This is a pre print version of the following article:

The effects of monetary policy on macroeconomic risk / Forni, M., Gambetti, L., Maffei-Faccioli, N., Sala, L.. - In: EUROPEAN ECONOMIC REVIEW. - ISSN 0014-2921. - 167:(2024), pp. 104789-104789. [10.1016/j.euroecorev.2024.104789]

Terms of use:

The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

16/06/2026 23:26

(Article begins on next page)

The Effects of Monetary Policy on Macroeconomic Risk[*]

Mario Forni
Università di Modena e Reggio Emilia, CEPR and RECent

Luca Gambetti[†]
Universitat Autònoma de Barcelona, BSE, Università di Torino and CCA

Nicolò Maffei-Faccioli
Norges Bank

Luca Sala
Università Bocconi, IGIER, Baffi CAREFIN

Abstract

Monetary policy expansions significantly reduce macroeconomic downside risk, measured as the difference between the median and the 5th percentile of the industrial production growth forecast distribution. However, the effects are smaller in magnitude than those of credit spread shocks, which we find to be a major driver of fluctuations in downside risk. As a consequence, large policy interventions are required to stabilize risk originating from the financial sector, with undesirable consequences in terms of both price and output stability. These findings are obtained using US data and a novel econometric approach which combines quantile regressions and Structural VAR analysis.

JEL classification: C32, E32.

Keywords: Macroeconomic Risk, Uncertainty, Skewness, Forecast Distribution, SVAR, Credit Spreads Shocks, Monetary Policy Shocks, Quantile Regressions.

---

[*] This paper should not be reported as representing the views of Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of the Norges Bank. We thank Ivan Petrella for useful comments. The authors acknowledge the financial support of the Italian Ministry of Research and University, PRIN 2017, grant J44I20000180001.

[†] Luca Gambetti acknowledges the financial support from the Spanish Ministry of Science and Innovation, through the Severo Ochoa Programme for Centres of Excellence in R&D (CEX2019-000915-S), the financial support of the Spanish Ministry of Science, Innovation and Universities through grant PGC2018-094364-B-I00, and the BSE Research Network.

1 Introduction

Macroeconomic risk dynamics have recently attracted considerable attention from both the academia and policymakers, see Adrian et al. (2019), Plagborg-Møller et al. (2020), Giglio et al. (2016), Delle Monache et al. (2020), Loria et al. (2019) and Carriero et al. (2020). Empirical evidence robustly shows that downside risk – the difference between the median and the 5th percentile of the GDP growth forecast distribution – is highly countercyclical and more volatile than upside risk – the difference between the 95th percentile and the median. Adrian et al. (2019) finds that fluctuations in downside risk are predicted by financial variables and consequently their main conclusion is that financial conditions represent a major source of risk fluctuations.[1]

A central question that naturally arises in this literature is what type of policy could be effective in stabilizing risk fluctuations. In this paper, we assess the role of monetary policy. We investigate whether policy easing can be effective in stabilizing risk, in particular whether it can offset downside risk fluctuations originating from the financial sector. To do so, we jointly identify monetary policy shocks and credit spread shocks using an econometric model which combines quantile regressions and structural VARs.[2] The approach builds on and complements the model in Forni, Gambetti and Sala (2021). Quantile regressions are employed to estimate the conditional quantiles of the forecast distribution of a target variable (industrial production growth) using a set of macroeconomic and financial predictors. Such predictors have a VAR representation and thus an impulse response functions representation in terms of structural shocks. This implies that the quantiles themselves and their linear functions (including risk) have an impulse response functions representation in terms of the structural shocks. The monetary policy shock is identified

---

[1] López-Salido and Loria (2020) provides a similar investigation for the dynamics of the forecast distribution of inflation in the US and the Euro Area. They find substantial variability in the tails of the inflation distribution even in the pre-pandemic period characterized by stable inflation.

[2] The motivation for our focus on credit spread shocks is twofold. On the on hand, the results in Adrian et al. (2019) suggest that financial conditions play a significant role in influencing risk fluctuations. On the other hand, Gilchrist and Zakrajšek (2012) found that credit spread shocks are important drivers of macroeconomic fluctuations, see also Peersman (2011), Meeks (2012), Peersman and Wagner (2015), Caldara et al (2016), Gambetti and Musso (2017), Furlanetto et al. (2019) and Brianti (2023).

using an external instrument approach (see Stock and Watson, 2018, Mertens and Ravn, 2013, Gertler and Karadi, 2015 and Miranda-Agrippino and Ricco, 2021). The credit spread shock is identified along the lines of Gilchrist and Zakrajšek (2012) using a recursive scheme and by also imposing orthogonality to the policy shock.

Specifically, the financial shock is defined as an innovation to the excess bond premium which has no effect on macroeconomic variables within a month but can affect financial variables contemporaneously. Admittedly, such shock may miss the simultaneous responses of macroeconomic variables or may partly capture the potentially non-linear response of the excess bond premium to large negative business cycle fluctuations. Since our aim is to study whether monetary policy can be effective in stabilizing risk, we believe that the identified financial shock represents a useful proxy for evaluating risk arising in the financial sector.

Our main findings are the following. First, in line with existing evidence, downside risk is considerably more volatile than upside risk, and it is highly countercyclical. Second, monetary policy shocks have significant effects on macroeconomic risk: a policy easing significantly reduces downside risk. Third, the effects of monetary policy shocks are substantially smaller than those of credit spread shocks, which are found to explain the bulk of fluctuations in downside risk.

Our main conclusion is that monetary policy can be effective in stabilizing risk. However, large policy interventions are required to stabilize risk arising from the financial sector. This has undesirable consequences in term of price stability since large expansionary policies significantly increase prices. From a back-of-the-envelope calculation, a two standard deviation monetary policy shock is needed to offset the increase in downside risk arising from a one standard deviation credit spread shock. Such a policy action would have destabilizing effects on prices: inflation increases by around 2.2% (at annualized rate) within 1 month after the shock.

This paper is closely related to Loria et al. (2019), which uses quantile local projections to study the effects of several macroeconomic shocks on risk. The main methodological difference relative to their paper is that our analysis is performed in a single model linking the Structural Vector Autoregression (SVAR) and quantile regressions. Our approach presents several advantages. First, the unified framework ensures consistency between the distribution dynamics and the responses of the variables included in the VAR. Second, variance and historical decompositions for different quantiles can be derived as in the SVAR literature and scenario and counterfactual analysis can be performed (see e.g. Antolín-Díaz et al., 2021, and the references therein). The different methodology could be at the root of the divergence in results, as Loria et al. (2019) find that both financial and monetary policy shocks are equally important for risk.

Our model is similar in spirit to the quantile VAR proposed by Chavleishvili and Manganelli (2024). The two approaches present advantages and disadvantages. The quantile VAR is more general than our approach since it considers the whole multivariate forecast distribution of the variables included in the model. However, it has the potential drawback that the approach is, by construction, order dependent (as quantiles of each of the variables are estimated conditioning on the contemporaneous quantiles of the variables ordered before the variables itself in the VAR as in a standard Cholesky identified VAR), thus requiring a strong prior on a particular ordering of the variables. The main advantage of our approach is that is very easy to estimate and very flexible in terms of identification schemes. Since shocks identification works exactly the same way as in standard SVARs, impulse response functions and variance decomposition analyses are easy to perform for any shock of interest. The main limitation, as mentioned above, is that the procedure models only univariate marginal distributions as opposed to modeling the (conditional) quantiles of the joint multivariate density. We plan to extend the model in this direction in our future research.

The remainder of the paper is organized as follows. Section 2 lays out the econometric approach. Section 3 presents the main findings and some robustness checks. Section 4 concludes.

2 Econometric approach

The model has two main ingredients. First, there is a SVAR representation for a set of macroeconomic variables. Second, there is a quantile regression that relates the quantiles of the forecast distribution of a variable of interest to the variables included in the VAR. These two features establish a link between quantiles and structural shocks, where the impulse response functions of the quantiles (or of any linear function of them) are linear combinations of the quantile regression coefficients and the impulse response functions of the predictors.

2.1 SVAR representation

To begin with, we assume that y_t, a vector of macroeconomic variables, follows (abstracting from the constant term) the VAR model:

$$A(L)y_t = \varepsilon_t, \tag{1}$$

where $\varepsilon_t \sim WN(0, \Sigma_\varepsilon)$ is a vector of reduced-form white-noise residuals and $A(L) = I - \sum_{k=1}^{p} A_k L^k$ is a matrix of degree-p polynomials in the lag operator L. By inverting the VAR, we obtain the moving average:

$$y_t = C(L)\varepsilon_t, \tag{2}$$

where $C(L) = \sum_{k=0}^{\infty} C_k L^k = A(L)^{-1}$ (with $C_0 = I_n$). From (2), we can derive the structural representation:

$$y_t = C(L)B_0 u_t = B(L)u_t, \tag{3}$$

where $B_0 B_0' = \Sigma_\varepsilon$, $u_t = B_0^{-1}\varepsilon_t \sim WN(0, I)$ is the vector of structural shocks and $B(L) = B_0 + B_1 L + B_2 L^2 + ...$ is a matrix of structural impulse response functions.

2.2 Forecast distribution quantiles

Let x_t be the target variable whose distribution has to be predicted and let y_t be the vector of n macroeconomic variables included in the VAR in (1). Let $w_t = Wy_t$ be the r-dimensional subvector of variables which are important to forecast x_t, where W is a $r \times n$ matrix of zeros and ones selecting the appropriate predictors in y_t.

