Banks’ Systemic Risk and Monetary Policy*

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First draft: April 2017. This version: January 2019.

Abstract

The risk-taking channel of monetary policy acquires relevance only if it affects systemic risk. We find robust evidence of a systemic risk-taking channel using cross-country and time-series evidence in panel and proxy VARs for 29 G-SIBs from seven countries. We detect a significant role for pecuniary externalities by exploiting the differential impact of monetary policy shocks on book and market leverage. We rationalize these findings through a model in which a fall in interest rates induces banks to increase leverage and reduce monitoring. In an interacted VAR, we find that macroprudential policy has a significant role in taming the unintended consequences of monetary policy on systemic risk.

JEL codes: E44, E52, G18, G21.

Keywords: Risk-taking channel of monetary policy, ΔCoVaR, LRMES, panel VAR, proxy VAR, monitoring intensity, leverage, macroprudential policy, policy complementarities.

*We thank our discussant Emanuel Moench for valuable comments and suggestions as well as for providing us with bank balance sheet data, and participants at other conferences and seminars. We also thank Refet Gürkaynak for sharing his data on monetary policy surprises with us and the research staff of New York University’s Volatility Lab for providing us with leverage and LRMES data. We gratefully acknowledge financial support from DFG grant FA 1022/1-2. Correspondence to: Ester Faia, Chair in Monetary and Fiscal Policy, Goethe University Frankfurt, Theodor W. Adorno Platz 3, 60323, Frankfurt am Main, Germany. E-mail: faia@wiwi.uni-frankfurt.de. Webpage: http://www.wiwi.uni-frankfurt.de/profs/faia/.
1 Introduction

Extensive evidence exists on the risk-taking channel of monetary policy, namely the notion that the monetary policy stance affects risk-taking behavior of banks\(^1\) based on individual bank risk metrics and panel data analysis. In the presence of such a channel policy makers face a potential trade-off of expansionary policy actions and potentially unintended consequences of monetary easing on bank risk. However, as mentioned by various academics and increasingly by policy makers (see Shin \((61)\) for instance) the risk-taking channel of monetary policy has relevance for macro policy markers, monetary or macroprudential, only to the degree that it affects systemic risk and that these effects are sizable. The fact that low rates might induce individual banks to increase the riskiness of their balance sheet is irrelevant for the monetary authority to the extent that it is accompanied by an increase in loss-absorption capacities, or that it can be tamed by prudential instruments. Equally, any increase in aggregate risk as resulting from the aggregation of banks’ individual risk-positions is negligible for macro policy makers to the extent that such an increase is modest in size. All the evidence gauged so far on the risk-taking channel (reviewed in the next section) has focused on various, albeit novel and original, measures of individual bank risk, and in many cases the quantitative effects have been small, at least by the standards considered significant for macro policy. The purpose of this paper is threefold. First, motivated by the above, we aim to assess if monetary policy can have significant and sizable effects on metrics of systemic risk. Indeed we find strong and robust evidence for such an effect. Second, we wish to assess the economic forces behind this channel and how those connect to macro externalities, more specifically to fire-sale externalities which have been considered a main channel of contagion\(^2\). We find evidence that market leverage is an important source of the transmission from policy rates onto systemic risk precisely because of the role played by movements in bank equity prices. This suggests an important role for fire-sale externalities, which we document through the differential impact of monetary shocks onto book and market leverage. We rationalize these empirical results through a model. Third, we ask whether macroprudential policy, increasingly employed after the financial crisis, can tame the risk-taking channel of monetary policy. Our findings suggest that it does.

There are at least three noteworthy aspects of our analysis. First, it goes beyond metrics of individual risk and this is important for two reasons. To begin with, prior to the recent financial crisis the role of banks’ interconnectedness, cross-assets holdings and fire-sale externalities has been central in the propagation of individual bank risk to the real economy\(^3\). What is more, systemic risk results from the externalities of bank distress onto the rest of the financial system or the real

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\(^{1}\)See Borio and Zhu \((19)\) and Adrian and Shin \((5)\) for early contributions.

\(^{2}\)See Allen and Gale \((11)\) and Greenwood, Landier and Thesmar \((41)\).

\(^{3}\)See Caballero and Simsek \((21)\), Cifuentes, Ferrucci and Shin \((29)\), Elliott, Golub, and Jackson \((33)\), Gai, Haldane and Kapadia \((35)\) and Aldasoro et al. \((6)\), among others.
economy (see Bernanke (16)) and only as such it has 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.

Second, our paper examines both empirically and through a simple model the main channels of transmission from policy rates to systemic risk. Theoretically monetary policy rates have an effect on systemic risk if they have an effect on individual bank risk and if there are some channels of contagion. The effects of low rates onto bank risk can be broken down as follows. First, under low rates banks in search for yield have an incentive to expand their asset portfolios to include riskier investments. Second, due to cheap funding, intermediaries tend to increase the amount of short-term funding relative to equity. Both of these forces tend to materialize as larger leverage ratios, particularly so for global banks who fund themselves in global repo markets. Hence global leverage is a key force behind the transmission from monetary policy to risk. However, as indicated, the increase in individual bank risk, even if present across many banks, does not necessarily induce concerns for the policy makers, unless contagious effects and macroeconomic externalities materialize. The literature has identified fire-sale externalities as a main source of propagation of financial instability. Specifically, as one or more banks are hit by adverse shocks, they attempt to satisfy their value-at-risk constraints by adjusting their balance sheet positions and they do so in part by raising equities. Due to the presence of market adjustment costs, the change in the demand for equity funds by one bank is followed by changes in bank equity prices, which affect the balance sheet, hence the risk position, of all other banks. This produces risk contagion effects. Fire sales can be measured as their presence implies that banks’ balance sheet variables, such as leverage, are more responsive to policy rates when they are marked to market than they would be under book accounting.

Third, and no less important, our paper takes into account not only the cross-sectional, but also the time-series dimension of risk. In contrast, most of the previous analyses, using individual risk metrics, focused mainly on panel data techniques. However, measuring the effects of monetary policy based on time-series methodologies is crucial for two reasons. First, it is well understood in the macro literature that only those techniques can account for the endogenous response of monetary policy, namely the fact that changes in risk might reflect second order effects of the policy response to aggregate variables. Second, the risk-taking channel of monetary policy may materialize...
with different intensities at different horizons, with more pronounced differences between short and medium run. Employing time series methodologies lets us take these considerations into account.

Our analysis can be broken into three parts. In the first part of the paper we assess the effects of monetary policy shocks on systemic risk. Our main econometric specification is a fixed-effects panel VAR, in which we identify shocks recursively. We employ monthly data for 29 global systemically important banks (G-SIBs) headquartered in seven economies and include in the model metrics of systemic bank risk, a monetary policy measure, and a set of macroeconomic control variables. In order to capture various dimensions of systemic risk, we employ two different risk metrics. The first is $\Delta$CoVaR (see Adrian and Brunnermeier (11)). This metric is meant to capture the codependency of institutions on each other’s health, hence it captures well the effects of fire-sale externalities on banks’ balance sheets. For robustness we compute this metric using both equity prices and CDS spreads. Both computed metrics depend on market values and are hence not distorted by bank-based accounting methods. Moreover we argue that the second $\Delta$CoVaR measure, based on CDS spreads, has also larger predictive power as CDS prices are based on the assessment of insurers of future bank default risk. As a second type of systemic risk metric we consider banks’ long-run marginal expected shortfall (LRMES, see Brownlees and Engle (20)), which measures how much bank equity would be lost in the event of a crisis. The results of this benchmark specification show unequivocally that a decrease in policy rates raises all metrics of systemic risk. We run several robustness checks and verify that our results are robust along many dimensions. In particular, we find that the risk-taking channel is not necessarily predicated on the occurrence of the financial crisis and ensuing Great Recession as we continue to find evidence when we exclude the post-2007 period from the sample.

A crucial aspect in properly quantifying the effects of monetary policy consists in obtaining an accurate metric for exogenous changes in the policy rate. While these can be derived solely from within a VAR model, in recent years a literature has developed that uses external information derived from market responses within a small time window around monetary policy announcements. As market participants would price in the endogenous responses of policymakers to macroeconomic developments, the intent is to capture those changes in the monetary policy stance that were not previously expected, and hence can be argued to isolate exogenous changes in policy. We feed such market surprise series as an external instrument into a proxy VAR and also under this identification scheme verify the systemic risk-taking channel of monetary policy.

In the second part of the paper we extend our VAR analysis to dissect the economic channels behind the systemic risk-taking channel. Specifically, we search for a comprehensive banks’ balance sheet variable that channels the effects from the policy stance onto systemic risk and we also try to isolate the role of fire-sale externalities. As banks are hit by adverse shocks, like an increase in the

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7Its specific definition is given in the text and in more detail in Appendix A.3. See Bisais et al. (17) for a survey on systemic risk metrics.
main policy rate, they adjust their balance sheet positions to meet their value-at-risk constraints. They do so primarily by reducing short-term liabilities and increasing equities, which results in a fall in leverage. To capture those effects we add to our models (both the panel VAR and the proxy VAR) measures of bank leverage. To quantify fire-sale externalities we examine the differential response of book and market leverage. If much of the transmission is channelled through adjustment in prices, the latter should respond more. We find, consistent with the theoretical arguments, that a fall in interest rates significantly and sizably increases bank market leverage in addition to systemic risk. Most intriguingly, we find that the response of market-based leverage is much stronger and more significant than the one of book leverage, pointing a clear role for fire-sale externalities. We then conduct a counterfactual experiment, in which we shut off the transmission of monetary shocks through market leverage. We find that systemic risk responses are substantially dampened, confirming the importance of the fire-sale based leverage channel.

Finally, to complete the second part of the paper we present a simple model that rationalizes the evidence. In the model, banks monitor risky projects on behalf of investors and choose how much to leverage. Projects’ default probabilities inversely depend upon banks’ monitoring. However, since monitoring is costly, banks face a moral hazard problem vis-à-vis outside financiers. For this reason, a contract regulates the relation between banks and investors by imposing an incentive compatibility constraint on banks. In response to a decline in the level of short-term interest rates, banks’ leverage ratios increase, relaxing the incentive compatibility constraint. Intuitively, the fall in interest rates increases banks’ risk-shifting incentives onto depositors. In equilibrium, banks then reduce their monitoring intensity as well as increase their leverage ratios, increasing projects’ default probabilities.

In the third part of our paper we ask to what extent the risk-taking channel of monetary policy can be counteracted by the presence and/or a tightening of macroprudential policy. To this purpose we use time-series data on the macroprudential regulation provided in Cerutti et al. (25) and interact their index with our monetary policy measures in our panel VAR. Our results suggest that tighter macroprudential policy might indeed be able to dampen the response of systemic risk, thereby pointing to policy complementarities of the monetary and prudential authorities.

The paper is structured as follows. Section 2 reviews the literature on the bank risk-taking channel and highlights the novel aspects of our analysis. Section 3 presents the benchmark specification of the panel and proxy VARs. Section 3 extends the benchmark specifications to include leverage measures. Section 4 studies the role of macro-prudential policy in the panel VAR setting. Section 5 concludes.

