The Impact of Financial Shocks on the Forecast Distribution of Output and Inflation*

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Abstract

Financial shocks represent a major driver of fluctuations in tail risk, defined as the 5th percentile of the forecast distributions of output and inflation. Since the variance and the asymmetry of the forecast distributions are largely driven by the left tail, financial shocks turn out to play a prominent role for distribution dynamics. Monetary policy shocks also play a role in shaping risk, although its effects are smaller than those of financial shocks. These findings are obtained using a novel econometric approach which combines quantile regressions and Structural VARs.

JEL classification: C32, E32.

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1 Introduction

Since the seminal contribution of Adrian et al. (2019), the dynamics of the forecast distribution of the growth rate of GDP have attracted increasing attention from both the academia and policy makers, see Plagborg-Møller et al. (2020), Giglio et al. (2016) and Delle Monache et al. (2020), among others. Existing evidence suggests that the distribution tends to become more dispersed and left-skewed at the onset of economic downturns. This empirical regularity is almost fully attributable to movements in the left tail, since the right tail displays very little variation. As Adrian et al. (2019) claim, left tail movements are predictable using financial variables. The topic has quickly become central in the current research agenda: if other moments of the growth rate distribution beside the mean are relevant for the agents' decision-making process, then understanding their dynamics becomes essential to better understand economic fluctuations.[1]

A recent and parallel stream of literature, developed from the seminal contribution of Gilchrist and Zakrajšek (2012), has studied the role of shocks originating from the financial sector as drivers of macroeconomic fluctuations, see among others, Peersman (2011), Meeks (2012), Peersman and Wagner (2015), Caldara et al (2016), Gambetti and Musso (2017), Furlanetto et al. (2019) and Brianti (2023).[2] All in all, these contributions, albeit with differences in terms of magnitude, point to financial shocks as important drivers of macroeconomic fluctuations.

[1]For instance, since Bloom (2009), a growing literature has shown that changes in uncertainty have sizable effects on real activity variables. Some prominent contributions are, among others, Jurado et al. (2015), Ludvigson et al. (2021), Fernandez-Villaverde et al. (2011), Bachmann et al. (2013), Bekaert et al. (2013), Caggiano et al. (2014), Rossi and Sekhposyan (2015), Scotti (2016), Baker et al. (2016), Caldara et al. (2016), Leduc and Liu (2016), Basu and Bundik (2017), Fajgelbaum et al. (2017), Piffer and Podstawski (2018), Nakamura et al. (2017), Bloom et al. (2018), Carriero et al. (2018a, 2018b), Shin and Zhong (2020), Jo and Sekkel (2019), Angelini and Fanelli (2019). For more references, see the survey articles in Cascaldi-Garcia et al. (2021), Fernandez-Villaverde and Guerron-Quintana (2020) and Berger et al. (2020). More recently, Salgado et al. (2019) and Dew-Becker (2020) have argued that also changes in the asymmetry of the distribution are important for economic fluctuations.

[2]Early theoretical works on the importance of the financial sector for real economic activity fluctuations include Bernanke and Gertler (1989), Carlstrom and Fuerst (1997), Bernanke, Gertler, and Gilchrist (1999) and Kiyotaki and Moore (1997). More recent contributions focusing on the role of the financial sector in economic fluctuations include Christiano, Motto and Rostagno (2003, 2007), Curdia and Woodford (2010), Gertler and Karadi (2011), and Gertler and Kiyotaki (2011), Mendoza (2010), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014).

In this paper we bring these two streams of literature together and study the effects of financial shocks on the forecast distribution of real variables and inflation. Relative to the first stream of literature, we contribute by adopting a causal perspective. Most of the existing contributions in this area have focused on reduced-form analysis where the aim was to assess potential predictors of changes in the forecast distribution. Relative to the second stream of literature, we study causal effects of financial shocks on the whole expected distribution of real economic activity variables and inflation, not limiting the focus to first-moment effects as it is the case in the existing literature. More specifically, we investigate how financial shocks affect tail risk (the 5th percentile), uncertainty and asymmetry of the forecast distributions of industrial production growth and inflation in the US. The financial shock is a credit spread shock, identified following Gilchrist and Zakrajšek (2012).

As for the method, building on Forni, Gambetti and Sala (2021), we propose an econometric approach which combines quantile regressions and structural VARs. Quantile regressions are employed to estimate the conditional quantiles of the forecast distribution of any variable of interest, using a set of predictors. Such predictors have a VAR representation and thus a VMA representation in terms of structural shocks. This implies that the quantiles themselves have an impulse response functions representation in terms of the structural shocks, so one can study how quantiles respond to a shock of interest.

While the model is that of Forni, Gambetti and Sala (2021), the way it is used here represent an original methodological contribution. While Forni, Gambetti and Sala (2021) use the model to identify novel shocks (shocks affecting the tails of expected real activity growth) and study their first moment effects on macroeconomic variables, here we do the other way round. That is, we analyze the effect of shocks already studied in the SVAR literature to the expected quantiles of macroeconomic variables.

Our main findings are the following. First, while for industrial production growth the left tail is substantially more volatile than the right tail, confirming previous results, for inflation both tails display fluctuations: the right tail shifts primarily before the mid 1980s, while the left tail mainly varies after the 2000s. Second, credit spread shocks are a major driver of fluctuations in the left tail of output, explaining

60% of the forecast error variance on impact and about one third at business cycle frequencies. Consequently, they explain a large fraction of real activity uncertainty (almost one half at the one-year horizon). This suggests that credit shocks may affect economic activity not only directly, by increasing the cost of credit, but also indirectly, via their effects on downside uncertainty. Third, also monetary policy, identified with an external instrument approach (see Miranda-Agrippino and Ricco, 2021), produces significant effects on the left tail of macroeconomic variables. The effects, however, are substantially smaller than those of financial shock. From a back-of-the-envelope calculation, a four standard deviation monetary policy shock would be needed to offset the real risk arising from a one standard deviation financial shock.

Our results are in line with the findings in Adrian et al. (2019) but in the context of a structural, rather than reduced-form, model. The paper is also closely related to Loria et al. (2019) and López-Salido and Loria (2020). The authors use quantile local projections to study the effects of several macroeconomic shocks, identified in separate SVAR models, on the tail risk of GDP growth and inflation. The main difference relative to their paper is that we perform the analysis in a single model linking the SVAR with quantile regression. Our approach presents several advantages. First, the fact that there is a single model ensures consistency between the distribution dynamics and the responses of the variables included in the VAR. Second, variance and historical decompositions for different quantiles are easily derived as in the SVAR literature. Third, one can also perform scenario and counterfactual analysis (see e.g. Antolín-Díaz et al., 2021, and the references therein), which are instead unfeasible (or at least not straightforward) in a local projection framework. The differences in the econometric approach could be at the root of the different results obtained. While Loria et al. (2019) find that both financial and monetary policy shocks are equally important for tail risk, we find that only financial shocks represent a major driver of fluctuations in the distribution dynamics.

Our model is similar in spirit to the quantile VAR proposed by Chavleishvili and Manganelli (2019). 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). Therefore one requires a strong prior on a particular ordering of the variables, which is however hard to justify in practice in many settings.

