Online Appendix

Supplementary Material for

Time-varying interactions between monetary and housing credit policy

Giacomo Rella

October 7, 2025

Appendix A. Data appendix

The following variables are used in the article (see also Table A.1):

- Shadow federal funds rate:
  - Units: percent.
  - Frequency: monthly.
  - Source: Wu and Xia (2016).
- Excess bond premium:
  - Units: percent.
  - Frequency: monthly.
  - Source: Gilchrist and Zakrajšek (2012).
- Consumer price index:
  - Units: index (1984=100).
  - Frequency: monthly.
  - Source: McCracken and Ng (2016) (FRED code: CPIAUCSL).
- Commodity price index: all items:
  - Units: index.
  - Frequency: monthly.
  - Source: Miranda-Agrippino and Ricco (2021).
- Industrial production index:
  - Units: index (2012=100).
  - Frequency: monthly.
  - Source: McCracken and Ng (2016) (FRED code: INDPRO)
- Residential mortgage debt:
  - Units: millions of 1984 dollars (deflated using the consumer price index).
  - Frequency: monthly
  - Source: Fieldhouse, Mertens, and Ravn (2018).
- Mortgage originations:
  - Units: millions of 1984 dollars (deflated using the consumer price index), seasonally adjusted.
  - Frequency: monthly
  - Source: Fieldhouse, Mertens, and Ravn (2018).
- Purchase originations:
  - Units: millions of 1984 dollars (deflated using the consumer price index), seasonally adjusted.
  - Frequency: monthly
  - Source: Fieldhouse, Mertens, and Ravn (2018).
- Refinancing originations:
  - Units: millions of 1984 dollars (deflated using the consumer price index), sea-

sonally adjusted.
  - Frequency: monthly
  - Source: Fieldhouse, Mertens, and Ravn (2018).
- Agency purchases as share of originations:
  - Units: millions of 1984 dollars (deflated using the consumer price index), seasonally adjusted.
  - Frequency: monthly
  - Source: Fieldhouse, Mertens, and Ravn (2018).
- Housing starts: total new privately owned:
  - Units: thousands of units, seasonally adjusted annual rate.
  - Frequency: monthly.
  - Source: McCracken and Ng (2016) (FRED code: HOUST)
- New one family homes for sale:
  - Units: thousands of units, seasonally adjusted.
  - Frequency: monthly.
  - Source: US Department of Housing and Urban Development (FRED code: HNFSEPUSSA)
- New one family houses sold:
  - Units: thousands of units, seasonally adjusted annual rate.
  - Frequency: monthly.
  - Source: US Department of Housing and Urban Development (FRED code: HSN1F)
- Construction employment:
  - Units: thousands of persons, seasonally adjusted.
  - Frequency: monthly.
  - Source: US Bureau of Labor Statistics, Employment Situation (FRED code: USCONS)

TABLE A.1. Dataset

Series	Units	T	Source
A. Macroeconomic and financial variables			
Shadow federal funds rate	Percent	1	Wu and Xia (2016)
Excess bond premium	Percent	1	Gilchrist and Zakrajšek (2012)
Consumer price index	1984=100	5	McCracken and Ng (2016)
Commodity price index	Index	5	Miranda-Agrippino and Ricco (2021)
Industrial production	2012=100	5	McCracken and Ng (2016)
B. Mortgage credit variables			
Residential mortgage debt	Mil. of 1984$	5	Fieldhouse, Mertens, and Ravn (2018)
Mortgage originations	Mil. of 1984$	5	Fieldhouse, Mertens, and Ravn (2018)
Purchase originations	Mil. of 1984$	5	Fieldhouse, Mertens, and Ravn (2018)
Refinancing originations	Mil. of 1984$	5	Fieldhouse, Mertens, and Ravn (2018)
Mortgage purchases as share of originations	Percent	1	Fieldhouse, Mertens, and Ravn (2018)
C. Housing variables			
Housing starts	1000 units	5	McCracken and Ng (2016)
Homes for sale	1000 units	5	FRED-HUD
Houses sold	1000 units	5	FRED-HUD
Construction employment	1000 units	5	FRED-BLS

Notes: Residential mortgage debt includes single-family (1-to-4) home mortgages and multifamily residential mortgages. Mortgage origination is total originations of long-term mortgage loans for 1-to-4 nonfarm homes and multifamily residential properties. T stands for Transformation code. T = 1 means no tran=sformation (levels), T = 5 means first difference of logarithm, T = 6 means second difference of logarithm. FRED = Federal Reserve Economic Data, HUD = US Department of Housing and Urban Development, BLS = US Bureau of Labor Statistics.

Appendix B. Tests for structural change

This Appendix report the results of two structural break tests. The first is a Chow test for breaks at two key dates: the onset of the Great Recession (2007M12) and the start of the QE program (2008M11). The second is the Bai and Perron (1998) test for multiple structural changes at unknown dates. All structural break tests are conducted, separately, on the following two regressions:

$$y_t = \alpha + \gamma(L)\mathbf{x}_t + \beta z_t + u_t, \tag{B1}$$

$$\Delta y_t = \alpha + \gamma(L)\Delta\mathbf{x}_t + \beta z_t \quad \text{with} \quad \Delta y_t = y_t - y_{t-1} \tag{B2}$$

where y is one of the mortgage credit variables studied in the paper (mortgage debt, mortgage originations, purchase originations, refinancing originations, and GSEs' mortgage purchases as a share of originations). The vector $\mathbf{x}$ includes all other variables used in the VAR (shadow federal funds rate, excess bond premium, consumer price index, commodity price index, and industrial production) with $L = 3$ lags, consistent with the VAR specification, while z are monetary policy surprises. I conduct the texts on the specification in levels and first differences. I test for the structural stability of all parameters in the regression, including the constant term. Each regression represents a mortgage credit variable equation in the VAR models. All tests are implemented using the **xtbreak** command by Ditzen, Karavias, and Westerlund (2021).

Table B.1 reports the results of the Chow test. The Bai and Perron (1998) results are shown in Table B.2 and Table B.3. Table B.2 reports the test of the null hypothesis of no breaks against the alternative of an unknown number of breaks (between 1 and s_{max}). To ensure sufficient subsample length, I allow for a maximum of five breaks. The test statistic (UDmax) is compared with the 5% critical value provided by Bai and Perron (1998). Table B.3 reports the results of the sequential procedure applied to the multiple breaks identified in Table B.2. The procedure works as follows:

a. The null hypothesis of no breaks is tested against the alternative of a single break. If the null cannot be rejected, the search for further breakpoints stops.
b. If the null is rejected, the breakpoint is estimated and the sample is split into two at the estimated breakpoint.
c. For each subsample, the null of no breaks is tested against the alternative of a single break. If no further break is found, the process stops with the existing breaks. Otherwise, new breakpoints are estimated, and the sample is split again.
d. This process continues until the null cannot be rejected.

Accordingly, Table B.2 reports the number and location of breakpoints, when found. Figure B1 plots the peak impulse responses together with any detected break dates.

According to the Chow test, both the onset of the Great Recession and the introduction of QE are structural breaks in the mortgage credit equations in the VAR. This is especially true for purchase originations and GSEs' mortgage purchases. The detection of these structural breaks is consistent with the importance of these events. The Bai and Perron (1998) test, however, suggests that the Great Recession and the introduction of QE are not the only events driving structural change in the mortgage credit equations in the VAR. For all equations tested, structural breaks cluster around specific intervals: 1994–95, 1998–99, 2002–03, 2005–07, and 2009–11. This suggests that time variation is driven by more than just a few major breaks, such as the mortgage debt crisis, the Great Recession, and the introduction of QE. Still, these events are all detected by the Bai and Perron (1998) test, confirming their role as important sources of structural change, albeit not the only ones. The fact that numerous structural breaks are identified, with some not directly linked to major economic events, reinforces the choice of using a general nonlinear model, such as a TVP-VAR with parameters that change smoothly over time. Several other breaks align with turning points in the time-varying effects of monetary policy and, in some cases, with notable developments in housing credit policy. For instance, one factor likely contributing to the breaks in 1994–95 is the introduction of the 1995 Affordable Housing Credit Goals.

TABLE B.1. Chow test

Equation	Date	T	F-statistics	P-value	Decision
Mortgage debt	2007M12	L	1.54	0.07	Cannot reject H_0
	2007M12	D	2.33	0.00	Reject H_0
	2008M11	L	0.97	0.50	Cannot reject H_0
	2008M11	D	1.28	0.19	Cannot reject H_0
Mortgage originations	2007M12	L	1.60	0.05	Reject H_0
	2007M12	D	0.96	0.52	Cannot reject H_0
	2008M11	L	0.70	0.82	Cannot reject H_0
	2008M11	D	0.60	0.92	Cannot reject H_0
Purchase originations	2007M12	L	2.72	0.00	Reject H_0
	2007M12	D	1.82	0.02	Reject H_0
	2008M11	L	3.01	0.00	Reject H_0
	2008M11	D	1.73	0.03	Reject H_0
Refinancing originations	2007M12	L	1.28	0.19	Reject H_0
	2007M12	D	0.72	0.80	Cannot reject H_0
	2008M11	L	0.60	0.91	Cannot reject H_0
	2008M11	D	0.39	0.99	Cannot reject H_0
Mortgage purchases (%, originations)	2007M12	L	15.04	0.00	Reject H_0
	2007M12	D	12.66	0.00	Reject H_0
	2008M11	L	5.35	0.00	Reject H_0
	2008M11	D	3.38	0.00	Reject H_0

Notes: H_0: no break at date τ, H_1: s breaks at date τ. Test executed using Stata command **xtbreak** (Ditzen, Karavias, and Westerlund 2021).