2 Literature Review

The risk-taking channel of monetary policy was first discussed in a contribution by Borio and Zhu (19) and Adrian and Shin (5). In the theoretical literature some contributions have rationalized
the effect of the monetary stance on bank risk. Angeloni and Faia (8), using a dynamic general equilib-rium model with fundamental bank runs, show that banks increase their leverage when policy rates are low since short-term funding becomes cheaper and banks do not internalize the effects of their choices onto the aggregate probability of a run. Dell’Ar-iccia, Laeven and Marquez (30) using a static bank model with oligopolistic competition show that monetary policy increases banks’ incentives to hold assets with higher return-risk profiles, hence focusing on banks’ asset risk. In section 4 we present a simple model, which results from an extension of Martinez-Miera and Repullo (53). In their model low rates increase banks’ risk-shifting incentives onto depositors. This results in lower monitoring intensity and higher project default probability. We add to this the choice of leverage and show that an increase in leverage is compatible with a decrease in monitoring intensity, hence an increase in risk.

On the empirical side, as mentioned above, there are numerous contributions testing and finding evidence of a risk-taking channel of monetary policy on bank risk. However, most of them use individual bank risk metrics and employ panel data techniques, hence focusing on the cross-sectional variations of risk. Importantly, in many of the existing papers the documented effects of changes in risk are rather small. Some studies address the issue of the endogeneity of monetary policy responses by employing time-series techniques. However, none of the empirical studies on the risk-taking channel uses systemic risk metrics in a time-series context that allows the identification of monetary policy shocks, including from an external instrument approach. While many of the above-cited studies employ banks’ balance sheet variables as determinants of the transmission from policy rates to bank risk, none examines the role of leverage using the comprehensive time series data we collect. Moreover, none of the above paper dissects the role of macroeconomic externalities, which we do by gauging the differential impact of policy rates on book and market leverage. At last, no study so far has addressed the complementarity between monetary policy and macroprudential policy on systemic risk as we do in Section 5.

3 Monetary Policy and Systemic Risk

We begin by assessing the role of monetary policy for systemic risk. In the first step we wish to assess the general validity of the relation without any assumption on the economic channels driving it. In sections 4 and 5 we will examine the role of banks’ balance sheet variables, macroeconomic

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8Among many others we list the following. Paligorova and Santos (57) use information on changes in lending standards from lending surveys, Altunbas, Gambacorta, and Marquez-Ibanez (12) use rating agency estimates, Jimenez et al. (45), Ioannidou, Ongena, and Peydro (44) use credit registry information on default history and Dell’Arriccia, Laeven and Suarez (31) use banks’ internal ratings on loans.

9For instance, in Dell’Arriccia, Laeven and Suarez (31) 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.

10See Buch, Eickmeier, and Prieto (21), Buch, Eickmeier, and Prieto (22), Neuenkirch and Nöckel (66) and Angeloni, Faia and Lo Duca (13).
externalities, and of macroprudential policy.

3.1 Panel VAR

Our benchmark results are based on a panel VAR covering seven countries, in which we identify shocks recursively. The benchmark model allows us to take into account both time series and cross-sectional dimensions, and enables us to trace out also the medium-run effects of monetary policy on systemic risk. We test robustness of our results under various model assumptions (reported in Appendix B.1) and under different monetary policy identification schemes, both for the US and the euro area. In particular, results remain robust, and are even stronger, when monetary policy shocks are identified through an external instrument based on high-frequency surprise series around monetary policy announcement dates.

3.1.1 Data, model and shock identification

We employ a monthly panel dataset over the sample period 1992-2016 for 29 global systemically important banks (G-SIBs), as defined by the Bank of International Settlements, from eleven countries.\footnote{See Table ?? in Appendix A.}

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:

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

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:

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

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 contemporaneous impact matrix of the mutually uncorrelated $G \times 1$ random disturbances $\epsilon_{i,t}$.

The main VAR specification considers seven countries as cross-sectional units, namely the United States, United Kingdom, Japan, euro area,\footnote{Spain, Germany, France, Italy and the Netherlands share the same monetary policy and are hence subsumed in the euro area.} China, Sweden, and Switzerland. The model includes an interest rate variable, two macroeconomic controls and the risk measures. The latter are computed on the bank level and then aggregated as weighted averages of all banks in the sample headquartered in the respective country.\footnote{In the baseline specification we use weights based on the banks’ market capitalization as is often done in the literature. Our main results remain robust to the use of unweighted averages or when weighting banks by their balance sheet sizes.}

As we estimate the model via fixed effects by
demeaning, we do not include constant terms in the baseline specification. In a series of additional analyses and robustness exercises, however, we include various deterministic components. All variables used in the analysis and their data sources are described in Appendix A.

The benchmark specification is a monetary VAR in levels which includes logged CPI and GDP, the monetary policy variable and the systemic risk metric. GDP is interpolated using the Chow-Lin (28) method with industrial production and retail sales as reference series. The systemic risk metrics are described in detail in Appendix A.3. The first is ∆CoVaR, 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. The second measure we employ is the long run marginal expected short-fall (LRMES), measuring how much equity would be lost in the event of a crisis. Both of these metrics are based on market accounting, which means that they are not distorted by potential biases in banks’ internal valuations. In other words the metrics capture how market participants assess the whole risk of a bank, both on the asset and liability side. The use of CDS for ∆CoVaR also ensures some predictive power as the pricing of insurance contracts is done by accounting for possible future development in balance sheet risk. Second, and most importantly, both metrics capture well the risk co-dependency stemming from macroeconomic externalities. In the section 4 we examine in more detail how the macroeconomic externalities, such as fire sales, operate and test their role in the transmission from leverage to risk via changes in the market price of bank equities.

Regarding the monetary policy variable in the benchmark model we proceed as follows. Central bank policy rates have remained at or near zero levels for a considerable time after the financial crisis in various economies. For this reason we use shadow rate estimates for our benchmark model where available. 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. In the baseline specifications we make use of the shadow rates provided by Krippner (46), which have been computed for the US, UK, Japan and the euro area. For countries where shadow rates are not available we resort to using the central bank policy rate. Our main results continue to hold when not using shadow rate estimates, however, as discussed in section B.1.

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 structural

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14 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. For additional details regarding Krippner’s estimates see Krippner (48).
15 These rates are based on affine term structure model approximations of the framework in Black (18) and uses a two-factor term structure model.
16 Of these remaining countries, China never hit the zero lower bound, Sweden did so only relatively briefly and while the Swiss central bank kept rates at zero for more than four years it adopted negative interest rates thereafter.
shocks. As common in the literature, we order the variables as follows: output, prices, monetary policy, and then add 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, and we validate our findings in a proxy VAR setting below which does not require the assumption of recursivity. What is more, the proxy VAR setting allows us to account for unconventional policy measures by employing longer-term interest rates without having to rely on shadow rate estimates.

The benchmark time sample is 1992:06-2016:12 for the two ∆CoVaR measures and 2000:06-2016:12 for LRMES metric, which is not available earlier.\(^{17}\) Lag length selection is guided by information criteria. Figure 11 in Appendix\(^{A}\) 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 there is little additional gain of more than three but less than twelve lags. In order to account for rich dynamics in the time series, our main panel VAR specification features twelve lags, while we conduct various robustness checks with fewer lags and in particular reduce lag lengths in the single-country proxy VAR models subsequently.

### 3.1.2 Benchmark results

Figure 1 shows estimated impulse responses to an exogenous increase in the interest rate for the benchmark VAR for all seven countries considered. The sequence of panels in each row of the figure represents the impulse responses of the 4-variable VAR with different risk metrics, namely ∆CoVaR based on equity returns, ∆CoVaR based on CDS spreads, and LRMES. In each model, GDP and the price level fall after a few quarters, with prices featuring only a small and short-lived initial increase.\(^{18}\) More central to the question at hand, all risk metrics fall significantly in all models, albeit with different patterns.

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 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. This process of increasing equity financing usually takes time due to market adjustment costs, which may well be

\(^{17}\)In order aid comparability with the LRMES measure and to avoid a potential structural break due to the introduction of the euro, in a robustness exercise we estimate the ∆CoVaR models additionally starting in mid-2000 as well but find our results hardly affected.

\(^{18}\)This "price puzzle" is commonly observed using recursive identification schemes, see for instance Ramey (60) and, inter alia motivates our use of a proxy VAR setting below.
reflected in the more sluggish responses of the system risk metrics. Interestingly, the ∆CoVaR metrics exhibit declines both at short-run and medium-run frequencies. This is well in line with the general perception surrounding the risk-taking channel of monetary policy. Due to lags in the adjustment of banks’ balance sheet positions indeed the whole adjustment in risk does not take place fully and immediately, but seems to reemerge at medium frequencies. At this point, we may also note that being able to capture these medium-run dynamics substantiates the use of a panel VAR framework, in which we can estimate twelve lags without strong prior assumptions.

Figure 1: Benchmark panel VAR

![Benchmark panel VAR](image)

Note. Impulse responses in the panel VAR(12) to a shock to the interest rate. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Variable ordering: GDP, CPI, interest rate, risk measure. Countries included: United States, Japan, United Kingdom, China, euro area (Germany, France, Spain, Netherlands, Italy), Sweden and Switzerland. Time sample: 1992:06-2016:12 for ΔCoVaR measures and 2000:06-2016:12 for LRMES. Shaded areas indicate 90% confidence bands.

Importantly, we contrast the size of the effects of monetary policy shocks onto systemic risk with the existing microeconometric literature (reviewed in section 2) and find substantially larger effects. One way to compare the size of the effects across econometric methodologies is to express the impact of a monetary tightening on risk in terms of the variables’ standard deviations. For instance, in Jimenez et al. (15), Altunbas et al. (12) and Dell’ Ariccia et al. (31), the marginal effect of a one-standard deviation increase in the interest rate measure in the respective main specifications lies roughly at 0.1 to 0.13 standard deviations of their respective bank risk variable. Performing similar computations based on the maximum response of the three systemic risk variables considered, our results suggest that a one-standard deviation shock to the interest rate decreases systemic risk by
roughly 0.45 (Delta CoVaR based CDS spreads) to 0.67 (Delta CoVaR based on equity returns) standard deviations. Differences in methodologies notwithstanding, we interpret these much larger effects as evidence of the importance of macroeconomic externalities and contagion channels in the bank-risk taking channel.

We verify that our results are robust along many dimensions and report a long series of robustness checks in Appendix B.1.

3.2 High-Frequency Identification of Monetary Policy Shocks

An important robustness check of our results relates to shock identification. A growing literature uses external information to derive structural monetary policy shocks. Notably, building on Kuttner (49) and Gürkaynak, Sack and Swanson (42), there are by now a number of papers that estimate monetary policy surprises based on high-frequency movements in futures or swap prices around monetary policy meetings or press conferences. These surprises indicate new information to market participants that was not priced into 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.

3.2.1 External instrument approach

As in Gertler and Karadi (39), we include market surprise series as an instrument in a proxy VAR. This framework is useful not only in addressing endogeneity concerns in general but is especially suitable for our analysis based on financial market variables. Since in the benchmark panel VAR we order our risk measures after the interest rate, they are allowed to contemporaneously 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 A.4. We employ this external instrument approach to the US and euro area economies, and hence obtain exogenous policy shocks for both economies.

