Online Appendix to
Financial Factors and the Business Cycle *

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April 29, 2020

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A Data

The data is mostly sourced from the Federal Reserve Economic Data (FRED), with a few series from other sources. "Adjust" refers to any data transformations: "ln" indicates natural logarithms, "Δ" indicates that the variable has been differenced, and 'break' indicates that the series has been adjusted for a break in the mean. Like Kamber and Wong (2020), we date the break using a sup-F statistic.

Series	**FRED Mnemonic or Source**	**Adjust**
Real Gross Domestic Product	GDPC1	ln, Δ
Real Personal Consumption Expenditures	PCECC96	ln, Δ
Real Gross Private Domestic Investment	GPDIC1	ln, Δ
Real Personal Income	PI	ln, Δ, break in 1984Q4
Industrial Production Index	INDPRO	ln, Δ
Capacity Utilization (Manufacturing)	CAPUTLB00004SQ	break in 2001Q1
All Employees: Total Nonfarm Payrolls	PAYEMS	ln, Δ, break in 2000Q2
Civilian Unemployment Rate	UNRATE	break in 1987Q2
Nonfarm Business Sector: Hours of All Persons	HOANBS	ln, Δ, break in 2000Q2
Nonfarm Business Sector: Real Output Per Hour of All Persons	OPHNFB	ln, Δ
Housing Starts: Total: New Privately Owned Housing Units Started	HOUST	ln, Δ
Real House Price Index	OECD	ln, Δ
Gross Domestic Product: Implicit Price Deflator	GDPDEF	
Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	ln, Δ, break in 1982Q1
Producer Price Index for All Commodities	PPIACO	ln, Δ, break in 1981Q3
Effective Federal Funds Rate	FEDFUNDS	break in 1991Q3
10-Year Treasury Constant Maturity Rate	GS10	break in 1997Q4
Real M1 Money Stock	M1SL	ln, Δ, break
Real M2 Money Stock	M2SL	ln, Δ
Total Credit to Private Non-Financial Sector, Adjusted for Breaks	CRDQUSAPABIS	ln, Δ, break in 2008Q1
Excess Bond Premium	Gilchrist and Zakrajšek (2012), updated by Board of Governors	
S&P 500 Index	Yahoo Finance	ln, Δ
Real Energy Prices	Pinksheet (World Bank) deflated by CPI	ln, Δ
CBOE Volatility Index	VXOCLS and backcasted through Caggiano et al. (2014)	

B Bayesian Estimation and Dummy Observations

We estimate the medium-sized 23 variable BVAR by utilizing the natural-conjugate Normal-Wishart prior which draws on elements of the Minnesota prior (see e.g. Litterman, 1986).

In order to estimate the BVAR, we cast Eq. (10) in the main text into a system of multivariate regressions of the form (see e.g. Robertson and Tallman, 1999; Banbura et al., 2010)

$$Y = X\beta + u, \tag{B.1}$$

where $Y = [Y_1, \ldots, Y_T]'$, $X = [X_1, \ldots, X_T]'$ with $X_t = [Y'_{t-1}, \ldots, Y'_{t-p}]$ and $u = [u_1, \ldots, u_T]'$. The Normal-Wishart prior distribution then takes the form

$$vec(\beta)|\Sigma \sim \mathcal{N}(vec(\beta_0), \Sigma \otimes \Omega_0) \quad \text{and} \quad \Sigma \sim \mathcal{IW}(S_0, a_0), \tag{B.2}$$

where we set the prior parameters β_0, Ω_0, S_0, and a_0 such that they are consistent with the structure given by Eqs. (11) and (12) in the main text and the expectation of Σ being $diag(\sigma_1^2, \ldots, \sigma_n^2)$. The prior in Eq. (B.2) can be implemented by means of dummy observations (see e.g. Del Negro and Schorfheide, 2011; Woźniak, 2016):

$$Y_d = \begin{pmatrix} 0_{np,n} \\ diag(\sigma_1 \ldots \sigma_n) \end{pmatrix}, \quad X_d = \begin{pmatrix} J_p \otimes diag(\sigma_1 \ldots \sigma_n)/\lambda \\ 0_{np,n} \end{pmatrix}, \tag{B.3}$$