TABLE B.2. Test for multiple breaks at unknown break dates

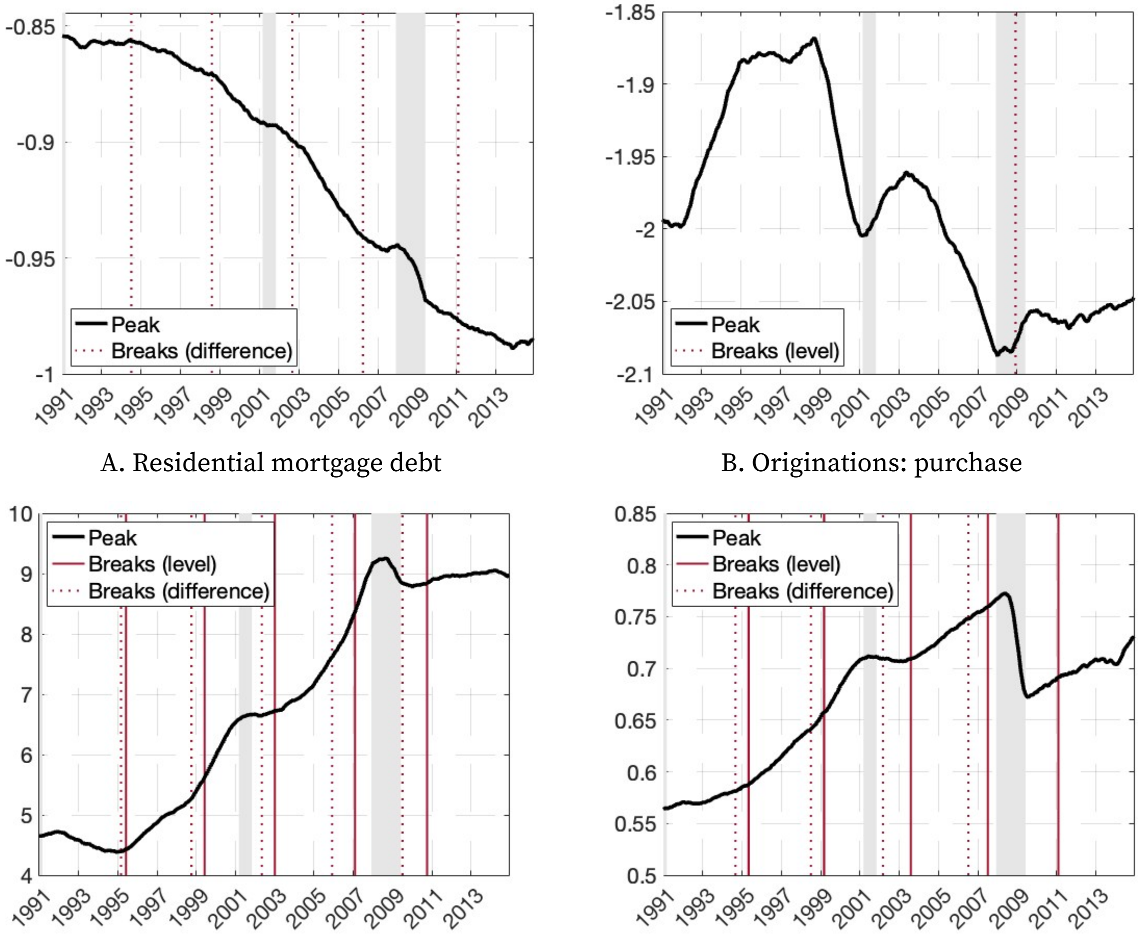
Equation	T	Test statistics	5% c.v.	Decision
B. Augmented models				
Mortgage debt	L	2.40	2.72	Cannot reject H_0
	D	3.29	2.72	Reject H_0
Mortgage originations	L	2.64	2.72	Cannot reject H_0
	D	1.76	2.72	Cannot reject H_0
Purchase originations	L	3.20	2.72	Reject H_0
	D	2.07	2.72	Cannot reject H_0
Refinancing originations	L	3.61	2.72	Reject H_0
	D	3.12	2.72	Reject H_0
Mortgage purchases (%, originations)	L	68.27	2.72	Reject H_0
	D	18.79	2.72	Reject H_0

Notes: H_0: no breaks, H_1: between 1 and s_{max} breaks, with s_{max} break. Implementation of Bai and Perron (1998) test using Stata command **xtbreak** (Ditzen, Karavias, and Westerlund 2021).

TABLE B.3. Sequential test for multiple breaks at unknown break dates

Equation	T	Breaks	Break dates
Mortgage debt	L	0	Cannot estimate breakpoints
	D	5	1994M7, 1998M8, 2002M9, 2006M4, 2011M2
Mortgage originations	L	0	Cannot estimate breakpoints
	D	0	Cannot estimate breakpoints
Purchase originations	L	1	2008M12
	D	0	Cannot estimate breakpoints
Refinancing originations	L	5	1995M6, 1999M6, 2003M1, 2007M2, 2010M10
	D	5	1995M3, 1998M10, 2002M5, 2005M12, 2009M7
Mortgage purchases (%, originations)	L	5	1995M5, 1999M3, 2003M8, 2007M7, 2011M2
	D	6	1994M9, 1998M7, 2002M3, 2005M7, 2011M2

Notes: H_0: s breaks, H_1: $s + 1$ breaks. Test executed using Stata command **xtbreak** (Ditzen, Karavias, and Westerlund 2021).



A. Residential mortgage debt

B. Originations: purchase

C. Originations: refinancing

D. GSEs' mortgage purchases

FIGURE B1. Structural break tests

Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model.

Appendix C. Estimation

The model is estimated using Markov chain Monte Carlo (MCMC) methods, as is standard with TVP-VAR models Primiceri (2005). Let $\boldsymbol{\beta}^{1:t}$ denote the history of parameters in $\boldsymbol{\beta}$ up to and including month $t = 1, \ldots, T$, Gibbs sampling is employed to evaluate the posterior distribution of $\boldsymbol{\beta}^T$ and the elements of $\mathbf{V}$. Bayesian estimation of the model requires specifying prior distributions for the hyperparameters, namely all parameters in $\boldsymbol{\beta}^T$ and $\mathbf{V}$. I follow Primiceri (2005) and Paul (2020), with slight modifications given the data.

The prior distributions are calibrated based on a constant parameter VAR estimated over a training sample of around 13 years (from September 1976 to December 1990). For a significant part of the training sample, the series of monetary policy surprises is unavailable because the futures market started trading in 1988. Thus, I set the surprises to zero for periods with no available data, as in other applications of the exogenous variable approach (Paul 2020). The OLS estimates for the training sample are then used to calibrate the prior distributions, which are assumed to be normal for the unobserved parameters and inverse-Wishart for the covariance matrices of the state equations:

$$
\begin{aligned}
\boldsymbol{\beta}_0 &\sim \mathcal{N}\left(\hat{\boldsymbol{\beta}}_{\mathrm{OLS}}, 4 \cdot V\left(\hat{\boldsymbol{\beta}}_{\mathrm{OLS}}\right)\right) \\
\boldsymbol{\Omega} &\sim \mathcal{IW}\left(\mathbf{I}_n, n+1\right) \\
\mathbf{Q} &\sim \mathcal{IW}\left(\kappa_Q^2 \cdot \tau \cdot V\left(\hat{\boldsymbol{\beta}}_{\mathrm{OLS}}\right), \tau\right)
\end{aligned}
$$

where $\hat{\boldsymbol{\beta}}_{\mathrm{OLS}}$ collects the OLS estimates from the training sample, $V\left(\hat{\boldsymbol{\beta}}_{\mathrm{OLS}}\right)$ is their variance, and $\tau = 169$ is the size of the training sample. The parameter κ_Q specifies the prior belief about the amount of time variation in $\boldsymbol{\beta}_t$ and is set to 0.015. The simulation of the model is based on 5,000 iterations of the Gibbs sampler, with the first 2,000 discarded for convergence. The lag length is set to $p = 3$ to reduce the dimensions of both $\boldsymbol{\beta}_t$ and $\mathbf{Q}$, ensuring convergence, as in other application of the external variable approach in a time-varying setting Paul (2020); Albuquerque, Iseringhausen, and Opitz (2020). The estimation sample runs from January 1991 to December 2014, due to limited availability of monthly mortgage market data.

Once the prior distributions are calibrated, the following steps of the Gibbs sampler are implemented to evaluate the posterior distributions:

a. Initialize $\mathbf{V}$,
b. Sample $\boldsymbol{\beta}^{1:T}$ from $p(\boldsymbol{\beta}^{1:T}|\mathbf{y}^{1:T}, z^{1:T}, \mathbf{V})$,
c. Sample $\mathbf{V}$ by sampling $\boldsymbol{\Omega}$ and $\mathbf{Q}$ from $p(\boldsymbol{\Omega}, \mathbf{Q}|\mathbf{y}^{1:T}, z^{1:T}, \boldsymbol{\beta}^{1:T})$,
d. Repeat step 2,

where $p(\cdot|\cdot)$ denotes the conditional density, $\mathbf{y}^{1:T} = [\mathbf{y}_1, \ldots, \mathbf{y}_T]'$ and $z^{1:T} = [z_1, \ldots, z_T]'$ are the histories of $\mathbf{y}_t$ and z_t for $t = 1, \ldots, T$, respectively.

Appendix D. Sensitivity analysis and further results

In this section, I replicate the main findings of the article using an alternative prior specification and a different monetary policy shock. Moreover, I present further results on time variation and sign-dependent effects of monetary policy.

Priors. In time-varying parameter models, Primiceri (2005) notes that the results may be sensitive to different values of κ_Q. In the sensitivity analysis, I slightly lower κ_Q to 0.01, which reduces the amount of time variation and makes the impulse response functions smoother relative to the baseline results. Figure D1 in Appendix E shows the medium-term response of residential mortgage debt, originations, agency pool issuance, and mortgage purchases to a different value of the parameter κ_Q, which controls the prior belief in the time variation of the model parameters. Overall, the results are qualitatively unchanged and the time variation and magnitude of the effects of monetary policy remain largely the same.

