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SYSTEMIC BANK RISK AND MONETARY POLICY

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JEL Classification: E44, E52, G18, G21

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

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Systemic Bank Risk and Monetary Policy*

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1 Introduction

Extensive and robust mirco evidence exists for the risk-taking channel of monetary policy, namely the notion that the monetary policy stance affects risk-taking behavior of banks.[1] Given this channel, monetary policy faces a trade-off between the beneficial effects of expansionary policies and the unintended increase in bank risk. Micro evidence provided so far focused on measures of individual bank risk and in many cases the quantitative effects were small. However, the risk-taking channel has relevance for macroeconomic policy markers only to the extent that it affects systemic risk and that effects are sizable. Indeed, any effect on individual bank risk are likely to be mitigated by microprudential regulation. Furthermore, most previous studies are based on panel data and neglect the time-series dimension, which is essential when tracing out and quantifying the dynamic effects of exogenous changes in monetary policy.

Motivated by the above, our goal is to assess the effects of shocks to monetary policy on metrics of systemic bank risk. We exploit both the time-series and cross-country dimension of our data with the help of a panel VAR as well as a proxy VAR for the US and the euro area. The first allows us to verify that the systemic risk-taking channel is not a single-country phenomenon. With the second we check robustness with respect to recently developed identification methods which measure high-frequency market surprises around monetary policy announcements.[2] We find strong and robust evidence that an increase in interest rates leads to sizable reductions in various systemic risk metrics. Second, we wish to identify the type of macroeconomic externalities that affect systemic risk following a monetary policy shock.[3] We find a significant role for pecuniary or fire-sale externalities,[4] which propagate through changes in *market leverage*.The latter, we find, are much larger than changes in book leverage due to movements in bank equity prices. A change in interest rates induces banks to rebalance their sources of funding and adjust the ratio between short-term liabilities and equity. Since banks' demand for equity financing does not immediately meet an increase in the supply of funds, due to adjustment costs or fire-sales, equity prices adjust, thereby affecting the market valuation of leverage.[5] Our identification strategy exploits the differential response between market and book leverage. We rationalize these empirical results through a simple model, where changes in interest rates affect banks' incentives of engaging in risk-shifting toward outside financiers. Third, we ask whether macroprudential policy can tame the risk-taking channel of monetary policy. Our findings suggest that it does.

[1] See Borio and Zhu (14)for first discussion of the channel. See Altunbas, Gambacorta, and Marquez-Ibanez (8), Dell'Arriccia, Laeven and Suarez (25), Jimenez et al. (37), Ioannidou, Ongena, and Peydro (36) for panel data evidence on banks' individual risk.

[2] See Gertler and Karadi (32), Altavilla et. al.(4).

[3] See Bernanke (12) for a discussion on the role of macroeconomic externalities for the risk-taking channel.

[4] The theoretic literature has considered both network or fire-sale externalities, see Allen and Gale (7), Caballero and Simsek (19), Greenwood, Landier and Thesmar (34) or Elliott, Golub, and Jackson (27).

[5] This adjustment can be well rationalized through the presence of adjustment costs on equity financing, see for instance Lenel, Piazzesi and Schneider (42).

Our analysis is structured in three parts. In the first, we estimate a panel VAR and on a proxy VAR. For the panel VAR we use monthly data for 29 global systemically important banks (G-SIBs) headquartered in seven economies. In this case we identify monetary policy through a traditional recursive ordering. The proxy VAR instead employs data on high-frequency market responses to monetary policy announcements in the United States and the euro area, which are used as external instruments. The advantage of the panel VAR is the possibility of testing the channel over more countries, while the proxy VAR allows us to test it under a more modern and rigorous identification procedure of monetary policy shocks. As metrics for systemic risk we compute and use both ΔCoVaR,[6] and banks' long-run marginal expected shortfall (LRMES hereafter).[7] The first metric measures the codependency of the financial system on a particular bank's value at risk and, as it is based on market prices, it is affected by fire-sale externalities. We compute this metric using equity prices as well as CDS spreads. The latter typically have larger predictive power. The LRMES metric measures how much bank equity would be lost in the event of a crisis and therefore indicates the dependency of a single institution on the financial system. For both VAR models our results show unequivocally that an increase in policy rates lowers all three metrics of systemic risk. We verify that our results are robust along many dimensions. Notably, the risk-taking channel is not predicated on the occurrence of the financial crisis as we continue to find evidence of it when we end our sample in 2007.

In the second part of the paper we extend both VARs and include measures of leverage. The first goal is to dissect the exact transmission mechanism from changes in policy rates to banks' balance sheets, summarized by changes in leverage, the ratio of bank assets over equity. The second goal is to measure the role of pecuniary or fire sale externalities. The latter has been identified as one of the leading propagator risk after the most recent financial crisis. [8] Our identification strategy exploits the differential response of book and market leverage. We find that a monetary policy tightening (loosening) reduces (increases) systemic risk and leverage, but that the impact is much stronger and significant on the market measure of leverage than on the book equivalent. Hence, much of the transmission goes through relative changes in the various sources of funding.

Consider an interest rate hike. Banks might wish to increase equity funding, relative to short-term liabilities, in order to meet equity requirements. If adjustment costs on the funding supply side hinders such adjustment, the relative movements in the prices of short-term versus long-term funding would affect market leverage on top and beyond book leverage.[9] The scarcity of equity raises its price relative to short-term liabilities, resulting in a fall of market leverage.[10] A fall in

[6]See Adrian and Brunnermeier (3).

[7]See Brownlees and Engle (15).

[8]See Allen and Gale (7), Caballero and Simsek (19) or Greenwood, Landier and Thesmar (34).

[9]See Lenel, Piazzesi and Schneider (42).

[10]Note that in response to a monetary tightening, bank equity prices might fall in absolute values, but what matters for movements in market leverage is the relative costs of the short-term versus the long-term source of funding.

market leverage intuitively leads to a fall in risk, as the bank is less exposed to liquidity dry-outs and has larger loss-absorption capacity.

To quantify more precisely how much of the market leverage response transmits into systemic risk we 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 that the response of market leverage accounts for a sizeable share of the response in systemic risk. We rationalize those results through a simple banking model with two channels: bank risk-taking and a variable price of bank capital and market leverage. First, bankers invest in risky projects using their own capital and raising funds from depositors[11] and act as delegated monitors. Monitoring activity induces a trade-off. On the one side, it increases projects' success probability more than proportionally,[12] hence it reduces risk. This in turn increases bankers' rents, net of the cost of funding. On the other side, it increases the costs of processing information. Costly monitoring induces moral hazard. A contractual agreement disciplines the delegated monitoring. Low policy rates, by reducing the cost of outside funding, increase bankers' rents, hence relax the bankers' incentive compatibility constraint. Their incentives to monitor fall and projects' risk rises. Second, bankers choose leverage endogenously, due to an elastic supply. This results in a variable price of equity capital and leverage. Falls in the policy rates, by relaxing the incentive-compatibility constraint, allow bankers to leverage more. The fall in the demand of equity capital, needed to satisfy incentive compatibility, reduces the equity returns that are needed to meet supply. The change in the value of bank capital in turn increases the market value of leverage.

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 macroprudential regulation provided in Cerutti et al. (20) and interact their index with our monetary policy measures in our panel VAR. We find markedly different responses in high and low regulatory environments. We take this finding as an indication that macroprudential policy can alleviate the systemic risk-taking channel of monetary policy and, most interestingly, that the two policies are complementary to each other.

The paper is structured as follows. Section 2 reviews the clostest 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 macroprudential policy in the panel VAR setting. Section 5 concludes.

[11] These refer more generally to investors in short-term liabilities.

[12] This captures in a simple way the notion of amplification of asset risk into systemic risk. In an extension of the model we adopt a further refinement of this notion.

2 Literature Review

The risk-taking channel of monetary policy was first discussed in a contribution by Borio and Zhu (14). In the theoretical literature some contributions have rationalized the effect of the monetary stance on bank risk. Angeloni and Faia (5), using a dynamic general equilibrium model with fundamental bank runs, show that low rates increase bank liability risk. Dell'Ariccia, Laeven and Marquez (24) using a static bank model with oligopolistic competition show that low rates increase banks asset risk. Martinez-Miera and Repullo (45) show that an increase of liquidity can reduce banks' monitoring incentives and increase banks' asset risk.

On the empirical side, there are various interesting and influential contributions testing and finding evidence of a risk-taking channel of monetary policy on bank risk. All of them use individual bank risk metrics and employ panel data techniques, hence focusing on the cross-sectional variations of risk. For instance Altunbas, Gambacorta, and Marquez-Ibanez (8) use rating agency estimates, Jimenez et al. (37), Ioannidou, Ongena, and Peydro (36) use credit registry information on default history and Dell'Arriccia, Laeven and Suarez (25) use banks' internal ratings on loans. The individual bank risk dimension however does not belong to the domain of the monetary policy maker, but rather to the one of the microprudential regulator. Moreover, in most papers, the documented changes in risk are small relative to the size that would concern macroeconomic policy makers.[13] Some studies address the endogeneity of monetary policy responses to financial and macroeconomic variables by employing time-series techniques.[14] None has focused on systemic risk metrics and employed modern techniques identifying policy shocks using high-frequency data. Finally, no study has identified the role of macroeconomic externalities and of market leverage.

3 Monetary Policy and Systemic Risk

Our analysis proceeds in three steps. At first, we wish to assess the general validity and robustness of the relation between monetary policy and risk, independently from the potential economic transmission that lay behind. Next, in section 4, we examine the transmission through banks' leverage and quantify the extent of the macroeconomic externalities. At last, in section 5, we address the topical question of the complementarities between monetary and macroprudential policy.

In terms of methodologies we use both a panel VAR and proxy VARs. The first specification allows us to test the cross-country and cross-bank validity of the risk-taking channel. Hence, we can ascertain that the channel is not an artifact of certain institutions or particularities of certain

[13] For instance, in Dell'Ariccia, Laeven and Suarez (25) a decrease in the short-term interest rate by one standard deviation is associated with an increase in loan risk by 13 percent of a standard deviation. Other studies find sometimes even smaller effects.

[14] See Buch, Eickmeier, and Prieto (16), Buch, Eickmeier, and Prieto (17), Neuenkirch and Nöckel (48) and Angeloni, Faia and Lo Duca (9).

countries' monetary policy. We use data for seven countries and 29 GSIBs. In this case however, we have to rely on traditional recursive ordering for shock identification, as externally information in the form of market surprises around monetary policy announcements are not available for several countries.

The proxy VAR allows us to test the validity of the results under more modern high-frequency identification techniques of monetary policy shocks. The latter are reliably available for the United States and the euro area. Results are qualitatively similar under both methodologies, but are quantitatively stronger when employing the more rigorous high-frequency identification schemes. We test robustness of our results under various model assumptions (reported in Appendix C.1 and Appendix C.2) Most notably, we can show that the risk-taking channel is not confined to either the post-crisis or the pre-crisis period alone.

3.1 Panel VAR

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.[15] The main VAR specification considers seven countries as cross-sectional units, namely the United States, United Kingdom, Japan, euro area,[16] China, Sweden, and Switzerland. 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 (23) method with industrial production and retail sales as reference series. 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.[17] The systemic risk metrics are described in detail in Appendix A.3. The first is ΔCoVaR, which captures 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 is the long-run marginal expected short-fall (LRMES), measuring how much equity would be lost in the event of a crisis. We estimate the model via fixed effects by demeaning.[18] All variables used in the analysis and their data sources are described in Appendix A. Due to the extended ubiquity of the zero-lower bound we use, as policy instruments, shadow rates whenever available.[19] Specifically, we make use of the shadow rates provided by Krippner (38), which have been computed for the

[15]See Table 1 in Appendix A.

[16]Spain, Germany, France, Italy and the Netherlands share the same monetary policy and are hence subsumed under the euro area.

[17]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.

[18]For this reason we do not include constant terms in the baseline specification. We do so in some robustness checks, see Appendix C.1

[19]Shadow rates can track monetary policy rates in normal times but also in times of unvoncentional policy, namely when the main policy rate remains near zero and does not respond to the changing macroeconomic environment.

US, UK, Japan and the euro area.[20] Identification is done here through a traditional Cholesky decomposition, where we order the variables as follows: output, prices, monetary policy, and then 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.[21] Finally, the time sample is 1992:06-2016:12 for the two ΔCoVaR measures and 2000:06-2016:12 for LRMES metric, which is not available earlier.[22] Lag length selection is guided by information criteria.[23]

Figure 1 shows estimated impulse responses to an exogenous increase in the interest rate for all seven countries. The sequence of panels in each row of the figure represents the impulse responses of the 4-variable VAR with different risk metrics, namely ΔCoVaR based on equity returns, ΔCoVaR 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.[24] More central to the question at hand, all risk metrics fall significantly in all models, albeit with different patterns. Interestingly, the whole adjustment of risk does not take place fully and immediately, but seems to reemerge at medium frequencies. This is in line with the theoretical underpinnings of this channel. Consider a monetary expansion. Banks become riskier since they increase their leverage or invest in riskier assets. However, portfolio rebalancing usually takes time, also since equity adjustment is often sluggish due to adjustment costs. On the contrary, on impact the beneficial effects of the expansionary policy, by reducing the probability of projects' defaults, tend to mask the risk-taking activity of banks and its medium-term contagious effects on the economy.

In order to appreciate the relevance of our estimates, we compare their magnitude to previous studies in the microeconometric literature (reviewed in section 2) and find substantially stronger effects. In Jimenez et al. (37), Altunbas et al. (8) and Dell' Ariccia et al. (25), the marginal effect of a one-standard deviation increase in the interest rate measure 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 (ΔCoVaR based on CDS spreads) to 0.67 (ΔCoVaR based on equity returns) standard deviations. Differences in methodologies notwithstanding, we interpret these much larger effects as evidence of the importance macroeconomic externalities and of contagion channels in the bank-risking taking channel.

