

Vulnerable Growth[†]

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We study the conditional distribution of GDP growth as a function of economic and financial conditions. Deteriorating financial conditions are associated with an increase in the conditional volatility and a decline in the conditional mean of GDP growth, leading the lower quantiles of GDP growth to vary with financial conditions and the upper quantiles to be stable over time. Upside risks to GDP growth are low in most periods while downside risks increase as financial conditions become tighter. We argue that amplification mechanisms in the financial sector generate the observed growth vulnerability dynamics. (JEL C53, E23, E27, E32, E44)

Economic forecasts usually provide point estimates for the conditional mean of GDP growth and other economic variables. However, such point forecasts ignore risks around the central forecast and, as such, may paint an overly optimistic picture of the state of the economy. In fact, policymakers' focus on downside risk has increased in recent years. In the United States, the Federal Open Market Committee (FOMC) commonly discusses downside risks to growth in FOMC statements, with the relative prominence of this discussion fluctuating with the business cycle. Globally, a number of inflation-targeting central banks publish GDP growth and inflation distributions. At the same time, surveys of economists (the Blue Chip Economic Survey), market participants (the Federal Reserve Bank of New York's Primary Dealer Survey), and professional forecasters (the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters) all collect respondents' beliefs regarding the probability distribution around the point forecast.

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In this paper, we model empirically the full distribution of future real GDP growth as a function of current financial and economic conditions. We estimate the distribution semiparametrically using quantile regressions. Our main finding is that the estimated lower quantiles of the distribution of future GDP growth exhibit strong variation as a function of current financial conditions, while the upper quantiles are stable over time. Moreover, we show that current economic conditions forecast the median of the distribution, but do not contain information about the other quantiles of the distribution.

Next, we smooth the estimated quantile distribution every quarter by interpolating between the estimated quantiles using the skewed t -distribution, a flexible distribution function with four parameters. This allows us to transform the empirical quantile distribution into an estimated conditional distribution of GDP growth, plotted in Figure 1. Two features are striking about the estimated distribution. First, the entire distribution, and not just the central tendency, evolves over time. For example, recessions are associated with left-skewed distributions while, during expansions, the conditional distribution is closer to being symmetric. Second, the probability distributions inherit the stability of the right tail from the estimated quantile distribution, while the median and the left tail of the distribution exhibit strong time series variation. This asymmetry in the evolution of the conditional distribution of future GDP growth indicates that downside risk to growth varies much more strongly over time than upside risk.

We summarize the downside and upside risks to the median GDP growth forecast using two metrics: (i) the upside and downside entropy of the unconditional distribution of GDP growth relative to the empirical conditional distribution; (ii) the expected shortfall and its upper tail counterpart (“expected longrise”). While downside relative entropy captures the conditional risks to the downside in excess of the downside risks predicted by the unconditional distribution, expected shortfall measures the total probability mass that the conditional distribution assigns to the left tail of the distribution. Similarly, upside relative entropy captures the conditional risks to the upside in excess of the upside risks predicted by the unconditional distribution, and the expected longrise measures the total probability mass that the conditional distribution assigns to the right tail of the distribution. We find that both measures of downside risk move with financial conditions, whereas both measures of upside risk are significantly more stable over time. This asymmetry echoes our finding that the dependence of future GDP growth on current financial conditions is significantly stronger for the lower quantiles of the distribution than for the upper quantiles.

We find that the conditional mean of GDP growth is negatively correlated with conditional volatility and measures of downside risk, with changes in conditional volatility leading changes in conditional mean by at least one quarter. These findings are consistent with the “volatility paradox” postulated in the recent literature on intermediary asset pricing (see, e.g., Brunnermeier and Sannikov 2014, Adrian and Boyarchenko 2012): periods of low volatility precede negative growth outcomes.