The quantiles of the h-period ahead forecast distribution of x_t are estimated using conditional quantile regressions. The τ-th quantile, Q_t^τ, of x_{t+h}, conditional on the predictors w_t, is a linear function of the predictors:

$$Q_t^\tau = \beta_\tau'(L)w_t = \beta_\tau'(L)Wy_t = \tilde{\beta}_\tau'(L)y_t,$$

where $\tilde{\beta}_\tau'(L) = \beta_\tau'(L)W$ and $\beta_\tau(L)$ is a r-dimensional vector of polynomials in the lag operator L. Since the quantiles are linear in y_t, any linear combination z_t^j of the quantiles can be written as a linear combination of current and lagged macroeconomic variables:

$$z_t^j = \gamma_j'(L)y_t, \tag{4}$$

where $\gamma_j(L) = \gamma_{j0} + \gamma_{j1}L + ...\gamma_{jq}L^q$ is an n-dimensional vector of polynomials in L.

The parameters $\beta_\tau(L)$ are estimated using the smoothed quantile regression estimator recently proposed by Fernandes et al. (2021) and Natal and Horta (2022). The basic novelty of this estimator is that it uses a smoothing of the standard objective function typically used in conditional quantile regressions.[3] The advantage of this estimator is that (i) it is more accurate than the standard estimator and (ii) it does not suffer from the curse of dimensionality, so that it is possible to use several predictors. In addition, (iii) the kernel estimator is continuously differentiable and increasing in the quantiles.[4] Moreover, (iv) it is possible to compute the asymptotic standard deviation of the estimated coefficients to get confidence bands and (v) obtain a consistent estimate of the conditional probability density function, without the need of resorting to an interpolation like the one used in Adrian et al. (2019). The estimator has a parameter governing the bandwidth. To set this parameter, we use the rule of thumb suggested by Fernandes et al. (2021).

Finally, estimates of the polynomials $\gamma_j(L)$ can simply be obtained by replacing the quantile parameters $\tilde{\beta}_\tau(L)$ with their estimates obtained from the quantile regression.

---

[3] See Koenker and Bassett (1978).

[4] The latter property holds for the average covariates, but in practice it is rarely violated elsewhere.

2.3 Distribution dynamics

By combining (4) and (3) we can see that any linear combination of the quantiles, $z_t^j = \gamma_j'(L)y_t$, has the following dynamic structural representation:

$$z_t^j = \gamma_j'(L)B(L)u_t, \tag{5}$$

where the polynomial $\gamma_j'(L)B(L)$ represents the impulse response functions to the structural shocks u_t.[5]

We focus here on four main features of the forecast distribution: downside risk, upside risk, uncertainty and asymmetry. *Downside risk* is a measure of the left tail and is defined as the distance of the median from the 5th percentile:

$$z_t^D = \gamma_L'(L)y_t = Q_t^{0.5} - Q_t^{0.05} = \left[\beta_{0.5}'(L) - \beta_{0.05}'(L)\right] B(L)u_t,$$

while *upside risk*, a measure of the right tail, is defined as the distance of the 95th percentile from the median:

$$z_t^U = \gamma_R'(L)y_t = Q_t^{0.95} - Q_t^{0.5} = [\beta_{0.95}'(L) - \beta_{0.5}(L)]B(L)u_t$$

From the two risk measures we also derive a measure of variance (or uncertainty) and asymmetry. *Uncertainty* is defined as the sum of the two risk measures, i.e. the difference between the 95th and 5th percentiles:

$$z_t^V = \gamma_U'(L)y_t = z_t^U + z_t^D = [\beta_{0.95}'(L) - \beta_{0.05}'(L)]B(L)u_t.$$

Asymmetry is measured as the non-normalized Kelley skewness (Kelley, 1947), i.e. the differences between the two risk measures, which is the sum of the 5th and 95th percentiles minus twice the median:

$$z_t^A = \gamma_A'(L)y_t = z_t^U - z_t^D = [\beta_{0.95}'(L) + \beta_{0.05}'(L) - 2\beta_{0.5}'(L)]B(L)u_t.$$

---

[5] Notice that, in this framework, u_t, although orthogonal to the past values of y_t, cannot be independent of them, since independence would imply that the conditional quantiles of u_t, and therefore those of y_t, are constant, contrary to the basic idea behind equations (4) and (5) and the empirical evidence below. We do not model explicitly the dependence of the distribution of u_t on y_{t-k}, $k > 0$, since this is not necessary for our purposes, see the discussion in Section 2.4.

2.4 Consistency between SVAR and quantile regressions

Here, we discuss two potential issues related to our econometric procedure. First, at first glance, the linearity of the VAR model for y_t might seem at odds with the idea that each conditional quantile of the forecast distribution of y_t is time varying and predictable. But this is not the case.

To explain the concept, we discuss a simple model which is compatible with the two modeling assumptions. Suppose that the n-dimensional vector y_t admits the VAR representation:

$$y_t = Ay_{t-1} + \varepsilon_t$$

where ε_t is serially independent. In this case, the τ-th conditional quantile of the i-th variable in the vector y_t, y_{it}, is:

$$Q_{it}^{\tau} = A_i y_{t-1} + Q_{\varepsilon_i}^{\tau}$$

where $Q_{\varepsilon_i}^{\tau}$ is the τ-th conditional quantile of ε_{it}, and A_i is the i-th row of A. Note that the term $A_i y_{t-1}$ is constant for all τ so that the difference between any two quantiles $\overline{\tau}$ and $\underline{\tau}$ is:

$$Q_{it}^{\overline{\tau}} - Q_{it}^{\underline{\tau}} = Q_{\varepsilon_i}^{\overline{\tau}} - Q_{\varepsilon_i}^{\underline{\tau}}.$$

By serial independence, $Q_{\varepsilon_i}^{\tau}$ is constant and does not depend on y_{t-1} so that $Q_{it}^{\overline{\tau}} - Q_{it}^{\underline{\tau}}$ is constant.

Suppose now that ε_t is not serially independent. For instance, assume $\varepsilon_t = \alpha' y_{t-1} v_t$, where v_t is a white noise vector, independent of the past history of y_t. Serial uncorrelation of ε_t is fulfilled, since $E(\varepsilon_t \varepsilon_{t-k}') = \alpha' E(y_{t-1} y_{t-k}')\alpha \; E(v_t v_{t-k}') = 0$ for any $k > 0$. The model becomes:

$$y_t = Ay_{t-1} + \alpha' y_{t-1} v_t. \tag{6}$$

This model is in line with a long tradition in the interest rate modeling, where generalizations of the Cox, Ingersoll and Ross (1985) model have appeared with exactly the same formulation of equation (6), but with Gaussian innovations (see Chan et al. (1992) for an in depth discussion).

The τ-th conditional quantile of y_{it} is now:

$$\begin{aligned} Q^{\tau}_{it} &= A_i y_{t-1} + \alpha' y_{t-1} Q^{\tau}_{v_i} \\ &= (A_i + Q^{\tau}_{v_i}\alpha') y_{t-1} \end{aligned}$$

where $Q^{\tau}_{v_i}$ is the τ-th conditional quantile of v_{it}. Interestingly, now the quantiles of y_{it} depend linearly on y_{t-1} and the coefficient $(A_i + Q^{\tau}_{v_i}\alpha')$ is quantile-dependent. The difference between two quantiles is:

$$Q^{\overline{\tau}}_{it} - Q^{\underline{\tau}}_{it} = (Q^{\overline{\tau}}_{v_i} - Q^{\underline{\tau}}_{v_i})\alpha' y_{t-1}.$$

which is now time-varying and is a linear function of the conditioning variables, y_{t-1}.

A second issue which warrants discussion is the consistency between the VAR responses and the response of the mean of the forecast distribution that one would obtain from the equations used to estimate the quantiles. Notice that the quantile regressions are simply local projections equations. If $W = I$ and the order of the polynomials $\beta(L)$ and $A(L)$ is the same, then the regressors in the local projections coincide with those used in the VAR. Plagborg-Møller and Wolf (2021) shows that, asymptotically, the responses obtained in the two models, VAR and local projections, coincide. To put it another way, if the VAR is the true data generating process, the mean forecast made using local projections and the VAR with the same variables and number of lags will be the same asymptotically. Thus, the impulse response functions of the mean forecast have to coincide. Of course, the estimated responses might be different in small samples.

2.5 Specification

We use a monthly VAR including the following variables: the log of industrial production (INDPRO), CPI inflation (CPI), the unemployment rate (UNRATE), the excess bond premium of Gilchrist and Zakrajšek (2012) (EBP), the Chicago Fed's National Financial Conditions Index (NFCI), the S&P Composite Stock Price

Index (SP500) and the federal funds rate (FFR).[6] The time span of the sample is 1973:M1 - 2019:M12. We use four lags in the VAR, which is the average of the number of lags suggested by AIC, BIC and HQC information criteria.

As a target variable in the estimation of the quantile regression, we focus on the one-year ahead forecast distribution of industrial production growth. The quantile regressions are estimated using the current value and three lags of all the variables included in the VAR (same lags as in the VAR). We include current and lagged macroeconomic and financial indicators to properly capture the forecast distribution of industrial production growth. The rationale for this choice is the concern that a model with financial variables only as predictors might not accurately capture a stable relation between stress in financial markets and tail risks for the economy, as shown in Plagborg-Møller et al. (2020).

