Online Appendix to “Systemic Bank Risk and Monetary Policy”

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A.1 Data Description and Sources

A.1.1 Variables Used

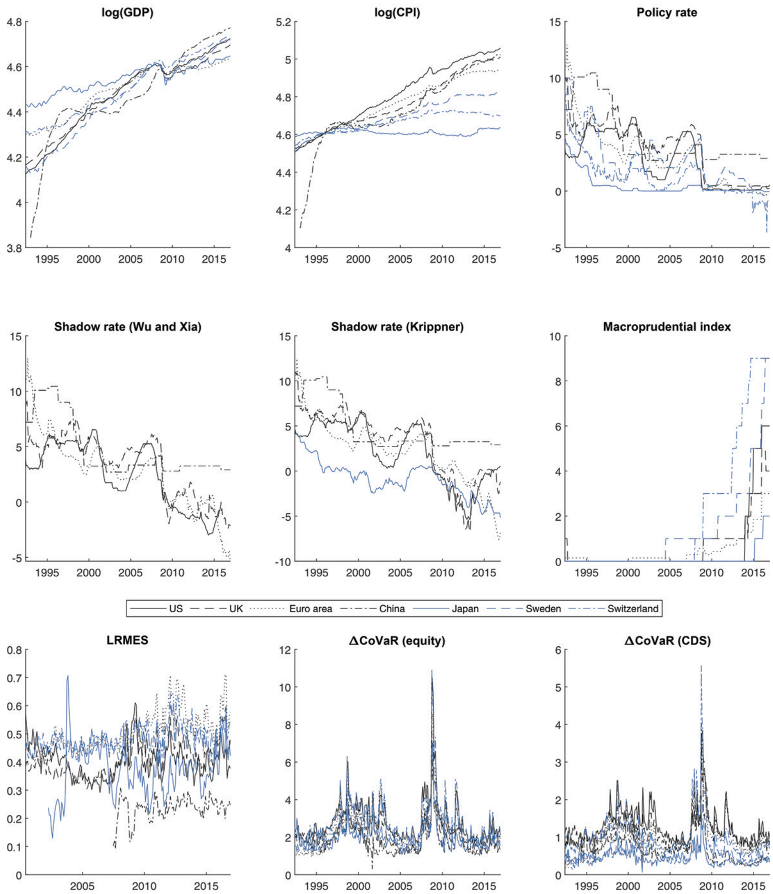
The panel VAR includes the following set of variables. Data sources for the country-level series are detailed in tables A.2–A.4.

- **GDP:** Interpolated from quarterly to monthly data using the Chow and Lin (1971) interpolation method with industrial production and retail sales as reference series.[1]
- **CPI**
- **Interest rates:** Policy rate (money market rates), shadow rates (Wu and Xia 2016; Krippner 2013).
- **Macroprudential regulation:** Index of macroprudential regulation of Alam et al. (2019), excluding reserve requirements.
- **LRMES:** Long-run marginal expected shortfall as in Acharya et al. (2017).
- **ΔCoVaR (based on equity returns and CDS spreads):** Authors' calculations based on Adrian and Brunnermeier (2016). Details on the measure and its computation are given in section A.1.3.

Figure A.1 depicts country averages of these variables (with weights based on banks' market capitalization), whereas details on the underlying time series and their sources are given in tables A.2–A.4. Table A.1 lists all banks for which the risk metrics are calculated.

[1]As Chinese industrial production is very volatile during the period under investigation, for China we use real GDP series (nominal GDP deflated by the CPI) interpolated to monthly values using quadratic-match averages.

Figure A.1. Time Series Used in Panel VAR



Additionally, for the proxy VAR we closely follow Jarocinski and Karadi (2020) and use the following variables:

- **HICP** for the euro area.
- **GDP** for the euro area.
- **Excess bond premium**: credit spread of Gilchrist and Zakrajšek (2012) for the United States, BBB bond spread for the euro area.

Table A.1. G-SIBs Used for Risk Measures

Country	Bank	Data for Weights
United States	Bank of America	VL, CC
	Bank of New York Mellon	VL, CC
	Citigroup	VL, CC
	Goldman Sachs	VL, CC
	JP Morgan Chase	VL, CC
	Morgan Stanley	VL, CC
	State Street	VL, CC
	Wells Fargo	VL, CC
		VL, CC
United Kingdom	Barclays	VL, CC
	HSBC	VL, WS
	Royal Bank of Scotland	VL, CC
	Standard Chartered	VL, WS
Switzerland	Credit Suisse	VL, CC, WS
	UBS	VL, CC, WS
Sweden	Nordea Bank	VL, WS
Spain	Banco Santander	VL, CC
Netherlands	ING	VL, CC, WS
Japan	Mizuho Financial Group	VL, CC
	Mitsubishi UFJ Financial Group	VL, CC, WS
	Sumitomo Mitsui Financial Group	VL, CC, WS
Italy	Unicredit	VL, WS
Germany	Deutsche Bank	VL, CC, WS
France	BNP Paribas	VL, WS
	Credit Agricole	VL, WS
	Societe Generale	VL, WS
China	Agricultural Bank of China	VL, WS
	Bank of China	VL, WS
	China Construction Bank	VL, WS
	Industr. and Comm. Bank of China	VL, WS

Notes: Global systemically important banks (G-SIBs) as defined in 2016 by the Financial Stability Board (FSB) in consultation with the Basel Committee on Banking Supervision (BCBS) at the Bank for International Settlements (BIS). Groupe BPCE is missing due to lacking data availability. For all banks we use market capitalization data from V-Lab (VL) from June 2000 onward. Additional balance sheet data: CC: Compustat/CRSP, WS: Thomson Reuters Worldscope.