where Y_d and X_d are the dummy observations chosen according to Eqs. (11) and (12) in the main text, $J_p = diag(1, \ldots, p)$, $S_0 = (Y_d - X_d B_0)'(Y_d - X_d B_0)$, $B_0 = (X_d' X_d)^{-1} X_d Y_d$, $\Omega_0 = (X_d' X_d)^{-1}$, and $a_0 = T_d - np$, where T_d is the number of rows for both Y_d and X_d. The first block of the dummy observations imposes the prior belief on the VAR slope coefficients and the second block contains the prior for the covariance matrix.

Consider the regression in Eq. (B.1) augmented with the dummy observations:

$$Y^* = X^*\beta + u^*, \tag{B.4}$$

where $Y^* = [Y', Y_d']', X^* = [X', X_d']'$ and $u^* = [u', u_d']'$. Estimating the BVAR then simply amounts to conducting least squares regression of Y^* on X^*. The posterior distribution than has the form

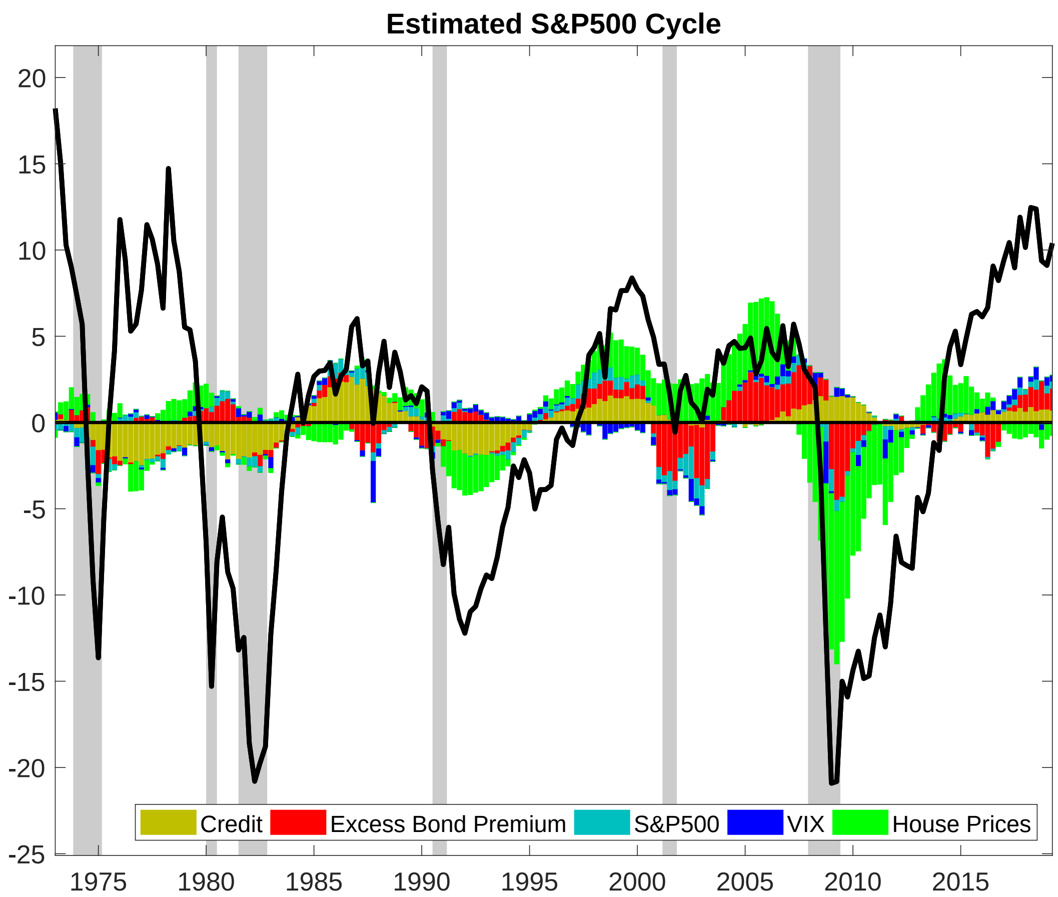
$$vec(\beta)|\Sigma, Y \sim \mathcal{N}(vec(\tilde{\beta}), \Sigma \otimes (X^{*\prime} X^*)^{-1}) \tag{B.5}$$

