

The Fed’s Footprint on House Prices

Justin S. Eloriaga*

International Monetary Fund

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Abstract

House prices reach the Federal Reserve two months late. Does that matter for how much monetary policy moves them, or for what the Federal Reserve could have done about the 2000s boom and the pandemic surge? In a monthly U.S. structural vector autoregression from 1987 to 2025, identified with sign, policy-rule, and narrative restrictions, the lag matters for identification but not for outcomes. When the rule cannot respond to house prices within the month, the posterior median trough of real house prices after a 25-basis-point tightening is 0.03 to 0.15 percent across three price indices, though imprecisely estimated, and under every prior over rotations policy shocks have a posterior mean share of at most 10.2 percent of house price variance at two years. When it can, the trough reaches 0.34 to 0.72 percent, mostly through June 2022, and market-based surprises do not settle which timing is right. Yet the lag barely constrains policy. The same rule responding a month sooner, as real-time data would allow, would have kept house prices within 0.02 percent of their actual path, and a lean that raised the policy rate by about a percentage point at both peaks would have left them no lower. Policy shocks contributed little to either cycle on the full sample, although prior-robust bounds allow up to a third of the surge, and only indicators that record the anticipated tightening of 2022 attribute most of the ensuing decline in house prices to policy.

JEL Classification: E52, R31, C32

Keywords: Monetary policy, House prices, Narrative restrictions, Prior-robust inference, Structural vector autoregressions

*International Monetary Fund, Shanghai Center, Shanghai, China. Email: JEloriaga@imf.org. I thank Juan Rubio-Ramírez for helpful comments. The views expressed herein are those of the author and should not be attributed to the IMF, its Executive Board, or its management.

1 Introduction

Twelve-month changes in U.S. real house prices are 2.7 times as volatile as those in real GDP, and how strongly monetary policy moves house prices matters for whether policy should lean against housing booms (Svensson, 2017; Benati, 2021) and for what part policy played in the boom of the 2000s (Taylor, 2007; Bernanke, 2010) and in the pandemic surge. I measure the effect of monetary policy shocks, the deviations of policy from its estimated rule, on U.S. house prices since 1987 and their contribution to the housing cycles of that period. House prices also reach the Federal Reserve two months late, so I ask as well whether a Federal Reserve that could respond to them within the month would have changed those cycles.

Figure 1 shows the cycles. Real house prices rose 59 log points from January 1997 to March 2006, fell 41 by February 2012, and rose 25 between February 2020 and May 2022, mostly through the price-rent ratio, which accounts for 48 log points of the first boom and rose 26 in the second while real rents fell 1. The correlation between twelve-month changes in the federal funds rate and in real house prices over rolling five-year windows has ranged from -0.5 to 0.9 , so their co-movement is no guide to how policy affects house prices.

I estimate a monthly structural vector autoregression for January 1987 to September 2025 with nine variables, among them real house prices, the price-rent ratio, the mortgage rate, and a policy rate that splices the federal funds rate with a shadow rate at the lower bound. A monetary policy shock raises the policy rate and lowers prices and money, and the rule that it disturbs responds positively within the month to output and prices, as in Arias et al. (2019). Following Antolín-Díaz and Rubio-Ramírez (2018), I add narrative restrictions from three monetary episodes, February 1994, June 2013, and June 2022, and two housing episodes, September 2007 and July 2020.

One identifying assumption decides the answer. The Case-Shiller index for a month averages sales that closed over three months, most of them agreed one to two months earlier, and it is published two months after the month ends. In the baseline I assume that the rule does not respond to house prices within the month, which also keeps each month's house price surprise out of the realized policy shock and so out of the narrative restrictions (Appendix A). Because the rule does respond within the month to output and prices, which are also published with a lag, I report throughout what changes when it may respond to house prices too.

Under the baseline the housing channel is small but imprecisely estimated. After a 25-basis-point tightening the posterior median trough of real house prices is 0.03, 0.04, and 0.15 percent with the Case-Shiller, contract-timed, and FHFA indices, with 68 percent credible sets that reach -0.26 , -0.28 , and -0.44 percent (Table 2). With the Case-Shiller index a

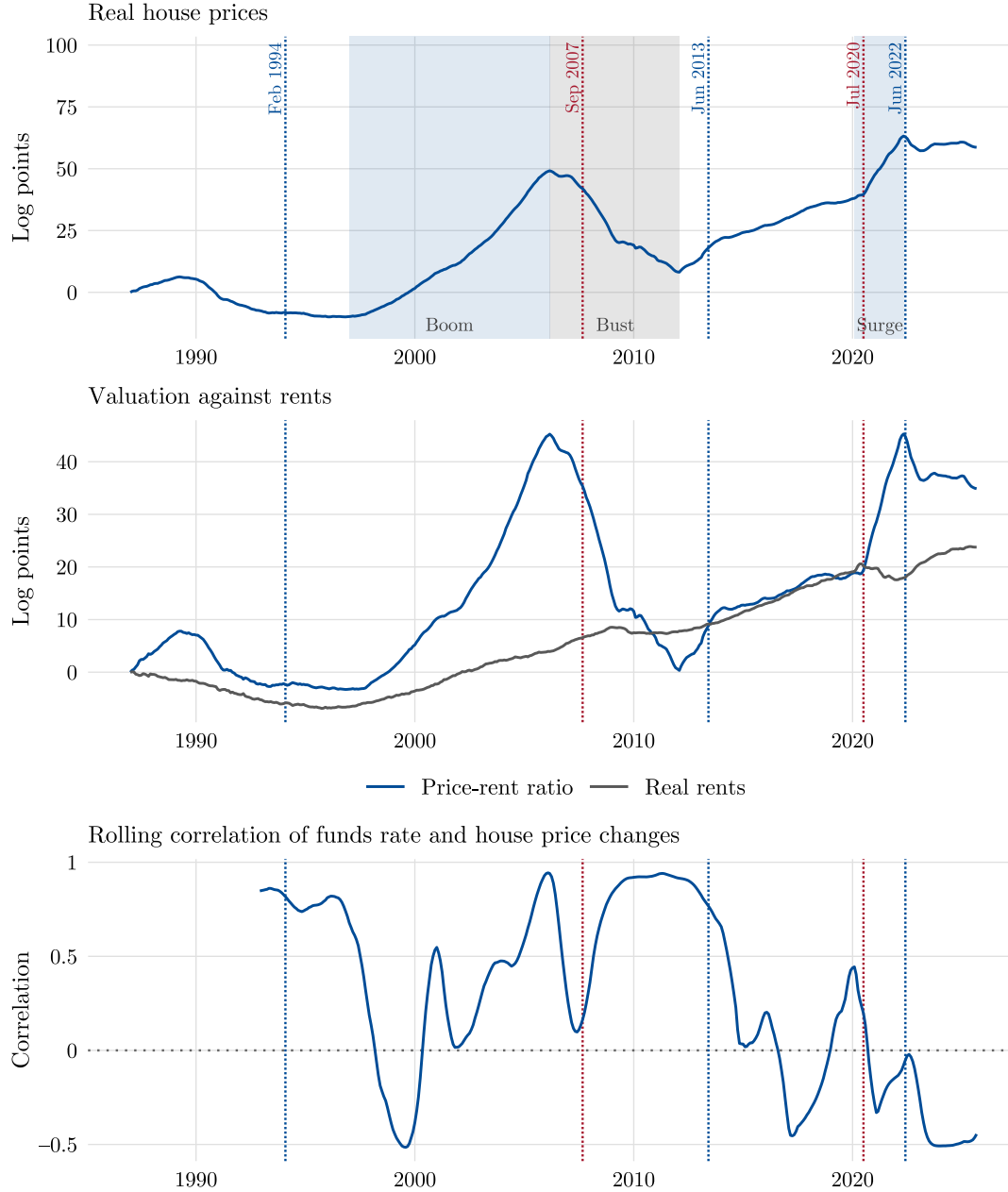


Fig. 1: House prices, valuations, and policy

Notes: Real house prices are the seasonally adjusted Case-Shiller national index deflated by the core CPI, the price-rent ratio is the index over the CPI rent of primary residence, and real rents are that rent index over the core CPI, all in log points relative to January 1987. The data end in September 2025. The bottom panel is the correlation between twelve-month changes in the effective federal funds rate and in real house prices over rolling five-year windows, dated at the last month of each window. In the top panel, light blue marks the boom from January 1997 to March 2006 and the pandemic surge from February 2020 to May 2022, and grey the bust to February 2012. Dotted vertical lines mark the five narrative episodes of Section 3.2, blue for monetary policy and red for housing demand. Sources in Table B1.

decline at two years is about as likely as a rise, so the data pin down the size of the response better than its sign. Policy shocks account for a median of 0.7 percent of the forecast error variance of house prices at two years, against 15.1 percent for housing demand shocks, which explain more than policy shocks whether or not the rule may respond to house prices within the month (Figure 4). The median share of policy shocks reflects the uniform prior over rotations, but its ceiling does not. Under every prior over rotations the posterior mean of the share is at most 10.2 percent, against 53.6 percent when the rule may respond to house prices (Table 3).

Under the uniform prior, policy shocks contributed -0.1 log points to the boom and 0.3 to the pandemic surge, against 3.6 and 4.9 for housing demand shocks (Table 4 and Figure 5), but the prior-robust bounds allow up to 22 percent of the boom and 36 percent of the surge (Table 3), and on a sample that ends in 2007 the boom contribution is 10.6 log points at the median (Appendix Table C4). Other policy indicators at the lower bound leave the baseline channel small, with one exception (Table 5). The two-year Treasury yield and the proxy funds rate, which record the anticipated tightening of 2022 when markets priced it, attribute 2.3 and 1.9 log points of the 3.2-log-point decline in house prices from March 2022 to July 2023 to policy shocks, against 0.3 with the Wu-Xia shadow rate.

When the rule may respond to house prices within the month, the median trough is 0.34 percent, and 0.72 percent when the policy shock must be the largest contributor to each episode’s policy rate surprise. About half of the gap comes from June 2022, when the first 75-basis-point increase since 1994 met the second most negative house price surprise of the sample, which the restriction on that month can then read as policy. Market-based surprises do not settle which identification is right. Those of [Bauer and Swanson \(2023\)](#) favor the rule that responds to house prices, and those of [Bu et al. \(2021\)](#) and [Nakamura and Steinsson \(2018\)](#) favor the baseline.

Would a faster Federal Reserve have mattered? In the baseline the rule responds to house prices only with a lag. Moving that response a month earlier, as real-time data would allow, keeps the policy rate within 0.12 percentage point of its actual path and real house prices within 0.02 percent of theirs, and a modest lean that raises the policy rate by about a percentage point at the peaks of the boom and the surge leaves house prices no lower (Figure 6). With the alternative identification, delaying the rule’s response to house prices by a month moves them by about 0.20 percent at those peaks. The publication lag thus decides how the effect of policy can be identified, but not what policy could have done about the boom or the surge.

Structural vector autoregressions find that a tightening lowers house prices ([Iacoviello, 2005](#); [Del Negro and Otrok, 2007](#); [Jarociński and Smets, 2008](#)), as do estimated models

(Iacoviello and Neri, 2010) and historical panels (Jordà et al., 2015), with responses that vary over time (Paul, 2020) and across regions (Aastveit and Anundsen, 2022). On the boom, Del Negro and Otrok (2007) find the contribution of policy shocks small, while Jarociński and Smets (2008) find that easy policy from 2002 to 2004 contributed to it. Closest to this paper, Benati (2021) restricts the systematic component of policy as Arias et al. (2019) do and finds that monetary shocks move real house prices three to five times as much as real GDP in the United States, Canada, and the United Kingdom. I cover the lower bound, the pandemic, and the 2022 tightening, add narrative restrictions and prior-robust bounds on the variance share and the historical contributions, show how the restriction on the rule’s response to house prices shapes what a narrative restriction on a single month can deliver, and ask what a faster response would have changed.

Section 2 describes the model and Section 3 the identification. Section 4 reports the house price response, Section 5 how much policy has mattered and whether a faster response would have mattered more, and Section 6 the robustness checks. Section 7 concludes.

2 Data and Model

The model has nine monthly U.S. variables for January 1987 to September 2025. Seven enter in logs, namely real reserves, real M2, real commodity prices, real house prices, the price-rent ratio, real GDP, and the core CPI, and two enter in levels, the thirty-year mortgage rate and the policy rate. Real house prices are the seasonally adjusted Case-Shiller national index deflated by the core CPI, and the price-rent ratio is the index over the CPI rent of primary residence. Real GDP is interpolated to monthly frequency from four coincident series. The policy rate is the effective federal funds rate, with the shadow rate of Wu and Xia (2016) in the 109 months in which the funds rate is at or below 0.25 percent. Responses are in percent and contributions in log points, both one hundred times log differences. Appendix B gives the sources.