Table A.2. Data Sources of Country-Level Data: United States, Japan, Switzerland, and United Kingdom

	United States	Japan	Switzerland	United Kingdom
Policy Rate	Call money rate, OECD via FRED, IRSTCI01USM156N	Call money rate, OECD via FRED, IRSTCI01JPM156N	Call money rate, OECD via FRED, IRSTCI01CHM156N until 1999. From then onward SNB	Call money rate, OECD via FRED, IRSTCI01GBM156N
CPI	OECD via FRED, CPALTT01USM661S	OECD via FRED, JPNCPIALLMINMEI	OECD via FRED, CHECPIALLMINMEI	OECD via FRED, GBRCPIALLMINMEI
GDP	OECD via FRED, LNBQRSA	OECD via FRED, LORSGPORJPQ661S	OECD via FRED, LNBQRSA	OECD via FRED, LNBQRSA
Industrial Production	Board of Governors of the Federal Reserve System via FRED, INDPRO	OECD via FRED, JPNPROINDMIS-MEI	OECD via FRED, CHEPROINDQISMEI (quarterly values interpolated to monthly frequency based on constant match average method)	OECD via FRED, GBRPROINDMISMEI
Shadow Rate, Wu Xia	Wu and Xia (2016)			Wu and Xia (2016)
Shadow Rate, Krippner	Krippner	Krippner		Krippner

(*continued*)

Table A.2. (Continued)

	United States	**Japan**	**Switzerland**	**United Kingdom**
VIX	Datastream	Datastream	Datastream	Datastream
Retail Sales	Datastream	Datastream	Datastream	Datastream
Stock Market Index	Datastream market index, Datastream	Datastream market index, Datastream	Datastream market index, Datastream	Datastream market index, Datastream
Real Estate Price Index	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream
Long-Term Interest Rate	10-year government bond rate, Datastream	10-year government bond rate, Datastream		10-year government bond rate, Datastream
Short-Term Interest Rate	Three-month Treasury bill rate, Datastream		Two-year government bond rate, Datastream	Three-month Treasury bill tender rate, Datastream
Interbank Rate	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream
Corporate Bond Rate	Moody's BAA corporate bond yield, Datastream			Five-year BBB corporate bond yield, Datastream

- **Stock prices**: S&P 500 for the United States, Euro Stoxx 50 for the euro area.
- **Interest rates**: One- and two-year government bond yields for the United States, money market and two-year German government bond yields for the euro area.
- **High-frequency market responses**: Miranda-Agrippino and Ricco (2021) and Cieslak and Schrimpf (2019) for the United States (10 minutes before until 20 minutes after press statements and press conferences, changes in three-month and two-year U.S. government bond yields and S&P 500), Altavilla, Brugnolini et al. (2019) for the euro area (monetary event window encompassing both press statements and press conferences, changes in two-year German government bond yields and Euro Stoxx 50).

Table A.3. Data Sources of Country-Level Data: Sweden, China, France, and Germany

	Sweden	**China**	**France**	**Germany**
Policy Rate	Call money rate, OECD via FRED, IRSTCI01SEM156N	Call money rate, OECD via FRED, IRSTCI01CNM156N	Call money rate, OECD via FRED, IRSTCI01FRM156N	Call money rate, OECD via FRED, IRSTCI01DEM156N
CPI	OECD via FRED, SWECPIALLMINMEI	OECD via FRED, CHNCPIALLMINMEI	OECD via FRED, FRACPIALLMINMEI	OECD via FRED, DEUCPIALLMINMEI
GDP	OECD via FRED, NAEXKP01SEQ661S	OECD via FRED, CHNGDPNQDSMEI	OECD via FRED, LNBQRSA	OECD via FRED, NAEXKP01DEQ661S
Industrial Production	OECD via FRED, SWEPROINDMISMEI	OECD	OECD via FRED, FRPROINDMISMEI	OECD via FRED, DEUPROINDMISMEI
Shadow Rate, Wu Xia			Wu and Xia (2016), used rates for European Monetary Union	Wu and Xia (2016), used rates for European Monetary Union
Shadow Rate, Krippner			Krippner, used rates for European Monetary Union	Krippner, used rates for European Monetary Union
VIX	Datastream	Datastream (used world VIX due to nonavailability	Datastream	Datastream
Retail Sales	Datastream	Datastream	Datastream	Datastream

(*continued*)

Table A.3. (Continued)

	Sweden	**China**	**France**	**Germany**
Stock Market Index	Datastream market index, Datastream	FTSE price index, Datastream	FTSE price index, Datastream	FTSE price index, Datastream
Real Estate Price Index	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream
Long-Term Interest Rate	10-year government bond rate, Datastream		10-year government bond rate, Datastream	10-year government bond rate, Datastream
Short-Term Interest Rate	90-day Treasury bill rate, Datastream		Three-month Treasury bill rate, Datastream	
Interbank Rate	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream
Corporate Bond Rate			TMO private rate, Datastream	Umlaufsrenditen inländ. Inhaberschuldvershreibungen/Anleihen von Unternehmen (Nicht-MFIs), Bundesbank, BBK01.WT0022

Table A.4. Data Sources of Country-Level Data: Spain, Netherlands, and Italy

	Spain	Netherlands	Italy
Policy Rate	Call money rate, OECD via FRED, IRSTC101ESM156N	Call money rate, OECD via FRED, IRSTCI01NLM156N	Call money rate, OECD via FRED, IRSTCI01ITM156N
CPI	OECD via FRED, ESPCPIALLMINMEI	OECD via FRED, NLDCPIALLMINMEI	OECD via FRED, ITACPIALLMINMEI
GDP	OECD via FRED, LNBQRSA	OECD via FRED, NAEXKP01NLQ661S	OECD via FRED, NAEXKP01ITQ661S
Industrial Production	OECD via FRED, ESPPROINDMISMEI	OECD via FRED, NLDPROINDMISMEI	OECD via FRED, ITAPROINDMISMEI
Shadow Rate, Wu Xia	Wu and Xia (2016), used rates for European Monetary Union	Wu and Xia (2016), used rates for European Monetary Union	Wu and Xia (2016), used rates for European Monetary Union
Shadow Rate, Krippner	Krippner, used rates for European Monetary Union	Krippner, used rates for European Monetary Union	Krippner, used rates for European Monetary Union
VIX	Datastream (used world VIX due to nonavailability)	Datastream	Datastream (used world VIX due to nonavailability)
Retail Sales	Datastream	Datastream	Datastream
Stock Market Index	FTSE price index, Datastream	FTSE price index, Datastream	FTSE price index, Datastream
Real Estate Price Index	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream
Long-Term Interest Rate	10-year government bond rate, Datastream	10-year government bond rate, Datastream	10-year government bond rate, Datastream
Short-Term Interest Rate	1–3 months Treasury bill rate, Datastream		Three-month Treasury bill auction rate, Datastream
Interbank Rate	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream
Corporate Bond Rate			

A.1.2 Balance Sheet and Market Capitalization Data

Aggregation Weights. We experiment with three types of bank weights to arrive at country-level figures for our bank-specific risk variables (and as an input in the computation of our ΔCoVaR series). Next to using simply unweighted averages, we construct weights from both market capitalization (which our main results are based on) and book assets. For this purpose we employ three data sources and proceed as follows.

