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Shaping the financial cycle through monetary policy

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Abstract

Financial cycles refer to fluctuations in credit and house prices that extend beyond typical business cycles. Despite its significance for both monetary and macroprudential policy, the question of how monetary policy shapes financial cycles remains largely unanswered. We extract innovations from a vector autoregression that account for most of the cyclical co-movement between credit and house price growth at medium frequencies. Our findings indicate that systematic monetary policy plays a crucial role in propagating this innovation and can significantly dampen financial cycles, particularly when counteracting house price movements. These stabilizing effects could have substantially mitigated the U.S. financial cycle during the 2000s.

JEL classification: C32, E32, E52

Keywords: Financial cycle, monetary policy, policy counterfactual

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1 Introduction

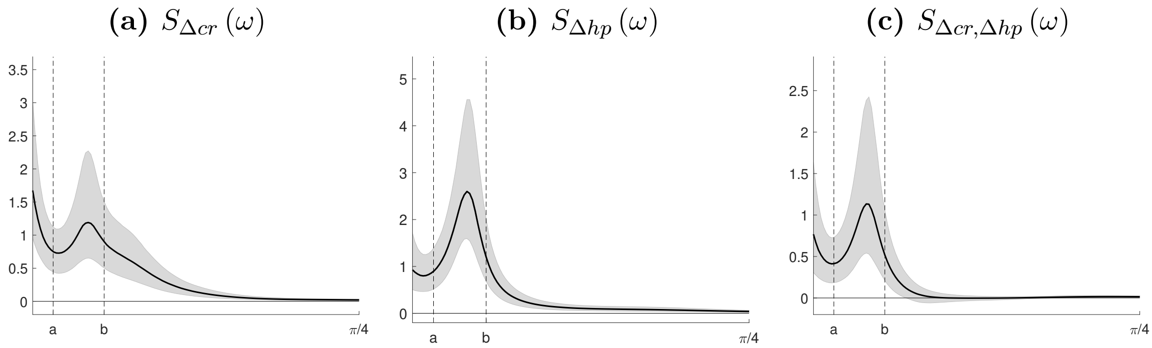
The concept of the “financial cycle” has gained significant prominence in academic research and policy making since the 2008 financial crisis. It is commonly characterized by joint fluctuations in private credit and house prices that extend well beyond the duration of a typical business cycle (Borio, 2014; Aikman et al., 2015). The financial cycle serves as a crucial indicator for central banks in the implementation of macroprudential instruments such as the countercyclical capital buffer (BCBS, 2024). However, the extent to which monetary policy influences the financial cycle remains unclear, a gap this paper seeks to address. Employing a vector autoregressive (VAR) framework, we first identify the main innovation driving the financial cycle and then demonstrate that systematic monetary policy plays a key role in propagating this innovation. Furthermore, a monetary policy that counteracts house price fluctuations has significant stabilizing effects on output, inflation, and financial variables. Counterfactual experiments indicate that such an approach could have substantially reduced house price volatility before and during the financial crisis.

We extract the main innovation driving the financial cycle using a VAR model estimated on U.S. data. Although there is no consensus on the definition of the financial cycle, it is generally thought to be best described in terms of credit and house prices (Drehmann et al., 2012; Borio, 2014; Schueler et al., 2020). Overwhelming evidence indicates that most cyclical variation in quarterly growth rates of credit and asset prices, particularly house prices, occurs at medium frequencies corresponding to cycles between 8 and 20 years (Claessens et al., 2011; Aikman et al., 2015; Schueler et al., 2020). These cycles extend beyond the conventional business cycle, which typically ranges from approximately 1.5 to 8 years (Burns and Mitchell, 1946). Figure 1 illustrates this pattern for the United States, presenting estimates of the normalized spectra of real credit growth and real house price growth, as well as their normalized cross-spectrum.[1] All measures peak at frequencies corresponding to cycles between 8 and 20 years, marked by the vertical lines a and b. We are interested in the innovation that explains most of variances of credit growth and house price growth between 8 and 20 years, which involves maximizing the area under the spectra between a and b in Figures 1a and 1b. We do so by employing the method by Faust (1998), Uhlig (2003), and Angeletos et al. (2020), to maximize sum of variance shares which can be attributed to a single shock.

We find that the identified innovation accounts for 60% and 86% of the volatility in credit growth and house price growth, respectively, within the 8-20 year frequency band. The macroeconomic propagation of this financial-cycle innovation differs from that of a typical business-cycle shock (Angeletos et al., 2020). The financial-cycle innovation likely reflects a combination of several structural shocks, yet it shares characteristics

[1]The normalized spectrum of a variable x is defined as $f_x(\omega) = S_x(\omega)/\sigma_x^2$, where $S_x(\omega)$ denotes the spectral density function of x at frequency ω and σ_x^2 denotes its variance. The normalized cross-spectrum of variables x and y is defined as $f_{xy}(\omega) = S_{xy}(\omega)/\sigma_x\sigma_y$.

Figure 1: Unconditional spectra and cross-spectrum between 1969-2019



Notes: The figure depicts the unconditional spectra and cross-spectrum of real credit growth and real house price growth obtained from a VAR with 8 lags on quarterly U.S. data between 1969:Q1 and 2019:Q4. The solid line shows the median estimate and the grey areas show the 68% probability bands. The vertical lines, a and b, mark the 8-20 year frequency band. More details can be found in Section 2. For illustration, we truncate the figure after $\pi/4$.

with both monetary policy and financial shocks. Specifically, following an expansionary financial-cycle innovation, credit, house prices, output, and inflation increase, while the short-term interest rate decreases. Although the effects on the real economy are similar in magnitude to those of an expansionary monetary policy shock, financial variables respond much more strongly to the financial-cycle innovation. In fact, credit and house prices react approximately two and a half times more to a financial-cycle innovation than to a monetary policy shock.

Our results show that monetary policy responds strongly to financial-cycle innovations, raising the question of how this response shapes the financial cycle. We assess the influence of systematic monetary policy using counterfactuals based on empirical impulse responses to monetary policy shocks from a VAR, employing the "sufficient statistics" approach of McKay and Wolf (2023) and Barnichon and Mesters (2023). This method enables the design of optimal monetary policies robust to the Lucas critique, as it accounts for the effects of both the current and expected future policy path on private-sector decisions, regardless of whether these arise from systematic policy or shocks. Specifically, we construct counterfactuals that minimize a quadratic loss function. In addition to a "dual mandate" policy targeting inflation and the output gap, we also explore optimal policies that target the credit gap or house prices, allowing us to empirically evaluate "leaning-against-the-wind" policies as proposed by Adam and Woodford (2021) and Christiano et al. (2010).

As expected, the dual mandate policy stabilizes inflation and the output gap but has limited impact on the standard deviations of the credit gap and house prices, reducing them by only about 4%. In contrast, the leaning-against-the-wind policies significantly stabilize financial variables, each reducing the standard deviation of the targeted variable by around 20%. Our results indicate that systematic monetary policy has lasting effects on financial variables, influencing the interdependence between the real and financial sectors and either increasing or reducing the economy's vulnerability to disturbances. This aligns with Grimm et al. (2023), who find that periods of loose monetary policy heighten the risk of financial turmoil due to credit expansion and asset price bubbles.

Our policy counterfactuals address the debated question of whether monetary policy contributed to the housing boom of the early 2000s in the United States, a topic that has sparked significant discussion among policymakers and in the academic literature (e.g., Bernanke, 2010; Taylor, 2007; Jarociński and Smets, 2008; Del Negro and Otrok, 2007). We find that optimal monetary policy, across all counterfactual rules, would have mitigated the financial boom-bust cycle of the 2000s. Specifically, a policy that systematically leans against house prices would have significantly softened both the boom and the subsequent bust, resulting in real house prices rising 20 percentage points less during the boom and falling by only 18% instead of 33% during the crisis. These findings align with those of Adam and Woodford (2021), indicating that monetary policy can effectively counteract house price fluctuations. However, this approach involves trade-offs, as our results indicate that a policy leaning against house prices would have resulted in an output gap and inflation approximately one percentage point lower than the actual figures during the 2000s housing boom.

The paper is structured as follows: The remainder of the introduction discusses the related literature. Section 2 introduces the VAR model, describes the identification of the financial-cycle innovation, and examines its propagation through impulse responses. Section 3 presents counterfactual monetary policy exercises and analyzes the role of systematic monetary policy. Finally, Section 4 concludes.

Related Literature. Our paper contributes to several strands of the literature. First, we build on extensive work that shows that credit cycles are closely linked to booms and busts in the housing market (e.g., Jorda et al., 2015; Guerrieri and Uhlig, 2016; Justiniano et al., 2019). We specifically focus on the financial cycle. There is overwhelming empirical evidence for the financial cycle, characterized by fluctuations at medium frequencies (Claessens et al., 2011; Aikman et al., 2015; Drehmann et al., 2012; Ruenstler and Vlekke, 2018; Schueler et al., 2020). However, relatively little research has examined the structural disturbances driving it. Our approach maximizes the joint variation in credit and house price growth at medium frequencies, directly addressing this question. This variance share maximization method, widely applied in the literature (e.g., Mertens, 2010; Barsky and Sims, 2011; Kurmann and Otrok, 2013), has typically been used at business cycle frequencies, most notably by Angeletos et al. (2020).

Second, our paper relates to Miranda-Agrippino and Rey (2020) and Miranda-Agrippino and Rey (2022), who examine the "global financial cycle," defined as the co-movement of international capital flows, financial asset prices, and credit at business cycle frequencies rather than medium frequencies. They demonstrate that U.S. monetary policy shocks influence financial variables associated with the global financial cycle; however, they do not address the broader structural disturbances affecting the financial cycle.

Third, our paper relates to the extensive literature on the impact of financial shocks. For example, Gilchrist and Zakrajšek (2012) construct a credit spread index from U.S. corporate bonds and derive an excess bond premium (EBP) that removes cyclical variation in default risk. A positive EBP shock has adverse macroeconomic consequences. Furlanetto et al. (2017) use sign restrictions in a VAR with credit spreads and other financial variables, including the EBP, to identify financial shocks and their macroeconomic effects. While this conventional approach could assess the role of financial shocks in the joint variation of credit and house prices at medium frequencies, it has limitations, particularly in ensuring that identified shocks explain most of the medium-frequency co-movement. Therefore, we reverse this logic. We first identify innovations that account for the majority of the co-movement between credit and house prices. Then we examine the economic implications of these innovations.

Fourth, our paper contributes to the emerging literature on policy counterfactuals related to changes in the systematic response of monetary policy. For example, Caballero et al. (2024) analyze the stabilizing effects of optimal monetary policies when financial conditions are incorporated into central banks' loss functions. Additionally, Georgiadis et al. (2024) investigate the propagation of a global risk shock under U.S. monetary policy aimed at stabilizing the U.S. dollar, while Ider et al. (2024) assess optimal monetary policy responses to energy shocks. Although this represents only a fraction of the expanding literature, to our knowledge, this paper is the first to present Lucas-critique robust optimal policy counterfactuals for systematic responses to credit and house prices.

