Monetary Policy Shocks and Local Housing Prices*

Shihan Xie
University of Illinois

This paper studies the channels by which monetary policy shocks affect local housing prices. It first documents there is a sluggish response of housing prices, suggesting that informational frictions may be potentially important. It then develops a structural model of housing prices with information frictions, and exploits variations in housing prices across metropolitan statistical areas to estimate it. The important finding is that although households are well-informed about local demand, they are ill-informed about how monetary policy affects the local housing market. A counterfactual experiment using the estimated model implies that deviations from the Taylor rule in the early 2000s contributed to about two-fifths of the subsequent housing boom.

JEL Codes: D83, E52, R21, R31.

1. Introduction

Interest rate changes play an important role in driving housing market dynamics. The large price boom in the U.S. housing market in the 2000s stirred up discussions on the effect of monetary policy on housing prices (e.g., Taylor 2007; Bernanke 2010). Recent empirical studies have pointed to the importance of local housing

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market heterogeneity in understanding the effects of monetary policy (Aastveit and Anundsen 2022; Cooper, Luengo-Prado, and Olivei 2022). While most existing studies focus on documenting the heterogeneous responses of local housing prices, this paper offers new insights into a novel transmission mechanism of monetary policy—the information channel.

This paper studies the transmission channels of monetary policy shocks to local housing markets by exploiting cross-sectional housing supply heterogeneity. Complementary to existing studies, I provide novel evidence on housing quantity dynamics in addition to housing prices, and a more comprehensive analysis of the effects of both unconventional and conventional monetary policy. The empirical findings motivate the structural model on two fronts. First, the empirical local housing price responses point to informational frictions as being central to the transmission of monetary policy shocks. Second, the cross-sectional estimates play a crucial role in identifying the key structural parameters of the model that are subsequently developed to quantify the importance of information frictions for housing prices. These estimates are essential to answer the question of how much of the increase in housing prices in the 2000s was the result of monetary policy shocks.

I begin by studying the effects of monetary policy shocks on local housing prices in a large sample of metropolitan statistical areas (MSAs). To document the empirical facts, I first identify and estimate monetary policy shocks during the pre-zero lower bound (pre-ZLB) period following the high-frequency identification literature (e.g., Kuttner 2001; Barakchian and Crowe 2013; Swanson 2021), by examining changes in interest rates of different maturities in narrow windows around key policy announcements.[1] Next, I exploit cross-sectional differences across MSAs in housing supply elasticities. My baseline results suggest that, given an expansionary shock that effectively decreases the federal funds rate (FFR)

[1]When the U.S. economy entered the ZLB period, the federal funds rate remained close to zero and the Federal Reserve used unconventional monetary policy tools such as quantitative easing. Therefore it involves a different identification strategy to study the post-ZLB period. While the main focus of this paper is the pre-ZLB period, I provide evidence that unconventional monetary policy had stimulative effects on the housing market through changes in the mortgage rate.

by 100 basis points, housing prices increase by 6 percent in cities with highly inelastic housing supply (e.g., San Francisco) but by only 2 percent in cities with very elastic housing supply (e.g., Iowa City) at the two-year horizon. In contrast, housing supply increases very quickly in cities with elastic supply but much more slowly in inelastic ones. Moreover, the effects of monetary policy shocks are regime-dependent. In particular, monetary policy shocks are more stimulative during policy loosening than tightening regimes.

The estimated impulse response functions also suggest that housing prices respond very sluggishly to monetary policy shocks. Such sluggish response of housing prices is inconsistent with assumptions of a frictionless housing market and full-information rational expectations. If households knew that an expansionary monetary policy shock would drive up future housing prices, why did they wait for a year or longer to act upon this good news? To solve this puzzle, I propose a model of housing prices with information friction. The model is based on Glaeser and Nathanson (2017), which I generalize to allow for endogenous housing supplies and monetary policy shocks. I assume that households have heterogeneous preferences for housing, and they know their own preferences. However, they imperfectly observe overall local demand and national factors that influence it. This becomes a complicated inference problem because local housing price is common knowledge among households but also an equilibrium outcome. I find the solution from a fixed point to the household's dynamic signal extraction problem. This allows me to derive the model's predicted equilibrium dynamic response of local house prices to aggregate shocks. The size of noise in the households' signals measures the degree of information friction in the transmission of monetary policy shocks.

To relate the model's predicted response of housing prices to my empirical findings, I use minimum chi-square estimation to estimate key structural parameters in this model. This method provides a general framework to estimate structural parameters in models with aggregate shocks and heterogeneous cross-sectional impacts. The estimation result suggests that households have little direct information about changes in the monetary policy stance. This implies that, in a rational expectation framework, explaining the sluggishness of housing prices in response to monetary policy shocks requires a significant size of information friction. This is the case even after

considering search frictions in the model. Finally, the counterfactual analysis based on the estimated structural model with information frictions shows that deviations from the Taylor rule could explain about 40 percent of the housing boom during the early 2000s.

There is growing literature on empirically estimating the effects of monetary policy on local house prices (see, for example, Del Negro and Otrok 2007; Luciani 2015; Williams 2015). The empirical strategy employed in this paper is closest to Aastveit and Anundsen (2022), where they examine the asymmetric effect of monetary policy on housing prices using a local projection approach using the Romer and Romer (2004) monetary policy shocks. Using different monetary policy shocks based on high-frequency identification, I provide corroborating evidence of the housing quantity dynamics in addition to housing price responses. Furthermore, I show that unconventional monetary policy is similarly effective in driving housing prices when I extend the analysis to include the zero lower bound period, which is not feasible when using shocks from Romer and Romer (2004). Work by Cooper, Luengo-Prado, and Olivei (2022) is also highly relevant, in which they exploit differences in the relative stance of policy across U.S. states. This paper is related, in that I document the differential impact of monetary policy on local house prices. The purpose of the empirical evidence, however, is noticeably different, as it motivates and facilitates the estimation of the structural model.

This paper also contributes to the literature on housing market rigidities. To my knowledge, this is the first paper that examines the role of information frictions in the transmission of monetary policy to local housing markets. In addition to this paper's focus on information frictions, a potentially important source of rigidity is search frictions in housing markets (e.g., Garriga and Hedlund 2020; Ngai and Sheedy 2020; Piazzesi, Schneider, and Stroebel 2020; Díaz, Jerez, and Rincón-Zapatero 2024). In particular, Head, Lloyd-Ellis, and Sun (2014) build a housing search model with housing construction and calibrate it to the impulse response functions (IRFs) generated from a panel vector autoregression (VAR). They show that searching improves the fit of housing price IRFs to income shocks, but its impact effect is about 80 percent of the overall response. Guren (2018) develops a search model to explain the housing price momentum by adding strategic complementarity and buyers with extrapolative beliefs. In my model, I show a simple method to allow

for search frictions by incorporating the estimated Weibull distribution for time spent on searching in Hamilton (2008). However, adding search frictions only mildly reduces the response in the first six months.

Finally, this paper contributes to the literature on understanding the role of housing market beliefs in driving house price dynamics.[2] The literature has recognized beliefs as an important factor in house price dynamics. For example, Kaplan, Mitman, and Violante (2020) argue that shifts in beliefs are essential in explaining the boom in the early 2000s, along with an unprecedented change in credit conditions. To endogenize belief formation, existing literature has used models on learning (Adam, Kuang, and Marcet 2012; Jacobson 2022), diagnostic beliefs (Chodorow-Reich, Guren, and McQuade 2024), extrapolative beliefs (Glaeser and Nathanson 2017; Guren 2018), as well as information dispersion (Favara and Song 2014). While the existing literature mostly focuses on modeling beliefs to understand boom-bust cycles in housing markets, this paper focuses on the effects of monetary policy shocks. Monetary policy shocks are relatively small in magnitude and are always difficult to identify in real time. Imperfect information about the evolution of shocks is a reasonable approximation that captures the essence of its mechanisms. In setting up the signal extraction problem in house price belief formation, this paper follows similar strategies in Favara and Song (2014) and Glaeser and Nathanson (2017).

The plan for the paper is as follows. Section 2 presents the identification of monetary policy shocks and the empirical estimation of housing price IRFs. Section 3 develops a housing price model with information frictions. Section 4 presents the structural estimation of this model. Section 5 discusses the application of model results to the 2000s housing boom. Section 6 concludes.

2. Empirical Evidence

This section documents the empirical evidence on the heterogeneous effects of aggregate monetary policy shocks on local housing prices and quantities. Section 2.1 presents data on the housing price index

[2]See Kuchler, Piazzesi, and Stroebel (2023) for a recent review of the literature on house price expectations.

and housing supply elasticities. Section 2.2 discusses the estimation of monetary policy shocks using high-frequency identification. Section 2.3 presents the empirical evidence based on the Jordà (2005) local projection method.

2.1 Data on House Price, Permits, and Housing Supply Elasticity

House Price Index. I use the Freddie Mac House Price Index (FMHPI) as my housing price index. This seasonally adjusted series covers most MSAs since January 1975 at monthly frequency. The FMHPI is constructed using a weighted repeat-transactions methodology and is estimated with data including transactions on single-family detached and townhome properties serving as the collateral on loans purchased by Freddie Mac or Fannie Mae. This method is standard in housing research and is based on a data set commonly used to construct other housing price indices such as that of the Federal Housing Finance Agency (FHFA).

Housing Construction Permits. New housing construction permit data are available from the Census Building Permits Survey at a monthly frequency since 1980. I use the total value of permits to measure changes in the quantity of housing at each MSA.

Housing Supply Elasticity. Data on MSA-level housing supply elasticities are based on estimates from Saiz (2010). This topology-based estimate is constructed based on physical and regulatory constraints on long-run housing construction in MSAs. It has been broadly used in other studies, including Mian and Sufi (2009, 2011) and Mian, Rao, and Sufi (2013), to identify the cross-sectional housing price heterogeneity.[3]

To understand the cross-sectional identification, consider an aggregate shock that drives local housing demand uniformly. The slope of the local housing supply curve determines the degree to which housing prices rise in an area. Areas with inelastic housing supply experience larger changes in housing prices but smaller changes in quantities. Specifically, after an expansionary shock, the

[3]Some recent studies argue that there are potential issues with Saiz (2010), such as underestimating the size of supply elasticities. I found similar results when using housing sensitivity estimates from Guren et al. (2021).

increase in the MSA-level housing price should be inversely proportional to the MSA-specific housing supply elasticity.

2.2 Identification of Monetary Policy Shocks

I identify shocks to monetary policy following the high-frequency identification (HFI) literature. To make an inference about the unexpected component of monetary policy announcements, I examine movements in financial markets within a narrow window around press releases of the Federal Open Market Committee (FOMC). There are about eight FOMC press releases a year, each following a regularly scheduled meeting and some occasional intermeeting announcements. My main analysis focuses on the period before the zero lower bound period. The effects of unconventional monetary policy during the ZLB period are considered in Appendix A.1.

To measure the unanticipated component of each FOMC press release, I compute the first principal component of these asset price responses in the 30-minute windows around the FOMC announcement between January 1991 and June 2008. Let a matrix X summarize changes in asset prices with rows corresponding to FOMC announcements and columns corresponding to n different assets; each element x_{ij} of X then reports the 30-minute response of the jth asset to the ith FOMC announcement. As in Gürkaynak, Sack, and Swanson (2005), I summarize this information in a factor model, $X = F\Lambda + \epsilon$, where F is a matrix of unobserved factors, Λ is a matrix of factor loadings, and ϵ is a matrix of white noise residuals. Following Swanson (2021), asset prices include the first and third federal funds futures contracts;[4] the second, third, and fourth Eurodollar futures contracts; and the 2-, 5-, and 10-year Treasury yields. Each column of F can be estimated with principal component analysis. Since the scale of F and Λ are indeterminate, each component of F is normalized such that a one-unit increase in the factor leads to a 100 basis point increase in the 10-year Treasury bill. Loadings on the first factor are reported in Table 1.

[4] As is standard in the literature, these contracts are scaled by the number of days remaining in the month to provide an effective estimate of the surprise change in the FFR after the announcement (see Kuttner 2001; Gürkaynak, Sack, and Swanson 2005 for details).