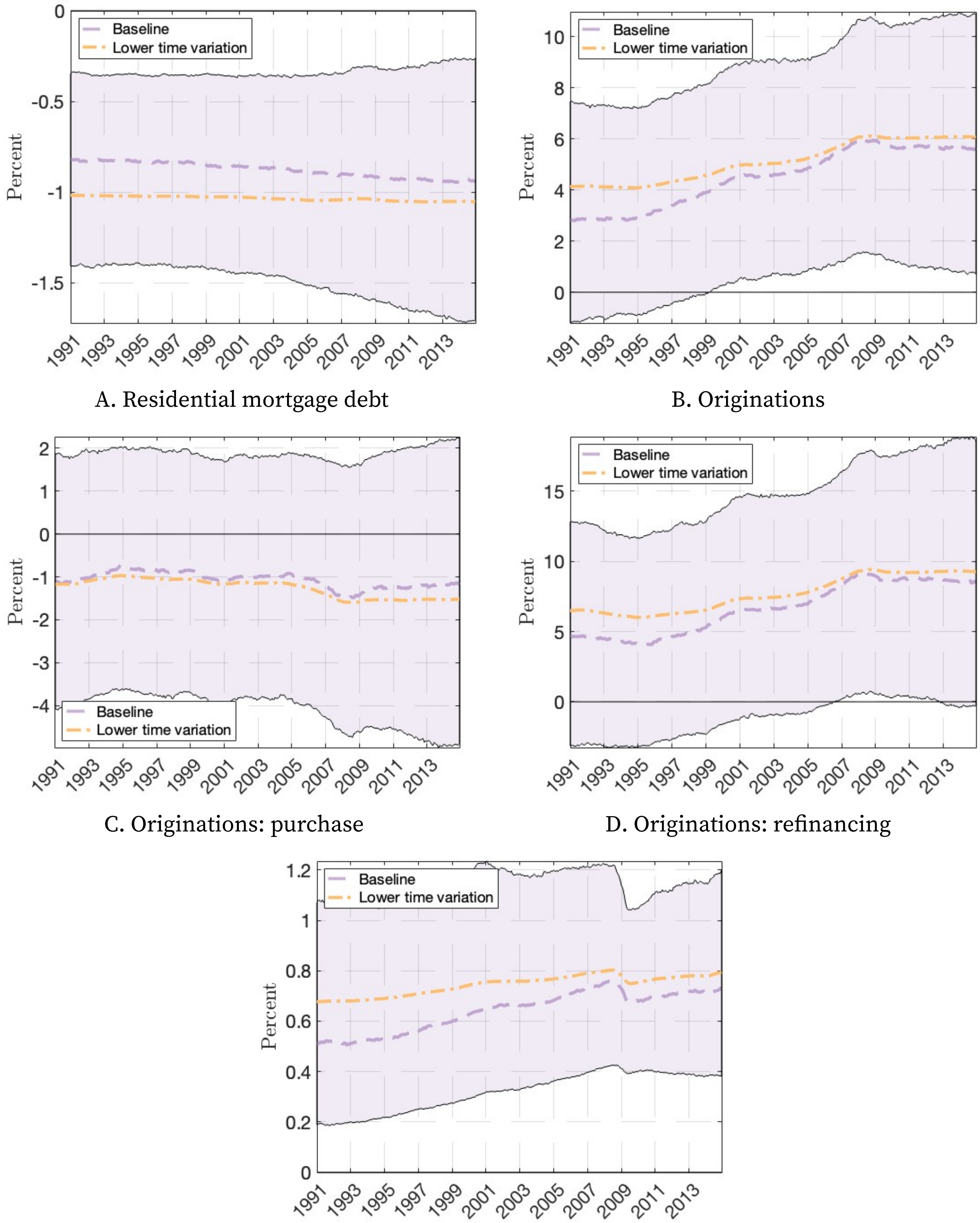
Monetary policy shocks. Throughout the paper, I use the orthogonalized monetary surprise series from Bauer and Swanson (2023) to address the predictability issue in high-frequency monetary policy surprises. Jarociński and Karadi (2020) propose an alternative approach to correct for this predictability issue by separating surprises into two components: a pure monetary policy shock and an information shock. The pure monetary policy shock is identified by the negative co-movement between interest rate and stock price changes around policy announcements. Figure D2 in Appendix E shows the medium-term response of residential mortgage debt, originations, and mortgage purchases when using the monetary policy shocks from Jarociński and Karadi (2020). The results remain qualitatively similar but the magnitude of the impulse responses is smaller compared to the baseline model. For mortgage purchases, the responses even fall outside the credibility intervals of the baseline estimates. These size differences arises from the differences in how the instruments are constructed and from using orthogonalized surprises which produce estimates of monetary policy effects that are purged of attenuation biases.

Uncertainty. To emphasize the trend in the time-varying impact of monetary policy, the main text presents only the median impulse response. However, to fully acknowledge the uncertainty surrounding these time-varying effects, Figures E4 and E5 in Appendix E display the short- and medium-term impulse responses of mortgage credit variables, accompanied by 68% credibility intervals. It's noteworthy that for some variables, despite the lower bound of the chosen interval, zero is often encompassed within the credibility band. Furthermore, Figure D3 illustrates the median differences in impulse responses between the initial period (January 1991) and the final period (December 2014) of the sample. This figure also includes 38%, 68%, and 90% credibility intervals derived from the posterior distribution. Also for the differences, statistical significance often emerges at lower confidence levels than conventionally employed. This characteristic is common to TVP-VAR models, as documented in previous literature (Primiceri 2005; Paul 2020).

State-dependent local projections. To identify episodes of expansionary housing credit policy, I purge GSEs' net commitments of the influence of credit, housing, and macro-financial indicators. As a robustness check, I re-estimate the state-dependent effects of monetary policy using an indicator that captures the stance of housing credit policy according to the narrative approach of Fieldhouse, Mertens, and Ravn (2018). More specifically, if a non-cyclically motivated housing credit policy intervention occurs in month t, then the stance of housing credit policy is classified as expansionary in that month and over the subsequent 12 months. I use a full-year interval following each event to account for implementation delays. Since these events are rare, the narrative-based state variable is extremely sparse. Therefore, I adopt a simpler local projections specification, in which the monetary policy shock is interacted directly with the state variable, rather than allowing all model coefficients to vary by state, as in the main specification (equation 13). This approach reduces the number of state-dependent parameters to estimate. The local projection model I estimate is:

$$\Delta y_{t+h} = \alpha^h + \gamma^h(L)\mathbf{x}t + \beta^h zt + \delta^h z_t I_{t-1} + u_t^h, \tag{D3}$$

where the state-dependent effect is captured by the interaction between the shock and the narrative-based housing credit policy stance indicator. When the stance of housing credit policy is expansionary ($I_{t-1} = 1$), the impulse response function is given by the sum of the linear and interaction terms, i.e., $\beta^h + \delta^h$. Figures D5 and D4 in Appendix E present the results of this robustness check. Each plot reports four impulse responses, derived from different specifications and definitions of the state variable: (1) baseline specification with regression-based state, (2) baseline specification with alternative (narrative-based) state, (3) interaction specification with regression-based state, and (4) interaction specification with alternative state. The baseline specification corresponds to the main state-dependent local projections model (equation 13). In most cases, the result that the effects of monetary policy on mortgage credit variables depend on the stance of housing credit policy is robust to using an alternative approach for identifying policy stance, as well as to a different modeling of state dependence in local projections. When the regression-based indicator is used, the state-dependent effects of monetary policy are qualitatively similar across models. However, there are notable exceptions in which the baseline impulse responses diverge from those in the robustness checks. For example, the impulse responses of mortgage debt, refinancing, house prices, and housing starts diverge across specifications at longer horizons, with the responses based on the narrative-based indicator exhibiting erratic jumps.



A. Residential mortgage debt

B. Originations

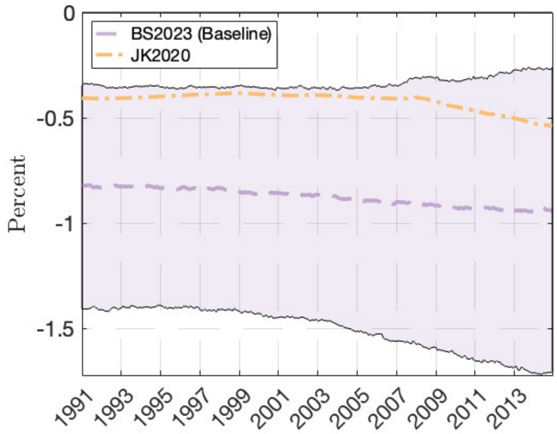
C. Originations: purchase

D. Originations: refinancing

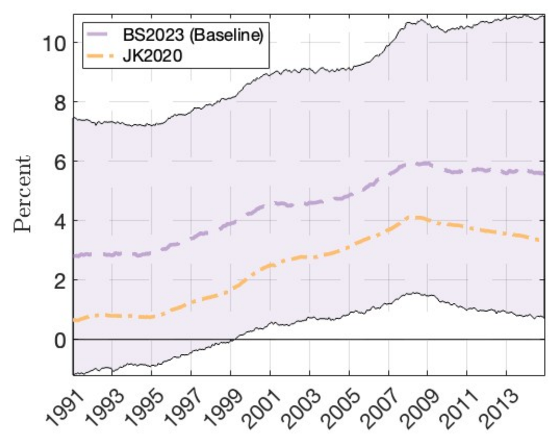
E. Mortgage purchases

FIGURE D1. Time-varying effects of monetary policy: robustness to priors

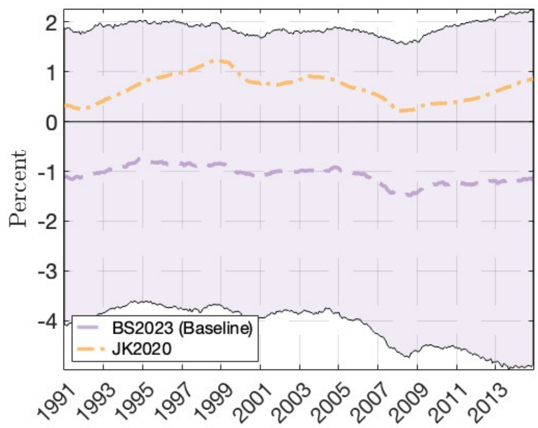
Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model. Median impulse responses along with 68 percent credibility intervals from the posterior distribution. Prior belief about time variation is κ_Q = 0.015 in Baseline and κ_Q = 0.01 in Lower time variation.