For the euro area we proceed as follows. We obtain the list of announcements of the ECB target rates from the ECB website and match these dates with the corresponding changes in the Euro Overnight Index Average (EONIA) swap rate for different maturities. Intraday data on the EONIA swap rates are not available before 2008, but we follow Corsetti et al. (26) and make use of the fact that the closing times of the Tokyo and London stock exchanges are 6 hours apart (13:00 and 19:00 CET) and naturally produce a time window all ECB press releases (13:45 CET) and press conferences (14:30 CET) fall into. Using daily closing price data therefore allows the construction of a monetary policy shock series starting already in 1999, without the need for

\footnote{We thank Joao Duarte for sharing this data with us.}
For the US model, we use changes in the fourth federal funds futures contracts (FF4) around a smaller 30-minute window around FOMC announcements. Before employing them, these shocks have been regressed on Greenbook forecasts and their revisions in order to cleanse them from information dissemination effects.

Using the external instrument approach, we estimate four-variable VARs for the US and euro area separately. As the number of observations in these cases is much smaller than in the panel

Note. Impulse responses in monthly US VAR(6) to a shock to the effective federal funds rate. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Dashed black lines denote Cholesky identification, solid blue lines identification with external instruments. Instrument used: high-frequency surprises adjusted for information dissemination effects (FF4 with average future contract maturity of 3 months). Time sample: 1992:06-2016:12 for ΔCoVaR measures and 2000:06-2016:12 for LRMES. Shaded areas and dotted lines indicate 90% credible sets.

Note that for the US economy past studies tend to focus on tighter windows, of 30 or 60 minutes surrounding the announcement of the Fed fund rate. In contrast, for the euro area a wider time window seems appropriate. Here, ECB target rates are announced at 13:45 CET, but unlike in the US, investors learn much about the future course of action during the press conference, followed by a Q&A with the president, which starts 45 minutes later, at 14:30 CET.

Specifically, while the raw shocks were employed by Gertler and Karadi (39), here we use the adjusted shock series of Miranda-Agrippino and Ricco (52). As convincingly argued by these authors, using the raw surprise series would conflate actual exogenous monetary shocks with information dissemination effects. The latter arise whenever the monetary authority reveals information about its assessment of the state of the economy that was not known to market participants before. In order to overcome this problem, Miranda-Agrippino and Ricco (52) regress the raw shock series on Greenbook forecasts revisions which are published contemporaneously with FOMC announcements, and then use the resulting residuals as shock series. Details regarding the econometrics and shock aggregation to monthly and quarterly values are given in Appendix A.4.
VAR employed before, we reduce the number of lags to 3 to 6 and impose additional structure by estimating the models using Bayesian methods with optimal prior selection in the spirit of Giannone et al. (40), but we also check that all our results remain robust to the use of uninformative priors. Details about the model and prior specifications are given in Appendix A.4.

Using the external instrument approach, we estimate four-variable VARs for the US and euro area separately. As the number of observations in these cases is much smaller than in the panel VAR before, we reduce the number of lags to 3 to 6. In addition, in order to avoid overfitting in the shorter time sample, we estimate the models using Bayesian methods, including optimal prior selection in the spirit of Giannone et al. (40), but we confirm that our results remain robust to the use of flat priors. Details about the model and prior specifications are given in Appendix A.4.

3.2.2 Results

Figure 2 shows impulse responses in the US model (solid blue lines). Results are compared to the specification with the traditional recursive ordering identification scheme (dashed black). We first note the absence of any empirical puzzles regarding price and output responses in the external instrument model. This stands in contrast to the recursive model and, in addition to the theoretical advantages of the external instrument approach, serves to substantially enhance our confidence in the US proxy VAR identification scheme. As for the responses of the risk metrics, we confirm our finding from the panel VAR. All three risk measures significantly decline following a contractionary monetary policy shock. While the dynamics differ from those found in the panel VAR, this is to be expected given the much shorter lag lengths and employment of Bayesian priors. A comparison with the dashed black lines, however, reveals that some of the differences stem from shock identification. Not only does the external instrument approach produce much more significant responses, the responses of the risk metrics are quantitatively much more pronounced.

Figure 3 shows the same set of responses for the euro area. Again, the conclusions regarding the risk responses are similar to before. Notably, F statistics are all comfortably above 10 but CPI responses feature a price puzzle in the ∆CoVaR models and an output puzzle in the LRMES model. These findings are perhaps not surprising given that, contrary to the procedure employed...
Figure 3: Euro area proxy VAR

Note. Impulse responses in monthly euro area VAR(6) (\(\Delta\text{CoVaR}\)) / VAR(3) (LRMES) to a shock to the EONIA rate. Each row represents a VAR with a different risk metric (\(\Delta\text{CoVaR}\) based on equity returns in the first row, \(\Delta\text{CoVaR}\) based on CDS in the second and LRMES in the third). Dashed black lines denote Cholesky identification, solid blue lines identification with external instruments. Instrument used: high-frequency surprises as in (26) based on 3-month (\(\Delta\text{CoVaR}\)) and 6-month (LRMES) OIS contracts. Time sample: 2000:06-2016:12. Shaded areas and dotted lines indicate 90\% credible.

for the US, our euro area shock series have not been regressed on Greenbook forecast revisions, the latter being unavailable for the euro area. This implies that the exogenous surprise shocks might still to some extent be conflated by information dissemination effects that induce some price or output puzzles.\(^{27}\) Reassuringly these puzzles are largely absent when we employ shocks constructed from the forthcoming monetary shock database Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa.\(^{7}\) Importantly, the conclusions regarding the risk responses are similar to before. In particular, while the identification scheme does not play a role in the LRMES model, both \(\Delta\text{CoVaR}\) measures show substantially larger and more significant responses when using external instruments. We conclude that employing external instruments substantiates the evidence in favor of the systemic risk taking channel and that, if anything, the traditional recursive

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\(^{27}\) This notion is also confirmed in some robustness tests we conduct. We experiment with using only those surprise events as monetary policy shocks that within the narrow time window around the event feature an inverse response of stock prices. We do so in order to isolate monetary policy shocks more precisely from the surprise series, and indeed in may specifications find price and output puzzles to be absent, while the risk measures continue to fall. As the F statistics are often relatively low, we prefer to report the results without this simple cleansing procedure. See the discussion in section B for details.

\(^{28}\) As these shocks are not public yet, we are not a position to show the responses at this stage, but they will be added once the database is made public. They mainly differ from the shocks Corsetti et al.\(^{26}\) use in that they are constructed from a narrower time window around ECB council meetings.
identification approach underestimates the responses of systemic risk to monetary policy shocks. We again verify this result in a variety of robustness checks, detailed in Appendix B.2.

4 The Role of Leverage and Fire-Sale Externalities

So far we have robustly established the existence of a systemic risk-taking channel of monetary policy. We now wish to assess the economic channels behind it by focusing on two aspects. The first relates to the role of banks' balance sheet variables as triggers of the channel. The literature examining the risk-taking channel of monetary policy at the individual bank level has already examined the role of various banks' balance sheet variables, but once more it has neglected the consequences for systemic risk. Also contrary to this literature we do not examine a single dimension of banks' balance sheets, such as assets or liabilities, but rather use a comprehensive measure of it, namely leverage. The latter, as argued further below, captures several dimensions of bank risk. Second, the literature has been largely silent on the role of macroeconomic externalities for the monetary transmission. The fact that low rates induce banks to leverage excessively or to search for yield does not necessarily imply that the resulting risk transmits to other banks or to the entire banking system. It is therefore of crucial importance to establish whether the unintended consequences of monetary policy have significant systemic effects. For this reason, and as argued further below, we examine the role of fire-sale externalities. The latter operates through changes in market valuations of banks' balance sheets in responses to the portfolio adjustment of a single bank experiencing a shock. According to most authors this channel represents the most powerful macroeconomic externality or source of distress propagation. The choice of bank leverage as a main variable for the transmission is motivated by the fact that it captures several dimensions of the banks' risk-taking behaviour. Banks can increase their risk appetite both along the liability and the asset side. First, as policy rates decline, short-term funding becomes cheaper relative to equity funding and banks tend to shift risk onto depositors or holders of short-term liabilities, thereby increasing leverage. In the medium run such a choice exposes the bank to higher liquidity risk. Second, with lower policy rates, banks tend to search for yield and invest more in riskier assets or monitor them less. As we lay out in a simple model in section 4.3 below, such a manoeuvre is also accompanied by risk-shifting onto investors of short-term liability, hence in an increase in leverage. At last, changes in the policy rate by affecting banks' cost of funding, also affect their value-at-risk constraints and induce a rebalancing of their funding composition, which typically results in changes of leverage. Based on this we augment our VAR specifications to include measures of bank leverage and study their role in the transmission of monetary shocks.

An interest rate hike induces one or more banks to reduce short-term funding and to increase equity financing. In the presence of adjustment costs this rebalancing brings about a change in

\footnote{See Allen and Gale (11) and Greenwood, Landier and Thesmar (41) among others.}
bank equity prices, that will ultimately affect the value of other banks’ balance sheets. Hence, empirically, market-based valuation of leverage should capture changes stemming from those pecuniary externalities. The ensuing change in the conditional value-at-risk constraints of the banks should account for the link between systemic risk and the pecuniary externalities described above. This is the sense in which changes in the policy rate affect systemic risk via fire-sale externalities. Book leverage, in contrast, based on accounting values of assets, would be affected to a much lesser extent. Following this logic, we include both book and market leverage in our panel VAR specification. The differential response of the two leverage measures will provide the extent to which fire-sale externalities materialize. To substantiate our arguments further, we investigate by means of a counterfactual analysis if indeed a large part of the transmission of monetary shocks to systemic risk can be attributed to responses in market rather than book leverage.

In what follows we repeat the estimation of our two VAR specifications, namely the panel and proxy models, by including leverage measures, both market- and accounting-based. A key challenge in this analysis lies in the fact that a consistent and reliable time-series dataset of bank leverage measures is difficult to come by. With data quality varying by source and time sample under consideration, we construct bank-individual times series of market leverage by relying on data provided by the Volatility Laboratory (V-Lab) at NYU augmented with information from Compustat/CRSP and Worldscope, which we also use for the construction of book leverage data. Following Adrian et al. we define market leverage as

\[
\text{market leverage} = \frac{(\text{book assets} - \text{book equity} + \text{market equity})}{\text{market equity}},
\]

whereas book leverage is simply

\[
\text{book leverage} = \frac{\text{book assets}}{\text{book equity}}.
\]

### 4.1 Panel VAR

We augment our benchmark panel VAR with book and market leverage, which are ordered between monetary policy and risk, capturing the reasonable notion that risk may contemporaneously respond to leverage, which in turn contemporaneously responds to policy. Since we now need to resort to quarterly data, we run the panel VAR using four lags.

Figure 4 shows responses of five of the six variables in the model to a monetary policy shock. We do not observe a price puzzle. All three risk measures significantly decline to a contractionary monetary shock also when leverage is included. In line with the reasoning above, we observe that market leverage falls and responds much more strongly than its accounting counterpart.