With $\mathbf{y}_t$ the vector of the $n = 9$ variables, the reduced form is

$$\mathbf{y}_t = \mathbf{\Pi}'\mathbf{x}_t + \mathbf{e}_t, \quad \mathbf{x}_t = (1, \mathbf{y}_{t-1}', \dots, \mathbf{y}_{t-6}')', \quad \mathbf{E}(\mathbf{e}_t\mathbf{e}_t') = \mathbf{\Sigma}, \quad (1)$$

with a Minnesota prior whose hyperparameters are set at their posterior mode (Giannone et al., 2015). The structural shocks are $\mathbf{u}_t = \mathbf{B}\mathbf{e}_t$, with identity covariance, so row j of $\mathbf{B}$ is structural equation j and column j of $\mathbf{\Theta}_0 = \mathbf{B}^{-1}$, written $\boldsymbol{\theta}_j$, holds the impact responses to shock j . With $\mathbf{\Psi}_h$ the moving-average coefficients of the reduced form, the response of variable k to shock j at horizon h is $\boldsymbol{\iota}_k'\mathbf{\Psi}_h\boldsymbol{\theta}_j$, where $\boldsymbol{\iota}_k$ is column k of the identity. The

monetary policy rule is the structural equation of the monetary policy shock, normalized to have a positive coefficient on the policy rate, and its response within the month to variable k is $\psi_k = -B_{\text{mp},k}/B_{\text{mp},\text{ff}}$.

3 Identification

3.1 Sign restrictions and the policy rule

I label two shocks and leave seven unlabeled (Table 1). A monetary policy shock raises the policy rate and lowers the core CPI, real commodity prices, and real M2 for twelve months, which rules out the price puzzle (Sims, 1992; Uhlig, 2005) and uses money in place of reserves, which after 2008 reflect balance-sheet policy (Ihrig et al., 2015). Following Arias et al. (2019), the rule must respond positively within the month to real GDP and the core CPI, and, as in Benati (2021), to real commodity prices. A housing demand shock raises real house prices and the price-rent ratio for six months. The responses of output, house prices, the price-rent ratio, and the mortgage rate to a policy shock are unrestricted.

In the baseline the rule does not respond to real house prices or the price-rent ratio within the month, a restriction that Benati (2021) applies to these and three other variables. The rule may still respond to lagged house prices and, within the month, to the mortgage rate, money, and reserves. The zero is an identifying assumption. The month’s core CPI and the indicators behind monthly output are also published after the month ends, yet the rule responds to them, because the Federal Reserve nowcasts its mandate variables, and some housing indicators also arrive within the month. Bjørnland and Jacobsen (2013), for example, let the policy rate and house prices respond to each other within the period. Applying the information criterion to every variable, so that the rule responds within the month only to reserves, money, and the mortgage rate, does not identify a recognizable policy shock. With the five episodes the effective sample falls to 19 draws, and output rises after the first month. I therefore keep the conventional responses to output and prices and report what changes when the rule may respond to house prices too (Section 4.2).

3.2 Narrative restrictions from five episodes

Narrative restrictions narrow the set of structural models with information from the historical record (Antolín-Díaz and Rubio-Ramírez, 2018). The February 1994 increase began a tightening that the bond market did not anticipate. The taper communication of May and June 2013 coincided with a rise in the mortgage rate from 3.5 to 4.4 percent with the funds rate at the lower bound. June 2022 delivered the first 75-basis-point increase since

Table 1: Identifying restrictions

<i>Sign restrictions on impulse responses</i>			
Shock	Variable	Sign	Horizons (months)
Monetary policy	Policy rate	≥ 0	0 to 11
Monetary policy	Core CPI, real commodity prices, real M2	≤ 0	0 to 11
Housing demand	Real house prices, price-rent ratio	≥ 0	0 to 5
<i>Restrictions on the policy rule within the month</i>			
Positive responses to real GDP, the core CPI, and real commodity prices			
No response to real house prices or the price-rent ratio (baseline only)			
<i>Narrative restrictions</i>			
Month	Shock	Restriction	Episode
February 1994	Monetary policy	Positive, majority	Surprise start of the 1994 tightening
September 2007	Housing demand	Negative	Collapse of subprime credit
June 2013	Monetary policy	Positive, majority	Taper communication
July 2020	Housing demand	Positive	Pandemic demand surge
June 2022	Monetary policy	Positive, majority	First 75-basis-point increase since 1994

Notes: A positive monetary policy shock is a contractionary surprise, and a positive housing demand shock raises real house prices. The rule’s structural equation has a positive coefficient on the policy rate, a normalization that never binds, so that a positive shock tightens, and its responses are ψ_k of Section 2. In the narrative block, the sign refers to the realization of the structural shock in that month. Majority means that the policy shock’s contribution c to the policy rate’s one-step-ahead forecast error e in that month satisfies $|c| > |e - c|$, so that with a positive surprise it accounts for more than half of it. The largest-contributor alternative requires instead that its contribution exceed in absolute value that of every other shock. When the rule may respond to house prices, the two zero responses are dropped. Seven of the nine shocks are unlabeled, and the rule’s other coefficients are unrestricted.

1994, six weeks after Chair Powell had said that a step of that size was not being actively considered. In each of these months the policy shock must have been positive, meaning that the Federal Reserve tightened by more than its rule implied, and must have accounted for more than half of the policy rate’s surprise. This majority attribution is a variant of the overwhelming-contributor restriction of [Antolín-Díaz and Rubio-Ramírez \(2018\)](#), and unlike their largest-contributor restriction it does not depend on how the unlabeled shocks are rotated. The housing demand shock must have been negative in September 2007, as defaults on subprime mortgages mounted and subprime lending collapsed ([Shiller, 2008](#); [Mian and Sufi, 2009](#)), and positive in July 2020, as purchase applications and prices accelerated while output remained far below trend ([Mondragon and Wieland, 2022](#); [Gamber et al., 2023](#)). Market-based surprises read some of these months differently ([Appendix C](#)).

A narrative restriction on a month draws on that month’s data. The share of the month’s

policy rate surprise that the policy shock accounts for equals its share of the policy rate’s innovation variance times one plus the alignment of its impact responses with the month’s other innovations (Result 1), so a restriction can be met by a shock that is important on average or by one that lines up with the month’s other surprises. A variable with a zero coefficient in the rule cannot enter that alignment (Result 2). With house prices out of the rule, the restriction on June 2022 cannot be met by lining the policy shock up with that month’s house price surprise.

3.3 Estimation and inference

I draw from the posterior under the sign and rule restrictions with the sampler of [Arias et al. \(2018\)](#) and impose the narrative restrictions with the importance weights of [Antolín-Díaz and Rubio-Ramírez \(2018\)](#), computed exactly (Appendix B). Specifications that share the reduced form and the rule restrictions use the same draws. Responses are to a tightening that raises the policy rate by 25 basis points at its median peak within the first year, and I report posterior medians, pointwise 68 percent credible sets, and effective sample sizes that count repeated draws once.

The data update the reduced form but update the prior over rotations only through the restrictions ([Baumeister and Hamilton, 2015](#)). For the variance share and the historical contributions I therefore also report the bounds of [Giacomini and Kitagawa \(2021\)](#) on the posterior mean over all priors over rotations. Because the importance weights come from a likelihood that conditions on the narrative restrictions and depends on the rotation, the bounds use the unconditional likelihood of [Giacomini et al. \(2023\)](#), under which the admissible draws receive equal weight, and Table 3 reports them beside the posterior under that likelihood and the uniform prior. The bounds average over 1,000 draws of the reduced form the outer bounds that a semidefinite relaxation gives for each draw (Appendix B).

4 The Housing Channel

4.1 The baseline

Figure 2 shows the responses to a 25-basis-point tightening. The policy rate rises by 25 basis points within the year and is still 25 basis points higher after three years, and the median mortgage rate rises by 7 basis points and stays about 6 basis points higher. Real house prices barely move. Their median response at two years is 0.01 percent, with a 68 percent credible set from -0.23 to 0.25 , and they are below baseline in 48 percent of the posterior. Their median trough over three years, -0.03 percent, is what the minimum of a noisy response

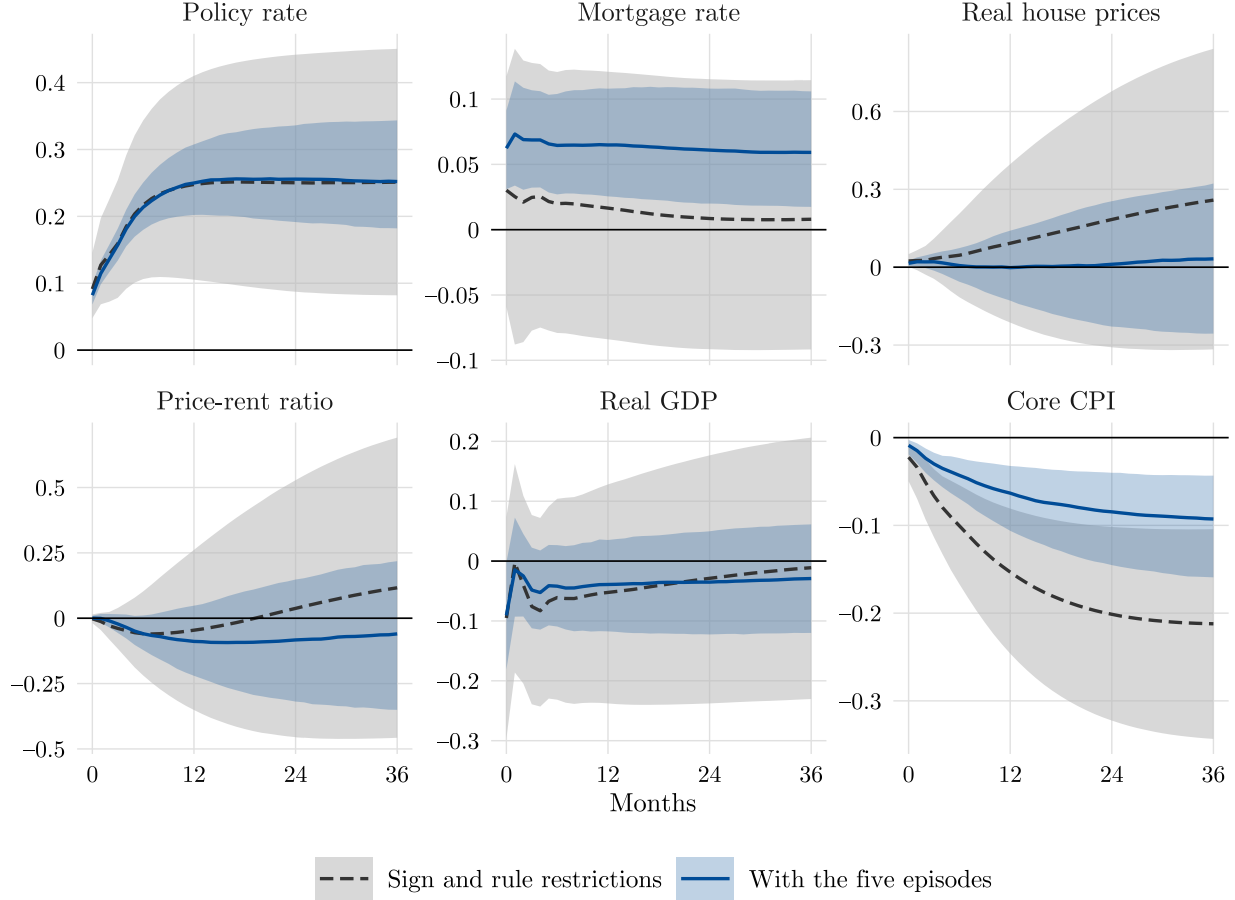


Fig. 2: Responses to a 25-basis-point tightening in the baseline

Notes: Posterior medians (lines) and pointwise 68 percent credible sets (shaded) of the responses to a monetary policy shock, January 1987 to September 2025, with house prices out of the rule within the month and exact importance weights. Grey areas and dashed lines show the sign and rule restrictions of Table 1 alone, and blue areas and solid lines add the five narrative episodes with majority attributions, with darker shading where the two sets overlap. Each identification is scaled by one constant so that the policy rate peaks at 25 basis points at its median within the first year. Percent for variables in logs, percentage points for interest rates. The responses of real reserves, real M2, and real commodity prices are not shown. Effective samples of 134,534 and 1,381 draws, respectively.

over 37 months reaches even when the true response is zero. The price-rent ratio is 0.08 percent lower at two years, so real rents rise. Under the sign and rule restrictions alone the median response at two years is 0.18 percent, and it stays positive in several specifications of Section 6, so the data pin down the size of the response better than its sign.