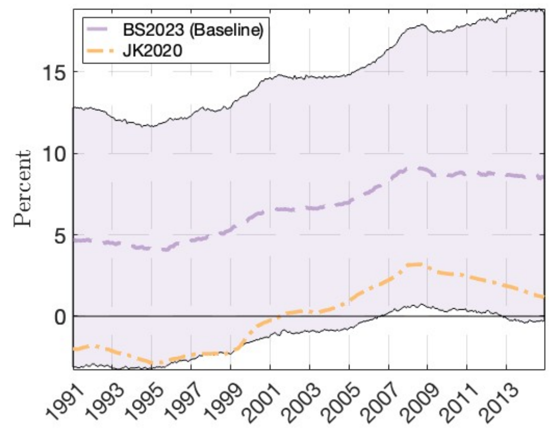
A. Residential mortgage debt



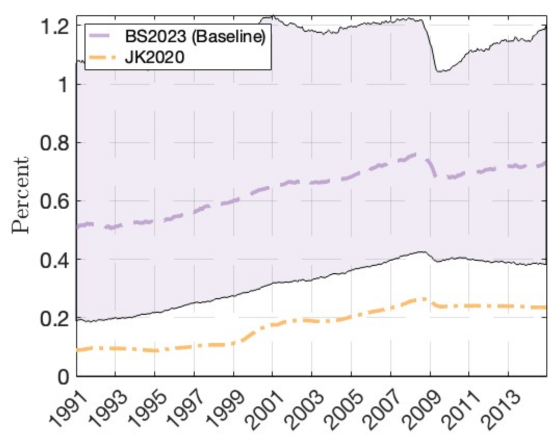
B. Originations



C. Originations: purchase



D. Originations: refinancing



E. Mortgage purchases

FIGURE D2. Time-varying effects of monetary policy: robustness to shock

Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model. Median impulse responses along with 68 percent credibility intervals from the posterior distribution. BS2023 is Bauer and Swanson (2023), JK2020 is Jarociński and Karadi (2020).

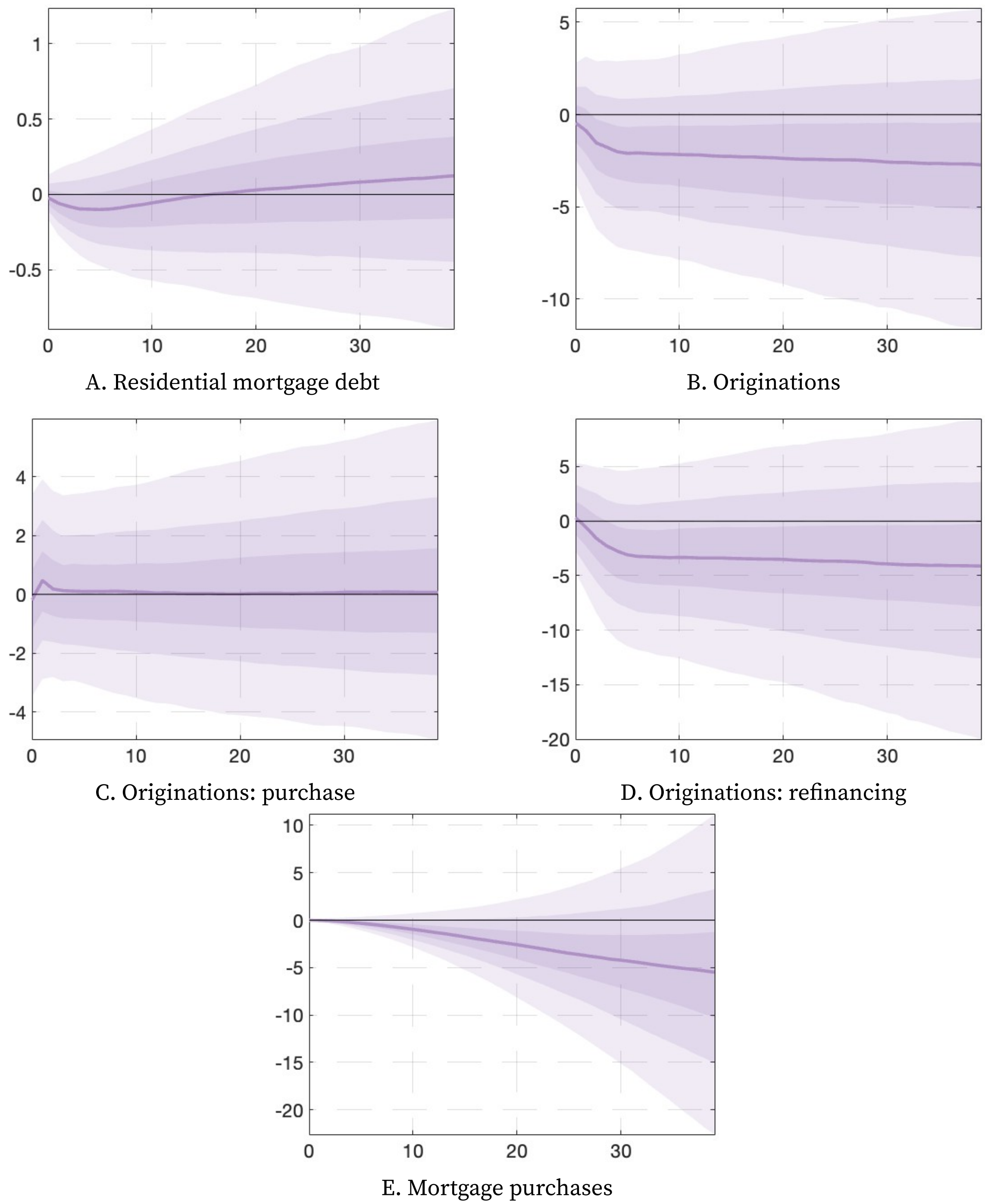
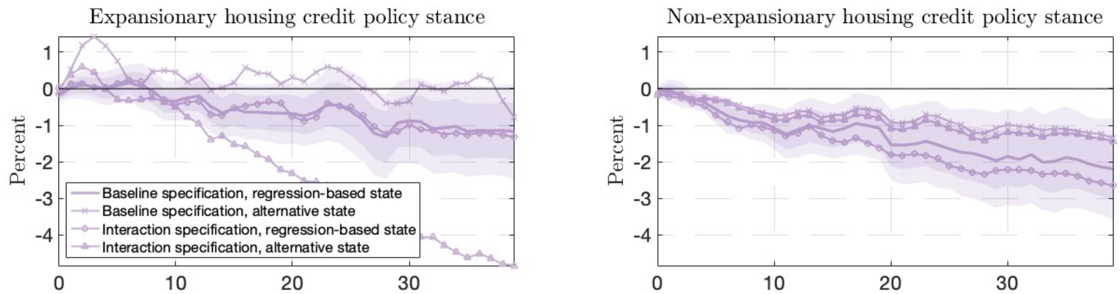
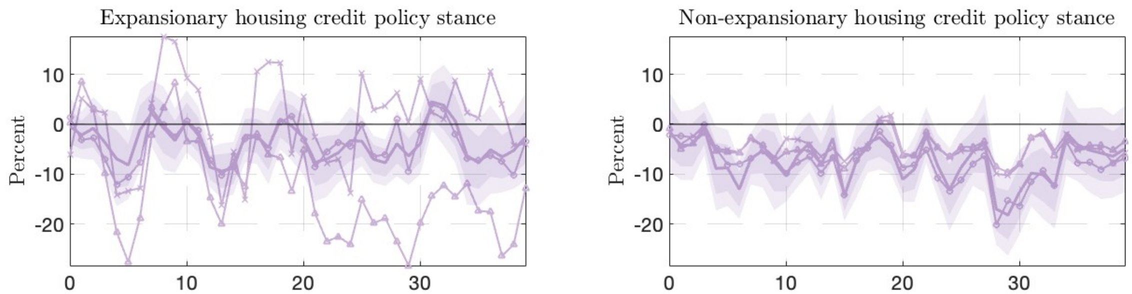


FIGURE D3. Differences in impulse responses (1991M1 - 2014M1)

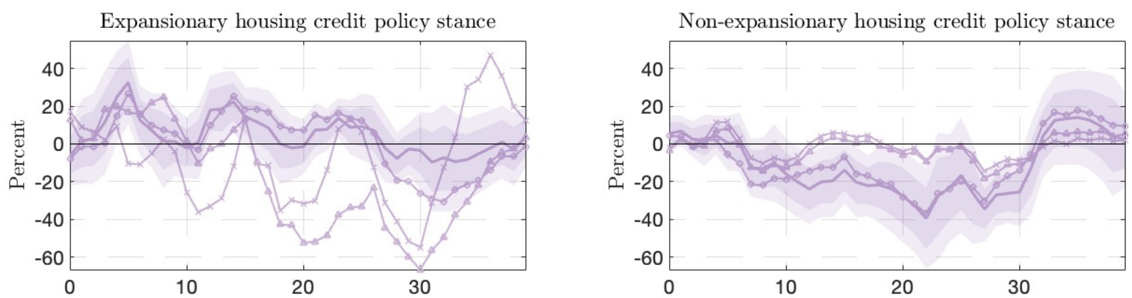
Notes: Median differences in cumulative impulse responses from TVP-VARX model together. Credibility intervals (38, 68, and 90 percent) based on iterations of the Gibbs sampler.



