Assessing Macroeconomic Tail Risk

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April 16, 2019

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Abstract

What drives macroeconomic tail risk? To answer this question, we borrow a definition of macroeconomic risk from Adrian *et al.* (2019) by studying (left-tail) percentiles of the forecast distribution of GDP growth. We use local projections (Jordà, 2005) to assess how this measure of risk moves in response to economic shocks to the level of technology, monetary policy, and financial conditions. Furthermore, by studying various percentiles jointly, we study how the overall economic outlook—as characterized by the entire forecast distribution of GDP growth—shifts in response to shocks. We find that contractionary shocks disproportionately increase downside risk, independently of what shock we look at.

Keywords: Macroeconomic Risk, Shocks, Local Projections
JEL Classification: C21, C53, E17, E37

We thank Marvin Nöller for excellent research assistance. We also want to thank seminar participants at the Chinese University of Hong Kong for helpful comments. *Disclaimer*: The views presented herein are those of the author and do not necessarily reflect those of the Federal Reserve Board, the Federal Reserve Bank of Richmond, the Federal Reserve System or their staff.

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1 Introduction

Economic policymakers and market participants are generally not only worried about what changes to economic conditions will do to the economy *on average*, but also how these changes affect the probability of large losses materializing.[1] Standard impulse response functions in linear models such as Vector Autoregressions (VARs) are not built to answer these questions as they track average outcomes. Our goal is to provide a flexible, yet simple framework that can directly tackle these issues. In the finance literature, the notion of *value at risk* is prevalent. What is meant by value-at-risk is the evolution of left-tail percentiles of the variable of interest under various scenarios. We borrow this idea to operationalize the concept of macroeconomic risk. To be more precise, we follow Adrian *et al.* (2019) and study the distribution of macroeconomic risk by estimating a quantile forecast regression of GDP growth four quarters ahead for various quantiles. We focus on the 10th percentile and, as reference points, the median and 90th percentiles. We interpret this 10th percentile of the forecast distribution of future GDP growth as *macroeconomic tail risk*. With that measure at hand, we ask how macroeconomic risk changes after structural shocks hit the economy by studying local projections as introduced by Jordà (2005). To do so, we collect various measures of a suite of macroeconomic shocks. In particular, we use various measures of technology shocks, monetary policy shocks, as well as a measure of shocks to financial conditions. Here we follow the large literature that directly uses measures of (or instruments for) structural shocks—see for example Ramey and Zubairy (2018), Romer and Romer (2004), or Mertens and Ravn (2013). With the changes in the 10th percentile as well as the median and the 90th percentile in hand, we can further follow in the footsteps of Adrian *et al.* (2019) and fit a flexible (skewed-t) distribution to match various estimated quantiles as well as trace out how the entire distribution of real GDP growth four quarters ahead changes after a shock hits the economy. We view changes in this distribution as summarizing changes in the *economic outlook* after a shock hits the economy.

One key point to emphasize is that our approach is constructed to be as flexible as possible: In the initial quantile regression stage, we model each quantile separately instead of assuming a specific distribution for the forecast distribution of real GDP growth. In the second stage, we use local projections to impose as few restrictions on the data generating process as possible.[2] Just as Adrian *et al.* (2019), we only use the skewed-t distribution *after*

[1] For research showing that the Federal Reserve is concerned by downside risk, see Kilian and Manganelli (2008). For direct evidence of a policymaker thinking about downside risk, see this March 2019 speech by Lael Brainard, member of the Board of Governors of the Federal Reserve System: `https://www.federalreserve.gov/newsevents/speech/brainard20190307a.htm`.

[2] As shown by Plagborg-Møller and Wolf (2019), local projections and VARs asymptotically estimate the same impulse responses, but are on diametrically opposite ends of the bias-variance trade-off in finite samples.

having estimated the quantiles separately. A common pattern emerges when we study our shocks: Expansionary shocks compress the distribution of future GDP growth, thus making "bad" outcomes (those in the left tail) more tolerable. Unfortunately, as we show later, this result also implies that contractionary shocks make the 10th percentile fall more than the median—hence leading not only to poor average outcomes, but also to a further increase in downside risk. Complementing the analysis in Adrian *et al.* (2019), we find that the key channel through which shocks affect macroeconomic risk is via their effect on financial conditions.

The remainder of the paper is organized as follows. Section (2) presents econometric methodology. Section (3) provides an intuition for how shocks might affect the shape of distribution in different manners. Section (4) presents the main findings, and Section (5) concludes.

2 Econometric Methodology

2.1 Conditional Quantiles

We compute conditional quantiles for annualized real GDP growth following the method proposed by Adrian *et al.* (2019). In particular, we run a quantile regression (Koenker and Bassett, 1978) for real GDP growth over the subsequent 4 quarters by conditioning on a constant, the National Financial Conditions Index (NFCI), and real GDP growth at time t.[3]

Formally, let y_{t+h} denote the average value of real GDP growth between t and $t+h$ and let x_t denote the vector of conditioning variables, then the quantile regression is given by:

$$\hat{\gamma}_\tau = \underset{\gamma_\tau \in \mathbb{R}^k}{\operatorname{argmin}} \sum_{t=1}^{T-h} \left(\tau \cdot \mathbb{1}_{(y_{t+h} \geq x_t \gamma)} |y_{t+h} - x_t \gamma_\tau| + (1-\tau) \cdot \mathbb{1}_{(y_{t+h} < x_t \beta)} |y_{t+h} - x_t \gamma_\tau| \right), \tag{2.1}$$

where $\mathbb{1}_{(\cdot)}$ denotes the indicator function and $\tau \in (0,1)$ indicates the τth quantile. The quantile of y_{t+h} conditional on x_t is then given by the predicted value from that regression[4], defined as

$$\hat{Q}_{y_{t+h}|x_t}(\tau|x_t) = x_t \hat{\gamma}_\tau \equiv q_{\tau,t}. \tag{2.2}$$

In the following, we will analyze how different quantiles react to aggregate shocks.

[3] In Appendix C, we show that our findings are robust to adding additional controls.