From the period of June 2000 onward we rely on data from New York University's V-Lab that for most banks in our sample has daily time series available on market capitalization. We compare this data with market capitalization series from Compustat/CRSP and Thomson Reuters Worldscope.[2] The latter sources have the advantage that time series go back longer in time for various banks, but are generally of lower quality on at least two fronts. First, Worldscope data are particularly for the pre-2000 years often in annual frequency. Second, Compustat/CRSP data are available for a lower number of banks, and the data on market capitalization seem incomplete for some in that the data would result in implausibly high market leverage figures. With these considerations in mind, for the computation of weights based on market capitalization, we use the highest quality V-Lab data whenever possible (i.e., from the year 2000 onwards) and use Compustat/CRSP data where necessary. We check the latter for plausibility mostly based on a comparison to the post-2000 V-Lab data. Whenever also Compustat/CRSP data are not available, we resort to (the often annual) Worldscope data.

For weights based on total assets, for which data are not available from V-Lab, we similarly first use Compustat/CRSP data and only afterwards resort to Worldscope. In this process, whenever there are differences in the level or units of measurement between the data sources we make sure to avoid any breaks in the constructed series by indexing. All results in the main text are based on weights using market capitalization figures.

[2] We thank our discussant Emanuel Moench for providing us with the Compustat/CRSP data.

Book Leverage Time Series. In section 3.2 we include book leverage measures in our monthly proxy VARs. These are constructed from the same data sources as the series used for the computation of aggregation weights. We define book leverage as (book assets − book equity)/(book equity). As the raw data is in quarterly frequency, we follow Miranda-Agrippino and Rey (2020) and use a shape-preserving piecewise cubic spline interpolation procedure to arrive at monthly series. We use the same method in order to compute monthly control variables for the estimation of the forward-ΔCoVaR, outlined in section A.1.3.

Short-Term Funding. In figure A.13 we include a measure of short-term wholesale funding in our monthly U.S. proxy VAR. In order to construct this variable, we closely follow the Federal Reserve's Financial Stability Reports. Specifically, we rely on balance sheet data contained in the *Consolidated Financial Statements for Holding Companies* (Form FR Y-9C), which is made available via the *Uniform Bank Holding Company Performance Reports* (BHCPR).[3] For all U.S. G-SIBs we download data on large time deposits with a maturity of less than one year, federal funds purchased and securities sold under agreements to repurchase, brokered deposits, other borrowed money, and other secured borrowings. We add these components up and divide by total assets to arrive at a short-term wholesale funding ratio. As the data are available only starting in 2002, for the earlier parts of our sample, we rely on call report data compiled by Drechsler, Savov, and Schnabl (2018) that begin in the 1970s and end in 2013.[4] Here, the definitions on the short-term funding components are not identical but very similar to the ones in the BHCPR, and we verify that the dynamics of the two resulting series are almost identical for the time samples in which the data are available from both sources. As in the case for bank leverage, we interpolate quarterly values to monthly frequency using shape-preserving cubic splines.

[3]The raw data are downloadable at https://cdr.ffiec.gov/public/ManageFacsimiles.aspx.

[4]Available at https://pages.stern.nyu.edu/~pschnabl/data/data_callreport.htm.

A.1.3 System Risk Metrics

In this section we describe the systemic risk metrics employed in the VAR analysis, namely LRMES and ΔCoVaR.

LRMES. The long-run marginal expected shortfall is based on a methodology by Brownlees and Engle (2017). The modeling framework is rationalized in Acharya et al. (2017). LRMES refers to the expected capital shortfall of a financial firm given a protracted decline in the market (more than 40 percent). The marginal shortfall is defined in general as the capital that would be needed for the bank in order to be adequately capitalized after a crisis. Technically, a bank's marginal expected shortfall is computed from the average return of its equity, R^b, during the 5 percent worst days for the overall market return:

$$MES_b = \frac{1}{\text{number of days}} \sum_{\text{t: system is in 5\% tail}} R_t^b. \quad \text{(A.1)}$$

We obtain LRMES time series for all banks in the sample from the V-Lab at the Leonard N. Stern School of Business at New York University.[5] There are two ways that V-Lab computes these series. In one, LRMES is the average cumulated expected return in the stock price of each bank over simulated crisis scenarios in the following six months computed using Monte Carlo simulations of market and bank returns. This simulation-based measure is, however, available only for U.S. banks. In order to arrive at a measure that is comparable across all banks in the sample, we therefore use LRMES time series that are calculated using each bank's beta coefficient with respect to the MSCI world index.

ΔCoVaR. The second metric that we consider is ΔCoVaR by Adrian and Brunnermeier (2016). They propose to measure systemic risk through the value-at-risk (CoVaR) of the financial system, conditional on institutions being in a state of distress. The contribution of a bank to systemic risk is then the difference between the CoVaR conditional on the institution being in distress and CoVaR in the median state of the institution. We compute two variants of this metric, one based on banks' equity prices and one based on banks' CDS

[5]We are grateful to the V-Lab team, in particular Michael Robles and Brian Reis, for supplying us with the data.

spreads, following Huang, Zhou, and Zhu (2012) and Faia, Laffitte, and Ottaviano (2019). The latter might have somewhat higher predictive power since typically insurance prices embed market forecasts about future risk of default.