The main advantage of our approach is that is very easy to estimate and use. Also, since shocks identification works exactly the same way as in SVARs, impulse response functions and variance decomposition analyses are easy to perform for any shock of interest. The main limitation 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

Our 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

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

where S is the Cholesky factor of Σ_ε, U is an orthonormal ($UU' = I$) identification matrix, $u_t = U'S^{-1}\varepsilon_t \sim WN(0, I)$ is the vector of structural shocks and $B(L)$ 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 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.

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

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

[3]See Koenker and Bassett (1978).

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

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

We focus here on three main features of the forecast distribution: tail risk, uncertainty and asymmetry. Let use define the 5th, $50th$ and 95th percentiles of the forecast distribution as

$$z_t^L = Q_t^{0.05} = \gamma_L'(L)y_t = \tilde{\beta}_{0.05}'(L)B(L)u_t \quad (6)$$

$$z_t^R = Q_t^{0.95} = \gamma_R'(L)y_t = \tilde{\beta}_{0.95}'(L)B(L)u_t. \quad (7)$$

$$z_t^M = Q_t^{0.5} = \gamma_M'(L)y_t = \tilde{\beta}_{0.5}'(L)B(L)u_t \quad (8)$$

The 5th percentile is our measure of *tail risk*. *Uncertainty* is defined as the difference between the two tails

$$z_t^U = z_t^R - z_t^L = \gamma_U'(L)y_t = (\beta_{0.95}'(L) - \beta_{0.05}'(L))B(L)u_t.$$

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

$$z_t^S = z_t^R + z_t^L - 2z_t^M = \gamma_S'(L)y_t = (\beta_{0.95}'(L) + \beta_{0.05}'(L) - 2\beta_{0.5}'(L))B(L)u_t.$$

2.4 Discussion

At first sight, 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 it is not.

To get the intuition, 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

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

[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.

where ε_t is i.i.d. In this case, the τ-th conditional quantile of the i-th element of the vector y_t, y_{it}, is:

$$Q_{i,\tau} = A_i y_{t-1} + Q_{\varepsilon_i,\tau}$$

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 the difference between any two quantiles $\overline{\tau}$ and $\underline{\tau}$ is:

$$Q_{i,\overline{\tau}} - Q_{i,\underline{\tau}} = Q_{\varepsilon_i,\overline{\tau}} - Q_{\varepsilon_i,\underline{\tau}}.$$

By the i.i.d assumption, $Q_{\varepsilon_i,\tau}$ is constant and does not depend on y_{t-1} so that $Q_{i,\overline{\tau}} - Q_{i,\underline{\tau}}$ 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 vector white noise, independent of the past history of y_t. Notice that ε_t, consistently with the assumptions of the VAR model, is serially uncorrelated 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

$$y_t = A y_{t-1} + \alpha' y_{t-1} v_t. \tag{9}$$

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 (9), but with Gaussian innovations (see Chan et al. (1992) for an in depth discussion).

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

$$\begin{aligned} Q_{i,\tau} &= A_i y_{t-1} + \alpha' y_{t-1} Q_{v_i,\tau} \\ &= (A_i + Q_{v_i,\tau}\alpha') y_{t-1} \end{aligned}$$

where $Q_{v_i,\tau}$ 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 $(A_i + Q_{v_i,\tau}\alpha')$ is quantile-dependent. The difference between two quantiles is:

$$Q_{i,\overline{\tau}} - Q_{i,\underline{\tau}} = (Q_{v_i,\overline{\tau}} - Q_{v_i,\underline{\tau}})\alpha' y_{t-1}$$

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

3 Empirical analysis

We discuss here the target variables for the quantile regressions and the shock identification in the SVAR model. We then present the main empirical findings. First, we describe the estimated measures of the forecast distributions of industrial production growth and inflation. Second, we assess the relevance of financial shocks in explaining fluctuations in these.

3.1 Target variables, specification and identification

We investigate the forecast distributions of industrial production growth and CPI inflation. In the baseline exercise we forecast the two variables one-year ahead. We consider the six-month ahead forecast as a robustness check. We use a monthly VAR including in y_t the log of industrial production (INDPRO), CPI inflation (CPI), the unemployment rate (UNRATE), the excess bond premium (EBP) of Gilchrist and Zakrajšek (2012), the Chicago Fed's National Financial Conditions Index (NFCI), the S&P Composite Stock Price Index (SP500) and the federal funds rate (FFR). The time span of the sample is 1973:M1 - 2016:M8. We use four lags in the VAR. In the quantile regressions we use the current value and one lag of all of the variables included in the monthly VAR.

3.2 The estimated forecast distributions

Figure 1 presents the estimated 5th, 50th and 95th quantiles of the one-year ahead forecast distributions of industrial production growth and inflation, together with their measures of uncertainty and skewness.

A few interesting findings emerge for the forecast distribution of industrial production growth. First, the 5th percentile is much more volatile than the 95th percentile, which is relatively flat over the sample. Second, the 5th percentile displays large and sudden drops in correspondence of economic downturns. Fluctuations in tail 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. 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.

Unlike real economic activity, both tails of the inflation forecast distribution exhibit substantial fluctuations over the sample considered. Movements in upside tail risk are particularly large before the mid 1980s. Tail risk displays a large and pronounced drop in correspondence of the Great Recession. Uncertainty has a declining trend until the mid 1990s and an increasing trend from 2000 until 2010 followed by another decline in the latest part of the sample. The three largest spikes in inflation uncertainty are observed in the late 1970s, early 1980s and at the onset of the Great Recession. Differently from industrial production, where fluctuations in uncertainty are exclusively driven by the left tail, both tails play a role for inflation uncertainty. For instance, the increase in uncertainty during the 1980s is largely driven by upside tail risk, while the increase in the aftermath of the Great Recession is driven by tail risk. Skewness presents a very interesting behavior. In the first part of the sample, before the 1990s, skewness presents several spikes driven by the right tail which make the distribution of inflation right-skewed. In the latest part of the sample, after 2000, the series presents two large negative peaks driven by the left tail, around 2003 and 2010, which make the distribution left-skewed. Below, we show that the asymmetry observed after 2000 is largely driven by financial shocks. Our results, however, do not shed light on what drives the right tail before the mid 1980s and this issue is left for future research.

3.3 The effects of financial shocks

Here we present our main results about the effects of financial shocks on the forecast distributions of growth and inflation. The financial shock is identified following Gilchrist and Zakrajšek (2012).

The shock is the 4th shock of a Cholesky identification where the Excess Bond Premium (EBP) is the 4th variable in y_t. The first 3 variables (INDPRO, CPI and UNRATE) represent slow moving variables and the remaining $n-3$ variables (EBP, NFCI, SP500, FFR) are fast moving variables. The financial shock has no contemporaneous effect on the slow-moving variables, while it has a contemporaneous impact on the fast-moving variables.

First, we show the impulse responses of the macroeconomic variables to financial shocks in the monthly SVAR. Second, we present the impulse responses to the different functions z_t^j of the forecast distributions of industrial production growth and inflation.

