Banks' Systemic Risk and Monetary Policy*

Ester Faia
Goethe University Frankfurt and CEPR

Sören Karau
Goethe University Frankfurt

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Abstract

The banks' risk-taking channel is crucial in judging monetary policy. We test it using time series evidence and systemic risk metrics for 29 GSIBs. We find robust evidence that an increase in policy rates reduces systemic risk. We consider different risk-metrics (volatility of equity returns, marginal short-fall, ΔCoVaR), econometric specifications (panel VAR, US-FAVAR, US-proxy VAR, local projections) and monetary policy measures. We do not find strong evidence for a role of banks' leverage in the risk-taking channel, while we find a significant role of Fed policy in systemic risk propagation.

JEL: E5, G21

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1 Introduction

Assessing the relevance of the risk-taking channel of monetary policy, namely the notion that policy rates affect the risk-taking behavior of banks,[1] has important policy implications. Extensive evidence of this channel exists using individual bank risk metrics and panel data analysis. However, as mentioned by various authors (see Shin(57) for instance), the impact on bank risk acquires importance in judging policy actions only to the extent that it increases aggregate/systemic risk in the economy.

For this reason, in this paper we examine the risk-taking channel of monetary policy onto aggregate and systemic bank risk using time series evidence. Going beyond metrics of individual risk is important for two reasons. First, prior to the recent financial crisis the role of banks' interconnectedness and cross-assets holdings was central in the propagation of individual bank risk to the real economy.[2] Second, systemic risk results from the externalities of bank distress onto the rest of the financial system or the real economy (see Bernanke(14)) and as such it might have a role in macroeconomic policies. To be sure, our analysis does not take a stand on the possible welfare costs/benefits of increased systemic risk vis-à-vis the benefits from expanding demand and liquidity from monetary expansions. Understanding whether monetary policy has a significant impact on financial-sector risk at a systemic level is important nonetheless.

Theoretically there at least three channels through which monetary policy can affect systemic risk. First, it may affect individual bank risk taking, both through more exposure to leverage and to risky portfolios.[3] If this happens equally for all banks, it results in an increase of aggregate risk. Second, with low interest rates banks tend to increase reliance on market funding by other banks and this increases their cross-holdings.[4] A larger extent of interconnectedness on the liability side in turn fosters default cascades. Third, when interest rates are low, the search for yield behavior induces banks to invest in the same risky assets and to increase the exposure to cross-holdings. Increased asset commonality and interconnectedness raise the probability of contagious effects of banks' idiosyncractic shocks, thereby leading to an increase in the probability of bank panics.[5]

[1] See Borio and Zhu(19), Adrian and Shin (4) for early contributions.

[2] See Caballero and Simsek(24), Cifuentes, Ferrucci and Shin(28), Elliott, Golub, and Jackson(32), Gai, Haldane and Kapadia(34) and Aldasoro et al.(5) among others.

[3] The literature on the bank individual risk-taking channel is extensive and reviewed in the next section.

[4] See a report by the ECB and ESRB(31) joint task force.

[5] Ibid.

Whereas the first channel is well accounted for by individual bank risk measures such as the realized volatility of banks' equity returns, the latter two channels are best captured by systemic risk metrics which take into account the co-dependency of banks' portfolios, as we describe below.

Our main econometric specification is a fixed-effects panel VAR using monthly data for 29 global systemically important banks (GSIBs) headquartered in seven economies which includes metrics of bank systemic risk, a monetary policy measure, and a set of macroeconomic control variables. The advantage of using time-series evidence is that we can take into account the dynamic effects and the endogenous changes in the monetary policy stance. We compare results among various econometric specifications: next to our panel VAR, which allows us to take into account the cross-country dimension, we estimate a FAVAR and a proxy VAR for the US economy and derive impulses responses also from local projections. The last two specifications allow us to control for the endogenous response of monetary policy to financial variables. What is more, we compare results with different systemic risk metrics and different policy measures and find robust evidence that an increase in the policy rates reduces systemic risk. The effects are sizable, also compared to the effects found in the previous literature which focused on individual bank data and panel-data analysis.[6]

In order to capture various dimensions of systemic risk and to make sure that our results are not driven by a specific measure, we employ three risk metrics. The first is an aggregate measure of risk, namely the realized volatility of bank equity returns. This market-based metric has the advantage that it is not affected by distortions in bank based risk-assessment through internal risk models. It also encompasses both aspects of bank risk, namely the asset side and the liability side. Second, since an important dimension of the propagation of monetary policy onto systemic risk is potentially played by interconnections, we employ ΔCoVaR (see Adrian and Brunnermeier(3)). This systemic risk metric is meant to capture the codependency of institutions on each other's health,[7] which we compute using both equity prices, like in the original framework, and CDS spreads. Finally, we consider banks' long-run marginal expected shortfall (LMRES, see Brownlees and Engle(20)), which measures how much equity would be lost in the event of a crisis. This systemic risk metric hence helps to assess changes in the probability of banking panics and their

[6] See comments on this in the next section.

[7] Its specific definition is given in the text and in more detail in Appendix C. See Bisais et al.(17) for a survey on systemic risk metrics.

correlation with macroeconomic factors.

Next, to make sure that the risk-taking channel is not linked to one particular policy measure, we use various instruments of conventional and unconventional monetary policy. Specifically, beyond using the main policy rates we consider shadow rate estimates and the size of the central bank balance sheet. Shadow rates indicate the level at which the main policy rate would have been set in the absence of any lower-bound constraint, and hence account for endogenous changes in the stance of monetary policy to the macroeconomic environment also in the post-crisis period.[8] Using shadow rates is also one way to at least partly account for unconventional monetary policies, like forward guidance that are reflected in changes in the yield curve. In addition, we use the size of central banks' balance sheets to specifically account for the unconventional conduct of monetary policy when central banks were constrained in their setting of interest rates.[9]

Results from all model specifications considered are in line with the risk-taking channel of monetary policy. Specifically, an increase in the policy rate reduces significantly all risk metrics considered. While realized volatility declines on impact (up to two quarters), LRMES (first to second) and in particular both ΔCoVaR measures (second to fifth quarter) feature more delayed responses. Notably, this risk-taking channel is not necessarily predicated on the occurance of the financial crisis and ensuing Great Recession, as we continue to find evidence when we exclude the post-2007 period from the sample (although the effects are somewhat smaller). In addition, we observe an increase in all systemic risk metrics also when we estimate our panel VAR for the post-2007 period and use as policy variable the change in the size of central banks balance sheets. Importantly, we find evidence of a risk-taking channel also when estimating a much richer FAVAR model for the US economy in the spirit of Bernanke et al.(15), and when identifying the monetary policy shocks based on high-frequency surprise series. While the former controls for a large number of variables potentially relevant for the policy stance, the latter allows for the mutual contemporaneous response of policy and fast-moving market-based risk measures. Finally, we confirm our findings when using local projections, which similarly lets us avoid restrictive timing assumptions and compute model-free impulse responses.

In the last part of the paper we extend our VAR analysis to dissect the economic channels

[8] See Wu and Xia(61) and Krippner(44).

[9] See Gambacorta, Hofmann and Persmann(35) for the use of the same policy measure in a VAR framework.

behind our monetary risk-taking channel. First, we verify how much of the systemic risk responses to policy shocks is channeled through banks' balance sheet movements. We find that variables like banks' leverage or size contribute, but only partly. This is an important result since it confirms, as we argue, that a large part of the risk-taking channel is not solely linked to individual banks' decisions, but is driven and amplified through additional channels related to macro externalities. (interconnections, fire sales, etc.). Second, we ask how much of the risk-taking channel is driven by national as opposed to monetary policy of the US, a leader country in the global context due to the dominant role of its currency. Our results suggest that both national and US monetary policy shocks influence the movements in risk.

The paper is structured as follows. Section 2 reviews the literature on the bank risk-taking channel. Section 3 starts by discussing the empirical benchmark specification and data. It then presents the main panel VAR results next to an extensive set of robustness checks. We then outline the FAVAR and proxy VAR models and corresponding results for the US economy and local projections. Finally, in sections 3.4.1 and 3.4.2 we dissect the systemic risk channel and explore to what extent it is driven by banks' balance sheets and whether US monetary policy shocks drive systemic risk also abroad. Section 4 concludes.

2 Literature Review

Various papers in the financial literature have examined the risk-taking behavior of banks. In this section we focus on papers that analyze the link between monetary policy and banks' risk-taking. This channel of monetary policy was discussed already in a contribution by Rajan(54) and later on by Borio and Zhu(19) and Adrian and Shin(4). It has since been examined and estimated extensively using individual bank-level panel data, although evidence that it operates also at an aggregate and systemic level is largely absent.

In the theoretical literature contributions can be divided into those which examine the risk-taking channel on the liability side, namely the tendency of banks to increase their exposure to short-term liabilities, and those which analyze it on the asset side, namely the tendency of banks to expose themselves to risky portfolios. Angeloni and Faia(6), using a dynamic general equilibrium model with fundamental bank runs, show that banks increase their leverage when policy rates are low. In their model, a fall in the policy rate reduces the cost of short-term funding relative to equity capital. Banks do not internalize the effect of their decisions on the aggregate default probability, but only on the privately observed probability of a bank run. Dell'Ariccia, Laeven and Marquez(29) using a static bank model with oligopolistic competition show that monetary policy increases banks' incentives to choose asset profiles with higher return-risk profiles, hence focusing on banks' asset risk.

The model that more closely represents the relation which we wish to study, namely the one between systemic risk and changes in the policy rate in a macroeconomic general equilibrium context, is Martinez-Miera and Repullo(49). They assess the relation between bank risk and interest rates in a general equilibrium model and, most importantly, in the dynamic version of the model employ a systemic risk metric. The latter is based on the latent risk factor á la Vasicek(60) and embeds various forms of banks' inter-dependency. In the model banks intermediate savings from investors to heterogenous risky entrepreneurs. Banks' choice of the monitoring intensity positively depends on their intermediation margin. As a result, a fall in the interest rate (which could be triggered by various factors), by reducing the banks' spreads, induces banks to economize on monitoring costs. This in turn increases their failure risk and hence produces a search-for-yield behavior and increase in systemic risk.

On the empirical side contributions are more numerous, each employing different risk metrics, which are, however, usually based on panel data or cross-sectional evidence. Various papers use information on changes in lending standards from lending surveys (for instance Paligorova and Santos(52)) or from rating agency estimates (Altunbas, Gambacorta, and Marquez-Ibanez(9)). Some papers use credit registry information on default history (for instance Jimenez et al.(42), Ioannidou, Ongena, and Peydro(41)). Those measures however are mostly at firm-loan level rather than bank level. Other papers introduce more granularity by using banks' internal ratings on loans (Dell'Arriccia, Laeven and Suarez(30)). While an internal risk assessment is in principle desirable, its reliability obviously depends on loan officers' incentives and the independence of internal risk models. Finally some papers examine risk information from syndicated loans (see Aramonte, Lee and Stebunovs(7)). While in this case bank assessment of risk might be very refined, syndicated loans account for a small fraction of loan portfolios. Taken together, the above studies have been advancing the assessment of the individual banks risk-taking channel by exploring very novel and rich dataset. In most cases however the effect of changes in risk are rather small.[10] Our empirical analysis, by taking into account the endogenous response of policy and the systemic risk dimension, uncovers much larger effects of changes in policy rates.

Also all of the above papers use panel data analysis and therefore cannot easily account for the endogenous response of monetary policy to risk-taking and other macro factors. The only exceptions are Buch, Eickmeier, and Prieto(21), Buch, Eickmeier, and Prieto(22) and Angeloni, Faia and Lo Duca(10). The first measures bank risk using the Federal Reserve's Survey of Terms of Business Lending (STBL) in a FAVAR model. They find that primarily small banks take up more risk. The second paper assesses the link between banks and the macroeconomy using a model that extends a macroeconomic VAR for the US with a set of factors summarizing conditions in about 1,500 commercial banks. They find that an expansionary policy reduces the backward-looking risk of individual banks, but increases forward-looking risk. The third paper finds evidence of a risk-taking channel primarily on the banks' liability side. None of the above papers takes up a multi-country perspective nor do they use systemic risk metrics. Our work instead tries to strike a balance between the cross-sectional and time-series dimension by using a panel VAR and specifically aims at taking into account contagion effects.

3 Empirical Analysis

We begin our discussion with the benchmark panel VAR, which our main results are based on. Subsequently we show that our findings are not driven by various potential biases in our baseline specification. First, in section 3.1.4 we reestimate the panel VAR using the mean-group estimator, which eliminates any heterogeneity-induced bias from fixed-effects estimates. Second, in section 3.2 we show that our results are not due to a lack of macroeconomic control variables inherent in small-scale VAR models. We do so by running a FAVAR model based on a large set of controls for the US economy. Finally, in section 3.3 we rule out that our benchmark results are an artifact of the recursive ordering employed to identify monetary policy shocks. In particular, they continue to hold when using external time series on US monetary policy surprises as an insrument in a proxy VAR and when computing agnostic impulse reponses from local projections. Following

[10]For instance, in Dell'Ariccia et al.(30) a decrease in the short-term interest rate by one standard deviation is associated by an increase in loan risk by 13 percent of a standard deviation. Other studies find sometimes even smaller effects.

all the robustness checks, we investigate the economic forces driving the transmission along two lines. First, we analyze the qualitative and quantitative role of banks' balance sheet responses in the propagation of risk. Second, we quantify the relative contribution of national versus the US monetary policy into the propagation of risk across countries.

3.1 Panel VAR

3.1.1 Model and variable description

We employ a monthly panel dataset over the sample period 1992-2016 for 29 global systemically important banks (GSIBs), as defined by the Bank of International Settlements, from eleven countries.[11]

We denote as Y_t the stacked version of the vector of G endogenous variables $y_{i,t}$ so that $Y_t = (y'_{1,t}, y'_{2,t}, ..., y'_{N,t})$, where $i = 1, ..., N$ is the cross-sectional index and $t = 1, ..., T$ is the time index. The structural panel VAR can then be written as:

$$A_0 y_{i,t} = v_{0i}(t) + A(L) y_{i,t-1} + \epsilon_{i,t}, \tag{1}$$

where $A(L) = A_1 + A_2 L + ... + A_p L^{p-1}$ is a polynomial in the lag operator L for each cross-sectional unit i and $v_{0i}(t)$ includes all deterministic components. The corresponding reduced-form VAR then is:

$$y_{i,t} = B_0(t) + B(L) y_{i,t-1} + u_{i,t}, \tag{2}$$

where $B_0(t) \equiv A_0^{-1} v_0(t)$, $B(L) \equiv A_0^{-1} A(L)$, and $u_{i,t} \equiv A_0^{-1} \epsilon_{i,t}$ such that A_0^{-1} is the contemporenous impact matrix of the mutually uncorrelated $G \times 1$ random disturbances $\epsilon_{i,t}$. In order to account for the persistent downward trend in interest rates over the sample period, similar to Iacoviello(40), we include in $B_0(t)$ a linear time trend. Indeed, Table 7 indicates that the policy rate is $I(1)$ in an ADF test without a trend, but $I(0)$ in the corresponding test including a linear trend.[12] Similarly, since the financial crisis might lead to breaks in the structural relationships in the model, we also include a crisis dummy.[13] In addition, the inclusion of such a dummy serves to alleviate concerns that the results might be driven by a few extreme observations during the height of the crisis,

[11] See Table 1 in Appendix A.

[12] In a set of robustness exercises we leave out the trend and also run a specification where the interest rate enters in first-differences to ensure stationarity. Our results continue to hold.

[13] We conduct a variety of structural break tests, see B.1.

which might, in the absence of the dummy, contaminate the estimated coefficients. While the risk measures are computed on the bank level, the other variables are related to the macroeconomy. Therefore, the main VAR specification considers seven countries as cross-sectional units (United States, United Kingdom, Japan, euro area, China, Sweden, Switzerland) where the risk metrics are averages of all banks in the sample headquartered in the respective country.[14]

All variables used in the analysis and their data sources are described in Appendix A. The benchmark specification is a stationary VAR, i.e. we include the year-on-year growth rates of the CPI and GDP, where the latter is interpolated using the Chow-Lin(27) method with industrial production and retail sales as reference series. In addition to a monetary policy indicator, we add to our VAR different risk metrics. First, we compute realized volatility as the average weekly absolute equity returns. This measure is an aggregate market-based assessment of risk in the banking sector. It encompasses risk on the banks' liability as well as risk on the asset side. Indeed market participants will require higher equity premia both when the banks' asset portfolio are very risky or when they fear the emergence of liquitiy risk (bank runs, dry-out in interbank or repo markets). Second, we employ two different systemic risk metrics.[15] The first is the long run marginal short-fall (LMRES), measuring how much equity would be lost in the event of a crisis. The second metric we consider is ΔCoVaR, which aims at examining the codependency of financial institutions on each other's health. We estimate this metric using equity returns as well as CDS spreads.

For the monetary policy indicator, we also consider different measures. Beyond the main policy rate used in the benchmark case, we also use two shadow rates for the full time sample, and the change in central banks' balance sheets for the post-2007 period, in which monetary authorities increasingly relied on unconventional monetary policy tools. Shadow rates can be employed to track regular monetary policy rates in normal times but also in times of unconventional policy, namely when the main rate remains near zero and does not respond to the changing macroeconomic environment. We consider two measures. The first is the rate computed by Wu and Xia(61), the second the one provided by Krippner(44). Both of these are based on affine term structure model

[14] Spain, Germany, France, Italy and the Netherlands share the same monetary policy. While one could in principle weight banks according to e.g. their market capitalization, we here compute unweighted averages in order to avoid substantial movement in the weights.

[15] Extensive details on those metrics are given in Appendix B.

approximations of the framework in Black(18) and differ mainly in that the former uses a three-factor, the latter a two-factor term structure model.[16]

The benchmark time sample is 2000:6-2016:12. The sample start was chosen in accordance with the beginning of LRMES data availability. Although for the other three risk metrics we could extend the sample (and do so in various robustness exercises throughout the paper), we also here choose mid-2000 as our starting date. This is done not only for comparability with the LRMES model, but also in order avoid a potential structural break due to the introduction of the euro in 1999. The lag length selection is guided by information criteria. Figure 14 in Appendix B plots the Schwarz Bayesian and the Akaike information criteria up to twelve lags, in addition to the saturation ratio, namely the ratio of observations to parameters to be estimated. While the Akaike information criterion prefers twelve lags, the plots suggest that the additional gain of going beyond three lags – as suggested by the SBC – is not large if one is not willing to estimate the full twelve lags. In order to account for rich dynamics in the time series, our panel VAR specifications feature twelve lags, while we conduct various robustness checks with fewer lags and in particular reduce lag lengths to three in the single-country VAR models subsequently.

In the panel VAR, we identify structural shocks by specifying the impact matrix A_0^{-1} as lower-triangular such that the ordering of the variables in the VAR implicitly identifies the shocks. As common in the literature, we order the variables as follows: output, prices, monetary policy and risk. This ordering implies that output and prices do not respond contemporaneously to monetary policy innovations, but that the largely market-based risk metrics potentially do. Our main results are robust to many different specifications, in particular to ordering the monetary policy measure last. More importantly, in section 3.3 we also identify monetary policy shocks using external surprise series for the US economy, which we feed into hybrid and proxy VARs.

3.1.2 Benchmark fixed-effects results

Figure 1 below shows estimated impulse responses to a one-standard deviation increase in the main policy rate (dashed line) for the benchmark VAR for all seven countries considered. As the

[16]Shadow rates are derived as closed-form expressions for lower-bound forward rates that serve as measurement equations when linked to observed yield-curve data. Combined with some autoregressive state variable process the shadow rate is then derived via a non-linear Kalman filter. On the relative merits of the two shadow rate measures see Francis, Jackson and Owyang(33) and Krippner(45). For additional details regarding Krippner's estimates see Krippner(46).

sample period under investigation features the post-2008 period when the main policy rates of many advanced economies were near zero, we might be concerned that the lack of response of interest rates to changing macroeconomic conditions in this period might contaminate estimates of the effects of monetary policy shocks. To be able to gauge the extent to which this might be the case, we also estimate the model using shadow rate measures. These indicate an appropriate level of interest rates while ignoring any of the lower bound constraints monetary authorities face in practice, and at the same time partly capture unconventional monetary policy measures such as forward guidance. In Figure 1 we show responses with Krippner's shadow rate as solid lines for a slightly reduced set of countries this measure is available for.[17]

The sequence of panels in each line of the figure represents the impulse responses of the VAR each with a different risk metric (LRMES, ΔCoVaR based on equity returns, ΔCoVaR based on CDS spreads, and realized volatility). In each model GDP falls after a few quarters and in particular inflation exhibits a somewhat more sluggish initial increase in the model with the policy rate. This phenomenon, often dubbed price (and output) puzzle in the VAR literature is substantially reduced when we use the shadow rate measure, indicating that taking into account the zero lower bound on policy rates may be important in empirical work.[18] More central to the question at hand, all risk metrics fall significantly in all models, albeit with different patterns. The decrease in absolute equity returns is usually sharp, relatively short-lived and of roughly the same size as the increase in the interest rate. Markets apparently react fast to policy announcements and adjust risk assessments comparatively quickly. The fall in the three systemic risk measures is less immediate and more persistent. Both ΔCoVaR do not respond immediately but only after several quarters. The responses of the systemic risk measures can be rationalized with a view on banks' capital structure and asset holdings. With an increase in the policy rate short-term debt funding becomes relatively more expensive. This induces a shift toward equity financing and results in a reduction of risk for at least two reasons. The fall in leverage reduces the possible impact of

[17]The Wu and Xia measure is available for the United States, United Kingdom and the euro area, Krippner's shadow rate additionally for Japan. Furthermore, since China during the entire sample period never came even remotely close to the zero-lower bound on its policy rate, for which the shadow rate is supposed to account, we also include it in both cases using China's main policy rate. Figure 16 in Appendix E shows responses for the Wu and Xia shadow rate with very similar results.

[18]Notably, while in some specifications we find relatively pronounced price and also output puzzles, this is not unusual for the time period under consideration (see e.g. Barakchian and Crowe(16) and Ramey(55)) and are substantially mitigated when we specify the model in log-levels as shown in Figure 21 in Appendix E. Also when we disentangle national and US monetary policy shocks in section 3.4 price and output puzzles largely disappear.