[4] While Adrian *et al.* (2019) define the predicted value of y_{t+h} as the conditional quantile at $t+h$, we define the predicted value as today's risk. That is, the predicted value of y_{t+h} corresponds to t.

2.2 Impulse Responses

We estimate responses of different GDP growth quantiles to a variety of aggregate shocks by applying the local projection method based on Jordà (2005). As a baseline, we run the following linear regression:

$$q_{\tau,t+s} = \alpha_{\tau,s} + \beta_{\tau,s} shock_t + \psi_{\tau,s} controls + \epsilon_{\tau,t+s}, \tag{2.3}$$

for $s = 0, \ldots, S$ and where $q_{\tau,t+s}$ is the measure of risk at period $t+s$ for the τth quantile (i.e., the quantile τ of the distribution of y_{t+s+h} conditional on information at time $t+s$), and *controls* is a vector of control variables that include the lagged quantiles and model-specific controls that we will explain in the next section. Note that that there are two distinct notions of "horizon" in our application. First, the horizon in the quantile regression h, which we keep fixed at 4 quarters. This first horizon captures how forward looking our measure of risk is. The second notion of horizon is s in the local projection, which we vary as we trace out how risk responds at different horizons to a shock at time t. The response of quantile q_τ at time $t+s$ to a *shock* at time t is then given by $\beta_{\tau,s}$. Thus, we construct the impulse-response functions by the estimating the sequence of the $\beta_{\tau,s}$'s in a series of univariate regressions for each horizon. Confidence bands are based on Newey-West corrected standard errors that control for serial correlation in the error terms induced by the successive leading of the dependent variable.

At this point it is useful to contrast our approach with another approach that aims to combine quantile regressions with local projections, an approach advocated for by Linnemann and Winkler (2016). We want to interpret the 10th percentile of 4-quarters ahead GDP growth as a measure of downside risk and we then ask how this measure of risk reacts to different shocks. Furthermore, by not only looking at the 10th percentile in isolation but various quantiles jointly, we can construct how the distribution of four-quarters ahead real GDP growth changes as shocks hit the economy. We study a number of shocks and find it useful to use the same quantile (or measure of risk) for all shocks we study in our local projections. Linnemann and Winkler (2016), instead, are interested in one shock only and model the conditional quantiles *conditional on, among other things, a fiscal shock* and thus include the shock directly in the quantile regression. By following their approach, Linnemann and Winkler (2016) cannot distinguish between the two horizons h and s that we emphasized above (given that they ask a different question, they probably would not want to).[5]

With impulse responses to various quantiles at hand, we fit a flexible distribution to our es-

[5] Another approach in empirical macroeconomics that uses quantile regressions is introduced in Mumtaz and Surico (2015), who use quantile autoregressive models to study state dependence in the consumption-interest rate relationship.

timated path of GDP growth distributions after each shock. To be specific, we start with the average distribution of real GDP growth four quarters ahead using the sample of Adrian *et al.* (2019). We then change four quantiles according to the estimated impulse response functions (IRFs) [6] to produce paths of those four quantiles. For each horizon, we then choose the four parameters of the skewed-t distribution (Azzalini and Capitanio, 2003) to exactly match those four quantiles. The skewed-t distribution is given by the following density function for a data point y:

$$f(y|\mu,\sigma,\alpha,\nu) = \frac{2}{\sigma} t\left(\frac{y-\mu}{\sigma};\nu\right) T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{\nu+1}{\nu+\left(\frac{y-\mu}{\sigma}\right)^2}};\nu+1\right). \tag{2.4}$$

As discussed in Adrian *et al.* (2019), t and T are the density and cumulative distribution function of the common t-distribution, μ is a location parameter, σ is a scale parameter, ν controls how fat the tails are (similar to the degrees of freedom in the common t-distribution), whereas α governs skewness because it controls how much the standard t-distribution is twisted (or skewed) according to T.

2.3 Data

We estimate responses in different quantiles of GDP growth to various aggregate shocks. All regressions are estimated at quarterly frequency and as a baseline we use four lags for all control variables. This section gives a brief overview of the various specifications and data transformations. Most of the shocks considered here are reviewed in Ramey (2016) and can be thus found in her data appendix. More details on our data sources are provided in Appendix A.

Narrative Monetary Policy Shocks We explore two types of monetary policy shocks. First, we use the Romer and Romer (2004) (RR henceforth) narrative-based monetary shocks. They regress the federal funds target rate on Greenbook forecasts at each FOMC meeting date and use the residuals as the monetary policy shock. We aggregate these monthly shocks by adding up the monthly values within each quarter. The sample period runs from 1973Q1 to 2007Q4. As a second measure, we use the monetary policy shocks identified by Antolín-Díaz and Rubio-Ramírez (2018) (AR henceforth) who add narrative sign restrictions to the VAR model in Uhlig (2005). Also in this case, monthly values are aggregated to quarterly

[6] Following Adrian *et al.* (2019), we use impulse responses for the 5th, 25th, 75th, and 95th percentiles to match the percentiles that Adrian *et al.* (2019) used to compute the distributions in their paper. We show the impulse responses for those quantiles in Appendix B. They tell the same story as our choice of percentiles.

frequency. Here the sample period runs from 1973Q1 to 2007Q3. For both types of shocks we include the following controls in the local projection regression: Lagged values of the shock itself, the log of both the consumer and the commodity price index (aggregated to quarterly frequency by simple averaging) in first-differences, the log of real GDP in first-differences, the federal funds rate (quarterly average), and the unemployment rate. We refrain from including contemporaneous controls.

Excess Bond Premium Shocks We take the Gilchrist and Zakrajšek (2012) excess bond premium (EBP henceforth) updated by Favara *et al.* (2016) to construct an aggregate shock[7]. The excess bond premium can transformed into an exogenous shock by setting the additional controls appropriately if we assume that the bond premium affects interest rates contemporaneously but has no impact on prices and economic activity within a quarter.[8] Thus, the set of controls consists of the contemporaneous federal funds rate and lags of the EBP, the log of the consumer price index, and the log of real GDP (the last two in first-differences). All other shocks we study are identified in a separate estimation. For EBP, we can instead identify the shock in the local projection step along the lines of Barnichon and Brownlees (2016) by controlling for the relevant variables. In this one step approach, the lagged "shocks" are implicitly controlled for in lags of endogenous variables. The sample period runs from 1973Q1 to 2015Q4.