[20] For the remaining countries, we use the actual policy rates. These either newer hit the zero lower bound (China), did so only briefly (Sweden) or adopted negative interest rates (Switzerland).

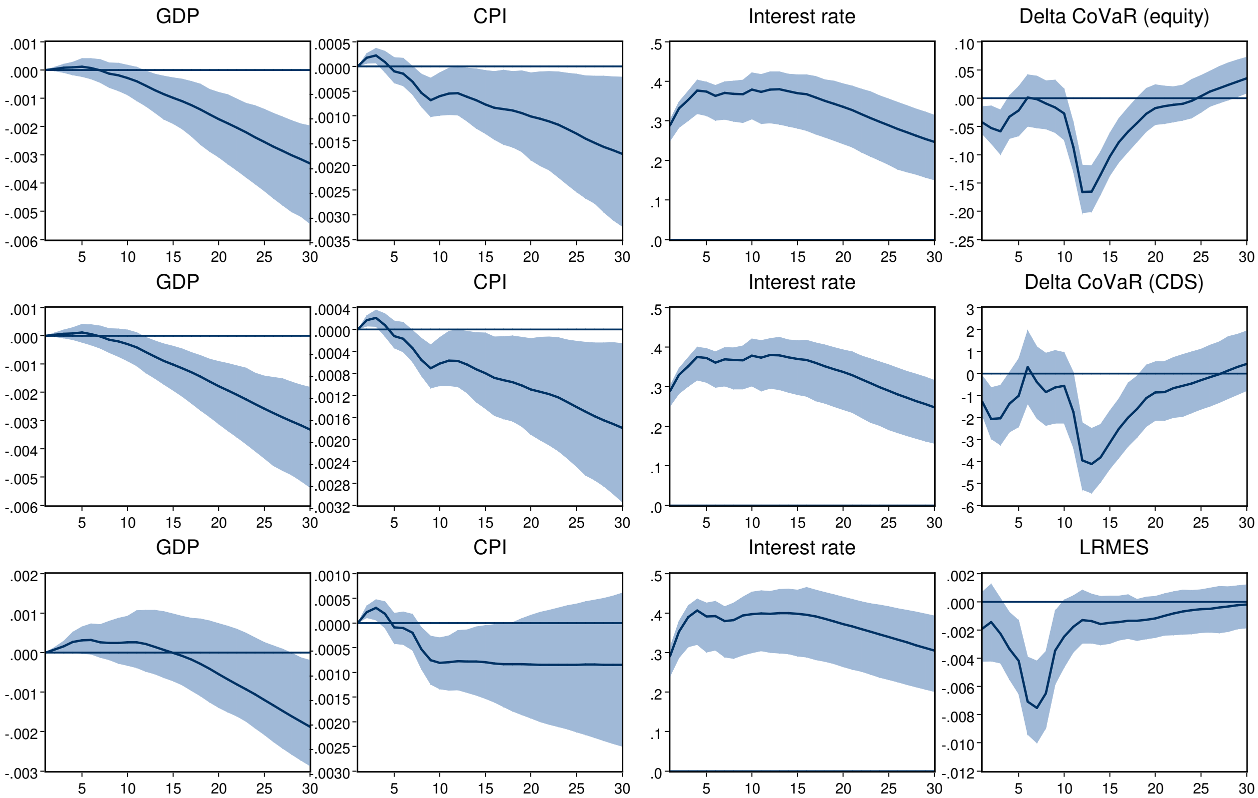
[21] In Appendix C.1 we discuss robustness of results for other orderings.

[22] In a robustness exercise, and throughout in section 4 when adding leverage measures, we harmonize the estimations of the two risk metrics starting in mid-2000. Results remain robust.

[23] We choose twelve lags in the baseline specification according to the Akaike information criterion, and confirm our results in Appendix C when using three lags as suggested by the Schwarz Bayesian information criterion.

[24] This "price puzzle" is commonly observed using recursive identification schemes, see for instance Ramey (51) and, *inter alia* motivates our use of a proxy VAR setting below.

Figure 1: Panel VAR



Note. Impulse responses in the panel VAR(12) to a monetary policy shock. 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.

3.2 Proxy-VAR Using External Instruments

Identification is of critical importance in the estimation of any structural VAR model. For this reason we test our results under recently developed and more rigorous methodologies for monetary policy shocks identification. These generally consist of feeding external information into the VAR. Most often, based on early the works of Kuttner (41) and Gürkaynak, Sack and Swanson (35), monetary policy shocks are identified 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.

We follow the approach in Gertler and Karadi (32) and include market surprise series as an instrument in a four-variable proxy VAR for the US and the euro area. 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.

For the US, we use changes in the fourth federal funds futures contracts (FF4) around a 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.[25] For the euro area, we employ comparable instruments constructed from the monetary policy shock database in Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (4). Since the number of observations is now smaller than in the panel VAR, we reduce lags to 6 and use Bayesian estimation methods with optimal prior selection in the spirit of Giannone et al. (33). Details about the model and prior specifications are given in Appendix A.4.

Figure 2 shows impulse responses in the US model (solid blue lines). Both output and prices decline following a monetary policy shock. More importantly, all three risk measures significantly decline as well, confirming our results so far. While the dynamics differ from those found in the panel VAR, this is to be expected given that the two methodologies differ along several dimensions. A comparison with the recursive ordering identification (dashed black) reveals that responses using the external instrument approach are much more significant and quantitatively pronounced.

Figure 3 shows the same set of responses for the euro area. All three systemic risk measures decline as before, while here the differences to the recursive identification approach are even more pronounced for both ΔCoVaR metrics. We conclude that employing external instruments substantiates the evidence in favor of the systemic risk taking channel and that, if anything, the traditional recursive identification approach underestimates the responses of systemic risk to monetary policy shocks.

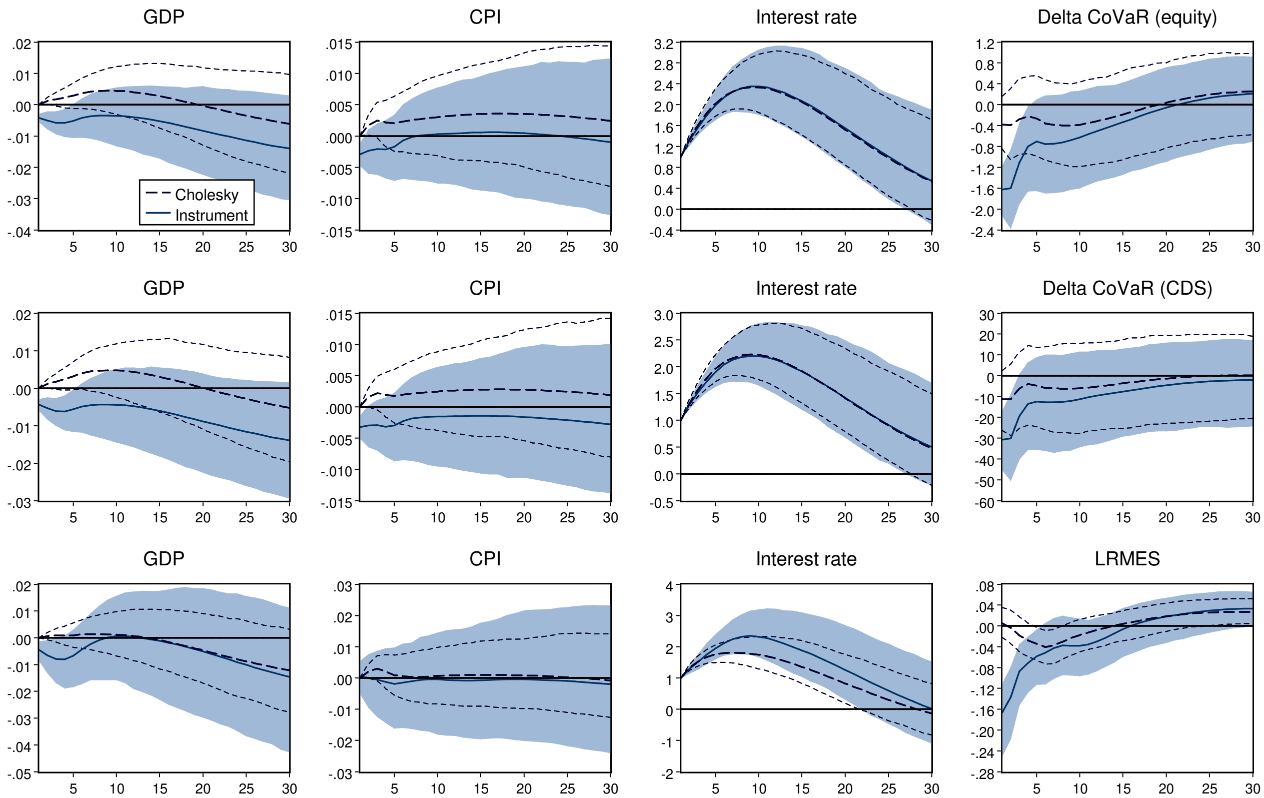
4 The Role of Leverage and Fire-Sale Externalities

So far we have established robust evidence of the existence of a systemic risk-taking channel of monetary policy. We now wish to disentangle the transmission mechanism and the economic channels through which interest rates affect systemic bank risk. This requires first identifying the channels through which interest rates affect individual bank risk, presumably through changes in balance sheets, and second how individual propagates into systemic risk.

In response to a fall in interest rates, banks rebalance their balance sheets, whose changes are summarized by changes in leverage. Hence, we include leverage measures in our VARs to verify

[25] See Miranda-Agrippino and Ricco (44).

Figure 2: US proxy VAR

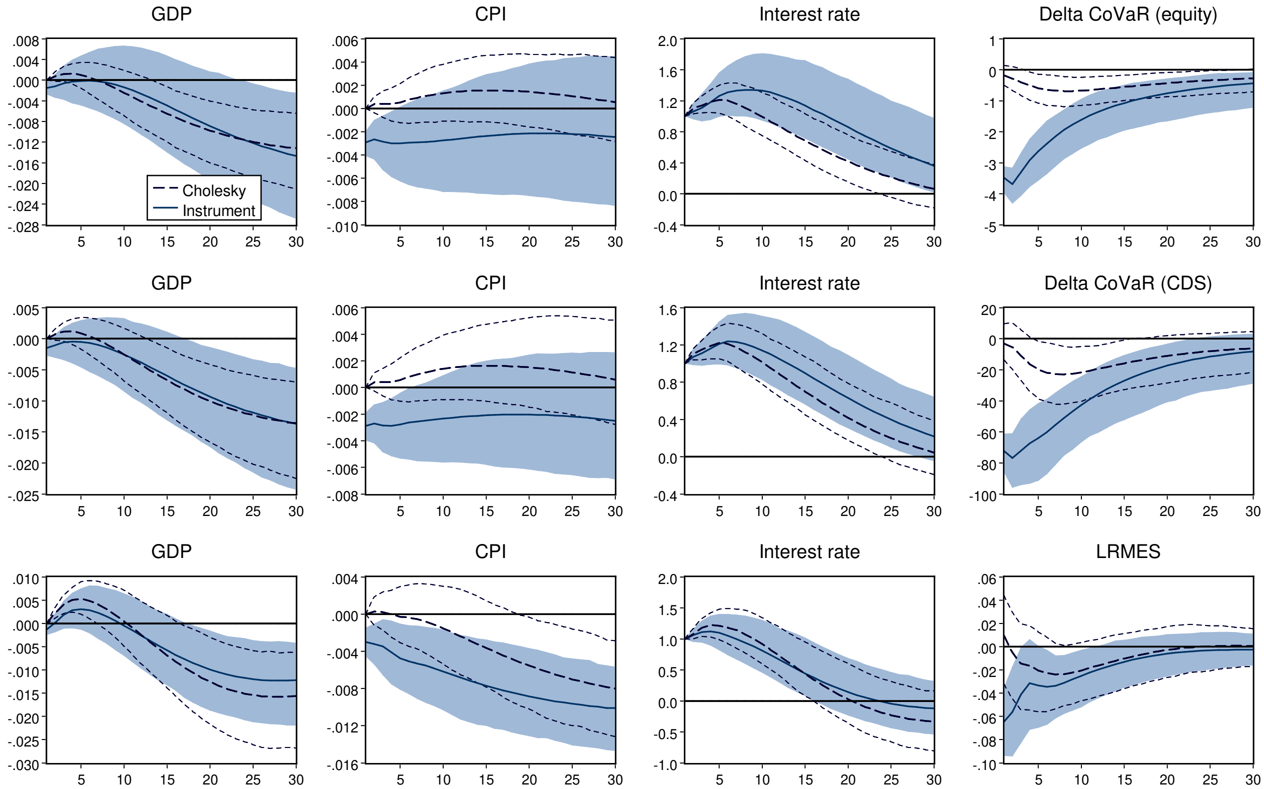


Note. Impulse responses in monthly US VAR(6) to a monetary policy shock. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Dashed black lines denote Cholesky identification, solid blue lines identification with external instruments. Instrument used: high-frequency surprises adjusted for information dissemination effects (FF4 with average future contract maturity of 3 months). Interest rate measure: effective federal funds rate. 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.

the negative response to monetary policy shocks and their positive relation with risk. Next, we wish to assess how individual turns into systemic risk and the role of pecuniary externalities in such a relation. The latter materialize when relative movements in the prices of the long-term versus the short-term sources of funding transmit to leverage. In response to an exogenous change in the policy rate, banks might wish to increase equity funding, relative to short-term liabilities, in order to meet equity requirements. If adjustment costs on the funding supply side hinder such adjustment, the relative movements in the prices of short-term versus long-term funding would affect market leverage on top of and beyond book leverage. The equity scarcity raises its price, relative to short-term liabilities, resulting in a fall of market leverage.[26] A fall in market leverage intuitively leads to a fall in risk, as the bank is less exposed to liquidity dry-outs and has larger

[26]Note that in response to a monetary tightening bank equity prices might fall in absolute values, but what matters for movements in market leverage is the relative costs of the short-term versus the long-term source of funding.