Technically, the definition of ΔCoVaR can be summarized as follows. Define the Value-at-Risk (VaR) of a bank as

$$\Pr(X^i \leq VaR_q^i) = q, \tag{A.2}$$

where X_i are the asset return values of bank i. The VaR of an institution j or of the financial system conditional on the event $\{X^i = VaR_q^i\}$ is given by the $CoVaR_q^{j|i}$ and the latter is defined as follows:

$$\Pr(X^j \leq CoVaR_q^{j|i} | X^i = VaR_q^i) = q. \tag{A.3}$$

The contribution of bank i to the risk of j is given by

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|i} - CoVaR_{50\%}^{j|i}, \tag{A.4}$$

where $CoVaR_{50\%}^{j|i}$ denotes the VaR of j's asset returns when i's returns are at their median (i.e., 50th percentile). Like Adrian and Brunnermeier (2016), we focus on the case in which $j = system$, namely when the portfolio return of all financial institutions is at its VaR level.

The procedure to estimate ΔCoVaR in practice is based on a set of quantile regressions which can be described as follows. First, we estimate the contribution of each bank's i losses to the systemwide losses by running the following quantile regressions:

$$\mathbf{X}_t^{system} = \alpha_q^{system} + \beta_q^{system|i} \mathbf{X}_t^i + \gamma_q^{system|i} \mathbf{M}_{t-1} + \varepsilon_t^i. \tag{A.5}$$

For the equity-based ΔCoVaR measure, $\mathbf{X}_t^k$, $k \in \{i, system\}$ denotes equity market returns in percent for bank i and of all banks in sample, respectively. For the CDS-based measure, $\mathbf{X}_t^i$ is the five-year CDS spread, whereas $\mathbf{X}_t^{system}$ refers to the weighted average CDS spread across all banks in the sample.[6] $\mathbf{M}_{t-1}$ is a set of lagged control variables specified below and $q = 0.05$ represents the quantile on

[6]We use weights based on each bank's market capitalization in U.S. dollars.

which the regression is based. We denote the estimated coefficient of each bank's contribution to systemwide losses as $\hat{\beta}_q^{system|i}$. Second, we run the following two quantile regressions to obtain estimates of the conditional VaR of each bank i for $q = 0.05$ and $q = 0.5$:

$$\mathbf{X}_t^i = \alpha_q^i + \gamma_q^i \mathbf{M}_{t-1} + \varepsilon_t^i, \tag{A.6}$$

$$\mathbf{X}_t^i = \alpha_{50}^i + \gamma_{50}^i \mathbf{M}_{t-1} + \varepsilon_t^i. \tag{A.7}$$

Finally, denoting the predicted values of (A.6) and (A.7) as $VaR_{q,t}^i \equiv \hat{\alpha}_q^i + \hat{\gamma}_q^i \mathbf{M}_{t-1}$ and $VaR_{50,t}^i \equiv \hat{\alpha}_{50}^i + \hat{\gamma}_{50}^i \mathbf{M}_{t-1}$, respectively,[7] we obtain $\Delta CoVaR_{q,t}^i$ as

$$\Delta CoVaR_{q,t}^i = \hat{\beta}_q^{system|i}(VaR_{q,t}^i - VaR_{50,t}^i). \tag{A.8}$$

In the set of lagged control variables $\mathbf{M}_{t-1}$ we include variables as suggested by Adrian and Brunnermeier (2016), where available. In particular, for U.S. banks we use (see tables A.2–A.4 for sources) the following:

- change in the three-month yield
- change in the slope of the yield curve, measured by the spread between a 10-year government bond yield and the three-month bill rate
- short-term TED spread, defined as the difference between the three-month LIBOR and Treasury bill rates
- change in the credit spread given by Moody's Baa-rated bond yield and the 10-year government bond rate
- return of the Datastream broad stock market index
- real estate sector return in excess of the market financial sector return
- implied volatility as measured by the VIX

Since for some countries not all of the above control variables are available, for all non-U.S. countries we use the U.S. controls

[7]Note that for each bank the sample length of the predicted values is based on the data availability of the right-hand-side variables. While choosing this (partly) out-of-sample prediction does not matter much for the case where $\mathbf{X}_t^i$ are equity returns, it significantly increases the sample length for the CDS-based ΔCoVaR measure since CDS spreads are generally not available before the year 2002 and, for some banks, even 2008.

wherever country-specific controls could not be obtained. These are described, along with the data sources, in tables A.2–A.4. Like Adrian and Brunnermeier (2016), we restrict estimation to banks with at least 260 weekly observations. The resulting ΔCoVaR time series are depicted as country averages in figure A.1.

Finally, we also compute forward-ΔCoVaR measures. Again we follow the procedure laid out in Adrian and Brunnermeier (2016). More specifically, we regress each bank's ΔCoVaR on lagged bank characteristics $\mathbf{X}^i$ and common control variables $\mathbf{M}$.

$$\Delta CoVaR^i_{q,t} = \alpha^i + \beta^i \mathbf{X}^i_{t-h} + \gamma^i \mathbf{M}_{t-h} + \varepsilon^i_t,$$

where $h = 24$, such that we compute the two-year forward-ΔCoVaR. Like in Adrian and Brunnermeier (2016), the common controls essentially consist of the same variables used in the computation of the real-time ΔCoVaR. As bank-specific characteristics we include a measure of size (the bank's market equity relative to the cross-sectional sum), market leverage ((book assets – book equity + market equity) / (market equity)), and a "boom" indicator (number of consecutive months of being in the top decile of the market-to-book ratio across banks). Additionally, we add each bank's lagged ΔCoVaR. Forward-ΔCoVaR is then obtained as

$$\Delta^{fwd}_h CoVaR^i_{q,t} = \hat{\alpha}^i + \hat{\beta}^i \mathbf{X}^i_{t-h} + \hat{\gamma}^i \mathbf{M}_{t-h}.$$

A.1.4 Details on Proxy (External Instrument) VAR

Shock Aggregation. As monetary policy announcements do not follow an exact monthly schedule, we have to aggregate intraperiod events to their respective months. Here we experiment with two different aggregation schemes. First, following Corsetti, Duarte, and Mann (2018), we compute the cumulative daily surprise over the past month (31 days) for each day in our sample and then take the average of this daily cumulative series over each period. This effectively amounts to an intraperiod weighting scheme where shocks at the beginning of the period are assigned a larger weight, reflecting the idea that they have more time to affect other variables of interest. Second, we follow Miranda-Agrippino and Ricco (2021) and simply compute the sum of all daily shocks arising in the particular month/quarter. All months without a monetary policy meeting are assigned a zero value. Experimenting with these two aggregation schemes, we find that the differences are most often not large. All results in the main text are based on the second aggregation scheme of simple sums.