We perform many robustness tests to our findings. First, we show that out-of-sample estimates of the conditional distribution of future growth are very similar to the in-sample distribution. This leads the out-of-sample estimates of growth vulnerability to likewise be similar to the in-sample estimates. Furthermore, we

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Vale
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E invece i
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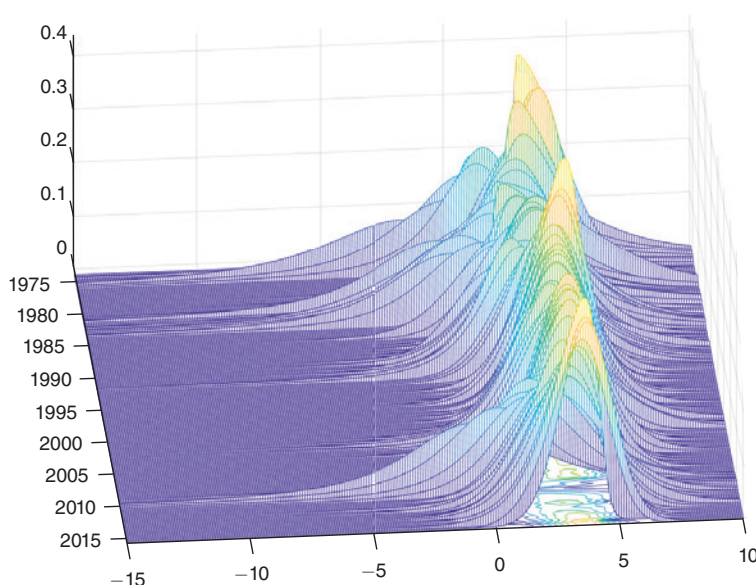


FIGURE 1. DISTRIBUTION OF GDP GROWTH OVER TIME

Note: One-year-ahead predictive distribution of real GDP growth, based on quantile regressions with current real GDP growth and NFCI as conditioning variables.

analyze predictive scores and probability integral transforms to document our strong out-of-sample performance. Second, we demonstrate that the strong time variation of lower quantiles of future GDP growth is not an artifact of our two-step linear quantile regression estimation procedure, but also arises both when we estimate the conditional distribution either fully parametrically or fully nonparametrically. Finally, in the online Appendix, we present alternative measures of financial conditions, focusing on specific variables whose predictive power for growth that has been emphasized in the recent macro finance literature, such as credit spreads, the term spread, and equity volatility. We find that the conditional quantile function is most sensitive to the overall financial conditions index, followed by equity volatility, term spread, and credit spread.

Our findings have strong implications for the recent macro-finance literature that emphasizes the link between financial stability and macroeconomic performance. We document a nonlinear relationship between financial conditions and the conditional distribution of GDP growth, suggesting that dynamic stochastic general equilibrium (DSGE) models with frictions in either the supply of or the demand for credit should allow for nonlinear equilibrium relationships. In such models, financial conditions create downside risk to the economy. For example, the buildup of leverage and maturity transformation in the financial sector can give rise to financial vulnerability. The arrival of unexpected productivity or credit demand shocks then causes the financial sector to disinvest from the real economy, which depresses real economic growth.

The relationship between financial conditions and downside risk to GDP growth could instead be noncausal, with financial conditions merely providing a better

signal of negative shocks to the economy. In this case, models that focus on the impact of Bayesian learning on aggregate outcomes (see, e.g., Orlik and Veldkamp 2014; Johannes, Lochstoer, and Mou 2016) should allow agents to use financial conditions as a signal in forming their beliefs.

Finally, our evidence suggests that GDP vulnerability changes at relatively high frequencies. Such frequent changes in downside risk are in contrast to what would be predicted by the recent literature on disaster risk and economic growth (see, e.g., Barro 2009, Gabaix 2012, Wachter 2013, Barro and Ursúa 2012, Gourio 2012), but are consistent with the evidence from the term structure of asset prices across multiple markets.

A large literature has documented the decline of GDP volatility before the financial crisis of 2008 (see, e.g., Kim and Nelson 1999; McConnell and Perez-Quiros 2000; Blanchard and Simon 2001; Bernanke 2012; Giannone, Lenza, and Reichlin 2008). In contrast to that influential literature, we focus not just on the second moment of GDP growth, but rather on the whole conditional distribution of GDP growth. Our striking finding is that GDP growth volatility is nearly entirely driven by the left side of the conditional distribution. In fact, we can attribute the decline in volatility during the Great Moderation period prior to the financial crisis to a decline in the downside risk to GDP growth.