The response is larger with prices dated closer to the transactions (Table 2). With the Case-Shiller index dated two months earlier, which approximates contract dates, the probability of a decline is 51 percent and the median trough -0.04 percent. The FHFA

Table 2: The house price response across identifications

	Pr below at 24 months	Response at 24 months	Trough	Ratio to output	Variance share	ESS
<i>A. House prices out of the rule within the month (baseline)</i>						
No narrative restrictions	35	0.18 [−0.31, 0.68]	−0.01 [−0.35, 0.04]	0.2 [−0.3, 1.7]	1.2 [0.2, 4.8]	134,534
Five episodes, majority	48	0.01 [−0.23, 0.25]	−0.03 [−0.26, 0.02]	0.3 [−0.2, 2.5]	0.7 [0.1, 2.8]	1,381
largest contributor	61	−0.08 [−0.38, 0.18]	−0.10 [−0.45, 0.01]	0.7 [−0.1, 2.4]	0.8 [0.1, 4.6]	175
without June 2022	37	0.08 [−0.16, 0.34]	0.00 [−0.20, 0.03]	0.0 [−0.5, 2.2]	1.0 [0.1, 3.9]	3,171
Contract-timed prices	51	0.00 [−0.25, 0.26]	−0.04 [−0.28, 0.00]	0.3 [−0.1, 3.3]	0.9 [0.1, 3.5]	722
FHFA prices, from 1991	72	−0.13 [−0.36, 0.09]	−0.15 [−0.44, −0.02]	1.1 [0.1, 3.8]	1.4 [0.2, 5.0]	725
<i>B. House prices in the rule within the month</i>						
No narrative restrictions	47	0.08 [−0.89, 1.04]	−0.09 [−0.96, 0.11]	0.7 [−0.9, 4.8]	4.1 [0.5, 16.0]	800,366
Five episodes, majority	79	−0.31 [−0.71, 0.07]	−0.34 [−0.78, −0.04]	2.6 [0.1, 7.2]	3.6 [0.4, 13.6]	4,819
largest contributor	93	−0.66 [−1.25, −0.23]	−0.72 [−1.31, −0.31]	3.4 [1.4, 7.7]	10.3 [1.8, 24.4]	360
without June 2022	60	−0.11 [−0.55, 0.32]	−0.15 [−0.60, 0.04]	1.5 [−0.6, 5.9]	2.9 [0.3, 11.5]	9,382
Contract-timed prices	72	−0.20 [−0.58, 0.14]	−0.24 [−0.62, −0.01]	1.9 [0.0, 6.1]	2.2 [0.3, 9.4]	1,861
FHFA prices, from 1991	90	−0.44 [−0.78, −0.09]	−0.48 [−0.89, −0.13]	3.2 [0.7, 8.1]	6.8 [0.9, 20.4]	1,765
Nowcasting timing	53	−0.02 [−0.24, 0.21]	−0.05 [−0.29, 0.01]	0.3 [−0.1, 2.7]	0.7 [0.1, 3.0]	848

Notes: Nine-variable model with six lags, January 1987 to September 2025 (459 months), from 1991 with the FHFA index and through July 2025 with contract-timed prices, with exact importance weights. Episodes and attributions as in Table 1. The columns give the probability, in percent, that real house prices are below baseline 24 months after a 25-basis-point tightening, the posterior median of their response at 24 months and of the trough of their response over three years, in percent, the median ratio of that trough to the trough of output, and the median share of monetary policy shocks in the forecast error variance of real house prices at two years, in percent, with 68 percent credible sets below the medians. ESS is the effective sample size, and the Monte Carlo standard error of a probability p is about $\sqrt{p(1-p)/\text{ESS}}$. The contract-timed rows date the Case-Shiller index two months earlier, and the FHFA rows rebuild both house price series from the FHFA index. Nowcasting timing keeps house prices in the rule and sets the impact responses of nominal house prices and the price-rent ratio to zero.

purchase-only index dates each sale by the month in which it closes, without averaging, and starts in 1991. With it the median trough is −0.15 percent, about four times that of the Case-Shiller index, the probability of a decline is 72 percent, and the credible set of the trough excludes zero.

The comparison with output depends on the horizon. The output trough of −0.11 percent

falls in the month of the shock in 61 percent of draws, and the median response of output is -0.09 percent on impact, -0.01 percent a month later, and -0.04 percent at two years. The median ratio of troughs is 0.3 with the Case-Shiller index and 1.1 with the FHFA index, but at two years FHFA prices are 0.13 percent below baseline and output 0.06 percent, and house prices are further below baseline in 64 percent of draws.

Benati (2021) finds that monetary shocks move real house prices three to five times as much as real GDP in the United States, Canada, and the United Kingdom. His identification also keeps house prices out of the rule, but it excludes money, reserves, and the mortgage rate as well, labels only the policy shock, and restricts its effects over two years. On my data for 1987 to 2007 his restrictions admit no draw in 150,000 attempts under a flat prior and few under the Minnesota prior, which give a median trough of -0.18 percent and a ratio to output of 1.2, and -0.60 percent and 2.3 with the February 1994 episode, with effective samples of 15 and 8. The baseline gives a ratio of 0.8 on that sample and episode (Appendix Table C4), and on the full sample his restrictions select a shock after which house prices rise. His larger ratio thus reflects the pre-2008 sample and his further restrictions rather than the zero on house prices, although samples this small make the comparison only suggestive.

4.2 Why the policy rule matters

Panel B of Table 2 lets the rule respond within the month to house prices. With the five episodes and majority attributions, real house prices are then below baseline at two years in 79 percent of the posterior, with a median trough of -0.34 percent, 2.6 times that of output. With the largest-contributor attribution the probability is 93 percent and the trough -0.72 percent, 3.4 times that of output, and policy shocks account for 10.3 percent of the variance at two years. Figure 3 shows the contrast for each price measure.

June 2022 accounts for about 49 percent of the gap in the trough between the two identifications and 24 percent of the gap in the probability of a decline, and for about 49 percent of the gap in the trough with FHFA prices. Without that month the other four episodes give 60 percent and a trough of -0.15 percent when the rule may respond to house prices, against 37 percent and 0.00 percent in the baseline. In June 2022 the policy rate surprised by 0.8 standard deviations and real house prices by -3.1 , the second most negative surprise of the sample. With house prices in the rule, the realized policy shock contains that surprise, and the June 2022 restriction barely moves the policy shock's share of the policy rate's innovation variance, from 0.12 to 0.14, while raising its alignment with the month's other innovations from 0.4 to 6.1, 80 percent of it through the two Case-Shiller series (Appendix A.1).

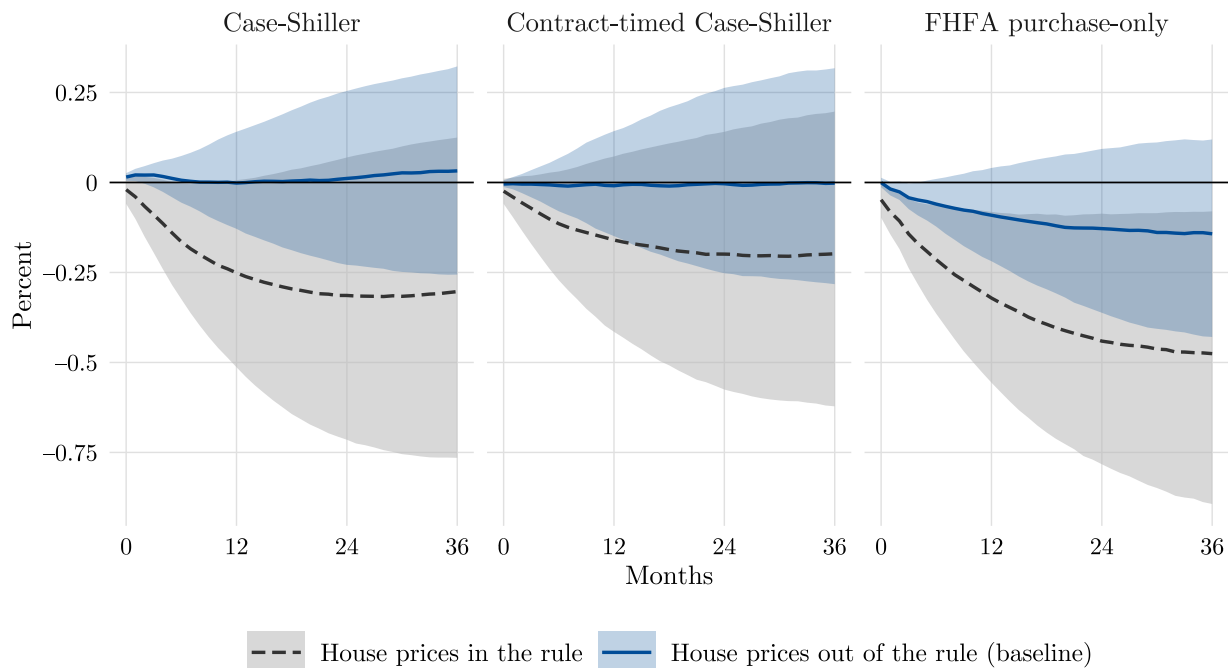


Fig. 3: The house price response with house prices out of and in the rule

Notes: Posterior medians (lines) and pointwise 68 percent credible sets (shaded) of the response of real house prices, deflated by the core CPI, to a 25-basis-point tightening, with the five narrative episodes, majority attributions, and exact importance weights. Blue areas and solid lines are the baseline, in which the rule does not respond to house prices within the month, and grey areas and dashed lines let it respond. The Case-Shiller panel covers January 1987 to September 2025, the contract-timed panel uses the Case-Shiller index dated two months earlier, through July 2025, and the FHFA panel the purchase-only index from 1991. Each identification is scaled so that the policy rate peaks at 25 basis points at its median within the first year. Effective samples in Table 2.

Two readings of that surprise are possible. On the first, the tightening of 2022 had been anticipated for months, the mortgage rate rose from 3.1 percent in December 2021 to 5.2 percent in May 2022, and part of the fall in house prices was the early effect of policy. On the second, most of the sales that the index records for June 2022 were agreed before the decision of June 15, and the restriction credits the June shock with a decline that other forces produced. Two diagnostics favor the second reading as the source of the large magnitudes. With house prices in the rule, nominal Case-Shiller prices fall in the month of the shock in 82 and 93 percent of draws under the two attributions, which a decision in the middle of the month can hardly produce in an average of earlier closings, although in the baseline they fall in only 27 percent. And imposing the June 2022 restriction with the largest-contributor attribution on each of 386 other months gives probabilities of a decline that correlate -0.76 with the month's house price surprise and -0.05 with its policy rate surprise. Section 6.1 supports the first reading in another form.

Setting to zero the impact responses of nominal house prices and the price-rent ratio instead of the rule's responses to them, a nowcasting timing that rules out an effect of policy on closings recorded before the decision, gives a probability of a decline of 53 percent and a median trough of -0.05 percent, close to the baseline.

5 How Much Policy Has Mattered

5.1 Variance decompositions

In the baseline the posterior median share of policy shocks in the forecast error variance of real house prices at two years is 0.7 percent, with a credible set from 0.1 to 2.8 percent, and the probability that it is below 10 percent is 99.6 percent. Under the unconditional likelihood and the uniform prior the median is 0.8 percent (Table 3). Under every prior over rotations the posterior mean lies between 0.0 and 10.2 percent. The ceiling is robust but the low median is not, since the lower posterior probability that the share is below 5 percent is only 5 percent. Without the narrative restrictions the bounds reach 17.0 percent, so the zero restrictions do most of the work. When the rule may respond to house prices, the bounds reach 53.6 percent, and 80.5 percent without the narrative restrictions, so the share is pinned down only by the prior over rotations, under which each of the nine shocks has an expected share of one-ninth, 11.1 percent, whatever the reduced form.

Figure 4 compares the shares of the two labeled shocks at horizons up to five years, and Appendix Table C5 reports them at one, two, and five years. Housing demand shocks explain much more of the variance of house prices than policy shocks do. In the baseline they account for 15.1 percent of the forecast error variance of real house prices at two years, with a credible set from 3.6 to 34.5 percent, some 21 times the share of policy shocks, and about as much at one and five years. Their share hardly changes when the rule may respond to house prices, 14.4 percent with majority attributions and 14.1 percent with the largest-contributor attribution, while the share of policy shocks rises to 3.6 and 10.3 percent, so housing demand shocks explain more than policy shocks whether or not the rule may respond to house prices. The housing demand shock is also set identified, by the signs of its effects on house prices and the price-rent ratio and by two narrative episodes, so its share reflects the uniform prior over rotations, and I do not bound it. Under that prior its median share is still 2.5 times that of a typical unlabeled shock, 6.2 percent, so its restrictions set it apart from the seven shocks that carry none, which together account for 82.8 percent.

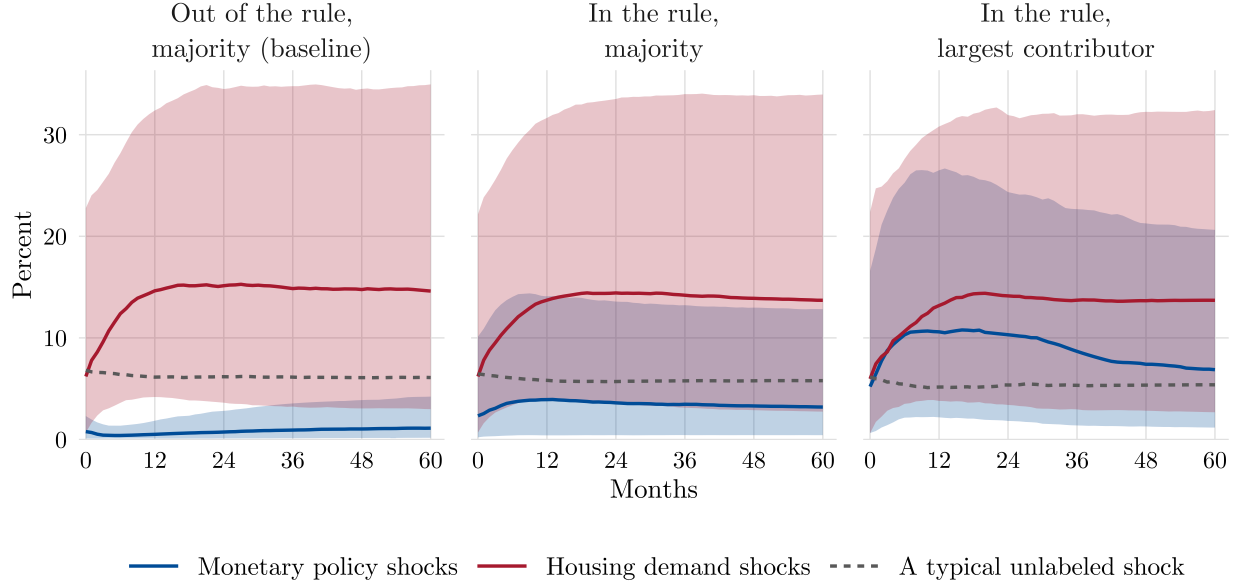


Fig. 4: Variance decomposition of real house prices

Notes: Posterior medians (solid lines) and pointwise 68 percent credible sets (shaded) of the shares of the monetary policy shock and the housing demand shock in the forecast error variance of real house prices over horizons 0 to h months, in percent, with the five narrative episodes and exact importance weights. The dashed line is the median share of a typical unlabeled shock, which pools the seven unlabeled shocks. Majority and largest contributor as in Table 1. Appendix Table C5 gives the shares at one, two, and five years with their credible sets.