$$\Sigma|Y \sim \mathcal{IW}(\tilde{\Sigma}, T_d + T - np + 2), \tag{B.6}$$

where $\tilde{\beta} = (X^{*\prime} X^*)^{-1} X^{*\prime} Y^*$ and $\tilde{\Sigma} = (Y^* - X^*\tilde{\beta})'(Y^* - X^*\tilde{\beta})$.

C Decomposition of the Stock Price Cycle

Figure C.1: Informational decomposition of the estimated stock price cycle.



Notes: Solid line plots the estimated stock price cycle in % deviations from the trend. Grey shaded areas indicate NBER recessions. The bars represent the contributions of each of the BVAR forecast errors from our five financial variables (credit, the excess bond premium, the stock price index, the VIX, and house prices) for the stock price cycle.

Figure C.1 presents the informational decomposition of the estimated stock prices cycle calculated using Equation (6) in the main paper. The contributions are calculated from the forecast errors of the five financial variables in our BVAR system: real credit, the excess bond premium, stock prices, the VIX, and house prices.

We note that the stock market cycle has characteristics like look very much like the output gap. Like the output gap, of all financial variables, we find that the forecast errors of the excess bond premium and of house prices contribute much to the stock price cycle.

We present Figure C.1 for completeness as we had mentioned in the main text, there is no consensus on the definition of the financial cycle. A reason why the financial cycle literature has not often considered the stock market cycle is because the stock market features a high degree of high frequency volatility. In fact, as we show, the stock market cycle appears more like the output gap than the credit and housing price cycle which we had estimated in the main text.

D Impulse Response Functions

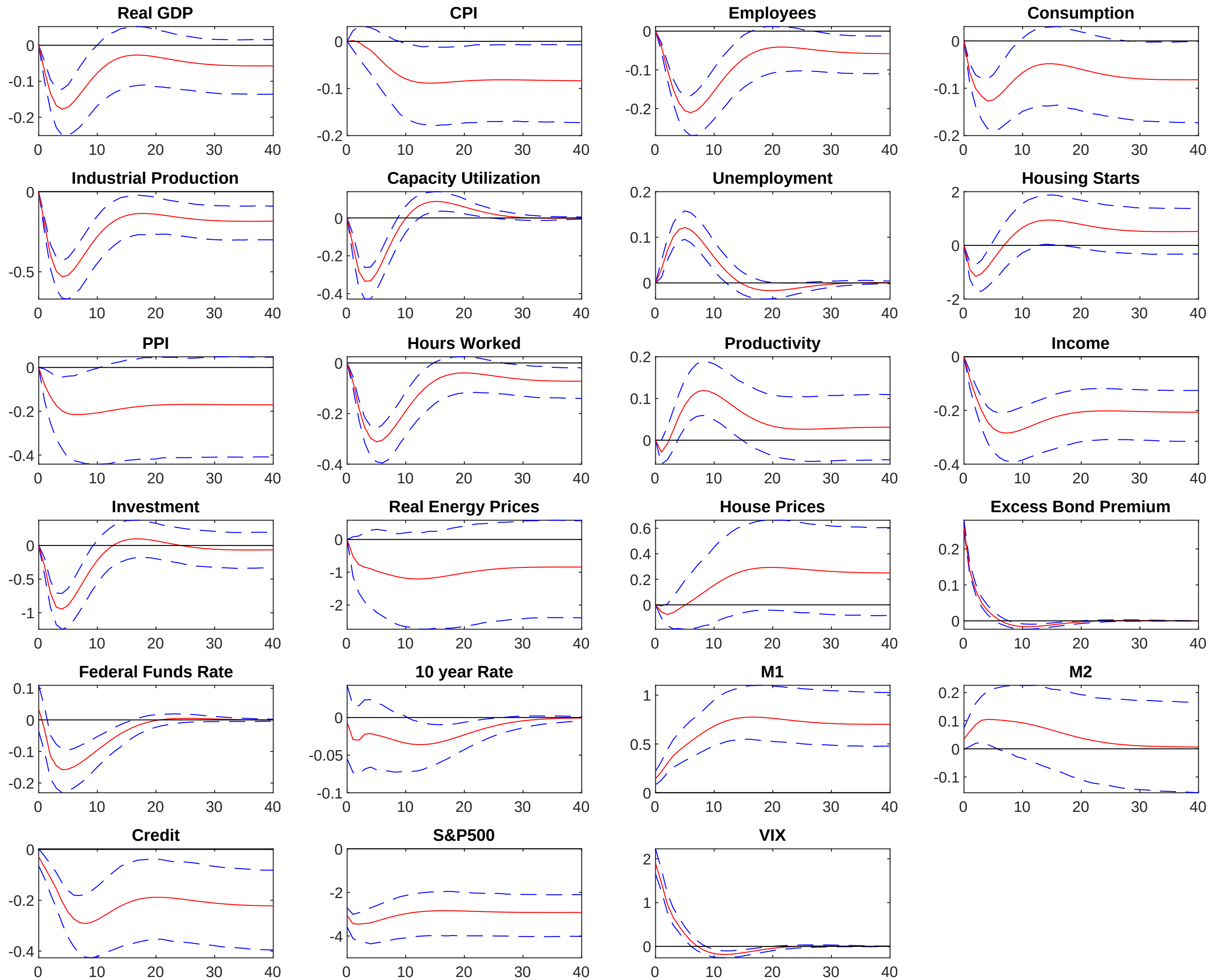
Figures D.2 to D.4 presents posterior distribution of the impulse response functions to a one standard deviation financial shock. Figures D.2 and D.3 present the posterior mean (taken from the solution from the posterior mean of the BVAR parameters) and equal tailed 68% credible sets. Figure D.4 presents the posterior median, together with equal tailed 68% credible sets from the sign and narrative restrictions identification.