From an econometric point of view, our paper is related to the statistical literature on estimating and evaluating conditional distributions. We develop a straightforward two-step procedure for the estimation of the conditional probability distribution function (PDF). In the first step, we employ the quantile regressions of Koenker and Bassett (1978) to estimate the conditional quantile function of future GDP growth as a function of current financial and economic conditioning variables. Ghysels (2014) and Schmidt and Zhu (2016) provide recent applications of quantile regressions to the estimation of the distribution of stock returns. In the second step, we fit a parametric inverse cumulative distribution function (CDF) with a known density function to the empirical conditional quantile function, for each quarter in the sample. The procedure is computationally straightforward, and allows us to transform the inverse cumulative distribution function from the quantile regression into a density function. Alternative ways to estimate conditional predictive distributions for GDP growth proposed in the literature include the two-state Markov chain (Hamilton 1989), the Bayesian vector autoregression with stochastic volatility (Cogley, Morozov, and Sargent 2005; Primiceri 2005; Clark 2011; D'Agostino, Gambetti, and Giannone 2013), and copula estimates (Smith and Vahey 2016). Our approach makes fewer parametric assumptions and is computationally much less burdensome. Importantly, the two-state Markov chain does not feature financial conditions as state variables, and the Bayesian vector autoregression features exogenous time variation of risk. Instead, we find that the conditional mean and the conditional volatility are negatively correlated as a function of current financial conditions. conditional volat should increase with worse fin conditions

Our approach differs from the recent literature that has analyzed GDP uncertainty in its finding of the preeminent role for downside risk, rather than symmetric measures of risk. Baker, Bloom, and Davis (2016) propose a measure of political uncertainty based on news announcements. Jurado, Ludvigson, and Ng (2015) and Clark, Carriero, and Massimiliano (2016) compute conditional volatility from a large number of macroeconomic variables. That literature also finds the conditional mean and

volatility of GDP growth to be negatively correlated. The main difference to our work is our emphasis on financial conditions as determinants of the conditional GDP distribution. Intriguingly, our measure of downside vulnerability correlates with the macroeconomic uncertainty index of Jurado, Ludvigson, and Ng (2015) but is more stable during the Great Moderation period.

More closely related to our paper, Giglio, Kelly, and Pruitt (2016) also use a quantile regression approach to evaluate the ability of various measures of systemic risk proposed in the literature to predict real activity outcomes. They find that, although some measures of systemic risk are statistically significant predictors of the left tail of real activity outcomes, systemic risk measures are unable to predict the right tail of real activity outcomes. Our approach differs as we focus on the entire GDP distribution.

The rest of the paper is organized as follows. Section I presents the measures of economic and financial conditions, and relates them to GDP growth in a descriptive fashion. Section II presents our estimates of the conditional GDP distribution, and introduces the concept of GDP vulnerability. Section III discusses out-of-sample results and alternative fully parametric and nonparametric approaches. Section IV discusses implications of our findings for macroeconomic theory. Section V concludes.

I. Economic and Financial Conditions and GDP Growth

To gauge economic and financial conditions, we use real GDP growth and the National Financial Conditions Index (NFCI).¹ The NFCI provides a weekly estimate of US financial conditions in money markets, debt and equity markets, and the traditional and shadow banking systems. The index is a weighted average of 105 measures of financial activity, each expressed relative to their sample averages and scaled by their sample standard deviations.² When the NFCI is positive, financial conditions are tighter than average. The methodology for the NFCI is described in Brave and Butters (2012) and is based on the quasi-maximum likelihood estimators for large dynamic factor models developed by Doz, Giannone, and Reichlin (2012). The data for the NFCI start in January 1973, which we use as starting point for our empirical investigation. We use real GDP data from the Bureau of Economic Analysis (BEA) to compute real GDP growth.³

Figure 2 shows the times series of real GDP growth and the NFCI.⁴ The time series plot is our first indication of a nonlinear relationship between future GDP growth and financial conditions. While GDP growth is, on average, much more

¹ The NFCI is computed by the Federal Reserve Bank of Chicago, available at <https://www.chicagofed.org/publications/nfci/index>.

² The list of indicators is available at <https://www.chicagofed.org/~media/publications/nfci/nfci-indicators-list-pdf.pdf>.

³ Downloaded from FRED (<https://fred.stlouisfed.org/series/A191RL1Q225SBEA>).

⁴ The NFCI is converted into quarterly frequency by averaging the weekly observations within each quarter. For the attribution of weeks to overlapping quarters we follow the convention of Federal Reserve Economic Data (FRED; <https://fred.stlouisfed.org/>), which is the source of our data. Weeks that start in one quarter and end in the next one are fully assigned to the latter quarter. For example, a weekly period that starts on Monday, September 28, 2015 and ends on Friday, October 2, 2015 is included in the aggregated value for the fourth quarter.