Unanticipated and Anticipated Technology shocks We consider three different technology shocks. First, a technology shock à la Galí (1999), constructed by imposing that a technology shock is the only shock affecting labor productivity in the long-run. For the Galí (1999) shock, we estimate a VAR with four lags that includes three variables: changes in labor productivity, changes in hours, and changes in the GDP deflator. The technology shock is identified as the only shock affecting labor productivity in the long-run. Second, we construct technology shocks by taking the growth rate of the Fernald (2012) utilization-adjusted TFP series for the aggregate economy. We refer to these shocks as "JF-TFP" shocks. Third, we consider the Barsky and Sims (2012) TFP news shocks. The news shock is identified in a VAR with four lags that includes TFP, consumption, real output, and hours per capita. The identification assumption is that the news shock is orthogonal to the innovation in current TFP that best explains variation in future TFP (in the subsequent 10 years). For the Galí (1999) shock and the TFP news shock, the sample period runs from 1975Q1 to 2007Q3. The JF-TFP shock is available from 1974Q1 up to 2015Q3. For all technology shocks we include

[7]We transform it to quarterly frequency by averaging the monthly values within each quarter.

[8]For a further discussion of how timing restrictions such as this can be incorporated in local projections see Barnichon and Brownlees (2016).

the following controls in local projections: lags of the shock itself, lagged log of real GDP per capita in first-differences, and lagged log of productivity in first-differences. The latter is measured as real GDP divided by total hours.

3 Some Intuition for Impulse Responses of Quantiles

This section gives three examples where an initial distribution of an outcome changes after a shock hits. We show these examples to convey how the change in quantiles is linked to the change in the distribution as a whole and how changes in specific moments translate into changes in quantiles. Our scenario is as follows: After an initial univariate distribution of an outcome is hit by a shock, we trace out how this distribution changes on impact and in the period after impact. We consider three experiments:

1. The shock leads to an increase in the variance of our distribution, which is Gaussian.
2. The shock leads to an increase in the mean of our distribution, which is Gaussian.
3. The shock leads to an increase in the shape parameter of our distribution, which is distributed according to a Gamma distribution.

Figure 1 plots three panels for each experiment. The first panel in each row shows the initial distribution, the distribution when the shock hits, and the distribution in the period after the shock has materialized. The middle panel in each row shows the evolution of the 10th and 90th percentile for those three periods. The last panel in each row gives the impulse responses for the 10th and 90th percentiles *under the assumption that if the shock that moved the distributions did not materialize, the distribution would have remained at its original position*. As the impulse response plots the difference between the relevant percentiles and the original values, the impulse response figures only show values for two time periods (the period where the shock hits and the period after). Each row presents the figures for one experiment. Note that the levels of the percentiles are not directly interpretable as IRFs because we do not subtract the baseline value from the quantiles in those figures. As we can see, an increase in the variance of a symmetric distribution makes the quantiles drift apart in a mirror-image fashion, whereas a change in the mean of a symmetric distribution makes the quantiles move in parallel, which in turn makes the impulse responses lie on top of each other. With a non-symmetric distribution (or if a shock makes a distribution non-symmetric) the quantiles can drift apart, but not necessarily in a mirror-image fashion, as is the case in the last example.

Interpreting changes in multiple quantiles jointly can be challenging because we have to envision how the entire distribution might change. We will later also plot changes in distributions to help the reader with interpretation. Nonetheless, it is useful to dig a bit deeper at this point. As an example, let us focus on the third experiment. As can be seen from the last panel on the bottom row of Figure 1, the 10th and 90th percentile drift apart because the 90th percentile *increases faster* than the 10th percentile. Thus the distribution *spreads out* as a result of the shock—this can also be seen by looking at the leftmost panel of the bottom row, where the yellow distribution is more spread out than the original blue distribution. Let us for a second imagine that this impulse response is the response to a "positive" shock and that quantiles react linearly to those shocks (as will be the case in our local projections), so that the response to a "negative" shock would just be the mirror image of the rightmost panel of the bottom row. What would happen to the distribution in that case? The 90th percentile would *decrease faster* than the 10th percentile. Hence the distribution would actually *compress* in that scenario.