For both the Cholesky decomposition and penalty function approach, the posterior distribution of the impulse response functions is constructed by taking 1000 draws from the posterior distribution of the reduced form, as per Eqs. (B.5) and (B.6).

The posterior distribution for the sign restrictions with the narrative is constructed using the algorithm by Antolín-Díaz and Rubio-Ramírez (2018), where we first take a draw from our reduced form posterior distribution, and multiplied a Cholesky factorization of the draw from the posterior distribution of the covariance matrix by a randomly drawn orthonormal matrix. If the draw satisfies the sign and narrative restriction, we keep the draw, otherwise we discard. We iterate the algorithm until we find 1000 draws that satisfy the sign and narrative restrictions from this first stage. Thereafter, we construct the resampled importance weights, as described by Antolín-Díaz and Rubio-Ramírez (2018), and use the importance weights to reweight the 1000 draws from the first stage to construct the posterior distribution of impulse response functions.

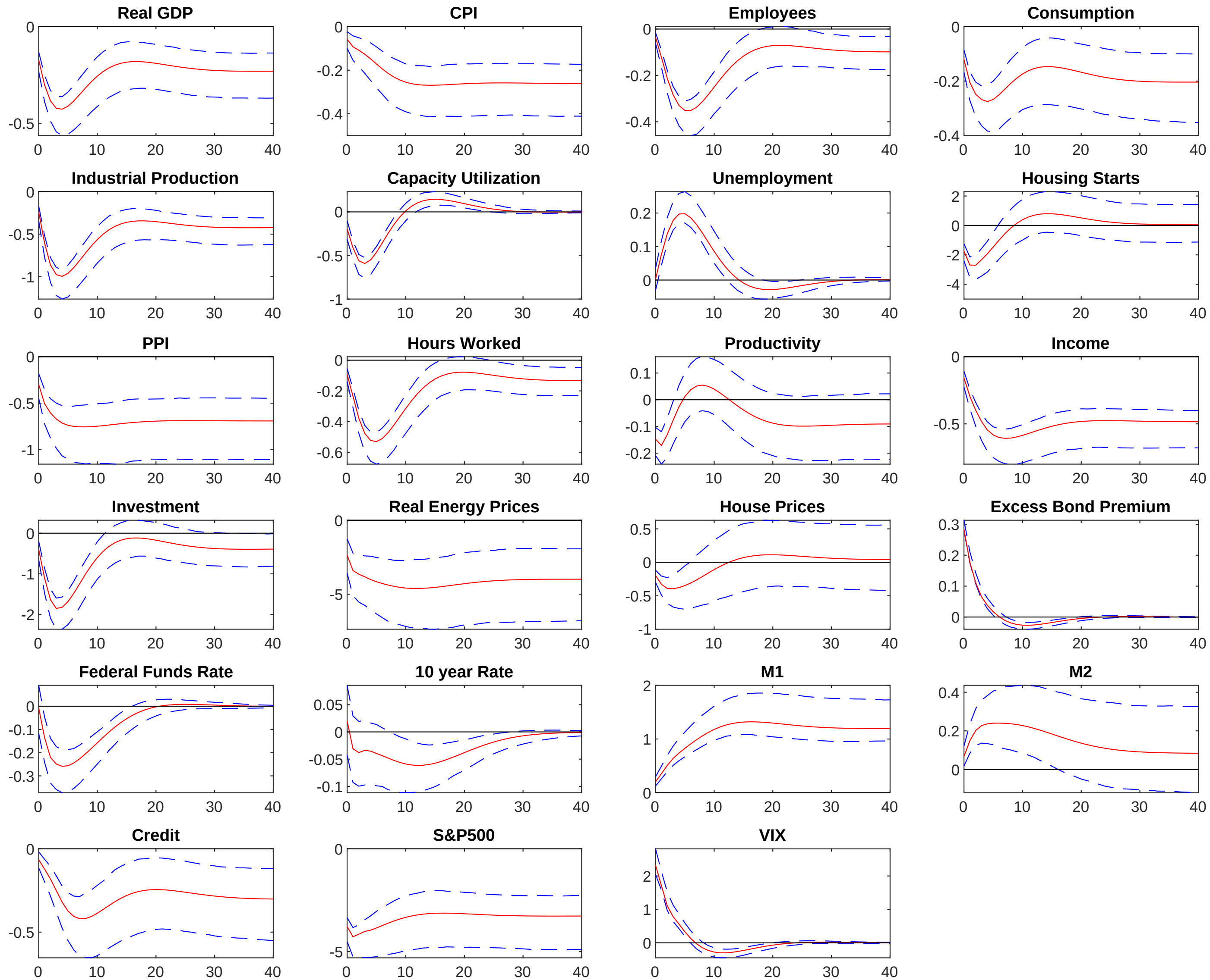
As we comment in the main text, all three identification procedures imply qualitatively very similar response to a financial shock. Overall, the responses identified with the Cholesky decomposition are less pronounced as compared to those identified with the Penalty Function and sign restrictions. For the penalty function approach this result is not surprising, because the objective function that we are using to identify the financial shock maximizes responses of the excess bond premium.

Figure D.2: Impulse response functions to a one standard deviation financial shock (Cholesky identification).