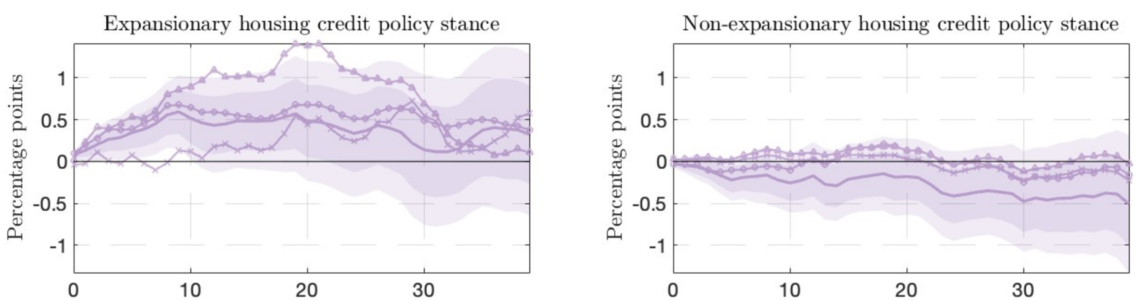
A. Residential mortgage debt



B. Originations: purchase



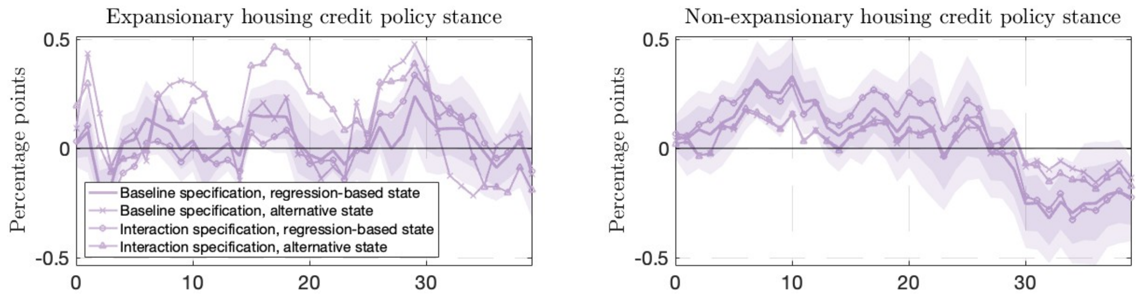
C. Originations: refinancing



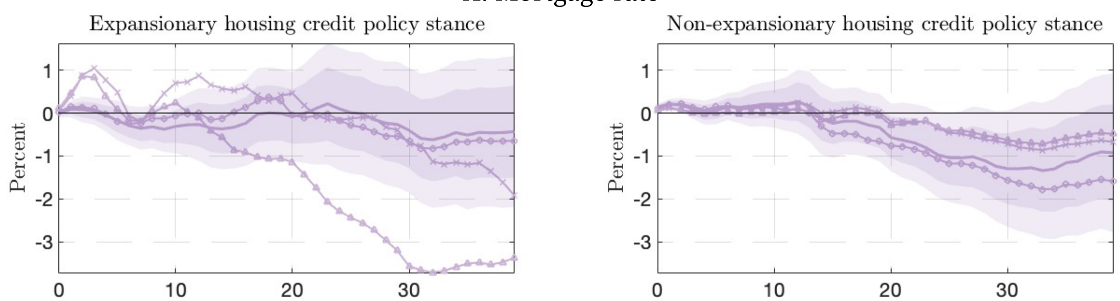
D. GSEs' share of residential mortgage debt

FIGURE D4. State-dependent effects of monetary policy I - robustness

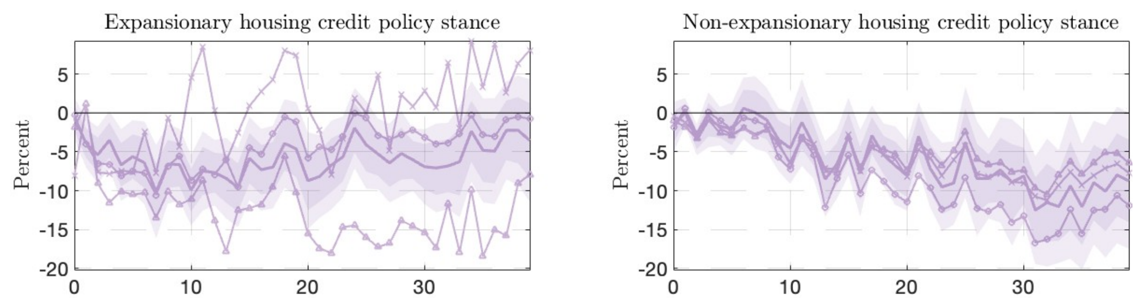
Notes: State-dependent local projections impulse responses to a monetary policy shock that increases the shadow federal funds rate by 0.16 percentage points, as in the macroeconomic proxy-VAR model. Bands are 68 and 90 percent confidence intervals. The left column shows the response in the expansionary housing credit policy stance state, while the right column shows the response in the non-expansionary housing credit policy stance state.



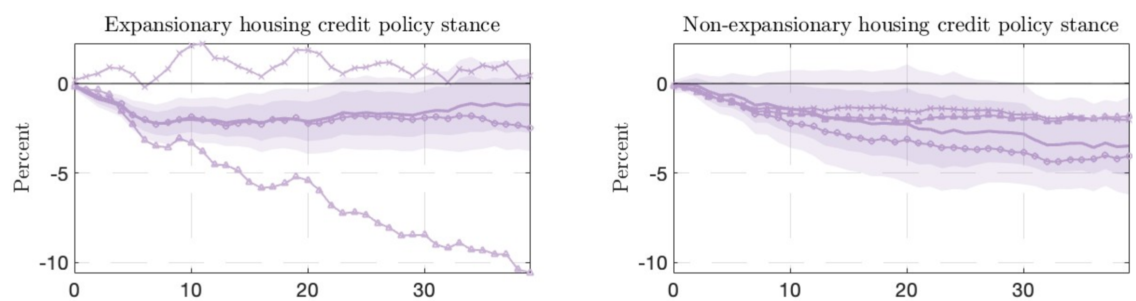
A. Mortgage rate



B. Real house prices



C. Housing starts

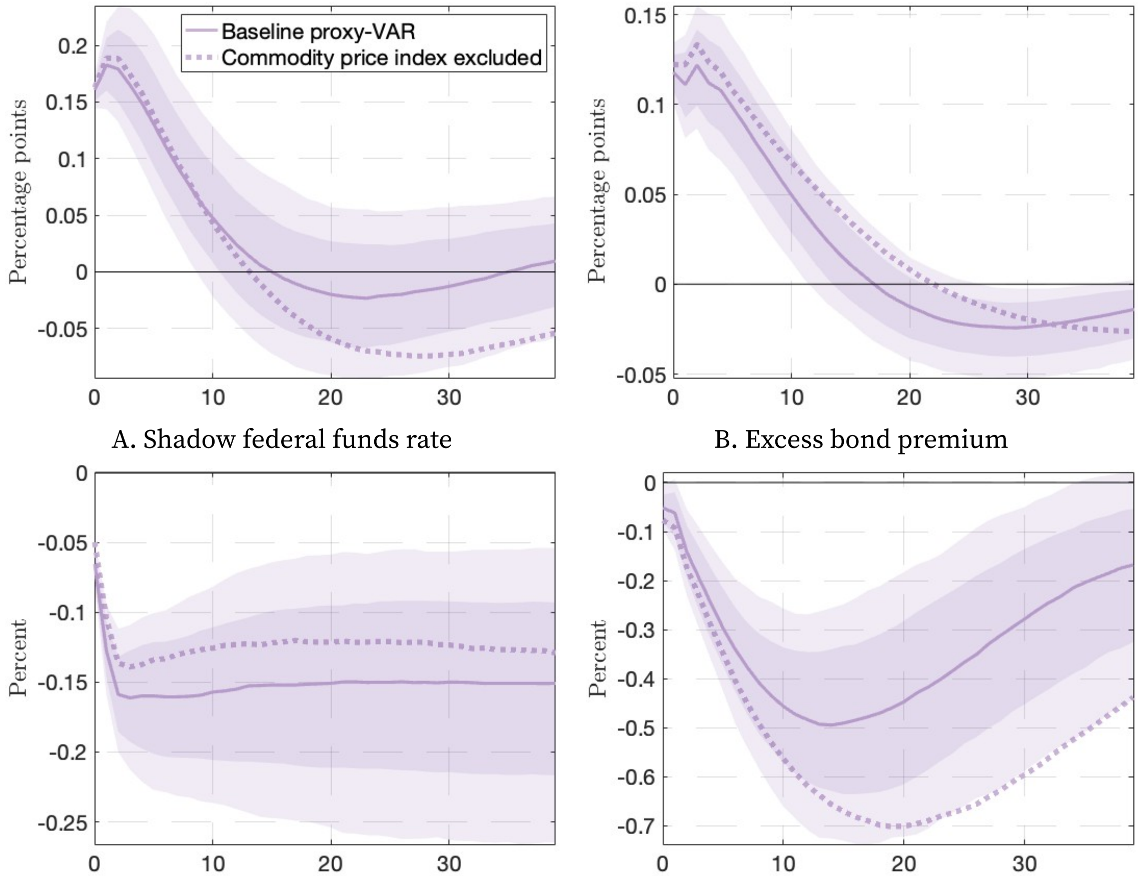


D. Construction employment

FIGURE D5. State-dependent effects of monetary policy II - robustness

Notes: State-dependent local projections impulse responses to a monetary policy shock that increases the shadow federal funds rate by 0.16 percentage points, as in the macroeconomic proxy-VAR model. Bands are 68 and 90 percent confidence intervals. The left column shows the response in the expansionary housing credit policy stance state, while the right column shows the response in the non-expansionary housing credit policy stance state.

Appendix E. Additional figures



A. Shadow federal funds rate

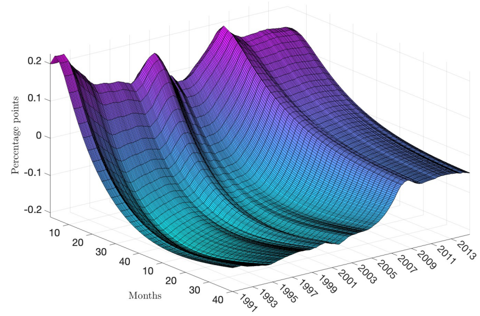
B. Excess bond premium

C. Consumer price index

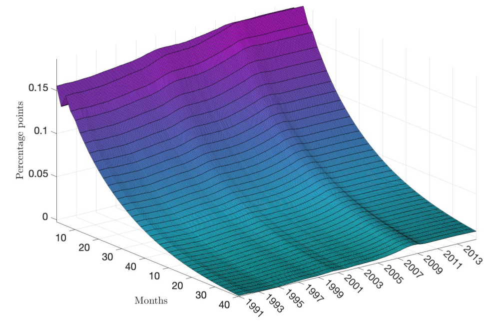
D. Industrial production

FIGURE E1. Macroeconomic effects of monetary policy

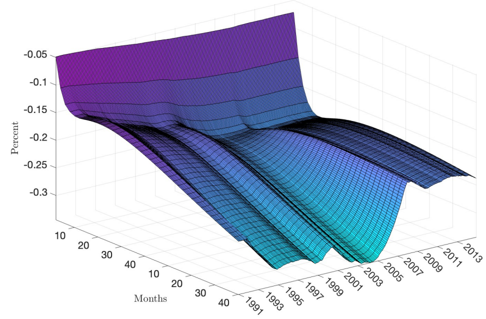
Notes: Impulse responses to a one-standard-deviation contractionary monetary policy shock, median responses along with 68 and 90 percent confidence intervals (proxy-VAR). Confidence bands obtained using the recursive wild bootstrap (Mertens and Ravn 2013). For the VARX, the size of the shock is normalized to match the initial increase in the shadow federal funds rate in the proxy-VAR.