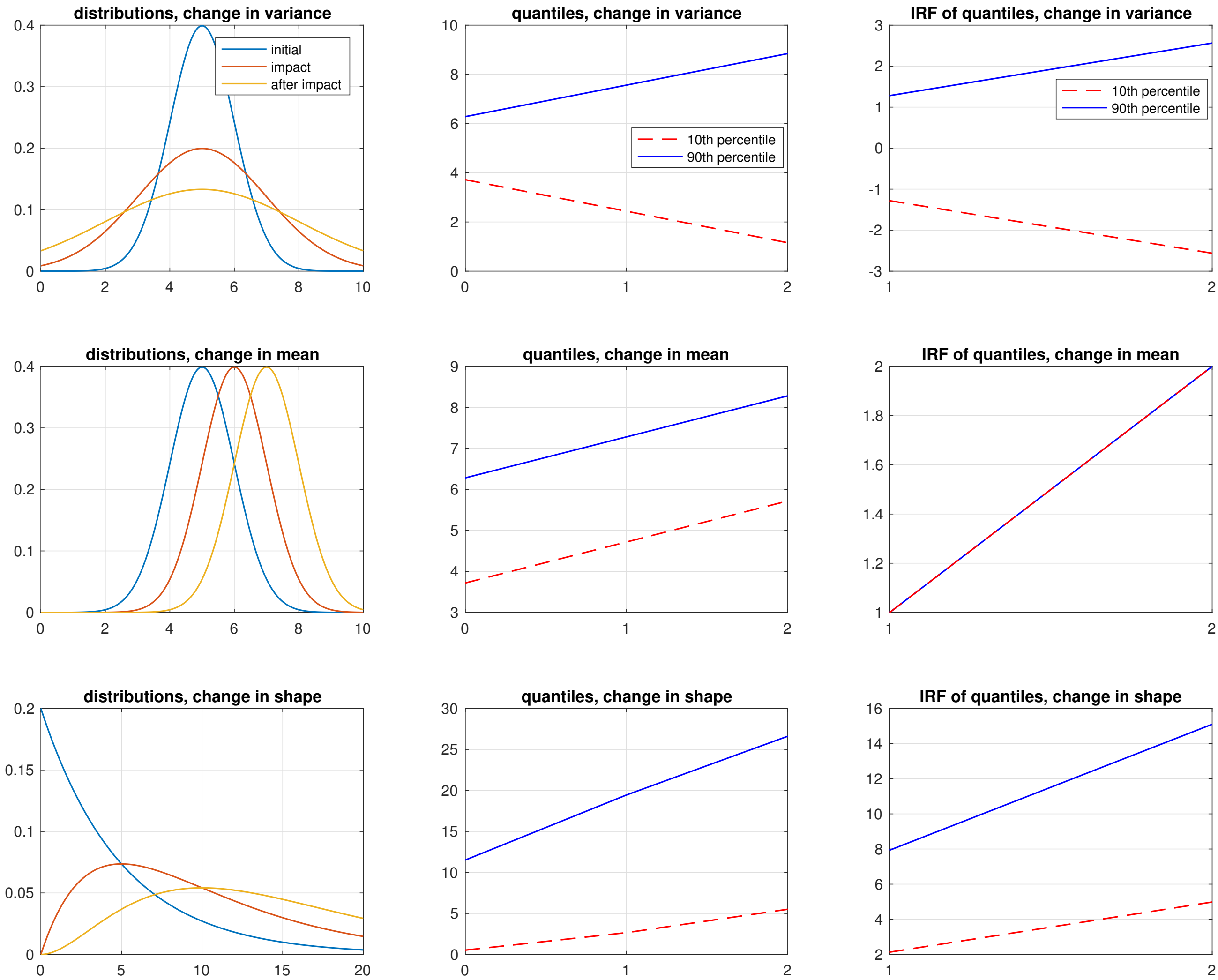

Figure 1: **Illustration of Changes in Percentiles.**

4 Results

In this section, we present various impulse responses (i.e. $\beta_{\tau,s}$) based on equation 2.3. The $\beta_{\tau,s}$ coefficients can be interpreted as responses to one standard deviation shocks. We present results for three groups: monetary policy shocks, credit shocks, and technology shocks. Additional figures can be found in Appendix B. We first plot the impulse responses of the 10th percentile, the median, and the 90th percentile in Figure 2. We show the error bands for the response for the median in the main text; the corresponding error bands for the other percentiles can be found in Appendix B. We then follow Adrian *et al.* (2019) and use those estimated quantiles to fit a flexible (skewed-*t*) distribution to match the quantiles. In Figure 3, we plot how various shocks change this distribution. In particular, we first compute the average distribution of four-quarters ahead real GDP growth in our total sample and then plot the difference between this initial distribution and the distribution affected by a specific shock at various horizons. In order to facilitate interpretation, each panel of Figure 3 plots three lines: the 10th percentile (in red), the median (in black), and the 90th percentile (in blue) of the original (average) distribution. This helps check in what direction a shock shifts the distribution. In particular, whenever a line is visible it means that posterior mass at that quantile of the original distribution has decreased.

4.1 Monetary Policy Shocks

The first panel of Figure 2 plots the responses to a contractionary RR monetary shock estimated via local projections. Those shocks affect the distribution of GDP growth disproportionately across quantiles. A contractionary (i.e., positive) monetary policy shock decreases the 10th percentile more than the median or the 90th percentile. This means that not only will a monetary policy shock lead to a decrease in *median* forecasted GDP growth four quarters ahead, but it will also make "bad" outcomes substantially worse by spreading out the left tail of the distribution.

The above result is robust to the use of an alternative monetary shock measure, namely the AR monetary shock (see the second panel in the top row of Figure 2). This shift is also evident from the top two panels of Figure 3, which plot the implied changes in the entire distribution of forecasted GDP growth.

4.2 Credit Spread Shock

The third panel of Figure 2 plots the responses to a contractionary (i.e., positive) shock to the excess bond premium, which we interpret as an unexpected deterioration of financial conditions, just as Gilchrist and Zakrajšek (2012). The entire conditional distribution of GDP growth is shifted, with the left tail being affected disproportionately more. On impact and up to one year, the interpretation of the effects of a contractionary credit shock is similar to the interpretation of the monetary policy shock given above. After one year, however, the responses of the 10th and 90th percentile cross, leading the distribution of future GDP growth to actually compress since the 10th percentile grows faster than the 90th percentile. One interpretation of these results is that policymakers counteract financial shocks, but that it takes around a year for these measures to take effect (potentially and partially due to lags in policy implementation).

4.3 Technology Shocks

The effects of a technology shock identified along the lines of Galí (1999) is shown in the second panel of the middle row of Figure 2. The bottom row of that figure shows the corresponding effects for a technology shock identified using Fernald (2012) and a TFP news shock following Barsky and Sims (2012). We discuss the findings together since the results for both risk (the effects on the 10th percentile of the forecast distribution) and the entire shape of the economic outlook are similar across these specifications. An expansionary technology shock of any of the three types we consider here compresses the distribution of real GDP growth one year ahead. This means that not only does a technology shock raise median GDP growth one year ahead, but it also makes low outcomes of future GDP growth more tolerable by shifting the distribution to the right—as can be seen in Figure 3. The only slight caveat to this interpretation is that at large horizons (more than three years out) the impulse response of the 10th percentile to a Fernald TFP shock becomes negative.

This positive view of an expansionary technology shock comes with a downside: A contractionary technology shock will increase downside risk. Indeed, the response to a negative shock would be the mirror image of the corresponding panels in Figure 2.