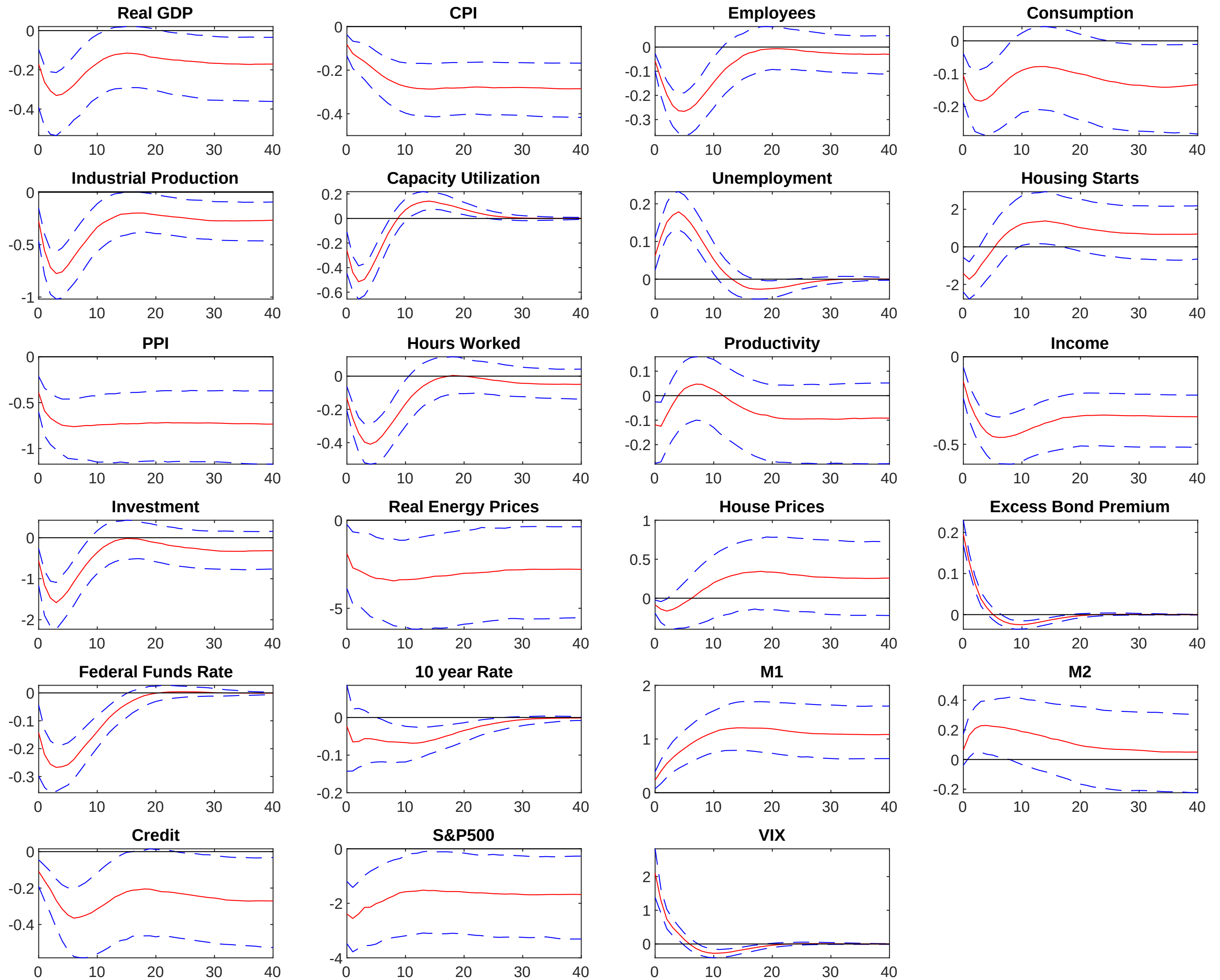
Notes: Posterior mean with 68% credible sets. The x-axis is in terms of quarters after the shock. Capacity utilization, unemployment, Federal funds rate, and 10 years rate are in terms of percentage point deviation. VIX and excess bond premium are in their natural units. All other variables are in terms of percentage change.

Figure D.3: Impulse response functions to a one standard deviation financial shock (penalty function identification)



Notes: Posterior mean with 68% credible sets. The x-axis is in terms of quarters after the shock. Capacity utilization, unemployment, Federal funds rate, and 10 years rate are in terms of percentage point deviation. VIX and excess bond premium are in their natural units. All other variables are in terms of percentage change.

Figure D.4: Impulse response functions to a one standard deviation financial shock (sign restrictions)



Notes: Posterior median with 68% credible sets. Posterior distribution are obtained as described in Antolín-Díaz and Rubio-Ramírez (2018). The x-axis is in terms of quarters after the shock. Capacity utilization, unemployment, Federal funds rate, and 10 years rate are in terms of percentage point deviation. VIX and excess bond premium are in their natural units.

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