Table 1. Composition of Identified Monetary Policy Shock Series

	MP1	MP2	ED2	ED3	ED4	2y Tr.	5y Tr.	10y Tr.
Loadings	0.2537	0.3069	0.3951	0.4012	0.3895	0.4009	0.3584	0.2888

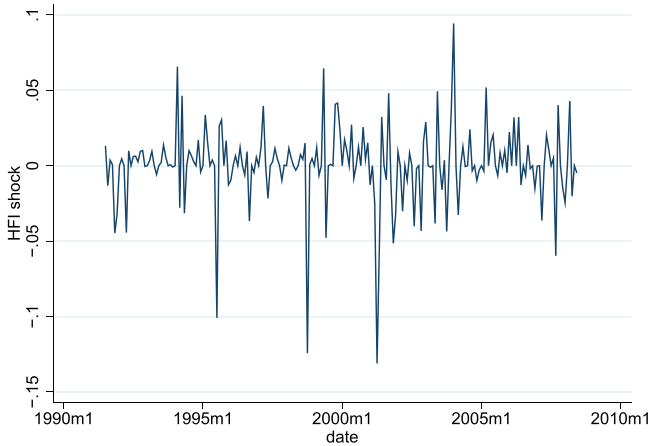
Note: This table reports loadings of identified monetary policy shock series. I estimate the first principal component in the factor model using changes in asset prices on FOMC meeting days as the monetary policy shock. The assets include the first (MP1) and third (MP2) federal funds futures contracts, the second (ED2), third (ED3), and fourth (ED4) Eurodollar futures contracts, and the 2-, 5-, and 10-year Treasury yields. The sum of squares of the loadings is normalized to 1.

This identification of monetary policy shocks involves more financial assets than most earlier literature using high-frequency identifications. For example, Gorodnichenko and Weber (2016), Nakamura and Steinsson (2018), and others consider changes only in the current month's federal funds futures contract. Barakchian and Crowe (2013) use the first factor of changes in six federal funds futures contracts up to five months. As Swanson (2021) argues, monetary policy communications have more than one dimension. By constructing the shock based on asset prices covering longer maturities, this measure captures the persistent component of monetary policy shocks, which is more relevant from a housing demand perspective. The key identifying assumption is that no other factor occurred within the window around the FOMC announcement that drives the prices of financial instruments. My results are robust to using other HFI shocks in the literature.

To construct monthly measures of monetary policy shocks, I aggregate the high-frequency estimates by simple summation within any month t. If there is no FOMC meeting in a particular month, the size of the monetary policy shock for that month is set to zero. Figure 1 plots the monthly monetary policy shock estimates.[5] A negative (positive) value of the HFI shock represents that the identified monetary policy shock is expansionary (contractionary) during that month. For example, the FOMC announced its plan to reduce the

[5]This measure of monetary policy shocks has a correlation of 0.6 with federal funds rate shocks and 0.7 with forward-guidance shocks in Swanson (2021).

Figure 1. Monetary Policy Shocks by High-Frequency Identification



Note: This figure plots monthly monetary policy shocks from January 1991 to June 2008. Shocks are estimated using the high-frequency identification (HFI) method. HFI shocks are identified using changes in asset prices in a narrow time window around FOMC meetings. One unit of the shock is normalized to effectively raise the rate on the 10-year Treasury bill by 100 basis points.

FFR target by 50 basis points to 4.5 percent after the meeting on April 18, 2001. This action surprised the market, as the size of the reduction was larger than what the market had anticipated. It led to a decrease in interest rates on all assets considered within the 30-minute window of the FOMC announcement.

2.3 Estimation with Jordà Local Projection

In this section, I provide an estimate of how an MSA's housing price or quantity, $y_{i,t+h}$, at horizon h behaves in response to a monetary policy shock at time t given its housing supply elasticity, $\epsilon_i^{\text{supply}}$. I use a panel local projection method in the spirit of Jordà (2005). The original local projection method, a direct forecast method, provides robust nonparametric estimates to IRFs, $\delta y_{t+h}/\delta S_t$, by running a series of separate regressions for each horizon, h. This method is suitable if external-identified shocks are available and it is less prone to misspecification issues in iterated methods such as structural VAR

models. My main analysis here focuses on the period from January 1991 to June 2008. I extend the analysis to the zero lower bound period in Appendix A.1.

To estimate the impulse response of the housing price growth in MSA i h-periods after a monetary policy shock, I regress the cumulative growth of housing prices, $\Delta_h y_{i,t+h} (= \log y_{i,t+h} - \log y_{i,t-1})$, on the interaction term of the change in monetary policy (ΔMP_t) and MSA i's housing supply elasticity $\epsilon_i^{\text{supply}}$, alongside a number of control variables. I use monetary policy shock S_t and its interaction with housing supply elasticity $\epsilon_i^{\text{supply}}$ as instruments for changes in the federal funds rate and the interaction term. Specifically, I estimate the following regression separately for $h = 0, 1, \ldots, H$:

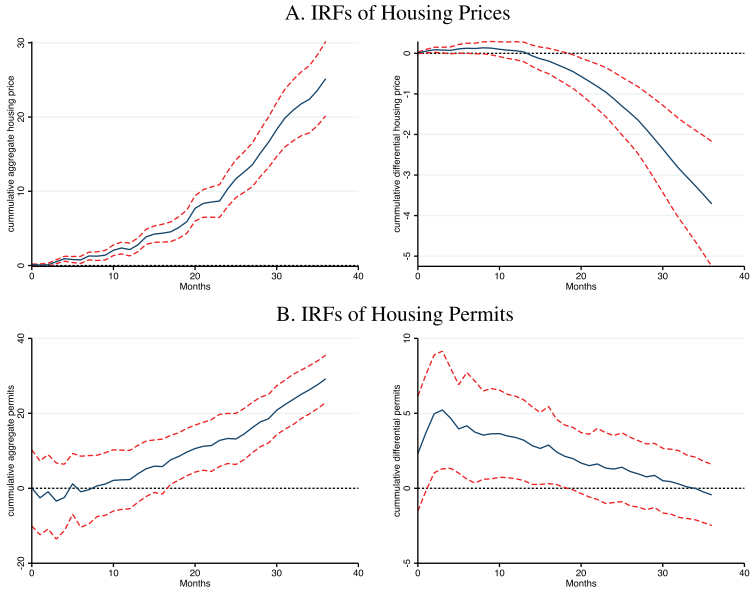
$$\Delta_h y_{i,t+h} = \alpha_h + \beta_h \, \widehat{\Delta \text{MP}}_t + \gamma_h \widehat{\Delta \text{MP}}_t \times \epsilon_i^{\text{supply}} + \Gamma_h X_{i,t} + \xi_i + u_{it}, \tag{1}$$

where ΔMP_t represents changes in monetary policy corresponding to a 100 basis point decrease in the federal funds rate. The vector $X_{i,t}$ denotes the control variables which include 12 lags of log house prices. I also include location fixed effects (ξ_i) to capture any MSA-specific trends that might be correlated with the housing supply elasticity. The key coefficients of interest, β_h and γ_h, summarize the dynamic aggregate and differences in local house price responses to monetary policy shocks. Intuitively, given an expansionary monetary policy shock, MSAs with a more elastic housing supply experience larger increases in housing supply and therefore smaller increases in housing prices. As a result, one should expect positive β_h and negative γ_h after an expansionary monetary policy shock. Under this specification, $\beta_h + \gamma_h \epsilon_i^{\text{supply}}$ is a linear approximation of $\frac{\delta y_{i,t+h}}{\delta \text{MP}_t}$ for MSA i.[6]

Figure 2A presents estimated β_h and γ_hs of Equation (1) for up to three years. The responses are the result of an expansionary monetary policy shock that effectively lowers the federal funds rate

[6]One may be worried about other concurrent aggregate shocks that affect housing prices, which can be resolved by including time fixed effects. However, given that the federal funds rate is colinear with time fixed effects, I am only able to estimate the differential effects once time fixed effects are included. In Appendix A.2 I show results on the differential effects (γ_h) where I include time fixed effects, and they are very close to the ones reported here.

Figure 2. Impulse Response Functions to Monetary Policy Shocks



Note: This figure plots the impulse response functions of housing prices (panel A) and housing permits (panel B) to monetary policy shocks estimated using Equation (1). The solid dark blue line plots the cumulative impulse response to an expansionary monetary policy shock. The shock effectively lowers the federal funds rate by 100 basis points. Left-side graphs show the upper limit of IRFs (β_h) if the housing supply is perfectly inelastic. Right-side graphs show the differential responses (γ_h) between two MSAs that differ in the housing supply elasticity by one unit. The dotted red lines outline the 95 percent confidence interval.

by 100 basis points. The estimates for β_h (left graph) represent the response for a city with a perfectly inelastic housing supply, and therefore an *upper limit* of housing price responses. The estimates for γ_h (right graph) represent the differential impulse response in the cumulative house price growth between two MSAs that differ in housing supply elasticity by one unit—for example, between San Francisco and Philadelphia or between Houston and Oklahoma City. Standard errors are clustered at the MSA level, allowing for arbitrary autocorrelation of the house price growth within each MSA. Table 2 summarizes the estimates of the two-year housing price impulse responses for selected MSAs.

Table 2. Selected MSA Housing Price Responses to Monetary Policy Shocks

Percentile	Supply Elasticity	MSA	Two-Year HPI
5	0.7	San Diego, CA/New York, NY	5.48
10	1.2	Pittsburgh, PA/Baltimore, MD	5.11
25	1.6	Washington, DC/Philadelphia, PA-NJ	4.81
50	2.3	Houston, TX/Ann Arbor, MI	4.29
75	3.3	Kansas City, KS/Oklahoma City, OK	3.54
90	4.4	Iowa City, IA/Mansfield, OH	2.73

Note: This table reports the MSA-level housing price response to an expansionary monetary policy shock at the two-year horizon. The shock effectively lowers the rate on the federal funds rate by 100 basis points. Column 1 reports the percentile of the MSA's housing supply elasticity. These estimates are calculated based on the Jordà local projection method.

The estimation results suggest that the overall housing price responses are large and highly persistent. Consistent with the hypothesis, the differential response to an expansionary shock is negative, revealing that housing prices in more inelastic MSAs respond more strongly to monetary policy shocks. The overall dynamics are sluggish with limited responses in the first year but are much amplified afterward.

To study the effects of monetary policy shocks on changes in housing quantities, I estimate Equation (1) using the log of cumulative housing permits in MSA i as the dependent variable. I include 12 lags of log house price and log permits as control variables, as well as location fixed effects (ξ_i). The key coefficients of interest, β_h and γ_h, summarize the dynamic aggregate and differences in local house quantity changes to monetary policy shocks. Intuitively, given an expansionary monetary policy shock, MSAs with a more elastic housing supply experience larger increases in housing quantities. Therefore, one should expect estimates β_h and γ_h to be positive after an expansionary monetary policy shock.

Figure 2B presents estimated β_h and γ_hs for up to three years. The estimates for β_h (left graph) represent the response for a city with a perfectly inelastic housing supply, and therefore a *lower bound* on the housing quantity responses. The estimates for γ_h (right graph)

represent the differential impulse response in the cumulative housing permits increase between two MSAs that differ in housing supply elasticity by one unit.

As the mirror image of the pattern for housing prices, housing quantities increase more in MSAs with a more elastic housing supply. The differential response picks up very quickly in the few months right after when the monetary policy shock is in effect. One potential explanation is that when the interest rate lowers, construction companies quickly enter the market to obtain permits. For the period of study, depending on the number of units in a building, it takes about 6–12 months of construction on average from start to completion. Therefore, the actual addition of housing quantity takes place about one year later. This observation is in line with the fact that the differential response of housing prices expands after one year.

To summarize, expansionary monetary policy shocks play an important role in stimulating local housing markets. The effects of monetary policy shocks are sluggish in the short run but become very sizable in the longer run. In particular, MSAs with more inelastic housing supply experience significantly larger housing price increases but smaller housing quantities increases.

2.4 Asymmetric and Nonlinear Effects

Next, I consider specifications that allow for an asymmetry between policy tightening and loosening cycles as well as nonlinearity with respect to the housing supply elasticity. Specifically, I consider the following regression model:

$$\begin{aligned}\Delta_h y_{i,t+h} = {} & \alpha_h^+ + \beta_h^+ \, \widehat{\Delta \mathrm{MP}}_t^+ + \gamma_h^+ \widehat{\Delta \mathrm{MP}}_t^+ \times \frac{1}{\epsilon_i^{\text{supply}}} \\ & + \Gamma_h^+ X_{i,t} + \xi_i^+ + u_{it}^+ \quad \text{if } t \in \text{tightening} \qquad (2) \\ \Delta_h y_{i,t+h} = {} & \alpha_h^- + \beta_h^- \, \widehat{\Delta \mathrm{MP}}_t^- + \gamma_h^- \widehat{\Delta \mathrm{MP}}_t^- \times \frac{1}{\epsilon_i^{\text{supply}}} \\ & + \Gamma_h^- X_{i,t} + \xi_i^- + u_{it}^- \quad \text{if } t \in \text{loosening}, \qquad (3)\end{aligned}$$

where $\Delta \mathrm{MP}_t^+$ ($\Delta \mathrm{MP}_t^-$) represent monetary policy tightening (loosening) corresponding to a 100 basis point increase (decrease) in

the federal funds rate. The interaction term $\frac{1}{\epsilon_i^{\text{supply}}}$ allows for nonlinearity in terms of housing supply elasticity. This setup accommodates a possible scenario where in a perfectly elastic market, expansionary monetary policy shocks do not affect house prices, but contractionary shocks could still have significant price effects given the durability of housing. Similar controls are included as in Equation (1).