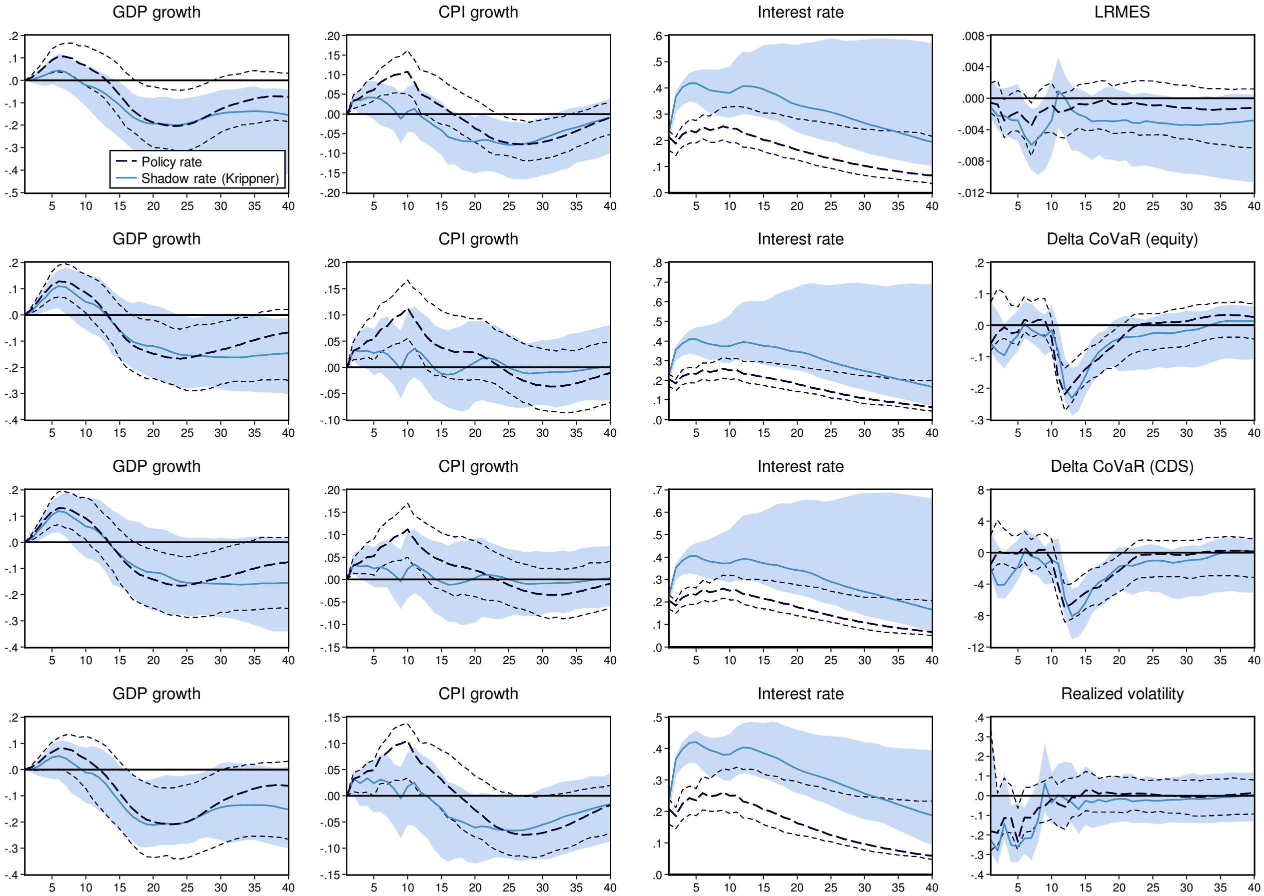
banks' liability risk stemming from bank runs and dry-outs of wholesale funding markets. Second, higher equity ratios increase banks' loss absorption capacity, which in turn reduces their default risk. The fact that this process of increasing equity financing usually takes time is reflected in the more sluggish responses of the system risk metrics. What is more, an increase in the policy rate, by increasing the returns on safe assets, induces banks to reduce their cross-holding exposure toward other banks. The latter is indeed typically associated with a search for yield behavior. The fall in the interconnectedness in turn reduces the risk of shock propagation and lets in particular the ΔCoVaR measures decline. One way to compare the size of the effects to those of the existing microeconometric evidence on the risk-taking channel is to express the impact of a monetary tightening on risk in terms of the variables' standard deviations. For instance, in Jimenez et al. (2014), Altunbas et al. (2014) and Dell'Ariccia et al. (2017), the marginal effect of a one-standard deviation increase in the interest rate in their main specifications lies roughly between 1/10 to 1/8 standard deviations of their respective bank risk variable. Performing similar computations based on the maximum response of the four risk variables considered, our results suggest that a one-standard deviation shock to the interest rate decreases systemic risk by 2/5 (LRMES) to one (Delta CoVaR based on equity returns) standard deviations.

An interesting question arises regarding the sample under analysis. On the one hand, although we do include a crisis dummy in the model and using shadow rate measures lets us get around the lower bound problem on interest rates, there might still be some concern that including the financial crisis and Great Recession period in the analysis may distort estimates. On the other hand, simply from a conceptional point of view it seems worthwhile to ask whether the occurrence of a systemic risk-taking channel is predicated on exceptional circumstances, like a near-zero interest rate environment and balooning central bank balance sheets. We therefore reestimate the model for the pre-crisis period 1992:06-2007:08 and report results for Krippner's shadow rate in Figure 2.[19] As the figure reveals, output and price responses become insignificant, but the risk-taking channel remains active for all risk measures considered.[20] Notably, although the responses are quantitatively somewhat less pronounced, it is perhaps worth stressing that the substantial decline

[19]We do so in order to take into account the zero lower bound on interest rates for Japan, which is included in Krippner's estimates but not in the Wu and Xia measure.

[20]As LRMES data availability only starts in mid-2000, we leave it out for this exercise. Notably, however, we show in section 3.3 that for the US economy even this short sample suffices to produce significantly negative responses of LRMES for US banks in a model with only 2 lags.

Figure 1: Benchmark panel VAR

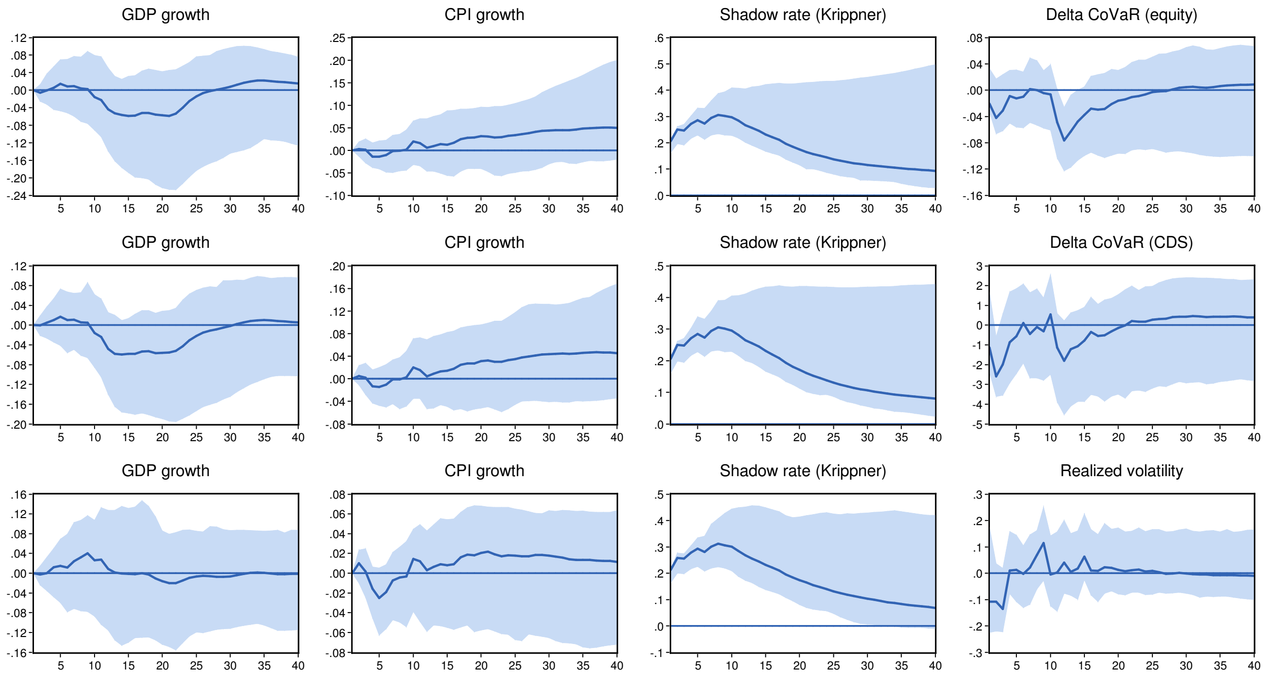


Note. Impulse responses in the panel VAR(12) to a one-standard deviation shock to the policy rate (dashed) and Krippner's shadow rate (solid). Each row represents a VAR with a different risk metric (LRMES in the first row, ΔCoVaR on equity returns in the second, ΔCoVaR on CDS in the third and volatility of equity prices in the fourth). Variable ordering: GDP growth rate, CPI growth rate, interest rate, risk measure. Countries included: United States, Japan, United Kingdom, China, euro area (Germany, France, Spain, Netherlands, Italy) in Krippner model, plus Sweden and Switzerland in policy rate model. All models include a constant, crisis dummy (2007:08-2009:12) and time trend. Time sample: 2000:06-2016:12. Dashed lines and shaded areas indicate 90% confidence bands.

in both ΔCoVaR measures after around one year continue to hold in the pre-crisis sample and is therefore not primarily driven by a few crisis-period observations.

Finally, to fully assess the role of the risk-taking channel in the face of unconventional policies we examine another specification of the policy stance, namely the first difference of central banks assets. This measure has been used also in Gambacorta et al.(35) to study the effectiveness of unconventional monetary policies on output and inflation, here we employ it to assess the effect of these policies on systemic risk. As the central bank balance sheet became an active instrument

Figure 2: Panel VAR in pre-crisis sample



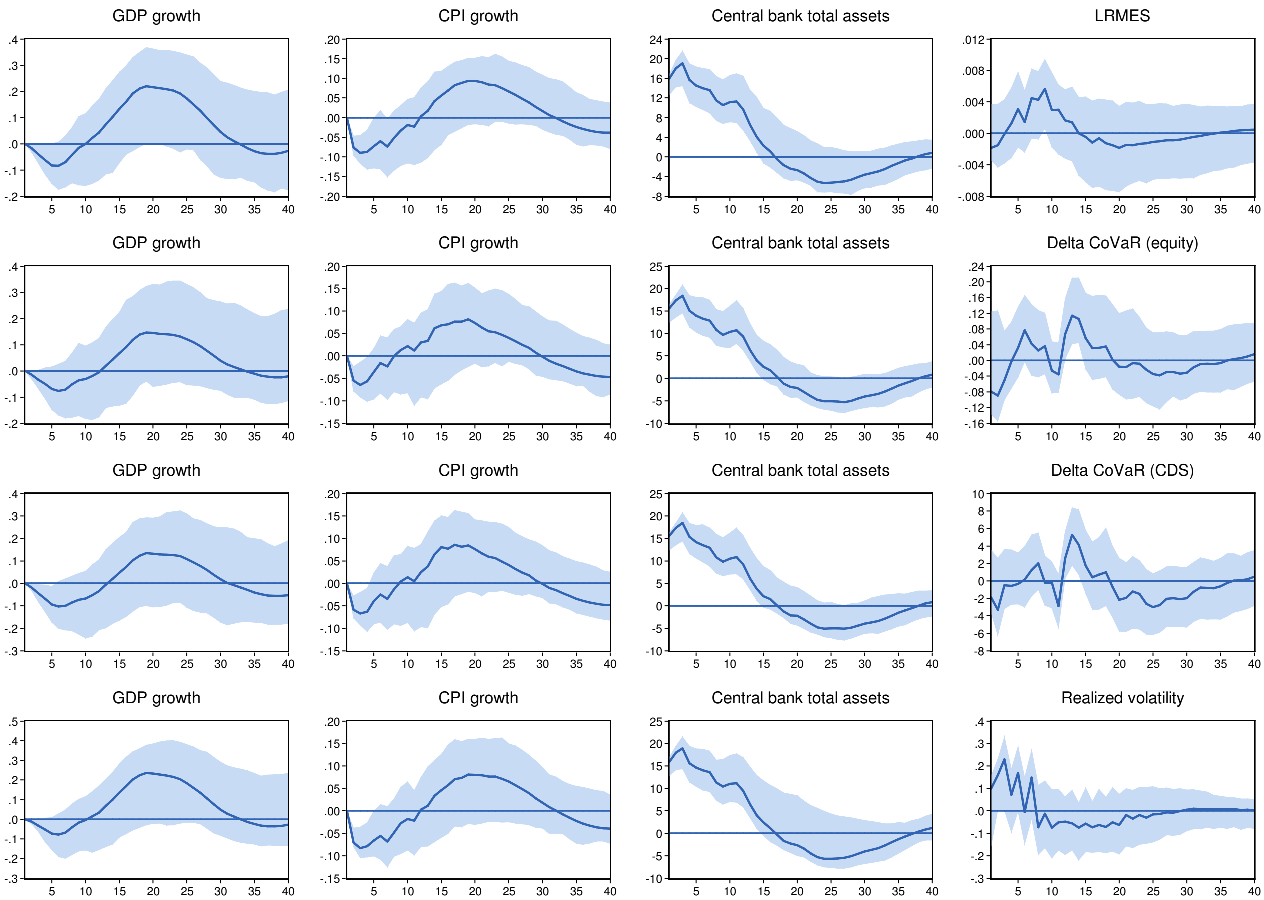
Note. Impulse responses in the panel VAR(12) to a one-standard deviation shock to Krippner's shadow rate. Countries included: US, Japan, UK, China, euro area (Germany, France, Spain, Netherlands, Italy). Model includes a constant and time trend. Time sample: 1992:06-2007:08. Remaining details as in Figure 1.

of monetary policy only after the financial crisis, we estimate the model under the reduced time sample from the end of 2007 onward.[21] Figure 3 shows the results. After small initial declines, an expansion in the central banks balance sheet induces positive output and price effects, although these are not always statistically significant. All four risk measures increase following the monetary expansion with realized volatility again exhibiting an immediate but short-lived reaction, while the systemic measures show again more delayed responses. It is noteworthy that the effects onto both macoreconomic controls as well as risk metrics are relatively similar to the ones of roughly 20 basis point shocks in conventional monetary policy instruments considered earlier. As our balance sheet measure is indexed to 100 in 2007, the model suggests that a doubling of the central bank balance sheet from the level before the crisis has effects roughly equivalent in size to that of a 80 basis point cut in the policy rate. However, the model also suggests that conventional and unconventional monetary policies introduce similar trade-offs between stimulating the real economy on the one,

[21]Notably, the results remain almost unchanged when we run the model using the full time sample, with even higher levels of statistical significance.

and systemic risk on the other hand.

Figure 3: Panel VAR with central bank total assets in (post-)crisis sample



Note. Impulse responses in the panel VAR(12) to a one-standard deviation shock to central bank total assets. Variable ordering: GDP growth rate, CPI growth rate, first-differenced central bank total assets, risk measure. Time sample: 2007:09-2016:12. Remaining details as in Figure 1.

3.1.3 Robustness of fixed-effects panel VAR

We consider various robustness tests of our benchmark fixed-effects panel VAR , and start with a discussion of those reported in Appendix E. Figure 17 shows the benchmark model estimated with three instead of twelve lags, as suggested by the SBC. As expected, the impulse responses look overall much smoother. In particular, the sudden delayed decline in both ΔCoVaR is not captured by the model and also the quantitative impact is smaller. However, qualitatively the risk-taking channel is preserved and the main results are therefore unaffected.[22] Figure 18 shows

[22]Notably, the risk-taking channel remains intact when we estimate a model using four to eleven lags as well.

results for a model where the monetary policy measure is ordered last, implying that also all risk measures do not respond contemporenously to monetary innovations. Despite the fact that now by construction risk responses start at zero, our main results are essentially unchanged.

In light of the discussion on the downward trajectory in interest rates above, Figure 20 in Appendix E presents impulse reponses of a model without a time trend. Results are hardly affected. Figure 21 features a specficiation in log-levels of both GDP and CPI. This levels specification can be justified by fear of overdifferencing the variables and therefore losing cointegrating relationships potentially present in the data. As the figure shows, we continue to find negative risk responses in all cases. While the LRMES response is not statistically significant at the 90% level, this changes when we again employ Krippner's shadow rate, where all four risk metrics decline significantly. Notably, in both levels specifications we find only very small price and output puzzles. In some sense polar to the specification in levels we also estimate a model with GDP and CPI growth rates and a first-differenced shadow rate measure. Although not our preferred specification, this model can again be rationalized on the grounds of the concerns related to potential non-stationarity of interest rates due to their persistent downward trend. As Figure 22 shows that, strikingly, all four risk measures continue to decline, with similar patterns and magnitudes, even in this specification.

We also conduct robustness tests with respect to each economy's regulatory environment since risk metrics might also be affected by macroprudential policies. We control for this by adding a macroprudential index as an exogenous variable to the benchmark VAR, which is derived from the dataset by Cerutti, Claessens and Laeven(25). More specifically, Cerutti et al. examine which types of macroprudential regulation are present in a large set of countries from 2000 to 2013 and construct indices based on the number and type of these measures.[23] We use their broadest index, which simply adds up all regulatory measures irrespective of classification.[24] Figure 23 shows that our main results are essentially unaffected by controlling for the macroprudential environment.

Additional robustness tests[25] include changing the time sample, the sample of countries and set of controls. In particular the risk-taking channel remains significant if one excludes China,

[23] Since data availability ends in 2013 and in the entire dataset all regulatory indices are monotonically increasing over time, we set variable to its 2013 value for the years 2014-16.

[24] We do so in order to maximize the number of countries that can be added to the analysis but still we have to drop the United Kingdom and Japan since over the entire sample period there were no changes even in the broadest regulatory index.

[25] Not reported for brevity but available upon request.

a less advanced and rapidly growing economy comparatively uneffected by the financial crisis, and/or Japan, an economy with sluggish price and output growth and near-zero interest rates over almost the entire sample period.[26] When we consider additional changes of the time sample, both extending it from 1992:06 to 2016:12 or starting after the crisis, 2007:08 to 2016:12, and results remain robust. Changes in the controls mainly affect the price or output puzzles. but the risk-taking channel remains robust for instance if we use industrial production as an output measure, both in growth rates or as a cyclical component of HP-filtered series. We also used a producer price index in place of the CPI, which lowers the price puzzle but leaves risk taking results unaffected. Finally results remain robust to enlarging the crisis dummy to span the entire post-2008 perio, focussing it on a few months at the end of 2009 (when the ΔCoVaR measures experienced their strongest increases) or excluding it altogether,[27] to the use of the simple pooled OLS (instead of fixed effects) estimator and to changes in the data frequency (quarterly instead of monthly).

3.1.4 Mean-group estimator of panel VAR

While the inherent bias in fixed-effects panel VAR estimates is negligable in our case (Nickel(51)), heterogeneity in the coefficient matrices among the countries would introduce an additional bias even when T is large. To overcome this potential problem and to make sure that our results are not driven by such a bias, we reestimate our benchmark model with the mean-group estimator, as proposed by Pesaran and Smith(53). This is derived as the unweighted average of estimates of all cross-sectional units and avoids the heterogeneity-induced bias in fixed-effects estimation. However, as it effectively does away with the additional number of observations stemming from the cross-sectional dimension, the mean-group estimator is also inherently less efficient. We therefore, as in the additional robustness exercise to the benchmark model and suggested by the SBC, reduce the lag length to three. Figure 4 compares results for the mean-group estimator (solid) with the fixed-effects estimates (dashed) using the main policy rate as a monetary policy indicator.[28]

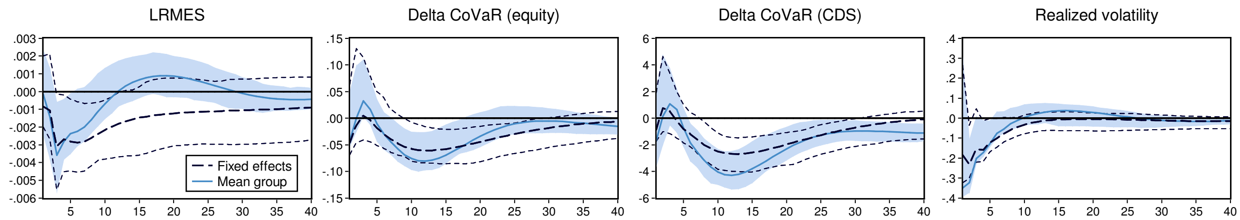
The figure shows that the mean-group estimator overall suggests somewhat stronger risk responses than its fixed-effects counterpart, and all four risk measures continue to significantly fall following the rate hike. While the dynamics of both ΔCoVaR measures and realized volatility

[26] Note that later we will also look at US data only when considering a FAVAR model and proxy VAR model.

[27] See Figure 19.

[28] To make comparison easier, we normalize the mean-group impulse responses to the same initial policy rate responses as those of the fixed-effects estimates (roughly 20 basis points).

Figure 4: Mean-group estimation of panel VAR



Note. Impulse responses in the panel VAR(3) to a one-standard deviation shock to the main policy rate. Solid lines refer to mean-group estimation, dashed lines indicate fixed-effects estimates for comparison. Countries included: United States, Japan, Switzerland, United Kingdom, Sweden, euro area. Remaining details as in Figure 1.

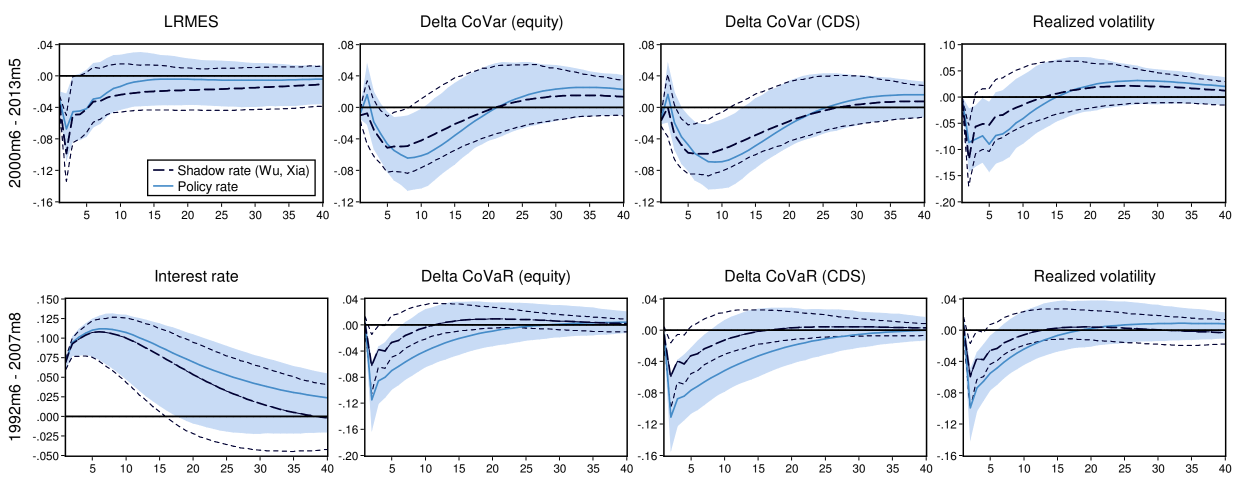
are similar, LRMES mean-group estimates suggest a much less persistent response than in the fixed-effects case. We again conduct several robustness tests. Results remain robust when using two lags, replacing the main policy rate with Krippner's shadow rate, and specifying the model in the log-levels of GDP and CPI.