In contrast to our findings, monetary policy has traditionally been viewed as having only short-run effects on the economy. However, a small but growing body of literature explores its longer-run consequences. Much of this literature has focused on the long-term impact of monetary policy through its effects on total factor productivity (TFP) and business innovation. For example, using a New Keynesian model with endogenous TFP, where monetary policy influences firms' incentives to innovate, Moran and Queralto (2018) demonstrate that monetary policy can significantly affect medium-run TFP dynamics. Empirically, Ma and Zimmermann (2021) find that monetary policy has a substantial impact on innovation activities in the U.S., such as research and development (R&D) spending, venture capital investment, and patenting in key technologies. Additionally, Jorda et al. (2023) show, using a cross-country panel of long historical data, that a monetary policy tightening leads to a persistent reduction in real GDP, primarily through lower TFP and a reduced capital stock. We contribute to this literature by showing that systematic monetary policy plays an equally important role in shaping housing and credit boom-bust cycles beyond typical business cycle frequencies. This finding aligns with Grimm et al. (2023), who argue that episodes of loose (accommodative) monetary policy can drive credit creation and asset price overheating. However, unlike their analysis, which relies on externally estimated variations in monetary stance, our study uses monetary policy counterfactuals to investigate these dynamics.

Finally, our results provide valuable insights into the ongoing debate about the costs and benefits of coordinating monetary and macroprudential policies (e.g., Stein, 2012; Angeloni and Faia, 2013; Korinek and Simsek, 2016; Svensson, 2017). While the transmission channels of monetary policy, credit policy, and macroprudential policy are intertwined and difficult to disentangle (e.g., Forbes et al., 2017; Fieldhouse et al., 2018), our finding that monetary policy plays a significant role in driving the financial cycle underscores the importance of analyzing the interactions between these policies. This suggests that policy coordination may be necessary to effectively manage price and financial stability.

2 Financial-cycle innovations

In this section, we first lay out the VAR framework, which allows us to study the cyclical properties of credit and house prices. From the VAR we extract financial-cycle innovations and document their propagation to the macroeconomy.

2.1 Identifying financial-cycle innovations

Consider a VAR model that admits the following reduced-form representation:

$$Y_t = \sum_{l=1}^{p} \mathbf{A}_l Y_{t-l} + \nu_t, \tag{2.1}$$

where Y_t is a $n \times 1$ vector of observables, $\mathbf{A}_l$ are p $n \times n$ coefficient matrices, and ν_t is a $n \times 1$ vector of reduced-form errors with variance-covariance matrix $\Sigma_\nu = E\left[\nu_t \nu_t'\right]$. The Wold representation of Eq. (2.1) is given by:

$$Y_t = \Psi\left(L\right) u_t = \sum_{l=0}^{\infty} \Psi_l u_{t-l}, \tag{2.2}$$

where u_t are orthogonalized Wold innovations, $u_t = \text{chol}\left(\Sigma_\nu\right)^{-1} \times \nu_t$, with $\Sigma_u = I$. Under invertibility, there is a linear mapping between the Wold innovations u_t and the structural shocks ε_t given by $u_t = P\varepsilon_t$ for some orthogonal matrix P. Then, the system also has a structural vector moving-average (SVMA) representation:

$$Y_t = \Theta\left(L\right) \varepsilon_t = \sum_{l=0}^{\infty} \Theta_l \varepsilon_{t-l}, \quad \text{with} \;\; \varepsilon_t \sim N\left(0, I\right), \tag{2.3}$$

where $\Psi(L) = \Theta(L)P'$. The matrices Θ_l denote the impulse responses of the vector of observables Y_t at horizon l to the structural shocks ε_t in period t. Finally, the autocovariance function Γ and the spectral density function S of the observables Y_t exist and are given by:

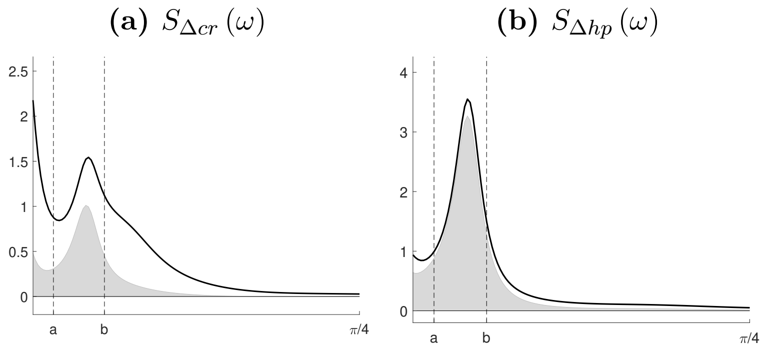
$$\Gamma_y^k = \sum_{m=0}^{\infty} \Theta_m \Theta'_{m+k} \tag{2.4}$$

$$S(\omega) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \Gamma_y^k \exp(-i\omega k) \quad \text{with} \quad -\pi \leq \omega \leq \pi \tag{2.5}$$

Aikman et al. (2015) show the importance of medium cycle fluctuation for credit growth. To this end, real credit growth together with real house price growth are in the focus of our baseline specification. In particular, the log-difference total credit to the private non-financial sector deflated by the GDP deflator and the log-difference of the nominal house price index deflated by the GDP deflator. Additionally, our baseline model comprises the log-difference of real GDP; the log-difference of the GDP deflator; and the effective federal funds rate spliced with the Wu-Xia shadow short rate between 2009:Q1-2015:Q4 (the Appendix provides detailed variable definitions and sources). The sample spans the period from 1969:Q1 to 2019:Q4 and all data are normalized. To approximate the spectrum of the variables of interest, we estimate the reduced-form VAR in Eq. (2.1) with a constant and $p = 8$ lags of the endogenous variables and using a Normal-Wishart prior for the coefficients and the variance-covariance matrix, in particular we apply a "weak" prior as in Uhlig (2005). The lag-length is chosen to capture the medium-frequency variation of interest. In this regard, we follow the recent literature that argues not to rely on conventional selection criteria to select the VAR lag length when, for example, impulse responses or long-run correlations are the object of interest (Antolin-Diaz and Surico, 2025). We perform robustness checks using different lag lengths; different credit volumes; a different house price index; and different samples, e.g. by excluding the Great Recession and the zero lower bound episode. The results obtained using the baseline model specification are robust to these variations. More details about the robustness exercises are reported in the Appendix.

Our aim is to identify the innovation that drives the financial cycle. Specifically, we want to identify the main innovation that gives rise to co-movement between credit growth and house price growth in the 8-20 year frequency range. Thus, the area between a and b in Figure 1 is the focus of our empirical strategy. Following Doyle and Faust (2005), we measure co-movement between these variables as the maximum variance share, by summing shares across both variables of interest. The financial-cycle innovation maximizes this sum of variance shares over medium frequencies in the 8-20 year range. To that end, we first apply a band pass filter F that passes only cycles between 8 and 20 years (32 to

Figure 2: Fraction of spectra explained by financial-cycle shock.



Notes: The figure depicts the fraction of spectra of credit growth and house price growth (grey areas) explained by the financial-cycle shock. All spectra based on point estimates of a VAR(8) model and standardized quarterly U.S. data between 1969:Q1 and 2019:Q4. The vertical lines, a and b, mark the 8-20 year frequency band, the black line represents the unconditional spectra.

80 quarters) to get the medium-cycle filtered spectral density $S_{\tilde{Y}}$:

$$S_{\tilde{Y}}(\omega) = \begin{cases} S_Y(\omega) & \forall|\omega| \in \left[\frac{2\pi}{80}, \frac{2\pi}{32}\right] \\ 0 & \text{otherwise.} \end{cases} \tag{2.6}$$

Next, the lead-lag covariance matrix of the filtered observable, $\tilde{Y}_t$, can be recovered from the medium-cycle filtered spectrum using the inverse Fourier transformation:

$$\Gamma^k_{\tilde{Y}} = E\left[\tilde{Y}_t \tilde{Y}_{t-k}\right] = \int_{-\pi}^{\pi} S_{\tilde{Y}}(\omega)\, e^{i\omega k} d\omega. \tag{2.7}$$

We then consider the following maximization problem over the frequency band $[a, b]$, under the assumption that there exists an orthonormal matrix Q (that is, $QQ' = I$) with column q associated with the financial-cycle innovation:

$$\begin{aligned} \max_q \quad & \int_{-\pi}^{\pi} S^h_{\tilde{Y}}(\omega)\, d\omega = q' \left(\int_{\omega \in [a,b]} \Theta\left(e^{-i\omega}\right)' h' h \Theta\left(e^{i\omega}\right) d\omega \right) q \equiv q' R q \\ \text{s.t.} \quad & q'q = 1, \end{aligned}$$

where h is an $n \times 1$ vector that selects the variables of interest, e.g., credit growth and house price growth, from the vector of observables (i.e., it picks the rows in matrix $\Theta(L)$ of the SVMA model). This maximization problem can be solved by choosing q as the eigenvector of R with the largest eigenvalue, i.e., its first principal component. The method is similar to the approach proposed by Faust (1998) and Uhlig (2003).[2] Our method is also closely related to the recent contribution of Angeletos et al. (2020) except for two differences: First, we target two variables, i.e., the sum of two shares of variances,

[2] Subsequent applications of this approach can be found in Mertens (2010), Barsky and Sims (2011), and Kurmann and Otrok (2013).

Table 1: Variance shares accounted for by financial-cycle innovation.