Bayesian Estimation. As in the singly-country proxy VAR models we have to work with fewer observations, we employ Bayesian techniques in order to impose more structure on the estimation and avoid overfitting. We use standard Minnesota priors (as in Litterman 1986) that we cast in the form of a normal-inverse-Wishart prior.

Consider the setup used throughout for the proxy VAR:

$$\mathbf{A}_0\mathbf{y}_t = \mathbf{k} + \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{I}), \tag{A.9}$$

where $\mathbf{y}_t$ is an $(n \times 1)$ vector of endogenous variables, and $\mathbf{k}$ is a vector of constants. The corresponding reduced-form VAR is

$$\mathbf{y}_t = \mathbf{c} + \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}), \tag{A.10}$$

with $\mathbf{c} = \mathbf{A}_0^{-1}\mathbf{k}$, $\mathbf{B}_i = \mathbf{A}_0^{-1}\mathbf{A}_i$, and $\mathbf{u}_t = \mathbf{A}_0^{-1}\boldsymbol{\epsilon}_t$.

For Bayesian estimation, we specify a multivariate normal distribution for the regression coefficients, and an inverse-Wishart distribution for the covariance matrix of the error term:

$$\boldsymbol{\Sigma} \sim \mathcal{IW}(\underline{\mathbf{S}}, \underline{\boldsymbol{\nu}}), \tag{A.11}$$

$$\beta | \Sigma \sim \mathcal{N}(\underline{\boldsymbol{\beta}}, \Sigma \otimes \underline{\boldsymbol{\Omega}}). \tag{A.12}$$

$\beta = vec([\mathbf{c}, \mathbf{B}_1, \ldots, \mathbf{B}_p]')$ are the stacked coefficient matrices and $\underline{\mathbf{S}}$, $\underline{\boldsymbol{\nu}}$, $\underline{\boldsymbol{\beta}}$, and $\underline{\boldsymbol{\Omega}}$ are hyperparameters. Specifically, $\underline{\mathbf{S}}$ and $\underline{\boldsymbol{\nu}}$ are, respectively, the scale matrix and the degrees of freedom of the prior inverse-Wishart distribution. As is standard, we specify $\underline{\mathbf{S}}$ as a diagonal matrix with entries σ_i^2 equal to the residual variance of the regression of each variable onto its own first lag. The degrees of freedom are set to $\underline{\boldsymbol{\nu}} = n + 2$ so as to ensure that the prior variances of the coefficient matrices exist and $\mathbb{E}(\boldsymbol{\beta}) = \underline{\boldsymbol{\beta}}$ and $\mathbb{V}ar(\boldsymbol{\beta}) = \underline{\mathbf{S}} \otimes \underline{\boldsymbol{\Omega}}$.

We use a standard "Minnesota"-type prior in the spirit of Litterman (1986), which assumes the coefficient matrices to be independently normally distributed. Specifically, their first two moments are

$$\mathbb{E}[(\mathbf{B_l})_{\mathbf{i,j}}|\mathbf{\Sigma}] = \begin{cases} \delta_i & i = j, l = 1 \\ 0 & \text{otherwise} \end{cases} \tag{A.13}$$

$$\mathbb{V}ar[(\mathbf{B_l})_{\mathbf{i,j}}|\mathbf{\Sigma}] = \begin{cases} \frac{\lambda^2}{l^2} & i = j, \forall l \\ \frac{\lambda^2}{l^2}\frac{\Sigma_{i,i}}{\sigma_j^2} & i \neq j, \forall l \end{cases}, \tag{A.14}$$

where $(B_l)_{i,j}$ is the response of variable i to variable j at lag l and $\delta_i = 1$, implying random-walk behavior of the underlying time series.[8] As is common, we formalize the idea that more recent lags of a variable tend to be more informative by specifying l^2 in the variance entries. Hence, equation (A.14) ensures a decaying variance of parameters for more distant lags and is, together with our assumptions above, achieved by specifying

$$\underline{\mathbf{\Omega}} = \begin{bmatrix} \phi & \mathbf{0} \\ \mathbf{0} & diag([1^2, 2^2, \ldots, p^2])^{-1} \otimes diag([\sigma_1^2, \sigma_2^2, \ldots, \sigma_p^2])^{-1} \end{bmatrix}, \tag{A.15}$$

where ϕ is a large number, implying a flat prior on the constant terms.

The hyperparameter λ controls the overall tightness of the Minnesota prior. In the benchmark case we have it determined optimally in the spirit of hierarchical modeling as in Giannone, Lenza, and Primiceri (2015), but verify that our results hold also when setting λ to a very large value, in which case the posterior coefficient estimates correspond to their maximum-likelihood estimates.

Combining the prior specification with the likelihood function, the posteriors can be shown to correspond to

$$\mathbf{\Sigma}|\mathbf{y} \sim \mathcal{IW}(\bar{\mathbf{S}}, \bar{\nu}) \tag{A.16}$$

[8]In the benchmark results we set $\delta_i = 1$ for all, i.e., also for our risk, variables, but our results are hardly affected when setting $\delta_i = 0$ for these, as in Banbura, Giannone, and Reichlin (2010) for potentially stationary variables.

$$\beta|\Sigma, \mathbf{y} \sim \mathcal{N}(\bar{\boldsymbol{\beta}}, \boldsymbol{\Sigma} \otimes \bar{\boldsymbol{\Omega}}), \tag{A.17}$$

with

$$\bar{\boldsymbol{\Omega}} = (\ \underline{\boldsymbol{\Omega}} + \mathbf{x}'\mathbf{x})^{-\mathbf{1}}, \tag{A.18}$$

