottom of the table. Standard errors are clustered at the zip code level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix B. Literature Review

B.1. Monetary Policy Transmission to Housing Markets through Credit Channel

A foundational strand of literature examines how credit supply influences house prices through mortgage markets Mian and Sufi (2009); Favara and Imbs (2015). Early work by Mian and Sufi (2009) and Favara and Imbs (2015) establish that expansions in credit availability, driven by securitization or deregulation, significantly amplify housing booms.

A strand of literature examines how Fed tightening impacted mortgage lending through the deposits channel. Monetary tightening causes deposit outflows from banks due to higher spreads between deposit rates and federal funds rates (Drechsler et al., 2017). This shift significantly reduces bank portfolio lending, pushing borrowers toward private-label securitization (PLS) and nonbank originators (Drechsler et al., 2022). Fed tightening thus induced a shift in mortgage lending away from stable, insured deposit funding toward run-prone and fragile capital markets funding with little impact on overall lending. Additionally, quantitative easing (QE) and quantitative tightening (QT) actions by the Fed and banks directly affect mortgage spreads and credit availability, as these institutions buy or sell mortgage-backed securities (MBS). Banks specifically adjust their holdings of MBS in response to deposit flows to match the interest-rate sensitivity of their income and expenses (Drechsler et al., 2024).

Greenwald (2018) underscores the role of mortgage market structure in macroeconomic transmission, particularly emphasizing the significance of payment-to-income (PTI) constraints alongside loan-to-value (LTV) ratios. His model highlights how PTI constraints amplify monetary policy shocks by influencing housing prices and mortgage borrowing, a mechanism he terms the mortgage credit channel. Greenwald emphasizes that PTI constraints have a more pronounced effect on boom-bust cycles than LTV constraints, offering important insights for macroprudential policies aimed at stabilizing housing markets.

Further examining credit supply dynamics, Bosshardt et al. (2024) focus on the distributional impacts of monetary tightening, specifically through debt-to-income (DTI) constraints. They show that during monetary tightening, borrowers near regulatory DTI limits (e.g., 45–50%) face sharper reductions in mortgage originations, with areas of high DTI exposure experiencing amplified declines in house prices, loan volume, and consumption. Adelino et al. (2025) estimate the causal impact of credit availability on house prices using exogenous variation from conforming loan limit (CLL) adjustments. Their difference-in-differences approach, leveraging the 80% LTV threshold, reveals that houses just eligible for conforming loans command higher values per square foot, implying a local house price elasticity to interest rates below 6.

Landvoigt et al. (2015) develop a segmented housing-market assignment model using detailed San Diego data. They find that during the early-2000s housing boom, cheaper and entry-level housing markets experienced stronger price responses to easier credit conditions. Their results highlight that lower-tier segments, typically associated with financially constrained buyers, are particularly sensitive to changes in borrowing conditions. Given that low-tier markets are correlated with high rental yield, their findings complement our findings that housing markets characterized by short-duration (high-rent-yield) markets exhibit greater sensitivity to interest rate changes.

The credit supply largely influences house prices and aggregate economic outcomes. Loutskina and Strahan (2015) explore financial integration's role in amplifying economic volatility by facilitating capital flows toward areas experiencing housing price booms. Di Maggio and Kermani (2017) similarly underscore the role of credit supply in fueling economic volatility through regulatory changes. Their study examines the impact of national bank preemption of local antipredatory lending laws, finding significant expansions in mortgage credit to riskier borrowers, which boosted local house prices and employment but also heightened economic volatility during the subsequent downturn. Mian and Sufi (2022) analyze how credit supply expansion specifically fueled housing speculation during the mid-2000s.

The refinancing channel, which involves households' ability to refinance mortgages to benefit from lower interest rates, plays a crucial role in monetary policy transmission. Beraja, Fuster, Hurst, and Vavra (2019) find that regions with higher housing equity experience greater refinancing activity and larger consumption responses during monetary easing periods. Di Maggio, Kermani, and Palmer (2020) highlight significant heterogeneity in refinancing outcomes between conforming and non-conforming loans during quantitative easing, emphasizing how targeted policy interventions in mortgage markets can lead to varied macroeconomic outcomes.

Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao (2017) exploit automatic resets in adjustable-rate mortgages (ARMs) to clearly identify the effect of reduced mortgage rates on household financial decisions. They document significant increases in durable consumption and voluntary deleveraging following interest rate reductions, emphasizing the importance of mortgage contract rigidity and household balance sheet conditions. Their regional analysis further underscores substantial spatial heterogeneity, with areas featuring higher ARM shares experiencing stronger rebounds in consumption, house prices, and employment. Berger, Milbradt, Tourre, and Vavra (2021) and Eichenbaum, Rebelo, and Wong (2022)) extend these insights by emphasizing path-dependent and state-dependent effects of monetary policy, indicating that past refinancing behavior significantly influences household responsiveness to subsequent interest rate changes.

B.2. Monetry Policy Surprise Measurement

Kroen, Liu, Mian, and Sufi (2021) examines how interest rate cuts in a low-interest-rate environment disproportionately benefit industry leaders through a stronger decline in the borrowing rate for industry leaders, who also borrow more, invest more aggressively, and acquire assets at a faster pace. To obtain the long-term rate shock measurement, Kroen et al. (2021) regress the monetary policy shocks (MPS) on a short-rate surprise measured within 30 minutes around FOMC announcements and obtain the residuals as the long-term rate surprise. Specifically, based on Gurkaynak, Sack, and Swanson (2005), high-frequency movements around FOMC announcements represent two separate factors, a short-run "current Federal Funds rate target" and a longer-run "future path of policy". Nakamura and Steinsson (2018) and Bauer and Swanson (2023b) calculate the first principal component of changes in the Federal Funds rate and Eurodollar futures contracts around FOMC announcements. The first principal component, therefore, reflects the unanticipated shift in the yield curve around the 30-minute FOMC announcement window starting at 10 minutes prior to the FOMC press release. Kroen et al. (2021) take the first principal component from Nakamura and Steinsson (2018) to more recent data as our default measure of ω. Then, they split ω into news about the short versus the long end of the yield curve. The variable ω^{ff} captures the response of Federal Funds rate Futures within a 30-minute time window (-10 minutes until +20 minutes) around FOMC meeting announcements. Kroen et al. (2021) obtain the shocks from Gorodnichenko and Weber (2016), which captures the response of the short end of the yield curve. Then, the long end of the yield curve is captured by $\tilde{\omega}$ which is obtained as the residual from regressing ω on ω^{ff} with the following regression

$$\omega_t = \alpha + \beta\,\omega_t^{ff} + \tilde{\omega}_t$$

Kroen et al. (2021) examines how interest rate cuts in a low-interest-rate environment disproportionately benefit industry leaders through a stronger decline in the borrowing rate for industry leaders, who also borrow more, invest more aggressively, and acquire assets at a faster pace. To measure long-term interest rate surprises, Kroen et al. (2021) leverages monetary policy shocks (MPS) constructed from high-frequency changes within a 30-minute window around FOMC announcements. Specifically, following the methodology of Gurkaynak et al. (2005), these high-frequency interest rate movements around FOMC announcements are decomposed into two distinct components: the short-term "current Federal Funds rate target" and the longer-term "future path of policy."

B.3. Duration and Term Structure of Equity Returns

Recent literature highlights the importance of duration in asset pricing, particularly emphasizing how asset sensitivity to interest rate fluctuations varies with the maturity of expected cash flows. The foundational work by Dechow et al. (2004) introduces the concept of equity duration derived from financial statements to assess equity risk analogously to fixed-income securities. Their research demonstrates that equity duration is positively correlated with stock price volatility and beta, which provide an improved measure of risk relative to equity factors such as the book-to-market ratio.