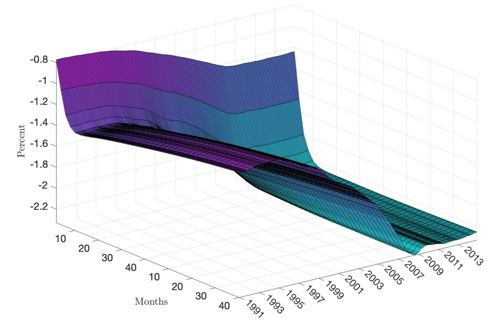
A. Shadow federal funds rate



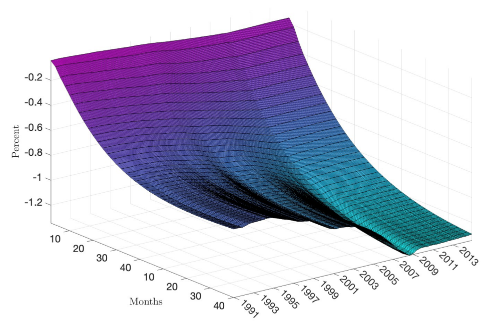
B. Excess bond premium



C. Consumer price index



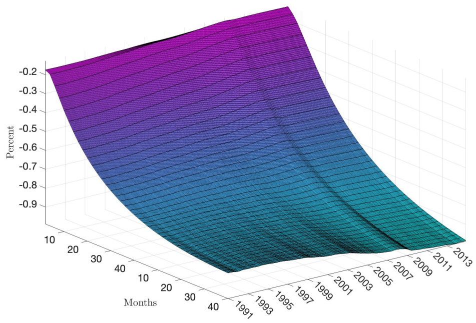
D. Commodity price index



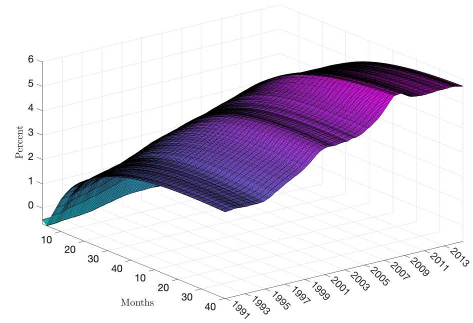
E. Industrial production

FIGURE E2. Time-varying effects of monetary policy on macroeconomic aggregates

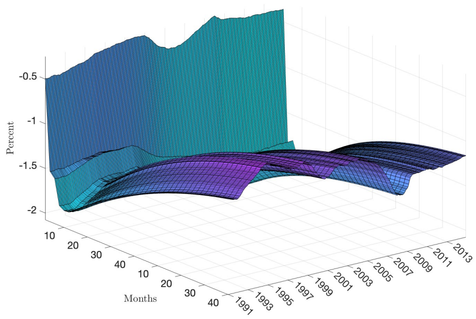
Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model.



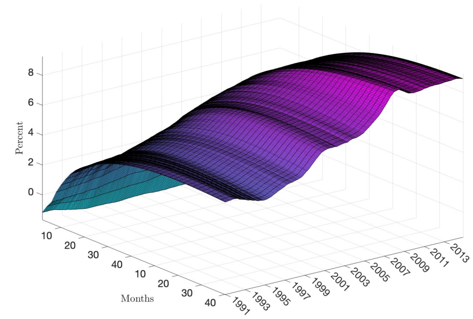
A. Residential mortgage debt



B. Originations



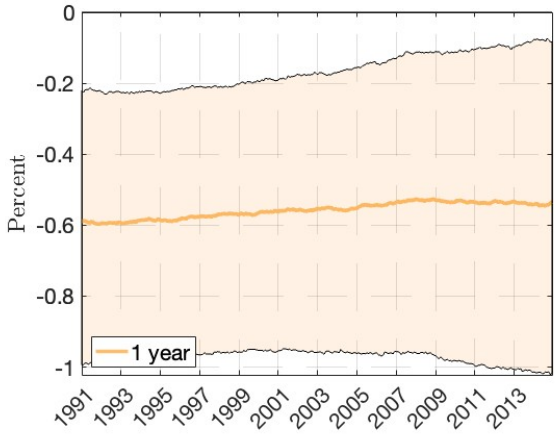
C. Originations: purchase



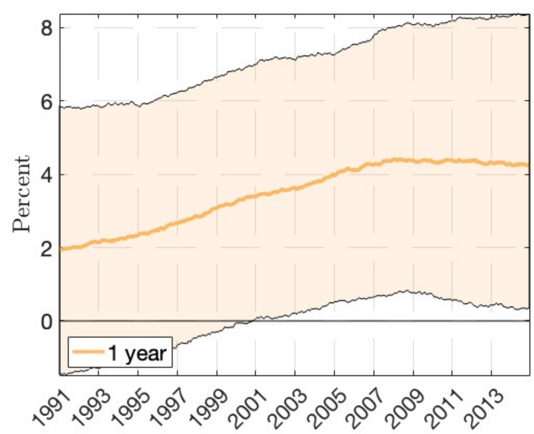
D. Originations: refinancing

FIGURE E3. Time-varying effect of monetary policy on mortgage credit: full impulse responses

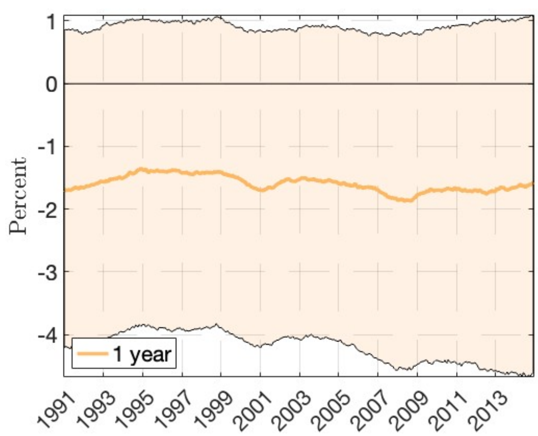
Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model.



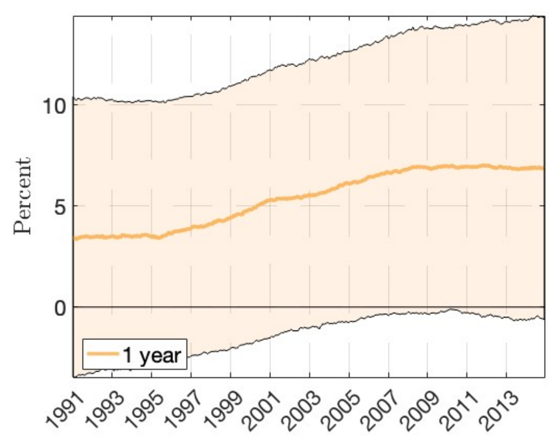
A. Residential mortgage debt



B. Originations



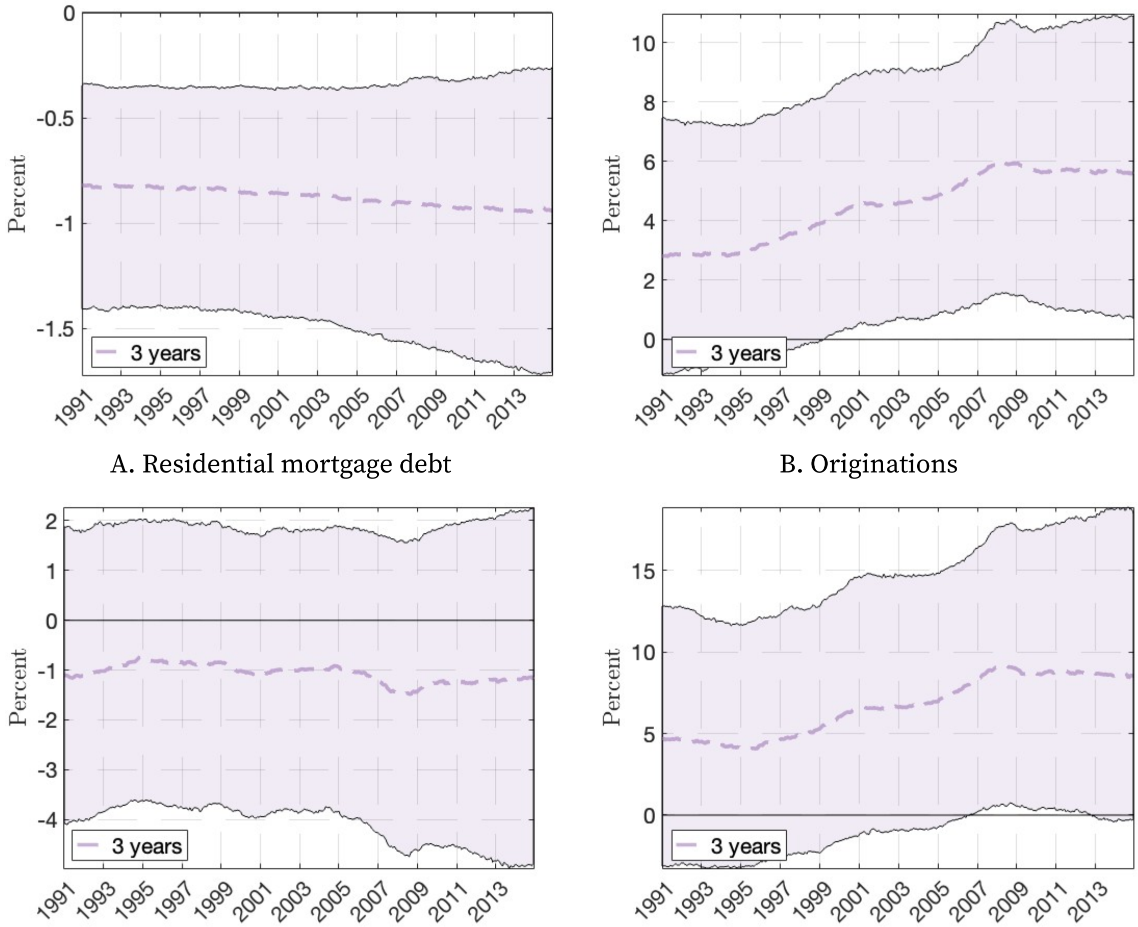
C. Originations: purchase



D. Originations: refinancing

FIGURE E4. Time-varying effects of monetary policy on mortgage credit: short term

Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model. Median impulse responses along with 68 percent credibility intervals from the posterior distribution.