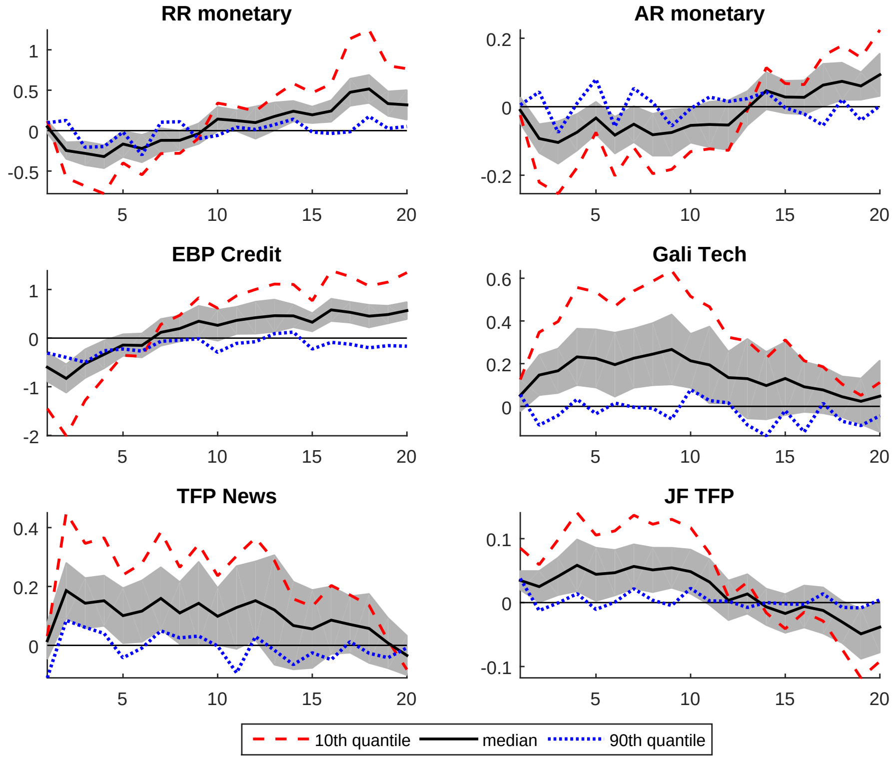

Figure 2: **Impulse Responses of Various Quantiles.**

Note: Red (dashed) is response of the 10th quantile, black (solid) is the median response, blue (dotted) is response of the 90th quantile. Confidence bands correspond to median response, 90% significance level, based on Newey-West standard errors.

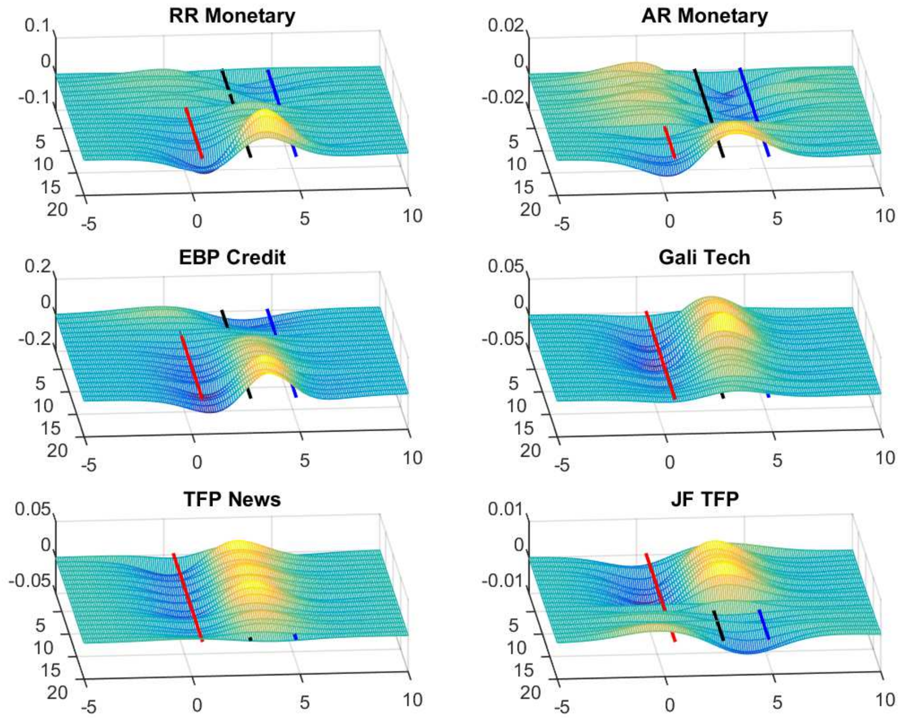

Figure 3: **Difference in Fitted t-Distributions.**

Note: Straight lines are 10th percentile (red), median (black), and 90th percentile (blue) of the average distribution of 4-quarters ahead real GDP growth in our sample.

4.4 Inspecting the Economic Mechanism

Through which channel do macroeconomic shocks affect the conditional distribution of GDP growth? To answer this question we look at how the conditioning variables used to construct the quantiles of GDP growth in (2.1) respond to the shocks studied in this paper. In particular, in Figure 4 we report the impulse responses of the National Financial Conditions Index (NFCI). Positive values indicate that financial conditions are tighter, while negative values indicate financial conditions that are looser. As expected, while contractionary monetary policy shocks and credit spread shocks make financial conditions tighter, the reverse is true for expansionary technology shocks. A key difference is that while there is, on average, strong mean reversion in the response to the shocks that make financial conditions tighter, technology shocks improve financial conditions for much longer. Notice that the impulse responses of the 10th quantile of the conditional GDP growth distribution in Figure 2 inherit the (inverse) pattern of the response of financial conditions.[9] This result suggests that of our two conditioning variables, i.e., financial conditions and current GDP growth, it is through the former channel that shocks affect macroeconomic tail risk. Our finding is in line with Adrian *et al.* (2019), who point out that including the NFCI as a conditioning variable is important to capture downside risk. Adrian *et al.* (2019) discuss various equilibrium models in the literature that help explain the central role of financial conditions in shaping future real GDP growth.