Figure 2 reports the impulse response functions of the variables included in the VAR to an unfavorable financial shock, namely an unexpected increase in the excess bond premium. Bold lines represent point estimates and shaded areas are 68% and 90% confidence bands. Results are very much in line with those found in the literature, see Gilchrist and Zakrajšek (2012). Real economic activity variables, stock prices and inflation significantly reduce following the shock, 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 finding confirms an important role for financial shocks as drivers of macroeconomic fluctuations.

Figure 3 reports the responses of the 5th and 95th percentiles (first row), the difference of the 5th and 95th percentiles with respect to the 50th percentile (second row), uncertainty (third row) and skewness (fourth row) of the one-year ahead forecast distributions of industrial production growth and CPI inflation to an unfavorable financial shock. Solid lines and shaded areas represent point estimates and 68% and 90% confidence bands, respectively.

An unfavorable financial shock reduces both tails of the distribution of industrial production growth and inflation. However, the effects on the 5th percentiles are much larger and persistent than those on the 95th percentiles, especially for industrial production. At the peak, a one-standard-deviation financial shock decreases the 5th percentile of the expected distribution of industrial production growth by roughly 1.2 percent, while it implies a decrease of the 95th percentile of about 0.4 percent. For inflation, the 5th percentile of the forecast distribution decreases by 0.25 percent, while the 95th percentile decreases by roughly 0.12 percent. When considering the results in deviation from the 50th percentile (5th and 95th percentiles minus the median), the results are very similar suggesting that the effects do not represent a median effect. Indeed, the 5th percentile in deviations from the median displays a pronounced drop following an unfavorable financial shock, while the 95th percentile is either increasing (for industrial production growth) or not moving significantly (for inflation). The financial shock significantly increases tail risk of both real economic activity and inflation. The dynamics of the left tail are reflected in the impulse responses of uncertainty and asymmetry. The fall of the 5th percentile with a relatively unchanged 95th percentile triggers an increase in uncertainty of both inflation and industrial production and makes the distribution of both variables more left-skewed. In other words, the probability of large drops in industrial production growth and inflation increases significantly in response to a worsening in financial conditions.

Table 2 reports the variance decomposition of tail risk, uncertainty and asymmetry of industrial production growth and inflation. Financial shocks explain a large portion of the left tail variance. For industrial production, 61% on impact and around 35% after one, two and four years. For inflation, 23% on impact and around 45% at one and two year horizons and 34% after four years. The effects on the median of both forecast distributions are substantially lower and those on the right tails even lower, especially for inflation. Financial shocks play a primary role in explaining fluctuations in uncertainty and skewness of the industrial production growth forecast distribution. Indeed, the shock explains slightly less than half of the variance of uncertainty and around one third of the variance of skewness. The percentages explained for inflation are slightly smaller since the 95th percentile plays a role in uncertainty and skewness dynamics, but the importance of the financial shock on the right tail is very modest.

The above findings shed new light on the transmission of credit shocks. They 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).

To complement the variance decomposition analysis, we also compute historical decompositions for various percentiles, uncertainty and skewness of the forecast distributions of inflation and industrial production growth. Figure 4 present the results for 5th, 50th and 95th percentiles and Figure 5 for uncertainty and skewness of the forecast distributions of industrial production growth and inflation. The black solid line represents the variable in deviation from its deterministic components. The dark gray bars represent the contribution of the financial shock and the light gray bars the contribution of the remaining shocks in the system, which we label as residual for simplicity and to which we do not provide an economic interpretation. Overall, financial shocks explain the bulk of the fluctuations in the left tail of the forecast distribution of both inflation and growth after 2000. Indeed, the lion's share of the large drops in correspondence to the early 2000s recession and the Great Recession are driven by financial shocks. On the contrary, the role played by financial shocks in explaining fluctuations in the median and the right tail is much more modest, with essentially no role for the upside tail risk. As a result, financial shocks appear to be the major drivers of uncertainty and skewness from the early 2000s.

Finally, from the impulse response functions we derive estimates of the Phillips curve slopes for different quantiles. The exercise should be taken with caution since we work with marginal distributions and not with the joint distribution. Still, we believe that numbers could provide some useful information. Since the financial shock is a demand shock, i.e. it moves output and inflation in the same direction, we can measure the Phillips curve slope with the response of prices relative to the response of industrial production, as previously done in Barnichon and Mesters (2020) and Galí and Gambetti (2020). More specifically, the slope is computed as the ratio between the sum of responses of the j-th quantile of industrial production over the sum of the response of the j-th quantile of inflation at an horizon of 12 months. We consider $j = 0.05, 0.5, 0.95$. The slopes are 0.17, 0.13 and 0.34 for the 5th, 50th and 95th percentiles respectively. The results show a much steeper Phillips curve for high levels of inflation and industrial production growth. The finding is in line with models with convex AS curves, arising for instance in presence of downward wage rigidites, and with the evidence in Daly and Hobijn (2014) and Debortoli et al. (2022).

3.4 Other checks

Tables 3 and 4 report the variance decompositions of the different statistics of the forecast distributions when using a horizon of 6- and 3-month ahead, respectively. Figure 6 reports the impulse response functions for the 6-month ahead only. The results are very similar to those of the baseline case when we use a 6-month horizon ahead, except that financial shocks are even more important for industrial production, especially for the left tail and for the median. For the 3-month ahead case, results are slightly different as far as industrial production is concerned. In particular, the shock appears to have more uniform effects on the three percentiles of the distribution. For inflation, the shock still is much more important for the left tail in both specifications.

Figure 7 reports the results obtained using no lags of the variables in the quantile regression. While for industrial production the results are virtually identical, for inflation a few differences are observed. The most remarkable change is that the left tail does not respond more than the right tail. The result is suggestive that lags of the variables are important predictors for the forecast distribution of inflation. Indeed, the coefficients in the quantile regression associated to the lags of the variables in the monthly VAR are significant for each quantile considered.

3.5 Is there a role for monetary policy?

What are the policy implications of the above findings? In this Section we investigate the extent to which monetary policy can be effective in mitigating the adverse effects on the left tail. The evidence discussed here is also novel since there are no studies on the effects of monetary policy on the distribution dynamics of both output and inflation, made exception for Loria et al. (2019).

The monetary policy shock is identified using an external instrument approach with the instrument of Miranda-Agrippino and Ricco (2021). The variable and lag specification of the VAR is the same as the one employed above for credit shocks. The reduced-form VAR is estimated from 1983:M1 to 2016:M8, but the regression of the reduced-form residuals on the instrument is estimated using data from 1991:M1 until 2009:M12, the time span for which the instrument is available. The responses are to a unitary variance shock.

Tables 5, 6 and 7 display the variance decomposition results using the 12-, 6- and 3-month ahead forecast distributions. Figure 8 shows the impulse response functions of the monetary policy shocks in the case of 3-month ahead, as this is the horizon for which the effects of monetary policy shocks are maximal. At a one-year horizon the shock accounts for around 20% of the variance of the left tail of industrial production and between 1% and 22% of the left tail of inflation depending on the horizon of the target variable. Hence, monetary policy has relevant effects on the risk of the distribution of the two variables suggesting that it can play a role in containing macroeconomic risk arising from the adverse effects of financial shocks. However it should be noted that, quantitatively, the effects are much smaller than those of the financial shock. From a back-of-the-envelope calculation, in order to offset the effects on the left tail of industrial production arising from a one standard deviation adverse financial shock, a four standard deviation expansionary monetary policy shock would be required. Such a large shock would more than offset the effects on inflation with the result of pushing on the right the whole distribution of inflation. So while there is a role for policy, stabilizing real risk would require actions associated to large and possibly unwanted inflationary effects.