Figure 3: Euro area proxy VAR



Note. Impulse responses in monthly euro area VAR(6) to a monetary policy shock. 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 based on three-month OIS contracts around ECB press releases. Time sample: 1992:06-2016:12. Shaded areas and dotted lines indicate 90% credible sets.

loss-absorption capacity.

To test the above channels we repeat the estimation of our two VAR specifications, namely the panel and proxy models, by including leverage measures, both market- and accounting-based.[27] To quantify how much of the market leverage response transmits into systemic risk we also conduct a counterfactual experiment, in which we shut off the transmission of monetary shocks through market leverage. We define market leverage as:

$$market\ leverage = (book\ assets - book\ equity + market\ equity)/(market\ equity), \tag{1}$$

whereas book leverage is simply

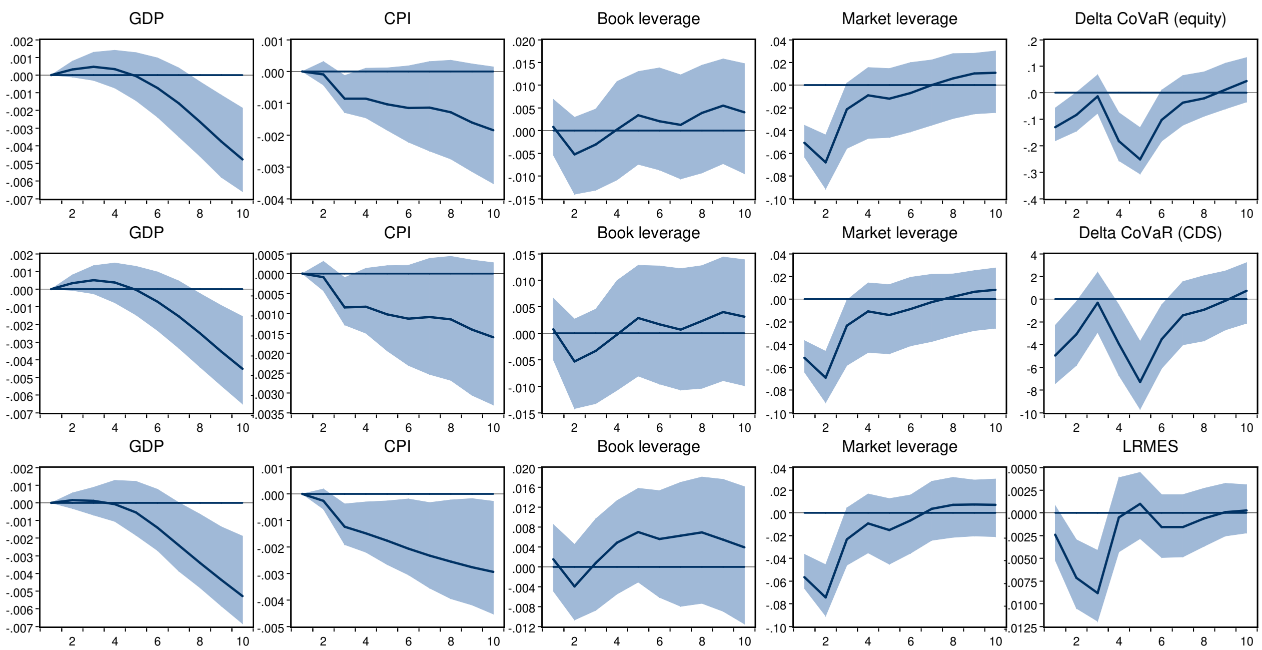
$$book\ leverage = (book\ assets)/(book\ equity). \tag{2}$$

[27] We construct bank-individual times series of market leverage using 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. Details regarding data sources and the construction of the leverage measures are reported in Appendix A.2.

4.1 Panel VAR

We order book and market leverage in the panel VAR between the interest rate and the respective risk measure in order to verify their relevance as an intermediate step in the transmission mechanism.[28] Since we now need to resort to quarterly leverage 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. As before, all three risk measures significantly decline in response to a contractionary monetary shock. Market leverage falls and responds much more strongly than its accounting counterpart. The fall in leverage is associated with a fall in risk since banks are less exposed to the risk of liquidity dry-outs and runs and have larger loss absorption capacity. Book values do not react significantly. This provides evidence that much of the transmission occurs through changes in the relative price of the various sources of funding, hence through pecuniary externalities.

Figure 4: Panel VAR with book and market leverage

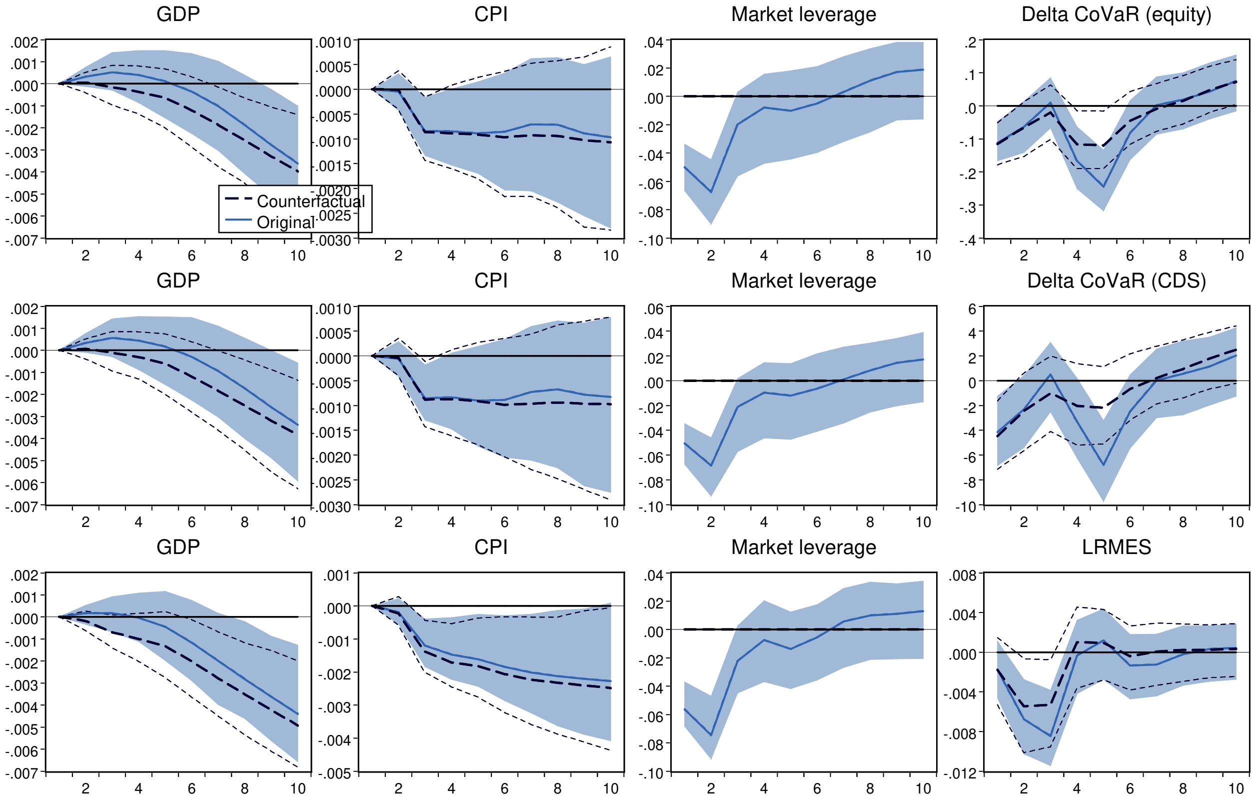


Note. Impulse responses in quarterly panel VAR(4) to a monetary policy shock. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Variable ordering: GDP, CPI, interest rate, book leverage, 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 pecuniary externalities in the systemic risk channel, we conduct a counterfactual exercise. In this experiment an original set

[28] 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.

Figure 5: Counterfactual analysis in panel VAR



Note. Impulse responses in quarterly panel VAR(4) to a monetary policy shock. 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.

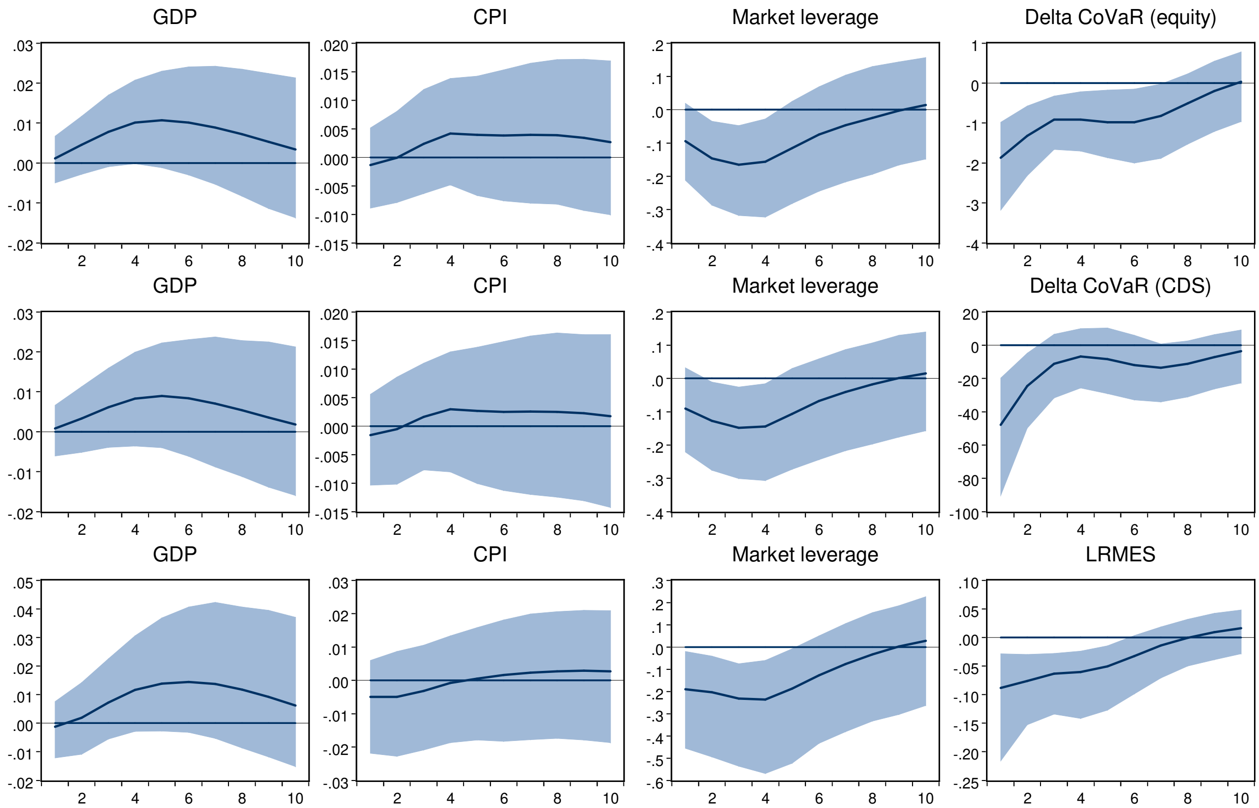
of impulse responses is compared to one that is computed with the response of market leverage to monetary policy shocks shutt off.[29] If the response of market leverage plays an important role in the transmission mechanism of monetary policy to systemic risk, we would expect the impulse responses of 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), and even become insignificant in the case of the ΔCoVaR CDS metric.

[29] Our benchmark results are based on the methodology used in Bachmann and Sims (10), see Appendix A.5, in which a series of offsetting shocks is computed to mute the response of the variable in question.

4.2 Proxy VAR

In parallel to section 3, we compute impulse responses by augmenting also the US and euro area proxy VARs with leverage. 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.