We can thus conclude that contractionary monetary policy shocks and credit spread shocks temporarily increase macroeconomic tail risk by tightening financial conditions. On the contrary, expansionary technology shocks reduce tail risk for substantially longer by loosening financial conditions. Over a horizon of five years, which is the largest horizon we study here, movements in the forecast distribution of GDP growth due to expansionary technology shocks are *not undone* and hence shift the entire distribution to the right.

Another feature of our results that stands out is that upside risk reacts substantially less to economic shocks than downside risk, as is evident from Figure 2. This is in line with the finding in Adrian *et al.* (2019) that upside risk moves substantially less over time relative to downside risk.

[9] In Appendix B, we show the corresponding figure for the other conditioning variable in the quantile regressions, GDP growth. There are substantially more pronounced differences in the responses of that variable to the shock relative to how the 10th percentile of the GDP growth forecast distribution reacts to shocks.

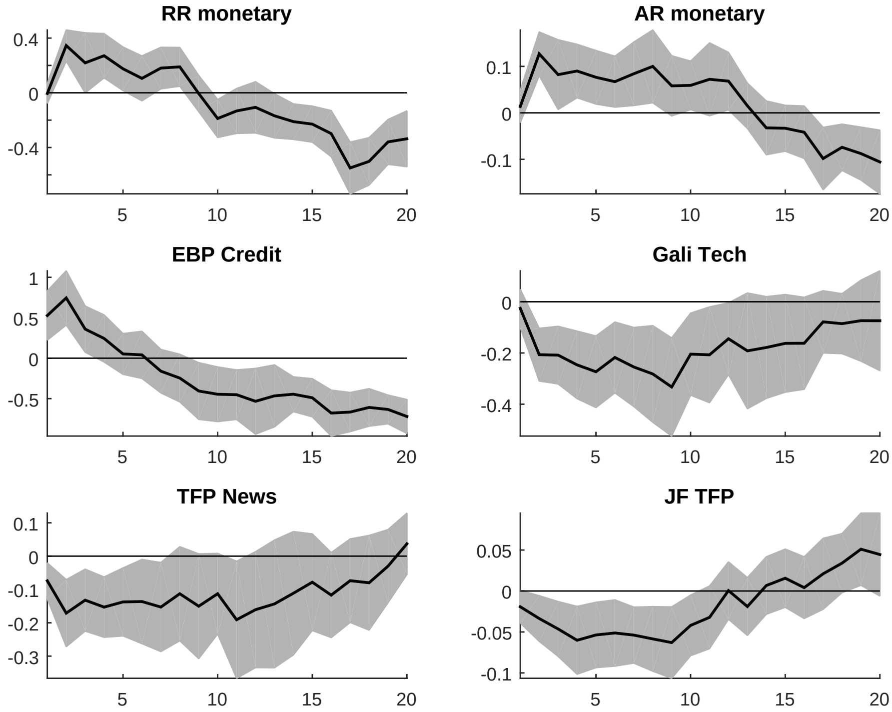

Figure 4: **Impulse Responses of the Chicago FED National Financial Conditions Index.**

5 Conclusion

The impact of macroeconomic shocks on average economic activity has been studied extensively, whereas the effect on lower quantiles—commonly referred to as "tail risk"—has been studied substantially less, even though it is of utmost importance to policymakers. This paper fills this gap by focusing on how macroeconomic shocks affect both tail risk and the entire distribution of future GDP growth. We find that all shocks we consider (monetary policy, credit conditions, and productivity shocks) affect the tail risk disproportionately more than other quantiles. This means that contractionary shocks deserve even more attention than what their effect on average outcomes suggests to the extent that they make poor economic conditions much more likely. Since this is also true of monetary policy shocks, there is reason to be especially wary of the consequences of contractionary policy shocks. We complement the findings in Adrian *et al.* (2019) by showing that financial conditions are the key channel through which shocks affect macroeconomic risk. This suggests that research on how structural shocks affect financial conditions is key to studying economic growth and its vulnerability.

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A Data

This section gives a brief overview of the data we use throughout this paper, which is mostly available at FRED. Additional data sources are provided.

To estimate the quantile regression we use seasonally adjusted and annualized real GDP growth as well as the Chicago FED National Financial Conditions Index (NFCI). This index is not seasonally adjusted and downloaded at quarterly frequency by relying on the average of weekly values within a quarter.

The control variables in the local projection stage are given as follows. At quarterly frequency we take seasonal adjusted real GDP, the seasonal adjusted civilian unemployment rate, total population (including armed forces overseas) and total hours worked given by the hours of wage and salary workers on non-farm payrolls. The latter two series are used to compute per capita GDP and productivity (real GDP divided by hours), respectively. Both the commodity price index and the consumer price index are available at monthly frequency. We take the CRB commodity index provided by Ramey (2016) and headline CPI (defined in FRED as "Consumer Price Index for all Urban Consumers: All Items"). Additionally, we take the monthly federal funds rate. All monthly series are aggregated to quarterly frequency by taking the quarterly average.

Finally, we utilize the following aggregate shocks. The Romer and Romer (2004) monetary shock is provided by Ramey (2016). We aggregate the monthly shock series to quarterly frequency by taking the quarterly sum. We take the narrative monetary policy shock provided by Antolín-Díaz and Rubio-Ramírez (2018), again aggregated to quarterly frequency by calculating the quarterly sum. To identify the credit shock we use the Gilchrist and Zakrajšek (2012) excess bond premium, frequently updated by Favara *et al.* (2016)[10]. The three technology shocks are identified by running the VARs described in Section (2).

[10]The series can be downloaded at `https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html`.

B Additional Impulse Responses

In this section we show the error bands for the 10th and 90th percentile responses that were not presented in the main text.