The coefficients β_h^+ (β_h^-) and γ_h^+ (γ_h^-) summarize the dynamic aggregate and differences in local house price responses to monetary policy shocks during policy tightening (loosening) periods. Given an expansionary (contractionary) monetary policy shock, MSAs with a more elastic housing supply experience larger increases (decreases) in housing supply, and therefore smaller increases (decreases) in housing prices. Now that the interaction term is the inverse of housing supply elasticity, one should expect negative β_h^+ and γ_h^+, but positive β_h^- and γ_h^- in housing price responses. In particular, β_h^+ and β_h^- represent responses of perfectly elastic markets where $\epsilon_i^{\text{supply}} \to \infty$ and therefore the *lower bounds* of housing price responses.

I estimate Equations (2) and (3) for periods of monetary policy tightening and loosening respectively, where the tightening and loosening cycles are defined in Figure A.3 (see Appendix A). The left (right) graph of Figure A.4 plots the coefficients of β_h^+ (γ_h^+) in blue and β_h^- (γ_h^-) in orange for horizons up to three years, capturing the asymmetric responses of *house price growths* to monetary policy shocks during tightening and loosening regimes. As the left graph illustrates, monetary policy shocks are more stimulative during policy loosening than tightening regimes. During loosening periods, I observe a moderate increase in baseline house prices but do not observe significant differences across MSAs in the first year. Over the medium to longer horizons, house prices in more elastic MSAs increase significantly more than inelastic ones. As housing construction takes time, house price growth in perfectly elastic markets stabilizes after new housing supplies enter the market. In contrast, monetary policy shocks do not have significant impacts on baseline house prices over the longer run during tightening regimes.

Turning to house quantities, panel B of Figure A.4 plots the asymmetric responses of *(log) housing permits* to monetary policy shocks during tightening and loosening regimes. Consistent with

house price responses, housing permits are more responsive to monetary policy shocks during policy loosening regimes.

3. A Housing Model with Information Friction

The estimated empirical impulse response functions in Section 2 show a very sluggish response to monetary policy shocks, suggesting that households are not fully aware of the future consequences of monetary policy shocks for housing prices. To capture these empirical regularities in the model, I introduce information friction to the housing market. More specifically, I consider a framework where households have idiosyncratic preferences for living in the local area and some knowledge about local housing demand and aggregate demand. However, they do not observe monetary policy shocks and local demand shocks perfectly, which I model as information frictions.

To achieve this, I generalize an asset pricing model of housing from Glaeser and Nathanson (2017) to allow for endogenous housing supply, which is a key feature of the housing market. Housing prices exhibit different dynamics across cities after an aggregate demand shock due to diverse housing supply conditions. Households within each city are heterogeneous in their idiosyncratic housing preferences. They have imperfect information about market fundamentals, but they form rational expectations. Details of the model setup are presented in Section 3.1. I discuss the solution method in Section 3.2, and derive housing price IRFs to monetary policy shocks in the model. I extend the model to account for search frictions in the housing market in Section 3.3.

3.1 Housing Demand and Housing Supply

In a large economy with one central bank and several cities, each city differs in its housing supply elasticity due to distinct geographical and regulatory constraints. Each city is populated with a continuum of households, indexed by $i \in [0.1]$. An individual household i in city m receives a flow of utility improvement $d_{i,m,t}$ if they decide to buy one unit of the house. I adopt the notion in Glaeser and

Nathanson (2017) that this overall utility combines an idiosyncratic element, $a_{i,m,t}$, with a city-specific component, $\widehat{D}_{m,t}$:

$$d_{i,m,t} = \widehat{D}_{m,t} + a_{i,m,t}. \tag{4}$$

These elements include returns from the local labor market and the utility derived from living in the current city. The idiosyncratic component $a_{i,m,t}$ is drawn independently at each period for each individual from a normal distribution.[7] The city-specific component, $\widehat{D}_{m,t}$, is subject to both city-specific and aggregate shocks such as monetary policy shocks. I specify it later when I discuss the dynamics of the fundamental states. Overall, $d_{i,m,t}$ captures an individual's marginal propensity to live in a specific city.

Given an individual's utility flow of $d_{i,m,t}$, and a price of $P_{i,m,t}$ for a preferred house type, their housing demand, $H_{i,m,t}$, satisfies

$$p_{i,m,t} = d_{i,m,t} - \frac{h_{i,m,t}}{\chi^{\mathrm{D}}} + \beta \mathbb{E}_{it} p_{i,m,t+1}, \tag{5}$$

where $p_{i,m,t} = \log P_{i,m,t}$, $h_{i,m,t} = \log H_{i,m,t}$, and χ^{D} is the individual housing demand elasticity. Equation (5) characterizes the individual housing demand in my model. To interpret it from an asset pricing perspective, $p_{i,m,t}$ is the individual's willingness to pay for the house, and it equals the current marginal utility of owning the house plus the discounted future value of owning the house of $\beta \mathbb{E}_{it} p_{i,m,t+1}$. As the number of housing units, $H_{i,m,t}$, increases, the marginal utility of owning the house, $d_{i,m,t} - h_{i,m,t}/\chi^{D}$, diminishes. This housing demand equation can also be motivated from the perspective of a utility-maximizing household in a typical dynamic stochastic general equilibrium (DSGE) model with housing: $d_{i,m,t}$ approximates the household's income and preference for housing versus other goods. Appendix B.1 presents details on the derivation of Equation (5) under this setup.

The aggregate housing price index of city m is $p_{m,t} = \int p_{i,m,t} di$. In the baseline model, I approximate the city-level housing supply

[7]We assume $a_{i,m,t} \sim i.i.d.$ for simplicity, but our result is robust to modifying the process of $a_{i,m,t} \sim AR(1)$ to allow for a persistent but idiosyncratic process across each individual.

with a log-linear relationship between the housing price and the housing quantity, subject to housing supply shocks that are orthogonal to housing demand shocks. Given price $p_{m,t}$, the available quantity of this type of housing in this city with housing supply elasticity χ^{S} is

$$h_{m,t} = \chi^{\mathrm{S}} p_{m,t} + s_{m,t}, \tag{6}$$

where $s_{m,t}$ denotes city-level housing supply shocks, which follow an $AR(1)$ process with persistence μ_{s} and noise σ_{s}.

Equation (6) captures the important feature that the housing quantity is more sensitive to housing price fluctuations in cities with more elastic housing supplies. I assume that the short-run fluctuations in interest rates do not transmit directly to the supply of housing, but only through housing prices.[8]

In the equilibrium, housing market clears such that $h_{m,t} = \int h_{i,m,t} di$. Therefore, the housing price index in each city satisfies the following law of motion:

$$p_{m,t} = \frac{\widehat{D}_{m,t}}{1 + \chi^{\mathrm{S}}/\chi^{\mathrm{D}}} + \frac{\beta}{1 + \chi^{\mathrm{S}}/\chi^{\mathrm{D}}} \bar{\mathbb{E}}_t p_{m,t+1} - \frac{s_{m,t}}{\chi^{\mathrm{D}} + \chi^{\mathrm{S}}}, \tag{7}$$

where $\bar{\mathbb{E}}_t p_{m,t+1} = \int \mathbb{E}_{it} p_{i,m,t+1} di$ is the average expectation of future housing prices across all households.[9] Given a demand shock, the housing price response depends on the dynamics of market fundamentals $\widehat{D}_{m,t}$, the evolution of household expectation formation $\bar{\mathbb{E}}_t p_{m,t+1}$, and city-specific supply shocks $s_{m,t}$. I specifically model the role of information frictions in driving households' expectations and subsequently their effects on short-run housing price dynamics.

Local housing market fundamentals are driven by both local demand factors and aggregate demand shocks. In particular, city-specific component of utility flow $\widehat{D}_{m,t}$ is driven by an unobserved

[8] For models that focus on the dynamics of housing volume and its relationship to prices, see DeFusco, Nathanson, and Zwick (2017), Nathanson and Zwick (2018), and others.

[9] Note that I have extended the housing price model in Glaeser and Nathanson (2017) to allow for variations in housing supply conditions. This model coincides with their setup in discrete time if it is restricted to the extreme case of inelastic housing supply, $\chi^{\mathrm{S}} = 0$.

housing demand factor $D_{m,t}$ and an idiosyncratic city-specific shock a_{mt} such that

$$\widehat{D}_{m,t} = D_{mt} + a_{mt}, \quad a_{mt} \sim i.i.d.N(0, \sigma_{\mathrm{a}}^2). \tag{8}$$

The housing demand factor in a city m is

$$D_{mt} = T_{mt} + \alpha Q_t. \tag{9}$$

In the above equation, T_{mt} represents the portion of the local demand factor arising from local amenities. This factor captures the utility flow of an average household in the overall benefit of living in this city. Q_t represents the aggregate demand factor that affects all cities uniformly. Since the focus is on monetary policy, Q_t captures the effect of monetary policy on housing demand. Here, α is a scaling factor that weighs the relative importance of the monetary policy to local demand.

The housing and aggregate demand factors, T_{mt} and Q_t, each respectively evolve over time according to

$$T_{mt} = T_{m,t-1} + g_{mt} + \epsilon_{mt}^{\mathrm{d}}, \qquad \epsilon_{mt}^{\mathrm{d}} \sim i.i.d.N(0, \sigma_{\mathrm{d}}^2) \tag{10}$$

$$g_{mt} = \rho g_{m,t-1} + \epsilon_{mt}^{\mathrm{g}}, \qquad \epsilon_{mt}^{\mathrm{g}} \sim i.i.d.N(0, \sigma_g^2) \tag{11}$$

$$Q_t = \theta Q_{t-1} + \epsilon_t^{\mathrm{MP}}, \qquad \epsilon_t^{\mathrm{MP}} \sim i.i.d.N(0, \sigma_r^2), \tag{12}$$

where g_{mt} is the growth factor of housing demand; ϵ_t^{d} and ϵ_t^{g} are shocks to the level and growth of local demand. A shock ϵ_t^{d} has a permanent impact on the utility of living in this city. For example, a city's investment in a good school district is a positive shock to local housing demand, while closing down large manufacturing plants would represent a negative housing demand shock. A shock to the growth of demand ϵ_t^{g} has persistent impacts on housing through the growth factor g_{mt}. This could come from news about future investments in the city. For example, housing demand increases if people expect that a large company will build a new headquarter in the city. ϵ_t^{MP} denotes monetary policy shock, which has a persistence of θ.

3.2 Solution to the Model

In this section, I propose a solution method that computes the housing price dynamics given the fundamental demand. To do this, I

first specify the information structure. Individual household demand for housing is heterogeneous due to idiosyncratic preferences. Each household knows its demand for housing ($d_{i,m,t}$) as stated in Equation (4), but does not fully observe $\widehat{D}_{m,t}$, the demand at the city level given by Equation (8). The household also observes the aggregate housing price history in the local market up to the current period, $\{p_{t-j}\}_{j=0}^{\infty}$, and a sequence of common signals of monetary policy stances $\{r_{t-j}\}_{j=0}^{\infty}$ which is related to the effect of monetary policy Q_t:

$$r_t = Q_t + q_t, \quad q_t \sim i.i.d.N(0, \sigma_{\mathrm{q}}^2). \tag{13}$$

In practice, one can think of r_t as interest rates observable by households, which is a noisy signal of the housing demand driven by monetary policies (Q_t). The variable q_t captures the signal noise with a standard error σ_{q}. To summarize, household i in city m has a time t information set, $\Omega_{i,m,t} = \{y_{i,m,t}, y_{i,m,t-1}, \ldots, y_{i,m,1}\}$, where $y_{i,m,t} = (p_{mt}, d_{i,m,t}, r_t)'$. In other words, individual households know their own demand ($d_{i,m,t}$), city-specific housing prices (p_{mt}), and interest rates (r_t). With this information, individuals make an effort to infer the market fundamentals which include the level and growth of city-specific demand (T_{mt} and g_{mt}), as well as the demand for housing driven by monetary policies (Q_t).[10]

This problem is unconventional since the housing price is an equilibrium object that depends on the households' decisions on housing demand. Meanwhile, households make decisions using the current price as a signal about market conditions. I solve this model by formulating it in a state-space framework in which the state matrix is computed through a fixed-point iteration.