Figure 6: US proxy VAR with market leverage



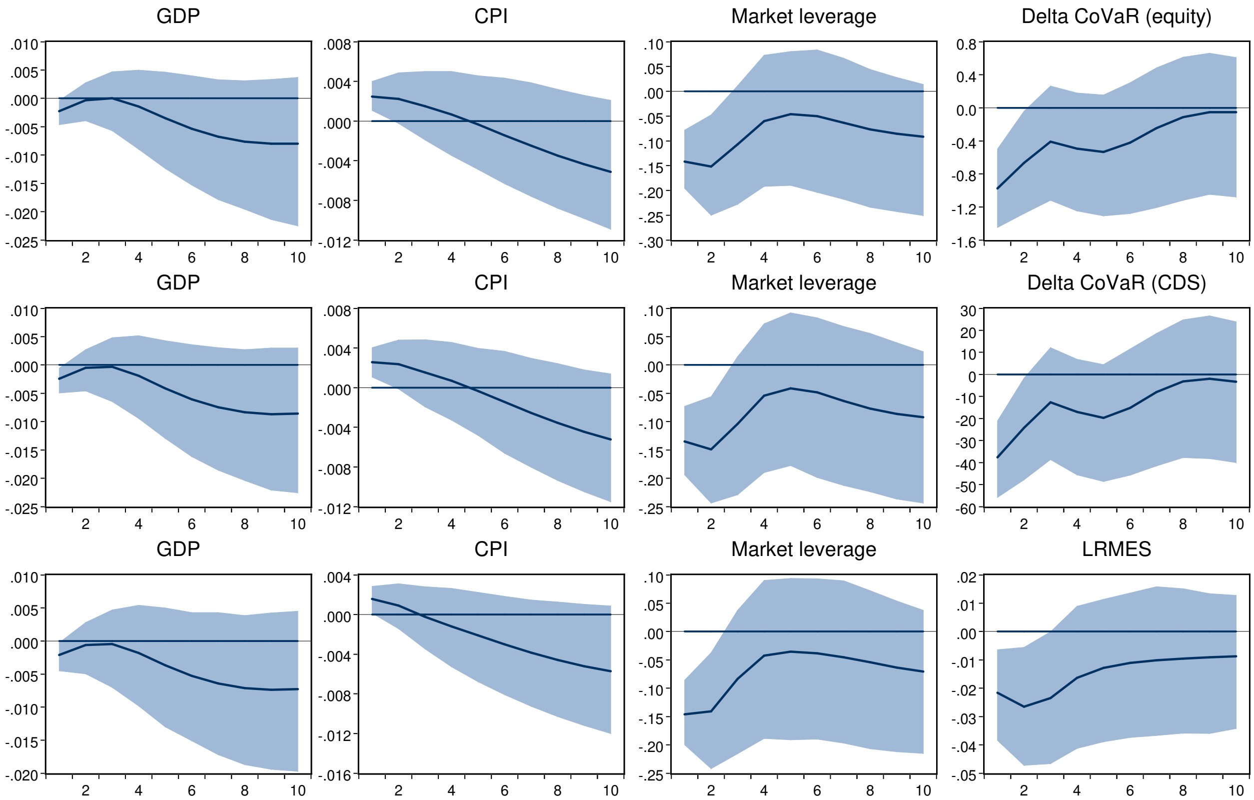
Note. Impulse responses in quarterly US proxy VAR(4) to a monetary policy shock. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Instrument used: high-frequency surprises adjusted for information dissemination effects (FF4 with average futures contract maturity of 3 months). Interest rate measure: effective federal funds rate. 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 for the US and in figure 7 for the euro area. As in the panel VAR model, we observe that market leverage falls with a peak decline of ten percent after around three to four quarters. This fall is even more pronounced in the euro area model.

4.3 A Simple Model to Rationalize the Evidence

The evidence above shows that banks have higher risk-taking incentives in the face of low rates, that there is a positive association between leverage and risk and that this last relation is more

Figure 7: Euro area proxy VAR with market leverage



Note. Impulse responses in quarterly euro area proxy VAR(4) to a monetary policy shock. 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 based on one-year OIS contracts around ECB press releases and press conferences. Time sample: 2000:Q2-2016:Q4. Shaded areas indicate 90% credible sets.

pronounced at market values. We rationalize those results through a simple banking model embedding two channels, bank risk taking and variable price of bank capital and market leverage. First, bankers invest in risky projects by employing their own capital and by raising funds from depositors, or investors in short-term liabilities. Bankers act as delegated monitors. Monitoring activity induces a trade-off. On the one side, it increases more than proportionally projects' success probability, hence it reduces bank risk. The convexity of the success probability with respect to monitoring intensity also helps to capture the notion of systemic risk, namely of an underlying common factor that propagate projects' risk more than proportionally to the bank portfolio. This in turn increases bankers' rents, net of the cost of funding. On the other side, it increases the costs of processing information.[30]. Since monitoring is costly, bankers have incentives to reduce its intensity and to shift risk onto depositors. A contractual agreement disciplines the delegated monitoring through an incentive-compatible rent sharing. Low policy rates, by reducing the cost of

[30]Compatibly with relationship lending, the more time and resources loan officers invest in monitoring projects, the more information efficiency they gain.

outside funding, increase bankers' rents and relax the bankers' incentive compatibility constraint. Their incentives to monitor fall and projects' risk rises. Second, bankers choose leverage endogenously, due to an elastic supply of equity capital. This results in a variable price of capital and leverage. Falls in the policy rates, by relaxing the incentive compatibility constraint, allow bankers to leverage more. The fall in the demand of bank equity funding, needed to satisfy incentive compatibility, reduces the equity returns that are needed to meet supply. The change in the value of equity capital in turn increases the market value of leverage.

Those two forces combined imply that reductions in the policy rates rise leverage, reduce monitoring and increase the default risk of projects. Below we lay out the details, derivations and results of the baseline model. In Appendix B we show that results remain valid also under a variant of the model, in which we consider a more general measure of systemic risk, obtained through the co-dependency with a Vasicek (57) factor.

Consider an economy with two dates ($t = 0, 1$), a large set of entrepreneurs with zero wealth and a large set of risk-neutral investors. Some investors, bank capitalists or bankers, possess a monitoring technology to run projects, but do not have enough funds to run them. The banker raises additional funds from holders of short-term liabilities (whom we also refer to as depositors) and run the projects, acting as delegated monitors. Projects' success probability, $p(m)$, is an increasing and convex function of banks' monitoring intensity, m.[31] The latter is costly to banks, but unobservable to investors, giving rise to moral hazard. This is in turn is regulated through an incentive-compatible contractual agreement. Depositors receive an expected return share, $p(m)R^d$. Bank capitalists obtain the remaining share, $R^b = R - R^d$. We refer to short-term liabilities as D and to equity capital as BK. Given the unitary size of the project, we can define leverage as $d = 1 - \frac{BK}{D} = 1 - bk$.

Each entrepreneur has a project that requires a unitary investment at $t = 0$,[32] and yields a stochastic return $\widetilde{R}$ at $t = 1$, given by:

$$\widetilde{R} = \begin{cases} R & \text{with probability} \quad p(m) \\ 0 & \text{with probability} \quad 1 - p(m) \end{cases} \tag{3}$$

where $R > 0$ is the overall gross project return, $p(m) \in (0, 1)$ is the success probability common to all projects, and $m \in [0, p]$ is the bank's monitoring intensity. Firms can only fund projects from banks and will pay a loan rate R. Monitoring increases the probability of getting the high return R, but entails a linear cost cm.[33] The fact that both revenues and costs depend upon the monitoring intensity makes its choice endogenous.

To endogenize the choice of leverage we introduce an elastic supply of bank equity capital. Depositors participate to the contract if they extract an expected rate at least equal to the risk-

[31] See also Martinez-Miera and Repullo (45).
[32] The contract can be easily extended to an investment with variable size.
[33] Results can be easily generalized to convex cost functions.

free policy rate, R^f. Bank capitalists participate if they extract an expected rate that is at least equivalent to a return on a diversified market portfolio, $R^m(d)$. The latter is larger than the risk-free rate, as bank capitalists bear the loss-absorption capacity. Moreover it is increasing and concave with respect to leverage. Higher leverage means that the amount of bank capital needed to satisfy incentive-compatibility has decreased, hence lower equity returns are needed to meet supply. The fall in the price of capital decreases at higher levels of bank capital.[34] In this context the optimal choice of leverage is the one that maximizes the rents extracted by bank capitalists, net of the cost of funding and of the returns on an outside option, namely a market portfolio $R^m(d)$.

In the optimal contract, the bankers choose the monitoring intensity, m, and the leverage ratio, d, to maximize the expected profit, net of returns to depositors, given bankers' incentive compatibility constraint and the participation constraints of bankers and depositors. Therefore the optimal contract reads as follows:

$$\max_{\left\{d,R^h,m\right\}} \left[p(m)R^b(1-d) - cm\right] \tag{4}$$

where $R^b = R - R^d$, subject to the bankers' incentive compatibility constraint:

$$m^* = \arg\max \left\{ \left[p(m)R^b(1-d) - cm\right] \right\}, \tag{5}$$

the bankers' participation constraint:

$$d^* = \arg\max \left\{ \left[p(m^*)R^b(1-d) - cm^*\right] - R^m(d)(1-d) \right\} \tag{6}$$

and a depositor participation constraint:

$$p(m^*)R^d d \geq R^f d. \tag{7}$$

and a balance sheet constraint:

$$bk + d - cm \geq 1. \tag{8}$$

The incentive compatibility constraint (5) characterizes the bank's choice of monitoring m^* given the rate on banks' external funds, R^d, and the loan rate, R. The participation constraints (6) and (7) ensure that the bankers 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. The contract can be solved sequentially and by backward induction. First, bankers choose the optimal leverage ratio and then the monitoring intensity.

We start from the second stage, namely the choice of the monitoring intensity. An interior solution to the contract is given by:

$$p'(m)(R - R^d)(1-d) - c = 0 \tag{9}$$

[34] Such assumptions could be rationalized with the presence of adjustment costs in the market for bank equity. See Lenel, Piazzesi and Schneider(42).

Given the return on deposits that satisfies depositors' participation constraint

$$R^d = \frac{R^f}{p(m)}, \tag{10}$$

we can re-write the banks' first-order condition on the monitoring intensity as follows:

$$R(1-d) = \frac{c}{p'(m)} + \frac{R^f}{p(m)}(1-d) \tag{11}$$

Next, given the optimal monitoring intensity, m^*, bankers choose leverage, d, to solve (6). The first order condition reads as follows:

$$p'(m^*)(R - \frac{R^f}{p(m)}) = -R'^m(d)(1-d) + R^m(d) \tag{12}$$

The term $-R'^m(d)(1-d)+R^m(d)$ is an increasing function of d, since its derivative, $-R''^m(d)(1-d) + 2R'^m(d)$, is positive since $R'^m(d) > 0$ and $R''^m(d) < 0$. This implies that if the policy rate falls, to maintain the equality in (12), leverage has to rise. Hence, the model is able to capture the negative relation uncovered in the data between leverage and the policy rate.

Let us define the function $d^*(R^f)$, whereby $\frac{\partial d^*}{\partial R^f} < 0$ as per the above result. To examine the relation between the policy rate and the optimal monitoring intensity, whose value determines bank risk, we substitute $d^*(R^f)$ into the optimality condition (12). This leads to:

$$R = \frac{c}{(1-d^*(R^f))p'(m)} + \frac{R^f}{p(m)} \tag{13}$$

To determine how changes in R^f affect the monitoring intensity, we totally differentiate (13):

$$\left[-\frac{c(1-d^*(R^f))p''(m)}{(1-d^*(R^f))p'(m))^2} - \frac{R^f p'(m)}{(p(m))^2}\right] dm + \left[-\frac{c(\partial d^*/\partial R^f)p'(m)}{(1-d^*(R^f))p'(m))^2} + \frac{1}{p(m)}\right] dR^f - dR = 0 \tag{14}$$

From the above we obtain:

$$\frac{dm^*}{dR^f} = -\left[-\frac{c(\partial d^*/\partial R^f)}{(1-d^*(R^f))^2 p'(m)} + \frac{1}{p(m)}\right]\left[-\frac{cp''(m)}{(p'(m))^2} - \frac{R^f p'(m)}{(p(m))^2}\right]^{-1} \tag{15}$$

Since $\frac{\partial d^*}{\partial R^f} < 0$, $p'(m) > 0$ and $p''(m) > 0$ it follows that $\frac{dm^*}{dR^f} > 0$ always. Intuitively, a fall in the policy rate, by raising bank revenues, relaxes the incentive compatibility constraint. This allows bankers to leverage more and to monitor less, which leads to a more than proportional increase in risk.

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. Notwithstanding 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 deal with 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,[35] in which we augment our baseline model by adding a macroprudential index and interact it with the interest rate in each model equation.[36] 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 et al. (20) which provides annual numerical values in the form of integers for all countries in our sample from the years 2000 to 2017.[37] 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 8. 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 ΔCoVaR 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 ΔCoVaR 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

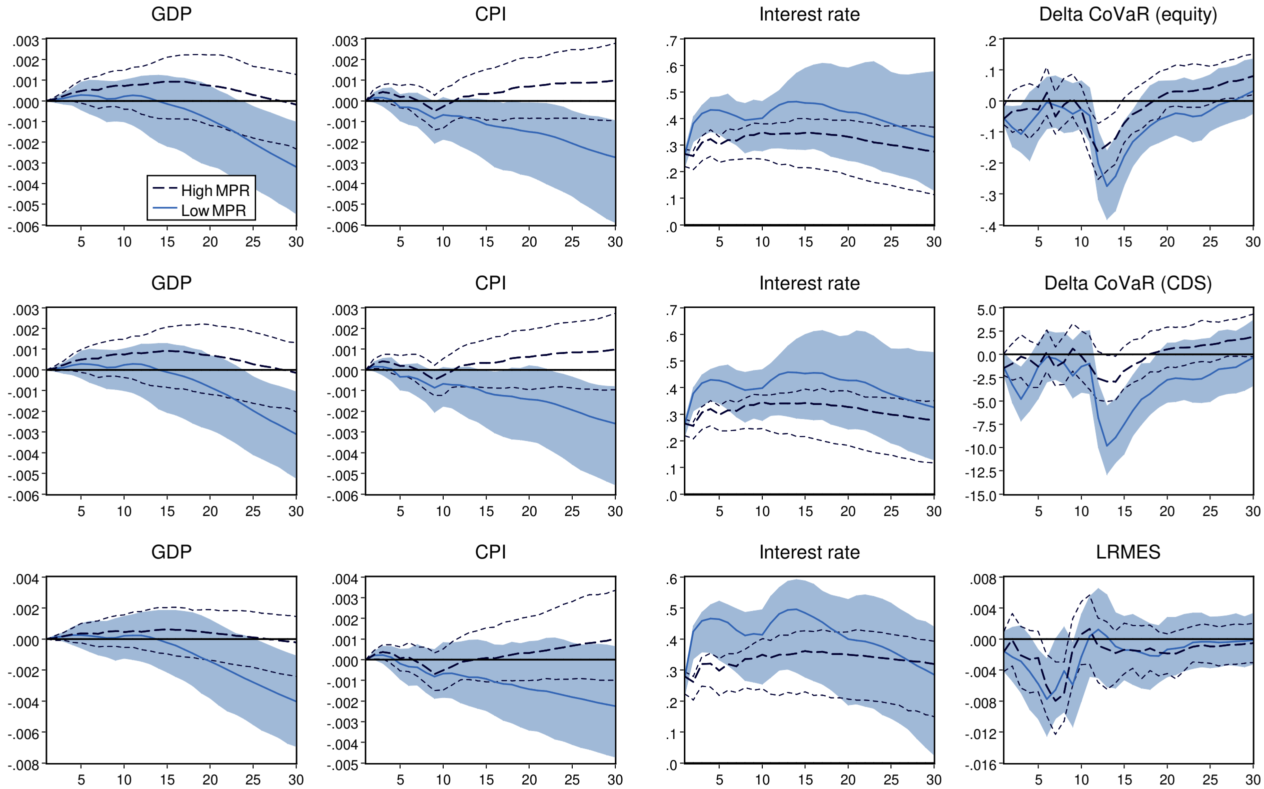
[35] This approach has been developed by Towbin and Weber (56), albeit in a entirely different context.