	Credit growth	GDP growth	House price growth	Inflation	Interest rate
Full cycle	31.0	19.6	67.8	12.5	18.6
$[0, 2\pi]$	$[18, 46]$	$[14, 27]$	$[52, 78]$	$[5, 27]$	$[8, 36]$
Medium cycle	60.2	63.6	85.7	28.4	48.8
$[2\pi/80, 2\pi/32]$	$[41, 75]$	$[46, 77]$	$[77, 91]$	$[12, 52]$	$[29, 67]$
Business cycle	21.9	16.0	48.8	12.7	28.7
$[2\pi/32, 2\pi/6]$	$[12, 36]$	$[9, 25]$	$[36, 62]$	$[5, 26]$	$[15, 44]$

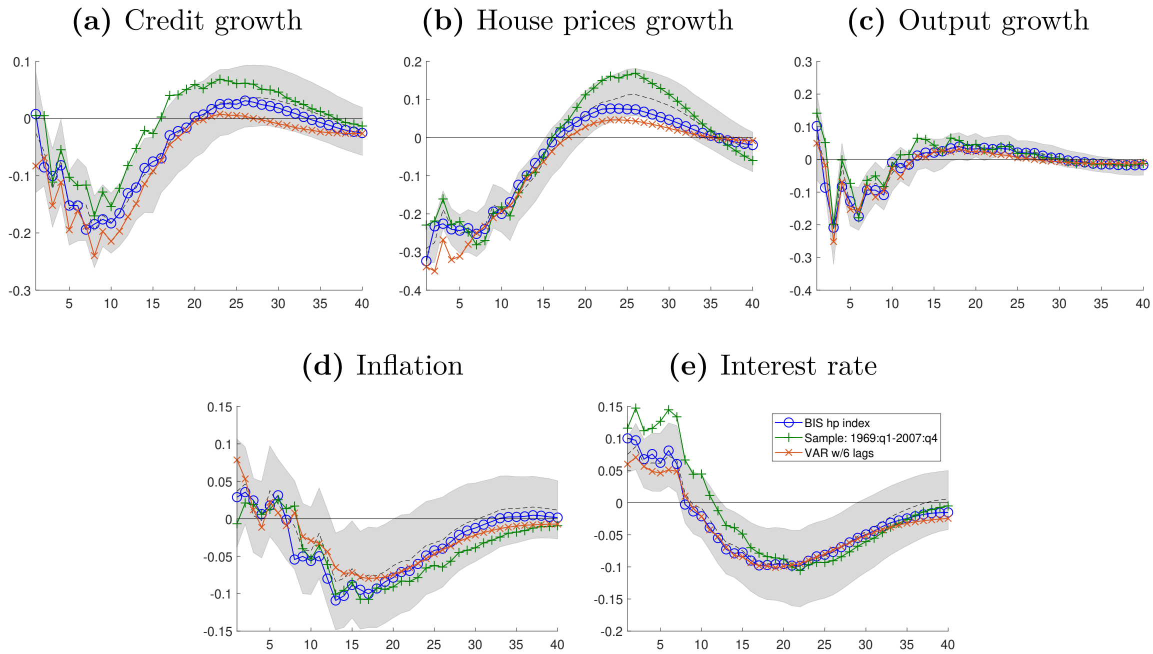
Notes: Contributions of the financial-cycle innovation to the forecast error variance of the endogenous variables over different frequencies (in %). The first row corresponds to the variance contributions calculated over all frequencies between 0 and 2π. The second row corresponds to the variance contributions calculated over the range between 32 and 80 quarters, and the third row corresponds to the variance contributions calculated over the range between 6 and 32 quarters. Each row shows the median contribution and the 68% HPDI in brackets, with all statistics computed on 10,000 draws from the posterior.

at once to explain the co-movement between them. Second, we are interested in a different frequency band that is associated with the length of a typical financial cycle rather than the business cycle.

Figure 2 illustrates the approach and the properties of the financial-cycle innovation calculated at the OLS point estimates. In particular, it shows the fraction of the spectra of credit growth and house price growth explained by the financial-cycle innovation (grey areas). This innovation explains a large fraction of the movements in credit growth and nearly all movements in house price growth in the 8-20 year frequency range. Of course, this innovation also explains some of the spectrum at other frequencies.

Table 1 reports the contribution of the financial-cycle innovation to the forecast error variance of the endogenous variables over medium frequencies, business cycle frequencies, and the full frequency range equivalent to the total variance. The financial-cycle innovation explains, respectively, 60% and 86% of the volatility of credit growth and house price growth over the targeted frequency band of 8-20 years. In addition, it accounts for a large part of the variation in house prices at business cycle frequencies (49%) and over the full frequency range (68%). It also plays an important role for the variation in credit growth at business cycle frequencies (22%) and over the full frequency range (31%). At the same time, the financial-cycle innovation also accounts for a surprisingly large fraction of the variation in GDP growth (63%) and a large fraction of the variation in the short-term interest rate (49%) and inflation (28%) over medium frequencies. However, its contribution to the variation in these variables over the full frequency range and the business cycle range is considerably lower. The appendix provides further robustness checks regarding different measures for credit and house prices, variation of the lag length, and sub-sample.

Figure 3: Impulse responses to a financial-cycle innovation



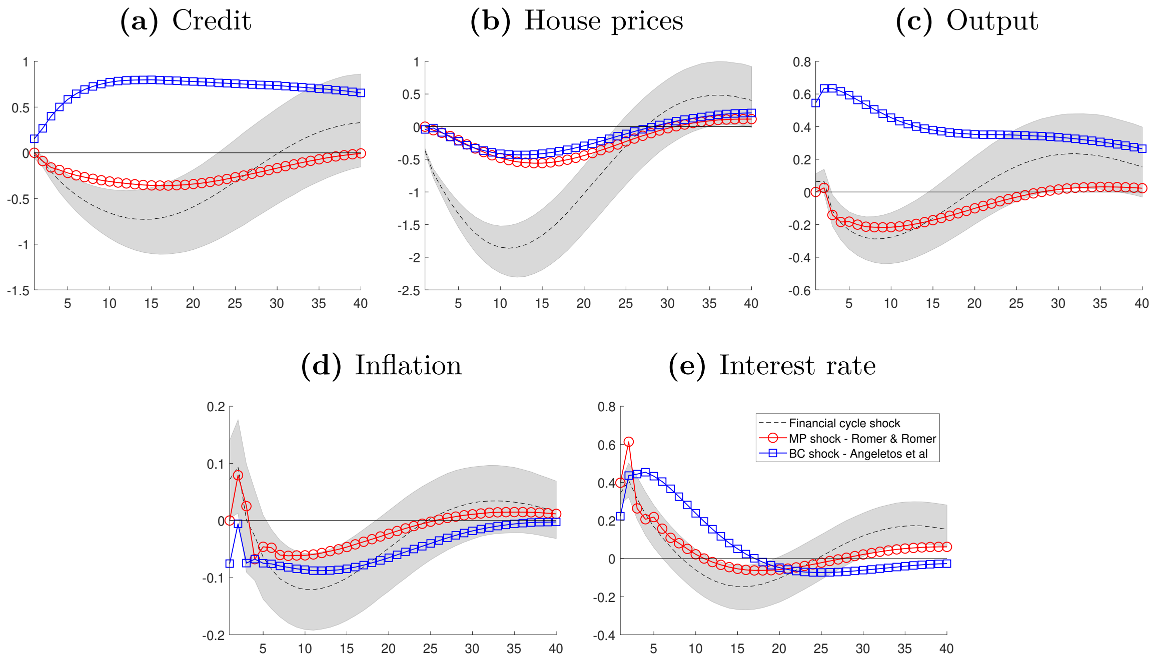
Notes: The figure show the IRFs of the financial-cycle innovation with grey areas represent the 16% and 84% probability bands.

2.2 Macroeconomic propagation of financial-cycle innovations

Next, we analyze the impulse response functions resulting from a financial-cycle innovation, as illustrated in Figure 3. A negative innovation of one standard deviation triggers a downturn in the financial cycle and a slowdown in the real economy. Credit growth declines, reaching a trough approximately 0.2 percentage points below the baseline eight quarters post-shock, before gradually returning to its pre-shock level after 20 quarters. House price growth decreases by about 0.3 percentage points immediately and remains significantly below the baseline for 15 quarters. Output growth decreases by around 0.2 percentage points within two quarters, returning to its pre-shock level after 11 quarters. Inflation decreases with a delay, reaching a trough of approximately 0.1 percentage points below the baseline 13 quarters post-shock. The short-term interest rate increases significantly by about 7.5 basis points on impact and returns to baseline after 10 quarters. The figure also shows, that the effects are robust to using an alternative house price index, considering a sample ending in 2007:Q4, and estimating the VAR with six lags. This is just a selection of robustness, more results are provided in the appendix.

We want further compare the effects of the financial cycle innovation with different structural shocks identified in the literature. In particular, with the main business-cycle (Angeletos et al., 2020) and monetary shocks identified in the literature. The business cycle shock accounts for the majority of variation in macroeconomic aggregates, such as

Figure 4: Impulse responses to a financial-cycle shock



Notes: The figure show the IRFs of the financial-cycle innovation with grey areas represent the 16% and 84% probability bands.

unemployment, at business cycle frequencies. We also obtain the monetary policy shock series from Romer and Romer (2004). For direct comparison, we extract the financial-cycle innovation series from our benchmark VAR. We then sequentially incorporate each shock series into a five-variable system. This system consists of credit, house prices, output (in log-levels), inflation, and the short-term interest rate. We order the shocks first in a recursive VAR scheme. Finally, We include two lags of the endogenous variables, a constant, and a time trend and estimate the VAR model using a Bayesian approach with a Normal-Wishart prior for the coefficients and covariance matrix.

Figure 4 displays the resulting impulse responses. Crucially, the effects of a financial-cycle innovation remain robust when using the internal instruments approach in a VAR estimated in levels. Moreover, the effects of the business-cycle shock extracted from Angeletos et al. (2020) differ qualitatively and quantitatively from those of our financial-cycle innovation: Credit and house prices move in opposite directions after a business-cycle shock, and output displays a positive and sustained response to this shock.

The effects of a monetary policy shock are more similar to those of a financial-cycle innovation. However, the latter has stronger effects on financial variables. After a contractionary monetary policy shock associated with a rise in the interest rate, output, inflation, credit, and house prices decrease.[3] While the effects on output, inflation, and

[3]Results for different monetary policy shock measures are provided in the appendix.

the interest rate are comparable in magnitude to those of a financial-cycle innovation, the response of credit and house prices to a monetary policy shock is significantly weaker than to a financial-cycle innovation.

Monetary policy is generally believed to have limited effects beyond business cycle frequencies and no long-term impact, though this view is being reexamined (see, e.g., Jorda et al., 2023). Additionally, Miranda-Agrippino and Rey (2020) demonstrate that U.S. monetary policy shocks significantly influence financial variables tied to the 'global financial cycle.' Consequently, distinguishing monetary policy shocks from our financial-cycle innovation may be challenging.

Moreover, the financial-cycle innovation shares both similarities and differences with financial shocks identified in the literature. A financial shock consistent with various structural models, as identified by Furlanetto et al. (2017), has comparable effects on real and financial variables. However, in various studies, the effects on the interest rate are more delayed, while the output response is immediate after a financial shock, as widely documented by Gilchrist and Zakrajšek (2012), Furlanetto et al. (2017), Caldara and Herbst (2019), and Romer and Romer (2017). This characteristic distinguishes the financial-cycle innovation also from a housing demand shock (Iacoviello and Neri, 2010; Jarociński and Smets, 2008). Moreover, the effects of a financial-cycle innovation also differ from those of a loan-to-value shock or credit supply shock (see Furlanetto et al., 2017; Justiniano et al., 2015).

More generally, Dou et al. (2025) demonstrate that the max-share identification approach as employed in this paper does not necessarily guarantee that the response to the identified shock is orthogonal to other, untargeted shocks. This warrants caution in interpreting the results, as part of the identified shock may be driven by other structural shocks. Consequently, the financial-cycle innovation identified here may represent a linear combination of multiple structural shocks, potentially including both financial and monetary policy shocks.

3 Monetary policy counterfactuals

Our results indicate that monetary policy reacts substantially to the main shock that moves the financial cycle. Thus, the question arises as to what role the response of monetary policy plays in how macro-financial aggregates respond to financial-cycle shocks. Put differently, we ask how the systematic behavior of monetary policy shapes the financial cycle. To explore this issue, we conduct counterfactual exercises under different monetary policy rules, using the approach proposed by McKay and Wolf (2023).