I start with the equilibrium housing price. Households' information sets differ only in individual demands, $d_{i,m,t}$, whose idiosyncratic parts, $a_{i,m,t}$, are independently normally distributed. Given that the equilibrium housing price is linear in housing demand, $\int \mathbb{E}_{it} p_{i,t+1} \mathrm{d}i = \mathbb{E}_t(p_{m,t+1}|\Omega_{mt})$, where $\Omega_{mt} = \{y_{mt}, y_{m,t-1}, \ldots, y_{m1}\}$ and $y_{mt} = (p_{mt}, \widehat{D}_{m,t}, r_t)'$. According to Equation (7), the

[10]Table B.1 in Appendix B provides a summary of all the variables and their definitions.

aggregate housing price in city m with housing supply elasticity χ_m^{S} follows

$$\begin{aligned} p_{mt} &= \tilde{s}_{mt} + \tilde{\hat{D}}^{s}_{mt} + \beta_m \mathbb{E}_t(p_{m,t+1}|\Omega_{mt}) \\ &= \tilde{s}_{mt} + \tilde{a}_{mt} + \tilde{T}_{mt} + \alpha_m Q_t \\ &\quad + \mathbb{E}_t\{[\beta_m(\tilde{s}_{m,t+1} + \tilde{T}_{m,t+1} + \alpha_m Q_{t+1}) \\ &\quad + \beta_m^2(\tilde{s}_{m,t+2} + \tilde{T}_{m,t+2} + \alpha_m Q_{t+2}) + \cdots]|\Omega_{mt}\} \\ &= \tilde{s}_{mt} + \tilde{a}_{mt} + \tilde{T}_{mt} + \alpha_m Q_t + \frac{\beta_m}{1-\beta_m}\tilde{T}_{m,t|t} \\ &\quad + \frac{\alpha_m \beta_m \theta}{1-\beta_m \theta} Q_{t|t} + \frac{\beta_m}{(1-\beta_m)(1-\beta_m \rho)}\tilde{g}_{m,t|t}, \end{aligned} \tag{14}$$

where $\tilde{s}_{mt} = -\frac{s_{mt}}{\chi^{\mathrm{D}}+\chi_m^{\mathrm{S}}}$, $\tilde{a}_{mt} = \frac{1}{1+\chi_m^{\mathrm{S}}/\chi^{\mathrm{D}}} a_{mt}$, $\tilde{\hat{D}}^{s}_{mt} = \frac{1}{1+\chi_m^{\mathrm{S}}/\chi^{\mathrm{D}}} \widehat{D}_{m,t}$, $\tilde{T}_{mt} = \frac{1}{1+\chi_m^{\mathrm{S}}/\chi^{\mathrm{D}}} T_{mt}$, $\tilde{g}_{mt} = \frac{1}{1+\chi_m^{\mathrm{S}}/\chi^{\mathrm{D}}} g_{mt}$, $\alpha_m = \frac{1}{1+\chi_m^{\mathrm{S}}/\chi^{\mathrm{D}}}\alpha$, and $\beta_m = \frac{1}{1+\chi_m^{\mathrm{S}}/\chi^{\mathrm{D}}}\beta$. $X_{m,t|t} = E_t(X_t|\Omega_{mt})$, $X = T, Q, g$, denotes optimal inference given the information set Ω_{mt}.

Equation (14) establishes a law of motion of housing prices at the city level. Housing prices are forward-looking and depend strongly on households' expectations about future local and aggregate demands. In particular, the impact of monetary policy would be larger the more persistent the monetary policy is. The cross-sectional difference in housing price responses comes from the supply elasticity χ^S. Cities with more inelastic housing supply have larger scale factors α_m, therefore exhibiting greater responses to monetary policy.

I assume no short-run interaction among local housing markets. The solution method applies uniformly to each local market. For simplicity of notation, I drop the subscript m in my presentation. The city-specific housing price behaves as if there is a representative agent in the housing market with the information set Ω_t. The equilibrium price depends not only on the fundamental demand at period t but also on the household's best inference about them. At this stage, the key step is to solve for the dynamics of $Q_{t|t}$, $T_{t|t}$, and $g_{t|t}$.

I solve for the dynamics of $\Phi_{t|t} = \{T_{t|t}, g_{t|t}, Q_{t|t}\}$ by finding a fixed point in the Kalman filter recursion. Specifically, I develop an algorithm to find the coefficient matrix $[c_p\ c_q\ c_d]$ in

$$\Phi_{t|t} = \Phi_{t|t-1} + c_p(p_t - p_{t|t-1}) + c_q(r_t - Q^{\mathrm{s}}_{t|t-1}) + c_d(\widehat{D}_t - \widehat{D}_{t|t-1}). \quad (15)$$

The coefficients c_t, c_q, and c_d represent the speed at which households update their expectations about market fundamentals, given the new information they receive. The sizes of the updates depend on the qualities of the new information relative to their confidence in their prior beliefs. Details of the solution method are presented in Appendix B.3.

Once I find the fixed point for the coefficient matrix, I establish a law of motion for the state variables and its inferences $(\Phi_t'\ \ \Phi_{t|t}')'$ as

$$\begin{bmatrix} \Phi_t \\ \Phi_{t|t} \end{bmatrix} = \begin{bmatrix} F & 0 \\ B_1 & B_2 \end{bmatrix} \begin{bmatrix} \Phi_{t-1} \\ \Phi_{t-1|t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ \epsilon_t^X \end{bmatrix}, \quad (16)$$

where

$$\begin{aligned} F &= \begin{bmatrix} 1 & 1 & 0 \\ 0 & \rho & 0 \\ 0 & 0 & \theta \end{bmatrix} \\ B_1 &= \begin{bmatrix} c_p & c_q & c_d \end{bmatrix} H_1 F \\ B_2 &= F - \begin{bmatrix} c_p & c_q & c_d \end{bmatrix} H_1 F \\ \epsilon_t^X &= \begin{bmatrix} c_p & c_q & c_d \end{bmatrix} H_2 v_t + \begin{bmatrix} c_p & c_q & c_d \end{bmatrix} H_1 \epsilon_t. \end{aligned}$$

Matrices H_1 and H_2 are specified in Appendix B.3. Equation (16) is the extended state-space model of the original housing market dynamics model. Expectations about current market fundamentals are included as new state variables because housing prices are not only an equilibrium outcome but also contained in the household information set at period t.

To find the housing price IRFs to monetary policy shocks, I rewrite Equation (14) as a matrix:

$$p_t = \begin{bmatrix} 1 & 0 & \alpha & \frac{\beta}{1-\beta} & \frac{\beta}{(1-\beta)(1-\beta\rho)} & \frac{\alpha\beta\theta}{1-\beta\theta} \end{bmatrix} \begin{bmatrix} \Phi_t \\ \Phi_{t|t} \end{bmatrix} + s_t. \quad (17)$$

Equations (16) and (17) imply the structural model's IRF is

$$\frac{\partial p_{t+h}}{\partial \epsilon_t^{\mathrm{MP}}} = \begin{bmatrix} 1 & 0 & \alpha & \frac{\beta}{1-\beta} & \frac{\beta}{(1-\beta)(1-\beta\rho)} & \frac{\alpha\beta\theta}{1-\beta\theta} \end{bmatrix} \times \begin{bmatrix} F & 0 \\ B_1 & B_2 \end{bmatrix}^h \begin{bmatrix} & & e_3 \\ [c_p & c_q & c_d] \end{bmatrix} H_1 e_3, \tag{18}$$

where $e_3 = (0, 0, 1)'$ is a choice vector that selects the monetary policy shock.

3.3 Search Frictions

Suppose some households take some time to search before purchasing a house so that their demand for housing after a shock to D_t is realized with some delay. I describe the cross-sectional distribution of search time with a Weibull density as in Hamilton (2008). Let ω_j denote the fraction of households who searched j months for houses predicted by the Weibull density with a scale parameter λ and a shape parameter κ. In this case, the equilibrium price is a weighted average of staggered prices using information updated at different time periods and is determined by

$$\begin{aligned} p_t = s_t + \omega_0 \Bigg(& T_t + \alpha Q_t + \frac{\beta}{1-\beta} T_{t|t} + \frac{\alpha\beta\theta}{1-\beta\theta} Q_{t|t} \\ & + \frac{\beta}{(1-\beta)(1-\beta\rho)} g_{t|t} \Bigg) + \sum_{j=1}^{\infty} \omega_j \Bigg(\frac{1}{1-\beta} T_{t|t-j} \Bigg) \\ & + \frac{\alpha}{1-\beta\theta} Q_{t|t-j} + \frac{\beta}{(1-\beta)(1-\beta\rho)} g_{t|t-j} \Bigg), \end{aligned}$$

where $\omega_j = \exp\big(-(\frac{j}{\lambda})^{\kappa}\big) - \exp\big(-(\frac{j+1}{\lambda})^{\kappa}\big)$.

The model can be solved using the same technique except that

$$\begin{aligned} p_t - p_{t|t-1} = s_t + \omega_0 \Bigg[& D_t - D_{t|t-1} + \frac{\beta}{1-\beta} (T_{t|t} - T_{t|t-1}) \\ & + \frac{\alpha\beta\theta}{1-\beta\theta} (Q_{t|t} - Q_{t|t-1}) + \frac{\beta}{(1-\beta)(1-\beta\rho)} (g_{t|t} - g_{t|t-1}) \Bigg]. \end{aligned}$$

This implies that p_t carries less information about D_t when $\omega_0 < 1$ because only a fraction of households receive signals about the current state.

Once I solve for (a_0, a_2, c_1', c_2') in a similar fashion, I can compute the IRFs as

$$\frac{\partial p_{t+h}}{\partial \epsilon_t^{\text{MP}}} = \omega_0 \phi_h + \sum_{j=1}^{h} \omega_j \psi_{h-j}$$

$$\phi_h = \begin{bmatrix} 1 & 0 & \alpha & \frac{\beta}{1-\beta} & \frac{\beta}{(1-\beta)(1-\beta\rho)} & \frac{\alpha\beta\theta}{1-\beta\theta} \end{bmatrix} \begin{bmatrix} F & 0 \\ B_1 & B_2 \end{bmatrix}^h \times \begin{bmatrix} e_4 \\ \begin{bmatrix} c_p & c_q & c_d \end{bmatrix} H_1 e_4 \end{bmatrix}$$

$$\psi_h = \begin{bmatrix} 0 & 0 & \alpha & \frac{\beta}{1-\beta} & \frac{\beta}{(1-\beta)(1-\beta\rho)} & \frac{\alpha\beta\theta}{1-\beta\theta} \end{bmatrix} \begin{bmatrix} F & 0 \\ B_1 & B_2 \end{bmatrix}^h \times \begin{bmatrix} e_3 \\ \begin{bmatrix} c_p & c_q & c_d \end{bmatrix} H_1 e_3 \end{bmatrix}.$$

Without loss of generality, the structural estimation in the following section is based on this version of the model that incorporates search friction. The baseline version of the model with no search friction is a special case with $\omega_0 = 1$.

4. Structural Estimation

To quantify the degree of information rigidity in the transmission of monetary policy shocks to housing markets, I estimate the structural model from Section 3. Given the complexity of the model, it is infeasible to estimate all structural parameters simultaneously. Since some model parameters have been well-studied in the literature, I focus on parameters that directly measure the degree of information friction. In particular, I estimate the model's signal-to-noise ratio, σ_a, and the relative importance of monetary policy in local housing prices, α, using a minimum chi-square estimator by matching the model's predicted moments to their empirical counterparts. Section 4.1 discusses the empirical moments used in the estimation. Section 4.2 presents calibrated parameters and estimation of key structural parameters.

4.1 Emprical Moments from the Proxy-SVAR Model

In this section, I present a panel structural VAR model to estimate the structural IRFs of housing price growth to monetary policy shocks. This method not only serves as a robustness check, but it also links the empirical IRFs to their model counterparts introduced in Section 3. Unlike the local projection method, where the IRF for each horizon is estimated separately, the SVAR method provides statistical inference on the correlation over IRFs across different horizons and MSAs. Although I no longer impose the same cross-sectional identification restriction, I show that estimated IRFs are broadly in line with an inverse relationship between the housing supply elasticity and the housing price response.