[36] 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.

[37] The indices are depicted in Figure 9 in Appendix A.

risk.

Figure 8: Interacted panel VAR with macroprudential index



Note. Impulse responses in the panel VAR(12) to a monetary policy shock. 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: 2000:06-2016:12. Blue solid and black dashed lines indicate macroprudential index at 10 and 90 percentiles, respectively. Dotted lines and shaded areas indicate 90% confidence bands.

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, 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 first note that, although we confirm a risk-taking channel also in the pre-crisis sample (see our results in Appendix C.1), responses are generally quantitatively smaller. Second, we exclude this possibility more directly, we conduct 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, while the high values are assigned in the post-crisis sample. We then estimate impulse responses for these placebo regulatory regimes. They are shown in Figure 14 in Appendix C. 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 8. In sum, our evidence suggests that macroprudential policy can tame systemic risk and complement 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 and cross-country evidence in a panel VAR for seven countries and 29-banks and a proxy VAR, for which we employ external instruments based on high-frequency surprises around monetary policy announcements for the US and Europe. The effects are visible for different systemic risk metrics (ΔCoVaR and LRMES) and we also find evidence of the systemic risk-taking channel in the pre-crisis period. We assess the economic channels behind this relation by augmenting our VARs with leverage. We identify the role of pecuniary externalities through the differential impact of monetary shocks on book and market leverage. The fact that the latter responds more sizeably and more significantly to monetary policy shocks shows that much of the transmission mechanism goes through changes in the market price of leverage, hence through pecuniary externalities. A counterfactual exercise, in which we shut off the response of market leverage, shows that the latter accounts for the bulk of the transmission onto systemic risk. We rationalize our results through a simple model with two channels. The first is a risk-taking channel, which arises from the bankers' delegated monitoring activity, whose intensity induces decreasing marginal costs and increasing projects' success probabilities. In this context, a fall in the policy rate increases bankers' incentives to shift risk onto depositors and reduces the costly monitoring intensity. This in turn increases projects' default risk. Second, bankers choose leverage endogenously, due to an elastic supply of equity capital. This results in a variable price of capital and leverage. Falls in the policy rate, by relaxing the incentive compatibility constraint, allow bankers to leverage more. The fall in the demand for bank equity funding reduces its price on the margin, hence raise market leverage.

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 showing that macroprudential policy are indeed be able to alleviate the systemic risk-taking channel of monetary policy we document.

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Appendix

A Data Description and Sources

A.1 Variables used

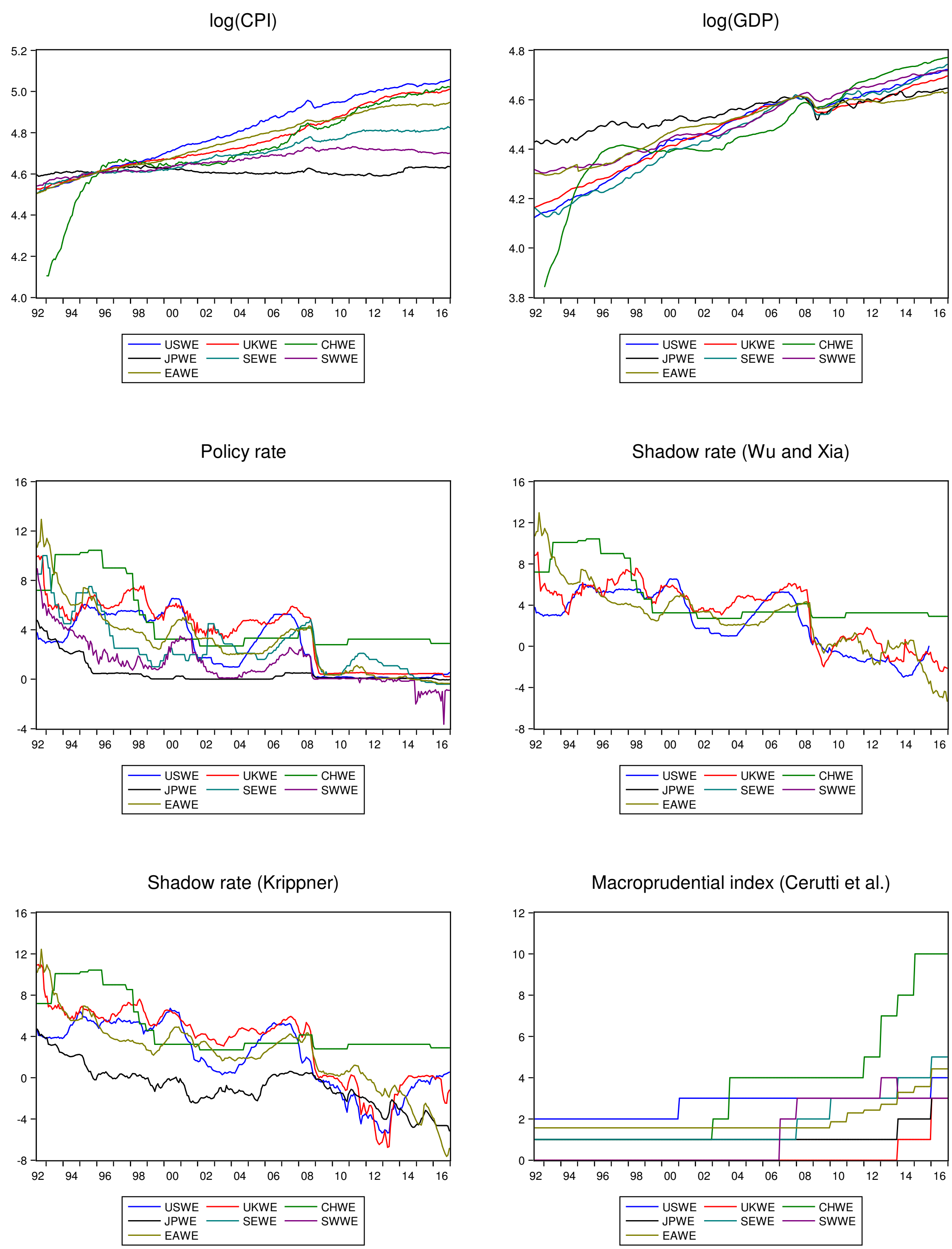
The panel VAR includes the following set of variables. Data sources for the country-level series are detailed in Table 2.

- **GDP:** Interpolated from quarterly to monthly data using the Chow-Lin (23) interpolation method with industrial production and retail sales as reference series.[38]
- **CPI**.
- **Monetary policy measures and instruments:**
  - Policy rate: Money market rates.
  - Wu and Xia (58) shadow rate
  - Krippner (38) shadow rate
  - US monetary policy shock series of Miranda-Agrippino and Ricco (44)
  - Euro area monetary policy shock series of Altavilla et al. (4)
- **Macroprudential regulation:** Index of macroprudential regulation (total) of Cerutti et al. (20)
- **LRMES:** Long-run marginal expected shortfall as defined in Acharya et al. (2)
- **ΔCoVaR (equity returns):** Authors' calculations based on Adrian and Brunnermeier (2016). Details on the measure and its computation are given in Appendix A.3.
- **ΔCoVaR (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 9 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 2. Table 1 lists all banks for which the risk metrics are calculated.

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

Figure 9: Time series used in panel VAR



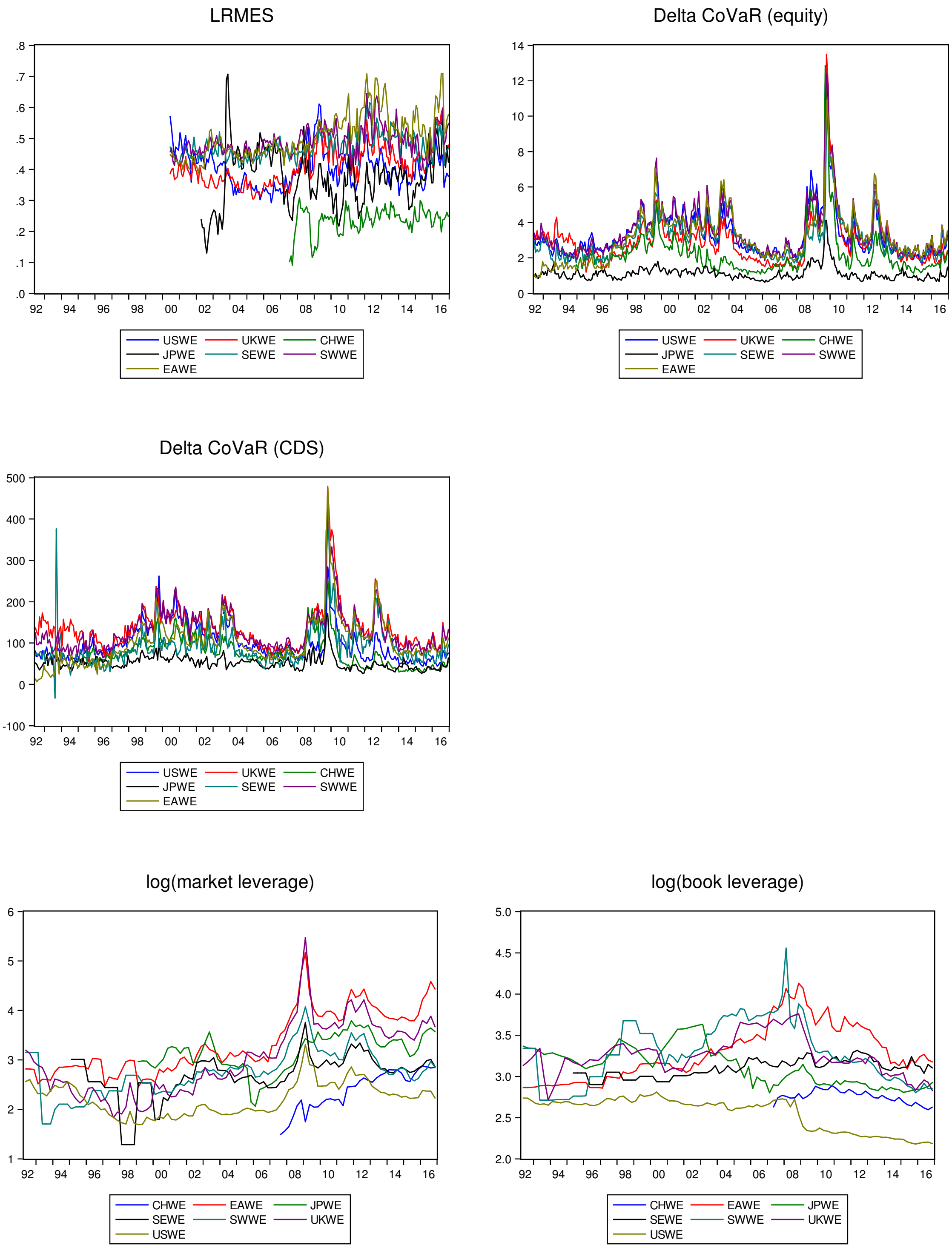


Figure shows data employed in the panel VAR model. Country series for bank-specific variables, namely the risk measures, are obtained by averaging over all banks headquartered in the respective country. *CHWE*- China, *EAWE* - Euro area, *JPWE* - Japan, *SEWE* - Sweden, *SWWE* - Switzerland, *UKWE* - United Kingdom, *USWE* - United States.

Table 1: G-SIBs used for risk measures

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

Global systemically important banks (G-SIBs) as defined in 2016 by the Financial Stability Board (FSB) in consultation with the Basel Committee on Banking Supervision (BCBS) at the Bank of International Settlements (BIS). Groupe BPCE is missing due to lacking data availability. For all banks we use market capitalization and market leverage data from V-Lab from June 2000 onward. Additional balance sheet data: *CC*: Compustat/CRSP, *WS*: Thomson Reuters Worldscope. Details on the construction of leverage measures and weights are given in section A.2.