3.2 US FAVAR

After having established a systemic risk-taking channel in an international sample in a small-scale VAR model, it is important to ask whether the channel can also be verified in a model that accounts for a much richer set of macroeconomic control variables like a FAVAR as suggested by Bernanke, Boivin and Eliasz(15). This is important for at least two reasons. First and foremost, it helps to alleviate concerns that small-scale VAR models are unlikely to fully capture the amount of information both the private sector and central banks have about the state of the economy. To the extent that this missing information is relevant in the setting of the policy stance, it might bias coefficient estimates. In contrast, a FAVAR model based on many dozens of variables is better able to control for many macroeconomic aspects of interest. Second, in order to preserve degrees of freedom, so far we have only considered each risk metric in isolation. A FAVAR model on the other hand allows us to include all relevant risk measures in a single model and to study their impulse responses simultaneously. For reasons of data availability we for now restrict our attention to the US economy, where we exploit a large set of macroeconomic variables very similar to the one used by Bernanke, Boivin and Eliasz(15). These variables are effectively summarized by a small number of factors, which then enter a VAR as described in detail in Appendix C. The number of factors is based on scree plots of a principle-component analysis, depicted in Figure

15 in Appendix B. There are two kinks in the plot, at three and five factors, indicating that the marginal contribution of increasing the number of factors to four and beyond five, respectively, is limited. Against the background of a relatively low number of observations (in the absence of any cross-sectional dimension, despite using monthly data), our benchmark FAVAR specification therefore features three factors, while we consider a model with five factors as a robustness check. For the same reason we estimate the FAVAR model using three lags.[29]

Figure 5: US FAVAR



Note. Impulse responses in the FAVAR(3) (full sample, top panel) and FAVAR(2) (pre-crisis, bottom panel) model with three factors to a one-standard deviation shock to the policy rate (solid) and Wu and Xia shadow rate (dashed). Each model includes a large set of macroeconomic variables (see Table A.2) and all depicted risk measures. Dotted lines and shaded areas indicate 90% confidence bands.

Figure 5 shows estimated impulse responses to a monetary policy shock based on the policy rate (solid) and the Wu and Xia shadow rate (dashed).[30] The top panel depicts results for the full sample, in which all four risk measures fall following a monetary tightening with similar trajectories as in the case when estimating the panel VAR with only three lags. As before, we also check if the risk-taking channel remains intact when considering only the pre-crisis sample, which is shown in the bottom panel. In order to achieve a meaningful number of observations and since LRMES data availability only starts in mid-2000, we drop the latter metric from the model and reestimate the FAVAR model for the period 1992:06-2007:08. The three remaining risk measures continue

[29]In order to maximize the number of variables to include in the FAVAR, we restrict the end of the sample to mid-2013, after which some series of interest are discontinued.

[30]We show results for the Wu and Xia(61) shadow rate here instead of for Krippner's mainly for comparability reasons with the proxy VAR shadow rate specification in section 3.3, for which Krippner's estimates yield too small F statistics.

to decline in the face of a monetary tightening, although their responses are significantly less persistent. We again conduct some robustness tests. In particular, Figure 24 in Appendix E shows that when using five factors results remain qualitatively unchanged, while they are quantitatively somewhat stronger and statistically more significant. Results are essentially unaffected when using two instead of three lags.

3.3 Incorporating exogenous US monetary policy shock series

Both the panel VAR and US FAVAR employed so far identify structural monetary policy shocks by a set of timing assumptions, whereby some variables are assumed to contemporenously respond to monetary innovations while other, more slow-moving variables like output and prices, are not. While this identification, based on a recursive ordering of the variables, is still widely employed and often serves at least as a benchmark, it has also met criticism. Not only do impulse responses often feature price and sometimes output puzzles, it is also questionable if a recursive identification is justified especially in large VAR systems and those including financial market variables. Against this background, particularly for the US economy, there is a growing literature that uses external information to derive structural monetary policy shocks. Notably, building on Kuttner(47) and Gürkaynak, Sack and Swanson(39), there is a growing number of papers that estimate monetary policy surprises based on high-frequency movements in Fed Funds Futures prices around FOMC meetings. These surprises indicate new information to market participants that was not priced in futures contracts before the monetary policy announcements. Since they are therefore orthogonal to consensus market expectations of future macroeconomic developments, endogeneity concerns are argued to be significantly alleviated. These shock series have been employed in at least two ways in VAR analysis. First, following Romer and Romer(56), Barakchian and Crowe(16) accumulate their high-frequency identified shock series and, in what Ramey(55) calls a *hybrid VAR*, simply include it in their small-scale VAR in place of the policy interest rate. They then again apply a standard recursive ordering. A second option, employed by Gertler and Karadi(38), is to include the external information from the surprise series as an instrument in a proxy VAR. We consider both these options in turn using the surprise series by Gürkaynak et al.(39) for the US economy, updated to October 2015.[31] In addition, we also estimate local projection impulse responses in

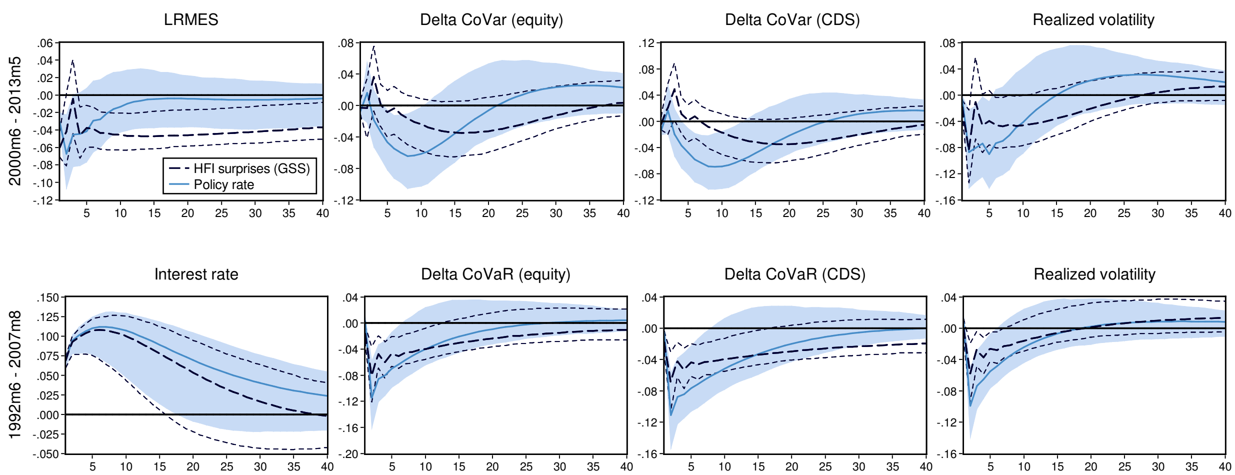
[31]We thank Refet Gürkaynak for sharing the data with us.

the spirit of Jorda(43) employing not only the surprise shocks but also an updated narrative shock series originally computed by Romer and Romer(56).

3.3.1 US Hybrid FAVAR

In the spirit of Barakchian and Crowe(16) we reestimate our US FAVAR model where we replace the interest rate with the accumulated Gürkaynak et al.(39) surprise series, and then apply the same recursive identification scheme as before, based on the contemporenous response of the set of fast-moving variables. Results are depicted in Figure 6, again for the full (top) and pre-crisis sample (bottom panel). All risk measures continue to decline mostly significantly following a monetary tightening. In the full sample, the responses (dashed) are somewhat more sluggish than the when using the policy rate (solid), but in the pre-crisis sample the dynamics are very similar.

Figure 6: US hybrid FAVAR with Gürkaynak et al. (2005) surprise series



Note. Impulse responses in the FAVAR(3) (full sample, top panel) and FAVAR(2) (pre-crisis, bottom panel) model with three factors to a one-standard deviation shock to the policy rate (solid) and cumulated Gürkaynak et al. surprise shock series (dashed). Each model includes a large set of macroeconomic variables (see Table A.2) and all depicted risk measures. Dotted lines and shaded areas indicate 90% confidence bands.

3.3.2 US proxy VAR

While including the accumulated monetary surprise series as a variable into the system is a simple way of incorporating external information on monetary policy shocks into a VAR framework, an alternative is to make use of the information in an instrumental variable framework as in Gertler and Karadi(38). This framework is useful not only in addressing endogeneity concerns in general but is especially suitable for our analysis which includes financial market variables. Since in the benchmark case we order our risk measures after the interest rate, they are allowed to contemporaneouly respond to policy innovations. However, using this recursive ordering precludes policy makers to in turn respond to financial market stress captured by the risk measures. Using the proxy VAR approach lets us avoid having to impose such timing restrictions as detailed in Appendix C.2. As an instrument we use of the updated surprise series of Gürkaynak et al.(39) which we assume to be correlated with the actual monetary policy shock and uncorrelated with other structural shocks.

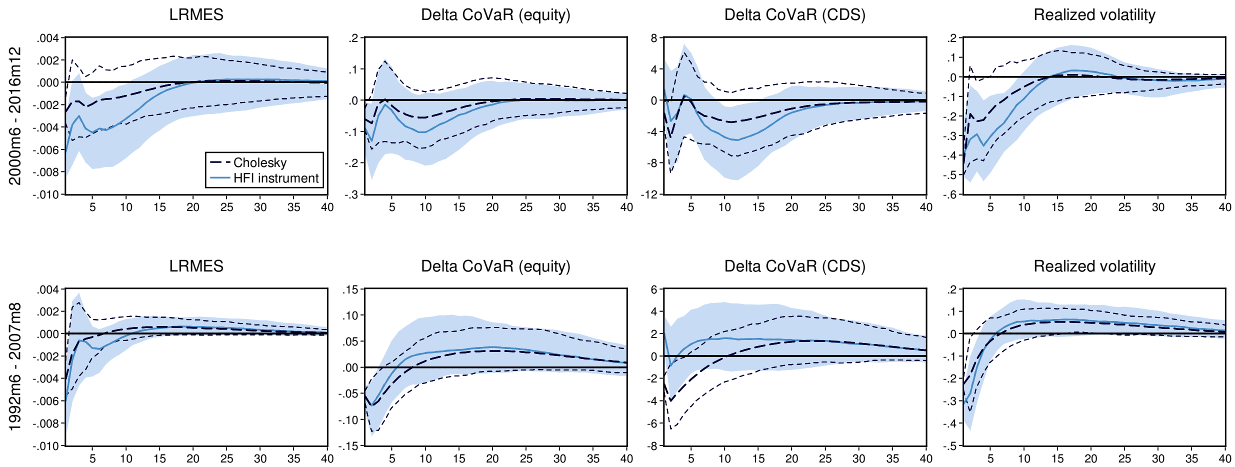
Figure 7 reports reponses for a small-scale US VAR using the main policy rate (the effective federal funds rate) as the monetary policy measure. Whereas the usual recursiveness-implied impulse responses are plotted as dashed lines, the solid lines indicate the responses under the instrumental variable identification. Comparing these reveals that, in the main sample (top panel), if anything, the standard Cholesky identification underestimates the negative response of systemic risk following a monetary tightening. In particular, the proxy VAR suggests that LRMES declines roughly twice as much following the same interest rate hike. Notably, the responses in the proxy VAR are different from zero at higher levels of statistical significance but the overall dynamics are similar. Reassuringly, in all four models the first-stage F statistic is very high, hence we have no reason to doubt the instrument's relevance.[32] In the bottom panel we again investigate the risk-taking channel in a sample excluding the financial crisis and ensuing Great Recession. Once more in line with earlier results, the risk responses are less persistent but continue to be significantly negative for LRMES, ΔCoVaR based on equity returns and their realized volatility.

We again run various robubstness tests. Impulse responses are hardly affected when using two instead of three lags in the main sample. Figure 25 in Appendix E shows that again results hold when using the Wu and Xia shadow rate, with somewhat lower but still high F statistics.[33]

[32]The F statistics are well above 30, as shown in Figure 26, which is substantially higher than those in Gertler and Karadi(38). The same is true for the R^2.

[33]We also ran a specification using Kripper's shadow rate and results are qualitatively the same and quantitatively even stronger, but F statistics were disconcertingly low (below four) throughout. This at least in part reflects the fact that Krippner's shadow rate estimates are based on a two-factor model, which puts more emphasis on the medium to long end of the yield curve. In contrast, since Wu and Xia use a three-factor model, their shadow rate is more closely related to the short end of the curve and therefore more strongly correlated with the short-run surprise series.

Figure 7: US Proxy VAR with main policy rate



Note. Impulse responses in the US VAR(3) (full sample, top panel) and FAVAR(2) (pre-crisis, bottom panel) to a one-standard deviation shock to the main policy rate. Solid lines refer to the proxy VAR in which the monetary policy shock is identified using high-frequency monetary policy surprise series, dashed lines refer to Cholesky-identified VAR with variable ordering: GDP growth rate, CPI growth rate, policy rate, risk measure. Model includes a constant, crisis dummy (2007:08-2009:12) and time trend. Time sample: 2000:06-2016:12. Dotted lines and shaded areas indicate 90% confidence bands.

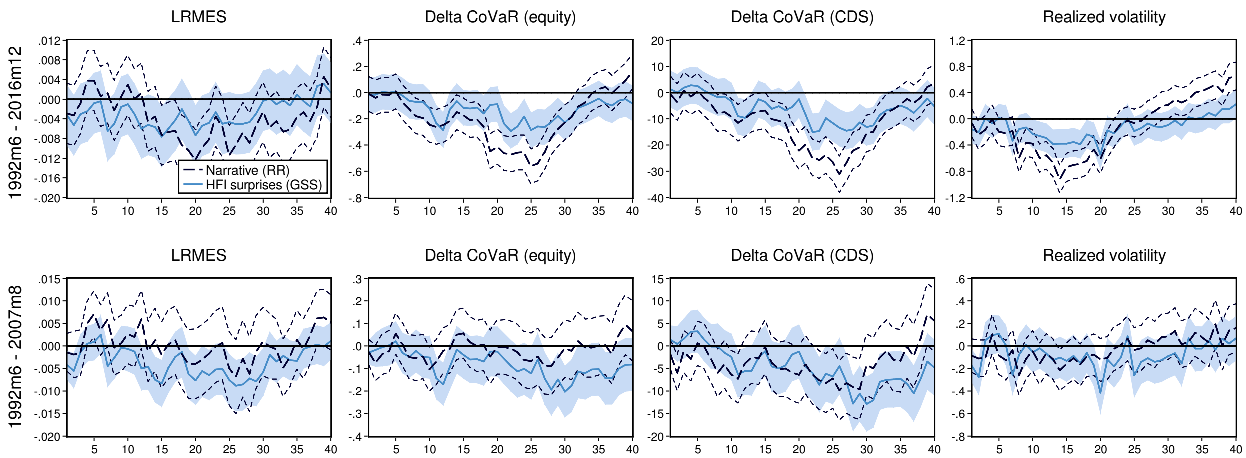
3.3.3 Local projections

One final and simple way to arrive at impulse reponses to exogenous shock series is by means of local projections in the spirit of Jorda(43). This framework has the advantage that responses are derived without relying on a certain model structure and are hence less prone to misspecification should the VAR dynamics not be able to adequately capture the actual data generating process. Impulse responses are simply the estimated β_1 coefficients in the series of regressions

$$y_{t+h} = \beta_0 + \beta_1 \epsilon_t + \Gamma controls_t + v_t, \tag{3}$$

with $h = 1, 2, ..., H$, ϵ_t being the exogenous shock series and y_t are the risk measures of interest. In the set of controls we include a time trend and lagged values of logged GDP and CPI as well as the policy rate and risk measure. Figure 8 reports impulse responses of the our four risk measures for the US economy to the Gürkaynak et al.(39) shock series. In addition, we also report as dashed lines the responses to an updated narrative shock series of Romer and Romer(56), which is available until the end of 2008. Since the methodologies of arriving at these two shock measures differ, there are also significant differences in the magnitude of the shocks. We hence normalize both shock series by dividing by their standard deviation. The upper panel of Figure 8 shows the

Figure 8: Local projections impulse responses to exogenous shock series



Note. Local projection impulse responses of all four US risk measures to exogenous shock series of Gürkaynak et al.(39) (solid) and Romer and Romer(56) (dased) for the full (top panel) and pre-crisis (bottom panel) sample. Dotted lines and shaded areas indicate 90% confidence bands.

responses in the full sample period. In line with our previous results we find that all risk measures fall significantly in response to both types of shocks even in this much more agnostic setting of arriving at impulse reponses. For the pre-crisis sample the high-frequency shocks again induce significant declines throughout, while the narrative shock series do so as well except in the case of LRMES.

3.4 Dissecting the systemic risk-taking channel

Having established robust evidence for a systemic risk-taking channel of monetary policy, a natural question to ask is which economic variables drive its propagation. More specifically we focus on two questions.[34] First, we ask how much of the banks' systemic risk is driven by the choices of their balance sheets. This is an important question in the context of our paper. Controlling for the response of banks' balance sheets allows us to gauge how much of the risk-channel is driven by banks' individual choices as opposed to macro externalities, such as interconnections or fire sale externalities, both of which clearly contribute to the movements in our systemic risk metrics. As we show below banks' balance sheet variables exhibit sizable responses, move qualitatively in a direction consistent with the risk-taking channel and as such they seem to play a role. However, as we show, their quantitative contribution to the systemic risk propagation does not appear to be

[34] We thank Emanuel Mönch for suggesting these additional analyzes.

strong. This has also important policy implications since it means that micro-prudential regulation alone would not undo the potential increase in risk. Second, as an important part of our research relates to the cross-country dimensions, we ask how much of the risk-taking channel is driven by domestic monetary policy as opposed to its US counterpart. Disentangling the two has important policy implications. To the extent that the US policy rate drives movements in systemic risk in other countries there is a role for coordination policy due to financial spillovers, hence well beyond the one assigned to terms of trade spillovers within the new open economy literature. We document that, while national actions are important as well, US policy indeed seems to drive systemic risk also abroad.

3.4.1 The role of banks' balance sheets

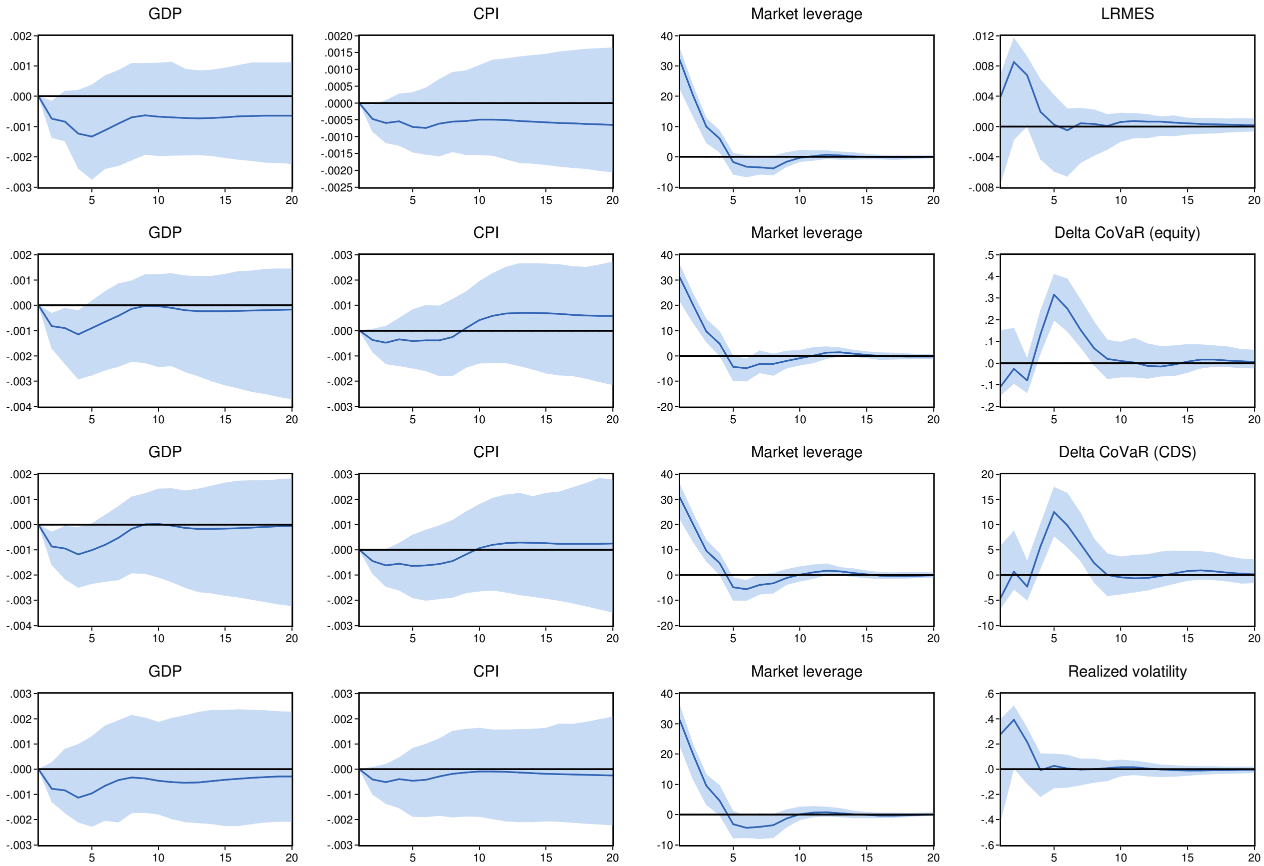
In the micro banking literature reviewed in section 2 it is often argued, and correctly so, that banks' risk-taking materializes in form of banks' balance sheet choices. Banks that tend to leverage more or to expose themselves more to risky assets tend to increase their overall equity risk and in turn also systemic risk. While this link is undoubtedly important, it is also crucial to determine whether the presence of macro externalities or interconnections can contribute to the propagation of banks' individual risk. Indeed, it has indeed been argued that crises often develop out of small shocks that tend to reinforce within the system and affect the real economy.