A. Residential mortgage debt

B. Originations

C. Originations: purchase

D. Originations: refinancing

FIGURE E5. Time-varying effects of monetary policy on mortgage credit: medium term

Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model. Median impulse responses along with 68 percent credibility intervals from the posterior distribution.

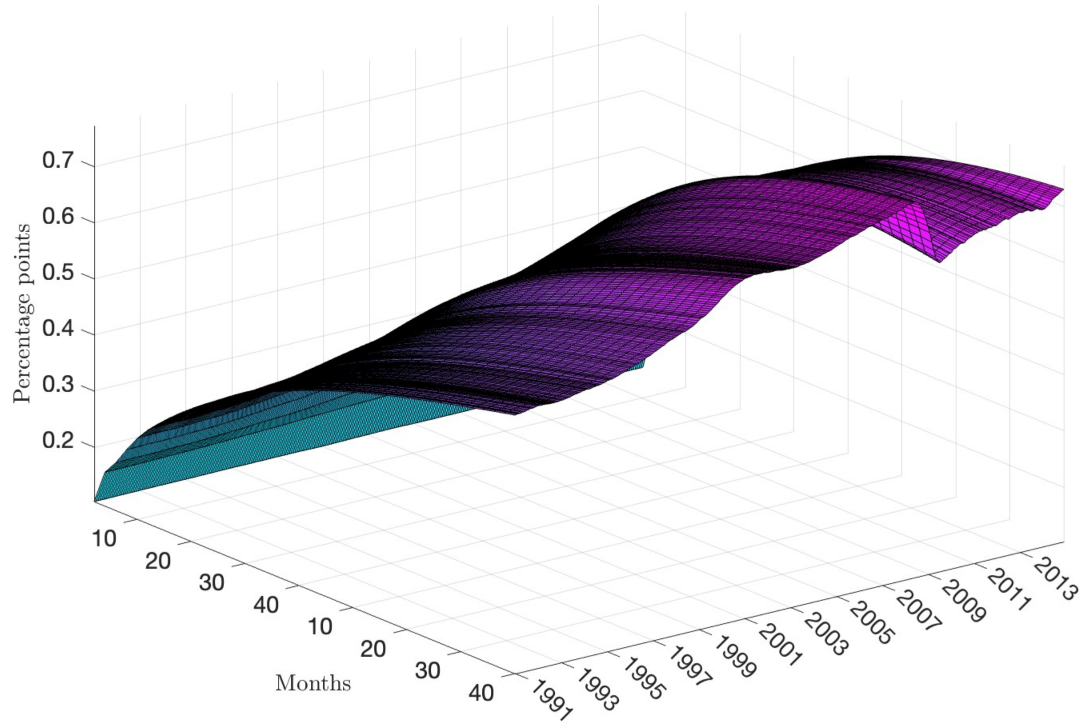
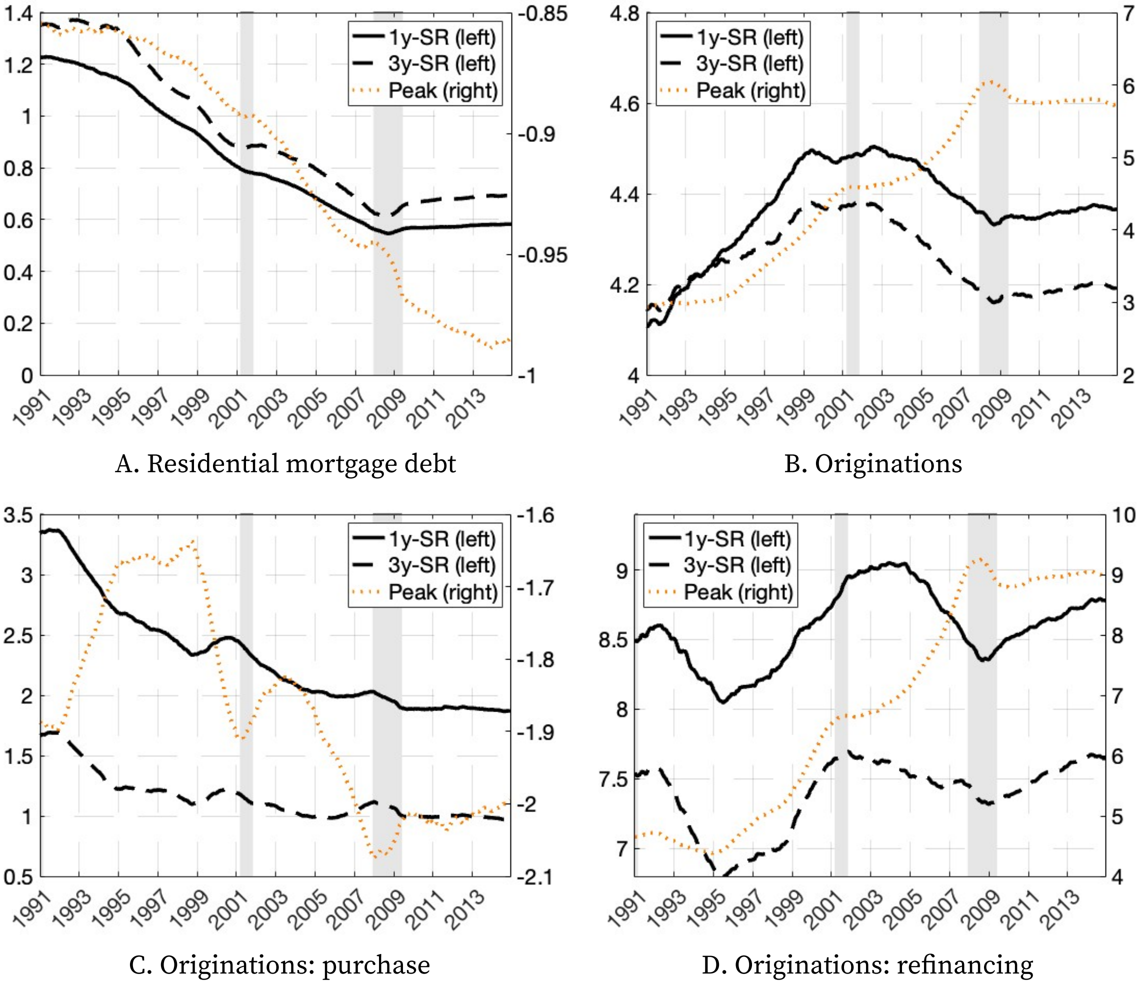


FIGURE E6. Time-varying effects of monetary policy on GSEs' mortgage purchases: full impulse responses

Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model.



A. Residential mortgage debt

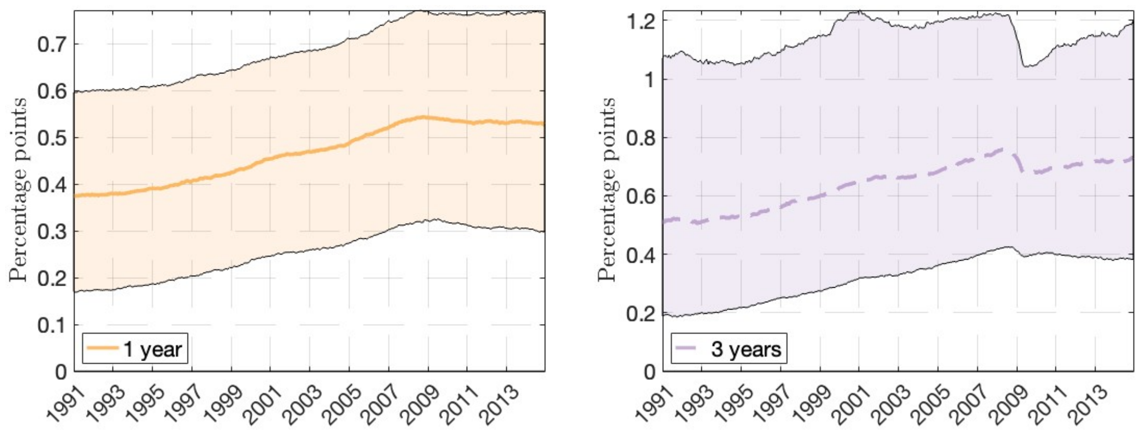
B. Originations

C. Originations: purchase

D. Originations: refinancing

FIGURE E7. Relative impulse responses (sacrifice ratios)