I identify the effect of structural monetary policy shocks in the VAR using external instruments measured from high-frequency financial market data. The estimation approach builds on methods pioneered by Stock and Watson (2012) and Mertens and Ravn (2013). Stock and Watson (2018) provide a detailed analysis of the identification and estimation of proxy-SVAR models and compare them with the local projection method. My VAR specification closely follows the work of Gertler and Karadi (2015) by combining both macrovariables and financial variables at the aggregate level. I then modify the SVAR model to include local housing prices. The modified specification could easily accommodate housing prices from all MSAs in one framework. For brevity, I present results for housing quartiles only.

Let y_t denote an $(n \times 1)$ vector of stationary macrovariables including the federal funds rate (FFR), output growth, inflation, and excess bond premium. Let p_t denote a (3×1) vector whose first two elements are the monthly growth rate of housing price in the top two quartiles while the third element is the bottom half,[11] and let $\bar{p}_t$ be the average price change over four quartiles. Let u_t be an $((n + 4) \times 1)$ vector of structural shocks. I estimate the following

[11]The difference in housing price responses is most striking in MSAs with inelastic housing supply. I combined the housing prices in the third and fourth housing supply elasticity quartiles since separating the two does not provide extra information for identification.

VAR system with the sample from January 1990 to December 2007 with 12 lags ($L = 12$):

$$\begin{bmatrix} y_t \\ p_t \end{bmatrix} = c + \sum_{l=1}^{L} \begin{bmatrix} \alpha_l & \beta_l \\ \gamma_l & \delta_l \end{bmatrix} \begin{bmatrix} y_{t-l} \\ \bar{p}_{t-l} \end{bmatrix} + Au_t. \tag{19}$$

To estimate the effects of monetary policy shocks, one only needs to identify the first column of the structural matrix A. I identify $A_{i,1}$ by running the following two-stage least-squares (2SLS) regression using HFI shocks (z_t) as external instruments for FFR_t:

$$x_{i,t} = A_{i,1}\mathrm{FFR}_t + \phi_i(L)Y_t + v_{i,t} \tag{20}$$

$$\mathrm{FFR}_t = \tau\ z_t + \phi_R(L)Y_t + v_{R,t}, \tag{21}$$

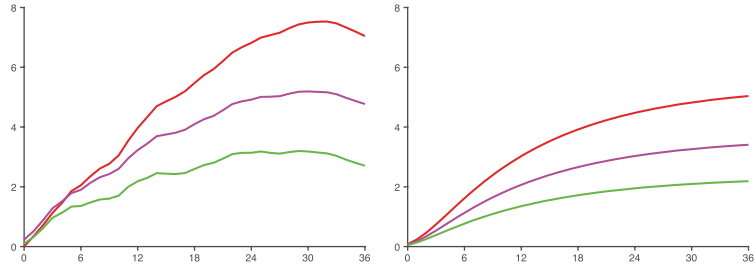
where $x_{i,t}$ is the ith element in $Y_t = (y_t, p_t)'$; $\phi_i(L)$ and $\phi_R(L)$ are coefficients lagged values of Y_t.

To construct the orthogonalized IRFs, I first compute the non-orthogonalized IRFs at horizon s from the reduced-form VAR $\Psi_s = \partial Y_{t+s}/\partial \epsilon_t'$. The orthogonalized IRFs of a monetary policy shock are simply $\Psi_s A_{\cdot,1}$. I construct the covariance matrix of the structural IRFs on four quartiles of housing prices over 36 horizons using a parametric bootstrap method. Details of estimating the IRFs and its covariance matrix are presented in Appendix A.4.

Estimated IRFs for each housing price quartile are reported in the left graph of Figure 3. Note that in the estimation with the proxy-SVAR model, I do not impose the restriction of an inverse linear relationship between local house price growth and housing supply elasticity. A disadvantage of this method is that the IRFs are less accurately estimated with larger confidence bands. The results line up roughly with the prediction that housing prices in more inelastic quartiles increase more after an expansionary monetary policy shock. The two-year IRF estimate is comparable in magnitude to the estimate from the Jordà local projection.[12]

[12]Table A.2 in Appendix A presents a comparison of the estimates from local projection and proxy-SVAR. The responses are similar in size at the two-year horizon but local projection estimates a much larger response at the three-year horizon.

Figure 3. Impulse Response Functions of Housing Prices to Monetary Policy Shocks Using the Proxy-SVAR (left) and the Structural Model (right)



Note: These curves show impulse response functions of the cumulative housing price growth to an expansionary monetary policy shock that lowers the federal funds rate by 1 percent, at the first quartile (red), second quartile (pink), and bottom half (green) of housing supply elasticity, respectively. The left graph reports estimates computed using the proxy-SVAR method (see Section 4.1); the right graph reports estimates computed using the estimated structural model in Section 4.

4.2 Calibration and Structural Estimation

Let me first discuss the choice of calibrated parameters, as presented in Table 3. The standard deviations of local demand shock σ_D and aggregate monetary policy shock σ_r are normalized to 1. With this normalization, the dispersion of the noise in the household's idiosyncratic demand, σ_a, can be interpreted as the signal-to-noise ratio. The discount factor β is set to a standard value of 0.96 at the annual frequency. ρ and σ_g are parameters that govern the persistence in innovation in the housing growth factor. θ measures the persistence of monetary policy shock, and a value of one is consistent with the effect of a level shock that changes the interest rate uniformly for assets of all maturities. I use the estimated shape and scale parameters in Hamilton (2008) to calibrate the Weibull distribution to capture the search frictions. Values of λ and κ are converted from the original quarterly to monthly frequencies. Lastly, χ^D converts the long-run housing supply elasticity to its short-run counterpart. The calibrated value of χ^D assumes that housing supply fully adjusts to housing demand shocks in three years. This premise is consistent with the fact that the peak effect of monetary policy is achieved

Table 3. Calibrated Parameters for the Structural Model of Housing Prices

Parameter	Value	Calibration
σ_D, σ_r	1	Normalization of Demand and Monetary Policy Shocks
β	$0.96^{1/2}$	Discount Factor (Monthly Frequency)
ρ	0.5	Persistence of Housing Demand Growth
σ_g	0.2	Standard Deviations of Shocks to Housing Demand Growth
θ	1	Persistence of Monetary Policy Shock
(λ, κ)	(3.7, 1.5)	Weibull Density Scale and Shape Parameter
χ_D	36	Conversion of Long-Run to Short-Run Housing Supply Elasticity

Note: This table reports the subset of parameters calibrated for the estimation of the structural model of housing prices.

after around three years. Given the size of this parameter, the disturbance in short-run housing supply shocks has negligible effects on housing prices relative to household demand shocks.

Let $\hat{\pi} = (\hat{\pi}_1', \hat{\pi}_2', \hat{\pi}_3')$ denote the empirical estimates of housing price IRFs in all quartiles, where $\hat{\pi}_i = (\Phi_{i,0}, \Phi_{i,1}, \ldots, \Phi_{i,36})$ is the vector of IRF estimates plotted in Figure 3 from Section 4.1. Let $\pi(\Lambda) = (\pi_1'(\Lambda), \pi_2'(\Lambda), \pi_3'(\Lambda))'$ denote the model-implied IRFs of housing prices to monetary policy shocks as calculated in Equation (18), with $\pi_i(\Lambda)$ being the IRFs using the ith quartile housing supply elasticity. The minimum chi-square estimator for $\Lambda = (\sigma_a, \alpha)'$ satisfies

$$\Lambda = \arg\min_{\Lambda} T[\hat{\pi} - \pi(\Lambda)]' \hat{V}^{-1} [\hat{\pi} - \pi(\Lambda)], \tag{22}$$

where $\hat{V}$, the weighting matrix, is the bootstrapped covariance matrix estimated in Section 4.1.

The structural parameters are estimated through numerical optimization and are reported in Table 4. I estimate the standard errors of estimated structural parameters by estimating the covariance matrix for $\hat{\Lambda}$ as $\text{cov}(\hat{\Lambda}) = T^{-1}(\hat{\Gamma}'\hat{V}^{-1}\hat{\Gamma})^{-1}$, where $\hat{\Gamma} = \partial\pi(\theta)/\partial\Lambda'|_{\theta=\hat{\Lambda}}$ (see Hamilton and Wu 2012). This set of estimates is based on a case where monetary policy signals are too noisy for households to extract useful information about the local housing

Table 4. Estimated Parameters in the Structural Model of Housing Prices

Parameter	Estimates (S.E.)	Structural Interpretation
σ_a	19.26 (8.51)	Quality of Demand Signal
α	0.19 (0.07)	Average Housing Price Response to Interest Rate Is 3 Percent

Note: This table reports the estimation results of the structural model of housing prices.

market.[13] As a result, households make decisions based solely on their own preferences and local housing prices. Since I have normalized the size of local demand shocks, σ_{D}, and monetary policy shocks σ_r to one, the amount of the noise in each individual household's perceived demand is interpreted as the inverse of signal-to-noise ratios. Equivalently, σ_a can be interpreted as the quality of a household's own demand signal about the local housing market. One period in the model corresponds to one month. At a monthly frequency, shocks are small and infrequent, while signals reveal little new information about market fundamentals. The estimate of σ_a, 19.26, suggests that it takes about 20 months for households to infer a monetary policy shock through their housing demand signals.

This result represents a case where households pay little attention to changes in monetary policy stances and do not associate them with the local housing market. After an expansionary monetary policy shock, households gradually learn about the impact on local housing markets via house price changes and local news about housing demand. Households adjust their housing demand based

[13]This is equivalent to setting the standard error of noise in monetary policy signals, σ_{q}, to infinity. This parameter measures the precision of households' perceptions of monetary policy. The larger its size, the less precise the signal on monetary policy is. When this parameter is simultaneously estimated, its value converges to very large numbers in numerical optimization, which is approximately equivalent to setting it at infinity. This evidence strongly rejects the case of no information frictions in the transmission of monetary policy to local housing markets. This suggests that households do not directly pay attention to monetary policy but only infer it from other signals.

on this information. In equilibrium, the local house price rises as the housing demand adjusts. The structural parameter α measures the relative importance of monetary policy to other local demand factors. Its estimate implies a median effect of about 3 percent in housing price response to a 1 percent decrease in interest rate.[14]

The right graph of Figure 3 presents the model-predicted housing price IRFs to monetary policy shocks using the estimated structural parameters. From top to bottom, each curve represents the IRFs from cities within each quartile of housing supply elasticity, with a larger response for cities with a less elastic housing supply. Model-predicted IRFs align well with their empirical counterparts in Figure 3.

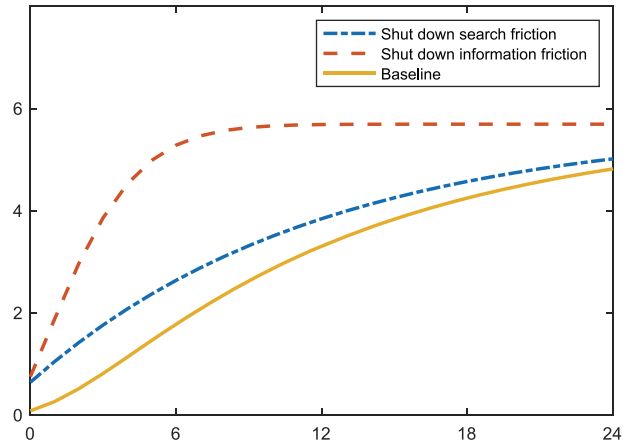
4.3 Counterfactual Analyses

Lastly, I conduct two counterfactual analyses under different parameter assumptions to visualize the importance of different sources of friction. In the first exercise, I shut down search frictions (i.e., setting $\omega_0 = 1$ and $\omega_j = 0$ for $j > 0$). In the second exercise, I shut down information frictions in demand signal (i.e., setting $\sigma_\alpha = 0$). Figure 4 provides the simulations of house price IRFs under these parameter assumptions. The solid yellow line represents the baseline house price IRF of MSAs with top-quartile supply elasticity. The dash-dotted blue line represents the case where I shut down search frictions but allow for information frictions. In this case, house price increases about 0.4 percent more on the impact as well as during the first few months. In other words, search frictions only mildly reduce the response of house prices in the initial periods. The dashed red line represents the case where I shut down information frictions but allow for search frictions. The house price IRFs in this case become much less sluggish and peak in about 8–10 months.

In conclusion, the counterfactual analyses suggest that information friction plays a crucial role in the transmission of monetary

[14]The value of the parameter itself does not have an economic meaning since it does not have a unit.