2.6 Shock identification

We identify two shocks: a monetary policy shock and a credit spread shock. The former is identified within an external instrument SVAR approach using, as instrument, the extended version of the Miranda-Agrippino and Ricco (2021)'s instrument from Degasperi and Ricco (2022). The latter is identified along the lines of Gilchrist and Zakrajšek (2012), with the additional restriction of being orthogonal to the monetary policy policy shock.

Identification of the policy shocks is standard and works as follows (see Forni et al., 2023). Consider the projection:

$$\varepsilon_t = \lambda z_t + \eta_t$$

where λ is a $n \times 1$ vector of parameters and z_t is the instrument, assumed to be correlated with the monetary policy shock (relevance condition) and uncorrelated with the remaining structural shocks (exogeneity condition). The impulse response

---

[6] Data on industrial production, the CPI deflator, the unemployment rate and the NFCI index is retrieved from the Federal Reserve Economic Data (FRED). The federal funds rate is the effective federal funds rate retrieved from FRED until 2008:M8. From 2008:M9 - 2016:M8, it corresponds to the shadow rate of Wu and Xia (2016). The S&P Composite Stock Price Index is retrieved from Robert Shiller's webpage.

functions to the unit-variance monetary policy shocks are

$$B_m(L) = C(L)b_m$$

where the vector $b_m = \lambda/\sqrt{\lambda'\Sigma_\varepsilon^{-1}\lambda}$ is the column of B_0 corresponding to the monetary policy shock. Now consider the projection

$$z_t = \delta'\varepsilon_t + \xi_t.$$

where δ is a $n \times 1$ vector of parameters. The unit-variance monetary policy shock is:

$$u_{mt} = \frac{\delta'}{\sqrt{\delta'\Sigma_\varepsilon\delta}}\varepsilon_t.$$

Conditional on the monetary policy shock, the identification of the credit spread shock works as follows. Let f be the position of the excess bond premium in the vector y_t (fourth in our baseline specification). Let:

$$v_t = \varepsilon_t - b_m u_{mt}.$$

This vector is n-dimensional, orthogonal to u_{mt} and with covariance matrix Σ_v of rank $n-1$.[7] Let V be the $n \times n-1$ matrix of eigenvectors of Σ_v and M the $n-1 \times n-1$ diagonal matrix with the non-zero eigenvalues of Σ_v on the main diagonal. We decompose vector v_t into $n-1$ orthogonal components as:

$$v_t = VM^{\frac{1}{2}}e_t = Ke_t$$

where the $n-1$-dimensional vector $e_t \sim WN(0, I)$. Let $\tilde{K}$ be the matrix formed by the first $n-1$ rows of K and let H be the Cholesky factor of $\Sigma_K = \tilde{K}\tilde{K}'$.[8] The fth column of the matrix $K\tilde{K}^{-1}H$, call it b_f, is the impact vector of the credit spread shock, i.e. the column of B_0 associated to the credit spread shock. Its impulse

---

[7] Orthogonality can be seen as follows. From the relationship $\varepsilon_t = B_0 u_t$, we have that $\varepsilon_t - b_m u_{mt} = \sum_{i \neq m} b_i u_{it}$ which is orthogonal to u_{mt} since $E(u_{it}u_{mt}) = 0$ for $i \neq m$.

[8] The first f rows of $\tilde{K}$ are the first f rows of K. The remaining $n-1-f$ rows can be any of the remaining $n-f$ rows of K.

response functions are:

$$B_f(L) = C(L)b_f.$$

Notice that $\tilde{K}^{-1}H$ is an orthogonal matrix so that $\nu_t = H'\tilde{K}^{-1\prime}e_t = H'\tilde{K}^{-1\prime}K^{-1}v_t \sim WN(0, I)$ (K^{-1} being a left inverse of K).[9] The credit spread shock is $u_{ft} = \nu_{ft}$; the shock is unit variance, orthogonal to u_{mt} and with zero effects on the variables ordered before the excess bond premium.[10]

3 Results

We discuss here our main empirical results. First, we describe the estimated forecast distribution of industrial production growth. Second, we assess the relevance of credit spread and monetary policy shocks.

3.1 The estimated forecast distribution

Figure 1 presents the estimated 5th, 50th and 95th quantiles together with the implied measures of downside and upside risk, uncertainty and skewness. A few interesting findings emerge. First, downside risk is substantially more volatile than upside risk, which is relatively flat over the sample considered. This is driven by the higher volatility of the 5th percentile compared to the 95th. Second, downside risk displays large and sudden drops in correspondence of economic downturns. Fluctuations in downside risk drive the behavior of uncertainty and skewness: uncertainty increases and the growth distribution becomes more left-skewed during recessions. The largest changes are observed in correspondence to the economic crises of the mid 1970s, the early 2000s and the Great Recession. All in all, our findings confirm those obtained in Adrian et al. (2019) and point to the left tail as the main driver of the dynamics in the forecast distribution of industrial production growth.

---

[9] It is easy to see that $\tilde{K}^{-1}H$ is an orthogonal matrix. Indeed $\tilde{K}^{-1}HH'\tilde{K}^{-1\prime} = \tilde{K}^{-1}\Sigma_K\tilde{K}^{-1\prime} = \tilde{K}^{-1}\tilde{K}\tilde{K}'\tilde{K}^{-1\prime} = I$.

[10] In the Appendix, we discuss how to identify the credit spread shock first and the monetary policy shock second. If the two identifications are correct, both approaches would deliver the same estimates. They should also coincide with the estimates obtained in two separate identifications without imposing orthogonality between the two shocks.

3.2 Shocks

Figure 2 reports the impulse response functions of the variables in the VAR to the monetary policy shock. Solid lines represent point estimates and shaded areas are 68% and 90% confidence bands. The horizontal axis measures time in months after the innovation has occurred. The shock generates significant contractionary effects on real economic activity variables and stock prices and significantly reduces inflation. Financial conditions worsen, with both the EBP and the NFCI significantly increasing. Table 1 shows that the effects of the monetary policy shock are sizable: about 16% of the variance of inflation and 30% of the variance of industrial production are accounted for by the shock. The results are in line with existing evidence, see for instance Miranda-Agrippino and Ricco (2021).

Figure 3 reports the impulse response functions to an unfavorable financial shock, namely an unexpected increase in the excess bond premium. Real economic activity variables, stock prices and inflation significantly reduce, while the financial stress index significantly increases. Table 1 reports the variance decomposition. The shock explains around 20% of the variance of real economic activity variables and stock prices. The findings align closely with those in the literature, see Gilchrist and Zakrajšek (2012), confirming an important role for financial shocks as drivers of macroeconomic fluctuations.

Figure 4 reports the responses of the 5th and 95th percentiles (first row), downside risk and upside risk (second row), uncertainty (third row) and skewness (fourth row) to one standard deviation contractionary monetary policy shocks (first column) and unfavorable financial shocks (second column). Solid lines and shaded areas represent point estimates and 68% and 90% confidence bands, respectively. The responses are similar for both shocks. A monetary policy contraction and an unfavorable financial shock increase both downside and upside risk, but the effects on the former are larger and more persistent than for the latter. The result is due to the fact that the 5th percentile reacts considerably more to both shocks than the 95th percentile. Uncertainty increases and skewness reduces (the distribution becomes more left-skewed). Although the effects are qualitatively similar for both shocks, there are important differences as far as the magnitudes are concerned. At the peak, a one standard deviation financial shock increases downside risk by 1 percent, while the monetary policy shock by 0.6 percent. These differences are reflected in the response of uncertainty and asymmetry.

Tables 1 and 2 report the variance decomposition of risk, uncertainty and skewness for the two shocks. The numbers confirm a substantial difference, from a quantitative viewpoint, between the two shocks. While monetary policy shocks explain around 16% of downside risk, the credit spread shock turns out to be the major driver of risk fluctuations, explaining more than 50%. Similar numbers are found for uncertainty and skewness. The result provides empirical support to the main conclusion in Adrian et al. (2019): disturbances originating in the financial sector explain the bulk of macroeconomic risk fluctuations. Also, the above findings shed new light on the transmission of credit spread shocks. These shocks not only reduce directly private expenditure by increasing the cost of credit, but also considerably increase uncertainty about real economic activity, which can in turn induce a further reduction in the demand for investment and consumption durables (Bloom, 2009). This indirect channel is all the more important as it concerns downside uncertainty, whose effects on growth are particularly strong (see Forni, Gambetti and Sala, 2021).

How effective monetary policy is to offset risk fluctuations arising from the financial sector? From a simple back-of-the-envelope calculation, a 1.5 standard deviation expansionary monetary policy is needed in order to offset the effects on downside risk arising from a one standard deviation adverse financial shock. Such a shock would increase inflation by 2.7% (annual rate) within the first month after the shock. Given that the financial shock reduces inflation by about 0.5% (annual rate), the total effect on inflation would be around 2.2%. It is true that monetary policy can stabilize risk, but the cost in terms of price stability can be high, since the policy intervention has to be particularly large.

3.3 Robustness

As a first robustness check, we reverse the ordering of identification. We identify a financial shock first and, conditional on this, we identify the monetary policy shock second. Now, if the two identification schemes are correct and consistent with each other, the results should be unchanged or presenting minor differences. Table 3 and

5 report the variance decompositions and Figure 5-7 report the impulse response functions of this alternative exercise. The results are qualitatively very similar to the baseline identification. The main difference is that the variance of downside risk explained by the monetary policy shock and the magnitude of the response are slightly smaller. The three main conclusions drawn above remain. First, monetary policy has significant effects on risk. Second, credit spread shocks are the major driver of macroeconomic downside risk. Third, monetary policy aimed at stabilizing risk can have a large cost in terms of inflation.