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30 We thank Michael Robles and Brian Reis for sending us the data.
31 Details regarding data sources and the construction of the leverage measures are reported in Appendix A.2.
32 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, and avoid having to impose an ordering altogether in the proxy VAR setting below.
First, this result suggests that leverage is a main trigger of the risk-taking channel. Second and most importantly, the differential impact between market and accounting-based leverage confirms the role of fire-sale externalities. Market-based leverage falls, while book values do not react significantly. As laid out in detail in section 4.3 below, we rationalize this finding in a simple model in which banks respond to a monetary tightening by increasing their monitoring efforts and by rebalancing their balance sheet positions. The latter is done by lowering short-term debt and increasing equity funding as banks’ risk-shifting incentives onto short-term investors tend to decline with higher monitoring. Due to adjustment costs in equity markets, quantities do not react immediately. Instead, market participants acknowledge the effective decline in bank risk attitudes and price banks’ equity accordingly. This, in turn, leads to higher bank equity prices, hence lower market-valued leverage for all banks. Book leverage responds much less, and in fact not significantly so. As the market value of equity has gone up, the need for raising actual book volumes fades away.

**Figure 4: Panel VAR with book and market leverage**

Note. Impulse responses in quarterly panel VAR(4) to a shock to the interest rate. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Variable ordering: GDP, CPI, interest rate, book leverage, market leverage, risk measure. Countries included: United States, Japan, United Kingdom, China, euro area (Germany, France, Spain, Netherlands, Italy), Sweden and Switzerland. Time sample: 2000:Q2-2016:Q4. Shaded areas indicate 90% confidence bands.

In order to more directly investigate the role of leverage and macroeconomic externalities in the systemic risk channel, we conduct a counterfactual exercise. In this experiment an original set of impulse responses is compared to one that is computed with the response of market leverage to monetary policy shocks shutt off.\(^{33}\) If the response of market leverage plays an important role

\(^{33}\)Our benchmark results are based on the methodology used in Bachmann and Sims (14), see Appendix A.5, in which a series of offsetting shocks is computed to mute the response of the variable in question.
in the transmission mechanism of monetary policy to systemic risk, we would expect the impulse responses of our risk measures to notably differ in this counterfactual scenario. Figure 5 shows results. For all three risk measures the peak responses in the counterfactual scenario (black dashed lines) are substantially lower than in the benchmark case (solid blue lines)\textsuperscript{34} and even become insignificant in the case of the ∆CoVaR CDS metric. We interpret these findings as again pointing to market leverage as a trigger and of fire-sale externalities as a main driver of the risk-taking channel.

![Figure 5: Counterfactual analysis in panel VAR](image)

\textit{Note.} Impulse responses in quarterly panel VAR(4) to a shock to the interest rate. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Variable ordering: GDP, CPI, interest rate, risk measure. Countries included: United States, Japan, United Kingdom, China, euro area (Germany, France, Spain, Netherlands, Italy), Sweden and Switzerland. Time sample: 2000:Q2-2016:Q4. Blue solid and black dashed lines indicate original and counterfactual (with market leverage transmission shut off) responses, respectively. Dotted lines and shaded areas indicate 90\% confidence bands.

### 4.2 Proxy VAR

In parallel to section \textsuperscript{3} we compute impulse responses for leverage also in the US and euro area proxy VARs. Verifying our results from a recursive identification scheme in an exogenous instrument setup seems even more desirable than in the benchmark case given the quarterly nature of the data. Here we compute global leverage measures as averages of country-specific bank leverage,
in line with Shin (61), who argues that measures of global leverage are important for systemic risk. In addition we find that country- or even bank-specific leverage responses to US monetary policy shocks are somewhat more heterogenous than in the case of the systemic risk metrics. Given the short time sample and in order to still arrive at a general picture of the responses we therefore average leverage measures across countries.

**Figure 6: US proxy VAR with market leverage**

Note. Impulse responses in quarterly US proxy VAR(3) (ΔCoVaR) / VAR(2) (LRMES) to a shock to the central bank policy rate. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Instrument used: high-frequency surprises adjusted for information dissemination effects (FF4 with average futures contract maturity of 3 months). Market leverage is an average of the country-level weighted averages of the US, UK, euro area, Sweden and Switzerland. Time sample: 1992:Q2-2016:Q4 for ΔCoVaR measures and 2000:Q3-2016:Q4 for LRMES. Shaded areas indicate 90% credible sets.

Results are shown in Figures 6 and 7. Starting with the US model, we again note the absence of any empirical puzzles and confirm that all three risk measures fall in response to monetary policy shocks. As in the panel VAR model, we observe that market leverage falls with a peak decline of ten percent after around three quarters. This fall is even more pronounced in the euro area model depicted in Figure 7. Here leverage dynamics look even more similar to the panel VAR. Also all three risk measures continue to fall and F statistics are comfortably above 10. In contrast to the

As a technical note we observe again low F statistic for the LRMES model, but larger values for ΔCoVaR models, which are estimated using a longer time sample starting in 1992 (We here hence rely not only on V-Lab data but additionally on Compustat/CRSP and Worldscope data, again see Appendix A.2 for details). In addition, we may note that for the pre-crisis sample, as shown in Figure 17 in Appendix B all F statistics are substantially larger and also the one in the LRMES model is around 10.
US model, we observe a price puzzle, again most likely due to the fact that an adjustment for information dissemination effects is, unlike in the US model, not made.

**Figure 7: Euro area proxy VAR with market leverage**

Note. Impulse responses in quarterly euro area proxy VAR(2) to a shock to the 2-year German government bond yield. Each row represents a VAR with a different risk metric (∆CoVaR based on equity returns in the first row, ∆CoVaR based on CDS in the second and LRMES in the third). Instrument used: high-frequency surprises as in (26) based on 1-year OIS contracts. Market leverage is an average of the country-level weighted averages of the US, UK, euro area, Sweden and Switzerland. Time sample: 2000:Q2-2016:Q4. Shaded areas indicate 90% credible sets.

### 4.3 A Simple Model to Rationalize the Above Evidence

The evidence suggests that one of the main channels affecting bank and systemic risk operates through bank leverage and that the effects are more pronounced at market values. Given this association it seems useful to examine which class of models can rationalize those facts. In this respect our evidence can also be employed to assess the validity of models with bank and financial frictions. Theoretically whether booms or low interest rate environments are associated with an increase in bank leverage, and contemporaneously bank risk, is debatable. Models of the financial accelerator family would suggest that this is not the case. Other authors instead argue that the risk-taking channel of monetary policy is characterized by a contemporaneous increase in leverage and risk. To rationalize our evidence in the following we lay down a simple model through which we uncover the association between high bank leverage and risk.

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36 A financial-accelerator type of model implies that in booms or in low interest rate environment banks would decrease external debt and the risk of default would fall.

37 See Angeloni and Faia (8) or Dell’Arriccia et al. (31) among others.
The model is an extension of Martinez-Miera and Repullo (53). In their model, both the partial and the general equilibrium version, banks fund projects whose probability of default is negatively related to banks’ monitoring intensity. The latter is costly to banks but unobservable to investors, giving rise to moral hazard. Martinez-Miera and Repullo (53) show that a fall in the depositors’ interest rate, due for instance to an expansionary monetary policy, induces banks to reduce their monitoring intensity. Specifically, the increase in the aggregate supply of savings has an extensive margin effect due to the shift of non-monitoring banks toward riskier entrepreneurs and an intensive margin effect due to the reduction in the intensity of monitoring banks. Hence, an increase in the supply of savings or a fall in the policy rate increases the risk of the banking system. We provide a simple extension of their model by introducing the possibility that projects are funded both through deposits (or investors of short-term liabilities, we will use the two terms interchangeably henceforth) and through bank equity. We show that in such a context there is a positive association between high leverage and low monitoring, hence higher project risk. Further, we show that such an increase in risk can come about by a fall in the deposit interest rate, which increases the risk-shifting incentives of banks onto investors of short-term liabilities.

4.3.1 Baseline model

Consider an economy with two dates (t = 0, 1), a large set of entrepreneurs with zero wealth, a large set of risk-neutral investors, and a single risk-neutral bank. Entrepreneurs fund investment projects through the bank, which, contrary to outside investors, possesses a monitoring technology. The bank acquires funds either from depositors, which are characterized by an infinitely elastic supply of funds at an expected return share equal to $R_h$, or via bank equity, with a return share of $R^b$. Each entrepreneur has a project that requires a unit investment at $t = 0$ and yields a stochastic return $\tilde{R}$ at $t = 1$, given by:

$$\tilde{R} = \begin{cases} R & \text{with probability } 1 - p + m \\ 0 & \text{with probability } p - m \end{cases}$$

where $R > 0$ is the overall gross project return, $p \in (0, 1)$ is the failure probability common to all projects, and $m \in [0, p]$ is the bank’s monitoring intensity. Monitoring increases the probability of getting the high return $R$, but entails a cost $c(m)$. The degree of monitoring is not observed by the investors, so banks face a moral hazard incentive. Following Martinez-Miera and Repullo (53) we assume that $c(m) = \gamma m^2$, implying $c'(m) > 0$ and $c''(m) > 0$. Firms can only fund projects from banks and will pay a loan rate $R$. The bank will raise a unit of funds from investors with a return share $R^h$, and, given the loan rate $R$, it will choose a monitoring intensity $m$. As mentioned before, the project can be funded either through banks’ equity capital, $bk$, or through deposits, $d$.

The optimal contract maximizes the expected profit of the bank given its incentive compatibility constraint and the participation constraints of the bank and the depositors. Therefore the optimal

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38The contract can be easily extended to an investment with variable size.
contract reads as follows:

\[
\max_{\{bk,d,R^h,m\}} [(1 - p + m)R^h - c(m)]
\]  

subject to the bank’s incentive compatibility constraint

\[
m^* = \arg \max_m \{(1 - p + m)R^b - c(m)\}
\]  

the bank’s participation constraint, stating that banks’ returns from the projects must equal the returns of investing banks’ wealth into some market outside option with return \( R^m \):

\[
[(1 - p + m^*)R^b - c(m^*)] \geq R^m bk,
\]  

and a depositor participation constraint, stating that depositors must receive from the contract the market deposit rate \( R^d \):

\[
(1 - p + m^*)R^h \geq R^d d.
\]  

The incentive compatibility constraint (7) characterizes the bank’s choice of monitoring \( m^* \) given the rate on banks’ external funds, \( R^h \), and the loan rate, \( R \). This condition is often also related to the value-at-risk constraint as it commands, for a given return on assets, how much monitoring the bank should undertake, hence how much risk the bank can load on without loosing funds from outside investors. A fall in the policy rate loosens this constraint. As deposits become cheaper, the bank can increase leverage and at the same type reduce monitoring, as the banks’ risk-shifting incentives onto depositors rise. The participation constraints (8) and (9) ensure that the bank makes profits in excess of the market outside option, net of the monitoring cost, and that depositors get the required expected return on their investment. Furthermore, in addition to a pre-bargained linear rule for return sharing

\[
R = R^h + R^b
\]

we augment the contract with a balance sheet constraint to obtain the equilibrium values of \( d \) and \( bk \):

\[
bk + d - c(m^*) \geq 1.
\]

We note that, given that the project size is normalized to unity, the variable \( \tilde{d} \equiv 1 - bk \), is effectively the leverage ratio, or the ratio between banks’ external funding and the project size.