4 Concluding remarks

We study the effects of financial shocks on the forecast distribution dynamics of industrial production growth and inflation. To this end, we use a novel econometric technique which combines quantile regressions and Structural VARs.

We find that financial shocks represent the major driver of fluctuations in the left tail of the forecast distributions of output and inflation. As the variance and the asymmetry of the forecast distributions are largely driven by the left tail, financial shocks turn out to play a very important role for distribution dynamics. After 2000, financial shocks are the dominant driver of the left tail of both industrial production growth and inflation forecast distributions. Monetary policy shocks have relevant effects on distribution dynamics, even though smaller than those of credit shocks. This suggests that monetary policy can help containing uncertainty and the adverse uncertainty effects of financial shocks.

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Tables

	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
INDPRO	0.0	16.6	21.7	19.6
CPI Inflation	0.0	2.3	2.3	2.4
UNRATE	0.0	18.2	25.4	23.7
EBP	97.8	78.2	73.3	69.5
NFCI	3.0	4.5	4.0	4.2
SP500	7.9	21.7	23.6	23.8
FFR	0.6	1.8	6.6	9.3

Table 1: Variance decomposition of the variables in the SVAR.

Industrial Production growth 12-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	61.0	37.7	35.6	33.2
50th percentile	33.3	15.2	15.2	16.1
95th percentile	33.7	8.5	10.3	10.0
Uncertainty	41.0	48.6	47.0	44.7
Skewness	32.7	36.2	33.7	29.8

CPI Inflation 12-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	23.3	47.2	42.2	34.0
50th percentile	3.3	2.4	1.9	4.8
95th percentile	0.3	1.1	1.1	2.3
Uncertainty	18.0	8.9	7.4	7.6
Skewness	1.8	24.3	26.4	23.1

Table 2: Financial shock: variance decomposition of the forecast distribution 12-month ahead.

Industrial Production growth 6-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	61.2	44.6	42.1	38.9
50th percentile	39.8	28.9	27.1	25.8
95th percentile	52.0	20.5	19.8	19.2
Uncertainty	14.4	53.3	51.9	49.0
Skewness	0.0	21.0	20.0	19.0

CPI Inflation 6-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	6.8	22.3	20.5	16.7
50th percentile	0.0	0.4	0.5	2.0
95th percentile	2.2	1.6	1.3	2.1
Uncertainty	12.4	11.5	10.4	9.8
Skewness	0.9	3.2	4.4	5.4

Table 3: Financial shock: variance decomposition of the forecast distribution 6-month ahead.

Industrial Production growth 3-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	8.4	24.0	22.9	22.6
50th percentile	26.4	28.6	27.3	25.7
95th percentile	13.5	23.7	23.2	23.7
Uncertainty	0.0	18.3	17.6	17.0
Skewness	1.3	9.8	9.8	11.2

CPI Inflation 3-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	11.9	30.7	30.9	25.2
50th percentile	1.3	0.9	0.8	2.8
95th percentile	0.9	8.8	7.6	7.9
Uncertainty	14.9	30.0	28.7	26.4
Skewness	14.0	11.5	12.3	12.2

Table 4: Financial shock: variance decomposition of the forecast distribution 3-month ahead.

Industrial Production growth 12-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	0.4	21.8	21.6	20.5
50th percentile	3.4	22.4	20.9	19.6
95th percentile	11.0	13.8	12.1	11.1
Uncertainty	2.6	22.6	22.8	21.9
Skewness	2.1	11.6	11.3	12.0

CPI Inflation 12-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	0.6	1.6	2.4	4.3
50th percentile	0.0	8.9	8.7	13.6
95th percentile	18.7	22.4	17.6	15.4
Uncertainty	7.1	9.0	8.0	7.0
Skewness	0.5	3.8	5.5	14.0

Table 5: Monetary policy shock: variance decomposition of the forecast distribution 12-month ahead.

Industrial Production growth 6-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	17.3	21.6	21.6	21.0
5oth percentile	10.0	18.6	17.5	18.2
95th percentile	5.6	7.6	7.7	8.8
Uncertainty	10.4	22.9	23.1	22.4
Skewness	0.3	1.2	1.3	9.2

CPI Inflation 6-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	0.1	6.1	6.3	8.8
50th percentile	1.9	10.9	11.5	15.2
95th percentile	8.5	21.3	19.5	18.0
Uncertainty	1.7	13.5	13.7	14.8
Skewness	4.9	6.0	5.9	9.9

Table 6: Monetary policy shock: variance decomposition of the forecast distribution 6-month ahead.

Industrial Production growth 3-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	22.2	18.1	17.8	18.4
50th percentile	11.1	20.8	20.2	20.4
95th percentile	0.7	5.8	6.0	7.4
Uncertainty	16.6	20.3	20.6	19.8
Skewness	3.1	10.2	10.9	11.0

CPI Inflation 3-month ahead				
	Horizon			
	$h = 0$	$h = 12$	$h = 24$	$h = 48$
5th percentile	21.3	22.8	21.5	22.4
50th percentile	19.7	18.2	19.3	23.7
95th percentile	5.7	18.2	16.3	15.3
Uncertainty	7.8	19.2	17.4	18.0
Skewness	17.3	10.8	11.4	20.6

Table 7: Monetary policy shock: variance decomposition of the forecast distribution 3-month ahead.