Lettau and Wachter (2011) further develop a dynamic risk-based model that jointly explains the term structures of interest rates and equity returns. The paper highlights a critical tension that equities exhibit a downward-sloping term structure of returns, while interest rates are typically upward-sloping. They resolve this through the interplay of shocks to dividend growth, real interest rates, and inflation expectations within a stochastic discount factor framework. Their model can account for the variation in aggregate market returns, bond yields, and the value premium.

Building on these theoretical foundations, empirical studies by Binsbergen et al. (2012) and Van Binsbergen and Koijen (2017) investigate dividend strip markets. They find that short-term equity claims, or dividend strips, have higher average returns and Sharpe ratios than the aggregate stock market, which is hard to reconcile with traditional macro-finance models. However, Schulz (2016) argues that tax considerations substantially influence dividend returns, providing adjustments that bring empirical findings closer to theoretical expectations.

Weber (2018) and Gonçalves (2021) expand on the implications of cash flow duration, documenting a robust "short-duration premium" where short-duration stocks outperform long-duration stocks. This premium is attributed primarily to reinvestment risk and investor sentiment, with Gonçalves notably demonstrating its dominance over traditional anomalies like value and profitability premiums. These results reinforce the critical role of duration in explaining cross-sectional equity returns.

Gormsen and Lazarus (2023) provide additional empirical support by utilizing single-stock dividend futures to show that expected returns generally decline with increasing cash flow maturity, which strengthens the theoretical link between duration and asset pricing. Andrews and Gonçalves (2020) expand this analysis across asset classes, finding distinct hump-shaped patterns for equity and real estate risk premia compared to traditional bond term structures. Their research underscores the importance of distinguishing safe from risky cash flows when analyzing maturity structures, highlighting significant differences in risk premia across asset classes.

Bansal, Miller, Song, and Yaron (2021) introduce regime-switching dynamics into equity term structures, finding downward-sloping equity returns during recessions and upward-sloping returns in expansions. Their approach reconciles conflicting evidence from dividend strip markets and macro-finance models by showing that unconditional equity risk premia are positively sloped once regime shifts are accounted for.

Giglio, Kelly, and Kozak (2024) enhance methodology by using equity returns data within an affine model framework to estimate equity term structures without relying on dividend strip data. Their approach accurately matches dividend strip prices and extends empirical evidence back to the 1970s, significantly enriching the analysis of equity term structures across economic cycles.

In the housing markets, Giglio et al. (2015) and Giglio et al. (2021) investigate very long-run discount rates and the term structure of housing returns using extremely long-term leasehold versus freehold property right contracts in the U.K. and Singapore. They document low discount rates applied by households for extremely long-run cash flows and a negative term structure of housing returns. These findings suggest households discount very long-run benefits at rates significantly lower than typically assumed, highlighting important policy implications for long-term investments.

Finally, Boguth et al. (2023) address measurement errors and leverage-induced biases present in earlier studies, demonstrating a generally flat equity term structure after accounting for these issues, which contrasts earlier findings of a downward-sloping structure.

B.4. Estimating Property-level Rental Yields and Total Housing Returns

Both Kermani and Wong (2024) and Diamond and Diamond (2024) measure the total housing returns of minorities. Diamond and Diamond (2024) develop a new method of estimating rental yield by using the joint distribution of rental value and resale price of the same home from American Housing Survey data. They use a house's resale price as the proxy for unobserved house characteristics to more accurately impute rental value. With the method, they measure the total return homeowners get from a housing investment and find that Black and Hispanic homeowners earn higher rental yields and, hence, higher total returns than White homeowners.

One existing method of measuring rent yields is directly observing the property price and rental income of the same individual housing units. Eichholtz, Korevaar, Lindenthal, and Tallec (2021) use the historical observations of prices and rents of the same individual houses in Paris and Amsterdam to construct the property-level rental yields. Chambers, Spaenjers, and Steiner (2021) collect the transaction prices, rental income, and costs for the same sample of individual properties in four large Oxford colleges in the early twentieth century. They construct the rental income growth and yield indices by property types.