Therefore, we first evaluate the propagation of the macroeconomy under observed monetary policy. To properly address systematic monetary policy in this paper, we use credit-gap and output-gap measures instead of aggregate series for credit and output in our VAR model, respectively.[4] We decide so to get a more direct interpretation from a monetary policy and macroprudential perspective. Additionally, we follow the literature (Ramey, 2016) by adding commodity prices.

In the following, we shortly describe the implementation of the method by McKay and Wolf (2023) before we present the counterfactual results for second moments, propagation and historical evolution of variables of interest.

3.1 Implementation

We implement the policy counterfactuals using the approach proposed by McKay and Wolf (2023) and extended by Caravello et al. (2024). Their approach is based on the idea that policy affects private-sector decisions only through the current and expected future path of policy, regardless of whether that path is the result of the systematic component of policy or because of a policy shock. For an invertible SVMA(∞) process as our model in Eq. (2.3), the Wold innovation together with policy causal effects Θ_ν are sufficient to construct the policy counterfactual of interest.

In line with McKay and Wolf (2023), we obtain the monetary policy causal effects Θ_ν by using empirical estimates of impulse responses to monetary policy shocks. The empirical impulse responses are estimated on a sample between 1969:Q1-2007:Q4. We drop the observations after the outbreak of the global financial crisis to avoid distortions of the causal effects due to unconventional monetary policy measures. Consistent with Caballero et al. (2024), we identify monetary policy shocks using the shock series constructed by Romer and Romer (2004) and Aruoba and Drechsel (2024).[5] To account for joint uncertainty in the estimation of the effects of monetary policy shocks, we add both shock series to the VAR model, as in McKay and Wolf (2023). We apply a recursive identification scheme, ordering the Aruoba and Drechsel (2024) shock series first and the Romer and Romer (2004) shock series before the federal funds rate. We estimate the VAR model with two lags, a constant, time trend, and use a Normal-Wishart prior for the coefficients and covariance matrix. The detailed impulse responses to both monetary policy shocks are provided in appendix B.

We construct counterfactuals in which monetary policy is assumed to minimize the following quadratic loss function:

$$\mathcal{L} = E_0 \left[\sum_{t=0}^{\infty} \beta^t \left\{ \lambda_\pi \pi_t^2 + \lambda_y y_t^2 + \lambda_\zeta \zeta_t^2 \right\} \right], \tag{3.1}$$

[4] The output-gap is estimated using an two-sided hp-filter with $\lambda = 1600$. Following Drehmann et al. (2012), we estimate the credit-gap using a one-sided hp-filter with $\lambda = 400,000$. While both approaches are controversially discussed in the literature, we follow the common approach applied at many central banks.

[5] In particular, instead of the original series provided by Romer and Romer (2004), we use the extended series by Wieland and Yang (2020) between 1969:Q1-2007:Q4. The Aruoba and Drechsel (2024) shock series is available from 1982:Q4 onward, so we set the missing values to zero.

where π_t and y_t represent inflation and the output gap, respectively, with their corresponding weights λ_π and λ_y. In our first counterfactual we focus on inflation and output gap only ($\lambda_\zeta = 0$), we refer to this policy as "dual mandate". The variable ζ_t refers to an additional variable of interest with weight λ_ζ.

The literature suggests different additional variables, ζ_t, a central bank should include into its loss function. For example, Cúrdia and Woodford (2010) propose credit spreads while Christiano et al. (2010) argues for credit volume to be included. Next to credit related measures, Bernanke and Gertler (1999) proposes asset prices in general and Adam and Woodford (2021) house prices in particular. More recently, Caballero et al. (2024) find a stabilizing effect of including a financial condition index into the central banks' loss function. In this paper, we are interested in the stabilizing properties of credit gap or house prices. Both variables are easily observed by policy makers, also in the past. Moreover, both variables play an actual role for macroprudential policy and house prices, for example, episodically did so already in the past Aastveit et al. (2023). In our counterfactual exercise below, we refer to both as "credit targeting" or "house price (hp) targeting" policies, respectively.

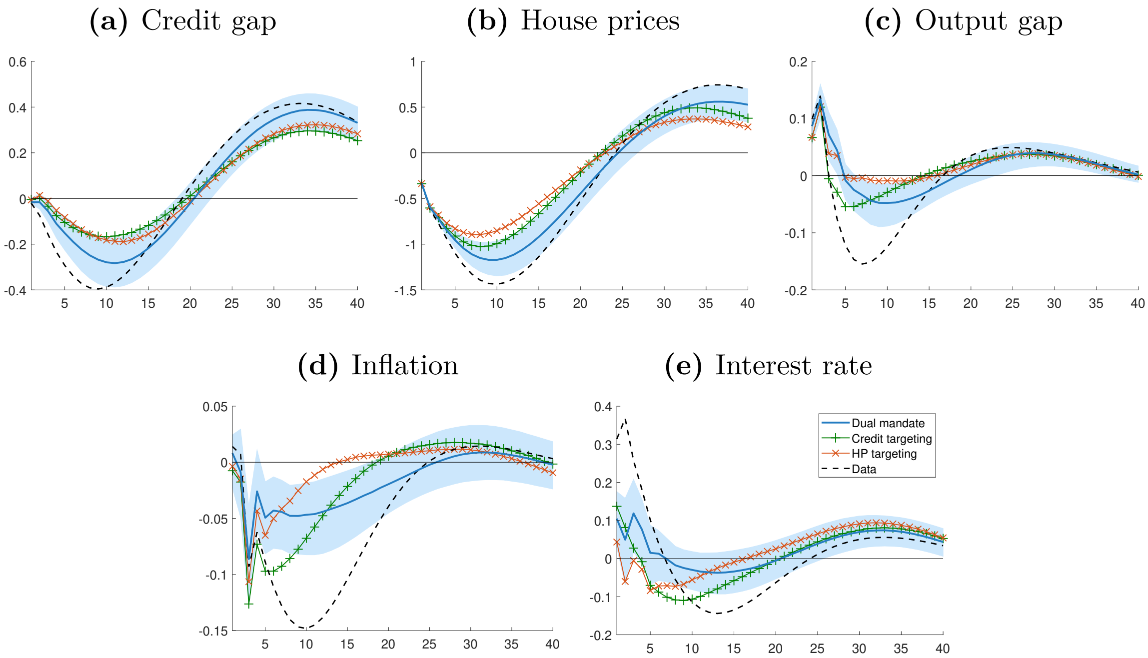
In our application, for "dual mandate" we set the weights on inflation and output gap, $\lambda_\pi = \lambda_y = 1$. In addition, under "credit targeting" the weight for credit is one, $\lambda_{cr} = 1$. For "house price (hp) targeting", we assume a weight $\lambda_{hp} = 0.1$, next to $\lambda_\pi = \lambda_y = 1$. The discount factor is set to $\beta = 1/1.01$, so the central bank puts more weight on recent episodes. Thus, given the monetary policy causal effects Θ_ν, we can calculate the counterfactual exactly as proposed in Proposition 2 of McKay and Wolf (2023).

3.2 Propagation of financial-cycle shock under counterfactual monetary policies

First, we investigate the propagation of the financial-cycle innovation under counterfactual monetary policies. Figure 5 depicts the counterfactual impulse responses, where for comparison the black dashed line shows the response under observed monetary policy.[6] The blue line and the corresponding shaded area represent the median and 68% probability responses under the dual mandate policy. The green and orange lines represent the median responses under credit targeting and house price targeting, respectively. Crucially, we find that all counterfactual policies have a substantial impact on the propagation of the financial-cycle shock. In particular, the transmission of a financial-cycle shock to the economy is substantially dampened under the dual mandate policy. Inflation, the output gap, and the policy rate show substantially muted responses under this counterfactual policy. In addition, the dual mandate policy also weakens somewhat the propagation of

[6]This black dashed line also shows that including commodity prices and gaps for credit and output instead of aggregates, have no impact on the propagation of this shock.

Figure 5: Policy counterfactual, impulse responses.



Notes: The figure show the IRFs of the financial-cycle shock under observed policy (black dashed, point estimate) and the different counterfactual policies. The blue solid line shows the impulse responses under credit targeting with the blue areas representing the 16% and 84% probability bands under this policy. The green and red dashed lines show the median impulse responses under inflation targeting and house price targeting, respectively.

the financial-cycle shock to the financial cycle through the credit gap and house prices. Not surprisingly, credit targeting and house price targeting policies dampen the propagation to the financial cycle even more strongly than the dual mandate policy. Interestingly, however, the dampening effects of these policies on inflation, the output gap and the policy rate are comparable to those of the dual mandate policy. Hence, an 'optimal policy' as in Eq. 3.1 does not only dampen the effect on financial variables but also disentangles the response of those variables from inflation and the output gap. Consequently, the systematic behavior of monetary policy plays an important part in the propagation of financial disturbances. Systematic monetary policy can make the real economy and the financial system less or more vulnerable to financial disturbances and can increase the interdependence between the real and financial sector. This relates to the finding by Grimm et al. (2023) that episodes of loose monetary policy increase the likelihood of financial turmoil related to credit creation and asset price overheating. Our results show similar stabilizing properties as proposed by Caballero et al. (2024).

To further investigate the stabilizing properties of the counterfactual monetary policies over different frequencies, we construct unconditional second moments and spectral densities for the counterfactuals. Therefore, we first estimate the Wold representation of

Table 2: Unconditional second moments under different counterfactuals

Variable	Credit gap	House prices	Output gap	Inflation	Interest rate
Data	6.495	10.034	1.481	1.683	2.784
Dual mandate	6.289	9.649	1.205	1.496	2.605
$[\lambda_\pi = \lambda_y = 1]$	$[5.84, 6.82]$	$[7.95, 11.88]$	$[0.99, 1.41]$	$[1.36, 1.64]$	$[2.32, 2.92]$
HP targeting	6.151	7.621	1.311	1.633	2.825
$[\lambda_\pi = \lambda_y = 1, \lambda_{hp} = .1]$	$[5.63, 6.58]$	$[5.46, 9.73]$	$[1.10, 1.49]$	$[1.52, 1.74]$	$[2.60, 3.15]$
Credit targeting	5.292	10.249	1.508	1.847	3.279
$[\lambda_\pi = \lambda_y = 1, \lambda_{cr} = 1]$	$[4.48, 6.10]$	$[8.10, 13.27]$	$[1.30, 1.75]$	$[1.68, 2.11]$	$[2.80, 3.97]$