Empirically the link between systemic risk metrics and banks' balance sheet has already been noted in Adrian and Brunnermeier(3), who find that ΔCoVaR is predicted by banks' size, leverage and maturity mismatch. We extend the analysis of such a link by adding balance sheet variables to our various VAR specifications. We collect GSIBs balance sheet and market valuation data and add the country averages of size and leverage as a fifth variable to the panel VAR.[35] We then proceed in three steps. First, we compute impulse responses to shocks of these measures. In a second step, we gauge to what extent size and leverage themselves respond to monetary policy. If the systemic risk-taking channel indeed operates through size and leverage, we would expect impulse responses to be significant in both steps. Finally, in order to gain a better understanding of

[35]Note that the Financial Stability Board bases the classification of banks as globally systemically important on various indicators covering cross-jurisdictional activity, interconnectedness and complexity of their business. Many of those variables are not availabel on time series and even cross-country dimensions. We therefore focus on size, which covers the largest component (20%) in the Board's indicator-based approach and for this reason is also the most used by prudential regulators.

whether the risk-taking channel is predicated first and foremost on the response of these variables, in a third step we also compute impulse responses of our risk measures to monetary policy shocks under the counterfactual scenario that size/leverage does not respond.

Figure 9: Panel VAR with market leverage as 5th variable



Note. Impulse responses in the quarterly panel VAR(4) to a one-standard deviation shock to the market leverage growth rate. Shocks are identified by the variable ordering: log GDP, log CPI , Kripnner's shadow rate, market leverage growth rate, risk measure. Time sample: 2000Q2-2016Q4. Remaining details as in Figure 1.

We use quarterly data on book assets, liabilities and equity as well as market capitalization (market equity) that stem from Compustat-CRSP for 19 GSIBs.[36] Since we are primarily interested in exposure and leverage, we use book liabilities as a measure of size and compute market leverage following Adrian et al.(2) as follows:[37]

$$Market\ leverage = (book\ assets - book\ equity\ +\ market\ equity)/(market\ equity).$$

[36]See Table 1 in Appendix A for details.

[37]We also experimented with book leverage and equity but the responses were generally less significant than using their market counterparts. Using book assets instead of liabilities as a size measure yields almost identical results.

In the benchmark case we order size and leverage measures between monetary policy and risk and therefore implicitly assume that risk may contemporanously respond to size/leverage, which in turn contemporanously responds to policy. We do so primarily in order to allow for the largest potential impact in the transmission mechanism from monetary policy to risk, but we also experiment with different orderings. Since we need to resort to quarterly data and have country averages on balance sheet measures for only four countries, we run the panel VAR using four lags.[38]

Figure 9 shows responses of all five variables in the model to a shock in market leverage. While the responses of the macro variables are largely insignificant, all four risk measures significantly increase following the shock, as required by the view that leverage drives systemic risk. However, as noted above, for the risk-taking channel of monetary policy to operate through leverage, we would also expect a significant response of leverage to policy shocks. This is assessed in Figure 10, which shows the familiar impulse responses to a monetary policy shock.

We may first note that we are largely able to confirm our main finding of a fall in the risk measures in response to a contractionary monetary policy shock also using quarterly data and with the additional leverage variable in the model. More central to the question at hand, the figure shows a decline of market leverage on impact, which is however not highly statistically significant. Although this finding casts doubts on the relevance of leverage in the transmission of policy shocks to systemic risk, we can more directly assess the transmission mechanism by computing impulse responses under the counterfactual assumption that market leverage does not respond to monetary policy shocks.[39] By switching off the leverage channel, this exercise gives an indication of how important the propagation of monetary policy shocks through leverage onto systemic risk is. Results, shown as dashed lines in Figure 9, seem to suggest that the bulk of the monetary transmission onto systemic risk does not run through leverage. While in all four models the peak decline in risk is somewhat smaller under the counterfactual scenario, the differences are generally minor. The same pattern is confirmed when changing the ordering of variables,[40] the

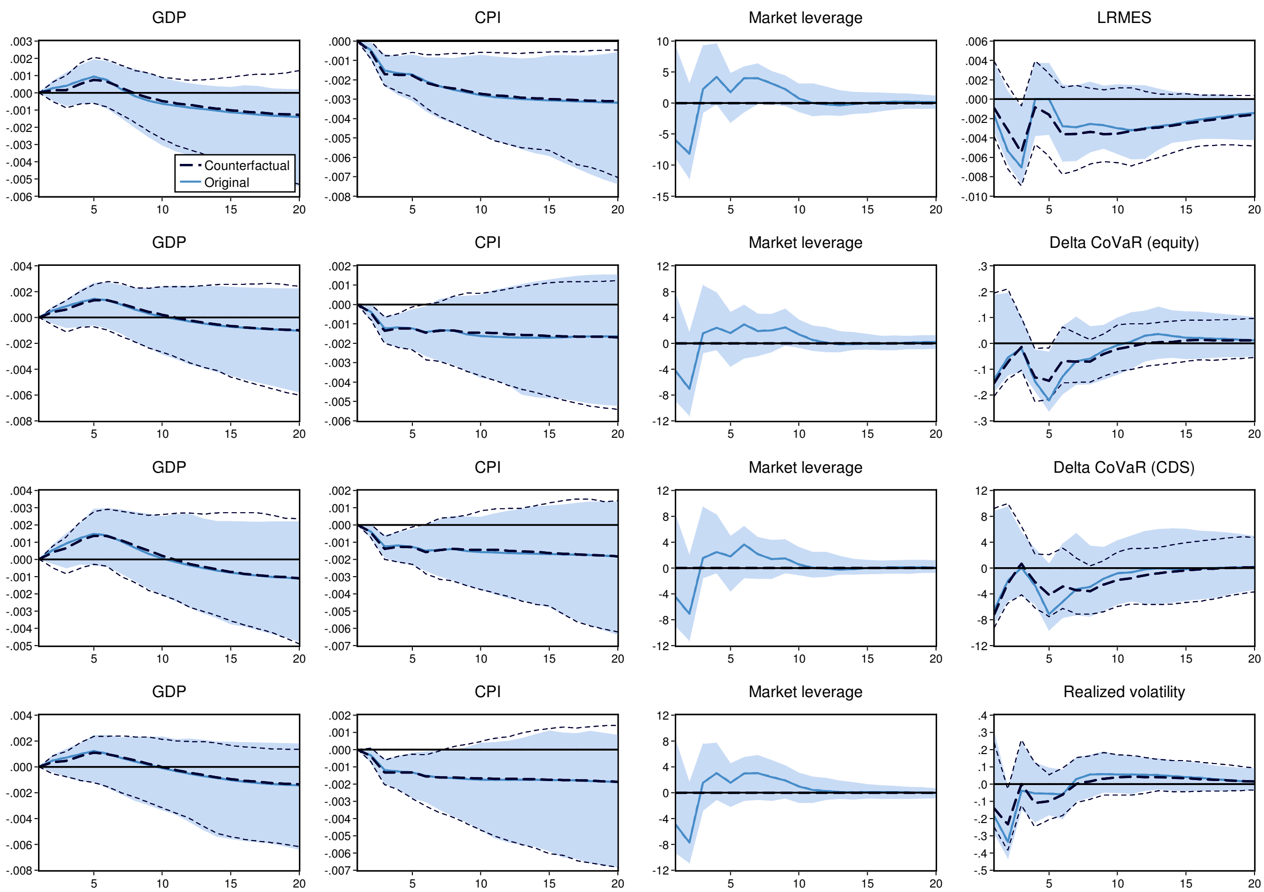
[38] In addition, we here report results using Krippner's shadow rate instead of the actual policy rate, which narrows the sample down to three economies. Using the policy rate produces qualitatively very similar but somewhat less significant results, particularly in the case of the responses of leverage to monetary policy shocks.

[39] Our benchmark results are based on the methodology used in Bachmann and Sims(11), see Appendix C.

[40] We experiment with reversing leverage and risk as well as ordering leverage in front of the policy rate but results hardly change.

controls in the model, the interest rate measure used as well as the time sample.[41]

Figure 10: Panel VAR with market leverage: monetary policy shocks



Note. Impulse responses in the quarterly panel VAR(4) to a one-standard deviation shock to Krippner's shadow rate. Shocks are identified by the variable ordering: log GDP, log CPI , Kripnner's shadow rate, market leverage growth rate, risk measure. Solid lines refer to the original model, dashed lines to the counterfactual responses with market leverage response to monetary policy shut off. Remaining details as in Figure 9.

To complete the assessment we repeat the above experiments using book liabilities as measure of size and exposure (see Figures 27 and 28 in Appendix E). In this case, results are weakened further. Indeed, Figure 27 shows that the ΔCoVaR measures decline following an increase in liabilities, while the other two measures do not significantly respond. Furthermore, Figure 28 shows that book liabilities do not fall for more than two years following a contractionary monetary policy shock and initially even increase. All in all, the above results show that the responses of banks' balance sheet variables and systemic risk are mostly in line with the traditional risk-taking

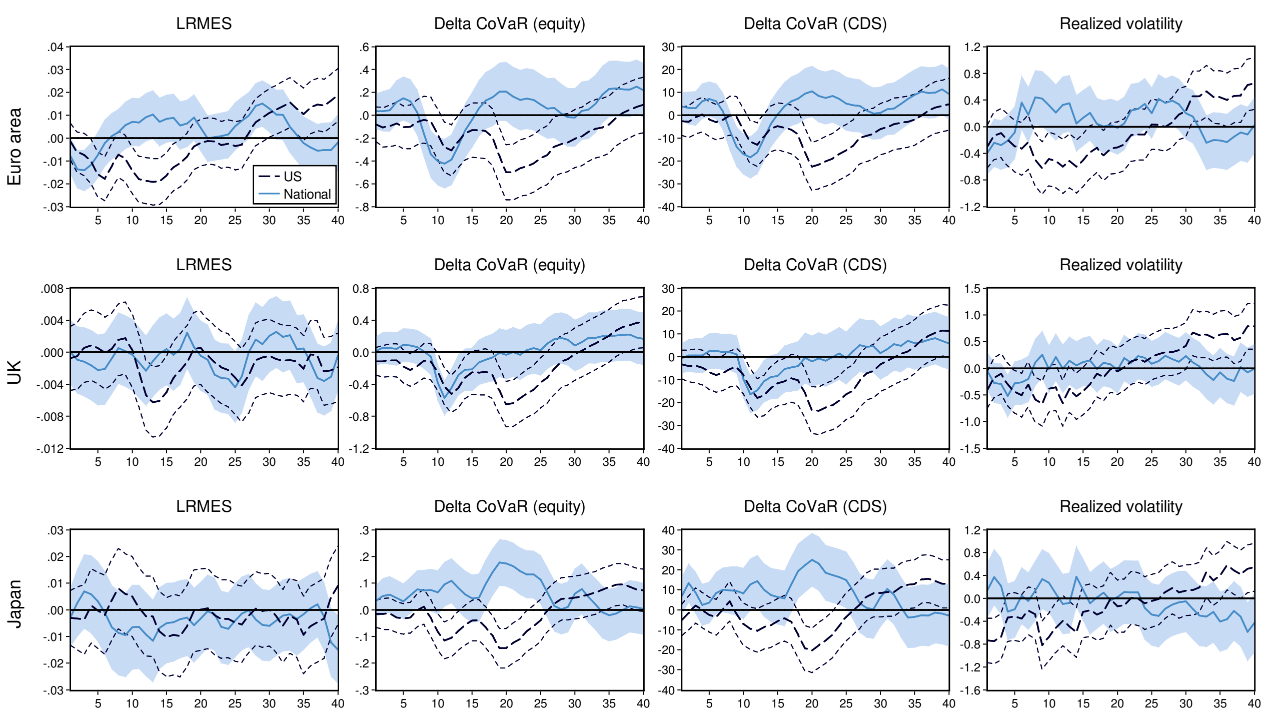
[41]The result is confirmed also under a different methodology for computing the counterfactual, namely by restricting to zero all the VAR coefficients that govern the responses of market leverage to monetary policy shocks.

channel of monetary policy. A fall in the policy rate induces banks to leverage more and this increases individual and aggregate risk. However, at closer inspection, it seems that leverage is not responsible for the bulk of the monetary transmission into systemic risk.

3.4.2 US versus national monetary policy

A final question that arises from the international context that we study is the extent to which the systemic risk-taking channel is primarily driven by national monetary policies or whether instead US policy, through the size of its economy and in particular its influence on global dollar funding markets, exerts a particularly pronounced influence also abroad. There is indeed suggestive and empirical evidence that national cycles are partly or largely driven by US monetary policy.[42] While the existence of a systemic risk-taking channel does not in priciple depend on its source, a strong US influence would call for more coordination among policy makers.

Figure 11: Local projections of national and US shocks identified in panel VAR



Note. Local projection impulse responses for selected countries of national risk measures to orthogonalized national (solid) and US shocks (dashed) identified in the benchmark panel VAR as in Figure 1. Dotted lines and shaded areas indicate 99% confidence bands.

[42]See for instance recently Miranda-Agrippino and Rey(48).

We assess the role of national versus US policy by using two different methodologies. In the first, we compare the risk responses of our four-variable panel VAR to national shocks with their US counterparts. Since our goal is to compare risk responses to shocks that are orthogonal to each other, we first cleanse the national shocks of any correlation with the US ones by using the residuals of a regression of national onto US shocks.[43] We then compute impulse responses in a local projection framework for each country separately.[44] Figure 11 reports the results for three selected large non-US economies and compares the responses to national (solid) with those to US shocks (dashed) along with 99% confidence bands. While the details vary somewhat by country, at least two main results emerge. First, systemic risk in most countries reacts quite similarly to US policy shocks whereas there is more heterogeneity in the reponses to national shocks. Second, responses to US shocks are generally more significant, delayed and often larger.

An alternative way to disentangle the effects of national and US shocks on risk is by directly incorporating US monetary policy as part of each country's system of equations. We hence estimate a five-variable panel VAR of all six non-US economies in which a US policy measure enters as an additional variable.[45] This approach takes more seriously the notion that world business cycles might be driven in part by US monetary policy, shocks to which are hence allowed to directly affect national variables, in particular risk measures. By again employing a recursive ordering to identify structural shocks we then obtain impulse responses to national and US shocks that are by construction orthogonal to each other. One additional advantage of the outlined approach is that we are able to also use in the panel VAR the US high-frequency surprise shock series which we employed earlier for the single-country US models only.

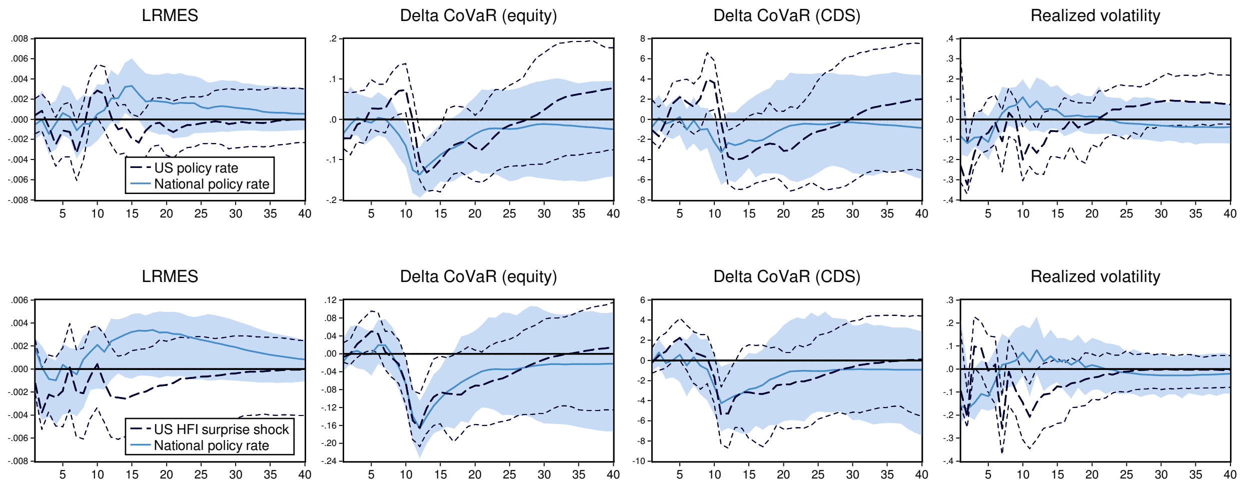
Figure 12 shows the responses of our four risk measures to a national monetary policy shock (solid) and the response to the US counterpart (dashed), either the US policy rate (top) or the cumulated high-frequency surprise series (bottom panel). The shocks are identified by ordering the US before the national interest rate, hence assuming that the latter contemporaneously responds

[43]This approach therefore assumes that all the correlation between the shocks stems from the national central banks following US monetary policy and only the remaining variation can be attributed to national actions. We consider the opposite approach below. We may, however, note that the correlations between the national and US shocks is generally rather low and results are largely unchanged when the residual is obtained by regressing US shocks onto the national ones, see Figure 29 in Appendix E.

[44]The local projection regressions include a constant, a trend as well as lags of the endogenous variable and GDP, CPI and the policy rate as controls. All shocks are normalized by their standard deviation.

[45]This is akin to Gavin and Theodorou(37) who similarly add a US interest rate in a panel VAR of non-US countries which includes national rates as well.

Figure 12: Panel VAR with US monetary policy as 5th variable



Note. Impulse responses in the panel VAR(12) (without US economy) to a one-standard deviation shock to the national (solid) and US (dashed) montery policy measure. Shocks are identified by the variable ordering: log GDP, log CPI , US monetary policy measure, national policy rate, risk measure. Top panel uses the US policy rate, bottom panel the cumulated surprise shock series of Gürkaynak et al. (2005). Remaining details as in Figure 1.

to the former but not vice versa, in line with the view that national rate changes are partly a response to US policy innovations.[46] Results suggest that US shocks cause the entire decline in LRMES while the picture is more mixed with regards to the other risk measures. There, both national and US shocks seem to play a role although the responses to the latter are somewhat more delayed and significantly more persistent. The results hence largely confirm the conclusions that emerged from the previous methodology that US shocks in particular play an important role in the propagation of monetary policy onto systemic risk. For completeness we note that also for this case several robustness checks have been performed.[47]

4 Conclusions

We test whether a risk-taking channel of monetary policy, namely the notion that the stance of monetary policy affects the risk-taking behavior of banks, holds at an aggregate and systemic level. This has important implications as the channel would be relevant for the setting of monetary policy only to the extent that it affects the real economy and the financial system as a whole. We address this question using time series evidence, which allows us to account for the endogenous response of

[46]We may note that disentangling national from US shocks makes price and output puzzles largely disappear and national prices seem to respond to both national shocks and those from abroad, see Figure 30 in Appendix E.
[47]Notably, we found that ordering national rates before their US equivalents hardly changes risk responses.

monetary policy, and using various systemic risk metrics, which capture contagion effects of bank risk stemming from interconnectedness, cross-exposure and asset commonality.

We compare our results across a suit of models. We take into account a cross-country dimension (panel VAR), control for a large set of macroeconomic variables that might drive the monetary policy stance (FAVAR) and incorporate external information derived from the high-frequency identifcation literature of monetary policy shocks (proxy VAR and local projections). We find robust evidence of a systemic risk-taking channel across all these specifications, notwithstanding the monetary policy instrument (policy and shadow rates as well as the size of central bank balance sheets) or shock identification (timing assumptions and employing external shock series). When we further investigate the economic channels behind the monetary transmission, we find that banks' balance sheet variables largely move in line with risk-taking channels, but do not account for the full transmission into systemic risk, pointing towards the importance of interconnectedness and contagion in systemic risk formation. Finally, and importantly, we find that not only national policies are drivers of the risk-taking channel but also monetary policy in the US.[48]

[48]See for instance Gourinchas and Rey(36). While these authors focus on the global financial cycle and uncertainty as measured by the VIX, our focus here is on the US as a dominant country in propagating sytemic risk.

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Appendix

A Data Description and Sources

A.1 Variables used in panel VAR

The panel VAR includes the following set of variables. Data sources are detailed in Table 2.

- **GDP:** Interpolated from quarterly to monthly data using the Chow-Lin(27) interpolation method with industrial production and retail sales as reference series
- **Monetary policy measures:**
  - Policy rate: Money market rates.
  - Wu and Xia(61)
  - Krippner(44)
  - US monetary policy surprise series of Gürkaynak et al.(39)
  - US monetary policy shock series of Romer and Romer(56)
  - Central bank assets: Total assets of each country's / monetary union's central bank, where available; otherwise monetary base.
- **Realized volatility:** Authors' calculations. Computed as average weekly absolute equity returns
- **LRMES:** Long-run marginal expected shortfall as defined in Acharya et al.(1)
- **ΔCoVaR (equity returns):** Authors' calculations based on Adrian and Brunnermeier (2016). Details on the measure and its computation are given in Appendix C.
- **ΔCoVaR (CDS spreads):** Authors' calculations based on Adrian and Brunnermeier (2016). Details on the computations are given in Appendix C.
- **CPI**.
- **Monetary policy surprise series**: updated series (MP1) from Gürkaynak et al. (2005).
- **Total liabilities**.
- **Market leverage**: Authors' calculations as (book assets - book equity + market equity) / (market equity).

Figure 13 depicts country averages of these variables, whereas details on the underlying time series and their sources are given in Table 2. Table 1 lists all banks the risk metrics are calculated for.

Table 1: GSIBs used for risk measures

Country	**Bank**	**Balance sheet data**
United States	Bank of America	yes
	Bank of New York Mellon	yes
	Citigroup	yes
	Goldman Sachs	yes
	JP Morgan Chase	yes
	Morgan Stanley	yes
	State Street	yes
	Wells Fargo	yes
United Kingdom	Barclays	yes
	HSBC	yes
	Royal Bank of Scotland	yes
	Standard Chartered	no
Switzerland	Credit Suisse	yes
	UBS	yes
Sweden	Nordea Bank	no
Spain	Banco Santander	yes
Netherlands	ING	yes
Japan	Mizuho Financial Group	yes
	Mitsubishi UFJ Financial Group	yes
	Sumitomo Mitsui Financial Group	yes
Italy	Unicredit	no
Germany	Deutsche Bank	yes
France	BNP Paribas	no
	Credit Agricole	no
	Societe Generale	no
China	Agricultural Bank of China	no
	Bank of China	no
	China Construction Bank	no
	Industrial and Commercial Bank of China	no

Global systemically important banks (GSIBs) as defined in 2016 by the Financial Stability Board (FSB) in consultation with the Basel Committee on Banking Supervision (BCBS) at the Bank of International Settlements (BIS). Groupe BPCE is missing due to lacking data availability. Balance sheet data is used in section 3.4.1 and is available for 19 banks from Compustat-CRSP. Time sample data availability varies by bank.