Halket et al. (2023) use CoreLogic MLS data and identify a set of properties for which there is both a rental and sale transaction within one year of each other. They run year-by-year hedonic regressions of prices and rents onto various property characteristics and zip-code- and CBSA-relevant fixed effects. By holding the property characteristics constant, they obtained the predicted property values and rents across zip codes.

Gilbukh, Haughwout, Landau, and Tracy (2023) applies a hedonic model to the American Housing Survey (AHS) and estimates property rents based on their characteristics. Colonnello, Marfè, and Xiong (2021) uses German rental and sale listing data to construct 1.5 million property-level rent-to-price ratios. They find a significant yield heterogeneity unexplained by property characteristics or zip-code-time level fixed effects. Because the rental and sale prices are originally listed for different properties, they match the two prices based on property characteristics.

Fama and French (2025) argue that the shared variation in house prices and price-rent ratios unrelated to expected rents is correlated across areas, which could be due to variation in discount rates for expected rents or irrational rent forecasts that do not forecast rent growth. This variation clouds the predictability of price-rent ratios for rent growth. The cross-section demeaning or adding the time fixed effects could mitigate the problem and restore the prediction.

Damen, Korevaar, and Van Nieuwerburgh (2025) find that the low-rent level areas provide high investment returns to institutional investors of residential properties. They derive the net rental income from mortgage loans on multifamily rental properties by using the loan-to-value (LTV) ratio and the debt service coverage (DSCR) ratio at loan origination. The net operating income (NOI), calculated as DSCR times debt service, will be the rent revenues minus operating expenses.

B.5. "Reaching-for-income" Investment Behavior

The "reaching-for-income" investment behavior is defined as the behavior where investors show increased demands for income-generating assets in response to low interest rates. It has gained popular attention in recent financial economics literature. This review summarizes recent findings in this area and emphasizes its implications for asset pricing and allocation within housing and broader financial markets.

Daniel et al. (2021) provide foundational evidence of "reaching-for-income" behavior, documenting that investors following a "living off income" rule-of-thumb substantially increase allocations to high-dividend stocks and high-yield bonds when interest rates decrease. This behavior significantly impacts asset prices by increasing demand from income-seeking investors. This creates a critical transmission channel of monetary policy, influencing firms' capital allocation decisions and aggregate consumption dynamics.

Gargano and Giacoletti (2022) find the "reaching-for-income" beahvior in housing markets. Using Australian tax filing data, the paper reveals that interest rate decreases make older individuals substitute interest income with rental income. This substitution effect markedly elevates individual participation in the rental market, increasing household exposure to local shocks and driving local house prices higher, consequently compressing rental yields.

Using evidence from 18th-century Amsterdam, Korevaar (2023) historically contextualizes "reaching-for-yield" behaviors in the housing market. The paper demonstrates that the"reach-for-yield" behavior of wealthy investors resulted in a large boom and bust in house prices and major changes in rental yields. investors living off capital income shifted their portfolios towards real estate and other higher-yielding assets when bond yields were low and decreasing, exacerbating price volatility and intensifying wealth inequality in housing markets.

Jiang and Sun (2020) highlight similar dynamics within equity income funds, where investors' increased preference for dividends in low-interest-rate environments results in systematic overweighting of high-dividend stocks by fund managers. Such "reaching for dividends" behavior notably inflates the prices of high-dividend stocks when rates drop, leading to lower subsequent excess returns as rates normalize.

Gomes et al. (2022) provide further evidence from household-level brokerage data, confirming retail investors' reaching-for-yield behaviors across asset classes. Notably, younger and less wealthy investors, who possess relatively larger human capital to financial wealth ratios, display stronger tendencies to reallocate towards riskier assets when interest rates decline. Prospect theory further explains that investors trading at a loss show heightened risk-taking behaviors in response to reduced rates.

Becker and Ivashina (2015) analyze corporate bond markets and show that insurance firms have a propensity to buy riskier bonds with higher yields conditional on their regulatory capital constraints. The paper suggests that "reaching-for-yield" behaviors can significantly distort market pricing mechanisms and enhance systemic risk, particularly during economic expansions.