Figures

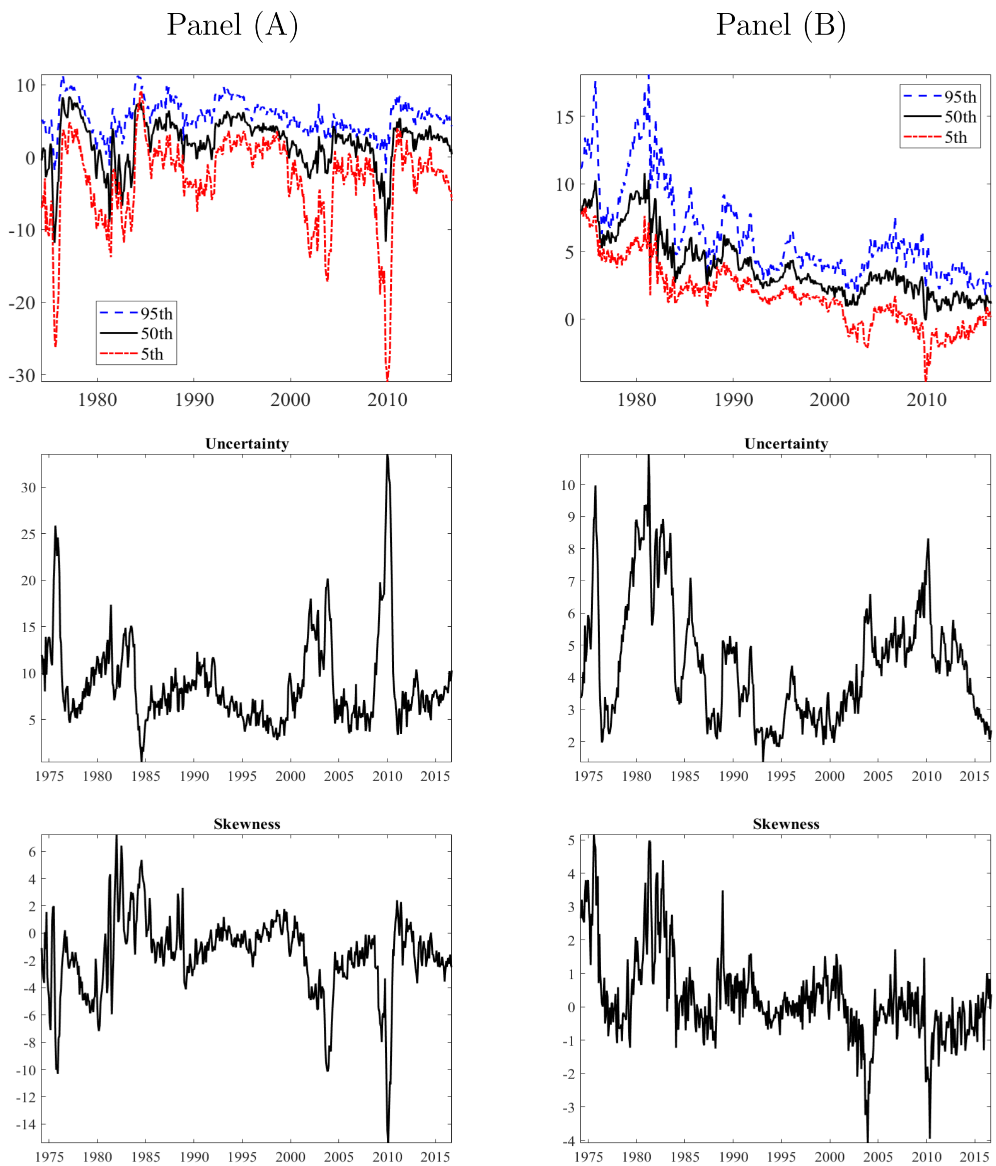

Figure 1: Forecast distributions. Panel (A): industrial production growth. Panel (B): inflation.

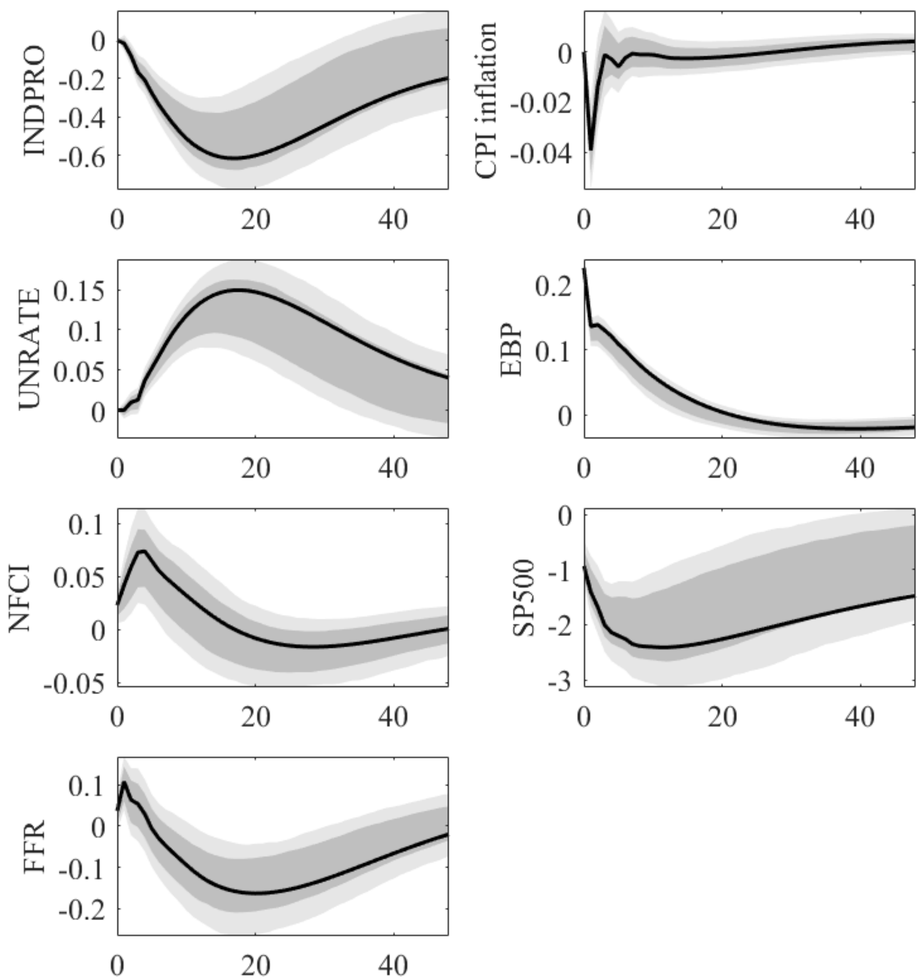

Figure 2: Impulse response functions of the variables to a financial shock. Solid lines are point estimates, while shaded areas are 68% and 90% confidence bands.