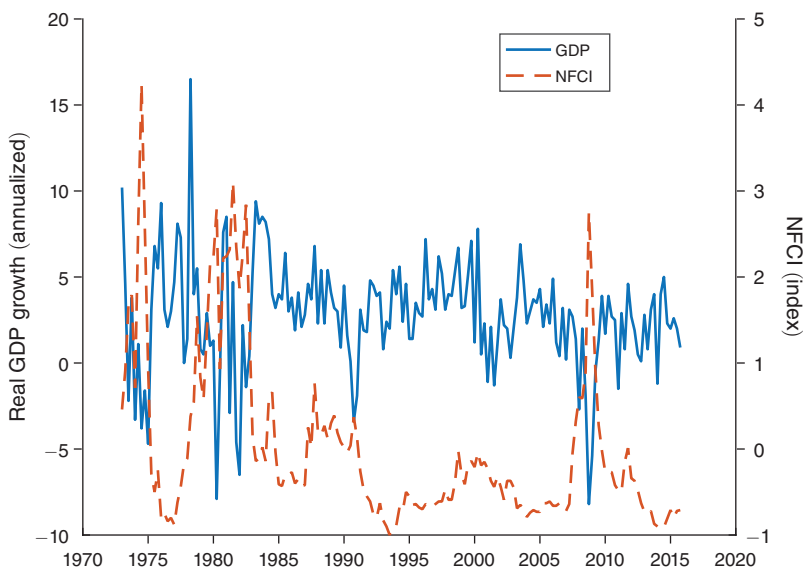


FIGURE 2. RAW DATA

Note: The figure shows the time series of the quarterly growth rate of real GDP growth and the NFCI.

volatile than the NFCI, extreme negative outcomes in GDP growth tend to coincide with extreme positive outcomes of the NFCI.

To characterize formally the conditional relationship between future GDP growth and current financial and economic conditions, we rely on **quantile regressions**. Let us denote by y_{t+h} the annualized average growth rate of GDP between t and $t+h$ and by x_t a vector containing the conditioning variables, including a constant. In a quantile regression of y_{t+h} on x_t the regression slope β_τ is chosen to **minimize the quantile weighted absolute value of errors**:

$$(1) \quad \hat{\beta}_\tau = \arg \min_{\beta_\tau \in \mathbb{R}^k} \sum_{t=1}^{T-h} (\tau \cdot \mathbf{1}_{(y_{t+h} \geq x_t \beta)} |y_{t+h} - x_t \beta_\tau| + (1 - \tau) \cdot \mathbf{1}_{(y_{t+h} < x_t \beta)} |y_{t+h} - x_t \beta_\tau|),$$

where $\mathbf{1}_{(\cdot)}$ denotes the indicator function. The predicted value from that regression is the quantile of y_{t+h} conditional on x_t ,

$$(2) \quad \hat{Q}_{y_{t+h}|x_t}(\tau|x_t) = x_t \hat{\beta}_\tau.$$

Koenker and Bassett (1978) show that $\hat{Q}_{y_{t+h}|x_t}(\tau|x_t)$ is a consistent linear estimator of the quantile function of y_{t+h} conditional on x_t . The quantile regression differs from an ordinary least squares (OLS) regression in two respects. First, the quantile regression minimizes the sum of absolute errors, rather than the sum of squared errors. Second, it puts differential weights on the errors depending on whether an error term is above or below the quantile.

Figure 3 shows the scatter plot of one-quarter ahead and four-quarters ahead GDP growth against the NFCI and the current realization of real GDP growth, as well as