As a second robustness check, we repeat the baseline analysis using the 6-month ahead forecast distribution of industrial production growth (see Figure 8). Figure 9 reports the impulse responses of different measures of the forecast distribution of industrial production growth to one standard deviation contractionary monetary policy shocks and unfavorable financial shocks. The results are again qualitatively similar, although with a few differences. The most notable one is that the importance of credit spread shocks for downside risk are smaller. This suggests that the shocks are more relevant at longer horizons. Second, the difference in the responses of the left and right tail are smaller than at a horizon of 12 months ahead.

4 Concluding remarks

We contribute to the literature on macroeconomic risk by assessing the role of monetary policy as a tool to stabilize risk. We draw two main conclusions. First, monetary policy has significant effects on risk. Second, the effects of monetary policy shocks are smaller than those of credit spread shocks. Indeed, the credit spread shock represents a major driver of downside risk fluctuations. This implies that large policy interventions are needed to stabilize macroeconomic risk arising from credit markets with relatively high cost in terms of inflation.

Appendix

The same identification as the baseline exercise can be obtained with the reverse ordering (we refer to this as Identification 2). First, we identify the financial shock and then the monetary policy shock. We can proceed as follows.

Consider the Cholesky shocks $v_t = S^{-1}\varepsilon_t$. The credit spread shock is the fth element in v_t, $u_{ft} = v_{ft}$ where f is the position of the excess bond premium in vector y_t (the fourth in the baseline specification). The impulse response functions to the financial shocks are:

$$B_f(L) = C(L)S_f$$

where S_f is the fth column of S. The column of U associated to the credit spread shock is just a vector of zeros with the fth element equal to one.

To identify the monetary policy shock we use the procedure Forni et al. (2023), modified to impose orthogonality with the credit spread shock. Let $\tilde{S}$ be $n \times n-1$ matrix formed by the columns of S but the column S_f. Let $\tilde{v}_t$ be the n-dimensional vector of Cholesky shocks excluding v_{ft}. Consider the linear projections[11]:

$$\tilde{v}_t = \psi z_t + e_t$$

where ψ is a $n-1 \times 1$ vector of parameters and z_t is the instrument correlated with the monetary policy shocks and uncorrelated with the remaining structural shocks. The impulse response functions to the monetary policy shocks are:

$$B_m(L) = C(L)\tilde{S}\frac{\psi}{\sqrt{\psi'\psi}}$$

The column of U associated to the monetary policy shock is the vector $\frac{\psi}{\sqrt{\psi'\psi}}$. The monetary policy shock is:

$$u_{mt} = \frac{\delta'}{\sqrt{\delta'\delta}}\tilde{v}_t$$

where δ is the column parameter vector in the linear projection of the instrument

---

[11] The projections involving z_t are estimated using the sample for which the instrument is available, i.e. 1991:M1 up to 2015:M12.

onto $\tilde{v}_t$,

$$z_t = \delta' \tilde{v}_t + \xi_t.$$

Notice that the orthogonality between the financial shock and the monetary policy is ensured by the fact that the monetary policy shock is a linear combination of shocks which are orthogonal to v_{ft}.

References

[1] Adrian, T., N. Boyarchenko and D. Giannone (2019), “Vulnerable growth”, American Economic Review, 109(4), 1263-89.

[2] Angelini, G. and Fanelli, L. (2019), “Exogenous uncertainty and the identification of structural vector autoregressions with external instruments”, Journal of Applied Econometrics 34, pp. 951-971.

[3] Antolín-Díaz, J., Petrella, I. and Rubio-Ramírez, J. (2021) ‘’Structural scenario analysis with SVARs”, Journal of Monetary Economics, vol. 117(C):798-815.

[4] Bachmann, R., Elstner, S. and E. R. Sims (2013),“Uncertainty and economic activity: evidence from business survey data”, American Economic Journal: Macroeconomics 5, 217-249.

[5] Baker, S. R., N. Bloom, and S. J. Davis (2016), “Measuring economic policy uncertainty”, The Quarterly Journal of Economics 131, 1593-1636.

[6] Barnichon, R. and G. Mesters (2020), ‘’Identifying modern macro equations with old shocks”, Quarterly Journal of Economics, 135(4): 2255-2298.

[7] Basu, S., and B. Bundick (2017), “Uncertainty shocks in a model of effective demand”, Econometrica 85, 937-958.

[8] Bekaert, G., M. Hoerova, and M. L. Duca (2013), “Risk, uncertainty and monetary policy”, Journal of Monetary Economics 60, 771-788.

[9] Berger, D., I. Dew-Becker, and S. Giglio (2020),“Uncertainty shocks as second-moment news shocks”, Review of Economic Studies, 87(1):40-76.

[10] Bernanke B. and M. Gertler (1989) “Agency costs, net worth, and business fluctuations”, The American Economic Review Vol. 79, No. 1, 14-31.

[11] Bernanke, B. S., M. Gertler and S. Gilchrist (1999), “The financial accelerator in a quantitative business cycle framework,” Handbook of Macroeconomics, in: J. B. Taylor & M. Woodford (ed.), Handbook of Macroeconomics, ed. 1, volume 1, chapter 21, 1341-1393.

[12] Bloom, N. (2009), "The impact of uncertainty shocks", Econometrica 77: 623-685.

[13] Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018), "Really uncertain business cycles", Econometrica 86, 1031-1065.

[14] Brianti, M. (2023), "Financial shocks, uncertainty shocks, and monetary policy trade-offs", mimeo.

[15] Brunnermeier, M. K., and Y. Sannikov (2014), "A macroeconomic model with a financial sector", American Economic Review, 104(2): 379-421.

[16] Caggiano G., E. Castelnuovo, and N. Groshenny (2014), "Uncertainty shocks and unemployment dynamics: an analysis of post-WWII US recession", Journal of Monetary Economics 67, 78-92.

[17] Caldara, D., C. Fuentes-Albero, S. Gilchrist, and E. Zakrajsek (2016), "The macroeconomic impact of financial and uncertainty shocks", European Economic Review 88, 185-207.

[18] Carlstrom C. and T. Fuerst (1997), "Agency costs, net worth, and business fluctuations: a computable general equilibrium analysis", American Economic Review, vol. 87, issue 5, 893-910.

[19] Carriero, A., T. E. Clark, and M. Marcellino (2018a), "Endogenous uncertainty", Federal Reserve Bank of Cleveland, WP 18-05.

[20] Carriero, A., T. Clark, and M. Marcellino (2018b), "Measuring uncertainty and its impact on the economy", The Review of Economics and Statistics 100, 799-815.

[21] Cascaldi-Garcia, D., C. Sarisoy, J. M. Londono, B. Sun, D. D. Datta, T. Ferreira, O. Grishchenko, M. R. Jahan-Parvar, F. Loria, S. Ma, M. Rodriguez, I. Zer, and J. Rogers (2021), "What is certain about uncertainty?", Journal of Economic Literature.

[22] Chan, K. C., Karolyi, G. A., Longstaf, G. A., and Sanders, A. B. (1992), ''An Empirical Comparison of Alternative Models of the Short Term Interest Rate", The Journal of Finance,VOL. XLVII, NO. 3.

[23] Chavleishvili, S., and S. Manganelli (2024), "Forecasting and stress testing with quantile vector autoregression", Journal of Applied Econometrics, 39(1), 66–85.

[24] Christiano, L. J., R. Motto, and M. Rostagno (2003), "The Great depression and the Friedman-Schwartz hypothesis," Journal of Money, Credit and Banking. 35, no. 6, pt. 2: 1119- 1198.

[25] Christiano, L., R. Motto, and M. Rostagno (2007), "Shocks, structures or monetary policies? The Euro Area and US after 2001", Journal of Economic Dynamics and Control, 32(8), 2476-2506

[26] Cox, J.C, Ingersoll, J.E., Ross, Jr, S.A. (1985), ''A Theory of the Term structure of Interest Rates", Econometrica, Vol. 53(2):385-407.

[27] Curdia, V. and M. Woodford (2010), "Credit spreads and monetary policy", Journal of Money, Credit & Banking, 42(S1): 47-74.

[28] Daly, M., and B. Hobijn (2014), "Downward nominal wage rigidities bend the Phillips curve", Journal of Money, Credit and Banking 46(2): 51-93.

[29] Debortoli, D., M. Forni, L. Gambetti, and L. Sala (2022). "Asymmetric effects of monetary policy easing and tightening", mimeo.

[30] Delle Monache, D., A. De Polis, and I. Petrella (2020). "Modelling and forecasting macroeconomic downside risk," EMF Research Papers 34, Economic Modelling and Forecasting Group.

[31] Dew-Becker, I (2020), ''Real-time forward-looking skewness over the business cycle", mimeo, Northwestern University.

[32] Fajgelbaum, P. D., E. Schaal, and M. Taschereau-Dumouchel (2017), "Uncertainty traps", Quarterly Journal of Economics 132, 1641-1692.

[33] Fernandes, M., E. Guerre and E. Horta (2021), “Smoothing quantile regressions”, Journal of Business & Economic Statistics, 39:1, 338-357.

[34] Fernandez-Villaverde, J., P. Guerrón-Quintana (2020), “Uncertainty shocks and business cycle research”, NBER wp 26768.

[35] Fernandez-Villaverde, J., J. F. Rubio-Ramirez, P. Guerron-Quintana, and M. Uribe (2011), “Risk matters: the real effects of volatility shocks”, American Economic Review 6, 2530-2561.