Figure 13: Time series used in panel VAR

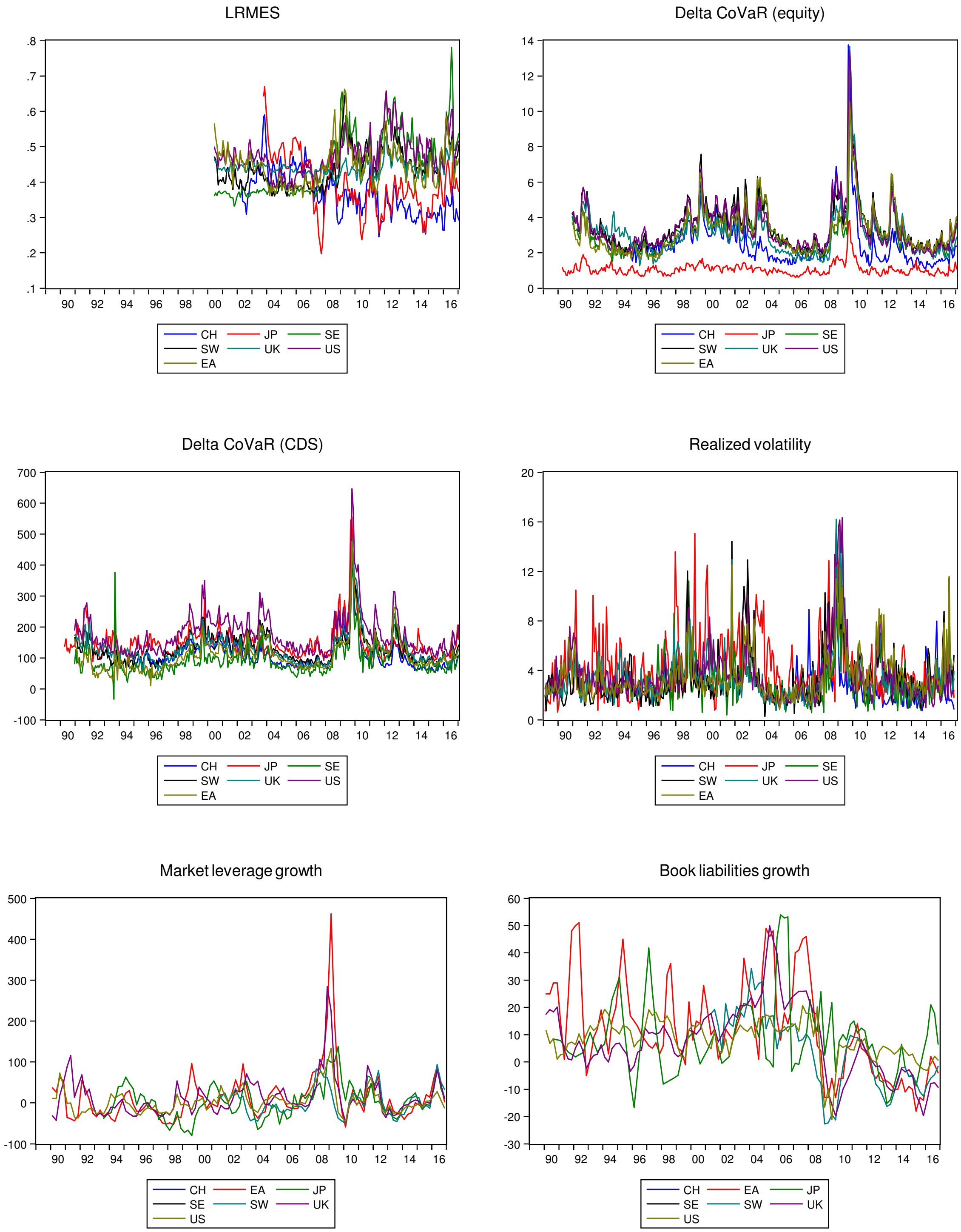


Figure shows data employed in the panel VAR model. Country series for bank-specific variables, namely the risk measures, are obtained by averaging over all banks headquartered in the respective country. *CH*- China, *FR* - France, *JP* - Japan, *SE* - Sweden, *SW* - Switzerland, *UK* - United Kingdom, *US* - United States.

Table 2: Data sources

	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, EPB@SNB.zimoma1TGT	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, JPNPROINDMISMEI	OECD via FRED, CHEPROINDQISMEI (quarterly values interpolated to monthly frequency based on constant match average method)	OECD via FRED, GBRPROINDMISMEI
Central bank total assets	Board of Governors of the Federal Reserve System via FRED, Monetary base (BOGMBASE) until 2003, from then onward Total Assets (WALCL). BOGMBASE indexed backwards so as to match WALCL. Monthly averages of WALCL weekly data	Bank of Japan via FRED, JPNASSETS	Swiss National Bank, SNBBIPO	Bank of England via FRED, MBM0UKM
Shadow rate Wu Xia	Wu and Xia (2016)			Wu and Xia (2016)
Shadow rate Krippner	Krippner, `https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures`	Krippner, `https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures`		Krippner, `https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures`
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	3-month treasury bill rate, Datastream		2-year government bond rate, Datastream	3-months 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			5-year BBB coporate bond yield, Datastream

	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, SWECPI-ALLMINMEI	OECD via FRED, CHNCPI-ALLMINMEI	OECD via FRED, FRACPI-ALLMINMEI	OECD via FRED, DEUCPI-ALLMINMEI
GDP	OECD via FRED, NAEXKP01SEQ661S	OECD via FRED, CHNGDPN-QDSMEI	OECD via FRED, LNBQRSA	OECD via FRED, NAEXKP01DEQ661S
Industrial production	OECD via FRED, SWEPROIND-MISMEI	OECD	OECD via FRED, FRAPROIND-MISMEI	OECD via FRED, DEUPROIND-MISMEI
Central bank total assets	Assetmacro `https://www.assetmacro.com/sweden/sweden-central-bank-balance-sheet` until 2006. From then onward Riksbank; monthly end-of-period values from weekly data.	Yardeni Research, `http://www.yardeni.com/pub/peacockfedecbassets.pdf`	European Central Bank via FRED, ECBASSETS	European Central Bank via FRED, ECBASSETS
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, , `https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures`, used rates for European Monetary Union	Krippner, used rates for European Monetary Union, , `https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures`
VIX	Datastream	Datastream (used world VIX due to nonavailability)	Datastream	Datastream
Retail sales	Datastream	Datastream	Datastream	Datastream
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		3-months 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. Inhaberschuldverschreibungen / Anleihen von Unternehmen (Nicht-MFIs), Bundesbank, BBK01.WT0022

	Spain	Netherlands	Italy
Policy rate	Call money rate, OECD via FRED, IRSTCI01ESM156N	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
Central bank total assets	European Central Bank via FRED, ECBASSETS	European Central Bank via FRED, ECBASSETS	European Central Bank via FRED, ECBASSETS
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, , `https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures`	Krippner, used rates for European Monetary Union, , `https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures`
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		3-months treasury bill auction rate, Datastream
Interbank rate	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream
Corporate bond rate			

A.2 Variables used in US FAVAR

Table A.2 lists all variables, in addition to the risk metrics, and their transformations used in the US FAVAR, alongside with their sources and an indication whether they are assumed to be slow-moving in the model. The underlying time series used to compute the ΔCoVaR measures are again given in the US column of Table 2.

Table 6: US FAVAR data description and sources

#	Series ID[1]	Slow[2]	Transf.[3]	Description
1	INDPRO	yes	5	Industrial Production Index
2	IPBUSEQ	yes	5	Industrial Production: Business Equipment
3	IPCONGD	yes	5	Industrial Production: Consumer Goods
4	IPDCONGD	yes	5	Industrial Production: Durable Consumer Goods
5	IPDMAN	yes	5	Industrial Production: Durable Manufacturing (NAICS)
6	IPDMAT	yes	5	Industrial Production: Durable Materials
7	IPFINAL	yes	5	Industrial Production: Final Products (Market Group)
8	IPMAN	yes	5	Industrial Production: Manufacturing (NAICS)
9	IPMAT	yes	5	Industrial Production: Materials
10	IPMINE	yes	5	Industrial Production: Mining
11	IPNCONGD	yes	5	Industrial Production: Nondurable Consumer Goods
12	IPNMAN	yes	5	Industrial Production: Nondurable Manufacturing (NAICS)
13	IPNMAT	yes	5	Industrial Production: Nondurable Materials
14	IPUTIL	yes	5	Industrial Production: Electric and Gas Utilities
15	BSCURT02USM160S	yes	1	Business Tendency Surveys for Manufacturing: Capacity Utilization: Rate of Capacity Utilization: European Commission and National Indicators for the United States©
16	RPI	yes	5	Real Personal Income
17	W875RX1	yes	5	Real personal income excluding current transfer receipts
18	CE16OV	yes	5	Civilian Employment Level
19	DMANEMP	yes	5	All Employees: Durable Goods
20	EMRATIO	yes	4	Civilian Employment-Population Ratio
21	MANEMP	yes	5	All Employees: Manufacturing
22	PAYEMS	yes	5	All Employees: Total Nonfarm Payrolls
23	SRVPRD	yes	5	All Employees: Service-Providing Industries
24	USCONS	yes	5	All Employees: Construction
25	USGOVT	yes	5	All Employees: Government
26	USINFO	yes	5	All Employees: Information Services
27	USMINE	yes	5	All Employees: Mining and logging
28	USPRIV	yes	5	All Employees: Total Private Industries

#	Series ID	Slow	Transf.	Description
29	AWHNONAG	yes	1	Average Weekly Hours of Production and Nonsupervisory Employees: Total private
30	CES1000000007	yes	1	Average Weekly Hours of Production and Nonsupervisory Employees: Mining and Logging
31	CES0800000007	yes	1	Average Weekly Hours of Production and Nonsupervisory Employees: Private Service-Providing
32	CES3100000007	yes	1	Average Weekly Hours of Production and Nonsupervisory Employees: Durable Goods
33	CES2000000007	yes	1	Average Weekly Hours of Production and Nonsupervisory Employees: Construction
34	CES5000000007	yes	1	Average Weekly Hours of Production and Nonsupervisory Employees: Information
35	CES4000000007	yes	1	Average Weekly Hours of Production and Nonsupervisory Employees: Trade, Transportation, and Utilities
36	CES6000000007	no	4	Average Weekly Hours of Production and Nonsupervisory Employees: Professional and Business Services
37	HOUST	no	4	Housing Starts: Total: New Privately Owned Housing Units Started
38	HOUSTMW	no	4	Housing Starts in Midwest Census Region
39	HOUSTNE	no	4	Housing Starts in Northeast Census Region
40	HOUSTS	no	4	Housing Starts in South Census Region
41	HOUSTW	no	4	Housing Starts in West Census Region
42	PERMIT	no	5	New Private Housing Units Authorized by Building Permits
43	SP500	no	5	S&P 500©
44	EXCAUS	no	5	Canada / U.S. Foreign Exchange Rate
45	EXJPUS	no	5	Japan / U.S. Foreign Exchange Rate
46	EXSZUS	no	1	Switzerland / U.S. Foreign Exchange Rate
47	EXUSUK	no	1	U.S. / U.K. Foreign Exchange Rate
48	AAA	no	1	Moody's Seasoned Aaa Corporate Bond Yield©
49	BAA	no	1	Moody's Seasoned Baa Corporate Bond Yield©
50	FEDFUNDS	no	1	Effective Federal Funds Rate
51	GS1	no	1	1-Year Treasury Constant Maturity Rate
52	GS10	no	1	10-Year Treasury Constant Maturity Rate
53	GS3	no	1	3-Year Treasury Constant Maturity Rate
54	GS3M	no	1	3-Month Treasury Constant Maturity Rate
55	GS5	no	1	5-Year Treasury Constant Maturity Rate

#	Series ID	Slow	Transf.	Description
56	BOGNONBR	no	5	Non-Borrowed Reserves of Depository Institutions
57	AMBSL	no	5	St. Louis Adjusted Monetary Base
58	M1	no	5	M1 Money Stock
59	M2	no	5	M2 Money Stock
60	MZM	no	5	MZM Money Stock
61	TOTLL	no	5	Loans and Leases in Bank Credit, All Commercial Banks
62	REALLN	no	5	Real Estate Loans, All Commercial Banks
63	BUSLOANS	no	5	Commercial and Industrial Loans, All Commercial Banks
64	CONSUMER	no	5	Consumer Loans at All Commercial Banks
65	CPIAUCSL	yes	5	Consumer Price Index for All Urban Consumers: All Items
66	CPIFABSL	yes	5	Consumer Price Index for All Urban Consumers: Food and Beverages
67	CPILFESL	yes	5	Consumer Price Index for All Urban Consumers: All Items Less Food and Energy
68	CPIMEDSL	yes	5	Consumer Price Index for All Urban Consumers: Medical Care
69	DNRGRG3M086SBEA	yes	5	Personal consumption expenditures: Energy goods and services (chain-type price index)
70	DPCXRG3M086SBEA	yes	5	Personal consumption expenditures: Market-based PCE excluding food and energy (chain-type price index)
71	PPICRM	no	5	Producer Price Index by Commodity for Crude Materials for Further Processing
72	PPIFCG	yes	5	Producer Price Index by Commodity for Finished Consumer Goods
73	PPIFGS	yes	5	Producer Price Index by Commodity for Finished Goods
74	PPIIEG	yes	5	Producer Price Index by Commodity Intermediate Energy Goods
75	PPIITM	yes	5	Producer Price Index by Commodity Intermediate Materials: Supplies and Components
76	CSCICP02USM661S	no	1	Consumer Opinion Surveys: Confidence Indicators: Composite Indicators: European Commission and National Indicators for the United States©
77	AHETPI	yes	5	Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private

#	Series ID	Slow	Transf.	Description
78	CES0600000008	yes	5	Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-Producing
79	CES0800000008	yes	5	Average Hourly Earnings of Production and Nonsupervisory Employees: Private Service-Providing
80	CES1000000008	yes	5	Average Hourly Earnings of Production and Nonsupervisory Employees: Mining and Logging
81	CES2000000008	yes	5	Average Hourly Earnings of Production and Nonsupervisory Employees: Construction
82	CES3000000008	yes	5	Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing
83	PPIACO	yes	5	Producer Price Index for All Commodities
84		yes	1	US ISM purchasing managers index (MFG survey), Datastream
85		no	1	Shadow policy rate, Wu and Xia (2016), https://sites.google.com/site/jingcynthiawu/home/wu-xia-shadow-rates
86		no	1	Shadow policy rate, Krippner, http://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures
87		no	1	Shadow policy rate, Lombardi and Zhu (2014), http://www.bis.org/publ/work452.pdf
88		no	1	ΔCoVaR (equity), authors' calculations, average of all GSIBS US banks
89		no	1	ΔCoVaR (CDS), authors' calculations, average of all GSIBS US banks
90		no	1	LRMES, V-Lab at the Leonard N. Stern School of Business, New York University, average of all GSIBS US banks, https://vlab.stern.nyu.edu/
91		no	1	Realized volatility, authors' caluclations, average of all GSIBS US banks
92		no	1	VIX, Datastream

[1] Code ID for FRED database, Federal Reserve Bank of St. Louis; empty cells indicate different source from FRED, given in the variable description. [2] Part of the set of variables assumed to be slow-moving in the FAVAR estimation. [3] 1 - no transformation, 2 - difference, 4 - logarithm, 5 - log-difference.

B Model selection criteria

Figure 14: Lag selection criteria in benchmark panel VAR model

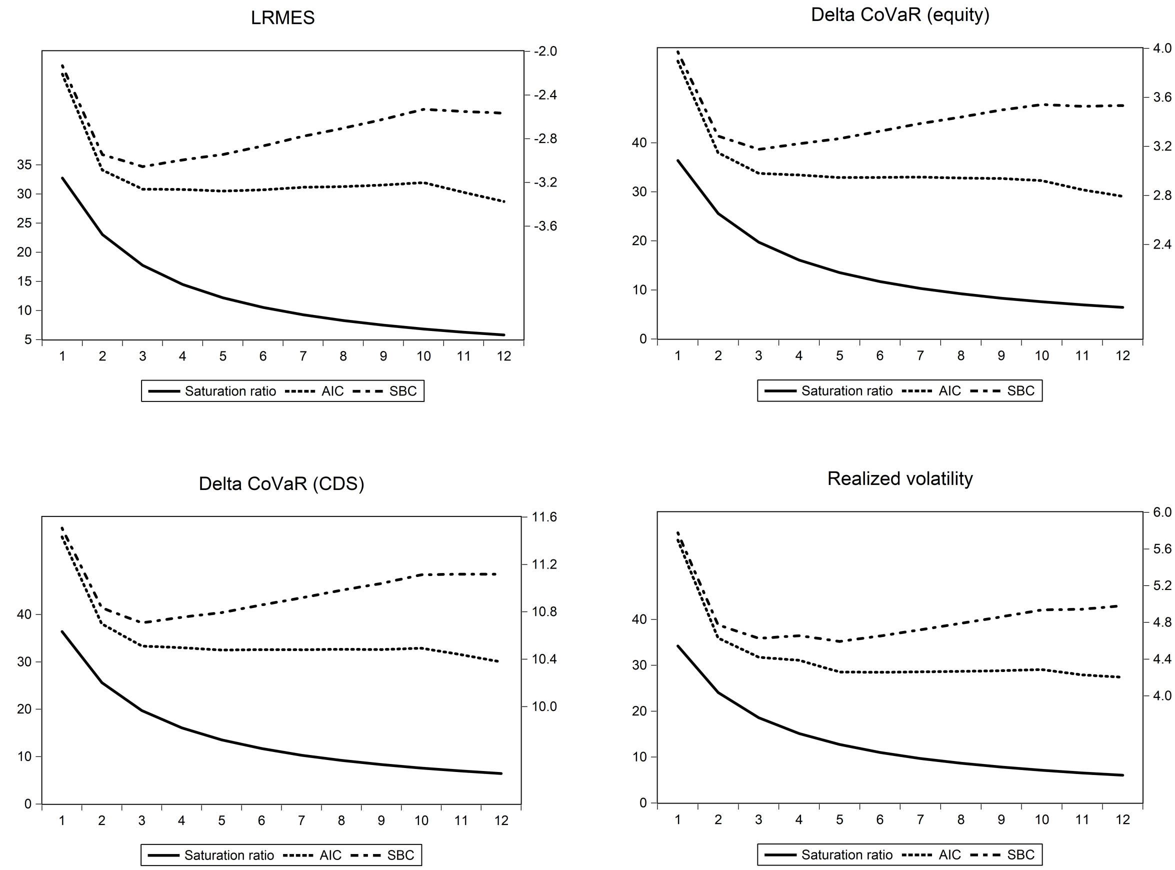


Figure shows lag selection criteria for the benchmark panel VAR model including the year-on-year GDP and CPI growth rates, the policy rate and respective risk measure. Each model includes a constant, a linear time trend and crisis dummy. AIC refers to the Akaike information criterion (right scale), SBC to the Schwarz Bayesian information criterion(right scale). The saturation ratio is defined as the ratio of observations to estimated paramaters (left scale). Time sample: 2000:06-2016:12.

Table 7: Unit root tests

	CPI	GDP	Policy rate	Shadow rate (Wu, Xia)	Shadow rate (Krippner)	Central bank assets	LRMES	Delta CoVaR (equity)	Delta CoVaR (CDS)	Realized volatility
Without trend										
diff=0	1.000	0.998	0.273	0.399	0.425	1.000	0.000	0.000	0.000	0.000
diff=1	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
With trend										
diff=0	0.425	0.841	0.008	0.221	0.676	0.636	0.000	0.000	0.003	0.017
diff=1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table shows p-values for Augmented Dickey-Fuller tests with and without a linear time trend. diff=0 refers to the series in levels, diff=1 to the one in first differences. All bank-specific risk measures are country averages according to Table 1.

Figure 15: Scree plot for benchmark US FAVAR

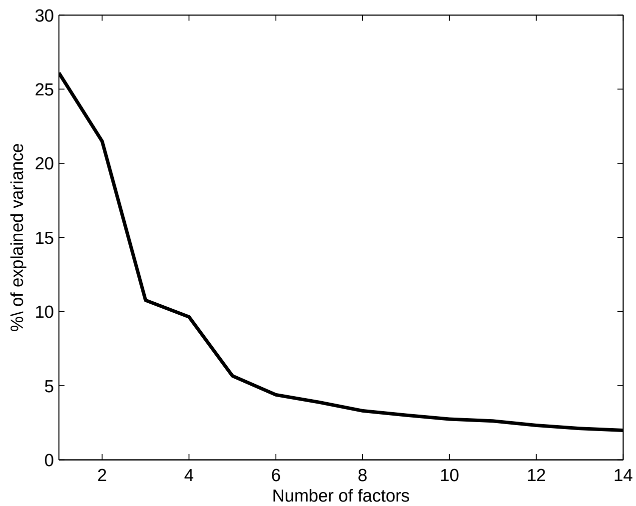


Figure shows scree plot, the proportion of explained variance per factor, for a set of 88 US macroeconomic variables based on principle-component estimation. Time sample: 2000:06-2013:05.

B.1 Structural break tests

We conduct a variety of structural break tests in our benchmark panel VAR to gauge the extent to which including the (post-)crisis period in the main sample might be a concern. First, the Bai-Perron (2003) test, testing the rival hypotheses of 0 vs. 1 unknown break date per VAR equation does point to potential breaks and various times identifies these around the crisis time of 2007-2009, but almost equally often around 1999-2000, the introduction of the euro. As we describe in the main text, this is one reason we choose the year 2000 as the starting date of our main analysis. Similarly, there are two tests we conduct in a non-panel setting for various country-specific VAR models. Results for the Chow breakpoint test (which has the advantage that it is not based on asymptotic theory) for the Null hypothesis of no breakpoint around 2007:08 vary by country and variable but p-values are generally small (a few percent), except for inflation (in particular in the euro area). The same is true for the Quandt-Andrews test for an unknown breakpoint, although p-values here are somewhat higher overall. As structural breaks are most problematic with respect the constant terms, introducing a crisis dummy should alleviate these concerns somewhat. In a robustness exercise we extend the dummy to include the whole second part of the sample until the end of 2016 and also drop it altogether. Our main results are unchanged, which continues to be the case even when we exclude the post-2007 period entirely.