5.2 Historical decompositions

Table 4 and Figure 5 turn to the cycles of Figure 1. In the baseline, policy shocks contributed -0.1 log points to real house prices over the boom, and the shocks of January 2002 to June 2004, the years of low rates, had contributed 0.0 by the peak. They contributed -0.1 over the bust, 0.3 over the pandemic surge, and -0.3 over the tightening of 2022 and 2023, and similar amounts under the unconditional likelihood (Table 3). Housing demand shocks contributed more, 3.6 log points of the 59-log-point rise in the boom, 9.4 of the 41-log-point fall in the bust, and 4.9 of the 25-log-point rise in the surge, although each of their credible sets includes zero. In the boom, which contains no episode for the housing demand shock, that is about as much as each unlabeled shock contributed, between 2.9 and 3.8 log points at the median. In the bust and the surge, which contain the episodes of September 2007 and July 2020, each unlabeled shock accounted for only 2.4 to 3.1 log points of the fall and 1.3 to 1.7 of the rise, so the housing demand shock stands apart from the unlabeled shocks mainly in the periods of its narrative episodes.

Most of each swing falls to the seven unlabeled shocks together, for example 39.6 log

Table 3: How much monetary policy shocks explain, under one prior and under all priors

	House prices out of the rule		House prices in the rule	
	Uniform prior	All priors	Uniform prior	All priors
Variance share at two years	0.8 [0.1, 3.1]	[0.0, 10.2] (0.0, 11.2)	2.6 [0.3, 10.9]	[0.0, 53.6] (0.0, 56.8)
Boom, 1997 to 2006	0.0 [-4.4, 3.9]	[-11.6, 13.3] (-16.1, 19.5)	0.6 [-4.4, 7.0]	[-19.5, 34.2] (-25.3, 42.9)
Bust, 2006 to 2012	-0.1 [-4.1, 3.7]	[-13.7, 10.9] (-17.4, 16.1)	-1.2 [-8.5, 3.1]	[-40.2, 14.8] (-48.3, 20.2)
Pandemic surge, 2020 to 2022	-0.1 [-3.5, 2.9]	[-6.9, 9.1] (-9.5, 12.9)	2.7 [-1.4, 8.1]	[-9.7, 23.4] (-12.1, 26.5)
Tightening, 2022 to 2023	-0.2 [-2.0, 1.3]	[-4.8, 3.8] (-6.2, 5.3)	-1.0 [-3.3, 1.1]	[-9.6, 6.9] (-11.4, 8.0)
Effective sample size	2,076		7,344	

Notes: Share of monetary policy shocks in the forecast error variance of real house prices over horizons 0 to 24, in percent, and the change in the cumulative contribution of all monetary policy shocks to real house prices over the boom (January 1997 to March 2006), the bust (to February 2012), the pandemic surge (February 2020 to May 2022), and the tightening (March 2022 to July 2023), in log points, with the five narrative episodes and majority attributions under the unconditional likelihood, which weights the admissible draws equally. Uniform prior gives the posterior median and, in square brackets, the 68 percent credible set. All priors gives, in square brackets, outer bounds on the set of posterior means over all priors over rotations, from the semidefinite relaxation of Appendix B averaged over 1,000 draws of the reduced form, and below them, in parentheses, the robust 68 percent credible region (Giacomini and Kitagawa, 2021).

points of the boom, and in the boom also to the deterministic component of the model in levels, the path that the initial conditions and the constant imply, since all shocks together account for 44.9 of its 59 log points. That component rises by about 1.5 log points a year, so the line in Figure 5, real house prices less the deterministic component, differs from the series in Figure 1. The bars there are pointwise medians, which are smaller and smoother than the contributions in any one draw, since the draws disagree about when the shocks hit. The largest absolute contribution of housing demand shocks within a draw has a median of 22.9 log points, against 5.7 for the largest pointwise median.

The prior-robust bounds on the contributions of policy shocks allow up to 22 percent of the boom, 33 percent of the bust, and 36 percent of the surge, and for the tightening they exceed the decline itself. When the rule may respond to house prices, the posterior attributes 3.8 log points of the surge to policy shocks with majority attributions and 6.4 with the largest-contributor attribution, about as much as or more than the 3.9 and 3.6 of housing demand shocks, with bounds from -9.7 to 23.4. These decompositions concern deviations from a rule estimated over the whole sample, which may treat some of the low rates of 2002 to 2004 as systematic, and they rest on that sample. From 1987 to 2007, with

Table 4: Monetary policy and housing demand shocks in the housing cycles

	Out of the rule, majority	In the rule, majority	In the rule, largest contributor
Boom, 1997 to 2006, change of 59.0			
Monetary policy shocks	−0.1 [−4.6, 3.9]	0.7 [−4.8, 7.5]	1.1 [−5.6, 10.7]
shocks of 2002 to mid-2004	0.0 [−0.9, 1.3]	0.4 [−0.8, 3.0]	1.1 [−0.8, 4.8]
Housing demand shocks	3.6 [−4.5, 18.9]	3.3 [−4.9, 17.9]	3.9 [−4.3, 17.5]
All shocks	44.9 [31.9, 58.5]	45.5 [31.7, 59.0]	46.2 [31.9, 58.6]
Bust, 2006 to 2012, change of −41.0			
Monetary policy shocks	−0.1 [−4.1, 3.7]	−1.7 [−10.4, 2.7]	−5.7 [−15.5, 1.5]
Housing demand shocks	−9.4 [−25.5, 0.5]	−9.4 [−26.7, 0.7]	−8.2 [−23.7, 1.1]
All shocks	−50.5 [−60.0, −40.9]	−50.3 [−59.9, −41.0]	−50.1 [−61.0, −40.6]
Pandemic surge, 2020 to 2022, change of 25.2			
Monetary policy shocks	0.3 [−3.0, 3.4]	3.8 [−0.5, 9.2]	6.4 [1.8, 12.4]
shocks of March to May 2021	0.0 [−1.4, 1.2]	2.2 [−0.1, 4.7]	3.6 [1.4, 5.8]
Housing demand shocks	4.9 [−0.3, 12.4]	3.9 [−1.0, 11.3]	3.6 [−1.0, 11.4]
All shocks	21.4 [16.7, 26.0]	21.5 [16.8, 26.1]	21.5 [16.3, 26.1]
Tightening, 2022 to 2023, change of −3.2			
Monetary policy shocks	−0.3 [−2.2, 1.2]	−1.3 [−3.7, 0.9]	−2.5 [−5.4, 0.1]
Housing demand shocks	−0.9 [−4.3, 2.1]	−0.6 [−4.3, 2.3]	−0.7 [−4.1, 2.0]
All shocks	−5.5 [−8.4, −2.6]	−5.4 [−8.3, −2.6]	−5.4 [−8.6, −2.6]
Effective sample size	1,381	4,819	360

Notes: Posterior medians, with 68 percent credible sets below them, with the five narrative episodes and exact importance weights, of the change in the cumulative contribution of each group of shocks to real house prices over each period of Table 3, in log points, with the change in real house prices in the data in each heading. All shocks gives the contribution of the nine shocks together, the data less the deterministic component of the model, which accounts for the rest of the change in the data. The rows for the shocks of January 2002 to June 2004 and of March to May 2021 give the contribution of the policy shocks dated in those months to real house prices at the end of the period. Majority and largest contributor as in Table 1.

February 1994 as the only episode, policy shocks contribute 10.6 log points to the boom, with a credible set from −0.3 to 26.9, although the shocks of January 2002 to June 2004 again contribute only 0.3 (Appendix Table C4).

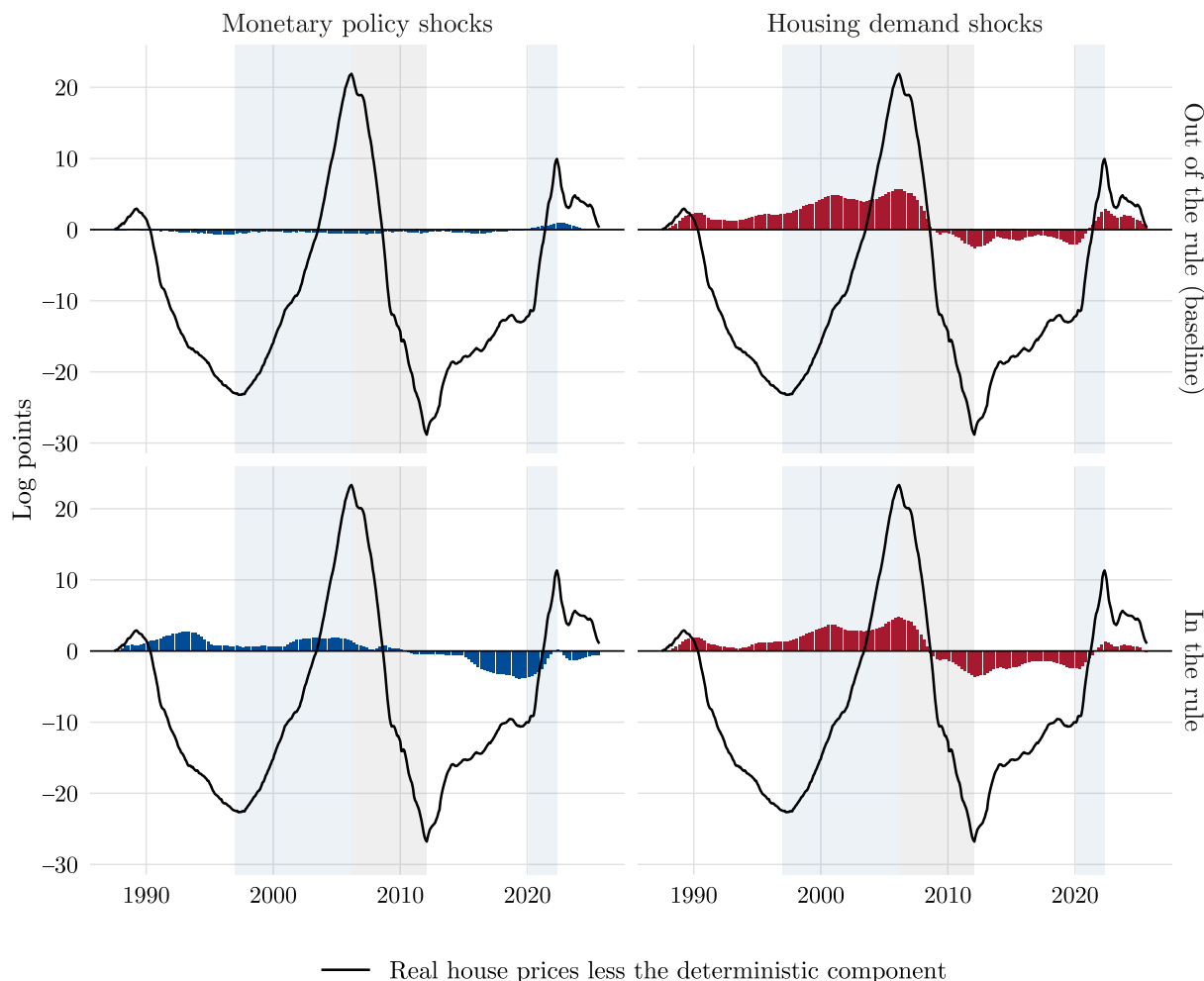


Fig. 5: Historical decomposition of real house prices

Notes: Bars are the pointwise posterior medians of the cumulative contributions of the monetary policy shocks (left) and the housing demand shocks (right) to real house prices since July 1987, in log points, as quarterly averages of the monthly values, with the five narrative episodes, majority attributions, and exact importance weights, when the rule does not respond to house prices within the month (top) and when it does (bottom). The line is real house prices less the deterministic component of the model, the path that the initial conditions and the constant imply, which is also the median contribution of all shocks together. Shading marks the boom, the bust, and the pandemic surge, as in Figure 1.