Table 2: Data sources of country-level data

	United States	Japan	Switzerland	United Kingdom
Policy rate	Call money rate, OECD via FRED, IRSTCI01USM156N	Call money rate, OECD via FRED, IRSTCI01JPM156N	Call money rate, OECD via FRED, IRSTCI01CHM156N until 1999. From then onward SNB, EPB@SNB.zimoma1TGT	Call money rate, OECD via FRED, IRSTCI01GBM156N
CPI	OECD via FRED, CPALTT01USM661S	OECD via FRED, JPNCPI-ALLMINMEI	OECD via FRED, CHECPI-ALLMINMEI	OECD via FRED, GBRCPI-ALLMINMEI
GDP	OECD via FRED, LNBQRSA	OECD via FRED, LORSGPOR-JPQ661S	OECD via FRED, LNBQRSA	OECD via FRED, LNBQRSA
Industrial production	Board of Governors of the Federal Reserve System via FRED, IND-PRO	OECD via FRED, JPNPROIND-MISMEI	OECD via FRED, CHEP-ROINDQISMEI (quarterly values interpolated to monthly frequency based on constant match average method)	OECD via FRED, GBRPROIND-MISMEI
Shadow rate Wu Xia	Wu and Xia (2016)			Wu and Xia (2016)
Shadow rate Krippner	Krippner,	Krippner,		Krippner,
VIX	Datastream	Datastream	Datastream	Datastream
Retail sales	Datastream	Datastream	Datastream	Datastream
Stock market index	Datastream market index, Datas-tream	Datastream market index, Datas-tream	Datastream market index, Datas-tream	Datastream market index, Datas-tream
Real estate price index	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream
Long-term interest rate	10-year government bond rate, Datastream	10-year government bond rate, Datastream		10-year government bond rate, Datastream
Short-term interest rate	3-month treasury bill rate, Datas-tream		2-year government bond rate, Datastream	3-months treasury bill tender rate, Datastream
Interbank rate	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream
Corporate bond rate	Moody's BAA corporate bond yield, Datastream			5-year BBB coporate bond yield, Datastream

	Sweden	China	France	Germany
Policy rate	Call money rate, OECD via FRED, IRSTCI01SEM156N	Call money rate, OECD via FRED, IRSTCI01CNM156N	Call money rate, OECD via FRED, IRSTCI01FRM156N	Call money rate, OECD via FRED, IRSTCI01DEM156N
CPI	OECD via FRED, SWECPI-ALLMINMEI	OECD via FRED, CHNCPI-ALLMINMEI	OECD via FRED, FRACPI-ALLMINMEI	OECD via FRED, DEUCPI-ALLMINMEI
GDP	OECD via FRED, NAEXKP01SEQ661S	OECD via FRED, CHNGDPN-QDSMEI	OECD via FRED, LNBQRSA	OECD via FRED, NAEXKP01DEQ661S
Industrial production	OECD via FRED, SWEPROIND-MISMEI	OECD	OECD via FRED, FRAPROIND-MISMEI	OECD via FRED, DEUPROIND-MISMEI
Shadow rate Wu Xia			Wu and Xia (2016), used rates for European Monetary Union	Wu and Xia (2016), used rates for European Monetary Union
Shadow rate Krippner			Krippner, , , used rates for European Monetary Union	Krippner, used rates for European Monetary Union, ,
VIX	Datastream	Datastream (used world VIX due to nonavailability)	Datastream	Datastream
Retail sales	Datastream	Datastream	Datastream	Datastream
Stock market index	Datastream market index, Datastream	FTSE price index, Datastream	FTSE price index, Datastream	FTSE price index, Datastream
Real estate price index	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream
Long-term interest rate	10-year government bond rate, Datastream		10-year government bond rate, Datastream	10-year government bond rate, Datastream
Short-term interest rate	90-day treasury bill rate, Datastream		3-months treasury bill rate, Datastream	
Interbank rate	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream
Corporate bond rate			TMO private rate, Datastream	Umlaufsrenditen inländ. Inhaberschuldverschreibungen / Anleihen von Unternehmen (Nicht-MFIs), Bundesbank, BBK01.WT0022

	Spain	**Netherlands**	**Italy**
Policy rate	Call money rate, OECD via FRED, IRSTCI01ESM156N	Call money rate, OECD via FRED, IRSTCI01NLM156N	Call money rate, OECD via FRED, IRSTCI01ITM156N
CPI	OECD via FRED, ESPCPIALLMINMEI	OECD via FRED, NLDCPIALLMINMEI	OECD via FRED, ITACPIALLMINMEI
GDP	OECD via FRED, LNBQRSA	OECD via FRED, NAEXKP01NLQ661S	OECD via FRED, NAEXKP01ITQ661S
Industrial production	OECD via FRED, ESPPROINDMISMEI	OECD via FRED, NLDPROINDMISMEI	OECD via FRED, ITAPROINDMISMEI
Shadow rate Wu Xia	Wu and Xia (2016), used rates for European Monetary Union	Wu and Xia (2016), used rates for European Monetary Union	Wu and Xia (2016), used rates for European Monetary Union
Shadow rate Krippner	Krippner, used rates for European Monetary Union	Krippner, used rates for European Monetary Union, ,	Krippner, used rates for European Monetary Union, ,
VIX	Datastream (used world VIX due to nonavailability)	Datastream	Datastream (used world VIX due to nonavailability)
Retail sales	Datastream	Datastream	Datastream
Stock market index	FTSE price index, Datastream	FTSE price index, Datastream	FTSE price index, Datastream
Real estate price index	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream	Datastream real estate price index, Datastream
Long-term interest rate	10-year government bond rate, Datastream	10-year government bond rate, Datastream	10-year government bond rate, Datastream
Short-term interest rate	1-3-months treasury bill rate, Datastream		3-months treasury bill auction rate, Datastream
Interbank rate	Interbank offered rate, Datastream	Interbank offered rate, Datastream	Interbank offered rate, Datastream
Corporate bond rate			

A.2 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 1 provides an overview of the data availability for each bank, we detail the process in the 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 (1). We compare this data with market leverage series constructed on our own from two additional data sources, namely Compustat/CRSP and Thomson Reuters Worldscope.[39] 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.[40] 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 plausbility 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 are, however, entirely based on the reliable post-2000 V-Lab data. We nevertheless use the other data sources to run robustness checks and in an extended data sample period. In this process, whenever there are differences in the level or units

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

[40]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 hundereds up to 10,000. Inspection of the data reveals that these clearly unrealistic values are most likely the results of inaccurate market capitalization figures.

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 ΔCoVaR.

The long-run marginal expected short-fall is based on a methodology by Bronwless and Engle (15). The modeling framework is rationalized in Acharya, Pedersen, Philippon, and Richardson (2). LRMES refers to the expected capital shortfall of a financial firm given a protracted decline in the market (more than 40%). The marginal short-fall is defined in general as the capital that would be needed for the bank in order to be adequately capitalized after a crisis. Technically a bank's marginal expected short-fall is computed from the average return of its equity, R^b, during the 5% worst days for the overall market return, R^m, where the market is proxied by the CRSP Value Weighted Index:

$$MES_b = \frac{1}{\text{number of days}} \sum_{\text{t: system is in 5\% tail}} R_t^b \tag{16}$$

LRMES is then the average cumulated expected return in the stock price of each bank over all simulated crisis scenarios in the following six months computed using Monte-Carlo simulations of market and bank returns. This measure has the advantage of being linked to both market and bank assessment of the default probability, which in this case is proxied by the likelihood of being under-capitalized. We obtain LRMES time series for all banks in the sample from the V-Lab at the Leonard N. Stern School of Business, New York University.[41]

The second metric that we consider is ΔCoVaR by Adrian and Brunnermeier (3). They propose to measure systemic risk through the value-at-risk (CoVaR) of the financial system, conditional on institutions being in a state of distress. The contribution of a bank to systemic risk is then the difference between the CoVaR conditional on the institution being in distress and CoVaR in the median state of the institution. This metric has two advantages. First, it captures institutional externalities such as "too big to fail" and "too interconnected to fail". Second, it does not rely on contemporaneous price movements so it can be used to predict systemic risk. We compute two variants of this metric, one based on banks' equity prices and one based on banks' CDS spreads. The second should have higher predictive power since typically insurance prices embed market forecasts about future risk of default. Technically the definition of ΔCoVaR can be summarized as follows. Define the Value at Risk of a bank as:

$$\Pr(X^i \leq VaR^i_q) = q \tag{17}$$

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

$$\Pr(X^j \leq CoVaR^{j|i}_q | X^i = VaR^i_q) = q \tag{18}$$

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

$$\Delta CoVaR^{j|i}_q = CoVaR^{j|i}_q - CoVaR^{j|i}_{50\%} \tag{19}$$

where $CoVaR^{j|i}_{50\%}$ denotes the VaR of j's asset returns when i's returns are at their median (i.e. 50th percentile). Like Adrian and Brunnermeier (3) we focus on the case in which $j = system$, namely when the portfolio return of all financial institutions is at its VaR level.

The procedure to estimate ΔCoVaR in practice is based on a set of quantile regressions 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:

$$X^{system}_t = \alpha^{system}_q + \beta^{system|i}_q X^i_t + \gamma^{system|i}_q M_{t-1} + \varepsilon^i_t. \tag{20}$$

For the equity-based ΔCoVaR measure, X^k_t, $k \in \{i, system\}$, denotes equity market returns in per cent for bank i and of all banks in sample, respectively. For the CDS-based measure, X^i_t is the 5-year CDS spread in basis points, whereas X^{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 $q = 0.05$ represents the quantile on which the regression is based. We denote the estimated coefficient of each bank's contribution to system-wide losses as $\hat{\beta}^{system|i}_q$. Second, we run the following two quantile regressions to obtain estimates of the conditional VaR of each bank i for $q = 0.05$ and

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

$q = 0.5$:

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_t^i, \tag{21}$$

$$X_t^i = \alpha_{50}^i + \gamma_{50}^i M_{t-1} + \varepsilon_t^i. \tag{22}$$

Finally, denoting the predicted values of (21) and (22) as $VaR_{q,t}^i \equiv \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}$ and $VaR_{50,t}^i \equiv \hat{\alpha}_{50}^i + \hat{\gamma}_{50}^i M_{t-1}$, respectively,[42] we obtain $\Delta CoVaR_{q,t}^i$ as

$$\Delta CoVaR_{q,t}^i = \hat{\beta}_q^{system|i}(VaR_{q,t}^i - VaR_{50,t}^i). \tag{23}$$

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

- change in the three-month yield
- change in the slope of the yield curve, measured by the spread between a ten-year government bond yield and the three-month bill rate
- short-term TED spread, defined as the difference between the three-month LIBOR and treasury bill rates
- change in the credit spread given by Moody's Baa-rated bond yield and the ten-year government bond rate
- return of the Datastream broad stock market index
- real estate sector return in excess of the market financial sector return
- volatility of each bank's market returns, defined as the weekly averages of 22-day rolling window standard deviations of daily market returns
- implied volatility as measured by the VIX

Since for some countries not all of the above control variables are available, for all non-US countries we use the US controls wherever country-specific controls could not be obtained. These are described, along the data sources, in Table 2. Like Adrian and Brunnermeier (3) we restrict estimation to banks with at least 260 weekly observations. The resulting ΔCoVaR time series are

[42] 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_t^i are equity returns, it significantly increases the sample length for the CDS-based ΔCoVaR measure since CDS spreads are generally not available before the year 2002 and for some banks even 2008.

depicted as country averages in Figure 9.[43]

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

$$A_0 Y_t = A(L)Y_{t-1} + \epsilon_t \tag{24}$$

with the corresponding reduced form

$$Y_t = B(L)Y_{t-1} + u_t \tag{25}$$

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

$$u_t = A_0^{-1}\epsilon_t. \tag{26}$$

We may partition the shock vectors into those of the monetary policy measure, indicated with a superscript p, and those of the remaining shocks with superscript q. The corresponding vectors then read as follows: $u_t = [u_t^p, u_t^{q\prime}]', \epsilon_t = [\epsilon_t^p, \epsilon_t^{q\prime}]'$. Denoting then the impact matrix A_0^{-1} as S, we are interested in that column of S, denoted as s, that gives the initial impact to a structural monetary policy shock ϵ_t^p.[44] In what follows, we denote as s^q the initial impact of ϵ_t^p on u_t^q, while s^p is the corresponding impact on the reduced-form monetary policy residual u_t^p.

Building on Stock and Watson (54) and Mertens and Ravn (46) and following Gertler and Karadi (32), we use instruments from the high-frequency identification literature of monetary policy surprises in the proxy VAR to identify the structural innovations ϵ_t^p. For these instruments to be valid, we assume the surprise series Z_t to be *relevant* and *exogenous* as follows:

$$\mathbb{E}[Z_t \epsilon_t^{p\prime}] = \phi \neq 0, \tag{27}$$

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

Since we are ultimately concerned with estimating impulse responses based on

$$Y_t = B(L)Y_{t-1} + s\epsilon_t^p, \tag{28}$$

we derive estimates of s in the following manner. We first run the reduced-form VAR and obtain

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

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

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

$$u_t^q = \frac{s^q}{s^p}\hat{u}_t^p + \xi_t. \tag{29}$$

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 (32) 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. (21) 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 (44) and simply compute the sum of all daily shocks arising in the particular month/quarter. All months without a monetary policy meeting a assigned a zero value. Experimenting with these two aggregation schemes we find that the differences are most often not large.