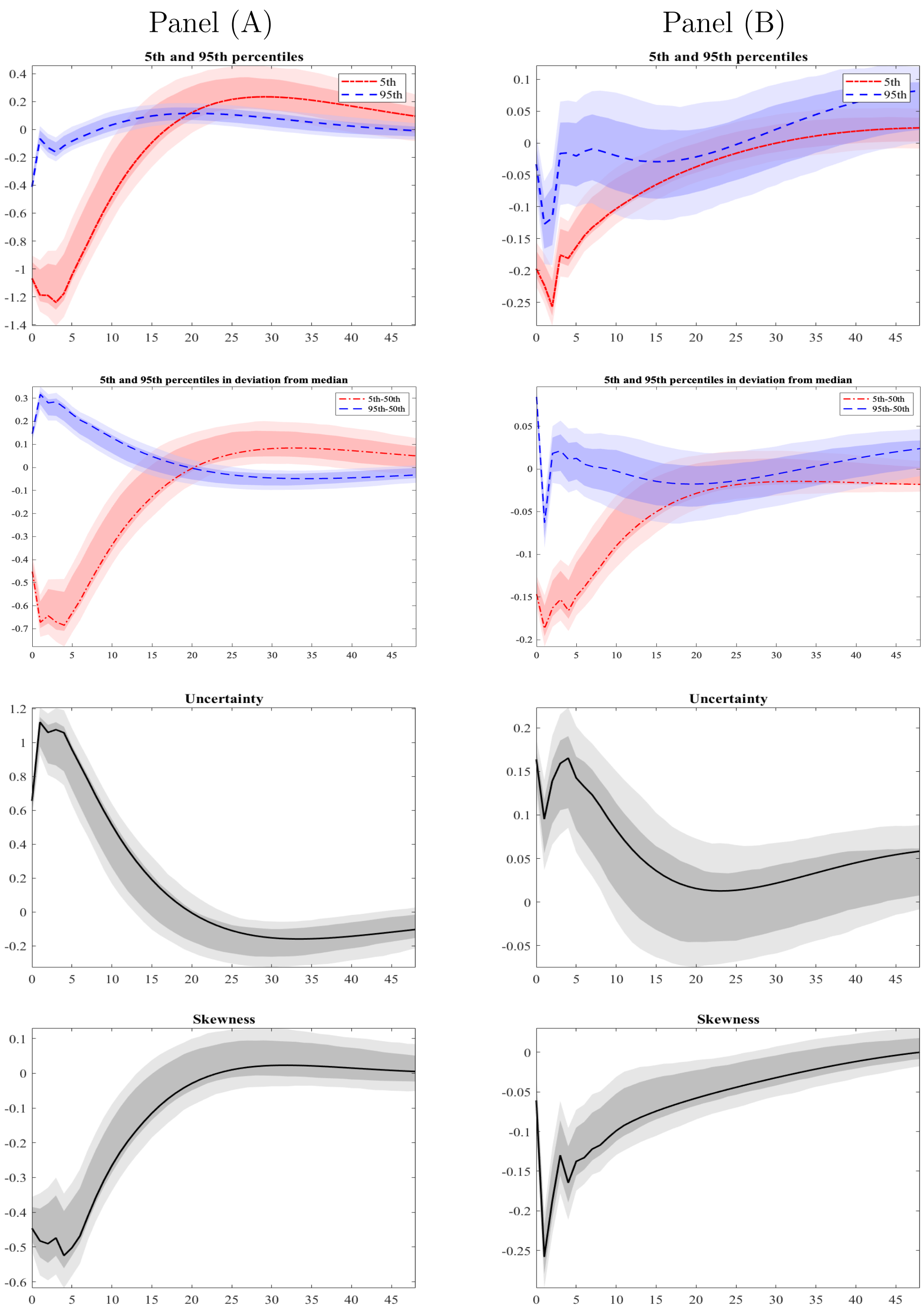

Figure 3: Impulse response functions. Panel (A): industrial production growth. Panel (B): inflation. Solid lines are point estimates, while shaded areas are 68% confidence bands.

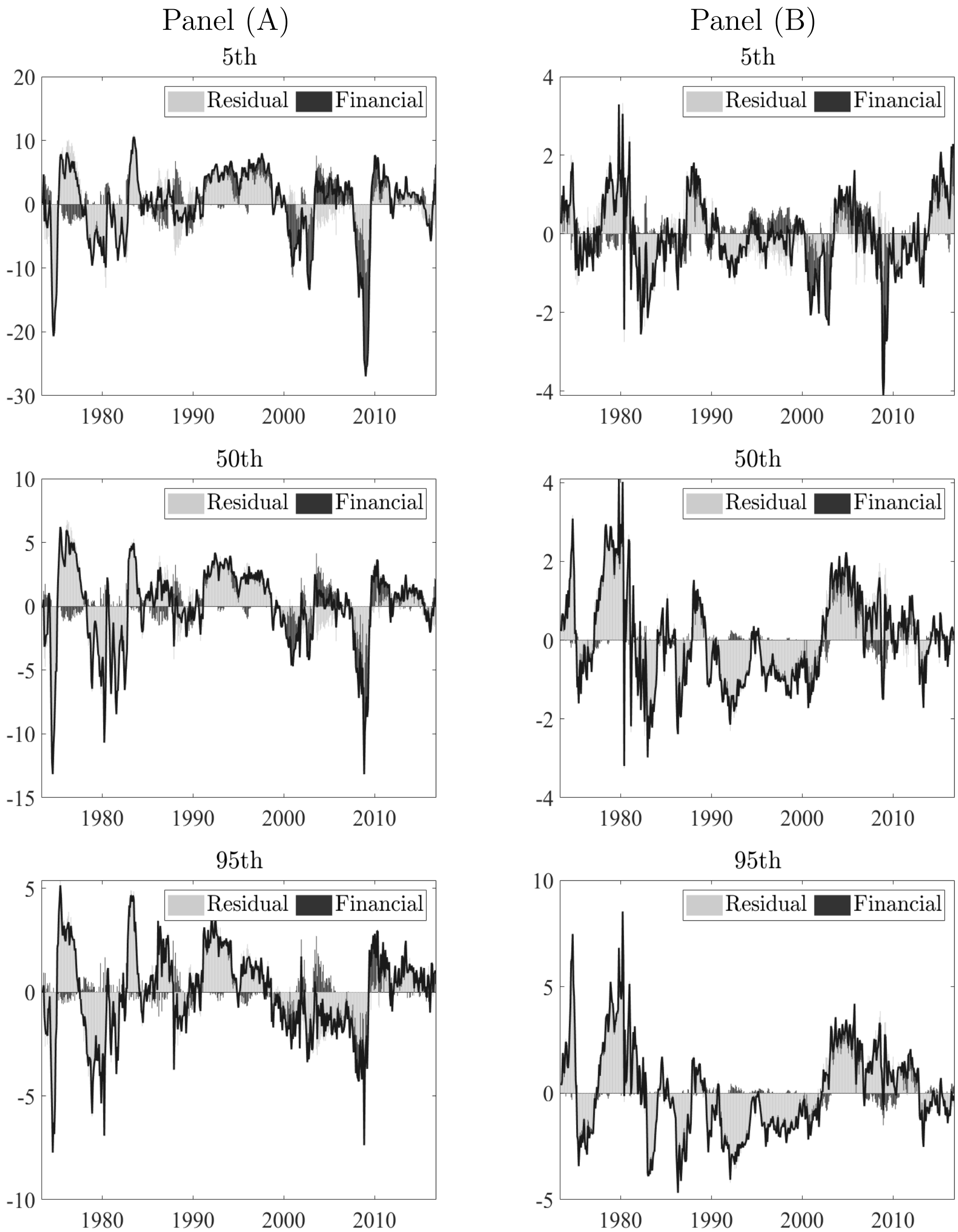

Figure 4: Historical decompositions. Panel (A): industrial production growth. Panel (B): inflation.