5.3 Would a faster Fed have mattered?

House prices reach the Federal Reserve two months late, which is why the baseline keeps them out of the rule within the month. Beside the identification question this raises a policy question, whether the Federal Reserve would have done differently if it could respond to house prices within the month. In the baseline the rule responds to house prices only with a lag, raising the policy rate by a median of 5 basis points in the month after a 1 percent rise

in real house prices, with a credible set from -2 to 14 . I replace the rule and keep the other eight equations of the model, which is the same as letting policy shocks move the policy rate onto the new rule in every month (Leeper and Zha, 2003). The first alternative is the same rule a month sooner, which responds within the month to real house prices and the price-rent ratio as the estimated rule responds a month later, as real-time house price data would allow. The second adds a modest lean, a within-month response of 2 basis points to each 1 percent change in real house prices.

Figure 6 shows that the timing of the response barely matters. After a housing demand shock that raises real house prices by 0.84 percent at two years, the policy rate is 6.5 basis points higher after a year under the estimated rule, 6.4 under the same rule a month sooner, and 7.4 with the lean, while house prices and output follow nearly the same paths under all three. Replayed with the estimated shocks, the history under the rule that responds a month sooner keeps the policy rate within 0.12 percentage point of its actual path and real house prices within 0.02 percent of theirs. The lean raises the policy rate by 1.0 percentage point at the peak of the boom and 1.1 at the end of the pandemic surge, yet leaves house prices no lower, 0.10 and 0.24 percent above their actual path at the median, with credible sets from -0.70 to 1.08 and from -1.11 to 1.98 , and lowers output by 0.11 and 0.09 percent.

Two features of the estimates explain the result. The rule responds little to house prices, so moving its response a month earlier changes the policy rate by basis points, and policy shocks move house prices little (Section 4), so even a lean of a percentage point leaves them almost unchanged. The conclusion does not rest on the timing assumption. When the rule may respond to house prices within the month, its response has a median of 19 basis points per 1 percent, with a credible set from -45 to 85 , and delaying it by a month lowers the policy rate by about 0.4 percentage point at the peak of the boom and at the end of the surge and raises house prices by 0.20 and 0.19 percent, with credible sets that include zero. Because the model identifies only surprise policy shocks, these counterfactuals do not let households and firms anticipate the new rule, which would require news shocks as well (McKay and Wolf, 2023). They are modest interventions in the sense of Leeper and Zha (2003), most reliable for small changes such as the one-month shift. The publication lag of house prices thus decides how the effect of policy can be identified, not what policy could have done about the boom or the surge.

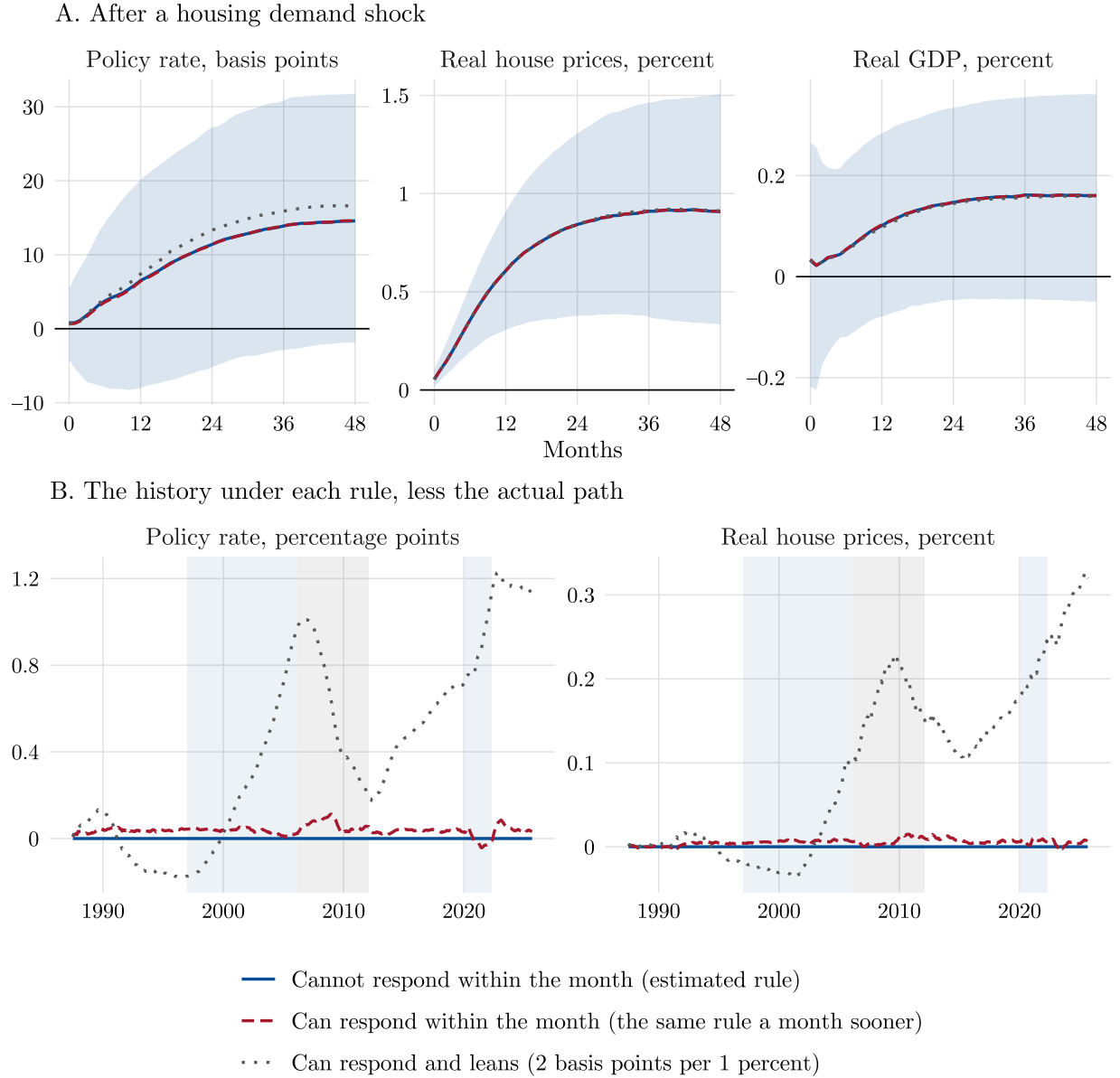


Fig. 6: Responding to house prices within the month

Notes: Posterior medians in the baseline model, with the five narrative episodes, majority attributions, and exact importance weights, under the estimated rule, which does not respond to house prices within the month, under the same rule with its responses to real house prices and the price-rent ratio moved one month earlier, and under that rule with an added within-month response of 2 basis points to each 1 percent change in real house prices. Panel A gives the responses to a one-standard-deviation housing demand shock, with the 68 percent credible set under the estimated rule (shaded). Panel B replays the history from the actual initial conditions with the estimated structural shocks under each rule and gives the difference from the actual path. Shading in panel B marks the boom, the bust, and the pandemic surge, as in Figure 1.

6 Robustness

6.1 The policy indicator at the lower bound and the pandemic volatility

In 109 months the baseline policy rate is the shadow rate of [Wu and Xia \(2016\)](#), an estimate from a term-structure model. It jumped where it joined the funds rate in December 2008, April 2020, and April 2022, and it fell by 1.5 percentage points between February and May 2021 while the funds rate, the pace of asset purchases, and one- and two-year Treasury yields stood still. Shadow rates differ across models ([Bauer and Rudebusch, 2016](#); [Krippner, 2020](#)), and one- and two-year Treasury yields remained responsive to macroeconomic news until late 2011 ([Swanson and Williams, 2014](#)).

Table 5 reports four alternatives, each with its own prior hyperparameters and posterior draws. The two-year Treasury yield, like the one-year rate of [Gertler and Karadi \(2015\)](#), moves with policy news over most of the sample, and its rise from 0.68 to 2.54 percent between December 2021 and April 2022 dates the anticipated tightening of 2022 to when markets priced it. The shadow short rate of [Krippner \(2013, 2015\)](#) joins the funds rate without a jump and rises in the spring of 2021, the proxy funds rate of [Choi et al. \(2022\)](#) maps twelve rates and spreads into the units of the funds rate, and the funds rate itself treats the lower-bound years as years without shocks. With house prices out of the rule, every indicator gives probabilities of a decline from 35 to 63 percent, median troughs from -0.17 to -0.02 percent, and contributions to the boom and the bust from -0.3 to 1.3 and from -0.1 to 0.6 log points. The tightening of 2022 and 2023 is the exception. With the two-year yield and the proxy funds rate, policy shocks account for -2.3 and -1.9 log points of the change in house prices from March 2022 to July 2023, most of the 3.2-log-point decline, against -0.3 with the Wu-Xia rate. Indicators that move when markets price policy thus attribute to policy the decline that followed the anticipated tightening, the first reading of June 2022 in Section 4.2. When the rule may respond to house prices, the contribution to the pandemic surge ranges from 1.5 to 7.5 log points across indicators.

Following [Lenza and Primiceri \(2022\)](#), I also let the residual standard deviation be s_0 , s_1 , and s_2 times larger in March, April, and May 2020 and decay geometrically at rate ρ thereafter, with the scales selected jointly with the prior hyperparameters (Appendix B). The rescaling raises the log marginal likelihood at the mode by 346, with scales of 4.1, 11.1, and 3.1 and $\rho = 0.93$. It lowers the baseline probability of a decline to 31 percent, with a median response at two years of 0.12 percent, and when the rule may respond to house prices it lowers the probability from 79 to 74 percent and raises the contribution to the surge from

Table 5: The policy indicator at the lower bound and the pandemic volatility

	Pr below at 24 months	Trough	Boom	Bust	Pandemic surge	Spring 2021	2022 to 2023	ESS
<i>A. House prices out of the rule (baseline)</i>								
Wu-Xia splice (baseline)	48	−0.03 [−0.26, 0.02]	−0.1 [−4.6, 3.9]	−0.1 [−4.1, 3.7]	0.3 [−3.0, 3.4]	0.0 [−1.4, 1.2]	−0.3 [−2.2, 1.2]	1,381
Funds rate	35	−0.04 [−0.18, 0.01]	−0.2 [−5.9, 5.3]	0.6 [−4.9, 5.6]	0.0 [−3.4, 3.5]	−0.1 [−0.8, 0.6]	−0.7 [−3.3, 1.6]	303
Two-year yield	63	−0.17 [−0.40, 0.00]	1.3 [−4.3, 9.0]	0.4 [−3.9, 5.6]	2.3 [−1.8, 6.3]	0.5 [−0.2, 1.2]	−2.3 [−4.9, 0.4]	201
Krippner splice	35	−0.02 [−0.14, 0.02]	−0.3 [−5.1, 4.4]	0.1 [−4.8, 6.7]	−0.1 [−4.0, 2.6]	−0.1 [−0.6, 0.2]	−0.3 [−2.4, 1.7]	135
Proxy funds rate	59	−0.11 [−0.30, 0.01]	1.0 [−3.5, 8.1]	0.5 [−4.3, 6.6]	2.5 [−1.2, 6.5]	0.4 [−0.3, 1.2]	−1.9 [−4.4, 0.5]	430
Volatility rescaled	31	0.00 [−0.12, 0.02]	−0.9 [−6.1, 3.0]	0.1 [−3.3, 4.3]	−1.4 [−6.7, 2.2]	−0.7 [−2.4, 0.8]	−0.7 [−2.8, 1.2]	488
<i>B. House prices in the rule</i>								
Wu-Xia splice (baseline)	79	−0.34 [−0.78, −0.04]	0.7 [−4.8, 7.5]	−1.7 [−10.4, 2.7]	3.8 [−0.5, 9.2]	2.2 [−0.1, 4.7]	−1.3 [−3.7, 0.9]	4,819
Funds rate	75	−0.33 [−0.68, −0.11]	2.2 [−4.4, 8.6]	−1.2 [−8.5, 4.4]	4.4 [−0.7, 10.6]	1.4 [0.1, 3.1]	−2.3 [−5.4, 0.4]	347
Two-year yield	87	−0.54 [−1.01, −0.21]	3.2 [−3.5, 11.7]	−1.2 [−9.6, 4.2]	6.7 [1.1, 13.0]	1.9 [0.6, 3.3]	−3.3 [−6.6, −0.3]	643
Krippner splice	49	−0.13 [−0.39, 0.01]	1.9 [−5.4, 9.6]	−0.4 [−6.5, 5.8]	1.5 [−3.1, 6.9]	0.2 [−0.3, 0.9]	−0.5 [−3.1, 2.0]	208
Proxy funds rate	86	−0.45 [−0.81, −0.16]	3.7 [−3.0, 12.0]	−0.7 [−8.5, 6.0]	7.5 [1.9, 14.4]	2.1 [0.7, 3.8]	−2.9 [−6.0, 0.3]	744
Volatility rescaled	74	−0.30 [−0.79, −0.02]	1.7 [−3.6, 10.0]	−1.6 [−10.1, 2.9]	4.7 [−1.7, 13.1]	2.5 [−0.6, 5.5]	−1.4 [−4.3, 1.0]	1,627

Notes: Each row uses a different policy rate or, in the last row of each panel, rescales the residual volatility of the pandemic months as in [Lenza and Primiceri \(2022\)](#), with its own prior hyperparameters and posterior draws, and imposes the five narrative episodes with majority attributions and exact importance weights. The policy rates are the effective federal funds rate with the shadow rate of [Wu and Xia \(2016\)](#) at the lower bound (the baseline), the effective federal funds rate throughout, the two-year Treasury yield, the effective federal funds rate through November 2008 and the shadow short rate of [Krippner \(2013, 2015\)](#) from December 2008, and the proxy funds rate of [Choi et al. \(2022\)](#). The funds rate and the proxy funds rate did not rise in June 2013, so with them the June 2013 episode carries its sign only. Columns as in Table 2, with the contributions of monetary policy shocks over the periods of Table 3 and that of the shocks of March to May 2021 to real house prices in May 2022, in log points, with 68 percent credible sets below the medians.