[36] Forni, M., L. Gambetti, and L. Sala (2021). ‘’Downside and upside uncertainty shocks”, CEPR Discussion Paper 15881.

[37] Furlanetto, F., F. Ravazzolo, and S. Sarferaz (2019), “Identification of financial factors in economic fluctuations”, The Economic Journal, vol. 129(617), pages 311-337.

[38] Galí, J., and L. Gambetti (2020), ‘’Has the U.S. wage Phillips curve flattened? A semi-structural exploration” in G. Castex, J. Gali and D. Saravia (eds.), Changing Inflation Dynamics, Evolving Monetary Policy, Central Bank of Chile.

[39] Gambetti, L., and A. Musso (2017), “Loan supply shocks and the business cycle”, Journal of Applied Econometrics, vol. 32(4), pages 764-782.

[40] Gertler, M. and P. Karadi (2011), “A model of unconventional monetary policy”, Journal of Monetary Economics, 58(1), 17-34.

[41] Gertler, M. and N. Kiyotaki (2011) “Financial intermediation and credit policy in business cycle analysis”, in Handbook of Monetary Economics, eds. Michael Woodford and Benjamin M. Friedman, North Holland, Elsevier.

[42] Giglio, S., B. Kelly, and S. Pruitt (2016). “Systemic risk and the macroeconomy: An empirical evaluation,” Journal of Financial Economics, vol. 119(3): 457-471.

[43] Gilchrist, S., V. Yankov, and E. Zakrajšek (2009), “Credit market shocks and economic fluctuations: evidence from corporate bond and stock markets”, Journal of Monetary Economics, 56 (4): 471-93.

[44] Gilchrist, S. and E. Zakrajšek (2012), “Credit spreads and business cycle fluctuations”, American Economic Review, 102(4), 1692-1720.

[45] He, Z., and A. Krishnamurthy (2013), “Intermediary asset pricing”, American Economic Review, 103(2): 732-70.

[46] Jo, S., and R. Sekkel (2019), “Macroeconomic uncertainty through the lens of professional forecasters”, Journal of Business and Economic Statistics 37, 436-446.

[47] Jurado, K., Ludvigson, S.C. and S. Ng (2015), “Measuring uncertainty”, American Economic Review 105, 1177-1216.

[48] Kelley, T. L. (1947), “Fundamentals of statistics”, Harvard University Press.

[49] Kiyotaki N. and J. Moore, (1997) “Credit cycles”, Journal of Political Economy Vol. 105, No. 2, 211-248.

[50] Koenker, R. W., and G. Bassett, Jr. (1978), “Regression quantiles”, Econometrica 46 (1): 33–50.

[51] Leduc, S., and Z. Liu (2016), “Uncertainty shocks are aggregate demand shocks”, Journal of Monetary Economics 82, 20-35.

[52] López-Salido, J. D., and Loria, F., (2020), ”Inflation at Risk,” Finance and Economics Discussion Series 2020-013, Board of Governors of the Federal Reserve System.

[53] Loria, F., C. Matthes, and D. Zhang (2019). “Assessing Macroeconomic Tail Risk,” Finance and Economics Discussion Series 2019-026, Board of Governors of the Federal Reserve System.

[54] Ludvigson, S., Ma, S., and Ng, S. (2021), “Uncertainty and business cycles: exogenous impulse or endogenous response?”, American Economic Journal: Macroeconomics, vol. 13, no. 4, 369-410.

[55] Meeks, R., (2012), "Do credit market shocks drive output fluctuations? Evidence from corporate spreads and defaults," Journal of Economic Dynamics and Control, vol. 36(4), 568-584.

[56] Mendoza, E. G. (2010), "Sudden stops, financial crises, and leverage", American Economic Review, 100(5): 1941-66.

[57] Miranda-Agrippino, S., and G. Ricco (2021). "The transmission of monetary policy shocks," American Economic Journal: Macroeconomics, American Economic Association, vol. 13(3), 74-107, July.

[58] Nakamura, E., D. Sergeyev, and J. Steinsson (2017), "Growth-rate and uncertainty shocks in consumption: cross-country evidence", American Economic Journal: Macroeconomics 9, 1-39.

[59] Natal, M. J. and E. Horta (2022), "Smoothing quantile regressions with time series data", mimeo.

[60] Peersman, G., (2011), "Bank lending shocks and the Euro area business cycle," Working Papers 11/766, Ghent University.

[61] Peersman, G., and W. Wagner (2015), "Shocks to bank lending, risk-taking, securitization, and their role for U.S. business cycle fluctuations", CEPR Discussion Papers 10547.

[62] Piffer, M. and M. Podstawski (2018), "Identifying uncertainty shocks using the price of gold", The Economic Journal, 128, 3266-3284.

[63] Plagborg-Møller, M., L. Reichlin, G. Ricco, and T. Hasenzagl (2020). "When is growth at risk?" Brookings Papers on Economic Activity, 167-229.

[64] Plagborg-Møller, M. and C. Wolf (2021). "Local Projections and VARs Estimate the Same Impulse Responses" Econometrica, 89(2), pp. 955–980, March 2021.

[65] Rossi, B. and T. Sekhposyan (2015), "Macroeconomic uncertainty indices based on nowcast and forecast error distributions", American Economic Review, 105(5): 650-55.

[66] Salgado, S., F. Guvenen and N. Bloom (2019), “Skewed business cycles,” NBER wp 26565.

[67] Scotti, C. (2016), “Surprise and uncertainty indexes: real-time aggregation of real-activity macro surprises,” Journal of Monetary Economics 82, 1-19.

[68] Shin, M. and M. Zhong (2020), “A new approach to identifying the real effects of uncertainty shocks”, Journal of Business and Economic Statistics 38:2, 367-379.

Tables

Variables				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
INDPRO	15.1	32.9	32.2	28.6
CPI	18.2	16.7	16.6	16.3
UNRATE	0.2	16.3	19.0	16.6
EBP	14.9	26.4	26.0	25.1
NFCI	19.9	10.8	9.6	9.8
SP500	8.3	14.1	13.9	13.5
FFR	9.2	2.7	2.9	4.1
12-Month ahead forecast distribution				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
Downside risk	4.5	16.4	15.5	15.2
Upside risk	4.8	8.6	7.6	10.5
5th Percentile	10.3	11.5	11.7	12.8
50th Percentile	11.4	5.9	7.7	10.0
95th Percentile	6.9	7.2	9.0	9.6
Uncertainty	4.9	14.7	14.1	14.7
Skewness	2.2	16.7	14.7	13.7

Table 1: Variance decomposition. Monetary policy shock.

Variables				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
INDPRO	0.0	14.1	17.9	15.3
CPI	0.0	5.6	5.6	5.8
UNRATE	0.0	14.6	21.4	19.9
EBP	99.8	86.4	84.5	81.0
NFCI	0.2	0.5	1.3	1.9
SP500	8.0	19.7	22.3	24.1
FFR	11.5	11.8	21.5	25.0
12-Month ahead forecast distribution				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
Downside risk	33.8	51.4	50.5	46.5
Upside risk	26.3	15.3	16.0	20.2
5th Percentile	45.9	33.9	31.4	28.5
50th Percentile	41.2	13.1	14.7	15.4
95th	20.6	11.0	12.0	12.0
Uncertainty	33.1	49.1	46.0	40.1
Skewness	24.0	45.1	46.1	45.5

Table 2: Variance decomposition. Credit spread shock.

Variables				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
INDPRO	24.6	32.4	28.5	24.9
CPI	29.8	23.8	23.5	22.9
UNRATE	0.3	11.5	11.6	9.4
EBP	1.1	9.4	9.5	9.1
NFCI	24.0	11.1	9.8	9.9
SP500	6.0	7.7	6.9	6.4
FFR	12.9	3.8	2.8	2.7

12-Month ahead forecast distribution				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
Downside risk	0.7	6.1	6.1	7.0
Upside risk	1.0	8.3	6.8	7.5
5-th percentile	1.9	3.5	4.5	6.4
50-th percentile	2.3	2.6	4.0	5.9
95-th percentile	1.4	3.5	5.1	6.1
Uncertainty	0.8	5.0	5.2	6.7
Skewness	0.2	8.9	8.1	7.8

Table 3: Variance decomposition. Monetary policy shock. Identification 2.

Variables				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
INDPRO	0.0	18.6	24.6	22.4
CPI	0.0	3.6	3.7	3.8
UNRATE	0.0	21.2	30.9	30.1
EBP	97.6	83.1	80.4	78.0
NFCI	4.1	5.6	5.1	5.6
SP500	9.9	27.1	29.6	30.5
FFR	0.5	2.1	8.7	13.5
12-Month ahead forecast distribution				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
Downside risk	23.1	54.8	53.2	47.8
Upside risk	21.0	18.1	16.8	22.4
5-th percentile	47.8	42.3	39.4	35.5
50-th percentile	49.9	19.8	20.5	21.6
95-th percentile	30.0	17.4	18.4	17.9
Uncertainty	23.9	52.7	49.9	44.1
Skewness	13.7	45.2	43.7	41.2

Table 4: Variance decomposition. Credit spread shock. Identification 2.