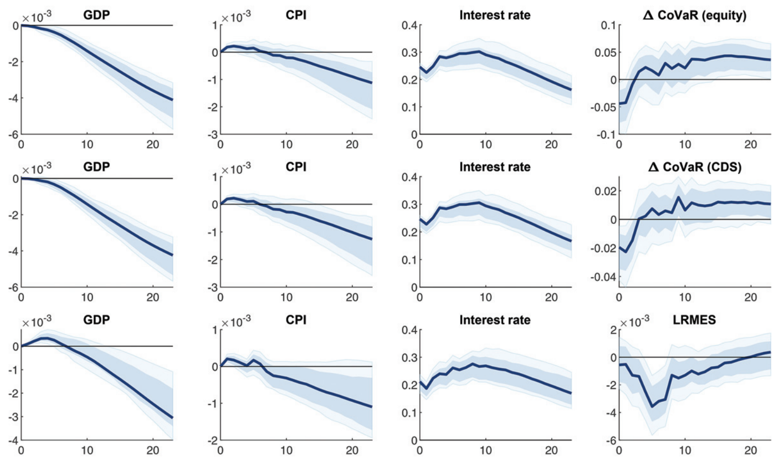
$$\bar{\boldsymbol{\beta}} = vec(\bar{\mathbf{B}}) = vec\big(\bar{\boldsymbol{\Omega}}\big(\underline{\boldsymbol{\Omega}}^{-1}\underline{\mathbf{B}} + \mathbf{x}'\mathbf{x}\hat{\mathbf{B}}\big)\big), \tag{A.19}$$

$$\begin{aligned}\bar{\mathbf{S}} = \hat{\mathbf{B}}'\mathbf{x}'\mathbf{x}\hat{\mathbf{B}} + \underline{\mathbf{B}}'\underline{\boldsymbol{\Omega}}^{-\mathbf{1}}\underline{\mathbf{B}} + \underline{\mathbf{S}} + \big(\mathbf{y} - \mathbf{x}\hat{\mathbf{B}}\big)'\big(\mathbf{y} - \mathbf{x}\hat{\mathbf{B}}\big) \\ -\bar{\mathbf{B}}'\big(\underline{\boldsymbol{\Omega}}^{-\mathbf{1}} + \mathbf{x}'\mathbf{x}\big)\bar{\mathbf{B}},\end{aligned} \tag{A.20}$$

where $\mathbf{x}_t = [\mathbf{1}, \mathbf{y}_{t-1}, \ldots, \mathbf{y}_{t-p}]$ is the projection set of lagged endogenous variables. The credible sets are then constructed by drawing from the posteriors and for each draw, making use of the external instruments approach outlined in the main text.

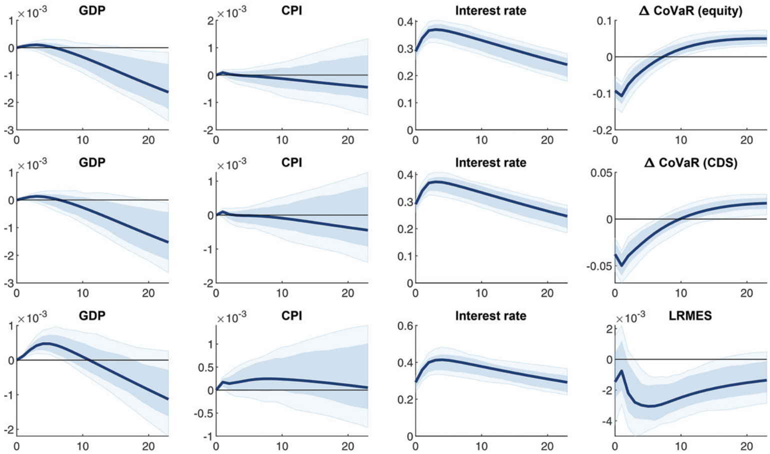
A.2 Additional Results and Robustness Checks

Figure A.2. Panel VAR with Central Bank Policy Rate (instead of shadow rate)



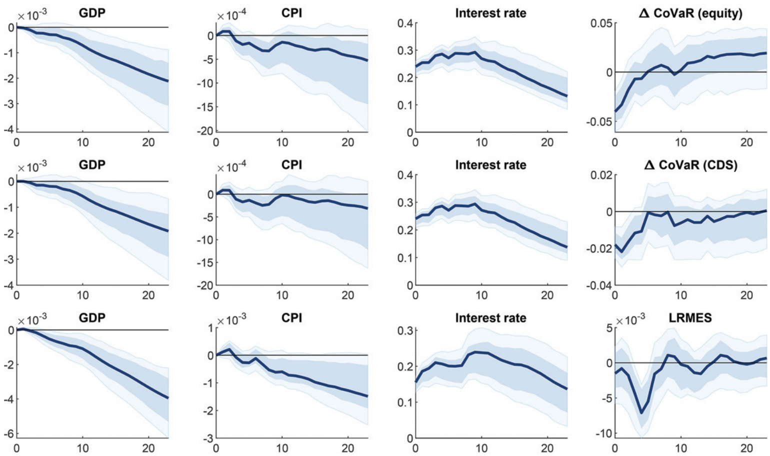
Notes: Impulse responses in the panel VAR(12) to a monetary policy shock with the policy rate as an interest rate measure. Remaining details as in figure 1.

Figure A.3. Panel VAR with 3 (instead of 12) Lags



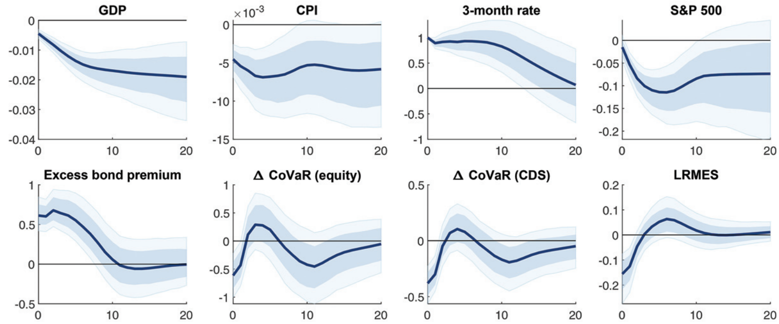
Notes: Impulse responses in the panel VAR(3) to a monetary policy shock. Remaining details as in figure 1.