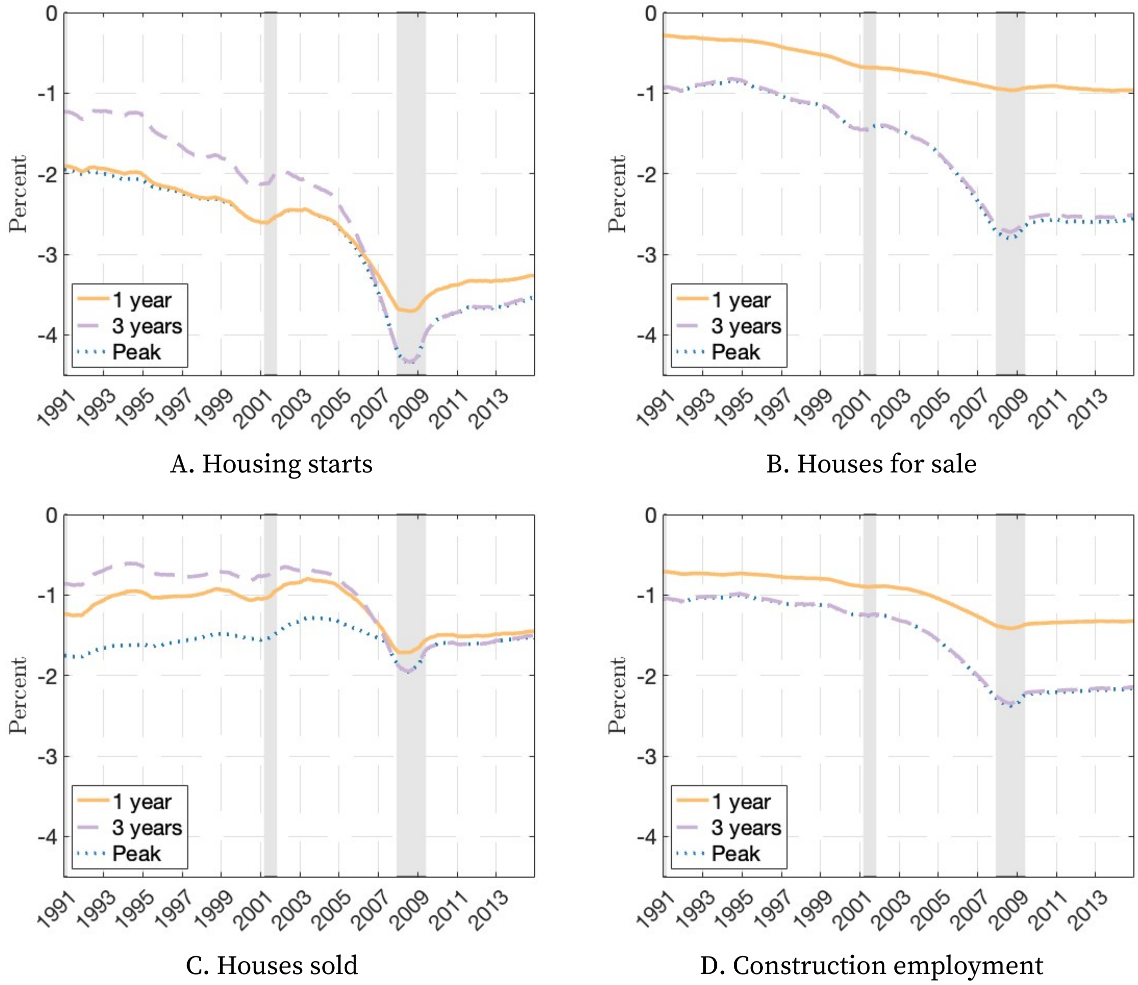
Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model.



A. Short-term impulse response B. Medium-term impulse response

FIGURE E8. Time-varying effects of monetary policy on GSEs' mortgage purchases

Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model. Median impulse responses along with 68 percent credibility intervals from the posterior distribution.



A. Housing starts

B. Houses for sale

C. Houses sold

D. Construction employment

FIGURE E9. Time-varying effects of monetary policy on housing activity: selected horizons

Notes: Cumulative impulse responses to a monetary tightening obtained using the TVP-VARX model. Median impulse responses from the posterior distribution.

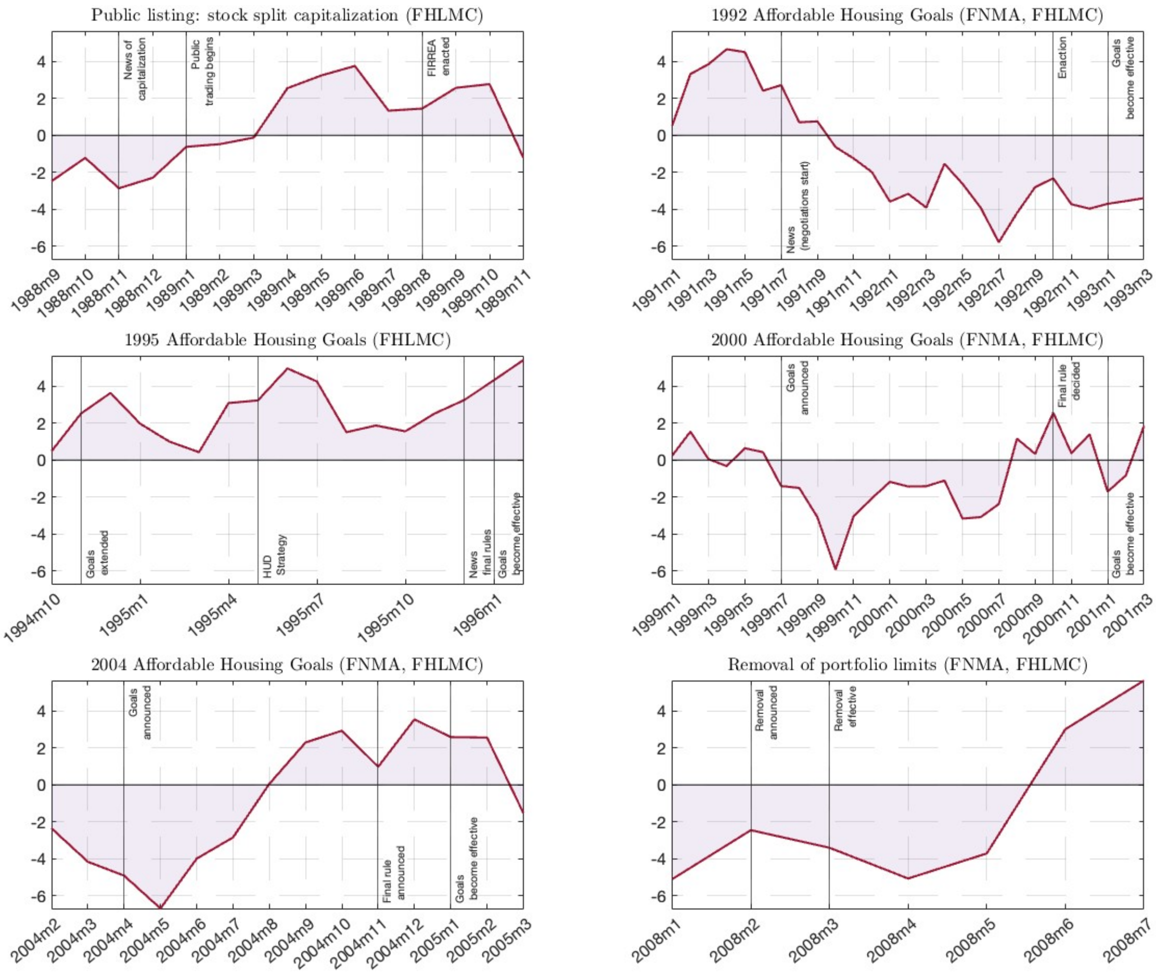


FIGURE E10. Cross-referencing the stance of housing credit policy

Notes: Solid red line is the stance of housing credit policy, $\hat{\xi}_t$. The stance is expansionary when $\hat{\xi}_t > 0$ and non-expansionary otherwise. Vertical lines capture policy events from Fieldhouse, Mertens, and Ravn (2018); Fieldhouse and Mertens (2017). FHMLC = Freddie Mac, FNMA = Fannie Mae, HUD = U.S. Department of Housing and Urban Development, FIRREA = Financial Institutions Reform, Recovery, and Enforcement Act.

References

Albuquerque, Bruno, Martin Iseringhausen, and Frederic Opitz. 2020. "Monetary policy and US housing expansions: The case of time-varying supply elasticities." *Economics Letters* 195: 109471.

Bai, Jushan, and Pierre Perron. 1998. "Estimating and testing linear models with multiple structural changes." *Econometrica*: 47–78.

Bauer, Michael D., and Eric T. Swanson. 2023. "A reassessment of monetary policy surprises and high-frequency identification." *NBER Macroeconomics Annual* 37 (1): 87–155.

Ditzen, Jan, Yiannis Karavias, and Joakim Westerlund. 2021. "Testing and estimating structural breaks in time series and panel data in Stata." *arXiv preprint arXiv:2110.14550.*

Fieldhouse, Andrew J., Karel Mertens, and Morten O. Ravn. 2018. "The macroeconomic effects of government asset purchases: Evidence from postwar US housing credit policy." *The Quarterly Journal of Economics* 133 (3): 1503–1560.

Gilchrist, Simon, and Egon Zakrajšek. 2012. "Credit spreads and business cycle fluctuations." *American Economic Review* 102 (4): 1692–1720.

Jarociński, Marek, and Peter Karadi. 2020. "Deconstructing monetary policy surprises—the role of information shocks." *American Economic Journal: Macroeconomics* 12 (2): 1–43.

McCracken, Michael W., and Serena Ng. 2016. "FRED-MD: A monthly database for macroeconomic research." *Journal of Business & Economic Statistics* 34 (4): 574–589.

Mertens, Karel, and Morten O. Ravn. 2013. "The dynamic effects of personal and corporate income tax changes in the United States." *American Economic Review* 103 (4): 1212–1247.

Miranda-Agrippino, Silvia, and Giovanni Ricco. 2021. "The transmission of monetary policy shocks." *American Economic Journal: Macroeconomics* 13 (3): 74–107.

Paul, Pascal. 2020. "The time-varying effect of monetary policy on asset prices." *Review of Economics and Statistics* 102 (4): 690–704.

Primiceri, Giorgio E. 2005. "Time varying structural vector autoregressions and monetary policy." *The Review of Economic Studies* 72 (3): 821–852.

Wu, Jing Cynthia, and Fan Dora Xia. 2016. "Measuring the macroeconomic impact of monetary policy at the zero lower bound." *Journal of Money, Credit and Banking* 48 (2–3): 253–291.