An interior solution to the contract is given by:

\[
(R - R^b) - c'(m^*) = 0
\]

Given the return on deposits that, for a given leverage ratio, satisfies the depositors’ participation constraint

\[
R^h = \frac{R^d}{(1 - p + m^*)} d,
\]
we can re-write the banks’ first-order condition on the monitoring intensity as follows:

\[ R - \frac{R^d}{(1 - p + m^*)} d = c'(m^*) \quad (14) \]

The above condition determines, for a given size of external funds, the optimal extent of bank monitoring, \( m^* \). More specifically, in part due to the strict convexity of monitoring costs, equation (14) implies a negative relation between bank leverage and the monitoring intensity. Hence, any monetary expansion in the form of a fall in the market deposit rate \( R^d \) optimally leads to less monitoring, and, through (7) and (11) to higher bank leverage. Since lower monitoring reduces the probability of project success, a lower level of interest rates in turn leads to more bank risk.

### 4.3.2 Adding systemic risk

Under the assumption that banks’ projects are fully correlated, aggregate or systemic risk in the model is just equal to \( (p - m) \). However, the model can be easily extended to account for partial correlation of projects, in which case bank risk transmits into systemic risk also through a latent variable. The latter can capture more generally the concept of risk propagation through macroeconomic externalities. The latent variable can be added to the model by employing the single risk factor model of Vasicek (65) in which the outcome of the projects of entrepreneurs of type \( p \) is driven by the realization of a latent random variable of the following form:

\[ y_p = -\Phi^{-1}(p - m) + \sqrt{\rho}z + \sqrt{1 - \rho}\varepsilon_p \quad (15) \]

where \( z \) is a systematic risk factor that affects all types of projects, \( \varepsilon_p \) is an idiosyncratic risk factor that only applies to projects of entrepreneurs of type \( p \). \( z \) and \( \varepsilon_p \) are standard normal random variables, which are independently distributed from each other and over time as well as across types. The parameter \( \rho \in (0, 1) \) controls the extent of correlation in the returns of the projects of entrepreneurs of different types, \( \Phi(\bullet) \) denotes the c.d.f. of a standard normal random variable, and \( \Phi^{-1}(\bullet) \) is its inverse.

The main implication of the above assumption is that now the entrepreneurs’ failure probability is given by:

\[ p - m = \Pr(y_p \leq 0) = \Pr(\sqrt{\rho}z + \sqrt{1 - \rho}\varepsilon_p \leq \Phi^{-1}(p - m)) \quad (16) \]

The above default probability depends also on the aggregate risk factor, \( z \), hence it embeds some contagion effects. The rest of the contract however remains unchanged, as does the positive association between high leverage and high risk, now measured through (16).

### 4.3.3 The role of market leverage

So far, our model captured well the contemporaneous link between leverage and bank risk through changes in monitoring intensity, also when adding to the model a general type of macroeconomic
externality through a latent factor. Our empirical analysis however highlighted more directly the role of fire-sale externalities occurring through changes in the valuation of equities in responses to changes in the interest rate. A direct and empirically sound way of modeling fire-sale externalities on equities comes from adding adjustment costs. The underlying idea is as follows. In responses to changes in the cost of funding, due to changes in the policy rate, the bank might wish to change its equity position, relative to the fraction of short-term liabilities, in keeping with its value-at-risk (or incentive compatibility) constraint. The presence of adjustment costs, due to either market search costs or to investors’ risk attitudes, make the quantity adjustment sluggish and induces changes in the price of equities. This is the sense in which market-based leverage reacts more immediately and more strongly to the interest rate shock. Adding adjustment costs amounts to introducing a downward-sloping supply of funds for bank capital. The latter links market equity prices to changes in the demand of bank capital funds from banks:

\[ q_{bk} = \phi' \left( \frac{\Delta bk}{bk} \right), \]  

where \( \phi' > 0 \), implying that as banks need to raise equity capital, its price would increase as well. Note that the change in equity capital, \( \Delta bk \), shall be interpreted as arising from a shock to the interest rate. The above relation can be easily derived from a model in which investors face adjustment costs on their bank equity portfolio (see for instance Lenel, Piazzesi and Schneider [50]). Under this new scenario we can adjust the contract constraints so as to include bank equity at market prices, rather than at accounting values. Leverage would then effectively be defined as \( \hat{d} = 1 - q_{bk}^{bk} \), so that any change in the price of equities, \( q_{bk}^{bk} \), would affect the banks’ incentives to risk-shifting or risk-taking, as determined by the incentive compatibility (or value-at-risk) constraint. As before, all contract equations remain valid, in particular the positive relation of risk and leverage are preserved, except that now the association arises primarily between market leverage and risk. To gauge the intuition also visually Figure 8 plots the envisaged relation for some illustrative model calibration. Specifically, the figure plots the optimal choices of monitoring and effective bank leverage against the level of the deposit interest rate. An increase in the risk-free rate induces banks to lower short-term liabilities and raise bank capital. Given the presence of adjustment costs on bank equity, stock prices, rather than quantities, increase, thereby inducing a fall in banks’ market leverage. The latter in turn increases banks’ monitoring intensity as per equation (14) and thereby lowers risk as per equation (5).

5 Complementarity of Monetary and Macroprudential Policies

As the evidence on the risk-taking channel kept growing, concerns were raised in policy and academic circles regarding the unintended consequences of recent monetary easing measures. Notwith-
standing the need for substantial monetary easing in the wake of the 2007-2008 financial and sovereign debt crises in the euro area, pundits have pointed to potentially detrimental effects of expansionary monetary policy on bank risk. While monetary easing might stabilize the financial system following the crash, these measures, critics argue, might fuel future systemic banking crises.

One response to those concerns has been that the effects on risk might be tamed by prudential policies. This view of policy complementarity entails that monetary policy should be concerned with its traditional role of price stability, whereas in particular macroprudential policies should be devoted to tame systemic risk. This section proposes a simple, yet effective way of testing this notion in our empirical time-series setup. Specifically, we estimate an interacted panel VAR in which we augment our baseline model by adding a macroprudential index and interact it with the interest rate in each model equation. We then compute impulse responses to monetary policy shocks for low (10th percentile of the distribution) and high (90th percentile) values of the index in order to investigate whether the systemic risk-taking channel is notably altered in the two environments. As a measure of macroprudential oversight we use the index developed by Cerutti

\[39\text{This approach has been developed by Towbin and Weber [64], albeit in a entirely different context.}\]

\[40\text{As we are not interested in having the model identify the policy regimes endogenously but instead measure the exogenous macroprudential environment directly, we prefer the simple interacted panel VAR to, e.g., regime-switching or time-varying-parameter VARs. Details are provided in Appendix A.6.}\]
et al. (25) which provides annual numerical values in the form of integers for all countries in our sample from the years 2000 to 2017. We therefore again make use of both the time series and cross-sectional dimensions of the data.

Results from this exercise are shown in Figure 9. The solid blue lines denote the responses in the benchmark environment in which macroprudential policy is in its 10th percentile, which yields risk responses very similar to those in our benchmark results in Figure 1. In contrast, the dashed black lines indicate the responses in the strong regulatory environment, in which the index is at its 90th percentile. While the responses hardly differ in the case of the LRMES measure, they are substantially altered in both ∆CoVaR models. Dynamics differ on impact. Following the shock, at high levels of the macroprudential index, risk responses become small and turn insignificant, whereas they decline for a few months in the benchmark case. Most notable, however, is the difference at longer horizons. In both ∆CoVaR models the decline in risk after around one year is substantially less pronounced at high levels of the index, pointing to potentially important role of macroprudential policy in undoing the unintended consequences of monetary policy on systemic risk.

Figure 9: Interacted panel VAR with macroprudential index

Note. Impulse responses in the panel VAR(12) to a shock to the interest rate. Each row represents a VAR with a different risk metric (∆CoVaR based on equity returns in the first row, ∆CoVaR based on CDS in the second and LRMES in the third). Variable ordering: GDP, CPI, interest rate, risk measure. Countries included: United States, Japan, United Kingdom, China, euro area (Germany, France, Spain, Netherlands, Italy), Sweden and Switzerland. Time sample: 2000:06-2016:12. Blue solid and black dashed lines indicate macroprudential index at 10 and 90 percentiles, respectively. Dotted lines and shaded areas indicate 90% confidence bands.}

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41The indices are depicted in Figure 10 in Appendix A.
A possible concern related to the above results is that the difference in responses might be due to other confounding factors operating during the period in which the macro-prudential index turned stricter, primarily after the 2007 financial crisis. Indeed a look at Figure 10 reveals that the index in all countries considered increased substantially following the financial crisis. From that perspective there is the possibility that the two sets of impulse responses presented would amount to not much more than a simple sample split. Against this notion we may first note that, although we confirm a risk-taking channel also in the pre-crisis sample (see our results in section B.1), responses are generally quantitatively smaller and less significant. Second, we test this notion more directly by conducting a placebo-like test. More specifically, we construct placebo index values representative in size of the low and high values our results are based on. The same low values are then assigned to all countries in the pre-crisis, the high values in the post-crisis sample. We then estimate impulse responses for these placebo regulatory regimes and depict them in Figure 16 in Appendix B. As the figure shows, the ”high” macroprudential environment now merely alters dynamics in the case of the LRMES, and produces even larger responses for both ΔCoVaR measures. These results indicate that it is indeed largely the cross-sectional variation in the macroprudential index that produces the dampened responses in Figure 9 implying that prudential policy may indeed be able to dampen the response of systemic risk to monetary policy.

6 Conclusions

Extensive evidence exists on the risk-taking channel of monetary policy using bank-level measures of risk and panel data analysis. However, the possible unintended consequences of changes in the monetary policy stance on risk are relevant only to the extent that they become evident at a systemic level. We test whether this is the case using time-series methodologies and find that indeed this is the case. The effects are visible for different systemic risk metrics (ΔCoVaR and LRMES) and when employing recently developed techniques for the identification of monetary policy shocks. We conduct extensive robustness checks along many dimensions, and in particular find evidence of the systemic risk-taking channel also in the pre-crisis period.

In order to assess the economic channels behind this relation we augment our VAR with leverage variables as measures of adjustment in banks’ portfolios to changes in policy rates. Also to assess the role of pecuniary externalities we examine the differential impact of monetary shocks on book and market leverage, the latter moving with fluctuations in equity market prices. If changes in market prices, hence pecuniary externalities, play a significant role in the transmission from policy to bank risk, we should observe a large impact channelled through market leverage. Indeed we find evidence that market leverage does respond more strongly and that it accounts for the bulk of the transmission onto systemic risk.

At last, advocates of the beneficial effects of expansionary monetary policy, mostly in the wake of the financial crisis, have argued that its unintended consequences on risk can be tamed through
macroprudential policies. In order to test this notion, we augment our VAR by including time-series measures of macroprudential instruments, and interact these with the monetary policy variable. We find markedly different responses in high and low regulatory environments, interpreted as evidence that macroprudential policy may indeed be able to alleviate the systemic risk-taking channel of monetary policy we document.
References


IV


Appendix

A Data Description and Sources

A.1 Variables used

The panel VAR includes the following set of variables. Data sources for the country-level series are detailed in Table 1.