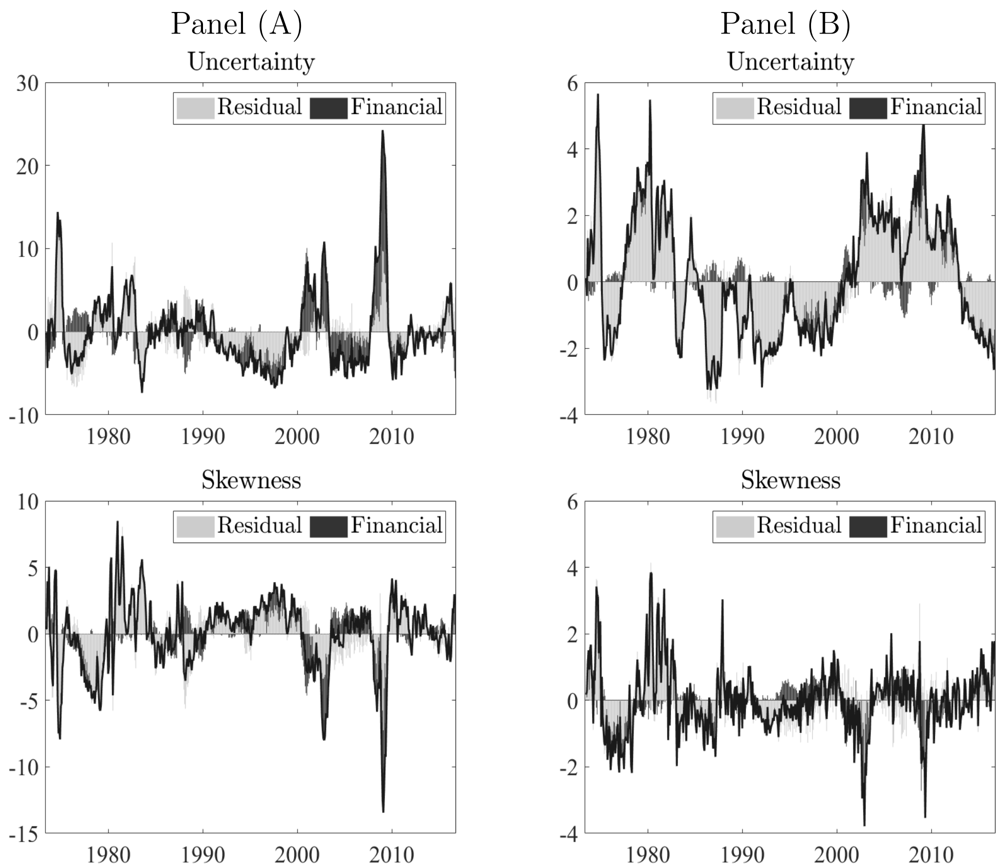

Figure 5: Historical decompositions. Panel (A): industrial production growth. Panel (B): inflation.

Panel (A) Panel (B)

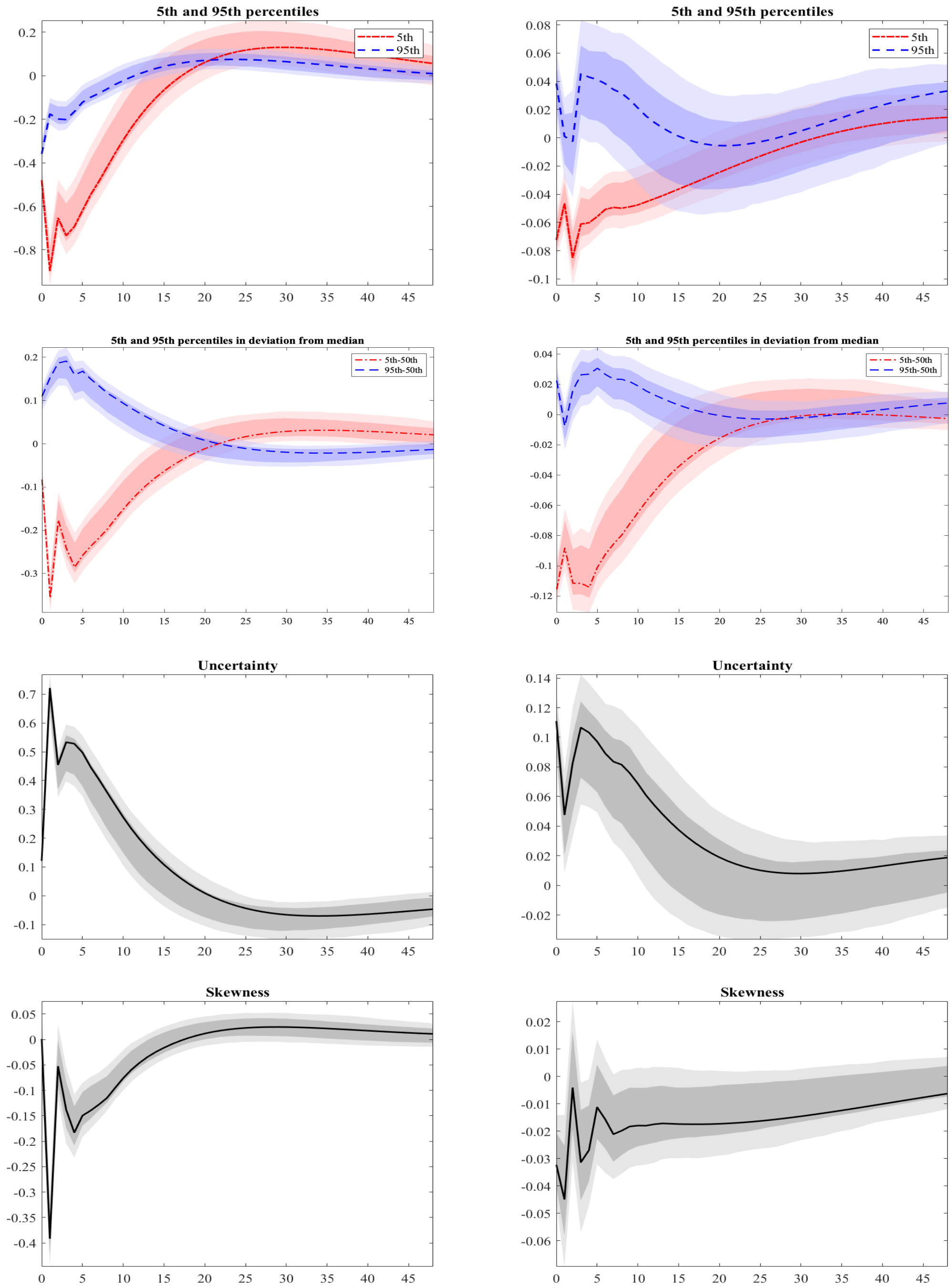

Figure 6: Robustness 1: 6-month ahead forecast distribution. Panel (A): industrial production growth. Panel (B): inflation. Solid lines are point estimates, while shaded areas are 68% confidence bands.