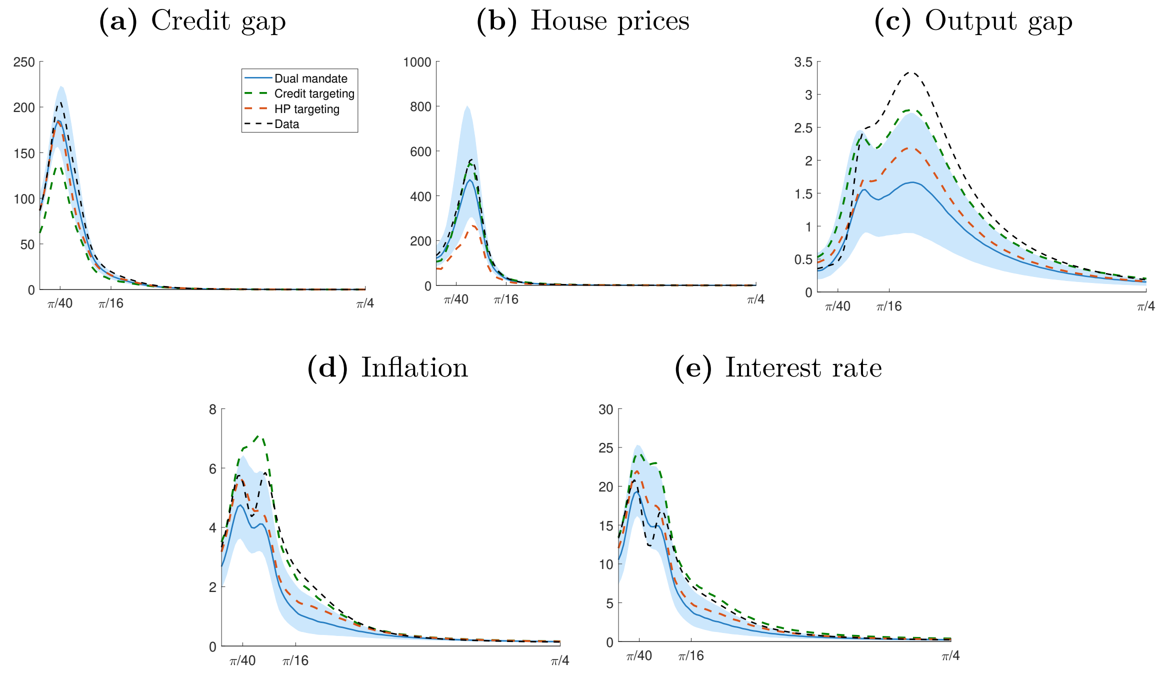
Notes: The first row shows the point estimate under the observed policy rule estimated from the observed data. The second, third and fourth rows show second moments under alternative policy rules. The numbers in brackets represent the 68% HPDI.

the observables. Next, we map the impulse responses to all individual shocks (Wold errors) into new impulse responses corresponding to the counterfactual policy rule. Then, we stack the new impulse responses to arrive at a new vector moving average representation and compute a new set of second moment properties (for more details, see McKay and Wolf, 2023).

Table 2 shows the standard deviations of the variables under the observed monetary policy rule as well as under different counterfactual rules. As expected, the dual mandate policy has stabilizing properties for inflation and the output gap, the standard deviation of which fall by 18% and 12%, respectively. However, the dual mandate policy has a minor impact on the standard deviation of the credit gap and house prices, reducing these only by around 4%. As intended, both augmented policies have a strong stabilizing impact on the targeted financial variable. The volatility of the credit gap is around 20% lower under the credit targeting rule, while the volatility of house prices is around 20% lower under the house price targeting rule than under the observed policy rule. However, the credit targeting rule does not have a stabilizing effect on any of the other variables. By contrast, the house price targeting rule additionally reduces the volatility of inflation by around 10% and the volatility of the credit gap and the output gap by between 3-5%. These results are in line with Caballero et al. (2024), who show that a loss function augmented by a financial condition index has stabilizing effects on inflation and the output gap, as well as on financial variables. At the same time, our results also indicate that it is preferable to focus on asset prices instead of credit aggregates.

Figure 6 shows the unconditional spectra of the observables under different policy rules, illustrating that the counterfactual policies have stabilizing properties over the whole spectrum. Fluctuations in inflation and the output gap are particularly dampened

Figure 6: Policy counterfactual, spectrum



Notes: The figure depicts the unconditional spectra under different monetary policies. The blue solid line shows the spectra and cross-spectrum under dual mandate with the blue areas representing the 16% and 84% probability bands. The green and red dashed lines show the median spectra under credit targeting and house price targeting, respectively. Finally, the black-dashed line shows the point estimate of spectra under observed policy.

under the dual mandate policy, especially at business cycle frequencies. At the same time, the credit and house price targeting policies strongly dampen fluctuations in the credit gap and house prices, respectively, at lower frequencies associated with the financial cycle. This finding underscores that systematic monetary policy is important for the evolvement of the financial cycle, suggesting that monetary and macroprudential policies cannot be treated independently of each other.

3.3 Historical evolution

Given on our result that monetary policy can stabilize the economy by accounting for real house price developments, an important question arises: did monetary policy contribute to the housing boom of the early 2000s, potentially setting the stage for the subsequent crisis? If so, could monetary policy have mitigated the boom and its adverse consequences? This question has been widely and controversially debated (e.g., Taylor, 2007; Bernanke, 2010), with support for both perspectives in the literature. For instance, Del Negro and Otrok (2007) argue that the impact of monetary policy was relatively limited. In contrast, Jarociński and Smets (2008) provide evidence suggesting that monetary policy played a significant role in fueling the house price boom and may have been excessively loose.

We revisit this question by investigating the impact of systematic monetary policy on the historical evolution of our variables of interest. In particular, we follow Caravello et al. (2024) and calculate historical counterfactuals, investigating the same counterfactual policies as before. We assume that the central bank follows an optimal rule as defined above from t^*=1995:Q1 until the end of the sample period. Formally, we evaluate the historical counterfactual, $\hat{y}_t$, which is

$$\hat{y}_t = \sum_{l=0}^{t-t^*} \hat{\Theta}_l \varepsilon_t + \hat{y}_t^*, \tag{3.2}$$

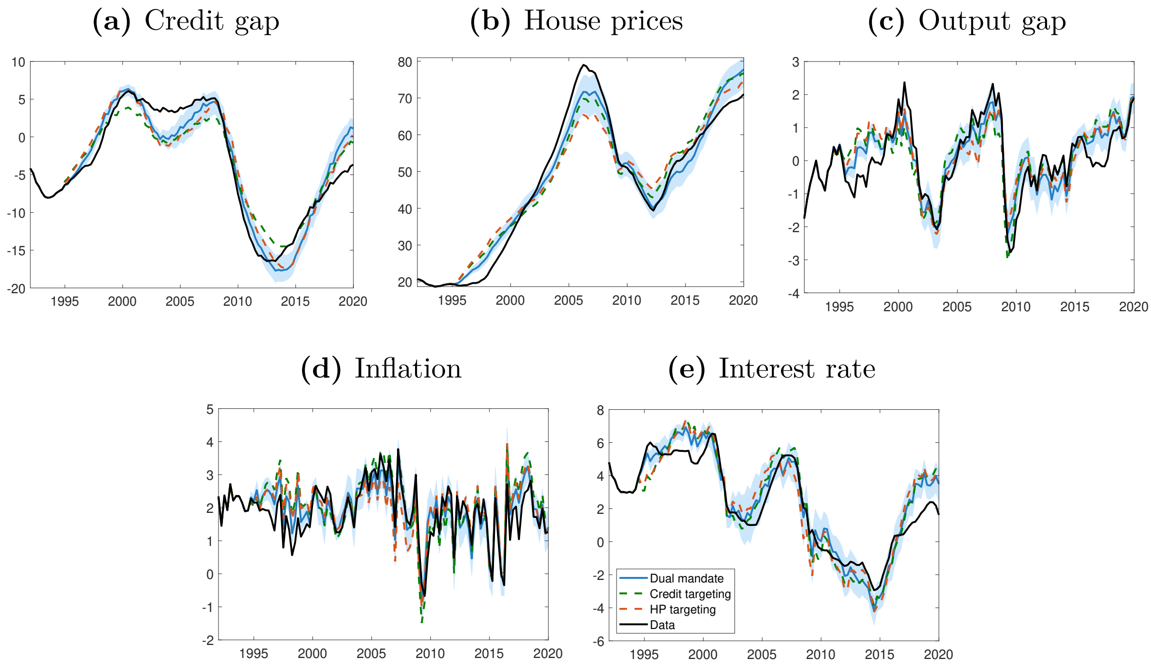
where the first part points to all newly arriving shocks after t^* which propagate according to the new counterfactual monetary policy, $\hat{\Theta}_l$. The second term, $\hat{y}_t^*$ represents the initial conditions at t^*, which is the expected value of the variable y_t formed under the new policy but given the information up to t^*. This ensures that the newly chosen policy path after t^* is embedded in the expectations of the agents and the revised forecasts remain consistent with all private-sector relationships.

Figure 7 depicts the data as well as the counterfactual evolution of the variables in the VAR under different monetary policy rules. The 2000s saw an unprecedented boom in US house prices, fueled by a surge in mortgage lending, which is clearly visible in the data (Figure 7a and 7b). Real house prices began their steep rise in 1998, surging by 74% until their peak in 2006:Q1. They subsequently fell by a staggering 33% between 2006:Q1 and 2012:Q1, accompanied by a credit crunch. Throughout this period, the Fed kept the federal funds rate low well into the mid-2000s, after easing monetary policy substantially in response to the 2001 recession (Figure 7e). The funds rate reached 1 percent in 2003:Q2 from 6.5 percent in 2000:Q4 and stayed there until the Fed embarked on a gradual tightening in 2004:Q4.

Judged by our counterfactuals, there is some indication that monetary policy may have been too loose during this time. Our results imply that the Fed should have started tightening the policy rate already as of early 2003, had it followed optimal policy under the dual mandate or the credit targeting rule. It should have tightened even earlier under the house price targeting rule. These results are in line with Jarociński and Smets (2008), who argue that monetary conditions may have been too loose in 2004 when taking the development of house prices into account. Strikingly, monetary policy also appears to have been too loose before the bust of the dotcom bubble and at the end of the sample from 2017 onward. On the contrary, monetary policy seems not to have been sufficiently accommodative during the zero lower bound episode, in spite of measuring the policy stance via a shadow short rate that encompasses unconventional policy measures.

Crucially, a tighter monetary policy under all counterfactual policy rules would have dampened the financial boom-bust cycle of the 2000s. An earlier tightening of the funds rate would have dampened the surge in real house prices. Their peak would have been

Figure 7: Historical evolution, policy counterfactual.



Notes: Counterfactual evolution of selected variables under different counterfactual policies starting from 1995:q1 onward. The blue solid line shows the historical evolution under dual mandate policy with the blue areas representing the 16% and 84% probability bands under this policy. The green and red dashed lines show the median evolution under credit and and house price targeting, respectively. Finally, the black line shows the evolution under observed policy.

around 20 percentage points below the actual peak under house price targeting and around 10 percentage points below the actual peak under the dual mandate or credit targeting. In addition, credit targeting would have implied a smaller credit boom in the late 1990s and mid-2000s, and the dual mandate and house price targeting would have dampened the credit cycle in the 2000s. Under the optimal policy rules, the financial downturn after the crisis would have also been cushioned. Under house price targeting and the dual mandate, real house prices would have fallen by 18% and 27%, respectively, compared to an observed 33% drop. Credit targeting would have implied a 22 percent drop in house prices and would have also cushioned the credit crunch.