3.8 to 4.7 log points.

6.2 Market-based evidence

Market-based surprises offer evidence from outside the sign and rule restrictions (Appendix Table C2). As external instruments ([Stock and Watson, 2018](#)), the surprises of [Bu et al. \(2021\)](#), [Bauer and Swanson \(2023\)](#), and [Nakamura and Steinsson \(2018\)](#) as updated by [Acosta et al. \(2024\)](#) are weak over all months, with first-stage F statistics of 2.7, 2.5, and 0.9, and stronger but below the threshold of [Montiel Olea and Pflueger \(2013\)](#) over the months through 2007, with 11.1, 16.1, and 8.6. The strongest gives a median trough of

−0.22 percent and a ratio to output of 3.3, and the other two give ratios close to zero. The surprises can also weigh the identifications against each other. With the measurement equation of a Bayesian proxy SVAR (Caldara and Herbst, 2019; Arias et al., 2021), the surprises of Bauer and Swanson (2023) are 5.0 times more likely over the months through 2007, and 2.0 times over all months, when the rule may respond to house prices, while those of Bu et al. (2021) and Nakamura and Steinsson (2018) favor the baseline by factors of 1.4 to 1.6. The market-based evidence does not settle the timing assumption.

6.3 Other specifications

Appendix Table C4 varies the specification of the baseline. A sample ending in December 2019 gives a probability of a decline of 32 percent, three and twelve lags give 54 and 28 percent, unadjusted house prices and rents 41 percent, and industrial production in place of GDP 27 percent. The median trough stays between −0.13 and 0.00 percent and the variance share at most 1.2 percent, but the median response at two years is positive with twelve lags and with industrial production. Dropping July 2020 leaves the contribution to the pandemic surge at 0.4 log points. Months chosen without reference to house prices also leave the sign open, with a probability of a decline of 26 percent for the six events of the monetary application of Antolín-Díaz and Rubio-Ramírez (2018) in the sample and a median of 41 percent for nine months of large market-based surprises (Appendix Table C3).

7 Conclusion

When the policy rule cannot respond to house prices within the month, deviations of the Federal Reserve from its rule have left a small footprint on U.S. house prices since 1987. A 25-basis-point tightening moves real house prices by a few hundredths of a percent with the Case-Shiller index and by 0.15 percent at the median trough with the FHFA index, with credible sets that reach −0.44 percent and, with the Case-Shiller index, include rises. Under every prior over rotations the posterior mean share of policy shocks in house price variance is at most about a tenth, and under the uniform prior housing demand shocks have a median share of 15.1 percent, more than policy shocks whether or not the rule may respond to house prices. Policy shocks contributed little to the pandemic surge and, on the full sample though not on one that ends in 2007, to the boom of the 2000s, and indicators that move when markets price policy attribute most of the decline after the anticipated tightening of 2022 to policy shocks. Nor would a faster Federal Reserve have done much differently. A rule that responded to house prices within the month, as real-time data would allow, or leaned

against them modestly would have left the boom and the surge nearly unchanged, because the rule responds little to house prices and policy moves them little.

Larger effects arise when the rule may respond to house prices within the month, mostly because the restriction on June 2022 can then read the fall in house prices recorded that month, most of it in sales agreed before the decision, as the effect of policy. Market-based surprises do not settle which timing is right, and contract-dated prices of individual sales would sharpen the answer. For the debate on leaning against the wind, the evidence suggests that deviations of policy from its rule have moved house prices little, and that a modest systematic lean would have moved them little too. It does not measure the welfare costs and benefits of leaning, the response of housing quantities or credit, or the effect of purchases of mortgage-backed securities.

Statements and Declarations

Funding. No funding was received for conducting this study.

Competing interests. The author has no relevant financial or non-financial interests to disclose.

Data availability. All data are publicly available, and Table B1 gives the sources and vintages. Two FRED series, the S&P Cotality Case-Shiller index and the Freddie Mac mortgage rate, carry copyright restrictions, so the replication package retrieves their vintage of August 30, 2026 from ALFRED rather than redistributing them. The shadow short rate of Krippner may be redistributed only with its provider’s written permission, so replicators download it from LJK Macro Finance Analysis.

Code availability. The replication package, with MATLAB, Python, and R code that reproduces every table, figure, and number in the paper, is available from the author and will be deposited in a public repository upon acceptance.

Use of artificial intelligence tools. I used an AI assistant (Claude, by Anthropic) to help write and test the code of the replication package, run and summarize the analyses, and draft and edit the text. I checked all code, results, and text before submission, and I take full responsibility for the content of the paper.

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A What a Narrative Restriction Identifies

In the notation of Section 2, the reduced form has innovations $\mathbf{e}_t$ with covariance Σ , and the structural shocks are $\mathbf{u}_t = \mathbf{B}\mathbf{e}_t$, with $\mathbf{B} = \mathbf{Q}'\mathbf{P}$, where $\mathbf{P}'\mathbf{P} = \Sigma^{-1}$ and the rotation $\mathbf{Q}$ is orthogonal. The contribution of shock j to the surprise in variable i is $c_{ij,t} = \theta_{ij}u_{j,t}$, where θ_{ij} is element i of $\boldsymbol{\theta}_j$. Fix a month t and a restricted variable i , here the policy rate, with $\sigma_i^2 = \Sigma_{ii}$, and split the month's innovations into the part that the surprise in variable i predicts and the rest,

$$\mathbf{e}_t = \boldsymbol{\lambda}e_{i,t} + \boldsymbol{\nu}_t, \quad \boldsymbol{\lambda} = \Sigma_{\cdot i}/\sigma_i^2, \quad (2)$$

where $\Sigma_{\cdot i}$ is column i of Σ and $\boldsymbol{\nu}_t$ is the month's residual co-movement. With $\tilde{\boldsymbol{\theta}}_j = \boldsymbol{\theta}_j/\theta_{ij}$ the shock's impact responses scaled so that variable i moves one for one, the shock's share of the innovation variance of variable i is $s_j = \theta_{ij}^2/\sigma_i^2$, its alignment with the month's residual co-movement is $a_{j,t} = \sigma_i^2 \tilde{\boldsymbol{\theta}}_j' \Sigma^{-1} \boldsymbol{\nu}_t / e_{i,t}$, and the size of the residual co-movement is $D_t = \sigma_i^2 \boldsymbol{\nu}_t' \Sigma^{-1} \boldsymbol{\nu}_t / e_{i,t}^2$, which does not depend on the rotation.

Result 1. *For every rotation with $\theta_{ij} > 0$ and every month with $e_{i,t} \neq 0$,*

$$c_{ij,t}/e_{i,t} = s_j(1 + a_{j,t}), \quad |a_{j,t}| \leq \sqrt{D_t(1 - s_j)/s_j}. \quad (3)$$

With $e_{i,t} > 0$, the narrative sign restriction $u_{j,t} > 0$ holds if and only if $1 + a_{j,t} > 0$, and the majority attribution $c_{ij,t}/e_{i,t} > 1/2$ if and only if $s_j(1 + a_{j,t}) > 1/2$. With $e_{i,t} < 0$, the sign restriction holds if and only if $1 + a_{j,t} < 0$ and cannot hold together with the majority attribution. When shock j is the only labeled shock and the other m shocks are unlabeled and free to rotate, and $e_{i,t} > 0$, the sign restriction and the largest-contributor attribution $|c_{ij,t}| \geq |c_{il,t}|$ for all l hold together for some rotation of the unlabeled shocks if and only if $s_j(1 + a_{j,t}) \geq 1/(m + 1)$. With a second labeled shock h , as in the paper, the two restrictions hold together for some rotation of the m unlabeled shocks if and only if $|c_{ij,t}| \geq |c_{ih,t}|$ and $mc_{ij,t} \geq |e_{i,t} - c_{ij,t} - c_{ih,t}|$.

Result 2. *For $e_{i,t} > 0$, the restrictions of Result 1 depend on month t 's innovations only through their direction, $\mathbf{e}_t/e_{i,t} = (c_{ij,t}/e_{i,t})\tilde{\boldsymbol{\theta}}_j + \sum_{l \neq j} \boldsymbol{\theta}_l u_{l,t}/e_{i,t}$, which equals the shock's scaled impact vector only if no other shock moves in month t . With B_{jk} the coefficient on variable k in structural equation j , the alignment is*

$$a_{j,t} = \frac{\sigma_i^2}{\theta_{ij}e_{i,t}} \sum_{k \neq i} B_{jk}\nu_{k,t}, \quad (4)$$

since $\nu_{i,t} = 0$, so if $B_{jk} = 0$ for some $k \neq i$, the sign restriction and the majority attribution

do not depend on $e_{k,t}$. A zero impact response, $\theta_{kj} = 0$, does not imply $B_{jk} = 0$.

Result 3. With independent standard normal shocks, $\mathbf{B}$ fixed, and $\theta_{ij} > 0$, the probability that shock j is positive and satisfies the majority attribution is $\arcsin(\sqrt{s_j})/\pi$, and the probability that it is positive and the largest contributor is

$$\int_0^\infty \phi(x) \prod_{l \neq j, \theta_{il} \neq 0} \{2\Phi(\theta_{il}x/|\theta_{il}|) - 1\} dx, \quad (5)$$

with ϕ and Φ the standard normal density and distribution function. For a single restricted shock, the scaled impact responses that satisfy sign and zero restrictions on the impulse responses and on the structural equation, narrative signs, and majority attributions form a convex set.

Proof of Result 1. Because $\mathbf{B} = \mathbf{Q}'\mathbf{P}$, $u_{j,t} = \boldsymbol{\theta}'_j \boldsymbol{\Sigma}^{-1} \mathbf{e}_t$ and $\boldsymbol{\theta}'_j \boldsymbol{\Sigma}^{-1} \boldsymbol{\theta}_j = 1$, hence $\tilde{\boldsymbol{\theta}}'_j \boldsymbol{\Sigma}^{-1} \tilde{\boldsymbol{\theta}}_j = 1/(s_j \sigma_i^2)$. Because $\boldsymbol{\Sigma}^{-1} \boldsymbol{\lambda} = \boldsymbol{\nu}_i/\sigma_i^2$, $\tilde{\boldsymbol{\theta}}'_j \boldsymbol{\Sigma}^{-1} \boldsymbol{\lambda} = \boldsymbol{\lambda}' \boldsymbol{\Sigma}^{-1} \boldsymbol{\lambda} = 1/\sigma_i^2$ and $\boldsymbol{\lambda}' \boldsymbol{\Sigma}^{-1} \boldsymbol{\nu}_t = 0$. By the split (2), $\tilde{\boldsymbol{\theta}}'_j \boldsymbol{\Sigma}^{-1} \mathbf{e}_t = (e_{i,t}/\sigma_i^2)(1 + a_{j,t})$, and $c_{ij,t} = \theta_{ij}^2 \tilde{\boldsymbol{\theta}}'_j \boldsymbol{\Sigma}^{-1} \mathbf{e}_t$ gives the identity (3). The bound follows from the Cauchy-Schwarz inequality in the inner product of $\boldsymbol{\Sigma}^{-1}$, applied to $(\tilde{\boldsymbol{\theta}}_j - \boldsymbol{\lambda})' \boldsymbol{\Sigma}^{-1} \boldsymbol{\nu}_t$, with $(\tilde{\boldsymbol{\theta}}_j - \boldsymbol{\lambda})' \boldsymbol{\Sigma}^{-1} (\tilde{\boldsymbol{\theta}}_j - \boldsymbol{\lambda}) = (1 - s_j)/(s_j \sigma_i^2)$. The sign condition follows from $u_{j,t} = \theta_{ij}(e_{i,t}/\sigma_i^2)(1 + a_{j,t})$, and the majority condition from the identity. For the largest contributor, rotating the m unlabeled shocks by an orthogonal $\mathbf{R}$ leaves $\boldsymbol{\Sigma}$ and the labeled shocks unchanged and makes the unlabeled contributions the diagonal of $\mathbf{R}'\mathbf{S}\mathbf{R}$, with $\mathbf{S} = (\boldsymbol{\gamma}\boldsymbol{\delta}' + \boldsymbol{\delta}\boldsymbol{\gamma}')/2$ built from their impacts $\boldsymbol{\gamma}$ and realizations $\boldsymbol{\delta}$. Their sum is the same under every rotation, $e_{i,t} - c_{ij,t}$ with one labeled shock, and by the Schur-Horn theorem (Schur, 1923; Horn, 1954) the vector with every element equal to $(e_{i,t} - c_{ij,t})/m$ is attainable while every attainable vector has an element at least as large in absolute value. So the attribution holds for some rotation if and only if $mc_{ij,t} \geq |e_{i,t} - c_{ij,t}|$, which with $c_{ij,t} > 0$ and $e_{i,t} > 0$ is $c_{ij,t} \geq e_{i,t}/(m+1)$. A second labeled shock does not rotate, so it adds its own comparison and leaves $e_{i,t} - c_{ij,t} - c_{ih,t}$ to the unlabeled shocks. $\square$