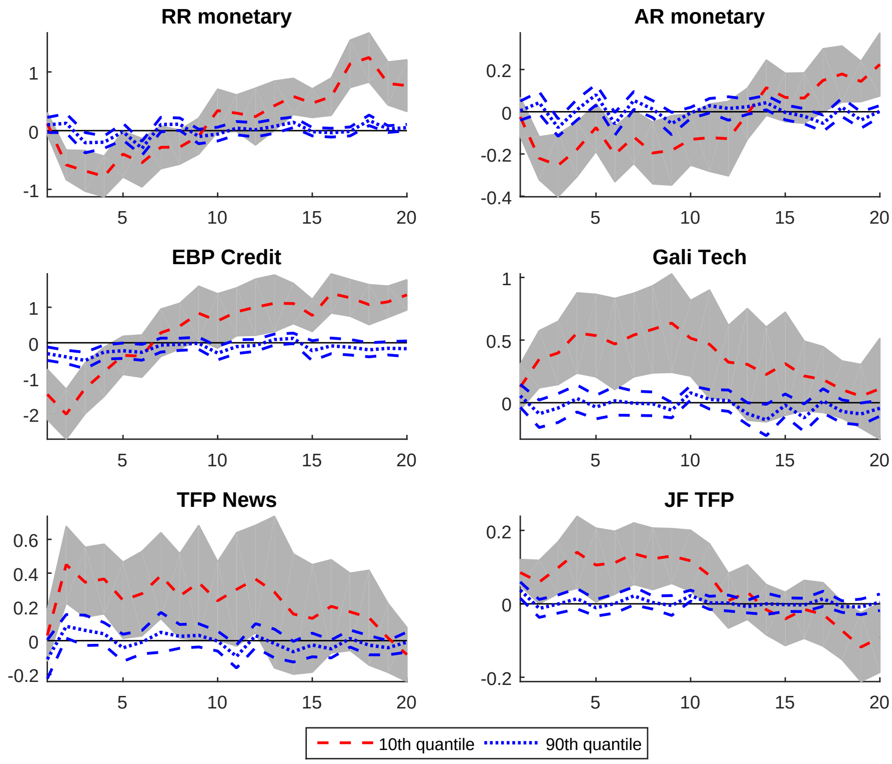

Figure 5: **Impulse Responses of Various Quantiles.**

Note: Red (dashed) is response of the 10th quantile, blue (dotted) is response of the 90th quantile. Confidence bands correspond to 10th quantile response, 90% significance level, based on Newey-West standard errors.

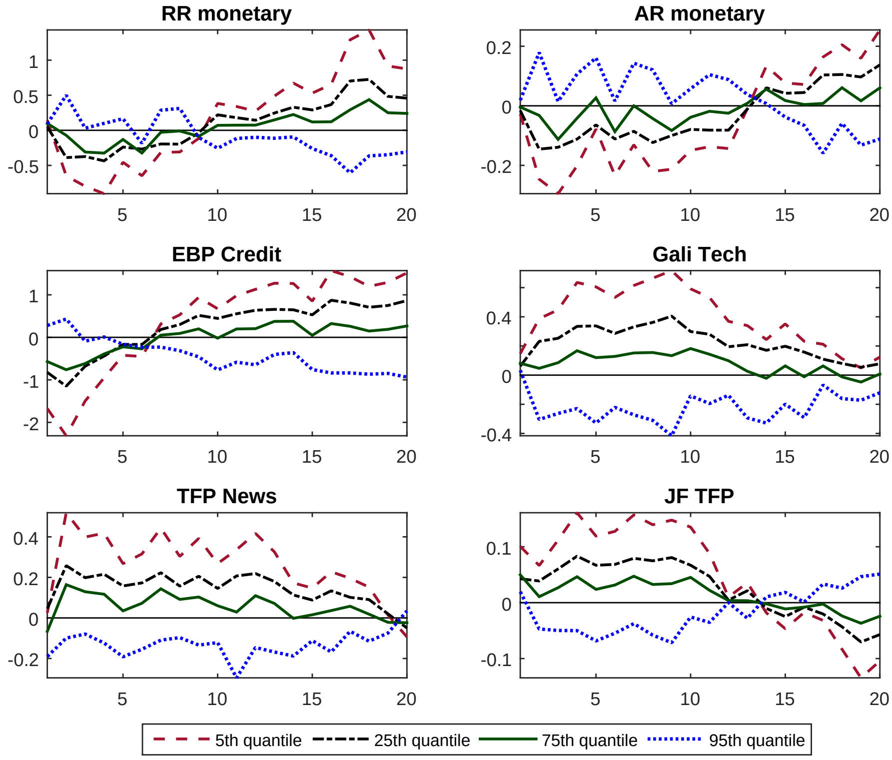

Figure 6: **Impulse Responses of Quantiles Used to Fit *t*-Distributions.**

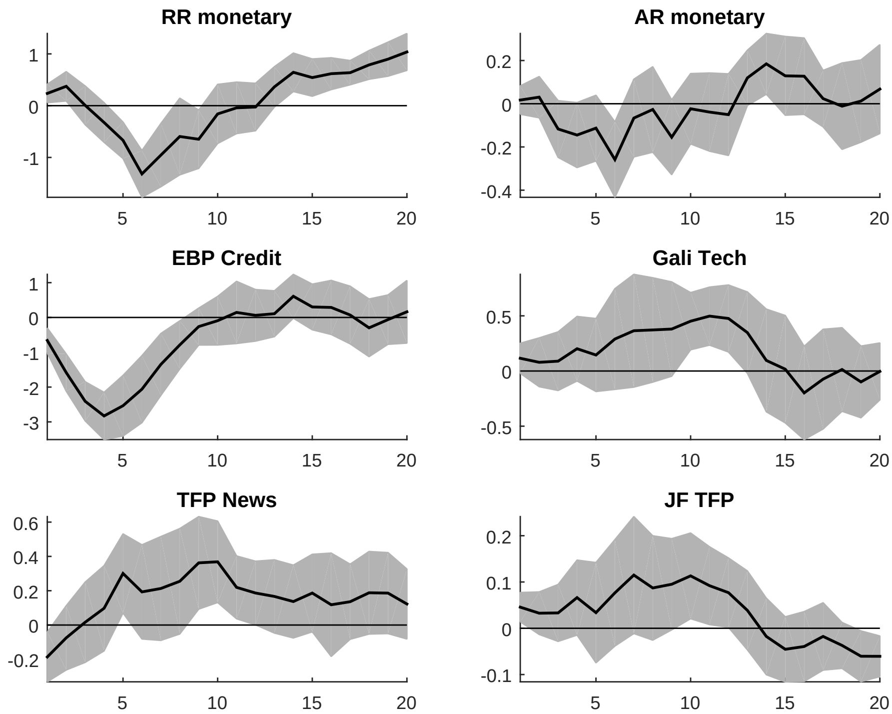

Figure 7: **Impulse Responses of Average GDP Growth y_{t+h}.**

C Allowing for More Controls in Quantile Regressions

To check whether or not our results are robust to adding additional controls in the quantile regression stage, we add the controls from the local projections stage already at the first quantile regression stage (except for the shock measures). This means that each impulse response is now based on a different set of quantiles.