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 (43)) 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:

$$\Sigma \sim \mathcal{W}^{-1}(\Psi, \nu) \tag{30}$$

$$\beta \sim \mathcal{N}(b, \Sigma \otimes \Omega). \tag{31}$$

Ψ 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 ψ_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

$$\mathbb{E}[(A_l)_{i,j}|\Sigma] = \begin{cases} \delta_i & i=j, l=1 \\ 0 & \text{otherwise} \end{cases} \tag{32}$$

$$\mathbb{V}ar[(A_l)_{i,j}|\Sigma] = \begin{cases} \frac{\lambda^2}{l^2} & i=j, \forall l \\ 0 & i \neq j, \forall l \end{cases} \tag{33}$$

where $(A_l)_{i,j}$ 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. (11) for potentially stationary variables). The hyperparameter λ controls the overall tightness of the Minnesota prior. In the benchmark case we have it determined optimally in the spirit of hierarchical modelling as in Gianonne et al. (33), but verify that our results hold also when setting λ to a very large value, in which case the posterior coefficient estimates correspond to their 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 specifiying 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 (10), 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).[45]

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

$$Y_t = D(L)\epsilon_t, \tag{34}$$

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

$$\hat{D}_h(4,3) = 0 \quad \forall h = 0, 1, ..., H. \tag{35}$$

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

$$\hat{\epsilon}_0^4 = -\frac{D_0(4,3)}{D_0(4,4)} \tag{36}$$

[45]As an alternative method to arrive at counterfactual impulse reponses we also compute responses based on a VAR model where we impose a zero response of the 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.

and then find the remaining ones recursively as

$$\hat{\epsilon}_h^4 = -\frac{D_h(4,3) + \sum_{k=0}^{h-1} D_k(4,4)\hat{\epsilon}_k^4}{D_0(4,4)}, \tag{37}$$

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

$$\hat{D}_h = D_h + \sum_{k=0}^{h-1} \hat{\epsilon}_k^4, \tag{38}$$

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 (56). In keeping with the notation used so far an interacted VAR can be written as

$$y_{i,t} = E_0 X_{i,t} + \sum_{l=1}^{p} (A_l Y_{i,t-l} + E_l Y_{i,t-l} X_{i,t}) + u_{i,t}, \tag{39}$$

where $X_{i,t}$ is the macroprudential index of Cerutti et al. (20) 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. (1) we use the 10th and 90th percentile of the distribution of the index across countries in the sample and write the model as

$$y_{i,t}^{high} = \hat{E}_0^{high} X_{i,t} + \sum_{l=1}^{p} (\hat{A}_l^{high} Y_{i,t-l} + \hat{E}_l^{high} Y_{i,t-l} X_{i,t}) + \hat{u}_{i,t}, \tag{40}$$

and

$$y_{i,t}^{low} = \hat{E}_0^{low} X_{i,t} + \sum_{l=1}^{p} (\hat{A}_l^{low} Y_{i,t-l} + \hat{E}_l^{low} Y_{i,t-l} X_{i,t}) + \hat{u}_{i,t}. \tag{41}$$

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_l 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 Addition to the theoretical model

To show that our model rationale remains valid under more extended settings we consider a more general measure of systemic risk. Under the assumption that banks' projects are fully correlated, aggregate or systemic risk in the model is just equal to $1-p(m)$. However, measure of systemic risk do take into account also risk correlation across banks. We therefore modify the model measure of systemic risk by making it dependent on a latent variable. We do so by employing the single risk factor model of Vasicek (57) 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:

$$y_p = -\Phi^{-1}(1-p(m)) + \sqrt{\rho}z + \sqrt{1-\rho}\varepsilon_p \tag{42}$$

where z is a systematic risk factor that affects all types of projects, ε_p is an idiosyncratic risk factor that only applies to projects of entrepreneurs of type p. z and ε_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:

$$1-p(m) = \Pr(y_p \leq 0) = \Pr(\sqrt{\rho}z + \sqrt{1-\rho}\varepsilon_p \leq \Phi^{-1}(1-p(m))) \tag{43}$$

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 (43).

C Additional results and robustness checks

C.1 Robustness checks for the panel VAR

We verify that our panel VAR results are robust along many dimensions.

- In Figure 12, 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.

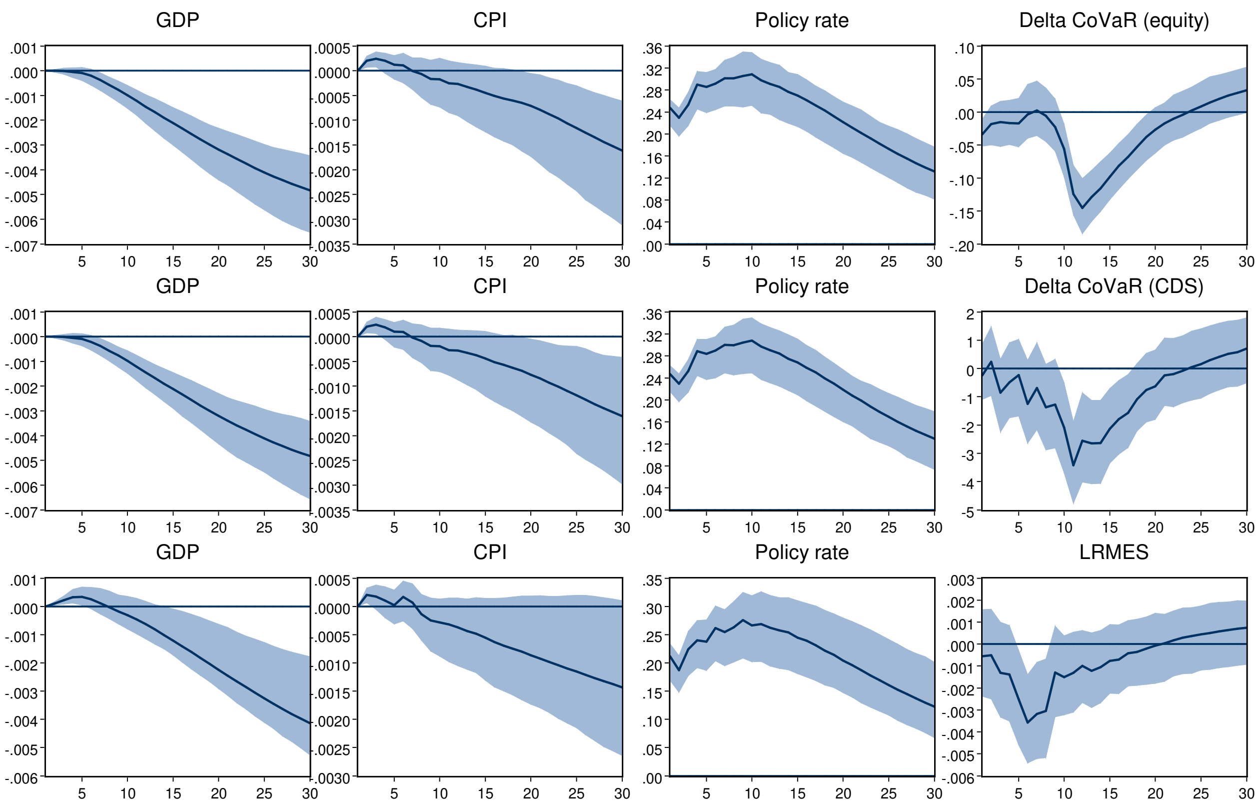
- Figures 10 and 11 show that systemic risk responses to a monetary tightening are similar when we use actual central bank policy rates and the shadow rate estimates by Wu and Xia (58), respectively.

- Figure 13 shows that the risk-taking channel is present even in the pre-crisis period.

In the following cases, figures are not reported for brevity, but available upon request. Results remain robust when we

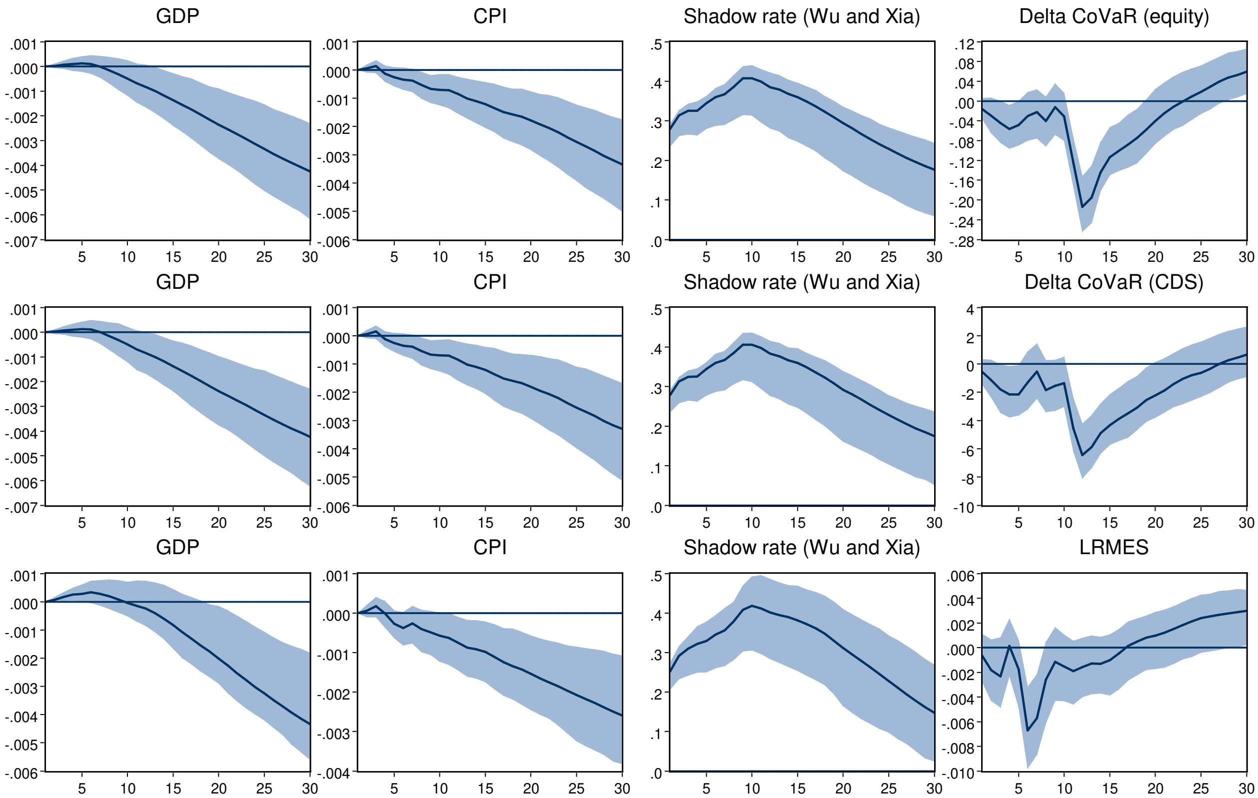
- estimate a stationary VAR in the growth rates of GDP and CPI or when we add a linear time trend.
- estimate our panel VAR with the mean-group estimator, as proposed by Pesaran and Smith (49), which alleviates concerns about parameter biases stemming from heterogeneity in the coefficient matrices across countries.
- estimate a FAVAR for the US (results are available in an earlier version of our paper).
- reverse the order of leverage and risk measures or extend back the time sample to start in 1992 in the ΔCoVaR models in the leverage augmented VARs.

Figure 10: Panel VAR with central bank policy rate (instead of shadow rate)



Note. Impulse responses in the panel VAR(12) to a monetary policy shock. 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 11: Panel VAR with Wu and Xia (instead of Krippner) shadow rate

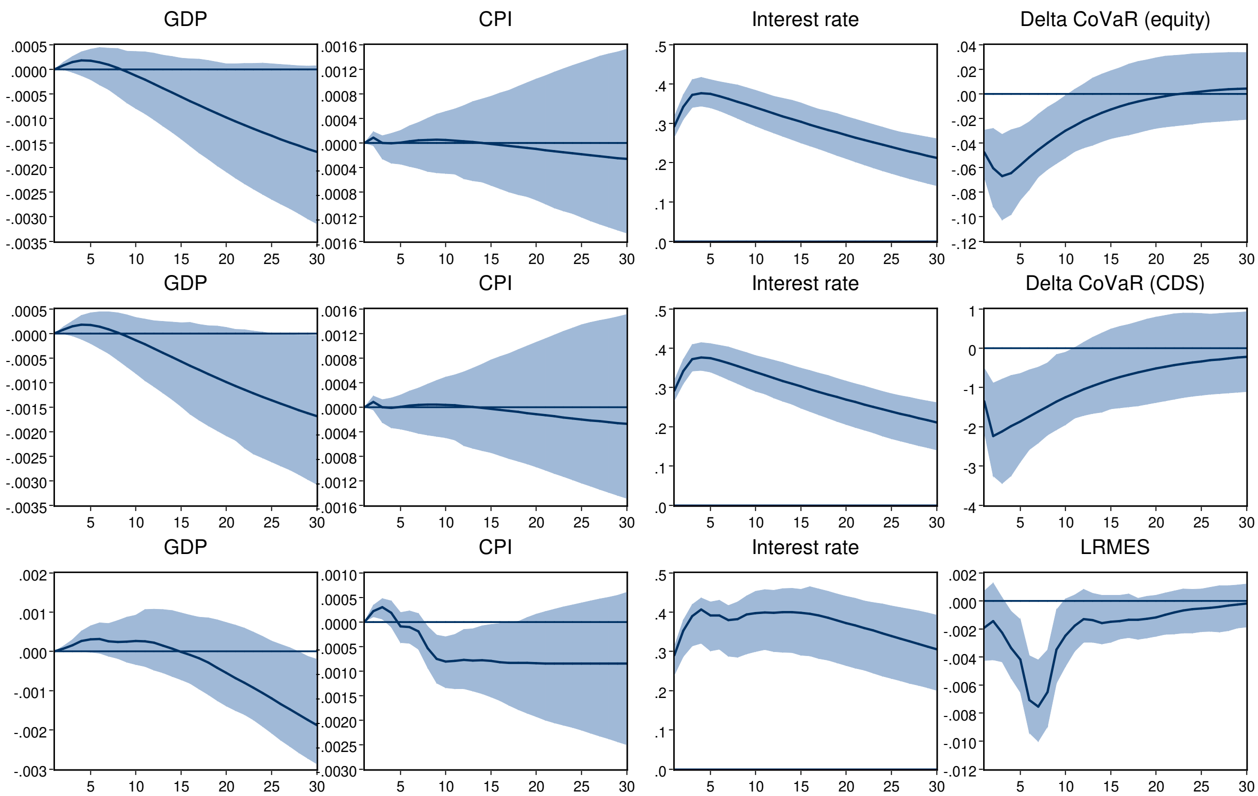


Note. Impulse responses in the panel VAR(12) to a monetary policy shock. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second and LRMES in the third). Variable ordering: GDP, CPI, interest rate, risk measure. Countries 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.