- **GDP**: Interpolated from quarterly to monthly data using the Chow-Lin (28) interpolation method with industrial production and retail sales as reference series.\footnote{As Chinese industrial production is very volatile during the period under investigation, for China we use real GDP series (nominal GDP deflated by the CPI) interpolated to monthly values using quadratic-match averages.}
- **CPI**.
- **Monetary policy measures and instruments**:
  - Policy rate: Money market rates.
  - Wu and Xia (66) shadow rate
  - Krippner (46) shadow rate
  - US monetary policy shock series of Miranda-Agrippino and Ricco (52)
  - Euro area monetary policy shock series of Corsetti et al. (26)
- **Macroprudential regulation**: Index of macroprudential regulation (total) of Cerutti et al. (25)
- **LRMES**: Long-run marginal expected shortfall as defined in Acharya et al. (2)
- **$\Delta$CoVaR (equity returns)**: Authors’ calculations based on Adrian and Brunnermeier (2016). Details on the measure and its computation are given in Appendix A.3
- **$\Delta$CoVaR (CDS spreads)**: Authors’ calculations based on Adrian and Brunnermeier (2016). Details on the computations are given in Appendix A.3
- **Book and market leverage**: Authors’ calculations as book leverage = (book assets)/(book equity) and market leverage = (book assets - book equity + market equity) / (market equity). Details are given in Appendix A.2

Figure 10 depicts country averages of these variables (with weights based on banks’ market capitalization), whereas details on the underlying time series and their sources are given in Table 1. Table ?? lists all banks for which the risk metrics are calculated.
Figure 10: Time series used in panel VAR

- **log(CPI)**
- **log(GDP)**
- **Policy rate**
- **Shadow rate (Wu and Xia)**
- **Shadow rate (Krippner)**
- **Macroprudential index (Cerutti et al.)**

VIII
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. CHWE- China, EAWE - Euro area, JPWE - Japan, SEWE - Sweden, SWWE - Switzerland, UKWE - United Kingdom, USWE - United States.
<table>
<thead>
<tr>
<th></th>
<th>United States</th>
<th>Japan</th>
<th>Switzerland</th>
<th>United Kingdom</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Policy rate</strong></td>
<td>Call money rate, OECD via FRED, IRSTC01USM156N</td>
<td>Call money rate, OECD via FRED, IRSTC01JPM156N</td>
<td>Call money rate, OECD via FRED, IRSTC01CHM156N until 1999. From then onward SNB, EPB@SNB, zimoma1TGT</td>
<td>Call money rate, OECD via FRED, IRSTC01GBM156N</td>
</tr>
<tr>
<td><strong>CPI</strong></td>
<td>OECD via FRED, CPALT01USM661S</td>
<td>OECD via FRED, JPNCP1-ALLMINMEI</td>
<td>OECD via FRED, CHECP1-ALLMINMEI</td>
<td>OECD via FRED, GBRCPI-ALLMINMEI</td>
</tr>
<tr>
<td><strong>GDP</strong></td>
<td>OECD via FRED, LNBQRSA</td>
<td>OECD via FRED, LORSPOR-JPQ661S</td>
<td>OECD via FRED, LNBQRSA</td>
<td>OECD via FRED, LNBQRSA</td>
</tr>
<tr>
<td><strong>Industrial production</strong></td>
<td>Board of Governors of the Federal Reserve System via FRED, INDPRO</td>
<td>OECD via FRED, JPNPROIND-MISMEI</td>
<td>OECD via FRED, CHEP-ROINDQISMEI (quarterly values interpolated to monthly frequency based on constant match average method)</td>
<td>OECD via FRED, GBRPROIND-MISMEI</td>
</tr>
<tr>
<td><strong>VIX</strong></td>
<td>Datastream</td>
<td>Datastream</td>
<td>Datastream</td>
<td>Datastream</td>
</tr>
<tr>
<td><strong>Retail sales</strong></td>
<td>Datastream</td>
<td>Datastream</td>
<td>Datastream</td>
<td>Datastream</td>
</tr>
<tr>
<td><strong>Stock market index</strong></td>
<td>Datastream market index, Datastream</td>
<td>Datastream market index, Datastream</td>
<td>Datastream market index, Datastream</td>
<td>Datastream market index, Datastream</td>
</tr>
<tr>
<td><strong>Real estate price index</strong></td>
<td>Datastream real estate price index, Datastream</td>
<td>Datastream real estate price index, Datastream</td>
<td>Datastream real estate price index, Datastream</td>
<td>Datastream real estate price index, Datastream</td>
</tr>
<tr>
<td><strong>Long-term interest rate</strong></td>
<td>10-year government bond rate, Datastream</td>
<td>10-year government bond rate, Datastream</td>
<td>10-year government bond rate, Datastream</td>
<td>10-year government bond rate, Datastream</td>
</tr>
<tr>
<td><strong>Short-term interest rate</strong></td>
<td>3-month treasury bill rate, Datastream</td>
<td>2-year government bond rate, Datastream</td>
<td>3-months treasury bill rate, Datastream</td>
<td>3-months treasury bill rate, Datastream</td>
</tr>
<tr>
<td><strong>Interbank rate</strong></td>
<td>Interbank offered rate, Datastream</td>
<td>Interbank offered rate, Datastream</td>
<td>Interbank offered rate, Datastream</td>
<td>Interbank offered rate, Datastream</td>
</tr>
<tr>
<td><strong>Corporate bond rate</strong></td>
<td>Moody’s BAA corporate bond yield, Datastream</td>
<td>Interbank offered rate, Datastream</td>
<td>Interbank offered rate, Datastream</td>
<td>Interbank offered rate, Datastream</td>
</tr>
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<td></td>
<td>Sweden</td>
<td>China</td>
<td>France</td>
<td>Germany</td>
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</tr>
<tr>
<td><strong>Policy rate</strong></td>
<td>Call money rate, OECD via FRED, IRSTCI01SEM156N</td>
<td>Call money rate, OECD via FRED, IRSTCI01CNM156N</td>
<td>Call money rate, OECD via FRED, IRSTCI01FRM156N</td>
<td>Call money rate, OECD via FRED, IRSTCI01DEM156N</td>
</tr>
<tr>
<td><strong>CPI</strong></td>
<td>OECD via FRED, SWECPI-ALLMINMEI</td>
<td>OECD via FRED, CHNPICPI-ALLMINMEI</td>
<td>OECD via FRED, FRACPI-ALLMINMEI</td>
<td>OECD via FRED, DEUCPI-ALLMINMEI</td>
</tr>
<tr>
<td><strong>GDP</strong></td>
<td>OECD via FRED, NAEXKP01SEQ661S</td>
<td>OECD via FRED, CHNGDPN-QDSMEI</td>
<td>OECD via FRED, LNBQRSA</td>
<td>OECD via FRED, NAEXKP01DEQ661S</td>
</tr>
<tr>
<td><strong>Industrial production</strong></td>
<td>OECD via FRED, SWEPROIND-MISMEI</td>
<td>OECD</td>
<td>OECD via FRED, FRAPROIND-MISMEI</td>
<td>OECD via FRED, DEUPROIND-MISMEI</td>
</tr>
<tr>
<td><strong>Shadow rate Wu Xia</strong></td>
<td>Wu and Xia (2016), used rates for European Monetary Union</td>
<td>Wu and Xia (2016), used rates for European Monetary Union</td>
<td>Wu and Xia (2016), used rates for European Monetary Union</td>
<td>Wu and Xia (2016), used rates for European Monetary Union</td>
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<tr>
<td><strong>VIX</strong></td>
<td>Datastream</td>
<td>Datastream (used world VIX due to nonavailability)</td>
<td>Datastream</td>
<td>Datastream</td>
</tr>
<tr>
<td><strong>Retail sales</strong></td>
<td>Datastream</td>
<td>Datastream</td>
<td>Datastream</td>
<td>Datastream</td>
</tr>
<tr>
<td><strong>Stock market index</strong></td>
<td>Datastream market index, Datastream</td>
<td>FTSE price index, Datastream</td>
<td>FTSE price index, Datastream</td>
<td>FTSE price index, Datastream</td>
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<tr>
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<tr>
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<td>10-year government bond rate, Datastream</td>
<td>10-year government bond rate, Datastream</td>
</tr>
<tr>
<td><strong>Short-term interest rate</strong></td>
<td>90-day treasury bill rate, Datastream</td>
<td>3-months treasury bill rate, Datastream</td>
<td>3-months treasury bill rate, Datastream</td>
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<tr>
<td><strong>Interbank rate</strong></td>
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<td>Interbank offered rate, Datastream</td>
<td>Interbank offered rate, Datastream</td>
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<tr>
<td></td>
<td>TMO private rate, Datastream</td>
<td>Umlaufsrenditen inländ. Inhaberschuldsverschreibungen / Anleihen von Unternehmen (Nicht-MFIs), Bundesbank, BBK01.WT0022</td>
<td>Umlaufsrenditen inländ. Inhaberschuldsverschreibungen / Anleihen von Unternehmen (Nicht-MFIs), Bundesbank, BBK01.WT0022</td>
<td>Umlaufsrenditen inländ. Inhaberschuldsverschreibungen / Anleihen von Unternehmen (Nicht-MFIs), Bundesbank, BBK01.WT0022</td>
</tr>
<tr>
<td>Country</td>
<td>Policy rate</td>
<td>CPI</td>
<td>GDP</td>
<td>Industrial production</td>
</tr>
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</table>
A.2 Balance sheet and leverage data

We employ three data sources for the construction of our book and market leverage series as well as bank aggregation weights. While Table ?? provides an overview of the data availability for each bank, we detail the process in the following.

**Market leverage.** From the period of June 2000 onward, which our main results are based on, we rely on data from NYU’s V-Lab who for most banks in our sample have daily time series available on market capitalization and market leverage as defined in equation (3). We compare this data with market leverage series constructed on our own from two additional data sources, namely Compustat/CRSP and Thomson Reuters Worldscope. The latter sources have the advantage that time series go back longer in time for various banks, but are generally of lower quality on at least two fronts. First, Worldscope data is particularly for the pre-2000 years often in annual frequency. Relying on this data therefore biases the results against finding significant effects of monetary shocks in quarterly models. Second, Compustat/CRSP data is available for a lower number of banks and the data on market capitalization seem incomplete for some in that it results in implausibly high market leverage figures. With these data limitations in mind, we proceed as follows. We use the highest quality V-Lab data whenever possible and enrich it with Compustat/CRSP data where necessary. We check the latter for plausibility mostly based on a comparison to the post-2000 V-Lab data. Whenever also Compustat/CRSP data is not available (or yields clearly implausible values) we resort to (the often annual) Worldscope data. This process of arriving at a comprehensive leverage dataset naturally involves some discretionary judgement. Our main results for role of market leverage in the panel VAR and in the euro area proxy VAR are, however, entirely based on the reliable post-2000 V-Lab data. We nevertheless use the other

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43 We thank our discussant Emanuel Moench for providing us with the Compustat/CRSP data.
44 Reassuringly, we verify that in particular for US banks, for which generally higher quality data is available, Compustat/CRSP and V-Lab data in quarterly frequency coincide in the pre-2000 sample for many banks. For other banks, however, using Compustat/CRSP data leads to leverage ratios of above several hundreds up to 10,000. Inspection of the data reveals that these clearly unrealistic values are most likely the results of inaccurate market capitalization figures.
data sources to run robustness checks and in an extended data sample period\textsuperscript{45}. In this process, whenever there are differences in the level or units of measurement between the data sources we make sure to avoid any breaks in the constructed series by indexing. In this way we also avoid distortions in country averages whenever leverage figures for different banks in the same economy stem from different data sources.