Figure 4. Counterfactual Analysis



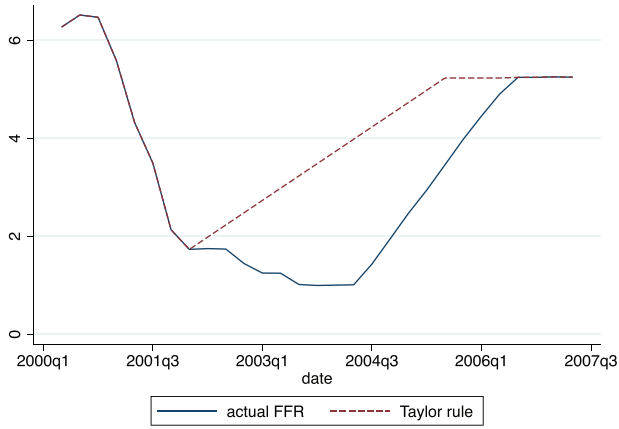
Note: This figure compares the housing IRFs of baseline with counterfactual scenarios.

policy shocks to local housing markets. Households pay little direct attention to changes in monetary policy stances but only learn about them through the news on local housing markets.

5. Implications for the 2000s Housing Boom

In this section, I study the 2000s housing boom by applying my estimates on the housing price response to monetary policy shocks. The Federal Reserve cut the federal funds rate aggressively starting in January 2001 in anticipation of an upcoming recession. The federal funds rate remained low for more than three years until the Fed started raising rates again in July 2004. During this period, the interest rate deviated significantly from the Taylor rule, which is proposed by Taylor (1993) to describe the path of interest rates in the U.S. and commonly adopted in monetary macro models (see Figure 5 for illustration). In particular, Taylor (2007) claimed the deviation in monetary policy from the Taylor rule contributed to the housing boom in the 2000s. Based on the deviation of the federal funds rate from the Taylor rule, I evaluate its contribution to local housing prices using my estimates.

Figure 5. Actual Federal Funds Rate and Taylor (2007) Counterfactual

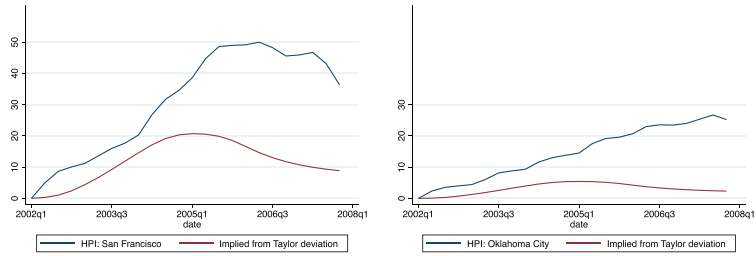


Note: The dark blue line shows the effective federal funds rate from 2000:Q2 to 2007:Q2. The red dashed line shows the counterfactual interest rate determined by Taylor (2007).

The deviation of the actual federal funds rate from the counterfactual Taylor rule is treated as cumulative of a sequence of monetary policy shocks $\hat{\epsilon}_t$. Using the estimated structural model from Section 4, I simulate paths of housing price responses given any monetary policy shock in each city using its housing supply elasticity. For each shock, $\hat{\epsilon}_t$, I compute the housing price IRF in city i for each horizon s as $\Phi_{i,t+s}$. For each period, I accumulate impacts from all previous shocks to obtain the cumulative effect due to this Taylor deviation. Figure 6 plots the actual price growth and the price growths attributed to the Taylor deviation in two cities, San Francisco and Oklahoma City. In San Francisco, this deviation explains the majority of the housing price increase up to mid-2003. However, housing prices increased by about 50 percent at the peak, but the monetary policy deviation explains only about two-fifths of the boom. In Oklahoma City, the Taylor deviation consistently explains about two-fifths of the housing price increase despite a more moderate housing price increase.

In summary, monetary policy plays an important role in driving housing market dynamics, especially during the boom period. In

Figure 6. Actual and Counterfactual Housing Price Growth during the 2000s Housing Boom in San Francisco and Oklahoma City



Note: Housing price growth for the period of 2002:Q1–2007:Q4 is shown for San Francisco and Oklahoma City in the left and right graphs, respectively. In each graph, the dark blue line shows the actual path of the housing price growth, and the red line shows the path of the housing price growth implied from the Taylor deviation. See Section 5 for details.

particular, deviations in monetary policy from the proposed Taylor rule in the early 2000s contributed to about two-fifths of the subsequent housing boom.

6. Conclusions

This paper studies the effects of monetary policy shocks on local housing prices. Empirically, I provide estimates on the differential responses of U.S. local housing prices to aggregate monetary policy shocks at more than 100 MSAs. As an example, given an expansionary shock that decreases the federal funds rate by 100 basis points, housing prices increase by 6 percent in cities with highly inelastic housing supplies (e.g., San Francisco), but by only 2 percent in cities with very elastic housing supplies (e.g., Iowa City) at the two-year horizon. The estimated responses are large and persistent, and this result is robust using different estimation strategies.

I build a housing price model with information frictions to explore the transmission mechanism of monetary policy and estimate this model by matching its impulse response functions to their empirical counterparts. The structural estimation suggests households pay little direct attention to changes in monetary policy stances but only learn about them through the news on local housing markets. I use

the model-implied city-specific housing price responses to study the impact of monetary policy on the housing boom in the early 2000s. My finding suggests that monetary policy plays an important role in driving housing prices, and could explain about 40 percent of the housing boom. The estimated result provides new implications for the role of monetary policy in driving the housing boom in the 2000s.

The framework of this paper can be extended to study the impact of monetary policy on the U.S. housing market during other periods. My finding suggests that monetary policy plays an important role in driving housing prices, and its impacts are heterogeneous across different cities. Cities that experienced larger booms subsequently suffered from larger busts during the Great Recession. The collapses in these local housing prices could lead to reductions in local employment. This implies that aggregate monetary policy could drive heterogeneous business cycles at different locations through housing prices, which provides new insights for the central banks seeking to design optimal policy rules.

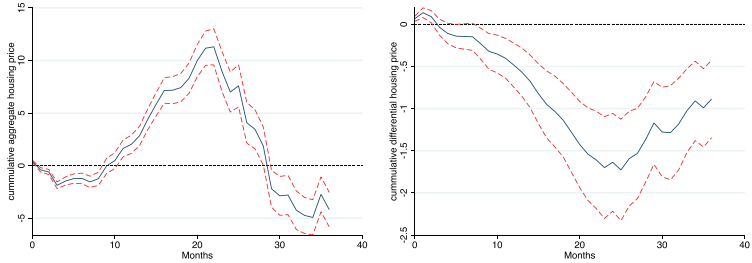
Appendix A. Supplementary Empirical Results

A.1 Effects of Unconventional Monetary Policy

In this appendix section, I extend the analysis to the zero lower bound period by estimating the effects of unconventional monetary policy on housing prices. During the ZLB period, monetary policy has become more multidimensional with the adoption of unconventional monetary policy tools. Even though the federal funds rate was constrained around zero, long-term interest rates such as the mortgage rate declined substantially thanks to quantitative easing and forward guidance. To extend my study to the ZLB period, I use the 30-year mortgage rate as the main policy variable and employ forward-guidance shocks and large-scale asset purchase (LSAP) shocks estimated in Swanson (2021) as instruments for changes in mortgage rates.

$$\Delta_h y_{i,t+h} = \alpha_h + \beta_h \, \Delta \hat{R}_t^{\text{mortgage}} + \gamma_h \Delta \hat{R}_t^{\text{mortgage}} \times \epsilon_i^{\text{supply}} + \Gamma_h X_{i,t} + \xi_i + u_{it} \tag{A.1}$$

Figure A.1. Impulse Response Functions of Housing Prices during ZLB



Note: The solid dark blue line plots the cumulative impulse response of housing price growth to an expansionary monetary policy shock. The shock effectively lowers the 30-year mortgage rate by 100 basis points. The left graph shows the upper limit of IRFs (β_h) if the housing supply is perfectly inelastic. The right graph shows the differential responses (γ_h) between two MSAs that differ in the housing supply elasticity by one unit. The dotted red lines outline the 95 percent confidence interval.

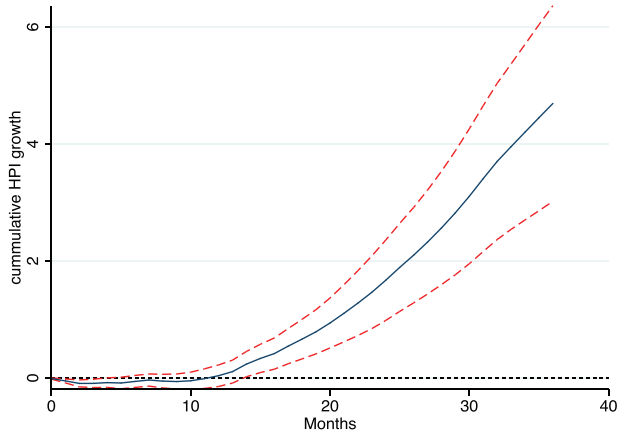
Figure A.1 reports the estimates of β_h and γ_h in Equation (A.1) for up to 36 months. When the unconventional monetary policy lowers the 30-year mortgage rate by 100 basis points, an MSA with a perfectly inelastic housing supply increases housing prices by about 10 percent after two years. While the dynamics of housing prices are very similar to the pre-ZLB period for the initial two years, the size of responses is much smaller and the effects are less persistent during ZLB.

A.2 Robustness Check on Local Projection Results

To demonstrate that the results reported in Section 2.3 are not driven by other concurrent aggregate shocks that also affect housing prices, I estimate a similar model to Equation (1) with time fixed effects:

$$\Delta_h y_{i,t+h} = \alpha_h + \beta_h \ \Delta\widehat{MP}_t \times \epsilon_i^{\text{supply}} + \sum_{j=1}^{12} c_{h,j} \Delta y_{i,t-j} + \xi_i + \nu_t + u_{it}, \tag{A.2}$$

Figure A.2. Impulse Response Functions of Housing Prices



Note: The solid dark blue line plots the cumulative impulse response of housing price growth to an expansionary monetary policy shock. The shock effectively lowers the federal funds rate by 100 basis points. The IRF shows the differential between two MSAs that differ in the housing supply elasticity by one unit. The dotted red lines outline the 95 percent confidence interval.

where 12 lags of changes in (log) house prices ($\Delta y_{i,t-j}$) are included as control variables and location fixed effects (ξ_i) capture any MSA-specific trends that might be correlated with the housing supply elasticity. I include time fixed effects (ν_t) to capture the housing price growth driven by other concurrent aggregate shocks. Under this specification, the coefficients, β_h, are linear approximations of $\frac{\delta y_{i,t+h}}{\delta \mathrm{MP}_t \ \delta \epsilon_i^{\mathrm{supply}}}$. The estimates measure the local equilibrium effects of monetary policy shocks on housing prices due to the inclusion of fixed effects.

Figure A.2 presents estimated β_hs up to three years. It represents the differential impulse response in the cumulative house price growth between two MSAs that differ in housing supply elasticity by one unit—for example, San Francisco and Philadelphia or Houston and Oklahoma City. The difference is the result of an expansionary monetary policy shock that effectively lowers the federal funds rate by 100 basis points. Standard errors are clustered at the MSA level, allowing for arbitrary autocorrelation of the house price growth

Table A.1. Selected MSA Housing Price Responses to Monetary Policy Shocks

Percentile	Supply Elasticity	MSA	Two-Year HPI
5	0.7	San Diego, CA/New York, NY	7.18
10	1.2	Pittsburgh, PA/Baltimore, MD	6.35
25	1.6	Washington, DC/Philadelphia, PA-NJ	5.68
50	2.3	Houston, TX/Ann Arbor, MI	4.51
75	3.3	Kansas City, KS/Oklahoma City, OK	2.84
90	4.4	Iowa City, IA/Mansfield, OH	1.00

Note: This table reports the MSA-level housing price response to an expansionary monetary policy shock at the two-year horizons. The shock effectively lowers the rate on the federal funds rate by 100 basis points. These estimates are calculated based on the Jordà local projection method.

within each MSA. The results are consistent with the right graph of Figure 2A.