C Model descriptions

This section features details on the FAVAR and proxy VARs as well as the construction of counterfactual impulse responses.

C.1 Description of the US FAVAR

Here we describe the FAVAR estimated for the US economy in section 3.2. The general specification of the model includes a set of observable variables y_t in a VAR together with a set of m common factors F_t. Denoting $Y_t \equiv (F_t', y_t')$ we can then write a structural VAR as:

$$A_0 Y_t = A(L) Y_{t-1} + \epsilon_t, \tag{4}$$

These factors themselves are not available directly, but we assume that a set of N variables X_t has the following factor structure:

$$X_t = \Lambda^f F_t + \Lambda^y y_t + \nu_t, \tag{5}$$

The variables in X_t are assumed to be either slow-moving (X_t^s) or fast-moving (X_t^f), as described in Table A.2, and y_t is the monetary policy measure. All four risk measures are as well contained in X_t and are assumed to be fast-moving. The key identifying assumption in Bernanke et al. (15) then holds that the N^s variables contained in X_t^s are not affected contemporenously by the monetary policy rate but only by the factors:

$$X_t^s = \Lambda^s F_t + \nu_t. \tag{6}$$

Bai and Ng (12) show that the first m principal components C_t^s of the N^s slow-moving variables asymptotically approximate the factors up to some scaling matrix H: $F_t = HC_t^s$. We can then write equation (6) as $X_t^s = \Lambda^s H C_t^s + \nu_t^s$ and equation (5) as

$$X_t = \Lambda^f H C_t^s + \Lambda^y y_t + \nu_t^s. \tag{7}$$

Given that we can map X_t into its principal components C_t^x via some weighting matrix W we can then describe C_t^x via the slow-moving principle components and the monetary policy measure as follows:

$$C_t^x = \underbrace{W\Lambda^f H}_{\equiv\Gamma_1} C_t^s + \underbrace{W\Lambda^y}_{\equiv\Gamma_2} y_t + W\nu_t. \tag{8}$$

We then define $\tilde{F}_t = C_t^x - \Gamma_2 y_t$ and follow Bernanke et al.(15) in running a VAR on $\tilde{Y}_t \equiv (\tilde{F}_t', y_t')$:

$$\tilde{Y}_t = \tilde{B}(L)\tilde{Y}_{t-1} + \tilde{u}_t, \tag{9}$$

in which we identify structural monetary policy shocks recursively by ordering y_t last. We then recover the impulse responses to some N^i variables of interest, X_t^i, by regressing $\tilde{Y}_t$ on X_t^i, with corresponding $N^i \times (m+1)$ coefficient matrix Ξ, and then computing:

$$\frac{\partial X_{t+h}^i}{\partial \epsilon_t} = \Xi D_h, \tag{10}$$

where D_h is the $(m+1) \times (m+1)$ MA-infinity coefficient matrix of horizon h of the corresponding structural VAR. X_t^i will in particular include our four risk measures.

C.2 Description of the US proxy VAR

In the following we describe identification in the US proxy VAR we employ in section 3.3.2. Consider again the structural VAR

$$A_0 Y_t = A(L)Y_{t-1} + \epsilon_t \tag{11}$$

with the corresponding reduced form

$$Y_t = B(L)Y_{t-1} + u_t \tag{12}$$

where $B(L) \equiv A_0^{-1}A(L)$ and u_t is the reduced-form shock

$$u_t = A_0^{-1}\epsilon_t. \tag{13}$$

We may partition the shock vectors into those of the monetary policy measure, indicated with a superscript p, and those of the remaining shocks with superscript q. The corresponding vectors then read as follows: $u_t = [u_t^p, u_t^{q\prime}]', \epsilon_t = [\epsilon_t^p, \epsilon_t^{q\prime}]'$. Denoting then the impact matrix A_0^{-1} as S, we are interested in that column of S, denoted as s, that gives the initial impact to a structural monetary policy shock ϵ_t^p.[49] In what follows, we denote as s^q the initial impact of ϵ_t^p on u_t^q, while s^p is the corresponding impact on the reduced-form monetary policy residual u_t^p.

[49] We may therefore leave the remaining columns of S undetermined.

Building on Stock and Watson(59) and Mertens and Ravn(50) and following Gertler and Karadi(38), we use instruments from the high-frequency identification literature of monetary policy surprises in the proxy VAR to identify the structural innovations ϵ_t^p. For these instruments to be valid, we assume the surprise series Z_t to be *relevant* and *exogenous* as follows:

$$\mathbb{E}[Z_t \epsilon_t^{p\prime}] = \phi \neq 0, \tag{14}$$

$$\mathbb{E}[Z_t \epsilon_t^{q\prime}] = 0.$$

Since we are ultimately concerned with estimating impulse responses based on

$$Y_t = B(L)Y_{t-1} + s\epsilon_t^p, \tag{15}$$

we derive estimates of s in the following manner. We first run the reduced-form VAR and obtain shocks u_t. These are then used in a two-stage least squares regression using Z_t as instruments. In the first stage, u_t^p is linearly projected on Z_t in order to obtain the fitted values $\hat{u}_t^p$. The latter, by assumption uncorrelated with the non-policy structural shocks ϵ_t^q, can be used in the second-stage regression:

$$u_t^q = \frac{s^q}{s^p}\hat{u}_t^p + \xi_t. \tag{16}$$

The above procedure ensures that $\frac{s^q}{s^p}$ is consistently estimated and can be used to obtain s. To do so, Gertler and Karadi(38) proceed to first obtain s^p from the reduced-form covariance matrix and then calculate s^q. As we are primarily interested in a comparison of the proxy VAR impulse responses with those of a conventional recursive ordering, we normalize s^p to its Cholesky-implied counterpart so as to make the initial monetary impulse identical in size.

C.3 Counterfactual impulse responses

This section provides details on how we compute the counterfactual impulse responses used in section 3.4.1. The benchmark results are based on the methodology in Bachmann and Sims(11), where a structural shock series is contructed that offsets the response of the target variable (here: size and leverage measures) to innovations of the impulse variable in question (here: the interest rate).

Abstracting from exogenous terms, let $Y_t = C(L)u_t$ denote the MA-infinity representation of the reduced-form panel VAR such that we can the structural model as

$$Y_t = D(L)\epsilon_t, \tag{17}$$

with $D(L) \equiv C(L)A_0^{-1}$. In the following we denote as $D_h(i,j)$ the impulse response of variable j at horizon h to an innovation of variable i. As we order the size and leverage variables 4th and monetary policy 3rd in the benchmark case, constructing counterfactual impulse reponses then amounts to finding an offsetting structural shock series such that

$$\hat{D}_h(4,3) = 0 \quad \forall h = 0, 1, ..., H. \tag{18}$$

For horizon $h = 0$ we can find the offsetting shock as

$$\hat{\epsilon}_0^4 = -\frac{D_0(4,3)}{D_0(4,4)} \tag{19}$$

and then find the remaining ones recursively as

$$\hat{\epsilon}_h^4 = -\frac{D_h(4,3) + \sum_{k=0}^{h-1} D_k(4,4)\hat{\epsilon}_k^4}{D_0(4,4)}, \tag{20}$$

for $h = 1, 2, ..., H$. The counterfactual impulse responses $\hat{D}_h$ are then constructed as

$$\hat{D}_h = D_h + \sum_{k=0}^{h-1} \hat{\epsilon}_k^4, \tag{21}$$

with $h = 1, 2, ..., H$. As an alternative method to arrive at counterfactual impulse reponses we also compute responses based on a VAR model where we impose a zero response of the size and leverage measures from the outset. I.e., we restrict all those reduced-form and impact matrix coefficients to zero that govern the response of the variable in question to the interest rate and its innovations. This alternative scheme gives very similar results.

D Systemic Risk Metrics

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

The long-run marginal expected short-fall is based on a methodology by Bronwless and Engle(20). The modeling framework is rationalized in Acharya, Pedersen, Philippon, and Richardson(1). LRMES refers to the expected capital shortfall of a financial firm given a protracted decline in the market (more than 40%). The marginal short-fall 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 short-fall is computed from the average return of its equity, R^b, during the 5% worst days for the overall market return, R^m, where the market is proxied by the CRSP Value Weighted Index:

$$MES_b = \frac{1}{\text{number of days}} \sum_{\text{t: system is in 5\% tail}} R_t^b \tag{22}$$

LRMES is then the average cumulated expected return in the stock price of each bank over all simulated crisis scenarios in the following six months computed using Monte-Carlo simulations of market and bank returns. This measure has the advantage of being linked to both market and bank assessment of the default probability, which in this case is proxied by the likelihood of being under-capitalized. We obtain LRMES time series for all banks in the sample from the V-Lab at the Leonard N. Stern School of Business, New York University.[50]

The second metric that we consider is ΔCoVaR by Adrian and Brunnermeier(3). 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. This metric has two advantages. First, it captures institutional externalities such as "too big to fail" and "too interconnected to fail". Second, it does not rely on contemporaneous price movements so it can be used to predict systemic risk. We compute two variants of this metric, one based on banks' equity prices and one based on banks' CDS spreads. The second should have higher predictive power since typically insurance prices embed market forecasts about future risk of default. Technically the definition of ΔCoVaR can be summarized

[50]We are greatful to the V-Lab team, in particular Michael Robles, for supplying us with the data.

as follows. Define the Value at Risk of a bank as:

$$\Pr(X^i \leq VaR_q^i) = q \tag{23}$$

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:

$$\Pr(X^j \leq CoVaR_q^{j|i} | X^i = VaR_q^i) = q \tag{24}$$

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

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|i} - CoVaR_{50\%}^{j|i} \tag{25}$$

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 Brunnermerier(3) 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 as follows. First, we estimate the contribution of each bank's i losses to the system-wide losses by running the following quantile regressions:

$$X_t^{system} = \alpha_q^{system} + \beta_q^{system|i} X_t^i + \gamma_q^{system|i} M_{t-1} + \varepsilon_t^i. \tag{26}$$

For the equity-based ΔCoVaR measure, X_t^k, $k \in \{i, system\}$, denotes equity market returns in per cent for bank i and of all banks in sample, respectively. For the CDS-based measure, X_t^i is the 5-year CDS spread in basis points, whereas X_t^{system} refers to the average CDS spread across all banks in the sample. M_{t-1} is a set of lagged control variables specified below and $q = 0.05$ represents the quantile on which the regression is based. We denote the estimated coefficient of each bank's contribution to system-wide 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 $q = 0.5$:

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_t^i, \tag{27}$$

$$X_t^i = \alpha_{50}^i + \gamma_{50}^i M_{t-1} + \varepsilon_t^i. \tag{28}$$

Finally, denoting the predicted values of (27) and (28) as $VaR^i_{q,t} \equiv \hat{\alpha}^i_q + \hat{\gamma}^i_q M_{t-1}$ and $VaR^i_{50,t} \equiv \hat{\alpha}^i_{50} + \hat{\gamma}^i_{50} M_{t-1}$, respectively,[51] we obtain $\Delta CoVaR^i_{q,t}$ as

$$\Delta CoVaR^i_{q,t} = \hat{\beta}^{system|i}_q (VaR^i_{q,t} - VaR^i_{50,t}). \tag{29}$$

In the set of lagged control variables M_{t-1} we include variables as suggested by Adrian and Brunnermeier(3), where available. In particular, for US banks we use (see Table 2 for sources) the

- change in the three-month yield
- change in the slope of the yield curve, measured by the spread between a ten-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 ten-year government bond rate
- return of the Datastream broad stock market index
- real estate sector return in excess of the market financial sector return
- volatility of each bank's market returns, defined as the weekly averages of 22-day rolling window standard deviations of daily market returns
- implied volatility as measured by the VIX

Since for some countries not all of the above control variables are available, for all non-US countries we use the US controls whereever country-specific controls could not be obtained. These are described, along the data sources, in Table 2. Like Adrian and Brunnermeiner(3) we restrict

[51] 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 X^i_t 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.

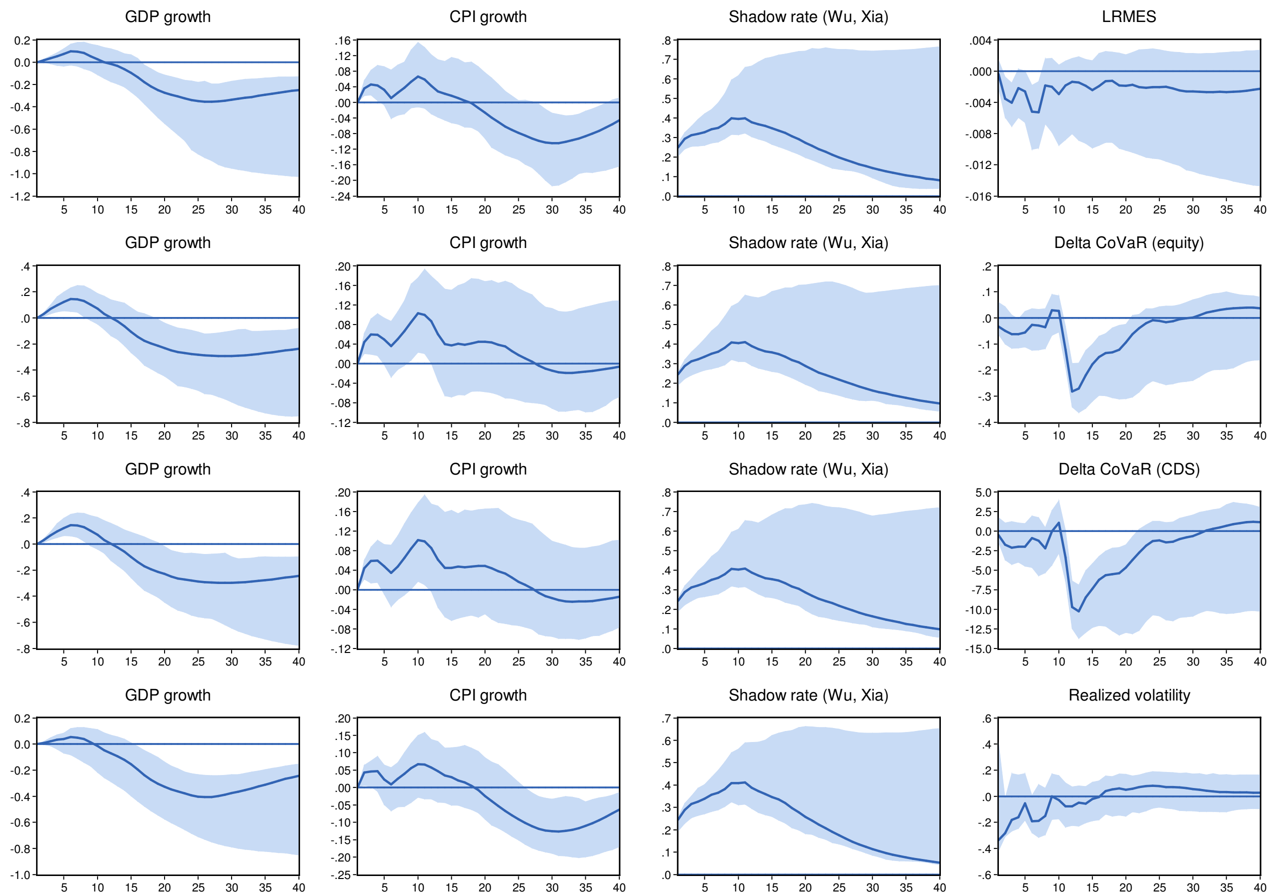
estimation to banks with at least 260 weekly observations. The resulting ΔCoVaR time series are depicted as country averages in Figure 13.[52]

[52] As the figure shows, Japanese ΔCoVaR based on equity returns are significantly lower than that of the other economies. This is mainly driven by the substantially lower correlations of Japanese banks' equity returns with that of US and European banks, which dominate the sample. While the same is true for Chinese banks (and the corresponding ΔCoVaR is indeed somewhat low as well), the effect is more limited there as we employ more US controls due to lower data availability of Chinese controls. Reassuringly, when we condition on the same set of variables in the quantile regressions, ΔCoVaR measures of Japanese banks are more similar to the others and our panel VAR results are qualitatively unaffected.

E Selected robustness tests

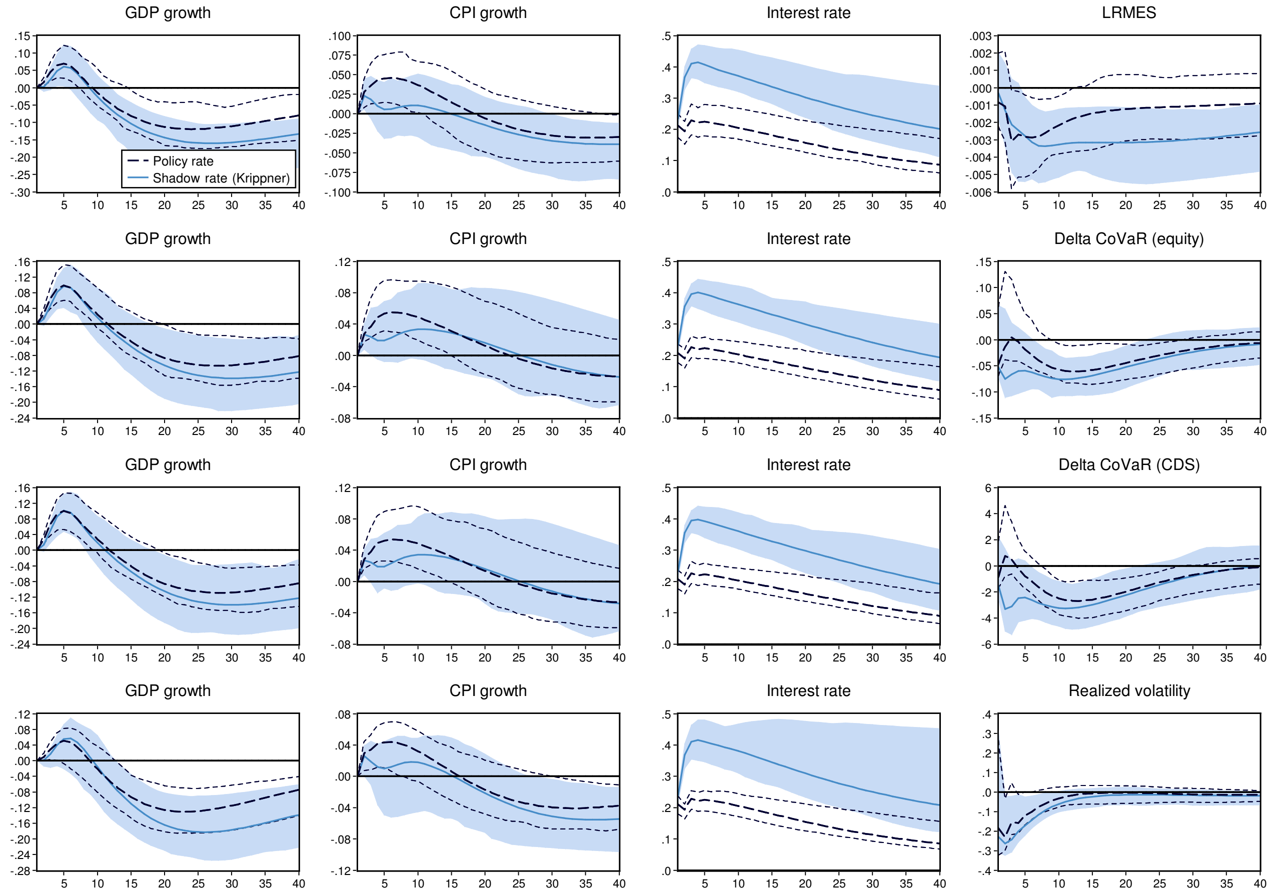
E.1 Panel VAR

Figure 16: Panel VAR with Wu and Xia (2016) shadow rate



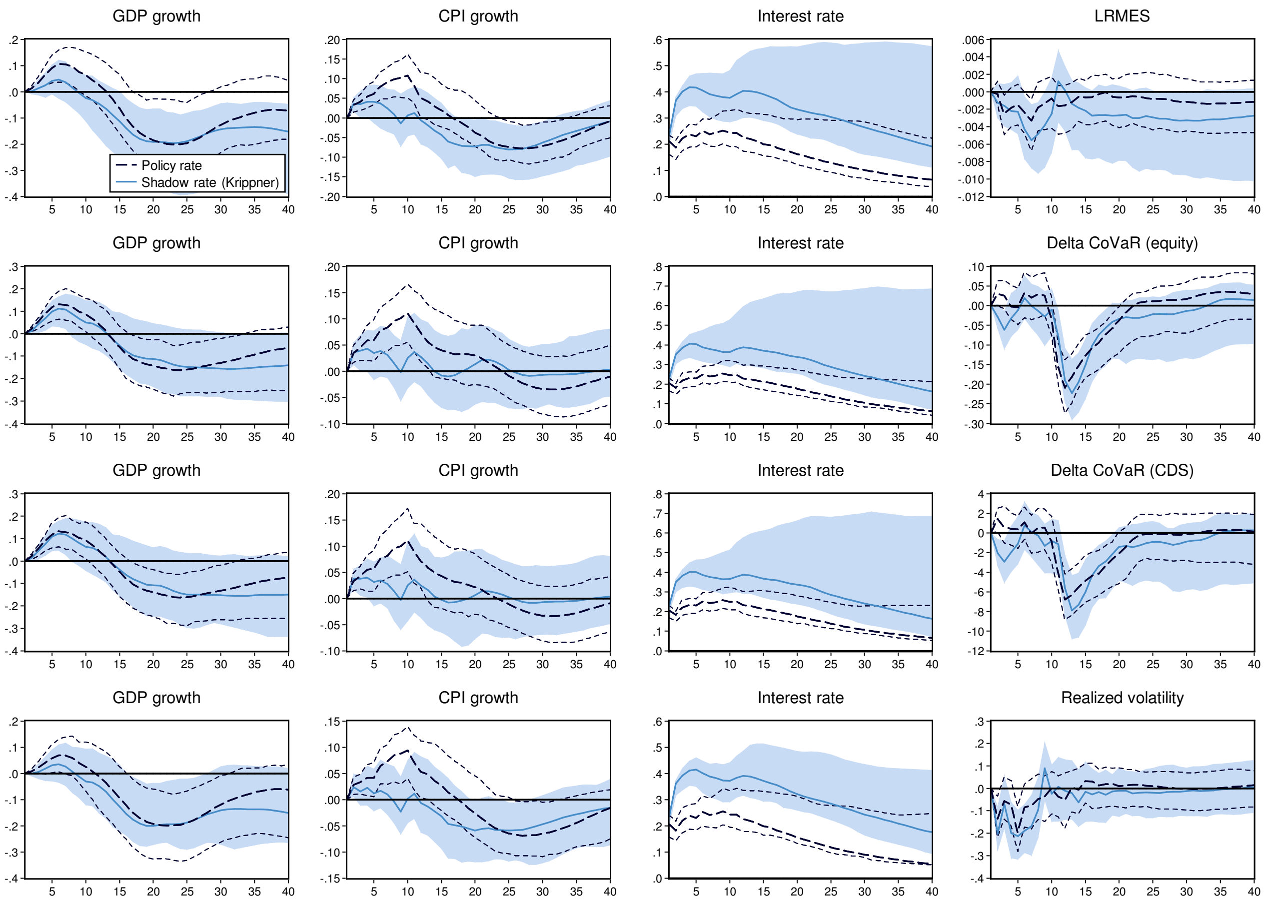
Note. Impulse responses in the panel VAR(12) to a one-standard deviation shock to the Wu and Xia shadow rate. Countries included: United States, United Kingdom, China, euro area (Germany, France, Spain, Netherlands, Italy). Remaining details as in Figure 1.