Figure A.4. Panel VAR in Pre-crisis Sample



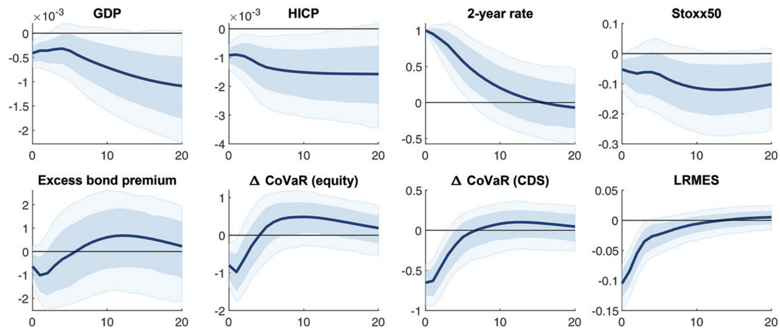
Notes: Impulse responses in the panel VAR(12) (ΔCoVaR) and VAR(9) (LRMES), respectively, to a monetary policy shock. Time sample: 1992:06–2007:12. Remaining details as in figure 1.

Figure A.5. U.S. Proxy VAR with Controls



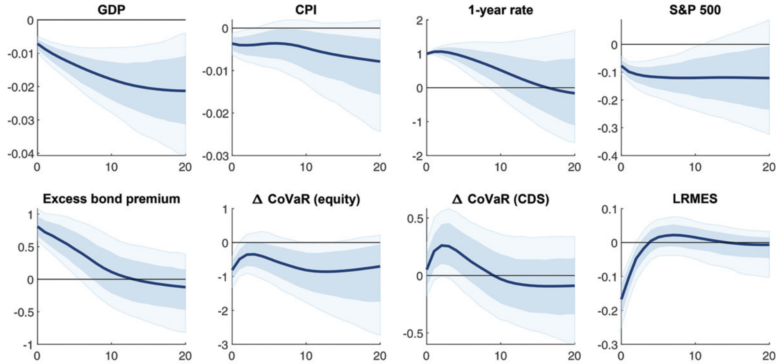
Notes: Impulse responses in monthly U.S. proxy VAR(12) with additional controls. Remaining details as in figure 2.

Figure A.6. Euro-Area Proxy VAR with Controls



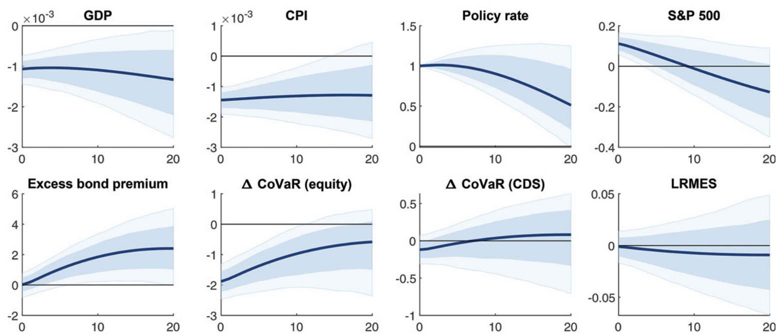
Notes: Impulse responses in monthly euro-area proxy VAR(12) with additional controls. Remaining details as in figure 3.

Figure A.7. U.S. Proxy VAR in Pre-crisis Sample



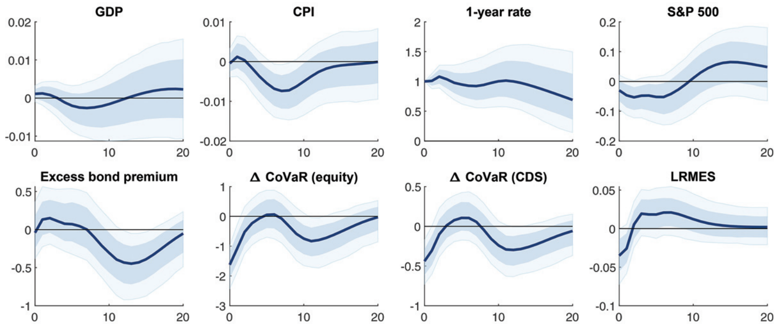
Notes: Impulse responses in monthly U.S. VAR(12) to a monetary policy shock. Time sample: 1992:06–2007:12. Remaining details as in figure A.5.

Figure A.8. Euro-Area Proxy VAR in Pre-crisis Sample



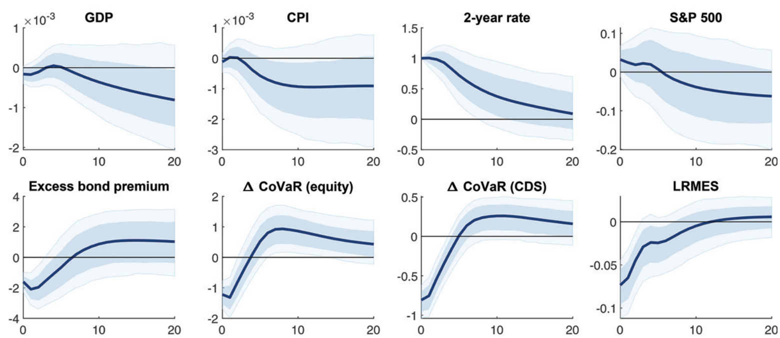
Notes: Impulse responses in monthly euro-area VAR(3) to a monetary policy shock. Time sample: 1999:01–2007:12. Remaining details as in figure A.6.