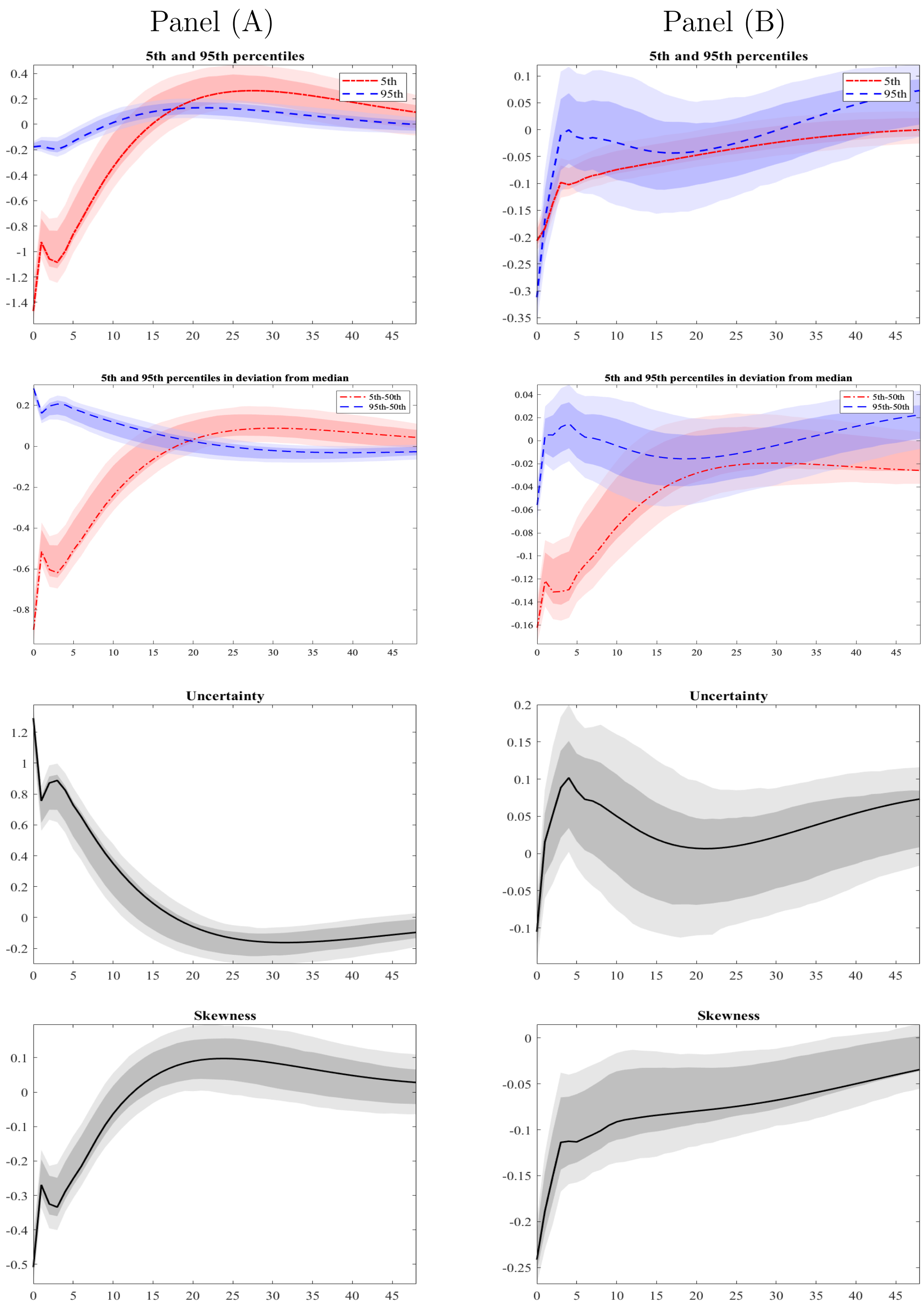

Figure 7: Robustness 2: no lags in the quantile regression. Panel (A): industrial production growth. Panel (B): inflation. Solid lines are point estimates, while shaded areas are 68% confidence bands.

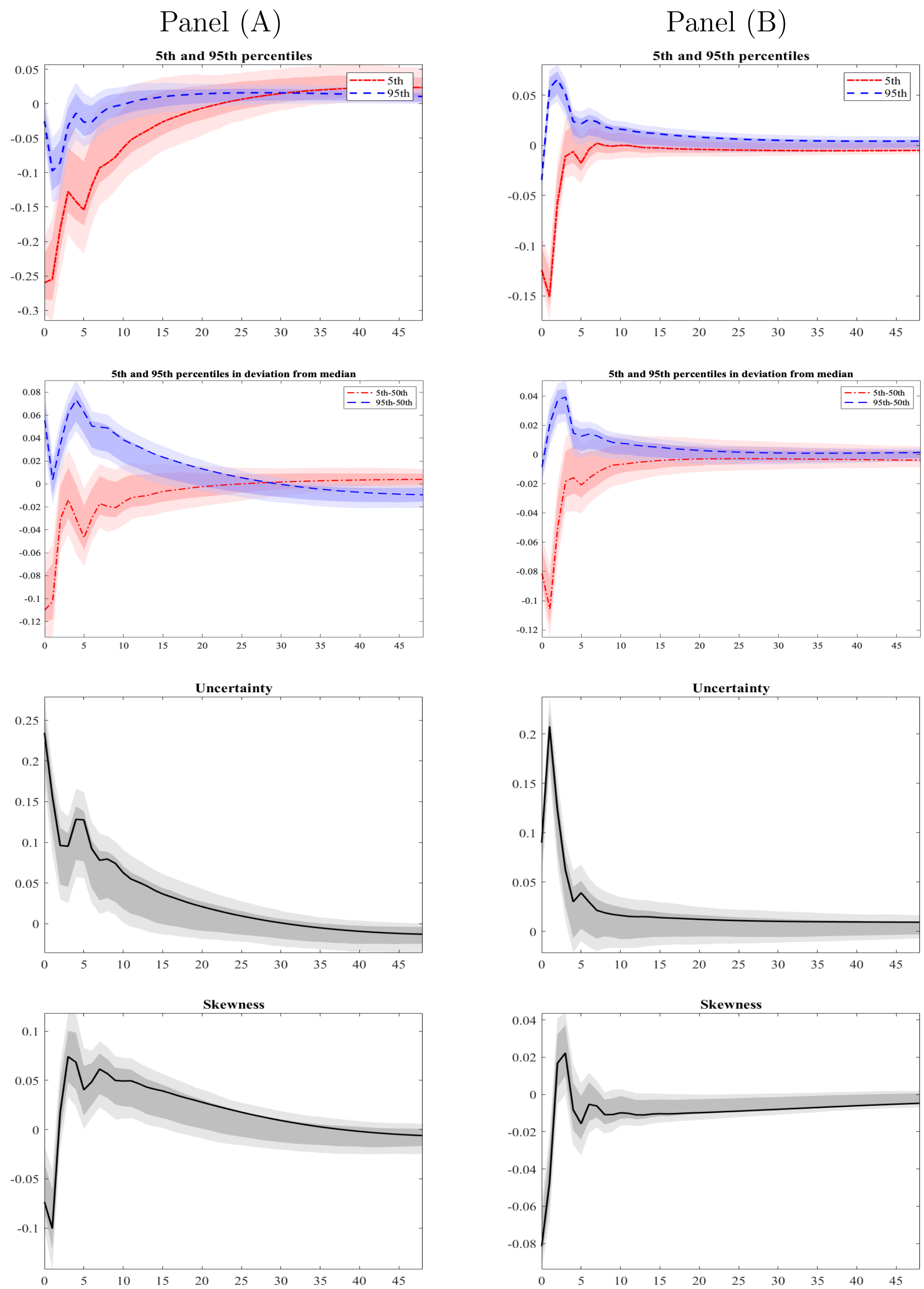

Figure 8: Impulse response functions of 3-month ahead forecast distributions to a monetary policy shock. Panel (A): industrial production growth. Panel (B): inflation. Solid lines are point estimates, while shaded areas are 68% confidence bands.