Figure 17: Panel VAR with main policy rate with 3 lags



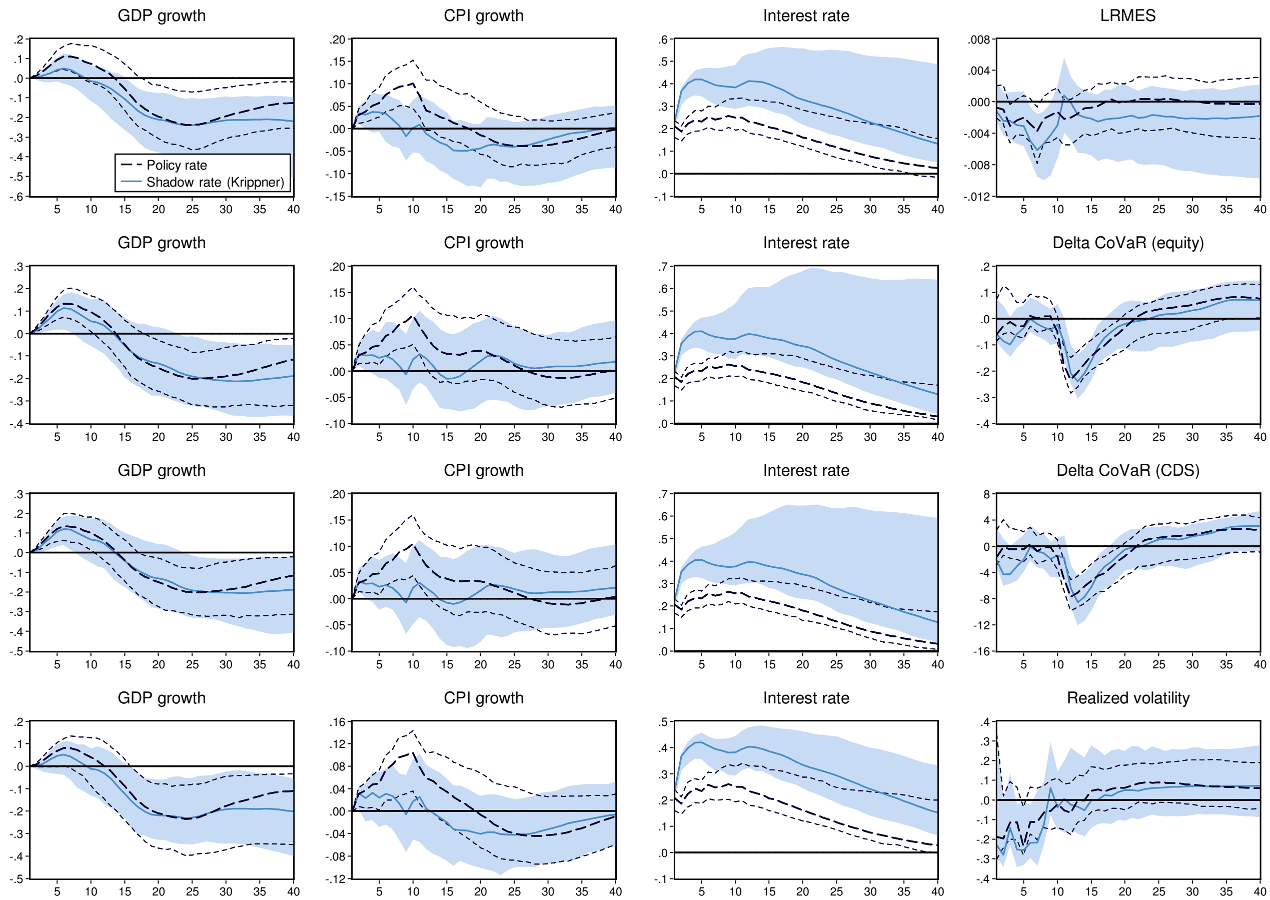
Note. Impulse responses in the panel VAR(3) to a one-standard deviation shock to the policy rate (dashed) and Krippner's shadow rate (solid). Remaining details as in Figure 1.

Figure 18: Panel VAR with main policy rate ordered last



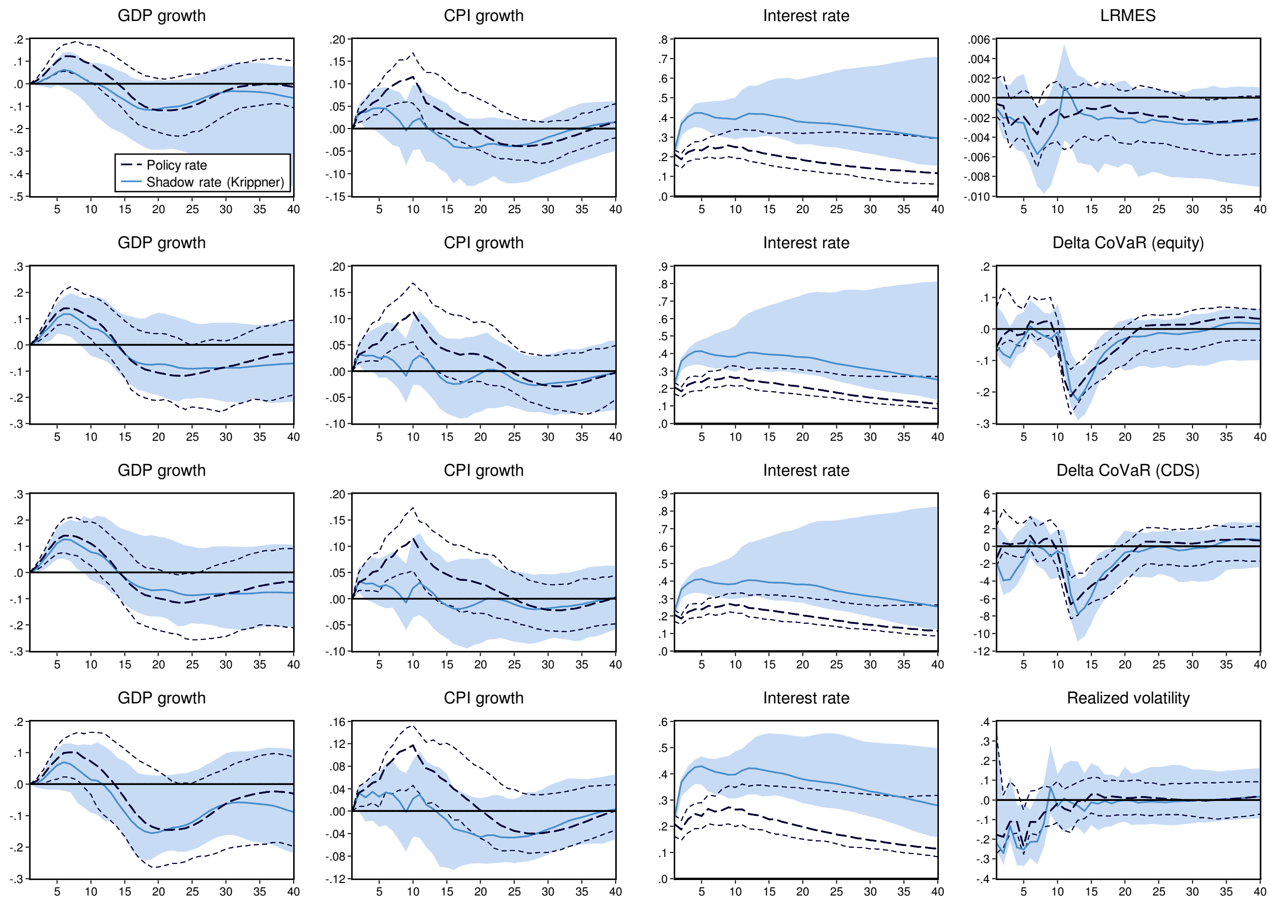
Note. Impulse responses in the panel VAR(12) to a one-standard deviation shock to the policy rate (dashed) and Krippner's shadow rate (solid). Variable ordering: GDP growth rate, CPI growth rate, risk measure, interest rate. Remaining details as in Figure 1.

Figure 19: Panel VAR with main policy rate, without crisis dummy



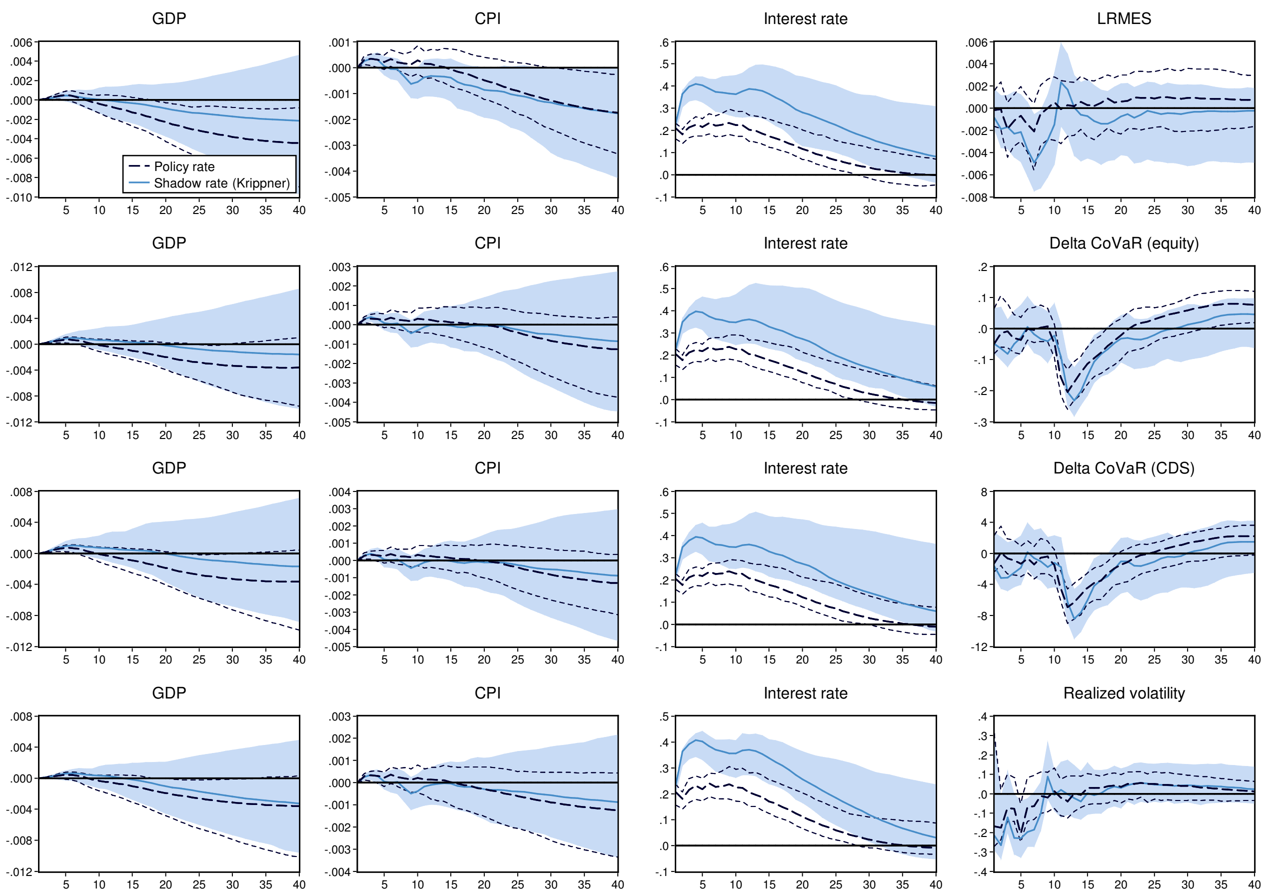
Note. Impulse responses in the panel VAR(12) to a one-standard deviation shock to the policy rate (dashed) and Krippner's shadow rate (solid). Model without a crisis dummy, remaining details as in Figure 1.

Figure 20: Panel VAR without trend



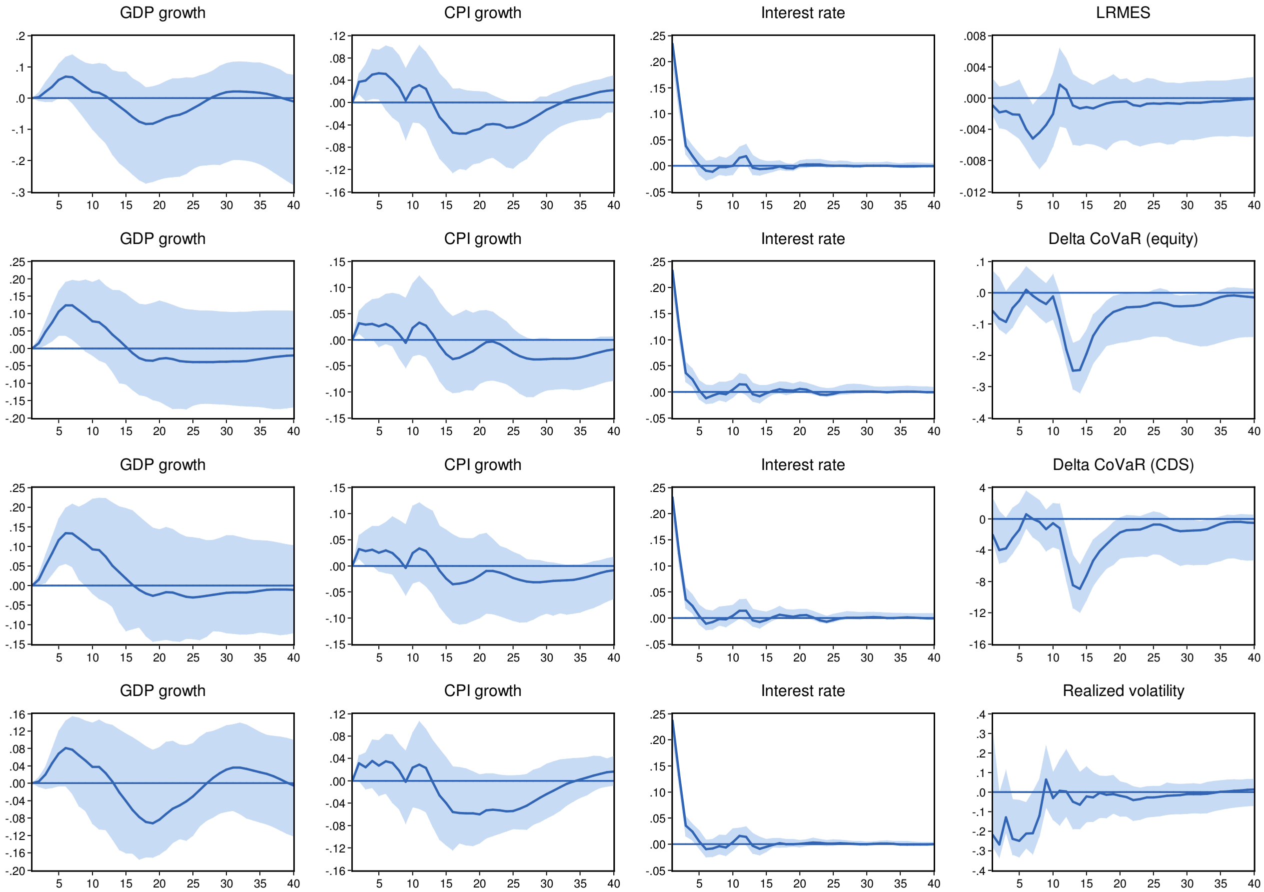
Note. Impulse responses in the panel VAR(12) to a one-standard deviation shock to the policy rate (dashed) and Krippner's shadow rate (solid). Model without a time trend, remaining details as in Figure 1.

Figure 21: Panel VAR in levels



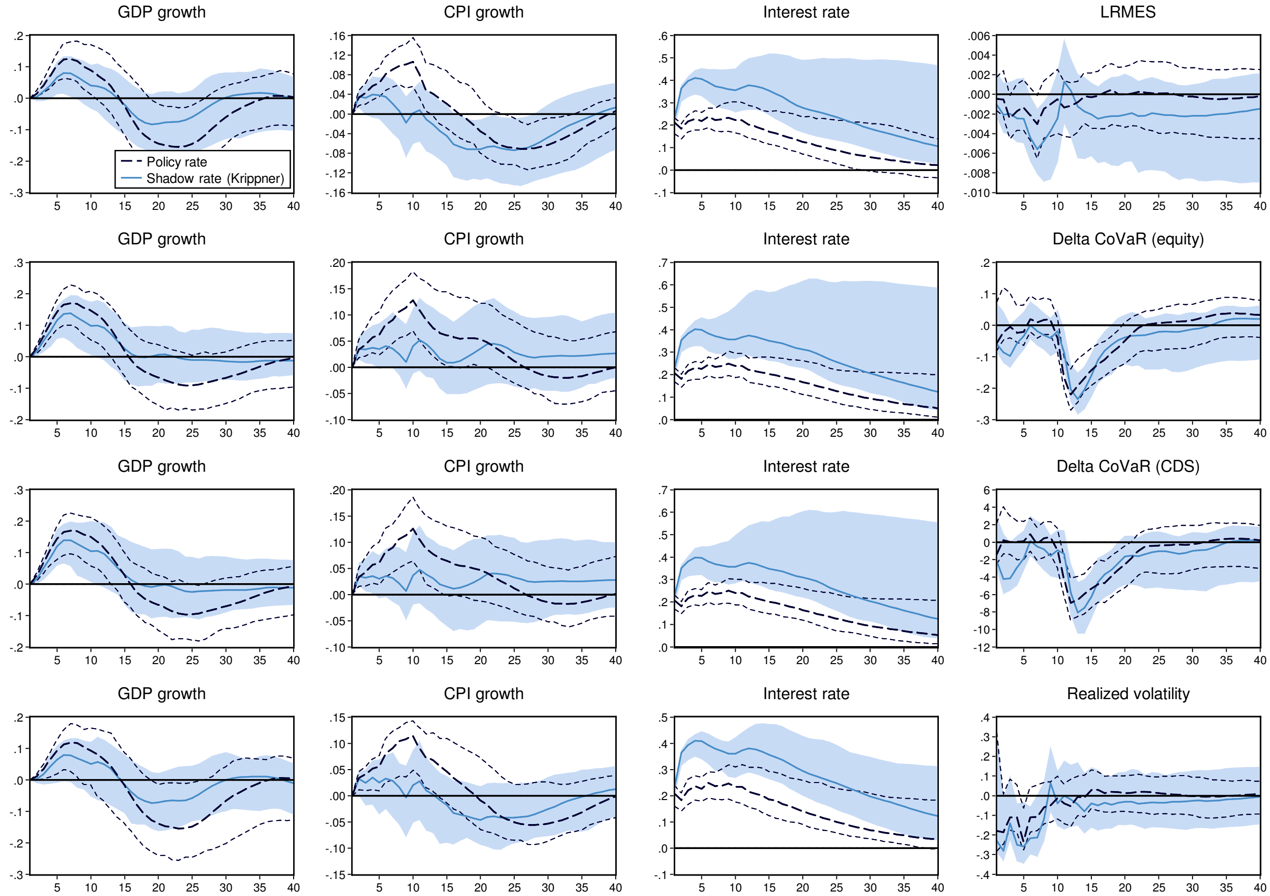
Note. Impulse responses in the panel VAR(12) to a one-standard deviation shock to the policy rate (dashed) and Krippner's shadow rate (solid). Model includes log-levels of GDP and CPI instead of growth rates, remaining details as in Figure 1.

Figure 22: Benchmark panel VAR with first-differenced policy rate



Note. Impulse responses in the panel VAR(12) to a one-standard deviation shock to the first-differenced Krippner's shadow rate. Remaining details as in Figure 1.

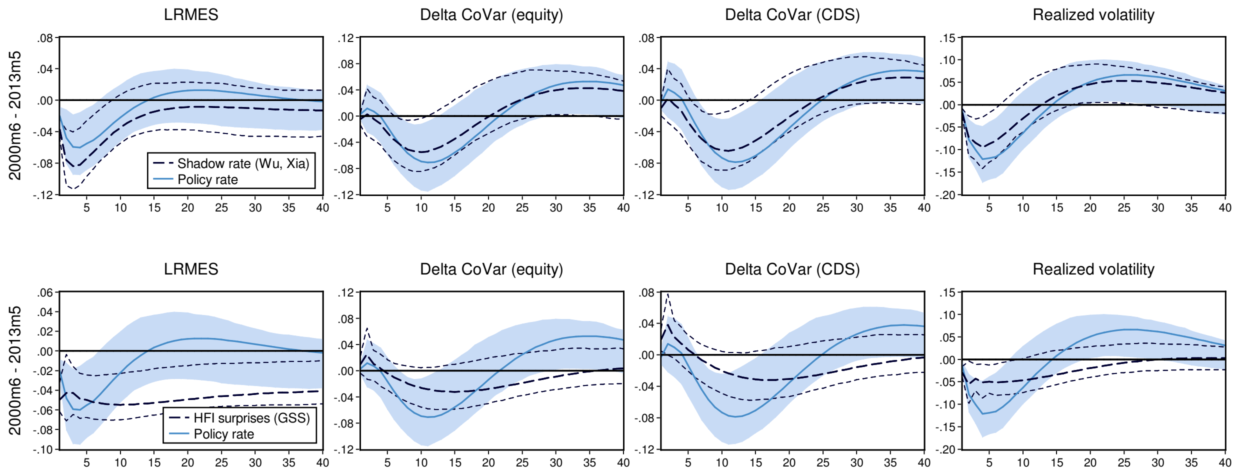
Figure 23: Panel VAR with macroprudential regulation as exogenous control variable



Note. Impulse responses in the panel VAR(12) to a one-standard deviation shock to the policy rate (dashed) and Krippner's shadow rate (solid). Model includes a macroprudential index based on Cerutti, Claessens and Laeven(25), remaining details as in Figure 1.