**Book leverage.** As book leverage data is not available from the V-Lab, we rely on Compustat/CRSP data where possible. As the construction of book leverage does not involve market capitalization figures, we feel much more confident in the quality of Compustat/CRSP data for this purpose and therefore again only resort to the partly annual Worldscope data when necessary. Again we use indexing whenever appropriate to avoid breaks and ensure comparable figures within economies.

**Aggregation weights.** We experiment with three types of bank weights to arrive at country-level figures for our bank-specific variables (risk and leverage). Next to using simply unweighted averages, we construct weights from both market capitalization (which our main results are based on) and book assets. In accordance with the discussion above, we use V-Lab data for market capitalization whenever possible and prefer the quarterly Compustat/CRSP book asset figures to the partly annual Worldscope data. Whenever data is missing for earlier years, we assume that the bank(s) in question had kept its weight constant relative to the other bank(s) in the country in question.

### A.3 Systemic risk metrics

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

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 (21). 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:

$$MES_b = \frac{1}{\text{number of days}} \sum_{t: \text{system is in 5\% tail}} R^b_t$$

(18)

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

\textsuperscript{45}This is of general interest but in particular required in the US proxy VAR for which we find our instrument to be strong only in the extended sample starting in 1992.
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.

The second metric that we consider is $\Delta \text{CoVaR}$ by Adrian and Brunnermeier (4). 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 $\Delta \text{CoVaR}$ can be summarized as follows. Define the Value at Risk of a bank as:

$$\Pr(X_i \leq \text{VaR}_q) = q$$

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 $\{X_i = \text{VaR}_q\}$ is given by the $\text{CoVaR}_j$ and the latter is defined as follows:

$$\Pr(X_j \leq \text{CoVaR}_{j|i} | X_i = \text{VaR}_q) = q$$

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

$$\Delta \text{CoVaR}_{j|i} = \text{CoVaR}_{j|i} - \text{CoVaR}_{j|50\%}$$

where $\text{CoVaR}_{j|50\%}$ denotes the VaR of $j$’s asset returns when $i$’s returns are at their median (i.e. 50th percentile). Like Adrian and Brunnermeier (4) we focus on the case in which $j = \text{system}$, namely when the portfolio return of all financial institutions is at its VaR level.

The procedure to estimate $\Delta \text{CoVaR}$ in practice is based on a set of quantile regressions which can be described as follows. First, we estimate the contribution of each bank’s $i$ losses to the system-wide losses by running the following quantile regressions:

$$X^\text{system}_t = \alpha^\text{system}_q + \beta^\text{system|i}_q X^i_t + \gamma^\text{system|i}_q M_{t-1} + \varepsilon^i_t.$$  \hspace{1cm} (22)

For the equity-based $\Delta \text{CoVaR}$ measure, $X^k_t$, $k \in \{i, \text{system}\}$, denotes equity market returns in per cent for bank $i$ and of all banks in sample, respectively. For the CDS-based measure, $X^i_t$ is the 5-year CDS spread in basis points, whereas $X^\text{system}_t$ 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 $q = 0.05$

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46 We are grateful to the V-Lab team, in particular Michael Robles, for supplying us with the data.
represents the quantile on which the regression is based. We denote the estimated coefficient of each bank’s contribution to system-wide losses as $\hat{\beta}_{q|\text{system}}^i$. Second, we run the following two quantile regressions to obtain estimates of the conditional VaR of each bank $i$ for $q = 0.05$ and $q = 0.5$:

$$X^i_t = \alpha^i_q + \gamma^i_q M_{t-1} + \varepsilon^i_t,$$

(23)

$$X^i_t = \alpha^{50}_i + \gamma^{50}_i M_{t-1} + \varepsilon^i_t.$$  

(24)

Finally, denoting the predicted values of (23) and (24) as $\text{VaR}^i_{q,t} \equiv \hat{\alpha}^i_q + \hat{\gamma}^i_q M_{t-1}$ and $\text{VaR}^i_{50,t} \equiv \hat{\alpha}^{50}_i + \hat{\gamma}^{50}_i M_{t-1}$, respectively,$^{47}$ we obtain $\Delta \text{CoVaR}^i_{q,t}$ as

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

(25)

In the set of lagged control variables $M_{t-1}$ we include variables as suggested by Adrian and Brunnermeier (4), where available. In particular, for US banks we use (see Table 1 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 wherever country-specific controls could not be obtained. These are

$^{47}$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 $\Delta \text{CoVaR}$ measure since CDS spreads are generally not available before the year 2002 and for some banks even 2008.
described, along the data sources, in Table 1. Like Adrian and Brunnermeier (4) we restrict estimation to banks with at least 260 weekly observations. The resulting ∆CoVaR time series are depicted as country averages in Figure 10.

A.4 Details on proxy (external instrument) VAR

Model description. In the following we describe identification in the US proxy VAR we employ in sections 3.2 and 4.2. Consider again the structural VAR

\[
A_0 Y_t = A(L) Y_{t-1} + \epsilon_t \tag{26}
\]

with the corresponding reduced form

\[
Y_t = B(L) Y_{t-1} + u_t \tag{27}
\]

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

\[
u_t = A_0^{-1} \epsilon_t. \tag{28}\]

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: \(u_t = [u^p_t, u^q_t]'\), \(\epsilon_t = [\epsilon^p_t, \epsilon^q_t]'\). 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 \(\epsilon^p_t\). In what follows, we denote as \(s^q\) the initial impact of \(\epsilon^p_t\) on \(u^q_t\), while \(s^p\) is the corresponding impact on the reduced-form monetary policy residual \(u^p_t\).

Building on Stock and Watson (63) and Mertens and Ravn (54) and following Gertler and Karadi (39), we use instruments from the high-frequency identification literature of monetary policy surprises in the proxy VAR to identify the structural innovations \(\epsilon^p_t\). For these instruments to be valid, we assume the surprise series \(Z_t\) to be relevant and exogenous as follows:

\[
\mathbb{E}[Z_t \epsilon^p_t'] = \phi \neq 0, \tag{29}\]

\[
\mathbb{E}[Z_t \epsilon^q_t'] = 0.
\]

Since we are ultimately concerned with estimating impulse responses based on

\[
Y_t = B(L) Y_{t-1} + s \epsilon^p_t, \tag{30}\]

48As the figure shows, Japanese ∆CoVaR 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 ∆CoVaR 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, ∆CoVaR measures of Japanese banks are more similar to the others and our panel VAR results are qualitatively unaffected.

49We may therefore leave the remaining columns of \(S\) undetermined.
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, \( u^p_t \) is linearly projected on \( Z_t \) in order to obtain the fitted values \( \hat{u}^p_t \). The latter, by assumption uncorrelated with the non-policy structural shocks \( \epsilon^q_t \), can be used in the second-stage regression:

\[
u^q_t = \frac{s^q}{s^p} \hat{u}^p_t + \xi_t.
\]  (31)

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 (39) proceed to first obtain \( s^p \) from the reduced-form covariance matrix and then calculate \( s^q \). Here we normalize \( s^p \) such that the initial interest rate response is equal to one percentage point.

**Shock aggregation.** As monetary policy announcements do not follow an exact monthly or quarterly schedule, we have to aggregate intra-period events to their respective months or quarters. Here we experiment with two different aggregation schemes. First, following Corsetti et al. (26) we compute the cumulative daily surprise over the past month (31 days) / quarter (93 days) for each day in our sample and then take the average of this daily cumulative series over each period. This effectively amounts to an intra-period weighting scheme where shocks at the beginning of the period are assigned a larger weight, reflecting the idea that they have more time to affect other variables of interest. Second, we follow Miranda-Agrippino and Ricco (52) and simply compute the sum of all daily shocks arising in the particular month/quarter. All months without a monetary policy meeting assigned a zero value. Experimenting with these two aggregation schemes we find that the latter generally produces higher F statistics for instrument relevance. While the differences are often not large, we therefore still prefer the second option use it in the results reported in the paper throughout.

**Bayesian estimation.** As in the singly-country proxy VAR models we have to work with fewer observations, we employ Bayesian techniques in order to impose more structure on the estimation and avoid overfitting. These also turn out to increase the F statistics of instrument relevance in the quarterly US model, but we use them for consistency throughout. We do verify, however, that our results also hold under frequentist estimation. We use standard Minnesota priors (as in Litterman (51)) that we cast in the form of a Normal-Inverse-Wishart (NIW) prior, which conveniently is the conjugate prior for the likelihood of a VAR with Gaussian innovations:

\[
\Sigma \sim \mathcal{W}^{-1}(\Psi, \nu)
\]  (32)

\[
\beta \sim \mathcal{N}(b, \Sigma \otimes \Omega).
\]  (33)

\( \Psi \) is the scale of the prior Inverse-Wishart distribution for the variance-covariance matrix of the residuals. As is standard, we specify it as a diagonal matrix with entries \( \psi_i \) chosen as a function of the residual variance of the regression of each variable onto its own first lag. We set the degrees
of freedom $\nu = n + 2$ to ensure that the mean of the inverse Wishart distribution exists. The stacked coefficient matrices $\beta = vec([c, A_0, ..., A_p])$, with prior mean $b$, are assumed to be a priori independent and normally distributed, with moments

$$
\mathbb{E}[(A_t)_{i,j} | \Sigma] = \begin{cases} \delta_i & i = j, l = 1 \\
0 & \text{otherwise} \end{cases} \quad (34)
$$

$$
\text{Var}[(A_t)_{i,j} | \Sigma] = \begin{cases} \lambda^2 l^2 & i = j, \forall l \\
0 & i \neq j, \forall l \end{cases} \quad (35)
$$

where $(A_t)_{i,j}$ is the response of variable $i$ to variable $j$ at lag $l$. In the benchmark results we set $\delta_i = 1$ for all, i.e. also for our risk, variables, but our results are hardly affected when setting $\delta_i = 0$ for these (as in Banbura et al. (15) for potentially stationary variables). The hyperparameter $\lambda$ controls the overall tightness of the Minnesota prior. In the benchmark case we have it determined optimally in the spirit of hierarchical modelling as in Gianonne et al. (40), but verify that our results hold also when setting $\lambda$ to a very large value, in which case the posterior coefficient estimates correspond to their OLS / maximum likelihood estimates. As is common, we formalize the idea that more recent lags of a variable tend to be more informative than more distant lags by specifying $l^2$ in the variance entries.