Figure A.9. U.S. Proxy VAR with Alternative Shock Identification



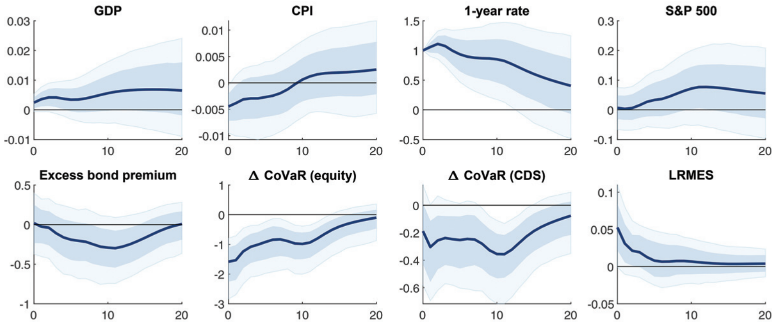
Notes: Impulse responses in monthly U.S. VAR(12) to a monetary policy shock identified using high-frequency market responses of two-year federal funds futures rate (Cieslak and Schrimpf 2019) around monetary policy announcements as external instruments (adjusted for information dissemination effects using stock price responses as in Jarocinski and Karadi 2020). Remaining details as in figure 2.

Figure A.10. Euro-Area Proxy VAR with Alternative Shock Identification



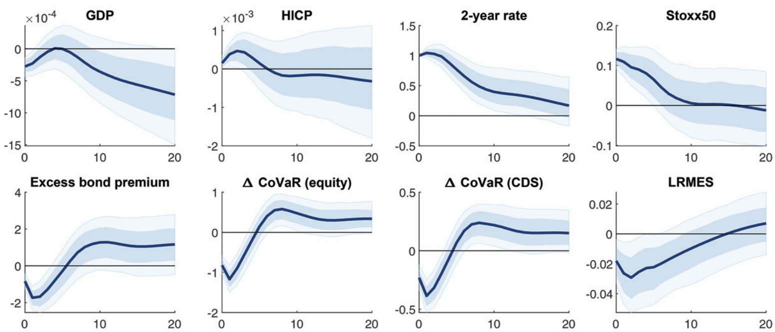
Notes: Impulse responses in monthly euro-area VAR(12) to a monetary policy shock identified using high-frequency market responses of two-year OIS rate (Cieslak and Schrimpf 2019) around monetary policy announcements as external instruments (adjusted for information dissemination effects using stock price responses as in Jarocinski and Karadi 2020). Remaining details as in figure A.6.

Figure A.11. U.S. Proxy VAR with Alternative Shock Identification and without Shock Cleansing



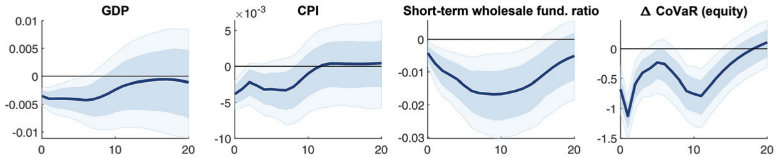
Notes: Impulse responses in monthly U.S. VAR(12) to a monetary policy shock identified using high-frequency market responses of two-year federal funds futures rate (Cieslak and Schrimpf 2019) around monetary policy announcements as external instruments (not adjusted for information dissemination effects). Remaining details as in figure 2.

Figure A.12. Euro-Area Proxy VAR without Shock Cleansing



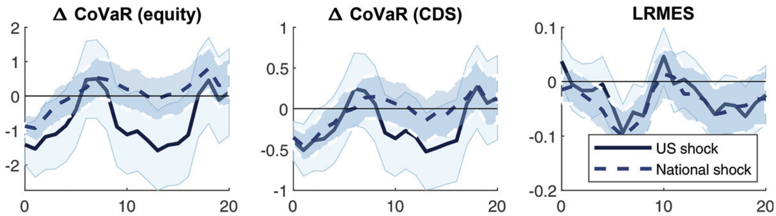
Notes: Impulse responses in monthly euro-area VAR(12) to a monetary policy shock identified using high-frequency market responses of two-year OIS rate (Cieslak and Schrimpf 2019) around monetary policy announcements as external instruments (not adjusted for information dissemination effects). Remaining details as in figure A.6.

Figure A.13. Short-Term Wholesale Funding Ratio in U.S. Proxy VAR



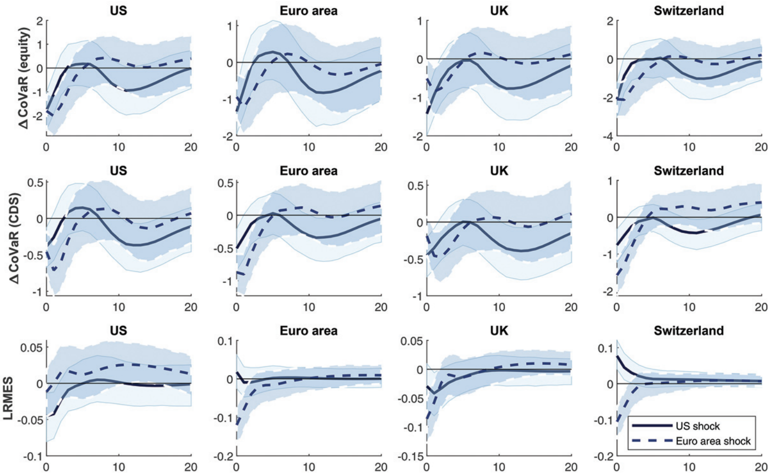
Notes: Impulse responses to a monetary policy shock in the U.S. proxy VAR identified using high-frequency market responses. Includes short-term wholesale funding ratio. Remaining details as in figure 2.

Figure A.14. U.S. vs. Domestic Monetary Policy Shock in Panel LP with Shocks Extracted from Panel VAR



Notes: Impulse responses to U.S. (solid lines, light blue) and domestic (dashed lines, dark blue) monetary policy shocks in panel local projection ($\{\beta_h\}_{h=0}^{H}$ in equation (3)). Shocks identified in the panel VAR as in figure 1. Remaining details as in figure 6.

Figure A.15. U.S. vs. Euro-Area Monetary Policy Shocks in Proxy VARs



Notes: Impulse responses to a monetary policy shock in U.S. (light blue solid) and euro-area (dark blue dashed) proxy VARs identified using high-frequency market responses, including additional controls as in figures A.5 and A.6, respectively. Time sample: 2000:06–2016:12. Shaded areas indicate 90 percent credible sets.

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