6-month ahead – Monetary policy shock				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
Downside risk	3.8	18.5	17.8	16.4
Upside risk	0.6	11.4	11.0	13.3
5-th percentile	20.6	16.3	15.4	15.8
50-th percentile	24.7	19.3	18.9	19.0
95-th percentile	24.4	17.4	18.1	18.0
Uncertainty	3.5	19.0	17.8	17.3
Skewness	1.4	11.9	12.2	12.8

6-month ahead – Credit spread shock				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
Downside risk	0.5	34.5	34.6	27.3
Upside risk	13.3	12.1	11.8	14.7
5-th percentile	30.2	34.5	31.5	27.6
50-th percentile	46.9	20.0	19.1	18.0
95-th percentile	28.1	21.1	20.9	20.5
Uncertainty	6.6	32.3	30.6	26.8
Skewness	4.5	22.3	25.0	19.0

Table 5: Variance decomposition. Credit spread shock.

Figures

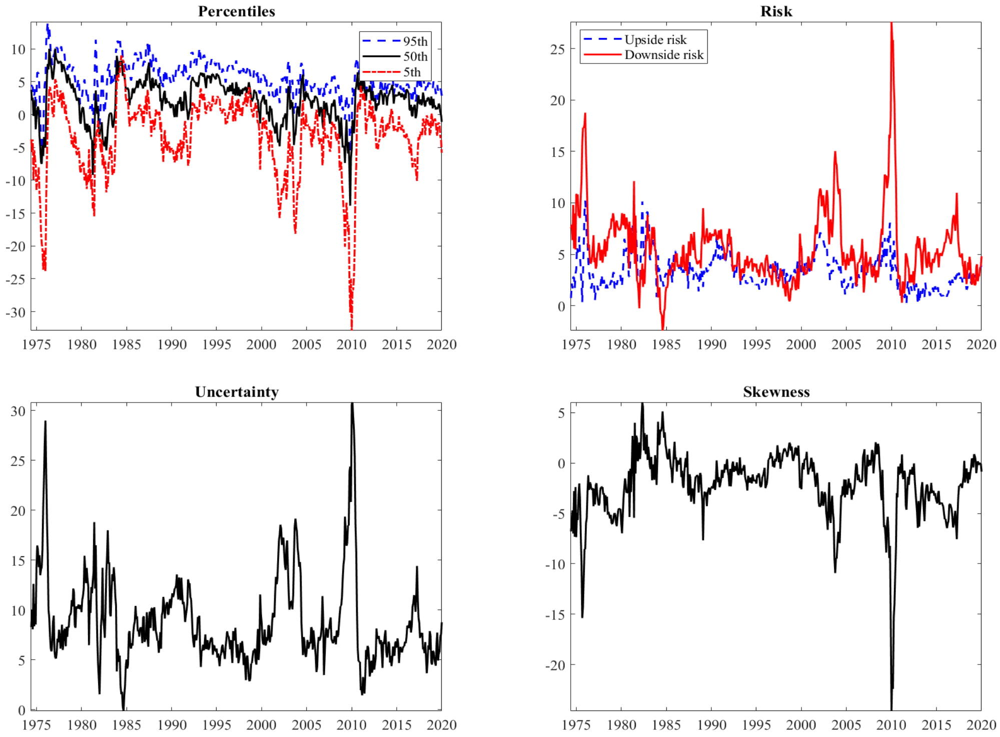

Figure 1: 12-Month ahead industrial production forecast distribution.

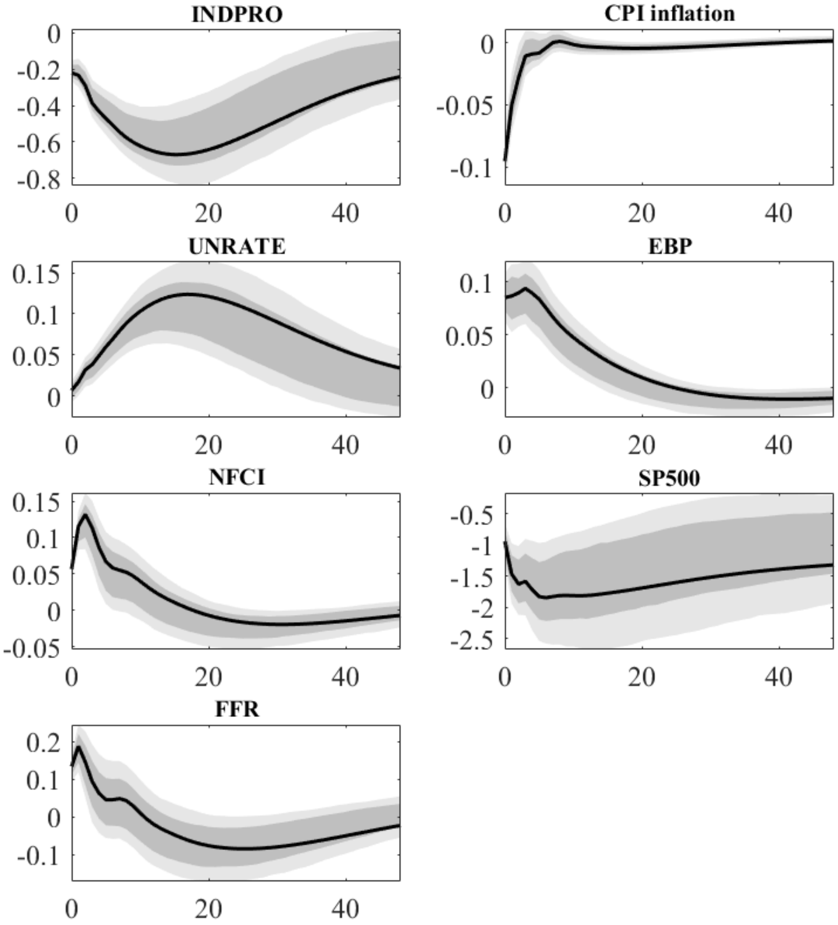

Figure 2: Impulse response functions of monetary policy shock. Solid lines are point estimates, while shaded areas are 68% and 90% confidence bands.

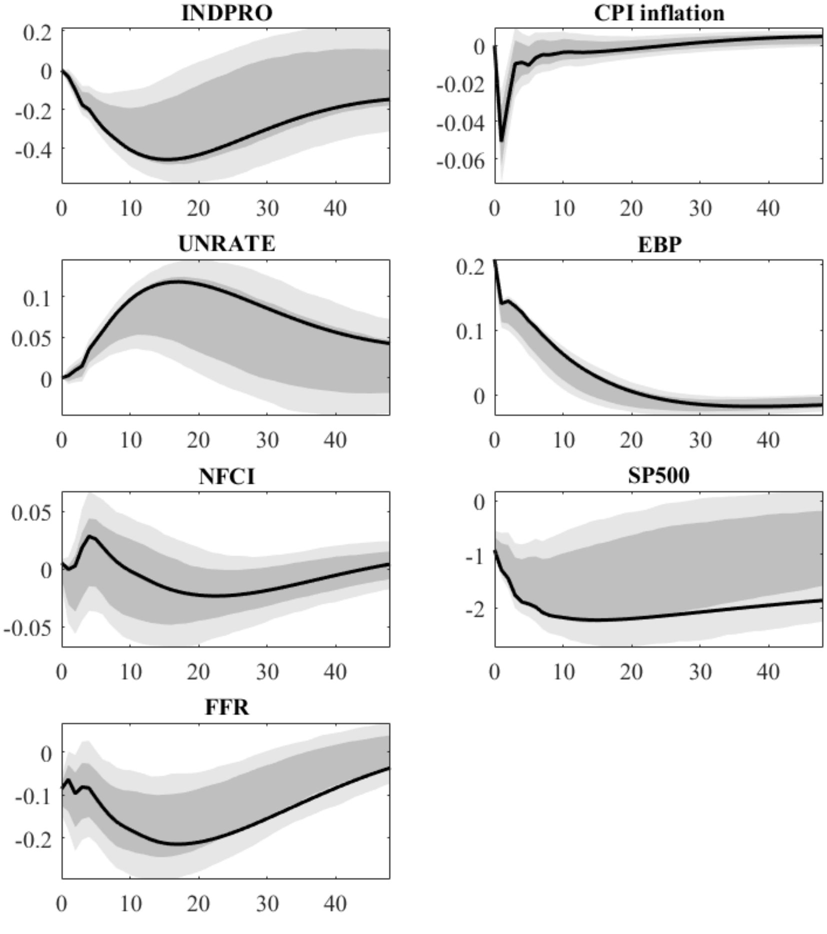

Figure 3: Impulse response functions of monetary policy shocks. Solid lines are point estimates, while shaded areas are 68% and 90% confidence bands.