Hanson and Stein (2015) document that monetary policy significantly influences long-term real rates through term-premium adjustments, largely driven by "yield-oriented" investors seeking to maintain portfolio yields. Such investor behavior generates substantial fluctuations in asset prices and yield structures, demonstrating how the "reaching-for-yield" can profoundly influence macroeconomic dynamics beyond traditional channels.

Choi and Kronlund (2018) further illustrate reaching-for-yield within corporate bond mutual funds, observing that funds strategically tilt portfolios towards higher-yielding, riskier bonds to boost returns and attract inflows, particularly during periods of low interest rates. However, this behavior ultimately leads to negative risk-adjusted returns, exacerbating liquidity risks and redemption pressures.

Using randomized investment experiments, Lian et al. (2019) find that individuals exhibit "reaching-for-yield" when interest rates are low. They suggest that reference dependence and salience significantly drive individuals' increased allocations to risky assets when facing low interest rates. The paper proposes psychological mechanisms beyond purely financial rationalizations.

Campbell and Sigalov (2022) propose a theoretical model linking "reaching-for-yield" behavior to sustainable spending constraints. Their model shows that investors increase risk-taking to maintain stable spending levels in low-rate environments, highlighting an important theoretical underpinning of the reaching-for-yield phenomenon observed empirically.

Appendix C. ATTOM Data Cleaning

C.1. Clean Housing Transaction Data

ATTOM record dataset contains all housing transaction and mortgage records of properties in the United States. Starting from the raw ATTOM record data, we perform the following steps to finalize our sample for analysis.

1. Through variable "`TransferInfoPurchaseTypeCode`", we keep only deed transfer and foreclosure records from the record data. We drop records of construction loans and mortgages.
2. Through variable "`PropertyUseGroup`", we keep only residential property transaction records by removing non-residential records such as commercial purposes and industrial purpose records.

Previous literature often employs various filters to eliminate transactions during the early stages of data cleaning. However, we retain those transaction records initially while identifying whether a transaction is valid or not and when a homeowner ends her ownership of a property. Our goal is to maintain a comprehensive sample that allows for the identification of key transitions, particularly the precise time points when homeowners enter and exit property ownership. In our main analysis and hedonic estimation, we will only use valid transactions, consistent with the approach taken in previous literature.

For each transaction, we assign a dummy variable to indicate whether it is a "valid" transaction based on specific criteria. However, it is important to clarify that a "non-valid" transaction is not necessarily invalid in a legal sense; rather, it only represents that these transactions will be excluded when creating certain measurements or statistics for analysis as previous literature does. For instance, intra-family transactions often involve extremely low transaction prices, which do not reflect arm's-length transactions or the actual state of the housing market. The abnormal housing returns from such transactions can bias our estimations, even though the transactions are legally valid. A transaction record will be classified as invalid if it meets any of the following criteria.

1. Non-arm's length transactions identified by variable "`ArmsLengthFlag`"
2. Foreclosure or auction transactions identified by variables "`TransferInfoPurchaseTypeCode`" and "`ForeclosureAuctionSale`"
3. Quit claim deed transactions identified by variable "`QuitclaimFlag`"

4. Transactions in which only a portion of the parcel is conveyed, or multiple parcels are conveyed, which are identified from variable "`TransferInfoMultiParcelFlag`"
5. Transactions with only partial interest conveyed, as indicated by variable "`PartialInterest`"
6. Transacted deeds fall into the categories of affidavit of death, intrafamily transfer, and gift deed, as indicated by variable "`DocumentTypeCode`"
7. The rest of the transactions with a transfer amount of less than 10,000.

For each transaction, we assign a dummy variable to identify whether a transaction ends the ownership of the homeowner. Similarly, we have the following criteria.