E.2 US FAVAR

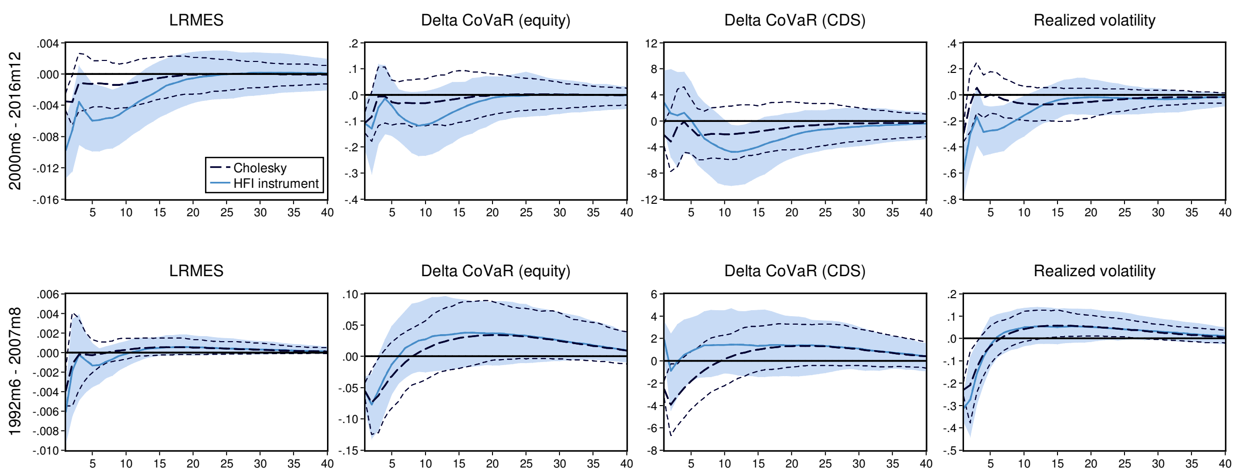
Figure 24: US FAVAR with 5 factors



Note. Impulse responses in the FAVAR(2) model with five factors to a one-standard deviation shock to the policy rate (solid) as well as Wu and Xia shadow rate (top dashed) and cumulated Gürkaynak et al. surprise shock series (bottom dashed). Remaining details as in Figure 5.

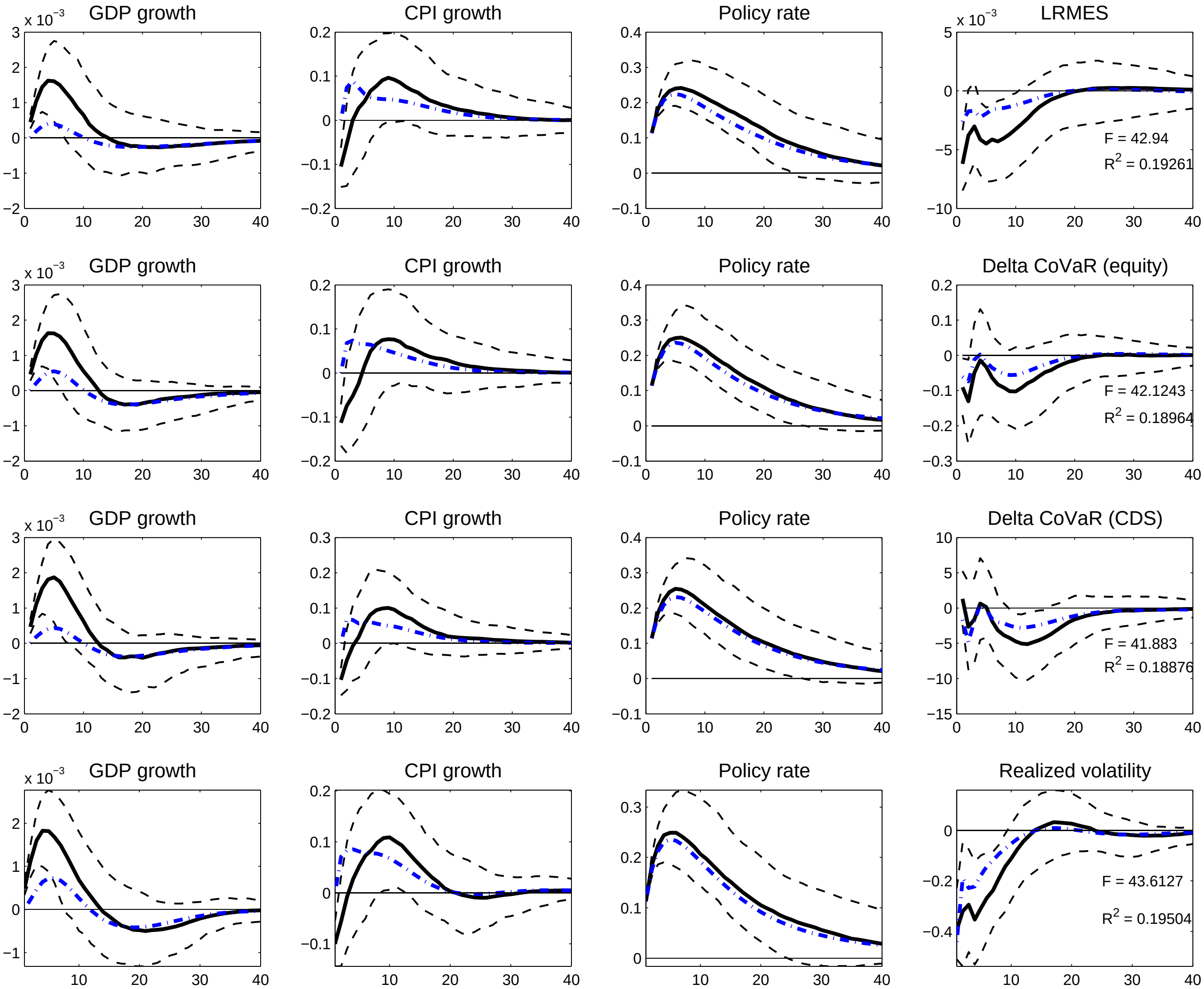
E.3 US Proxy VAR

Figure 25: US Proxy VAR withWo and Xia shadow rate



Note. Impulse responses in the US VAR(3) (top) and VAR(2) (bottom) to a one-standard deviation shock to the Wu and Xia shadow rate. Solid lines refer to the proxy VAR in which the monetary policy shock is identified using high-frequency monetary policy surprise series, dashed lines refer to Cholesky-identified VAR with variable ordering: GDP growth rate, CPI growth rate, shadow rate, risk measure. Remaining details as in Figure 7.

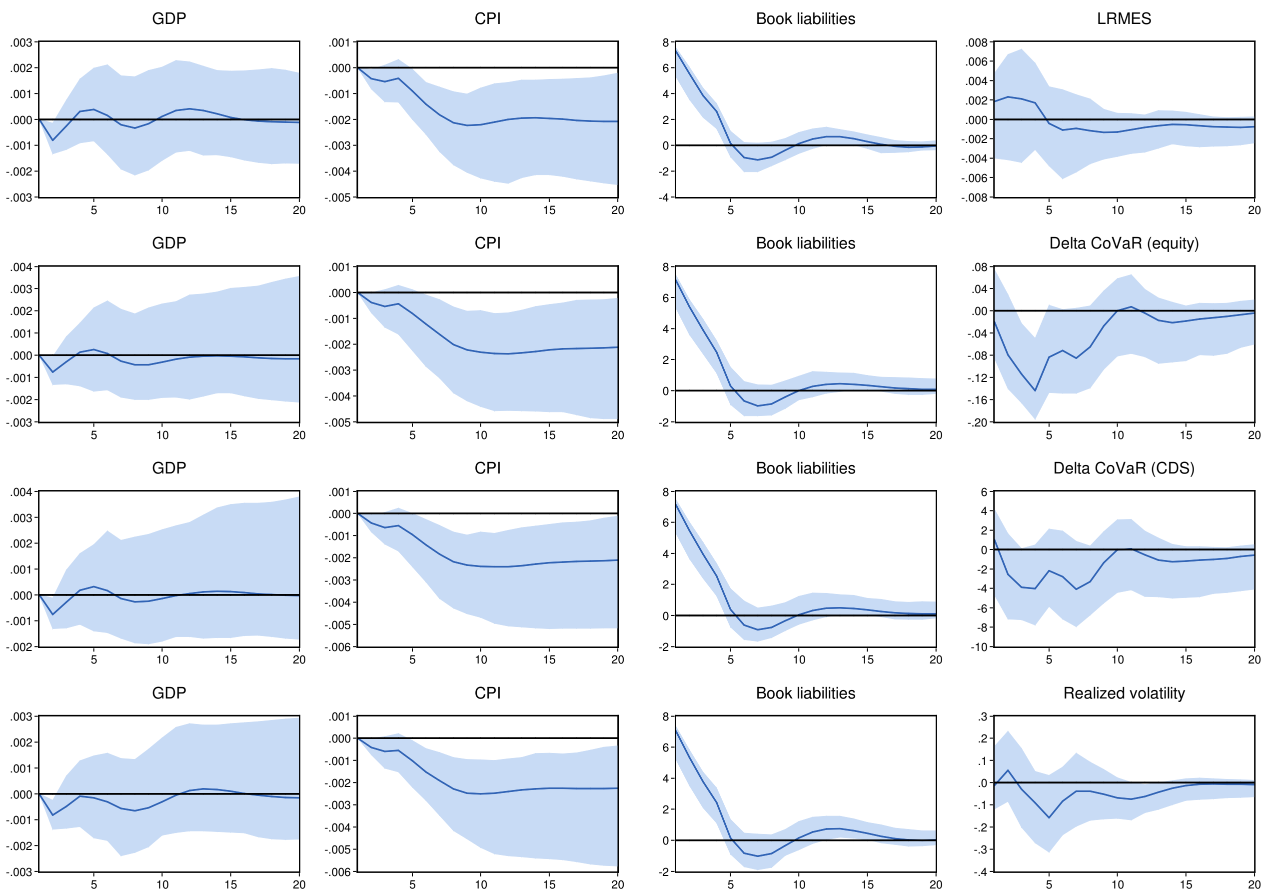
Figure 26: US Proxy VAR (all variables)



Note. Impulse responses in the US proxy VAR(3) (top) and VAR(2) (bottom) to a one-standard deviation shock to the policy rate. Solid lines refer to the proxy VAR in which the monetary policy shock is identified using high-frequency monetary policy surprise series, dashed lines refer to Cholesky-identified VAR with variable ordering: GDP growth rate, CPI growth rate, shadow rate, risk measure. F and R^2 refer to the respective statistics from the first-stage regression. Remaining details as in Figure 7.

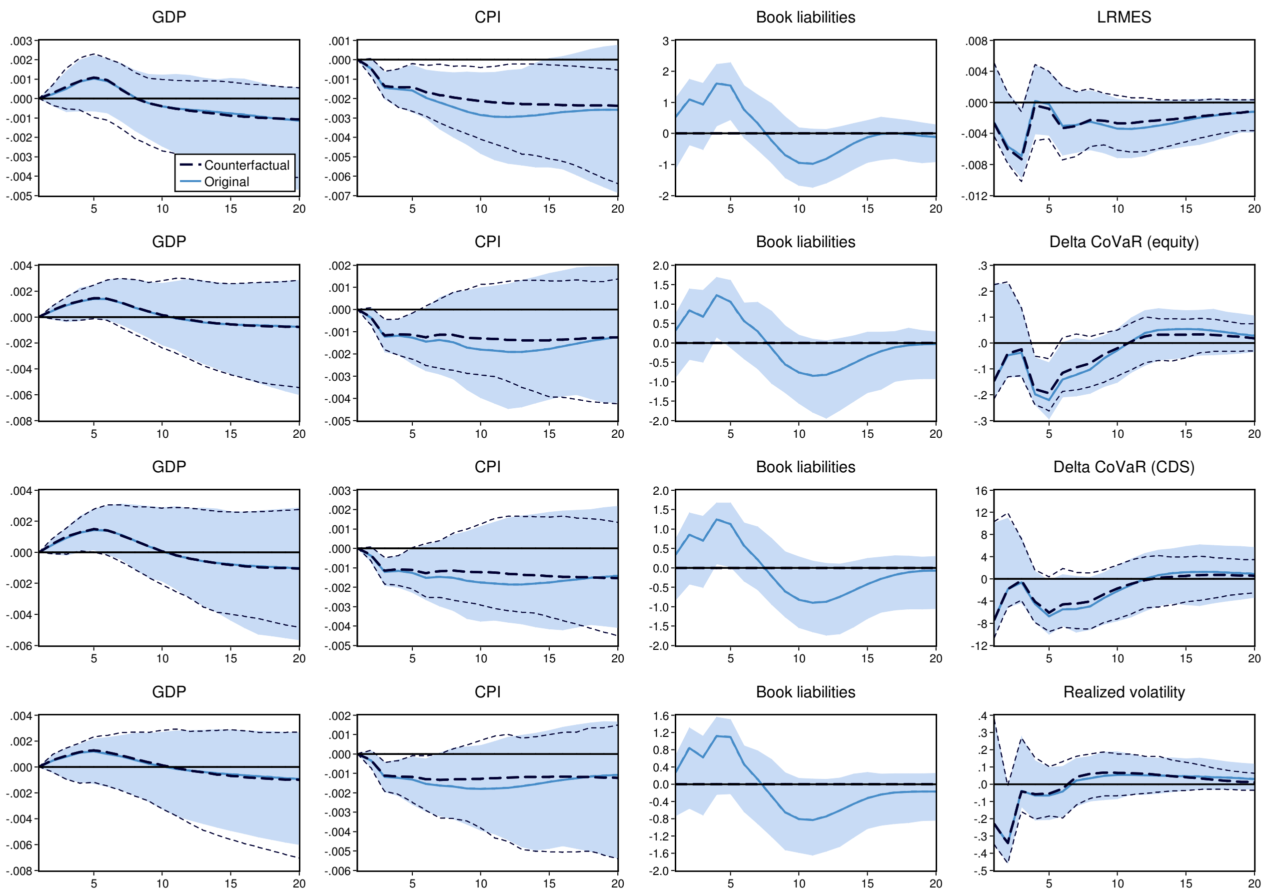
E.4 5-variable panel VAR

Figure 27: Panel VAR with book liabilities as 5th variable



Note. Impulse responses in the quarterly panel VAR(4) to a one-standard deviation shock to thebook liabilities growth rate. Shocks are identified by the variable ordering: log GDP, log CPI, Kripnner's shadow rate, book liabilities, risk measure. Remaining details as in Figure 9.

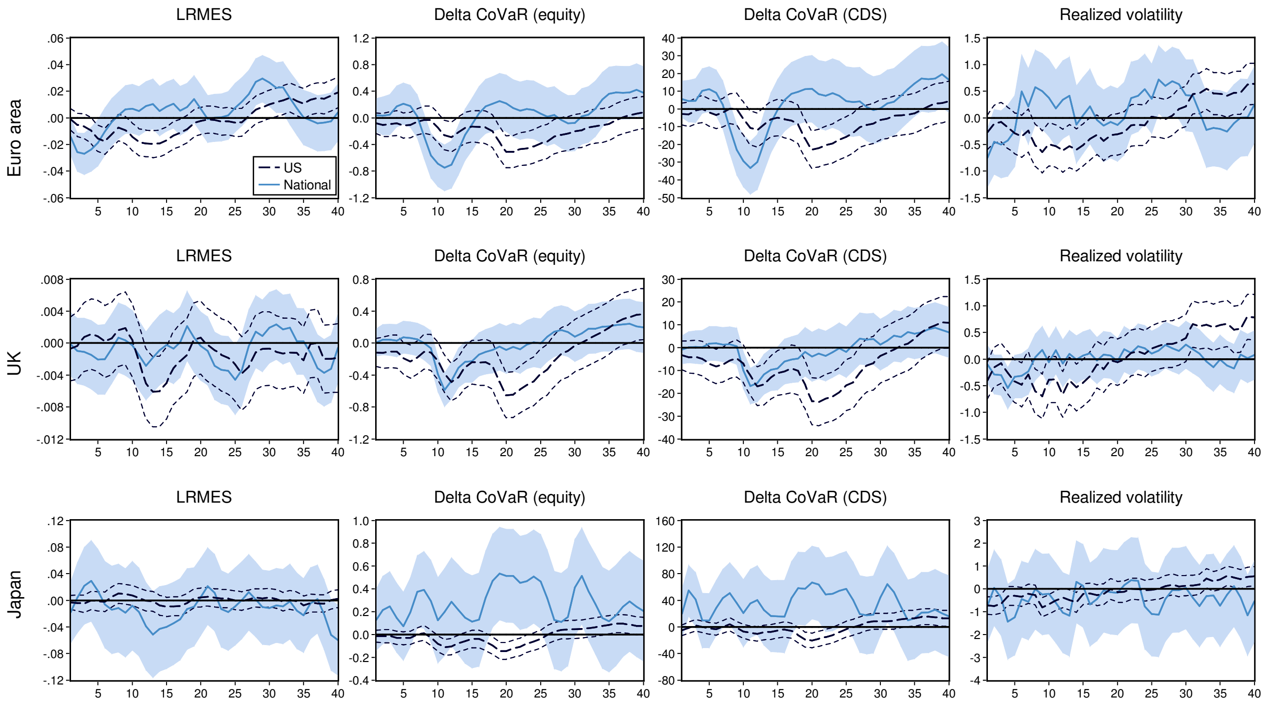
Figure 28: Panel VAR with book liabilities as 5th variable



Note. Impulse responses in the quarterly panel VAR(4) to a one-standard deviation shock to Krippner's shadow rate. Shocks are identified by the variable ordering: log GDP, log CPI, Kripnner's shadow rate, book liabilities growth rate, risk measure. Solid lines refer to the original model, dashed lines to the counterfactual responses with book liabilities response to monetary policy shut off. Remaining details as in Figure 10.

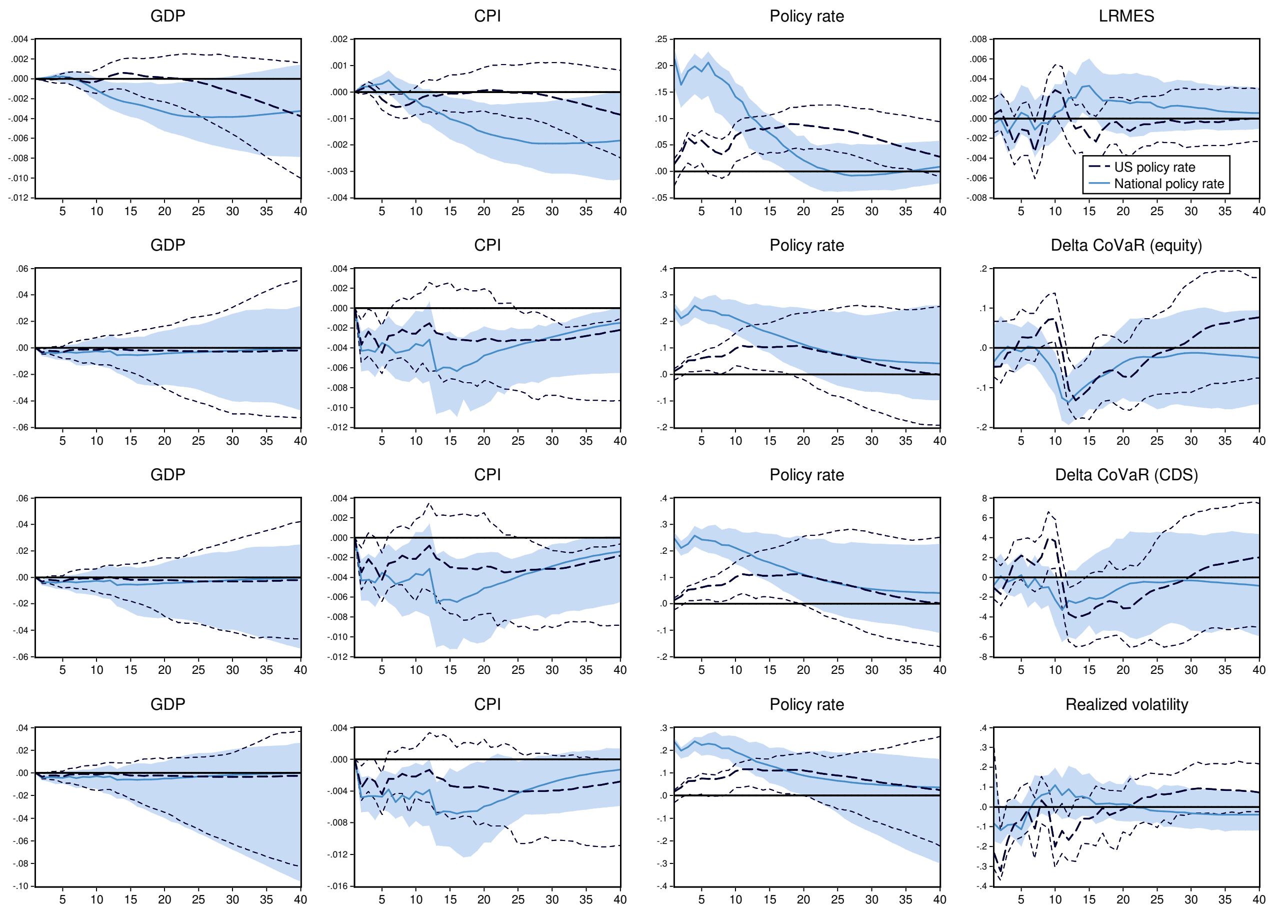
E.5 US versus national policy shocks

Figure 29: Local projections of national and US shocks identified in panel VAR with reversed orthogonalization



Note. Local projection impulse responses for selected countries of national risk measures to national (solid) and orthogonalized US shocks (dashed) identified in the benchmark panel VAR as in Figure 1. Remaining details as in Figure 1.

Figure 30: Panel VAR with US policy rate as 5th variable (all variables)



Impulse responses in the panel VAR(12) (without US economy) to a one-standard deviation shock to the policy rate. Remaining details in as Figure 12.