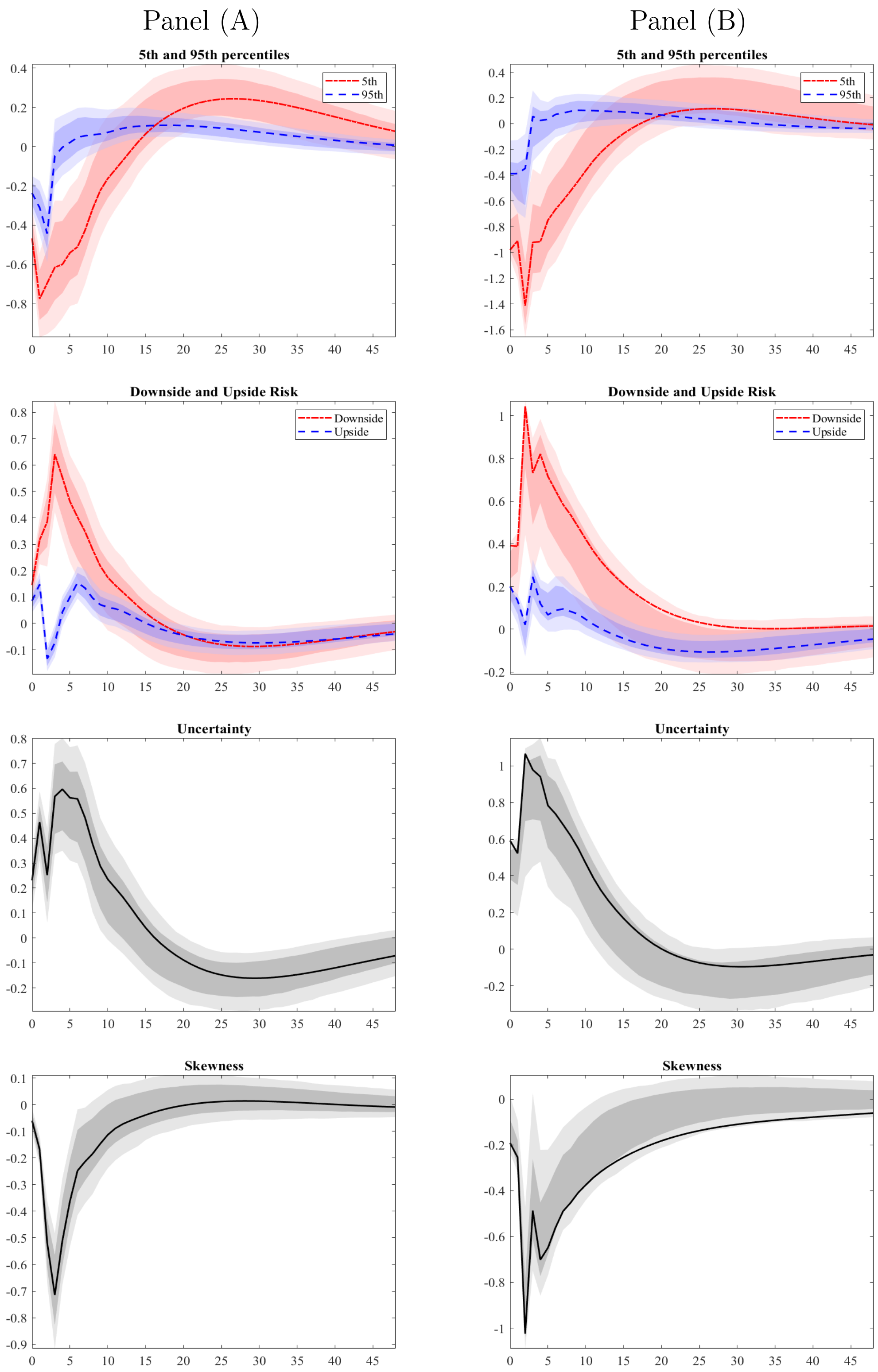

Figure 4: Impulse response functions. 12-Months ahead industrial production growth. Panel (A): monetary policy shocks. Panel (B): credit spread shocks. Solid lines are point estimates, while shaded areas are 68% and 90% confidence bands.

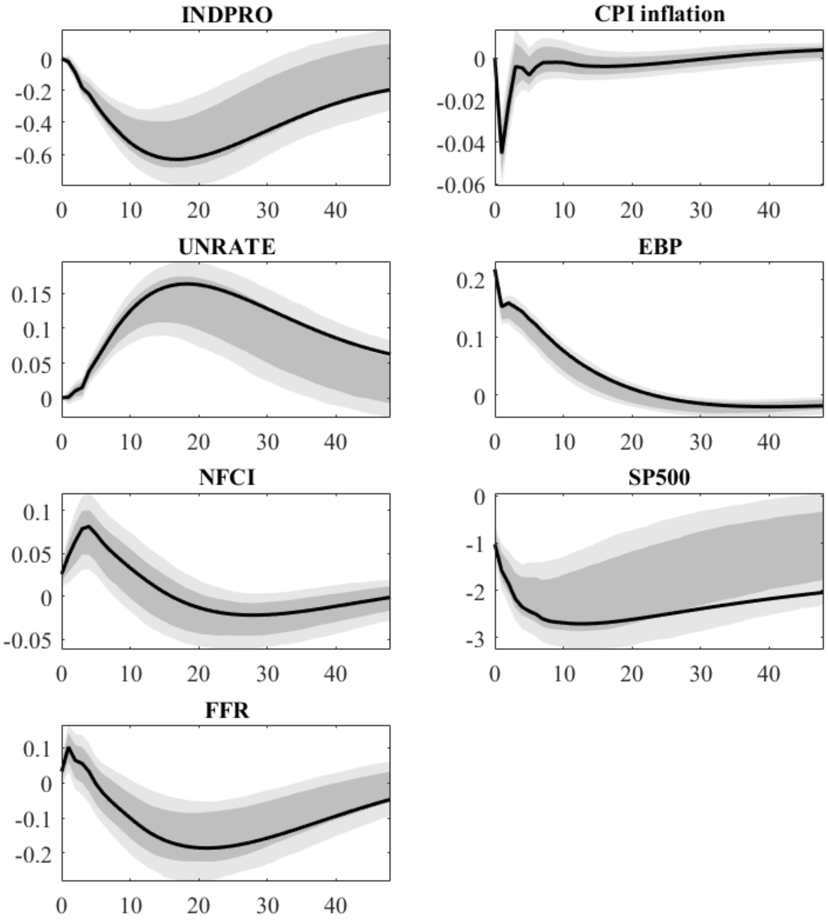

Figure 5: Impulse response functions of credit spread shocks. Identification 2. Solid lines are point estimates, while shaded areas are 68% and 90% confidence bands.

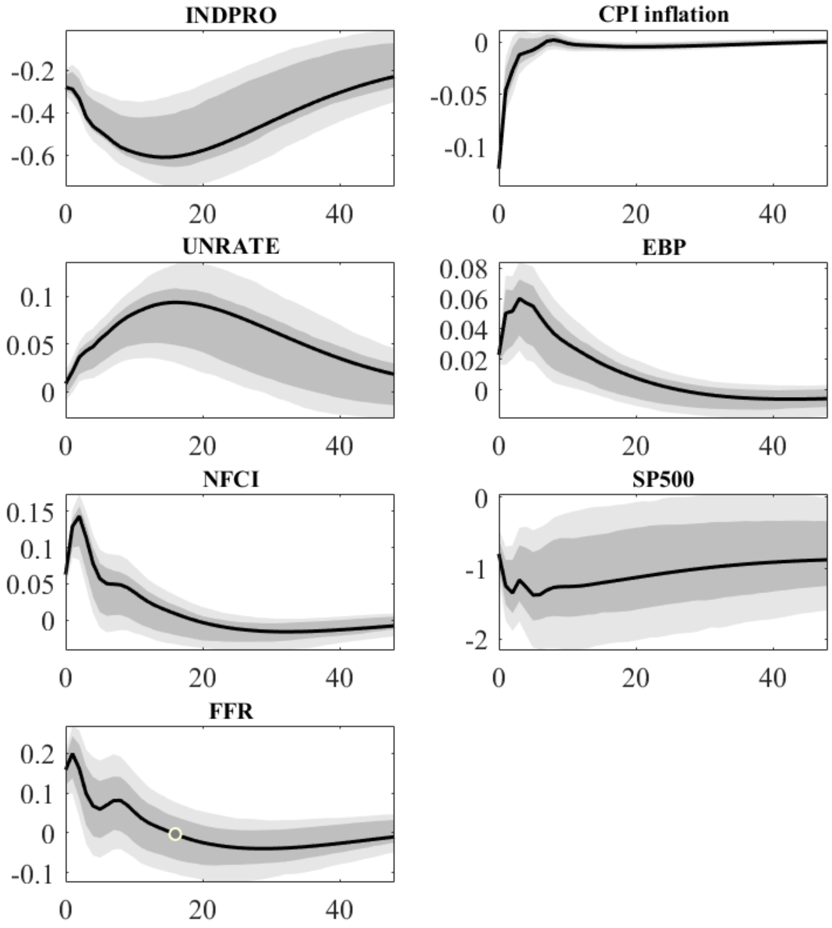

Figure 6: Impulse response functions of monetary policy shocks. Identification 2. Solid lines are point estimates, while shaded areas are 68% and 90% confidence bands.