Proof of Result 2. Every realization is linear in $\mathbf{e}_t$, so the restrictions depend on its direction only. Row j of $\mathbf{B}$ is $\theta_{ij} \tilde{\boldsymbol{\theta}}'_j \boldsymbol{\Sigma}^{-1}$, which gives (4), and if $B_{jk} = 0$ the sum does not involve $\nu_{k,t}$, while the other elements of $\boldsymbol{\nu}_t = \mathbf{e}_t - \boldsymbol{\lambda}e_{i,t}$ involve only their own innovations and $e_{i,t}$. $\square$

Proof of Result 3. The sum of the other contributions is normal with variance $\sigma_i^2 - \theta_{ij}^2$ and independent of $u_{j,t}$, so the majority event is a cone of half-angle $\arcsin(\sqrt{s_j})$ under a rotationally symmetric bivariate normal, and conditional on $u_{j,t} = x > 0$ the events $|\theta_{il}u_{l,t}| \leq \theta_{ij}x$ are independent. The majority attribution is the ellipsoid $(\tilde{\boldsymbol{\theta}}_j - \mathbf{e}_t/e_{i,t})' \boldsymbol{\Sigma}^{-1} (\tilde{\boldsymbol{\theta}}_j - \mathbf{e}_t/e_{i,t}) < (1 + D_t)/\sigma_i^2$, and the other restrictions are half-spaces or hyperplanes in $\tilde{\boldsymbol{\theta}}_j$, so their intersection is convex. $\square$

A.1 How June 2022 identifies the housing response

Table A1 applies the identity (3) to every draw of the posterior in which the rule may respond to house prices within the month. Under the sign and rule restrictions the policy shock’s share of the policy rate’s innovation variance has a median of 0.12, and the June 2022 largest-contributor attribution raises it only to 0.14. What it moves is the alignment with June 2022’s residual co-movement, from a median of 0.4 to 6.1. At the posterior median, June 2022’s policy rate surprise was 0.8 standard deviations, while real house prices surprised by -3.1 , output by -0.9 , and the core CPI by 1.8 . Real house prices and the price-rent ratio carry 80 percent of the alignment that this attribution selects. This split by variable depends on how the variables are written, since part of the surprise in real house prices is the surprise in the core CPI that deflates them. When the sign-restricted draws are sorted by their alignment with June 2022’s residual co-movement, the probability that house prices are below baseline at two years rises from 9 percent in the lowest decile to 89 percent in the highest, while sorting them by variance share moves it from 53 to 37 percent. When I impose the June 2022 sign and largest-contributor attribution on each of the 386 other months with an effective sample of at least 200, the probability of a decline at two years has a median of 43 percent and a correlation of -0.76 with the month’s house price surprise and of -0.05 with its policy rate surprise. In six of the 11 months whose probability matches or exceeds that of June 2022, the policy rate surprised downward, which the largest-contributor attribution allows and the majority attribution does not.

B Data and Computation

Data. The system contains nine monthly U.S. series from January 1987 to September 2025, giving 465 observations, of which the first six serve as initial conditions (Table B1). The start date is that of the Case-Shiller national index, and the sample stops in September 2025 because the core CPI, which deflates every nominal quantity and price, was not published for October 2025. Real GDP is interpolated to monthly frequency by the Chow and Lin (1971) procedure on industrial production, nonfarm payrolls, real personal income less transfers, and real manufacturing and trade sales.

Prior. The Minnesota prior is centered on univariate random walks, with lag decay of two and scale parameters given by the residual variances of univariate autoregressions. Its overall tightness and the scales of the sum-of-coefficients and dummy-initial-observation priors are set at their posterior mode in the hierarchical framework of Giannone et al. (2015), with gamma hyperpriors, for each data set. For the baseline they are 0.34, 0.016, and 0.50.

Table A1: What the attributions select when the rule responds to house prices

Narrative information	Pr below at 24 months	s	Alignment a_t			$s(1 + a_t)$, June 2022	ESS
			February 1994	June 2013	June 2022		
No narrative information	47	0.12	0.9	0.4	0.4	0.14	800,366
Five narrative signs	68	0.14	1.3	1.0	2.5	0.42	77,388
February 1994, largest contributor	65	0.19	1.4	0.6	1.9	0.51	119,469
June 2013, largest contributor	53	0.18	1.0	1.9	1.2	0.38	62,133
June 2022, largest contributor	92	0.14	1.6	0.9	6.1	0.91	5,666
June 2022, majority	86	0.14	1.5	0.8	5.9	0.83	160,029
Five episodes, largest contributor	93	0.17	1.8	2.1	5.3	1.08	360
Five episodes, majority	79	0.30	1.2	1.3	2.6	1.08	4,819
Size of the residual co-movement, D_t			1.6	3.8	27.4		

Notes: Full sample, on the 800,366 draws of the posterior under the sign and rule restrictions in which the rule may respond to house prices within the month, with exact importance weights. The first column is the probability, in percent, that real house prices are below baseline 24 months after a 25-basis-point tightening. The next five columns are posterior medians of the policy shock's share s of the policy rate's innovation variance, a fraction, of its alignment a_t with each episode month's residual co-movement, and of its share of the June 2022 policy rate surprise, $s(1 + a_t)$, all defined in equations (2) and (3). Largest contributor and majority as in Table 1. The last row reports the median of D_t under the sign and rule restrictions. ESS is the effective sample size.

With a policy indicator that does not splice in the Wu-Xia shadow rate, the selected sum-of-coefficients scale is about ten times larger, a looser prior. The inverse-Wishart prior on Σ has $n + 2$ degrees of freedom, the fewest for which its mean exists. In 99.8 percent of the posterior draws the largest root of the companion matrix is just above one, as is usual in a model in levels under a sum-of-coefficients prior, and I do not truncate the posterior, so decompositions over long windows propagate these roots.

Sampling and weights. The sampler of [Arias et al. \(2018\)](#) draws the reduced form from its posterior and the rotation from the uniform distribution subject to the zero restrictions, keeps the draws that satisfy the sign restrictions, and resamples them in proportion to the importance weights that account for the zeros. When every zero restriction involves only the structural equation and the impact responses, as here, the weight reduces to a function of the impact block, which I compute from singular values. The baseline pool has 337,768 draws, 208,838 of them distinct. The narrative restrictions are imposed with the importance weight of [Antolín-Díaz and Rubio-Ramírez \(2018\)](#), the reciprocal of the probability that independent standard normal shocks satisfy them under the draw's impact matrix. Because the shocks are independent across months, that probability is the product over the restricted months of the probabilities of Result 3, one half for a sign alone, which I evaluate in closed form for the majority attribution and by quadrature for the largest contributor. The effective sample size treats repeated draws as one draw carrying their combined weight, and the Monte

Table B1: Data sources

Variable	Description, source, code, and transformation
Real reserves	Total reserves of depository institutions, Board of Governors (FRED TOTRESNS), deflated by the core CPI, log
Real M2	M2 money stock, seasonally adjusted, Board of Governors (M2SL), deflated, log
Real commodity prices	Producer price index for all commodities, BLS (PPIACO), deflated, log
Real house prices	S&P Cotality Case-Shiller U.S. national home price index, seasonally adjusted (CSUSHPISA), deflated, log
Price-rent ratio	Case-Shiller index over the CPI rent of primary residence, seasonally adjusted, BLS (CUSR0000SEHA), log
Mortgage rate	Thirty-year fixed-rate mortgage average, Freddie Mac (MORTGAGE30US), percent
Policy rate	Effective federal funds rate, Board of Governors (FEDFUNDS), in percent, with the shadow rate of Wu and Xia (2016) from Cynthia Wu’s website in the 109 months in which the funds rate is at or below 0.25 percent
Real GDP	Real gross domestic product, BEA (GDPC1), interpolated monthly with INDPRO, PAYEMS, W875RX1, and CMRMTSPL, log
Core CPI	CPI for all urban consumers less food and energy, seasonally adjusted, BLS (CPILFESL), log
<i>Series used in robustness checks</i>	
FHFA house prices	Purchase-only house price index for the United States, seasonally adjusted, Federal Housing Finance Agency, from January 1991, deflated, with the price-rent ratio built from it
Contract-timed prices	The Case-Shiller index dated two months earlier, with the core CPI and rents at their own dates, through July 2025
Two-year yield	Treasury constant-maturity yield, monthly average, Board of Governors H.15 (GS2)
Krippner shadow rate	Shadow short rate of Krippner (2013, 2015) , monthly average, from December 2008, LJK Macro Finance Analysis
Proxy funds rate	Proxy funds rate of Choi et al. (2022) , monthly, Federal Reserve Bank of San Francisco
Unadjusted series	Case-Shiller index (CSUSHPINSA) and CPI rent (CUUR0000SEHA), not seasonally adjusted
Surprise series	Monetary policy shocks of Bu et al. (2021) , January 1994 to September 2023, and of Bauer and Swanson (2023) , orthogonalized, February 1988 to December 2019, and the policy news shock of Nakamura and Steinsson (2018) as updated by Acosta et al. (2024) , February 1995 to January 2024, summed within months and zero in months without an announcement, from the authors’ files

Notes: FRED series as published on August 30, 2026, averaged to months where weekly or daily. The Wu-Xia shadow rate was obtained in August 2026, and the FHFA, H.15, Krippner, and proxy series in October 2026. Deflated means divided by the core CPI. Reserves and commodity prices are not seasonally adjusted at the source.

Carlo standard error of a probability $\hat{p}$ is about $\sqrt{\hat{p}(1 - \hat{p})/\text{ESS}}$, 1.3 percentage points for the baseline probability of a decline.

Prior-robust bounds. For each draw of the reduced form, the monetary policy shock’s direction $\mathbf{q}$, column one of $\mathbf{Q}$, ranges over unit vectors in a cone. With $\boldsymbol{\epsilon}_t = \mathbf{P}\mathbf{e}_t$ the orthonormalized innovations and $\mathbf{r} = (\mathbf{P}^{-1})'\boldsymbol{\iota}_{\text{ff}}$, so that $u_{\text{mp},t} = \mathbf{q}'\boldsymbol{\epsilon}_t$ and $\theta_{\text{ff},\text{mp}} = \mathbf{r}'\mathbf{q}$, the sign and rule restrictions and the narrative signs are linear inequalities in $\mathbf{q}$, the zeros of the rule

linear equalities, and each majority attribution in a month with $e_{\text{ff},t} > 0$ the homogeneous quadratic inequality

$$(\mathbf{r}'\mathbf{q})(\boldsymbol{\epsilon}'_t\mathbf{q}) \geq e_{\text{ff},t}\mathbf{q}'\mathbf{q}/2, \quad (6)$$

taken with its weak inequality. A draw with $e_{\text{ff},t} \leq 0$ in a restricted month has an empty identified set, and the bounds average over the 99 percent of draws whose set is not empty. The share of variance is $\mathbf{q}'\mathbf{M}\mathbf{q}/\text{tr}(\mathbf{M})$, with $\mathbf{M} = \sum_{h=0}^{24} \mathbf{g}_h\mathbf{g}'_h$ and $\mathbf{g}_h$ the responses of real house prices to the orthonormalized shocks, and the contribution of the monetary policy shocks over a period is $\mathbf{q}'\mathbf{N}\mathbf{q}$, with $\mathbf{N}$ the change over the period of $\sum_{s=1}^{\tau} \mathbf{g}_{\tau-s}\boldsymbol{\epsilon}'_s$, summed from the first month of the estimation sample. With $\mathbf{K}$ equal to $\mathbf{M}/\text{tr}(\mathbf{M})$ for the share and to the symmetric part of $\mathbf{N}$ for a contribution, I find the extremes of $\mathbf{q}'\mathbf{K}\mathbf{q}$ by sequential quadratic programming from the best of many admissible directions, drawn uniformly from the cone, and bound them from outside by the semidefinite relaxation that maximizes or minimizes $\text{tr}(\mathbf{K}\mathbf{X})$ over positive semidefinite $\mathbf{X}$ with unit trace, with the linear inequalities lifted pairwise and the attributions written as linear inequalities in $\mathbf{X}$. The problem is not convex, so the relaxation is what certifies the bounds. It coincides with the local value in 40 percent of draws for the share in the baseline, and where they differ the extreme lies between the two, so Table 3 reports the relaxation's values, which hold in every draw. The attained values are close, with averages of 0.0 and 9.3 percent for the bounds on the share in the baseline, against 0.0 and 10.2. The housing demand shock must exist, which a linear program checks at the directions that attain each bound. The robust credible region is the shortest interval that contains the identified set with posterior probability 0.68 (Giacomini and Kitagawa, 2021), and its coverage under narrative restrictions is studied by Giacomini et al. (2022).