C.2 Robustness checks for the proxy VAR

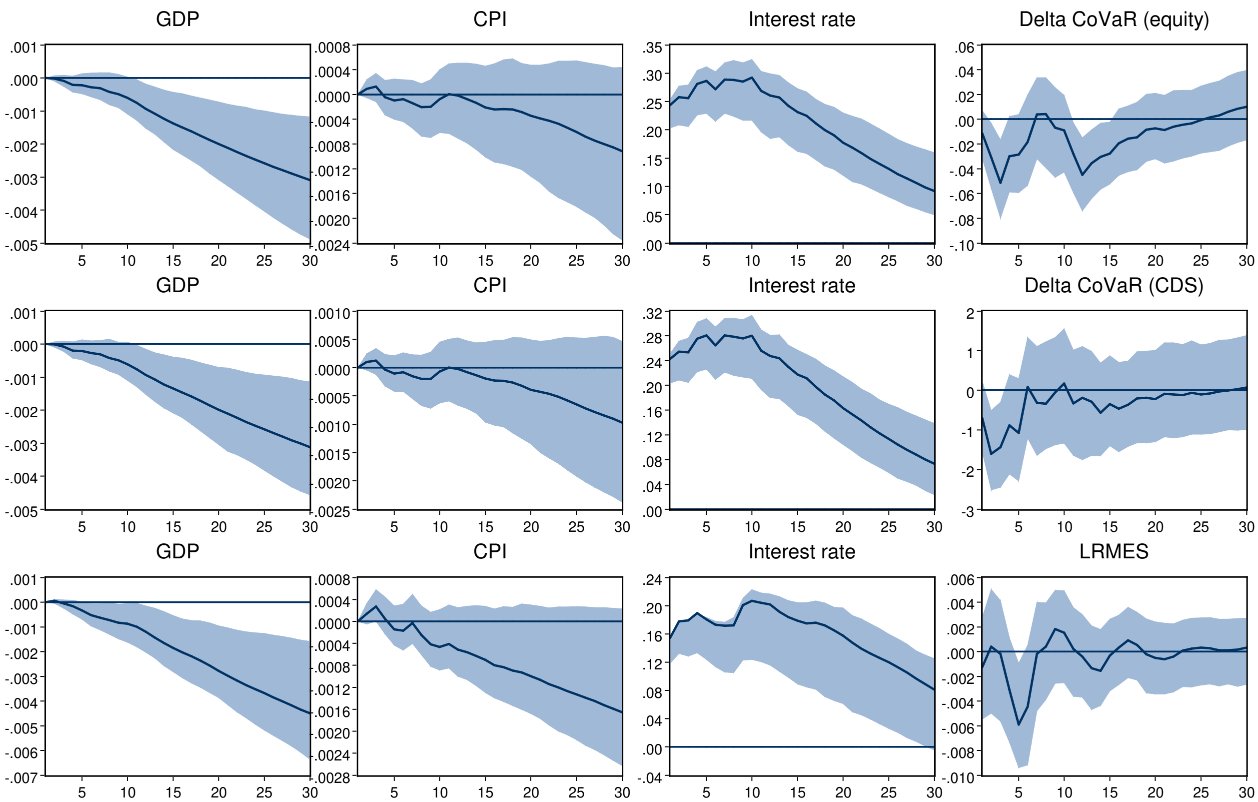
- Figure 16 shows that the risk-taking channel remains intact when we use flat priors.
- Figure 15 shows results for the pre-crisis sample, for which we still find evidence for the systemic-risk taking channel.
- Changes in lag lengths do not meaningfully alter our results.
- We experiment with different 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. The finding that systemic risk metrics fall following a monetary policy shock is robust to these variations.

Figure 12: Panel VAR with three (instead of twelve) lags



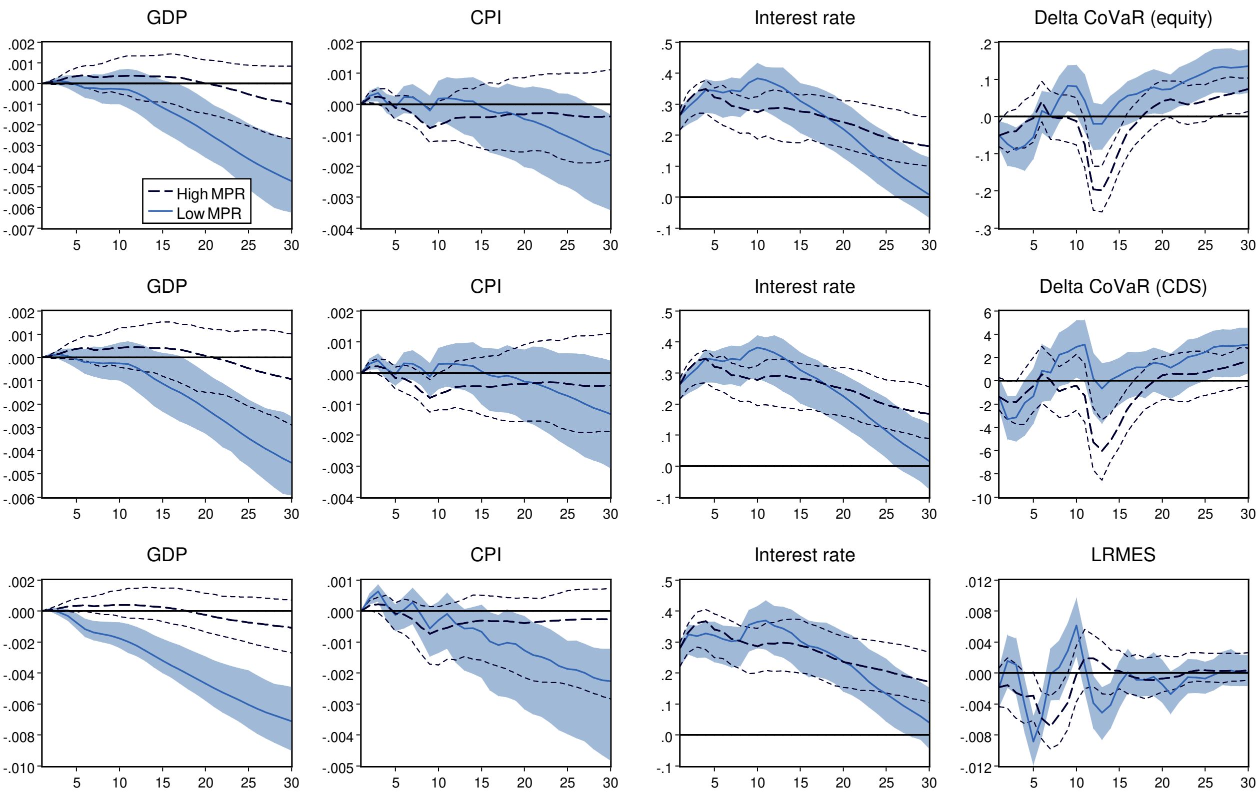
Note. Impulse responses in the panel VAR(3) to a monetary policy shock. Remaining details as in Figure 1.

Figure 13: Panel VAR in pre-crisis sample



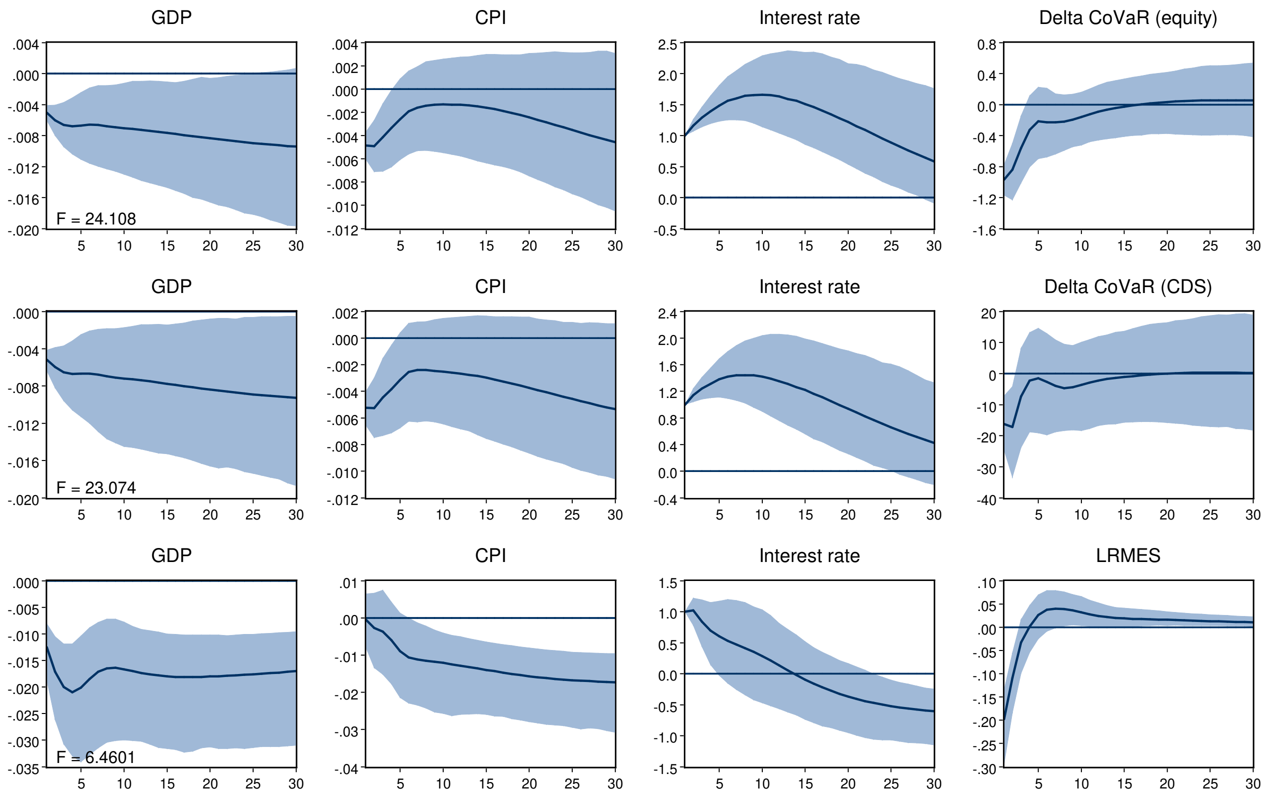
Note. Impulse responses in the panel VAR(12) (ΔCoVaR) and VAR(9) (LRMES), respectively, to a monetary policy shock. Time sample: 1992:06-2007:09. Remaining details as in Figure 1.

Figure 14: Placebo test in interacted panel VAR



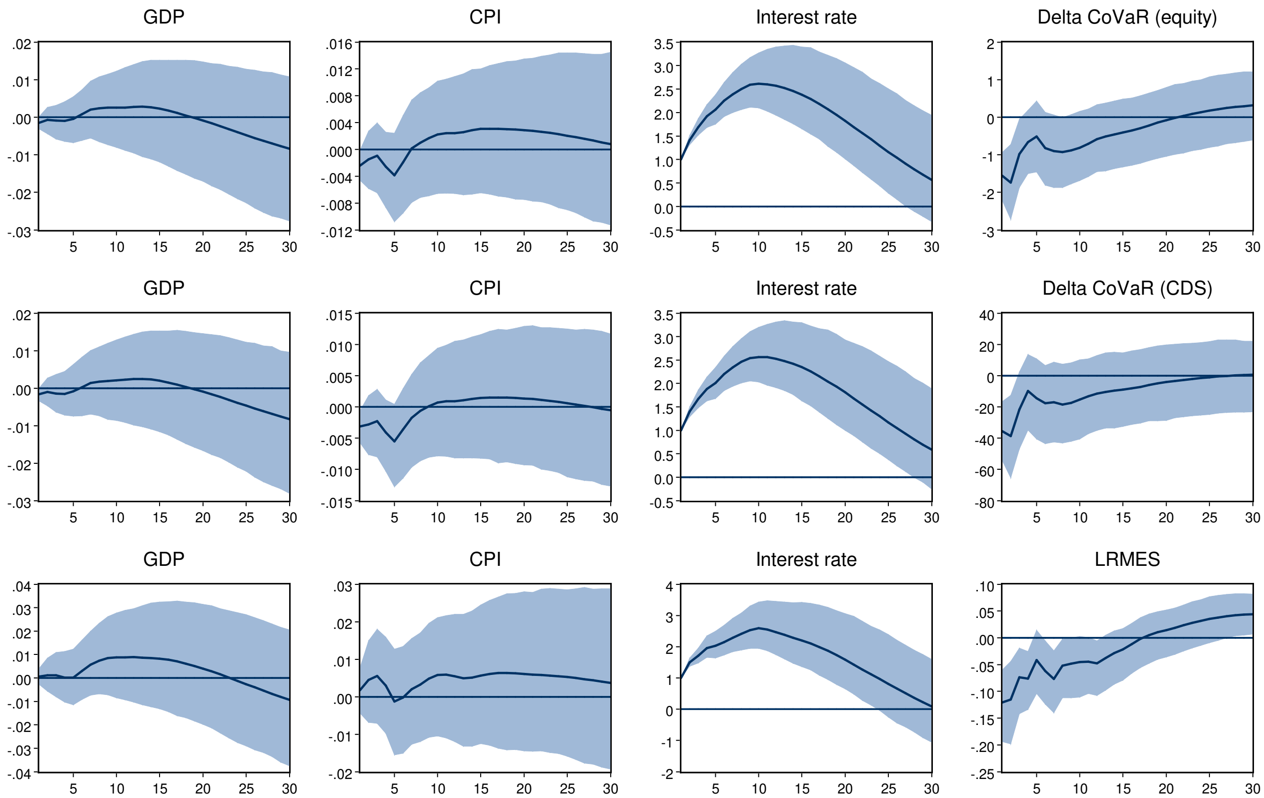
Note. Impulse responses in the panel VAR(12) to a shock to the interest rate. Blue solid and black dashed lines indicate an artificial macroprudential index of 1 and 4 (representative of the 10th and 90th percentiles used in Figure 8, respectively, in the sample 2000:06-2007:07 and 2007:08-2016:12. Dotted lines and shaded areas indicate 90% confidence bands.

Figure 15: 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 16: 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.