1. If a transaction is not an arm's length transaction (identified by "`ArmsLengthFlag`") and the transaction price is greater than or equal to 10,000, it will end the ownership of the previous homeowner. If the non-arm's-length transaction has a transaction price of less than 10,000, we will *not* consider it a legitimate transfer of ownership and will continue the ownership of the homeowner. For example, some homeowners may transfer the deed from their own names to family trusts with a transaction price of zero. We will not consider such transactions as the end of ownership.
2. If a transaction is a foreclosure or auction (identified by "`TransferInfoPurchaseTypeCode`" and "`ForeclosureAuctionSale`"), we consider it as the end of the ownership of the prior homeowner.
3. If a transaction is a quit claim deed transfer, has only a portion of the parcel or multiple parcels conveyed, only partial interest conveyed, or is an intrafamily transfer or gift deed transfer and the transaction price is greater than or equal to 10,000, we interpret this as a legitimate transfer of ownership and, hence, the end of ownership for the previous homeowner. If the transaction price is less than 10,000, we consider it a non-legitimate transfer and assume that the previous homeowner retains the property ownership.
4. If a transaction is the transfer type of affidavit of death, we consider it as the property ownership end for the previous homeowners.

Appendix D. Merge Altos Lab Rental Listing and ATTOM Housing Data

D.1. Clean Addresses in Altos Lab Rental Listing Data

Altos Lab rental data provides historical rental listing information from 2011 until today. The data provider claims that the data has a 98% national coverage on the active rental market for single-family residences and multi-unit apartment buildings. It tracks data points such as rental rate, property type, square footage, beds and baths, and amenities. The rental data sources (independent from MLS) do not include sources such as Craigslist but are private proprietary sources the data provider contracts with and covers most major metro areas and states, essentially every zip code in the US where there are houses/units. The company refreshes data weekly to provide a most updated picture of the rental market.

The rental property addresses in the data include the unit name, street address, city, state, and zip code. While the city, state, and zip code fields are relatively standard and clean, the unit name and street address fields are messy and cannot be directly used to merge with the ATTOM property addresses. Specifically, in ATTOM data, the property address is broken down into the following granular fields: `unit prefix`, `unit value`, `house number`, `street direction`, `street name`, `street suffix`, `city`, `state`, and `zip code`. In the Altos rental listing data, the unit prefix and number are included in the `"unit name"` field, while the house number, street direction, street name, and street suffix are mixed together in the `"street address"` field.

To effectively merge the rental property addresses with the ATTOM property addresses, we need to parse and standardize the rental property addresses to match the structured format provided by the ATTOM data. We aim to ensure that the rental property addresses have the same address components as those in the ATTOM data. To achieve that, we use ArcGIS Pro to parse and standardize the rental addresses in the Altos data.[6]. After processing the rental addresses in ArcGIS Pro, we obtain standardized fields, including unit prefix and number, street direction, name, and suffix, for each rental property address, aligning them with the ATTOM address fields.

[6]We followed the procedure outlined on the ArcGIS Pro website (https://pro.arcgis.com/en/pro-app/latest/tool-reference/geocoding/split-address-into-components.htm)

D.2. Merge Altos Lab Rental Properties and ATTOM Properties

We merge the rental property addresses with the ATTOM property addresses by using parsed and standardized addresses. The merging process is conducted on a *zip code-by-zip code* basis, meaning we merge properties *within the same zip code*. We require exact matches for each merging criterion rather than allowing for fuzzy matching. Given the same zip code, we match the rental property addresses to the Attom addresses in the following order.