Pandemic volatility. The reduced form becomes $\mathbf{y}_t = \boldsymbol{\Pi}'\mathbf{x}_t + v_t\mathbf{e}_t$, with $v_t = 1$ before March 2020, $v_t = s_0, s_1, s_2$ in March, April, and May 2020, and $v_t = 1 + (s_2 - 1)\rho^{\tau-3}$ in the τ th month after February 2020 for $\tau \geq 4$ (Lenza and Primiceri, 2022). Dividing each month's observation and regressors by v_t gives a homoskedastic model, and the log marginal likelihood of the data adds $-n \sum_t \log v_t$. The scales and ρ are selected with the prior hyperparameters at the joint posterior mode, with Pareto priors on the scales and a beta prior with mode 0.8 and standard deviation 0.2 on ρ . The narrative restrictions are unaffected by the scale of a month's innovations, which multiplies every shock of the month alike, and the historical decompositions use the shocks at their scale.

Variance and historical decompositions. The share of a shock in the forecast error variance of real house prices at horizon H is the sum over $h = 0, \dots, H$ of the squared response of real house prices to that shock, divided by the same sum over all nine shocks. The share of a typical unlabeled shock pools the seven unlabeled shocks, each draw entering once for

each of them with a seventh of its weight. The historical contribution of a shock is the path of real house prices from simulating the model from the first usable month, with zero initial conditions and without the constant, driven by that shock’s realizations alone. Driven by all the innovations, the same simulation gives the data less the deterministic component that the initial conditions and the constant imply. Posterior medians and credible sets use the importance weights of the draws that satisfy the narrative restrictions.

Counterfactual rules. Write the rule as the equation of the policy rate, with coefficient $\psi_{k,\ell}$ on variable k at lag ℓ , so that $\psi_{k,0} = \psi_k$. For the rule a month sooner, $\psi_{k,\ell}$ for real house prices and the price-rent ratio takes the estimated value of $\psi_{k,\ell+1}$, and $\psi_{k,6} = 0$. For the lean, $\psi_{k,0}$ for real house prices rises by 2 basis points per 1 percent and $\psi_{k,1}$ falls by as much, a response to the month’s change. For the rule a month later, used with house prices in the rule, $\psi_{k,\ell}$ takes the estimated value of $\psi_{k,\ell-1}$, $\psi_{k,0} = 0$, and the new $\psi_{k,6}$ is the sum of the estimated $\psi_{k,5}$ and $\psi_{k,6}$, so that the coefficients keep their sum. The other eight structural equations are unchanged. The history is simulated from the actual initial conditions with the estimated structural shocks, which reproduces the data under the estimated rule.

Predictive densities of the surprise series. For a surprise series z_t observed in T_z announcement months, the measurement equation is $z_t = \beta u_{\text{mp},t} + \eta_t$ with $\beta > 0$ and normal errors, under a Zellner g prior with $g = T_z$. Its marginal likelihood given each draw’s policy shocks is available in closed form, and averaging it over the posterior draws of an identification, with the draws’ importance weights, gives the predictive density of the series. The ratio of these densities across identifications is a Bayes factor for the identifications given the macroeconomic data, with Monte Carlo standard errors from 200 bootstrap resamples of the draws.

C Additional Results

Table C1 adds the episodes one at a time under both identifications, Table C2 collects the market-based evidence of Section 6.2, Table C3 imposes months chosen without reference to house prices, Table C4 varies the specification of the baseline (Section 6.3), and Table C5 gives the variance decompositions of Section 5.1 at one, two, and five years. With house prices out of the rule, no single episode leaves real house prices below baseline at two years in more than 59 percent of the posterior. When the rule may respond to house prices, June 2022 on its own gives 86 percent, more than the five episodes together. The market-based surprises read the monetary episodes differently, in standard deviations of their announcement months. In February 1994 the surprises of Bu et al. (2021) and Bauer and Swanson (2023) were 2.4 and 2.5. In June 2013 only the first records a tightening, of 1.2, while the second and that

of Nakamura and Steinsson (2018) are close to zero, at -0.1 and 0.1 . In June 2022 the first records an easing of -3.1 , as yields fell when an increase that markets had priced in was announced, and the third a tightening of 1.5 .

Table C1: The house price response, episode by episode

	House prices out of the rule					House prices in the rule				
	Sign		Sign and majority			Sign		Sign and majority		
	Pr	Trough	Pr	Trough	ESS	Pr	Trough	Pr	Trough	ESS
February 1994	36	-0.01	30	0.01	31,653	48	-0.10	61	-0.19	120,201
September 2007	36	-0.01				48	-0.10			
June 2013	40	-0.02	45	-0.02	28,209	49	-0.10	50	-0.06	100,081
July 2020	35	-0.01				44	-0.06			
June 2022	45	-0.05	59	-0.12	25,424	68	-0.42	86	-0.85	160,029
All five	47	-0.06	48	-0.03	1,381	68	-0.38	79	-0.34	4,819

Notes: Probability, in percent, that real house prices are below baseline 24 months after a 25-basis-point tightening, and the posterior median trough of their response over three years, in percent, when each episode's narrative restrictions are added to the sign and rule restrictions, on the same draws, with exact importance weights. Within each panel, the Sign columns impose the sign of the episode's shock, and the Sign and majority columns add the majority attribution of the monetary episodes. The housing episodes carry no attribution. ESS is the effective sample size.

Table C2: Evidence from market-based surprises

<i>A. External instruments, months through 2007</i>						
	Pr below at 24 months	Trough	Ratio to output	Variance share	F , months through 2007	F , all months
Bu, Rogers, and Wu	38	0.00 [−0.35, 0.07]	−0.1 [−0.5, 2.8]	1.9 [0.3, 7.8]	11.1	2.7
Bauer and Swanson	69	−0.22 [−0.70, 0.00]	3.3 [0.1, 9.8]	1.9 [0.2, 7.7]	16.1	2.5
Nakamura and Steinsson	32	0.00 [−0.33, 0.06]	−0.1 [−0.8, 3.0]	1.6 [0.3, 5.8]	8.6	0.9
<i>B. Log Bayes factors relative to house prices out of the rule</i>						
	House prices in the rule		Nowcasting timing		Months	
	Log factor	s.e.	Log factor	s.e.		
Bu, Rogers, and Wu, to 2007	−0.47	0.04	−0.06	0.04	112	
all months	−0.41	0.03	−0.41	0.03	236	
Bauer and Swanson, to 2007	1.60	0.09	−0.09	0.06	170	
all months	0.68	0.10	−0.65	0.08	266	
Nakamura and Steinsson, to 2007	−0.33	0.04	0.11	0.05	104	
all months	−0.38	0.03	−0.10	0.03	231	

Notes: Panel A uses each surprise series as an external instrument for the policy rate ([Stock and Watson, 2018](#)) over the months through 2007, for 2,000 draws of the reduced form with a moving-block bootstrap ([Jentsch and Lunsford, 2022](#)) of the instrument’s covariance, with responses scaled to a 25-basis-point tightening. It reports the probability that real house prices are below baseline at 24 months, the median trough and its ratio to the trough of output, the median share of the forecast error variance of real house prices at two years, with 68 percent sets below the medians, and the first-stage F statistics with Newey-West standard errors over the months through 2007 and over all months. The threshold of [Montiel Olea and Pflueger \(2013\)](#) for a bias of at most 10 percent is 23.1. Panel B gives, for each surprise series and number of announcement months, the log Bayes factor of each identification relative to the baseline, with the five narrative episodes and majority attributions ([Appendix B](#)), positive when the series favors the alternative, and its bootstrap standard error.

Table C3: Months chosen without reference to house prices

	Pr below at 24 months	Response at 24 months	Trough	Variance share	ESS
<i>A. Events of Antolín-Díaz and Rubio-Ramírez (2018) in the sample</i>					
All six events	26	0.14	0.01	1.1	1,836
<i>B. Months of large surprises in two of three series</i>					
February 1994, tightening	30	0.15	0.01	1.2	31,653
July 1995, easing	11	0.52	0.01	3.2	492
June 2001, tightening	31	0.25	−0.01	1.3	26,079
June 2003, tightening	27	0.40	0.01	1.3	22,789
January 2004, tightening	46	0.05	−0.08	0.9	26,091
September 2007, easing	41	0.12	−0.05	1.1	19,789
March 2008, tightening	58	−0.12	−0.18	1.1	1,457
September 2008, tightening	49	0.01	−0.19	0.9	42 [†]
March 2022, tightening	53	−0.05	−0.13	1.0	8,947

Notes: Each row imposes the listed months with their signs and majority attributions on the sign and rule restrictions of the baseline, with exact importance weights. The first row imposes the six events of the monetary application of [Antolín-Díaz and Rubio-Ramírez \(2018\)](#) that fall in the sample. The other rows impose, one at a time, the nine months in which at least two of the three surprise series of [Table C2](#) exceed two standard deviations with the same sign. Columns as in [Table 2](#). ESS is the effective sample size, and [†] marks effective samples below 100.

Table C4: Other specifications of the baseline

	Pr below at 24 months	Trough	Ratio to output	Variance share	Boom	Pandemic surge	ESS
Baseline	48	−0.03 [−0.26, 0.02]	0.3	0.7	−0.1 [−4.6, 3.9]	0.3 [−3.0, 3.4]	1,381
Ending in December 2019	32	−0.01 [−0.26, 0.04]	0.2	1.0	−2.1 [−10.9, 4.8]	− [−, −]	1,585
1987 to 2007, February 1994	59	−0.13 [−0.51, 0.04]	0.8	1.0	10.6 [−0.3, 26.9]	− [−, −]	4,246
Three lags	54	−0.10 [−0.28, 0.02]	0.5	1.0	0.4 [−5.4, 6.0]	1.5 [−2.9, 6.3]	122
Twelve lags	28	0.00 [−0.14, 0.02]	0.0	1.2	1.1 [−5.3, 8.2]	−0.2 [−3.7, 4.0]	684
Unadjusted prices and rents	41	−0.12 [−0.25, −0.02]	0.8	1.1	0.5 [−5.0, 6.6]	0.3 [−3.1, 4.6]	732
Industrial production	27	0.00 [−0.13, 0.03]	0.0	1.1	1.1 [−4.4, 8.9]	−0.3 [−4.4, 3.3]	469
Without September 2007	49	−0.04 [−0.28, 0.02]	0.3	0.7	0.0 [−4.3, 4.1]	0.3 [−3.0, 3.5]	4,149
Without July 2020	50	−0.04 [−0.28, 0.02]	0.3	0.8	0.0 [−4.3, 4.1]	0.4 [−2.9, 3.6]	2,823

Notes: The baseline identification, with house prices out of the rule within the month, and the five narrative episodes with majority attributions, with exact importance weights, except that the sample ending in December 2019 imposes February 1994, September 2007, and June 2013, the sample from 1987 to December 2007 imposes February 1994 alone, and the last two rows drop one housing episode. In the row with industrial production, output is industrial production. Columns as in Table 2, with the contributions of monetary policy shocks to the boom and the pandemic surge, in log points, and 68 percent credible sets below the trough and the contributions. ESS is the effective sample size.

Table C5: Variance decompositions of real house prices

	House prices out of the rule		House prices in the rule	
	Majority	Largest contributor	Majority	Largest contributor
Monetary policy shock				
one year	0.5 [0.1, 1.8]	0.6 [0.1, 3.1]	3.9 [0.4, 14.1]	10.6 [2.2, 26.5]
two years	0.7 [0.1, 2.8]	0.8 [0.1, 4.6]	3.6 [0.4, 13.6]	10.3 [1.8, 24.4]
five years	1.1 [0.2, 4.2]	1.1 [0.2, 5.3]	3.2 [0.4, 12.8]	6.9 [1.2, 20.6]
Housing demand shock				
one year	14.6 [4.2, 32.4]	13.0 [2.2, 30.6]	13.7 [3.9, 31.6]	13.2 [3.8, 30.8]
two years	15.1 [3.6, 34.5]	13.6 [1.5, 32.2]	14.4 [3.6, 33.5]	14.1 [3.4, 31.9]
five years	14.6 [3.0, 35.0]	12.8 [1.2, 31.5]	13.7 [2.7, 34.0]	13.7 [2.7, 32.4]
A typical unlabeled shock				
one year	6.1 [0.7, 23.8]	6.2 [0.7, 23.4]	5.8 [0.7, 22.1]	5.2 [0.7, 20.1]
two years	6.2 [0.7, 23.4]	6.2 [0.8, 22.9]	5.7 [0.7, 22.1]	5.4 [0.7, 20.0]
five years	6.1 [0.7, 23.5]	6.2 [0.7, 22.8]	5.8 [0.7, 22.5]	5.4 [0.7, 20.8]
Seven unlabeled shocks together				
one year	84.3 [66.2, 94.9]	85.4 [68.2, 95.5]	78.6 [58.9, 91.6]	71.2 [51.3, 86.1]
two years	82.8 [64.1, 95.0]	84.5 [66.8, 95.2]	78.1 [57.6, 91.6]	72.6 [51.0, 86.9]
five years	83.1 [62.8, 94.8]	84.3 [65.9, 95.2]	79.5 [57.6, 92.7]	73.9 [54.1, 89.2]
Effective sample size	1,381	175	4,819	360

Notes: Posterior medians, with 68 percent credible sets below them, of the shares of each shock or group of shocks in the forecast error variance of real house prices over horizons 0 to 12, 0 to 24, and 0 to 60 months, in percent, with the five narrative episodes and exact importance weights. A typical unlabeled shock pools the seven unlabeled shocks. Majority and largest contributor as in Table 1. ESS is the effective sample size.