Optimal monetary policies would have dampened the business cycle throughout the 2000s, in line with our earlier results on the stabilizing properties for inflation and the output gap over the business cycle. All counterfactual policies, but house price targeting in particular, imply a lower output gap and inflation during the boom before the 2008 financial crisis (Figure 7c-7d). At the same time, however, counterfactual policies also cushion the downturn. Our results are in line with Adam and Woodford (2021). When rising house prices pose a concern, the central bank can successfully 'lean against' such price movements. However, this policy comes at the cost that the central bank undershoots (overshoots) its targets for inflation and the output gap.

4 Conclusion

U.S. credit and housing markets exhibit strong co-movement over periods extending beyond the conventional business cycle, giving rise to the concept of the financial cycle. We examine the primary disturbance behind this co-movement and identify a financial-cycle innovations that explains 60% and 86% of the variation in credit growth and real house price growth, respectively, at medium frequencies (8–20 years). Our findings indicate that this shock propagates qualitatively similarly to a monetary policy shock. This contributes to the existing literature on the influence of monetary policy on financial variables (Miranda-Agrippino and Rey, 2020) and its effects at frequencies beyond the business cycle (Jorda et al., 2023).

Using recent policy counterfactual methods, we show that systematic monetary policy has persistent effects, particularly on financial variables, well beyond the business cycle. As a result, it can either mitigate or amplify the vulnerability of the real economy and financial system to disturbances, shaping the interdependence between the two. This contributes to the ongoing debate on the long-run effects of monetary policy and its implications for financial stability.

Following the global financial crisis, many central banks have been given a mandate to safeguard financial stability. As part of this mandate, they now closely monitor credit and housing cycles. The role of monetary policy in financial cycle fluctuations raises important questions for future research. Our findings suggest that incorporating financial stability concerns into monetary policy can stabilize not only financial variables but also inflation and the output gap. In particular, a policy that systematically leans against house price movements appears to enhance overall stability. Such an approach could have significantly reduced housing market volatility in the U.S. during the 2000s. Finally, our findings provides valuable insights into the ongoing debate about the costs and benefits of coordinating monetary and macroprudential policies (e.g., Stein, 2012).

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Appendix

This appendix contains supplementary material for "Shaping the fianncial cycle through monetary policy'. Section A describes all the data, its sources, and potential transformations which were made. Moreover, we present in Section B several additional results related to the different sections of the paper.

A Data

In this paper we use several macro and financial time series. All data are at quarterly frequency. Throughout the paper we run different VAR models either in log-first difference or levels. To this end, some data start at 1969:q1 while some start already at 1968:q4. All data end in 2019:q4 before the onset of the COVID pandemic.

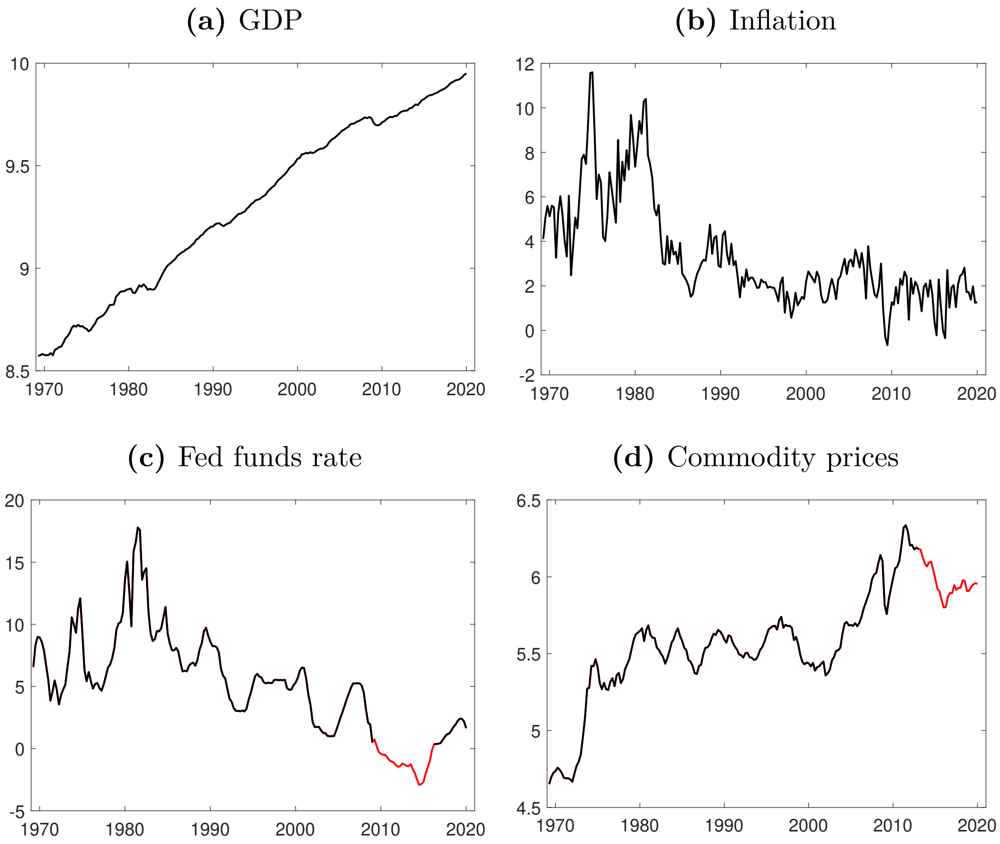
Real GDP: Real Gross Domestic Product in billions of chained 2017 Dollars, seasonally adjusted annual rate from U.S. Bureau of Economic Analysis, *(A191RX1)*, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GDPC1. The final series is in log, see figure A.1a.

GDP deflator: Gross Domestic Product: implicit price deflator, Index 2017=100, seasonal adjusted from U.S. Bureau of Economic Analysis, *(A191RD)*, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GDPDEF.

Inflation: Inflation is the log-difference of the **GDP deflator** and in annualized percentage rates, see figure A.1b.

Fed funds rate: Federal Funds Effective Rate from Board of Governors of the Federal Reserve System (US), retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/FF. The quarterly aggregation is average of period. Between 2009:q1-2015:q4 the federal funds rate is spliced with the Wu-Xia shadow short rate (Wu and Xia, 2016), retrieved from https://sites.google.com/view/jingcynthiawu/shadow-rates. Figure A.1c shows the final time series with the period of the shadow short rate in red.

Figure A.1: Time series

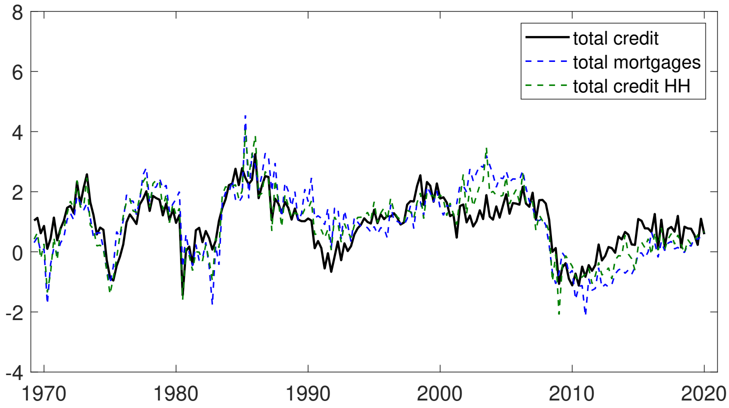


Commodity prices: Commodity prices are obtained from the replication files of Ramey (2016) *(lpcom)*, which is downloaded from her website: https://econweb.ucsd.edu/~vramey/research/Ramey_HOM_monetary.zip. Because the data end in 2012:q4, the time series is spliced with the non-fuel commodity price index from International Monetary Fund, retrieved from https://www.imf.org/en/Research/commodity-prices. Figure A.1d shows the final time series with the spliced price index from the IMF in red.

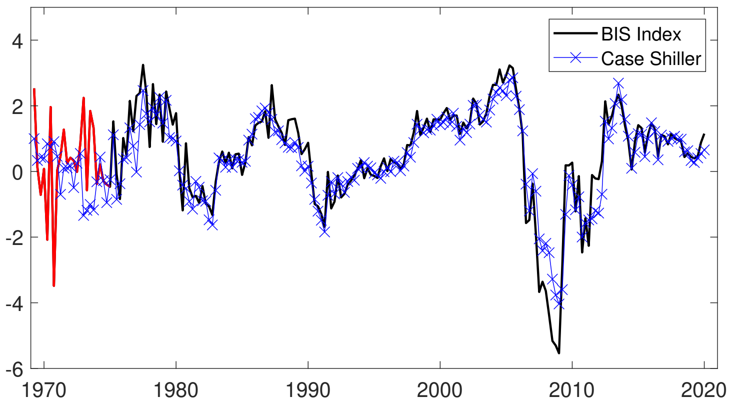
Credit: Throughout the paper, we use three different credit aggregates. The baseline model uses (1) *Total Credit to Private Non-Financial Sector* from the Bank for International Settlements, *(CRDQUSAPABIS)*, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CRDQUSAPABIS. The next aggregates, mainly for robustness checks, are (2) *Total Credit to Households and Non-Profit Institutions Serving Households*, from the Bank for International Settlements, *(CRDQUSAHABIS)*, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CRDQUSAHABIS and (3) *Households and Nonprofit Organizations - Total Mortgages* from Board of Governors of the Federal Reserve System, *(HNOTMLQ027S)*, retrieved

Figure A.2: Time series

(a) Credit growth



(b) House price growth



from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/HNOTMLQ027S. The data are seasonally adjusted using the US Census Bureau's X13-ARIMA-SEATS. Finally, all credit data are transformed into real by dividing the GDP deflator from above. The quarterly real growth rates are presented in Figure A.2a.

House prices: House prices are quarterly averages of the nominal home price index (2000=100) by Shiller (2015), the updated series is retrieved from https://shillerdata.com/. Alternatively, for robustness, we use the series nominal selected residential property prices, index (2010 = 100) from the Bank for International Settlements; *(Q.US.N.628)*, retrieved from https://data.bis.org/topics/RPP/BIS,WS_SPP,1.0/Q.US.N.628. Before 1976:q1 the time series is spliced with the residential property price index of new single family houses from the Bank of International Settlement; *(Q.US.0.2.2.1.0.0)*, retrieved from https://data.bis.org/topics/RPP/BIS,WS_DPP,1.0/Q.US.0.2.2.1.0.0. All house price series are seasonally adjusted using the US Census Bureau's X13-ARIMA-

SEATS. Finally, house prices are transformed into real by dividing the GDP deflator from above. The final real growth rates are presented in figure A.2b, where the red line marks the spliced extensions for the BIS series.