Nonetheless, the results from the main section are broadly in line with what we find for this robustness check, in particular when it comes to the responses of the 10th percentile.

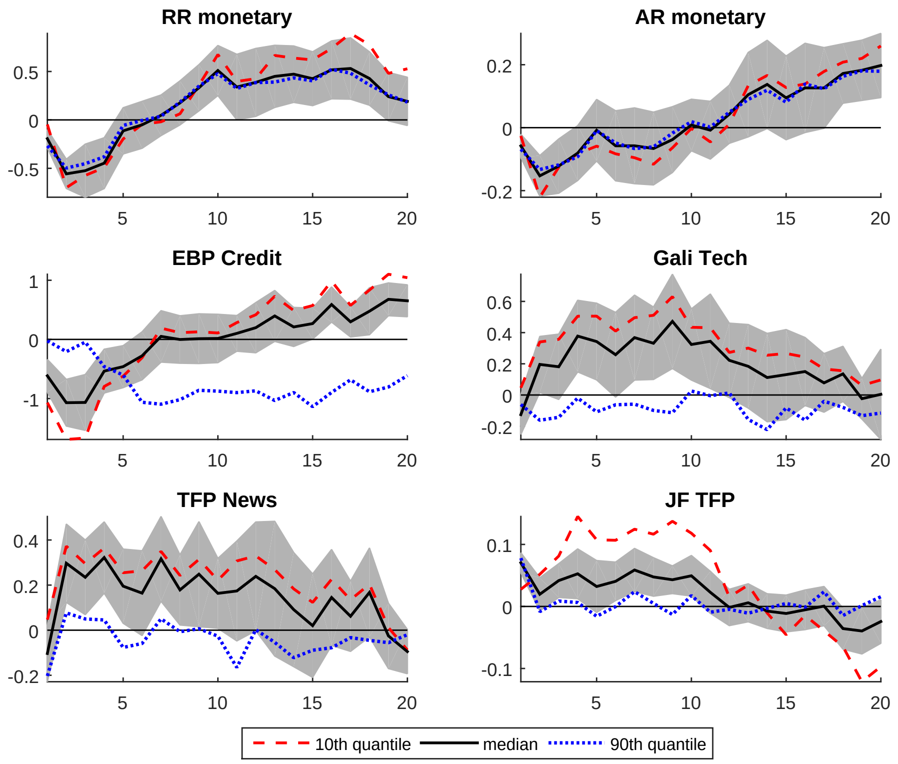

Figure 8: **Impulse Responses of Various Quantiles.**

Note: Red (dashed) is response of the 10th quantile, black (solid) is the median response, blue (dotted) is response of the 90th quantile. Confidence bands correspond to median response, 90% significance level, based on Newey-West standard errors.

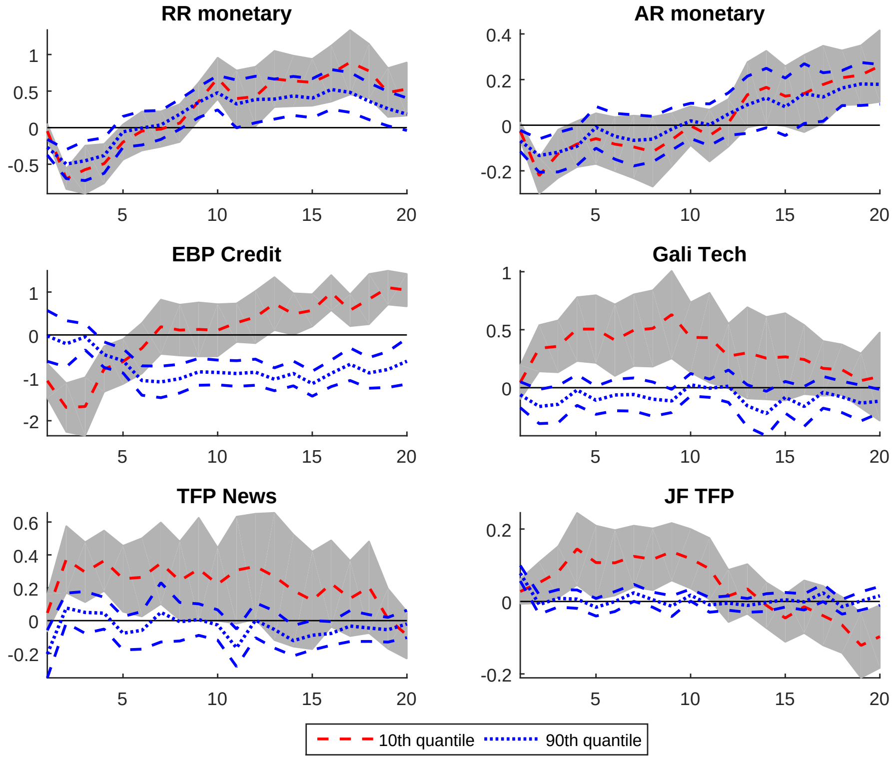

Figure 9: **Impulse Responses of Various Quantiles, More Controls in Quantile Regression.**

Note: Red (dashed) is response of the 10th quantile, blue (dotted) is response of the 90th quantile. Confidence bands correspond to 90% significance level, based on Newey-West standard errors.