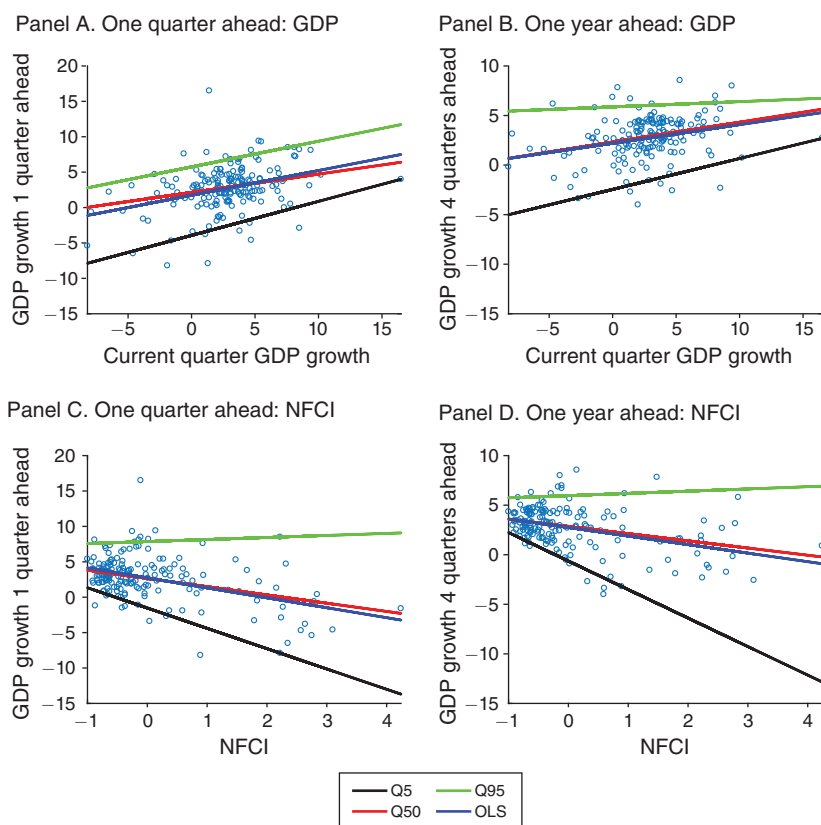


FIGURE 3. QUANTILE REGRESSIONS

Note: The figure shows the univariate quantile regressions of one-quarter-ahead (left column) and four-quarters-ahead (right column) real GDP growth on current real GDP growth and the NFCI.

the univariate quantile regression lines for the fifth, fiftieth, and ninety-fifth quantiles and the OLS regression line. For the NFCI, the slopes differ significantly across quantiles and from the OLS regression line. Indeed, Figure 4 shows that, at both the lower and the upper quantiles, the estimated slopes are significantly different, at the 10 percent level, from the OLS slope.⁵ The regression slopes change dramatically for the NFCI across the quantiles, but are stable for current GDP growth. Importantly, the regression slopes for the NFCI do not change significantly when current GDP growth is also included in the regression, indicating that most of the explanatory power of future GDP vulnerability arises from the information content of financial conditions. On the other hand, for economic conditions, the quantile regression slopes are not statistically significantly different from each other nor

⁵The confidence bounds plotted in Figure 4 are the 95 percent confidence bounds for the null hypothesis that the true data-generating process is a flexible and general linear model for growth and financial conditions. In particular, we estimate a vector autoregression (VAR) with four lags, Gaussian innovations and a constant using the full-sample evolution of the NFCI and real GDP growth, and bootstrap 1,000 samples to compute the bounds at different confidence level for the OLS relationship. Quantile coefficient estimates that fall outside this confidence bound thus indicate that the relation between GDP growth and the predictive variable is nonlinear.

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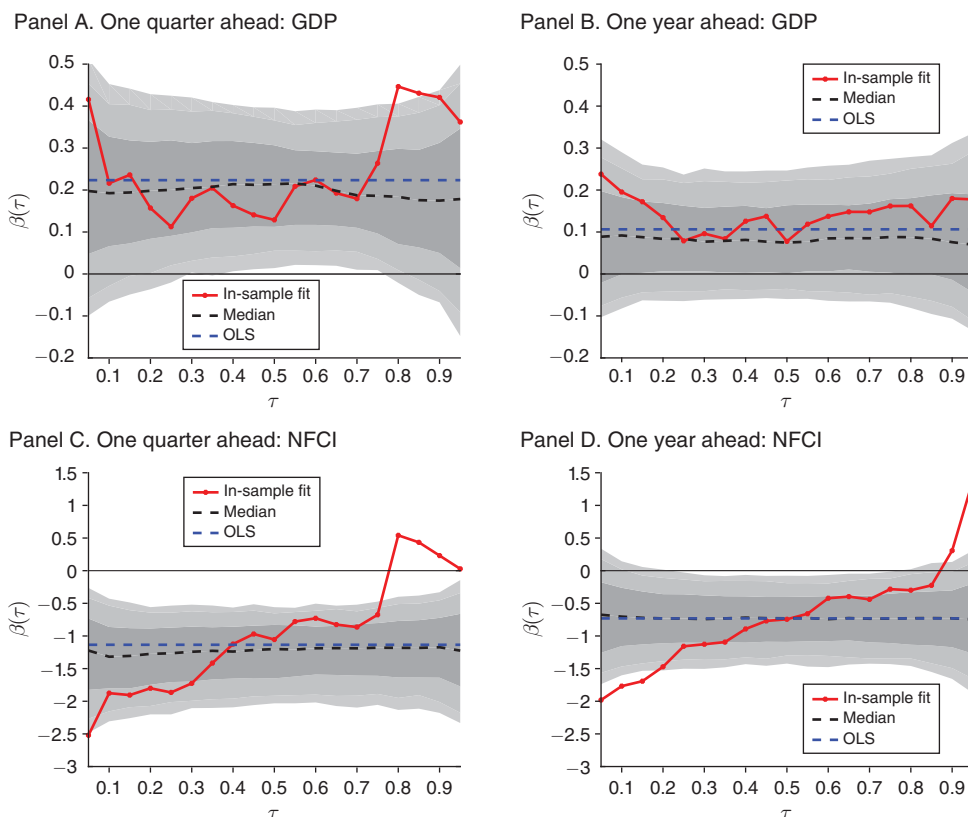