Next to the described time series, we use several shock series from the literature as internal or external instruments. The following list describes the instruments and their source. Besides the *mbc* shock by Angeletos et al. (2020) and the narrative series by Aruoba and Drechsel (2024), all remaining shock series are from the replication file of McKay and Wolf (2023) which is retrieved from https://github.com/ckwolf92/policy_cnfctls. While the shock series are not available for our whole sample between 1969:q1-2019:q4, we set if necessary the missing values to zero. All shock series are aggregated to quarterly frequency.

Romer & Romer: This is the extended series of the original Romer and Romer (2004) shock series by Wieland and Yang (2020)

Gertler & Karadi: We use two high-frequency monetary policy surprise series by Gertler and Karadi (2015). Specifically, the surprise on the current future rate named *mp1* and the surprise in the three month ahead futures rate *ff4*

Miranda-Agrippino & Ricco: This is the SVAR-IV shock series constructed at the posterior mode of the estimated reduced-form VAR of Miranda-Agrippino and Ricco (2021).

Aruoba & Drechsel: This is new narrative shock series by Aruoba and Drechsel (2024) retrieved from https://econweb.umd.edu/~drechsel/research.html

MBC: This series is the main business cycle shock by Angeletos et al. (2020) and retrieved from https://sites.northwestern.edu/angeletos/home/. Specifically, we use the shock series which targets unemployment.

B Supplementary material ...

B.1 ... for section 2.1

We run different robustness checks regarding observables, sample, and lag length. In particular, we substitute the house prices series based on Shiller (2015) with an alternative series from the BIS (see data appendix A). Moreover, we substitute the credit growth series with two different measures: *Total Credit to Households and Non-Profit Institutions Serving Households* and *Households and Nonprofit Organizations - Total Mortgages*. Additionally, we run the identification approach on a smaller sample which ends in 2007:q4 and therefore stops before the financial crises. Eventually, we specified different lag length of $p = 6$ and $p = 4$ as robustness checks.

Tables B.1, B.2, and B.3 presents the variance contributions of financial-cycle shock in comparison to the results in table 1 for the baseline model. Figure 3 in the main text and B.2 and B.3 in the next subsection provide the impulse responses based for these robustness checks.

Table B.1: Variance contributions of medium-cycle shock - robustness

Variable	Credit growth	GDP growth	House price growth	Inflation	Interest rate
			$VAR(p = 6)$		
Full cycle	39.5	19.1	73.7	14.2	20.9
$[0, 2\pi]$	$[26, 53]$	$[13, 27]$	$[58, 83]$	$[6, 30]$	$[8, 40]$
Medium cycle	61.5	54.6	88.0	21.8	32.8
$[2\pi/80, 2\pi/32]$	$[45, 74]$	$[38, 69]$	$[79, 93]$	$[8, 41]$	$[16, 51]$
Business cycle	30.1	19.1	70.1	14.0	25.1
$[2\pi/32, 2\pi/6]$	$[19, 44]$	$[11, 29]$	$[55, 81]$	$[7, 26]$	$[11, 42]$
			$VAR(p = 4)$		
Full cycle	55.9	24.6	71.2	15.4	27.6
$[0, 2\pi]$	$[40, 69]$	$[15, 37]$	$[55, 83]$	$[6, 33]$	$[10, 49]$
Medium cycle	70.7	55.8	82.9	19.9	28.6
$[2\pi/80, 2\pi/32]$	$[55, 82]$	$[39, 69]$	$[72, 90]$	$[7, 38]$	$[12, 47]$
Business cycle	42.2	25.9	81.0	16.1	13.2
$[2\pi/32, 2\pi/6]$	$[24, 61]$	$[13, 43]$	$[65, 91]$	$[8, 27]$	$[6, 23]$

Notes: Variance contributions of financial-cycle shock for VAR models with different lag length. For each robust exercise, the first row (full cycle) corresponds to the full variance calculated over all frequencies between 0 and 2π. The second row (medium) corresponds to the range between 32 and 80 quarters and the third row (business cycle) corresponds to the range between 6 and 32 quarters. The numbers in brackets represent the 68% HPDI.

Table B.2: Variance contributions of medium-cycle shock - robustness

Variable	Credit growth	GDP growth	House price growth	Inflation	Interest rate
			$VAR(p = 12)$		
Full cycle	39.9	23.9	67.0	17.1	20.7
$[0, 2\pi]$	$[26, 55]$	$[17, 33]$	$[49, 79]$	$[8, 33]$	$[9, 39]$
Medium cycle	62.2	72.2	85.8	37.9	51.1
$[2\pi/80, 2\pi/32]$	$[43, 77]$	$[56, 84]$	$[73, 93]$	$[19, 60]$	$[30, 70]$
Business cycle	39.4	25.6	54.5	22.6	38.8
$[2\pi/32, 2\pi/6]$	$[26, 54]$	$[16, 37]$	$[39, 67]$	$[12, 37]$	$[23, 55]$
			$VAR(p = 16)$		
Full cycle	38.7	25.2	62.7	23.4	28.0
$[0, 2\pi]$	$[26, 54]$	$[18, 35]$	$[47, 75]$	$[11, 42]$	$[13, 47]$
Medium cycle	60.2	66.2	81.4	38.9	50.9
$[2\pi/80, 2\pi/32]$	$[43, 75]$	$[50, 79]$	$[68, 90]$	$[18, 62]$	$[30, 70]$
Business cycle	35.7	24.9	46.0	19.5	35.5
$[2\pi/32, 2\pi/6]$	$[23, 50]$	$[15, 36]$	$[31, 60]$	$[10, 34]$	$[19, 53]$
			$VAR(p = 20)$		
Full cycle	39.0	26.4	55.3	27.6	28.8
$[0, 2\pi]$	$[27, 55]$	$[19, 36]$	$[42, 68]$	$[15, 45]$	$[16, 46]$
Medium cycle	59.3	61.2	74.8	43.4	54.6
$[2\pi/80, 2\pi/32]$	$[44, 73]$	$[47, 74]$	$[60, 85]$	$[23, 64]$	$[37, 70]$
Business cycle	27.9	23.0	29.6	15.6	19.7
$[2\pi/32, 2\pi/6]$	$[17, 43]$	$[14, 34]$	$[18, 42]$	$[9, 28]$	$[11, 35]$

Notes: Variance contributions of financial-cycle shock for VAR models with different lag length. For each robust exercise, the first row (full cycle) corresponds to the full variance calculated over all frequencies between 0 and 2π. The second row (medium) corresponds to the range between 32 and 80 quarters and the third row (business cycle) corresponds to the range between 6 and 32 quarters. The numbers in brackets represent the 68% HPDI.

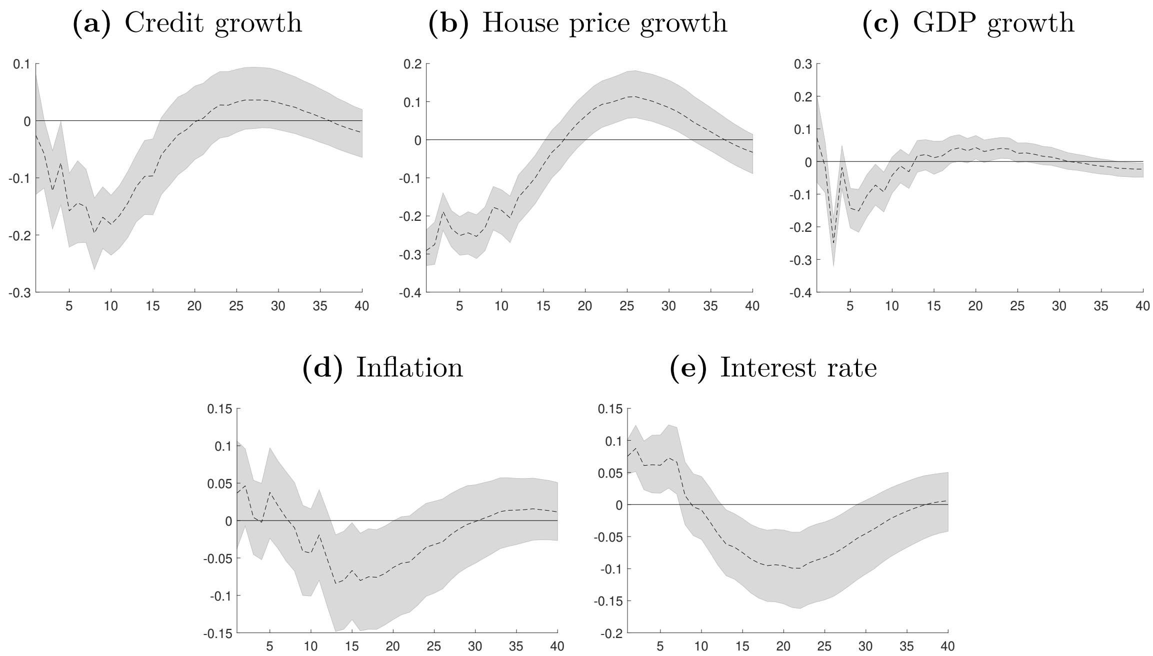
Table B.3: Variance contributions of medium-cycle shock - robustness

Variable	Credit growth	GDP growth	House price growth	Inflation	Interest rate
BIS house price index					
Full cycle	33.2	20.3	63.9	16.7	22.2
$[0, 2\pi]$	$[20, 49]$	$[14, 28]$	$[49, 74]$	$[7, 34]$	$[10, 40]$
Medium cycle	55.6	63.5	83.2	31.9	46.3
$[2\pi/80, 2\pi/32]$	$[35, 72]$	$[46, 77]$	$[71, 90]$	$[14, 53]$	$[27, 65]$
Business cycle	26.2	19.3	48.7	17.0	32.4
$[2\pi/32, 2\pi/6]$	$[14, 44]$	$[11, 29]$	$[35, 61]$	$[7, 34]$	$[18, 48]$
Total credit to households					
Full cycle	34.6	21.3	66.7	13.0	18.6
$[0, 2\pi]$	$[22, 49]$	$[15, 29]$	$[52, 77]$	$[5, 28]$	$[8, 35]$
Medium cycle	65.9	63.0	84.9	30.3	51.6
$[2\pi/80, 2\pi/32]$	$[49, 79]$	$[46, 77]$	$[76, 90]$	$[13, 54]$	$[32, 70]$
Business cycle	27.5	16.6	45.5	15.3	32.5
$[2\pi/32, 2\pi/6]$	$[17, 40]$	$[10, 25]$	$[31, 60]$	$[7, 29]$	$[17, 49]$
Total mortgages - households					
Full cycle	37.8	22.6	65.2	13.3	18.8
$[0, 2\pi]$	$[23, 53]$	$[16, 31]$	$[50, 76]$	$[6, 27]$	$[9, 34]$
Medium cycle	70.7	61.8	84.2	30.3	53.0
$[2\pi/80, 2\pi/32]$	$[55, 82]$	$[45, 76]$	$[74, 90]$	$[13, 54]$	$[33, 71]$
Business cycle	32.2	18.5	41.9	18.1	39.6
$[2\pi/32, 2\pi/6]$	$[21, 45]$	$[11, 28]$	$[28, 57]$	$[8, 32]$	$[22, 56]$
Sample: 1969:q1-2007:q4					
Full cycle	31.8	22.5	65.7	22.2	32.3
$[0, 2\pi]$	$[17, 52]$	$[15, 33]$	$[47, 79]$	$[9, 43]$	$[16, 53]$
Medium cycle	58.1	54.8	81.8	41.5	55.0
$[2\pi/80, 2\pi/32]$	$[31, 77]$	$[29, 74]$	$[67, 90]$	$[19, 66]$	$[32, 74]$
Business cycle	23.5	19.2	53.8	17.2	33.4
$[2\pi/32, 2\pi/6]$	$[11, 44]$	$[9, 32]$	$[34, 70]$	$[7, 37]$	$[16, 53]$

Notes: Variance contributions of financial-cycle shock for different set of observable and different sample length. For each robust exercise, the first row (full cycle) corresponds to the full variance calculated over all frequencies between 0 and 2π. The second row (medium) corresponds to the range between 32 and 80 quarters and the third row (business cycle) corresponds to the range between 6 and 32 quarters. The numbers in brackets represent the 68% HPDI.