### A.5 Counterfactual impulse responses

This section provides details on how we compute the counterfactual impulse responses used in section 4. The benchmark results are based on the methodology in Bachmann and Sims (14), where a structural shock series is constructed that offsets the response of the target variable (here: 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 write the structural model as

$$
Y_t = D(L)\epsilon_t, \quad (36)
$$

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 responses then amounts to finding an offsetting structural shock series such that

$$
\hat{D}_h(4, 3) = 0 \quad \forall h = 0, 1, ..., H. \quad (37)
$$

As an alternative method to arrive at counterfactual impulse responses we also compute responses based on a VAR model where we impose a zero response of the 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.
For horizon $h = 0$ we can find the offsetting shock as
\[ \hat{\epsilon}_0^4 = -\frac{D_0(4,3)}{D_0(4,4)} \] (38)
and then find the remaining ones recursively as
\[ \hat{\epsilon}_h^4 = -\frac{D_h(4,3) + \sum_{k=0}^{h-1} D_k(4,4) \hat{\epsilon}_k^4}{D_0(4,4)}, \]
(39)
for $h = 1, 2, ..., H$. The counterfactual impulse responses $\hat{D}_h$ are then constructed as
\[ \hat{D}_h = D_h + \sum_{k=0}^{h-1} \hat{\epsilon}_k^4, \] (40)
with $h = 1, 2, ..., H$.

### A.6 Interacted panel VAR

In the following we provide some details on the interacted panel VAR we use in section 5 to evaluate the impact of macroprudential regulation in the systemic risk channel. The model builds on the interacted panel VAR developed by Towbin and Weber (64). In keeping with the notation used so far an interacted VAR can be written as
\[ y_{i,t} = E_0 X_{i,t} + \sum_{l=1}^{p} (A_l Y_{i,t-l} + E_l Y_{i,t-l} X_{i,t}) + u_{i,t}, \] (41)
where $X_{i,t}$ is the macroprudential index of Cerutti et al. (25) for economy $i$ at time $t$, $E_0$ is the coefficient vector on this index, and the $E_l$ matrices contain the coefficients of the interaction terms of the endogenous variables with macroprudential policy. As we are primarily interested in the response to monetary shocks we interact only the interest rate measure in the model with the macroprudential index.

We then estimate this model and compute impulse responses to a monetary policy shock at two different levels of the macroprudential index, a low and a high one. Following Aastverit et al. (11) we use the 10th and 90th percentile of the distribution of the index across countries in the sample and write the model as
\[ y_{i,t}^{high} = \hat{E}_0^{high} X_{i,t} + \sum_{l=1}^{p} (\hat{A}_l^{high} Y_{i,t-l} + \hat{E}_l^{high} Y_{i,t-l} X_{i,t}) + \hat{u}_{i,t}, \] (42)
and
\[ y_{i,t}^{low} = \hat{E}_0^{low} X_{i,t} + \sum_{l=1}^{p} (\hat{A}_l^{low} Y_{i,t-l} + \hat{E}_l^{low} Y_{i,t-l} X_{i,t}) + \hat{u}_{i,t}. \] (43)

Computing two sets of impulse responses is then straightforward. It effectively amounts to adding the vector of interaction coefficients times the index values, at their low and high values, to that
row in \( A_t \) which governs the response of each endogenous variable to lagged interest rates, and then applying a standard Cholesky factorization to the resulting MA-infinity coefficient matrices.
B Additional results and robustness checks

B.1 Panel VAR

We verify that our results are robust along many dimensions. While we address the perhaps most important issue of shock identification in section 3.2 in detail, in the following we briefly discuss various robustness exercises we perform for the benchmark panel VAR \(^{51}\). As shown in Figure 14, all three risk measures continue to decline significantly when we change the lag length to three, as preferred by the Schwarz Bayesian criterion, or indeed any other number between four and twelve. The same is true when we reverse the order of the interest rate and risk measure in the model. Additionally, we experiment with a variety of interest rate measures. While shadow rates are a useful measure of monetary conditions at the zero lower bound, there is some uncertainty regarding their exact level. In order to verify that our results are not primarily driven by the choice of the particular measure, Figures 12 and 13 shows that systemic risk responses to a monetary tightening look very similar to our benchmark results when using actual central bank policy rates and the alternative shadow rate estimates by Wu and Xia \(^{66}\), respectively. We also estimate our panel model as a stationary VAR in the growth rates of GDP and CPI and also here find that all three risk measures significantly decline.

Our results are similarly unaffected when, as in Iacoviello \(^{43}\), we add a linear time trend to the model or other exogenous terms. In particular, we attempt to alleviate concerns that a few outliers during the crisis period drive our results by adding a crisis dummy around the period of 2007-09. Again we find that our results are basically unchanged. For similar reasons we additionally estimate the model in the pre-crisis period ending in the Summer of 2007. Not only does this rule out that structural breaks or extreme crisis observations drive our main results, also 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. As Figure 15 shows, we continue to find significantly negative responses of all three risk measures even in the pre-crisis period, although the responses are quantitatively somewhat less pronounced \(^{52}\).

While the inherent bias in fixed-effects panel VAR estimates is negligible in our case (Nickel \(^{55}\)), 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 \(^{58}\). This is derived as the unweighted average of estimates of all cross-sectional units and avoids the heterogeneity-induced bias in fixed-effects estimation. Also in this case we continue to find significant declines of all three risk measures. Moreover, an

\(^{51}\)We show various figures of these robustness exercises below. The remaining figures are available upon request.

\(^{52}\)Note that even in this pre-crisis period, Japan was at the zero-lower bound for a long period of time. We take this into account with our interest rate measure that uses Krippner’s shadow rate estimates for Japan.
earlier version of this paper included results for a US FAVAR. Also in this model, which controls for dozens of variables that are potentially important for the endogenous response of monetary policy and/or for the transmission of monetary policy to systemic risk, we find significant declines of all risk measures following a monetary tightening.

At last, also in the quarterly panel VAR models including leverage measures we conduct several robustness exercises. For instance, reversing the order of leverage and risk measures leaves results basically unchanged. While we choose 2000 as the starting year in this analysis–which makes it possible to rely on high-quality market leverage data from a single source, see Appendix A.2–results are again hardly changed when we extend the sample in the ∆CoVaR models to 1992.

B.2 Proxy VAR

Also in the case of the proxy VARs we conduct a variety of robustness tests. We find that changing the lag lengths does not meaningfully alter our results.\(^{53}\) The same is true when using flat priors, as shown in Figure 18. We also verify for the US case that all our results hold when using the original FF4 shock series employed by Gertler and Karadi (39) which has not been adjusted for information dissemination effects. Consistently with Miranda-Agrippino and Ricco (52), with those shocks we find strong output puzzles for the period under investigation, but still all our risk measures continue to decline. In addition, we experiment with cleansing the surprise series from information shocks also in the euro area. As Greenook forecasts are not available here, we resort to the following procedure in a robustness exercise. We compute the change in broad euro-area stock indices (for instance the Euro Stoxx50) in a narrow window around the ECB announcement events and adjust the monetary policy shock series in that we keep only those events in which stocks fall following a surprise interest rate increase. The idea behind this adjustment is that a surprise policy rate increase that coincides with an increase in stocks most likely signals information dissemination rather than an exogenous monetary tightening. Indeed we find that in most specifications output and price puzzles vanish, while our risk measures continue to fall. The resulting F statistics for instrument relevance are substantially lower, however, often below 10.

Furthermore, we investigate the systemic risk taking channel again in the pre-crisis sample and report the results in Figure 17. Also here we find all three risk measures to fall, although the ∆CoVaR responses are on impact around one third smaller than those found in the model of the full time sample. Particularly reassuring is the fact that in the pre-crisis sample all F statistics are significantly larger than before (above 20 for the ∆CoVaR measures and practically 10 for LRMES). Finally, especially in the euro area case we experiment with different combinations of instruments and policy indicators, like using 3-month, 1-year or 2-year interest rates or different contract lengths for the OIS swaps on which the surprise series is based. Although some combinations

\(^{53}\) Any lag length from two to six (in all US and in the euro area ∆CoVaR models) and three (in the euro area LRMES model) delivers significant declines of all three risk measures.

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Figure 11: Lag selection criteria in benchmark panel VAR model

Figure shows lag selection criteria for the benchmark panel VAR model including the logs of GDP and CPI, the central bank policy rate and respective risk measure. 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 parameters (left scale). Time sample: 2000:06-2016:12.

deliver significantly lower F statistics than our benchmark specification, the result that the risk measures fall in response to a monetary tightening is remarkably robust.
Figure 12: Panel VAR with central bank policy rate (instead of shadow rate)

Note. Impulse responses in the panel VAR(12) to a shock to the central bank policy rate. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Variable ordering: GDP, CPI, interest rate, risk measure. Countries included: United States, Japan, United Kingdom, China, euro area (Germany, France, Spain, Netherlands, Italy), Sweden and Switzerland. Time sample: 1992:06-2016:12 for ΔCoVaR measures and 2000:06-2016:12 for LRMES. Shaded areas indicate 90% confidence bands.
Figure 13: Panel VAR with Wu and Xia (instead of Krippner) shadow rate

Note. Impulse responses in the panel VAR(12) to a shock to the interest rate. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Variable ordering: GDP, CPI, interest rate, risk measure. Countries included: United States, United Kingdom, euro area (Germany, France, Spain, Netherlands, Italy), China. Time sample: 1992:06-2016:12 for ΔCoVaR measures and 2000:06-2016:12 for LRMES. Shaded areas indicate 90% confidence bands.
Figure 14: Panel VAR with three (instead of twelve) lags

Note. Impulse responses in the panel VAR(3) to a shock to the central bank policy rate. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Variable ordering: GDP, CPI, interest rate, risk measure. Countries included: United States, Japan, United Kingdom, China, euro area (Germany, France, Spain, Netherlands, Italy), Sweden and Switzerland. Time sample: 1992:06-2016:12 for ΔCoVaR measures and 2000:06-2016:12 for LRMES. Shaded areas indicate 90% confidence bands.
Figure 15: Panel VAR in pre-crisis sample

Note. Impulse responses in the panel VAR(12) ($\Delta$CoVaR) and VAR(9) (LRMES), respectively, to a shock to the interest rate. Time sample: 1992:06-2007:09. Remaining details as in Figure 1.

Figure 16: Placebo test in interacted panel VAR

Note. Impulse responses in the panel VAR(12) to a shock to the interest rate. Blue solid and black dashed lines indicate an artificial macroprudential index of 1 and 4 (representative of the 10th and 90th percentiles used in Figure 9, respectively, in the sample 2000:06-2007:07 and 2007:08-2016:12. Dotted lines and shaded areas indicate 90% confidence bands.
**Figure 17: US proxy VAR in pre-crisis sample**

Note. Impulse responses in monthly US proxy VAR(3) to a shock to the effective federal funds rate. Time sample: 1992:06-2007:07 for ΔCoVaR measures and 2000:06-2007:07 for LRMES. Remaining details as in Figure 2.

**Figure 18: US proxy VAR with flat priors**

Note. Impulse responses in monthly US proxy VAR(6) (ΔCoVaR) / VAR(3) (LRMES) to a shock to the effective federal funds rate. Estimation with flat priors. Remaining details as in Figure 2.