These estimates of the β_hs provide only a comparative measurement of the house price response, but it is feasible to make a conservative inference on the overall response of each MSA. Assume that house prices in MSAs with housing supply elasticity above the 95 percent quantile ($\epsilon_i^{\text{supply}} \geq 5$) do not respond to monetary policy shocks. Now I can estimate the MSA-specific house price growth impulse response to a contractionary shock by simply calculating $(\epsilon_i^{\text{supply}} - 5) \times \beta_h$ for MSAs that are below the 95 percent threshold. Table A.1 summarizes the estimates of the two-year housing price impulse responses for selected cities. The results are reasonably close to those reported in Table 2.

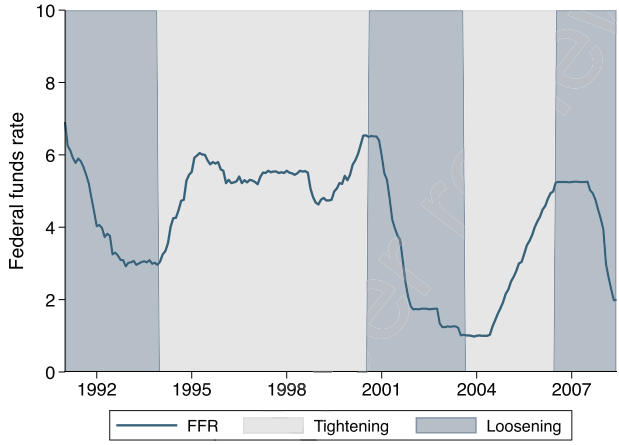
A.3 Asymmetric and Nonlinear Effects

This section presents additional figures for Section 2.4 of the main paper. Figure A.3 defines periods of monetary policy loosening and tightening during the sample period.

A.4 Details of the Proxy-SVAR Model

This section presents details of the estimation of the proxy-SVAR model in Section 4.1. The VAR model in Equation (19) is equivalent to

Figure A.3. Monetary Policy Regimes



Note: This figure plots the tightening and loosening monetary cycles during the sample period of January 1991–June 2008. The red solid line represents the federal funds rate. Blue- and orange-shaded regions represent periods of monetary loosening and tightening respectively.

$$(I - \Phi(L)) \begin{bmatrix} y_t \\ p_t \end{bmatrix} = \epsilon_t = Au_t,$$

where

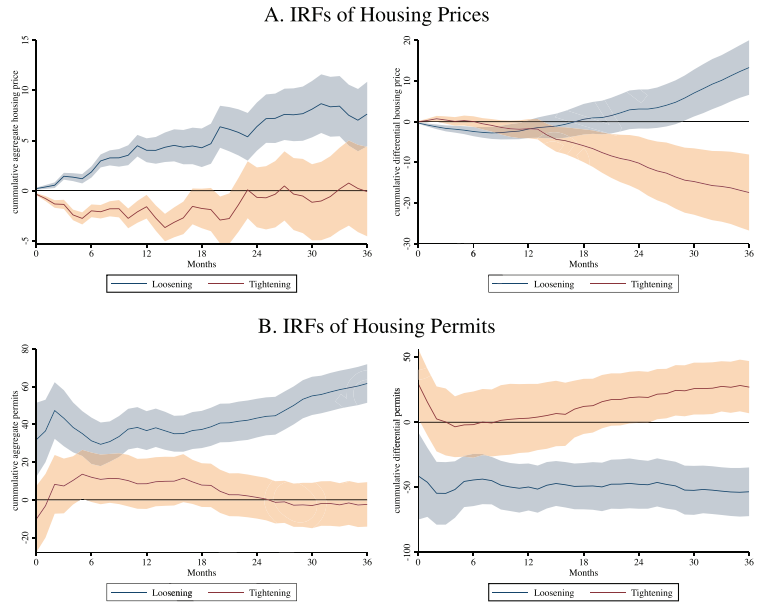
$$\Phi_l = \begin{bmatrix} \alpha_l & \beta_l/J, \ldots, \beta_l/J \\ \gamma_l & \delta_l/J, \ldots, \delta_l/J \end{bmatrix}, \quad J = 4.$$

Based on this VAR specification, I first compute the non-orthogonalized IRFs, Ψ_s, for each horizon, s, from the reduced-form VAR in a standard way (see Hamilton 1994 for details). The orthogonalized IRFs of a monetary policy shock are simply $\Phi_s = \Psi_s A_{\cdot,1}$, where $A_{i,1}$ is identified by running the 2SLS regression using HFI shocks (z_t) discussed in Section 2.2 as external instruments for FFR_t:

$$\begin{aligned} x_{i,t} &= A_{i,1} FFR_t + \phi_i(L) Y_t + v_{i,t} \\ FFR_t &= \tau \; z_t + \phi_R(L) Y_t + v_{R,t}, \end{aligned}$$

where $x_{i,t}$ is the ith element in $Y_t = (y_t, p_t)'$; $\phi_i(L)$ and $\phi_R(L)$ are coefficients lagged values of Y_t.

Figure A.4. Impulse Response Functions by Monetary Policy Regimes



Note: This figure plots the impulse response functions of housing prices (panel A) and housing permits (panel B) to monetary policy shocks during tightening (orange) and loosening (blue) periods. The left graphs show the lower limits of IRFs (β_h) if the housing supply is perfectly elastic. The right graphs show the differential responses (γ_h) between two MSAs that differ in the housing supply elasticity by one inverse unit ($1/\epsilon^{\text{supply}}$). The shaded areas represent the 95 percent confidence interval.

Next, I compute the covariance matrix of the structural IRFs, $\Phi(p_{j,s})$ for $j = 1, \ldots, 4$ and $s = 0, 1, \ldots, 36$. This is done with 1,000 draws from a parametric bootstrap. For each draw, I generate a sample of size T equivalent to my original sample time length for $(\tilde{Y}_t, \tilde{z}_t)$ from the stationary VAR

$$\begin{bmatrix} I - \hat{\Phi}(L) & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} Y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \tilde{\epsilon}_t \\ \tilde{e}_t \end{bmatrix},$$

where

$$\begin{bmatrix} \tilde{\epsilon}_t \\ \tilde{e}_t \end{bmatrix} \sim \text{i.i.d. } N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \hat{\Sigma}_\epsilon & \hat{\Sigma}_{\epsilon e} \\ \hat{\Sigma}_{\epsilon e} & \hat{\Sigma}_e \end{bmatrix} \right),$$

Table A.2. Housing Price Responses Estimated from Local Projection and SVAR

	24-Month		30-Month		36-Month	
Percentile	**LP**	**SVAR**	**LP**	**SVAR**	**LP**	**SVAR**
1st Quartile	5.04	6.03	10.45	6.60	14.73	6.14
2nd Quartile	4.59	4.41	9.33	4.61	12.86	4.18
Above Median	3.55	2.87	671	2.89	8.48	2.43

Note: This table reports the MSA-level housing price response to an expansionary monetary policy shock at the 24-, 30-, and 36-month horizons. The shock effectively lowers the rate on the federal funds rate by 100 basis points. These estimates are calculated based on the Jorda local projection method and proxy-SVAR method, respectively.

where $\hat{\Phi}(L)$ is estimated from the reduced-form VAR and the $\hat{\Sigma}$s are sample covariances for VAR residuals $\hat{\epsilon}_t$ and instruments z_t.

To initialize the bootstrap sample, I discard the first 1,000 draws. For each sample $n = 1, 2, \ldots, 5000$, I first compute the first-stage F-stat ($F^{(n)}$) to test for instrument relevance and discard draws with $F^{(n)} < 5$. Next, I compute the structural IRFs $\Phi_{j,s}^{(n)}$ as illustrated above. The covariance of $\Phi_{j,s}^{(n)}$ provides the bootstrapped covariance matrix of $IRF(p_{j,s})$.

Table A.2 provides a comparison of results from local projection and proxy-SVAR. The sizes of housing price responses estimated local projection and proxy-SVAR matches reasonably well within 30 months. Local projection predicts a much larger response at 36 months, potentially due to a lack of recursive structure.

Appendix B. Supplementary Model Details

B.1 Housing Demand

This section provides justification for the setup of Equation (5) in Section 3.1, the housing demand equation, from the perspective of a utility-maximizing household. I drop the m subscripts for simplicity. Here are some notations used in this appendix:

H_{it} = real quantity of housing owned by household i in period t

P_{it} = real price of housing for household i in period t
r_t = real interest rate in period t
β = discount factor
C_{it} = consumption of household i in period t
Γ_{it} = relative preference for housing by household i in period t
B_{it} = borrowing of household i at period t

Households maximize a lifetime utility function given by

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln C_{it} + \Gamma_{it} \ln H_{it}\right]$$

with per-period budget constraint

$$C_{it} + P_{it}\Delta H_{it} + (1 + r_{t-1})B_{i,t-1} = B_{i,t} + Y_{it}.$$

Consider the first-order condition

$$\frac{1}{C_{it}} = \beta E_t(1 + r_t)\frac{1}{C_{i,t+1}}$$
$$\frac{P_{it}}{C_{it}} = \frac{\Gamma_{it}}{H_{it}} + \beta E_t \frac{P_{i,t+1}}{C_{i,t+1}}.$$

Log-linearize the above equations and use lowercase letters to denote the log-linearized variables:

$$-c_{it} = r_t - E_t c_{i,t+1}$$
$$p_{it} - c_{it} = (1 - \beta)(\gamma_{it} - h_{it}) + \beta E_t(p_{i,t+1} - c_{i,t+1}).$$

Rearranging,

$$p_{it} = [(1 - \beta)(\gamma_{it} + E_t c_{i,t+1} - h_{it}) - r_t] + \beta E_t p_{i,t+1}.$$

Compare this expression with our setup where

$$p_{it} = d_{it} - \frac{h_{it}}{\chi^D} + \beta E_t p_{i,t+1}.$$

It is equivalent to

$$d_{it} = (1-\beta)(\gamma_{it} + c_{it}) - \beta r_t$$

and $\chi^D = 1/(1-\beta)$.

So the demand for housing is higher when households have a stronger preference for housing and higher nondurable consumption. Therefore, I approximate the process of $d_{i,m,t}$ using

$$d_{i,m,t} = \widehat{D}_{mt} + a_{i,m,t},$$

where $\widehat{D}_{mt}$ captures the combined effects from monetary policy and local demand factors through income and consumption, and $a_{i,m,t}$ captures the idiosyncratic effects such as preference.

B.2 Summary of Variable Definitions

Table B.1. Summary of Variable Definitions

Variable	Definition	Observable
$d_{i,m,t}$	Marginal Utility of Household i in City m	Y
$a_{i,m,t}$	Idiosyncratic Individual-Specific Housing Demand Shock	N
$\hat{D}_{mt}$	City-Specific Component of Utility Flow	N
D_{mt}	City-Specific Housing Demand Factor	N
a_{mt}	Idiosyncratic City-Specific Housing Demand Shock	N
r_t	Signal of Monetary Policy (Interest Rate)	Y
Q_t	Aggregate Housing Demand Factor Driven by Monetary Policy	N
q_t	Noise in Monetary Policy Signal	N
T_{mt}	Local Housing Demand Factor Arising from Local Amenities	N
g_{mt}	Growth Factor of Local Housing Demand	N
p_{mt}	House Price in City m	Y
ϵ^d_{mt}	Local Demand Shock (with a Permanent Impact on Housing Utility)	N
ϵ^g_{mt}	Shock to the Growth of Local Demand	N
ϵ^{MP}_t	Monetary Policy Shock	N

Note: This table summarizes the notations of variables from the model and their definitions. The last column indicates whether the variable is directly observed by individual households.