1. Based on the parcel number (referred to as `APNFormatted` in ATTOM and `parcel_number` in Altos), we merge properties from the two datasets. We believe that using the parcel number for matching provides the most accurate way to combine the two datasets, as each parcel number serves as a unique identifier for individual properties. Any rental addresses that do not match with ATTOM addresses will proceed to the next step in our merging process.
2. We merge two addresses based on the unit number, house number (i.e., street number), street direction, and street name. For apartments, we consider two properties to be the same if they have the same unit number, street number, direction, and name. Any rental addresses that remain unmatched will proceed to the next step of the merging process.
3. We merge two addresses based on the unit number, house number (i.e., street number), and street name. In this phase, we remove the requirement for street direction. We observed that some addresses failed to match due to variations in how the street direction was included. For example, "Unit 2, 1234 N Main Street" may not match "Unit 2, 1234 Main Street" because the street direction is omitted, even though both refer to the same location within the same zip code. To address the failed matches caused by these inconsistencies, we assume that two properties are considered the same if the unit number, street number, and street name all match, as long as they are within the same zip code. Any rental addresses that remain unmatched will proceed to the next step of the merging process.
4. We merge two addresses based on the house number (street number), street direction, and street name. Single-family residential (SFR) properties typically do not include a unit number in their addresses; therefore, this step focuses primarily on merging SFR houses. We believe that an address without a unit number can be accurate enough to identify an SFR property but may not be sufficient for identifying other types, such as condos. Any rental addresses that remain

unmatched will proceed to the next step of the merging process.

5. We merge two addresses based on the house number (i.e., street number) and street name without requiring the street direction. Similarly, single-family residences (SFR) addresses do not include unit numbers. Some matching failures occurred due to the absence of street directions, even though the addresses referred to the same property. This merging step applies only to SFR matching and not to other property types. The entire matching process concludes at this stage.

When the property type is a condo or townhouse, it is essential that the unit number matches in both datasets. In other words, steps 4 and 5 do not apply to condos or townhouses. If two apartments share the same street number and name within the same zip code, we cannot confidently match the two properties. This is because different apartments with distinct characteristics and transaction prices may exist in the same building at that address.

If an apartment is listed for rent without a specific unit number, we cannot accurately determine which apartment within the building it corresponds to, nor can we identify its characteristics and transaction details. To ensure a more unbiased estimation of rental yields in the next step, we implement a very strict matching process of requiring unit number matching for condos or townhouses. This helps ensure that the rental listing information is accurately matched to housing transactions and property characteristics.

We believe that, at this point, we have identified the most comprehensive set of matching property addresses between the rental and ATTOM datasets. The rental properties that did not match an address in the ATTOM data may not match due to typos in the addresses or because those rental properties have never been publicly transacted.

D.3. Find Last Valid Purchase Transactions for Rental Properties

We have now merged the rental property data with the ATTOM property data. To obtain the joint distribution of rents and transaction prices, we need to identify properties that have been purchased and subsequently rented out within a narrow timeframe (i.e., 12 months). This method allows us to treat transaction prices and rents as contemporaneous, which more accurately reflects the expected rental yield for landlords.

To achieve that, we will first identify the most recent end-ownership purchase transaction for each rental listing. This step aims to obtain the landlord's purchase transaction record for buying the rental property. Next, we will determine the time gap between the property purchase and the rental listing date. Finally, we will gather the contemporaneous rents and *valid* transaction prices for the same property, calculate its rental yield, and perform rent estimation using the rent hedonic model.

For each rental property, we have assigned a unique ATTOM property ID (i.e., "`[ATTOM ID]`") by merging the rental dataset with the ATTOM dataset in the previous section. Within each ATTOM property ID, we search the historical deed records that were assigned to that ID prior to the rental listing date. However, it is important to note that not all ATTOM deed records represent transactions that end the ownership of a property. For instance, a deed record may be filed to add family members as co-owners. To identify the landlord's purchase transaction for the rental property, we need to locate the most recent transaction prior to the rental listing date that qualifies as an end-ownership transaction. A detailed description of end-ownership transactions can be found in Appendix Section C.

To obtain the joint distribution of contemporaneous rents and transaction prices, we have established more stringent requirements for matched purchase transactions of rental properties. Specifically, we only consider transactions that are deemed valid as outlined in Appendix Section C. That is important because there may be invalid transactions, such as non-arm's length transactions or foreclosures. Those invalid transactions often lead to abnormally low transaction prices due to personal relationships or other issues related to defaults. Including such invalid transactions in our estimation of rental yields could introduce bias in both transaction prices and rental yield estimations.