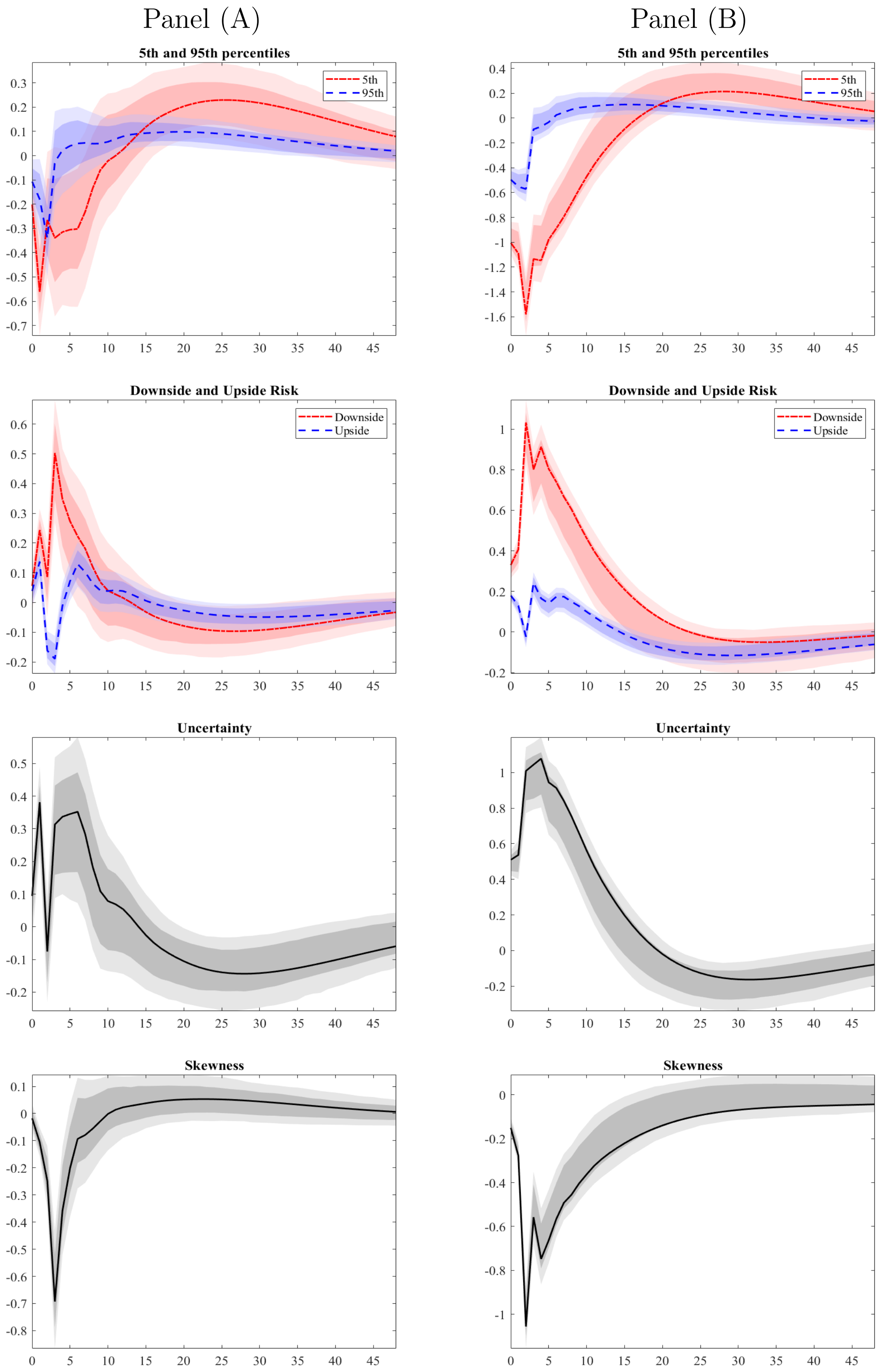

Figure 7: Impulse response functions. Identification 2. 12-Months ahead industrial production growth. Panel (A): monetary policy shocks. Panel (B): credit spread shocks. Solid lines are point estimates, while shaded areas are 68% and 90% confidence bands.

Additional Figures

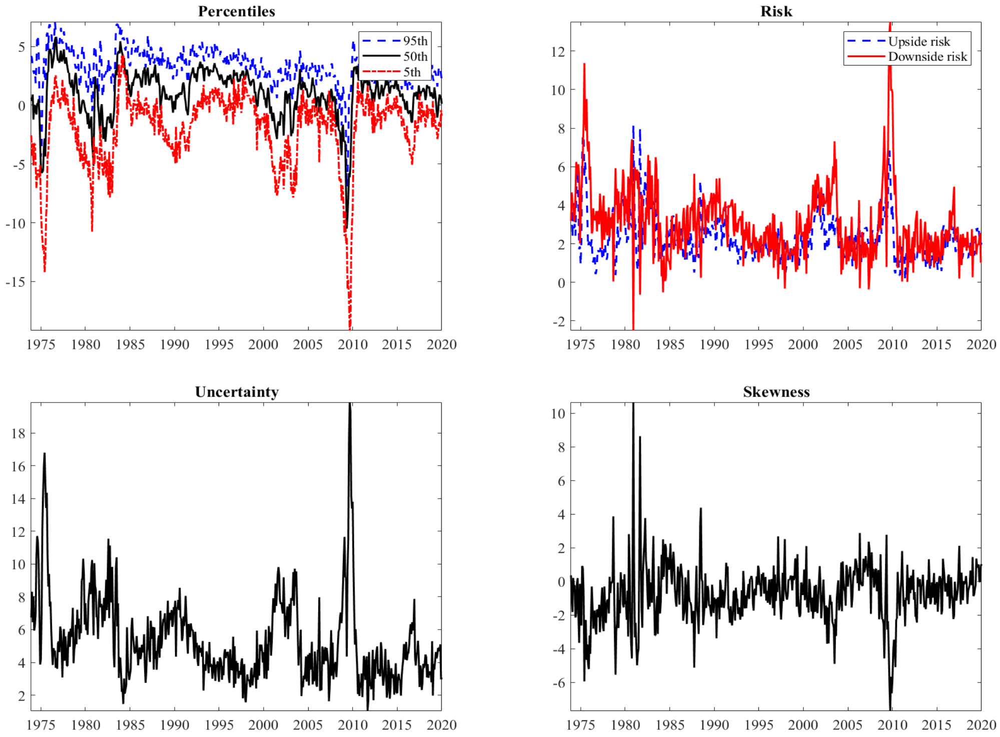

Figure 8: 6-Month ahead industrial production forecast distribution.

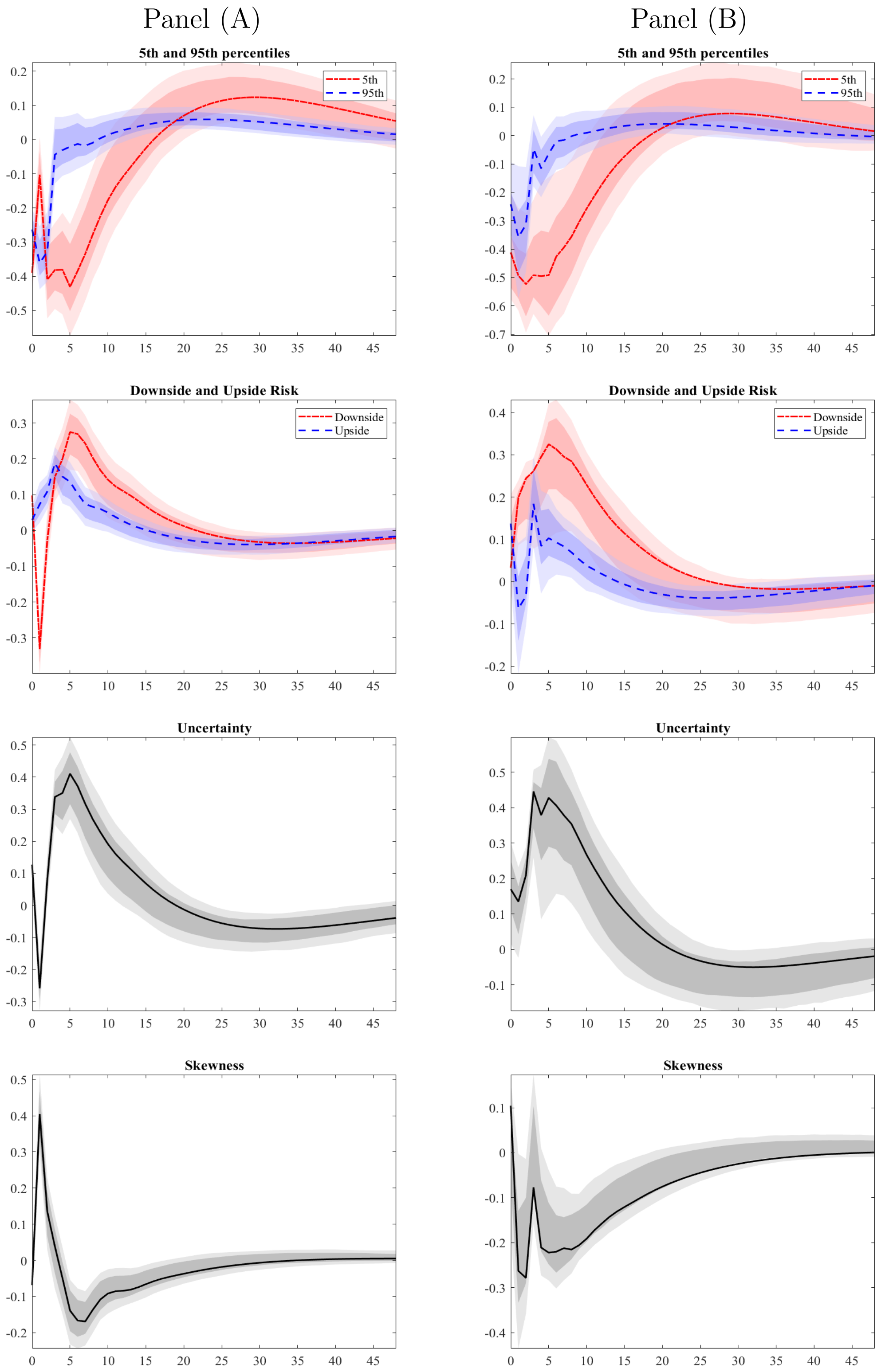

Figure 9: Impulse response functions. 6-Months ahead industrial production growth. Panel (A): monetary policy shocks. Panel (B): credit spread shocks. Solid lines are point estimates, while shaded areas are 68% and 90% confidence bands.