B.3 Solution to the Housing Price Model

This section presents details of the solution to the housing price model in Section 3.2. State Equations (10)–(12) can be written in matrix form as

$$\begin{bmatrix} T_{m,t+1} \\ g_{m,t+1} \\ Q_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & \rho & 0 \\ 0 & 0 & \theta \end{bmatrix} \begin{bmatrix} T_{mt} \\ g_{mt} \\ Q_t \end{bmatrix} + \begin{bmatrix} \epsilon^{\mathrm{d}}_{m,t+1} \\ \epsilon^{\mathrm{g}}_{m,t+1} \\ \epsilon^{\mathrm{MP}}_{t+1} \end{bmatrix}.$$

Let $\Phi_{m,t} = (T_{m,t+1}, g_{m,t+1}, Q_{t+1})'$ denote state variables and F denote the state matrix:

$$\Phi_{m,t+1} = F\Phi_{m,t} + \epsilon_{m,t+1}.$$

From here, I drop the subscript m since the solution method applies uniformly to every city. I conjecture that households at period t have a prior of $\Phi_{t|t-1}$ with variance $\Sigma_{t|t-1} = \mathbb{E}(\Phi_t - \Phi_{t|t-1})^2$. Note that

$$p_{t|t-1} = \frac{1}{1-\beta} T_{t|t-1} + \frac{\alpha}{1-\beta\theta} Q_{t|t-1} + \frac{\beta}{(1-\beta)(1-\beta\rho)} g_{t|t-1}$$
$$\widehat{D}_{t|t-1} = D_{t|t-1}$$
$$r_{t|t-1} = Q_{t|t-1}.$$

Let $y_t = (p_t, r_t, \widehat{D}_t)$ be observed variables. The next step is to solve for the updating equation to find $\Phi_{t|t}$.

$$\Phi_{t|t} = \Phi_{t|t-1} + c_{pt}(p_t - p_{t|t-1}) + c_{qt}(r_t - Q_{t|t-1}) + c_{dt}(\widehat{D}_t - \widehat{D}_{t|t-1}) \tag{B.1}$$

The coefficient matrix $\begin{bmatrix} c_{pt} & c_{qt} & c_{dt} \end{bmatrix}$ is an unknown 4×3 matrix that satisfies

$$\begin{bmatrix} c_{pt} & c_{qt} & c_{dt} \end{bmatrix} = \Sigma^{-1}_{yy,t} \Sigma_{y\Phi,t}, \tag{B.2}$$

where

$$\Sigma_{yy,t} = \mathbb{E}[(y_t - y_{t|t-1})(y_t - y_{t|t-1})']$$
$$\Sigma_{y\Phi,t} = \mathbb{E}[(y_t - y_{t|t-1})(\Phi_t - \Phi_{t|t-1})']$$
$$\Phi_{t+1|t} = F\Phi_{t|t}$$
$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma'_{y\Phi,t}\Sigma^{-1}_{yy,t}\Sigma_{y\Phi,t}$$
$$\Sigma_{t+1|t} = F\Sigma_{t|t}F' + Q.$$

To implement the recursion, note that

$$\begin{aligned} p_t - p_{t|t-1} &= s_t + D_t - D_{t|t-1} + \frac{\beta}{1-\beta}(T_{t|t} - T_{t|t-1}) \\ &\quad + \frac{\alpha\beta\theta}{1-\beta\theta}(Q_{t|t} - Q_{t|t-1}) + \frac{\beta}{(1-\beta)(1-\beta\rho)}(g_{t|t} - g_{t|t-1}) \\ &= s_t + D_t - D_{t|t-1} + \begin{bmatrix} \frac{\beta}{1-\beta} & \frac{\beta}{(1-\beta)(1-\beta\rho)} & \frac{\alpha\beta\theta}{1-\beta\theta} \end{bmatrix} \\ &\quad \times \begin{bmatrix} c_{pt} & c_{qt} & c_{dt} \end{bmatrix} \begin{bmatrix} p_t - p_{t|t-1} \\ r_t - Q_{t|t-1} \\ D^{\mathrm{s}}_t - D^{\mathrm{s}}_{t|t-1} \end{bmatrix}. \end{aligned}$$

After rearranging,

$$\begin{aligned} p_t - p_{t|t-1} &= s^*_t + a_{0t}(D_t - D_{t|t-1}) + a_{dt}(\widehat{D}_t - \widehat{D}_{t|t-1}) \\ &\quad + a_{qt}(r_t - Q_{t|t-1}), \end{aligned}$$

where

$$a_{0t} = \frac{1}{1 - \begin{bmatrix} \frac{\beta}{1-\beta} & \frac{\beta}{(1-\beta)(1-\beta\rho)} & \frac{\alpha\beta\theta}{1-\beta\theta} \end{bmatrix} c_{\mathrm{p}t}}$$
$$a_{xt} = a_{0t}\left(\begin{bmatrix} \frac{\beta}{1-\beta} & \frac{\beta}{(1-\beta)(1-\beta\rho)} & \frac{\alpha\beta\theta}{1-\beta\theta} \end{bmatrix} c_{xt} \right), \quad x \in \{\mathrm{d}, \mathrm{q}\}$$
$$s^*_t = a_{0t}s_t.$$

We can now see that

$$y_t - y_{t|t-1} = H_{1t}(\Phi_t - \Phi_{t|t-1}) + H_{2t}\begin{pmatrix} s_t \\ q_t \\ a_t \end{pmatrix}$$

$$\Sigma_{yy,t} = H_{1t}\Sigma_{t|t-1}H'_{1t} + H_{2t}RH'_{2t}$$

$$\Sigma_{y\Phi,t} = H_{1t}\Sigma_{t|t-1},$$

where $H_{1t} = \begin{bmatrix} a_{0t} + a_{dt} & 0 & a_{qt} + \alpha(a_{0t} + a_{dt}) \\ 0 & 0 & 1 \\ 1 & 0 & \alpha \end{bmatrix}$,

$H_{2t} = \begin{bmatrix} a_{0t} & a_{qt} & a_{dt} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, and $R = \begin{bmatrix} \sigma_{\mathrm{s}}^2 & 0 & 0 \\ 0 & \sigma_{\mathrm{q}}^2 & 0 \\ 0 & 0 & \sigma_{\mathrm{a}}^2 \end{bmatrix}$.

The solution to this model is a fixed point to Equation (B.2) in which the matrix $[c_{pt}\ c_{qt}\ c_{dt}]$ calculated from the right-hand side has the same values on the left-hand side. The fixed point can be found through convergence in $\Sigma_{t+1|t}$. I denote its value at the fixed point as $(a_0, a_{\mathrm{q}}, a_{\mathrm{d}}, c'_{\mathrm{p}}, c'_{\mathrm{q}}, c'_{\mathrm{d}})$.

References

Aastveit, K. A., and A. K. Anundsen. 2022. "Asymmetric Effects of Monetary Policy in Regional Housing Markets." *American Economic Journal: Macroeconomics* 14 (4): 499–529.

Adam, K., P. Kuang, and A. Marcet. 2012. "House Price Booms and the Current Account." *NBER Macroeconomics Annual 2011,* Vol. 26, ed. D. Acemoglu and M. Woodford, 77–122. Chicago: University of Chicago Press.

Barakchian, S. M., and C. Crowe. 2013. "Monetary Policy Matters: Evidence from New Shocks Data." *Journal of Monetary Economics* 60 (8): 950–66.

Bernanke, B. S. 2010. "Monetary Policy and the Housing Bubble." Speech at the annual meeting of the American Economic Association, Atlanta, Georgia.

Chodorow-Reich, G., A. M. Guren, and T. J. McQuade. 2024. "The 2000s Housing Cycle with 2020 Hindsight: A Neo-Kindlebergerian View." *Review of Economic Studies* 91 (2): 785–816.

Cooper, D., M. J. Luengo-Prado, and G. Olivei. 2022. "Monetary Policy and Regional House-Price Appreciation." *International Journal of Central Banking* 18 (3, September): 173–227.

DeFusco, A. A., C. G. Nathanson, and E. Zwick. 2017. "Speculative Dynamics of Prices and Volume." NBER Working Paper No. 23449.

Del Negro, M., and C. Otrok. 2007. "99 Luftballons: Monetary Policy and the House Price Boom across U.S. States." *Journal of Monetary Economics* 54 (7): 1962–85.

Díaz, A., B. Jerez, and J. P. Rincón-Zapatero. 2024. "Housing Prices and Credit Constraints in Competitive Search." *Economic Journal* 134 (657): 220–70.

Favara, G., and Z. Song. 2014. "House Price Dynamics with Dispersed Information." *Journal of Economic Theory* 149 (January): 350–82.

Garriga, C., and A. Hedlund. 2020. "Mortgage Debt, Consumption, and Illiquid Housing Markets in the Great Recession." *American Economic Review* 110 (6): 1603–34.

Gertler, M., and P. Karadi. 2015. "Monetary Policy Surprises, Credit Costs, and Economic Activity." *American Economic Journal: Macroeconomics* 7 (1): 44–76.

Glaeser, E. L., and C. G. Nathanson. 2017. "An Extrapolative Model of House Price Dynamics." *Journal of Financial Economics* 126 (1): 147–70.

Gorodnichenko, Y., and M. Weber. 2016. "Are Sticky Prices Costly? Evidence from the Stock Market." *American Economic Review* 106 (1): 165–99.

Guren, A. M. 2018. "House Price Momentum and Strategic Complementarity." *Journal of Political Economy* 126 (3): 1172–1218.

Guren, A. M., A. McKay, E. Nakamura, and J. Steinsson. 2021. "Housing Wealth Effects: The Long View." *Review of Economic Studies* 88 (2): 669–707.

Gürkaynak, R. S., B. Sack, and E. T. Swanson. 2005. "Do Actions Speak Louder Than Words? The Response of Asset Prices to

Monetary Policy Actions and Statements." *International Journal of Central Banking* 1 (1, May): 55–94.

Hamilton, J. D. 1994. *Time Series Analysis.* Princeton, NJ: Princeton University Press.

———. 2008. "Daily Monetary Policy Shocks and New Home Sales." *Journal of Monetary Economics* 55 (7): 1171–90.

Hamilton, J. D., and J. C. Wu. 2012. "Identification and Estimation of Gaussian Affine Term Structure Models." *Journal of Econometrics* 168 (2): 315–31.

Head, A., H. Lloyd-Ellis, and H. Sun. 2014. "Search, Liquidity, and the Dynamics of House Prices and Construction." *American Economic Review* 104 (4): 1172–1210.

Jacobson, M. 2022. "Beliefs, Aggregate Risk, and the US Housing Boom." Finance and Economic Discussion Series No. 2022-061, Board of Governors of the Federal Reserve System.

Jordà, Ò. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95 (1): 161–82.

Kaplan, G., K. Mitman, and G. L. Violante. 2020. "The Housing Boom and Bust: Model Meets Evidence." *Journal of Political Economy* 128 (9): 3285–345.

Kuchler, T., M. Piazzesi, and J. Stroebel. 2023. "Housing Market Expectations." In *Handbook of Economic Expectations,* ed. R. Bachmann, G. Topa, and W. van der Klaauw, 163–191. Elsevier.

Kuttner, K. N. 2001. "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market." *Journal of Monetary Economics* 47 (3): 523–44.

Luciani, M. 2015. "Monetary Policy and the Housing Market: A Structural Factor Analysis." *Journal of Applied Econometrics* 30 (2): 199–218.

Mertens, K., and M. O. Ravn. 2013. "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States." *American Economic Review* 103 (4): 1212–47.

Mian, A., K. Rao, and A. Sufi. 2013. "Household Balance Sheets, Consumption, and the Economic Slump" *Quarterly Journal of Economics* 128 (4): 1687–726.

Mian, A., and A. Sufi. 2009. "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis." *Quarterly Journal of Economics* 124 (4): 1449–96.

———. 2011. "House Prices, Home Equity-Based Borrowing, and the U.S. Household Leverage Crisis." *American Economic Review* 101 (5): 2132–56.

Nakamura, E., and J. Steinsson. 2018. "High-frequency Identification of Monetary Non-neutrality: The Information Effect." *Quarterly Journal of Economics* 133 (3): 1283–330.

Nathanson, C. G., and E. Zwick. 2018. "Arrested Development: Theory and Evidence of Supply-Side Speculation in the Housing Market." *Journal of Finance* 73 (6): 2587–633.

Ngai, R., and K. D. Sheedy. 2020. "The Ins and Outs of Selling Houses: Understanding Housing Market Volatility." CEPR Discussion Paper No. 14331.

Piazzesi, M., M. Schneider, and J. Stroebel. 2020. "Segmented Housing Search." *American Economic Review* 110 (3): 720–59.

Romer, C. D., and D. H. Romer. 2004. "A New Measure of Monetary Shocks: Derivation and Implications." *American Economic Review* 94 (4): 1055–84.

Saiz, A. 2010. "The Geographic Determinants of Housing Supply." *Quarterly Journal of Economics* 125 (3): 1253–96.

Stock, J. H., and M. W. Watson. 2012. "Disentangling the Channels of the 2007–09 Recession." *Brookings Papers on Economic Activity* (Spring): 81–156.

———. 2018. "Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments." *Economic Journal* 128 (610): 917–48.

Swanson, E. T. 2021. "Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets." *Journal of Monetary Economics* 118 (March): 32–53.

Taylor, J. B. 1993. "Discretion versus Policy Rules in Practice." *Carnegie-Rochester Conference Series on Public Policy* 39 (December): 195–214.

———. 2007. "Housing and Monetary Policy." NBER Working Paper No. 13682.

Williams, J. C. 2015. "Measuring Monetary Policy's Effect on House Prices." FRBSF Economic Letter No. 2015-28.