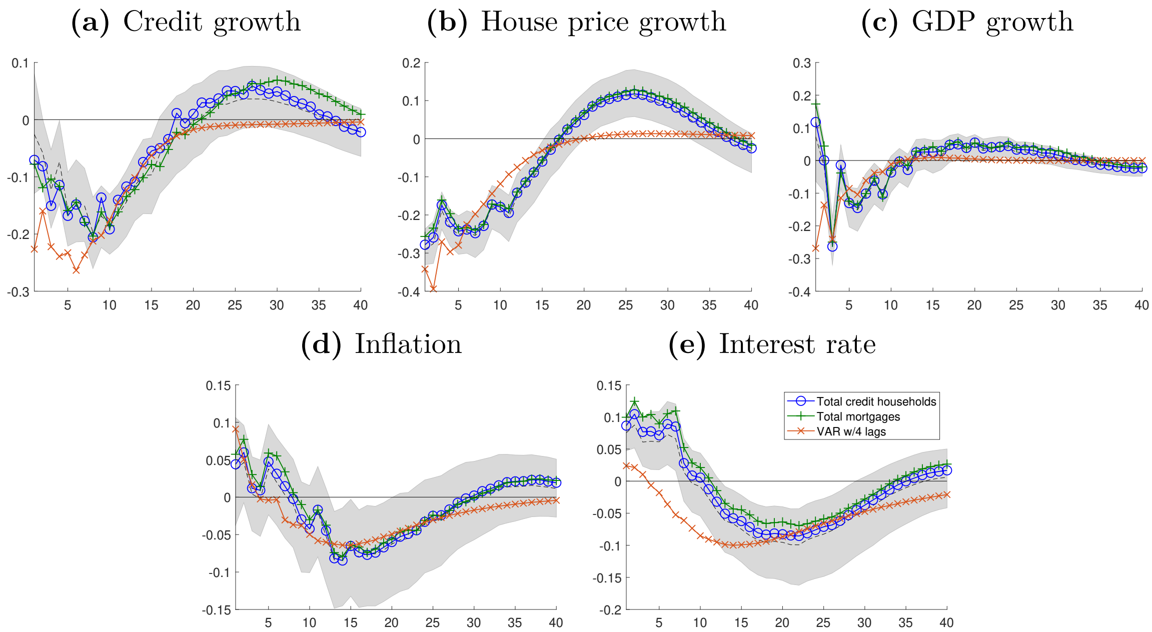
B.2 . . . for section 2.2

Figure B.1: Impulse responses to a financial-cycle shock.



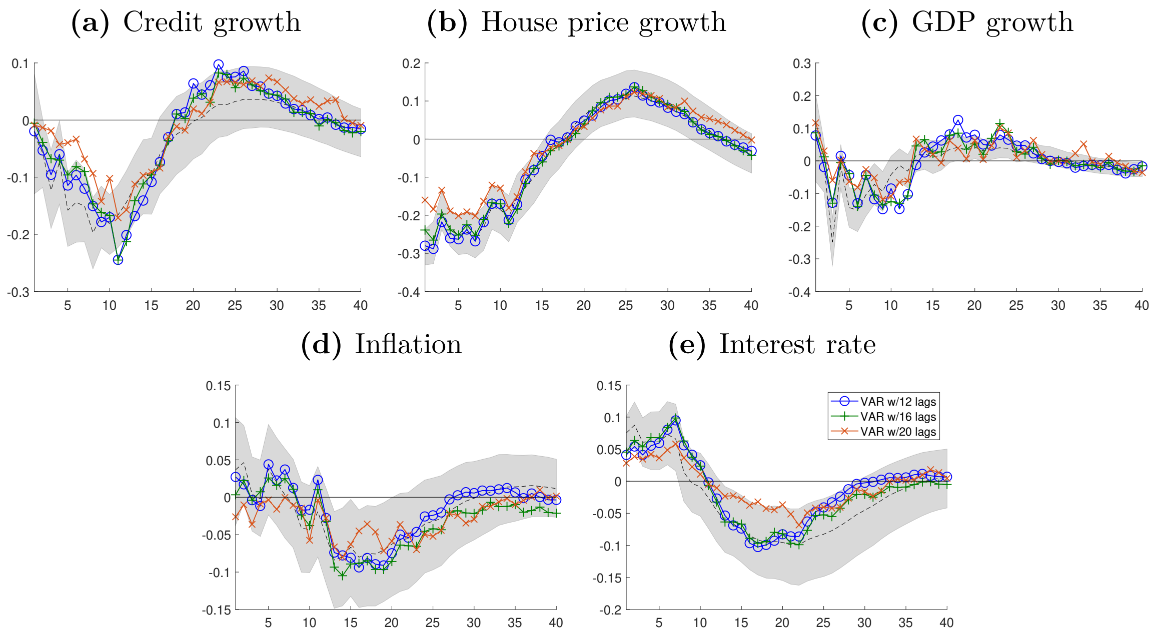
Notes: The figure show the IRFs of the financial-cycle shock out of the identification procedure described in Section 2. The grey areas represents the 16% and 84% probability bands.

Figure B.2: Impulse responses to a financial-cycle shock - robustness 2.



Notes: The figures show the IRFs of the financial-cycle shock. The dashed line and the grey areas represent the medium response and the 16% and 84% probability bands, respectively. The green-star line, blue-circle line, red-squares, and orange-cross line show the medium responses of a financial-cycle shock identified with alternative observable/sample.

Figure B.3: Impulse responses to a financial-cycle shock - robustness 3.

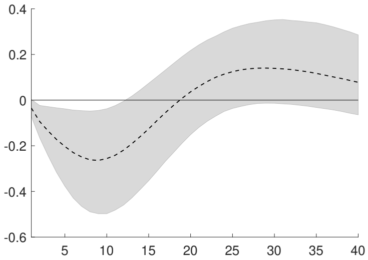


Notes: The figures show the IRFs of the financial-cycle shock. The dashed line and the grey areas represent the medium response and the 16% and 84% probability bands, respectively. The green-star line, blue-circle line, red-squares, and orange-cross line show the medium responses of a financial-cycle shock identified with alternative lag length.

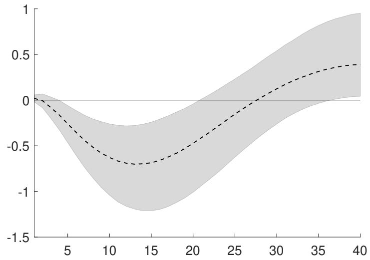
B.3 ... for section 3.1

Figure B.4: Aruoba and Drechsel (2024) monetary policy shock

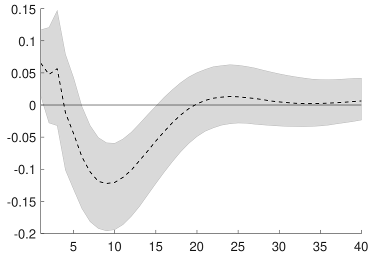
(a) Credit gap



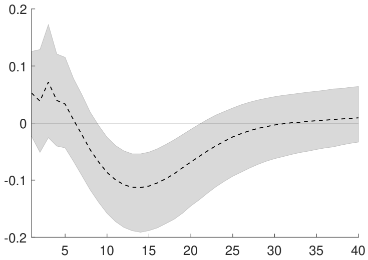
(b) House prices



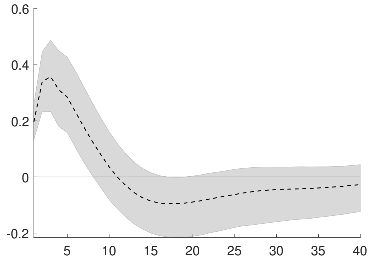
(c) Output gap



(d) Inflation



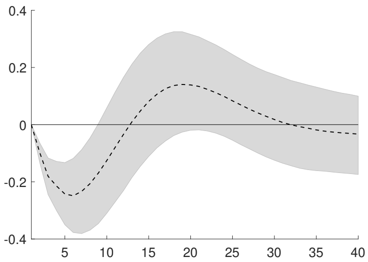
(e) Interest rate



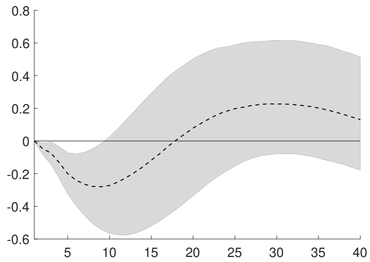
Notes: Impulse responses after the Aruoba and Drechsel (2024) monetary policy shock estimated from 1969:q1-2007:q4. The grey areas represents the 16% and 84% probability bands based on 10k draws.

Figure B.5: Romer and Romer (2004) monetary policy shock

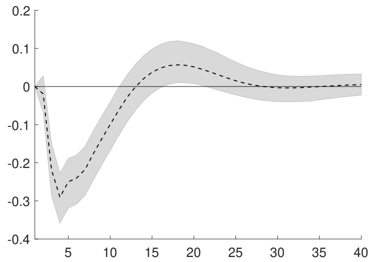
(a) Credit gap



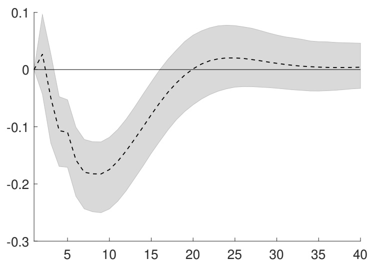
(b) House prices



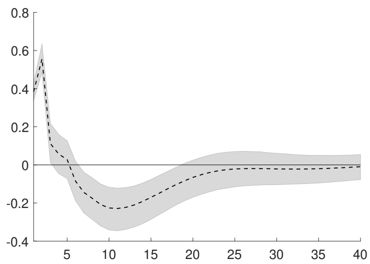
(c) Output gap



(d) Inflation



(e) Interest rate



Notes: Impulse responses after the Romer and Romer (2004) monetary policy shock estimated from 1969:q1-2007:q4. The grey areas represents the 16% and 84% probability bands based on 10k draws.

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