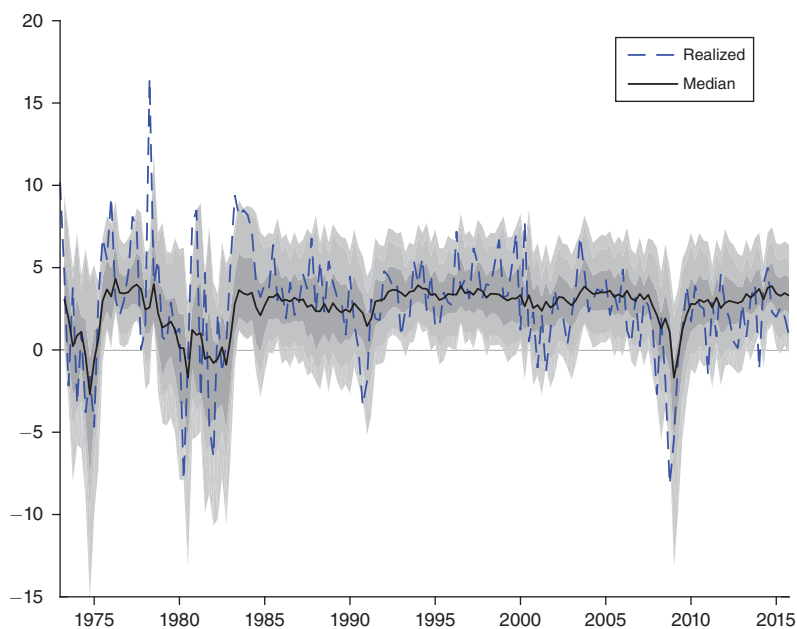
FIGURE 4. ESTIMATED QUANTILE REGRESSION COEFFICIENTS

Notes: The figure shows the estimated coefficients in quantile regressions of one-quarter-ahead (left column) and one-year-ahead (right column) real GDP growth on current real GDP growth and NFCI. We report confidence bounds for the null hypothesis that the true data-generating process is a general, flexible linear model for growth and financial conditions (VAR with four lags); bounds are computed using 1,000 bootstrapped samples.

from the linear regression slopes, suggesting that economic conditions are uninformative for predicting tail outcomes.

Figure 5 shows one- and four-quarter GDP growth together with its conditional median and its conditional 5, 25, 75, and 95 percent quantiles. This figure demonstrates the main result of the paper: the asymmetry between the upper and lower conditional quantiles. While the lower quantiles vary significantly over time, the upper quantiles are stable. Figure 6 shows that the median and interquartile range are strongly negatively correlated. Deteriorations of financial conditions coincide with increases in the interquartile range and decreases in the median (panels A and B). Thus, the left tail of the distribution shifts to the left, as illustrated in panels C and D: the fifth quantile has a negative relationship with the interquartile range. On the other hand, for the upper quantiles, the movements in the median and the interquartile range are offsetting. Thus, changes in financial conditions have relatively little predictive information for the upper quantiles of future GDP growth, as is visible in Figure 5. This strong asymmetry of the quantiles of GDP growth is striking. We study it more extensively in the next section.

Panel A. One quarter ahead



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del grafico
(quantili predetti)
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verso il basso
che verso l'alto.
Questa è la tesi
del paper

Panel B. One year ahead

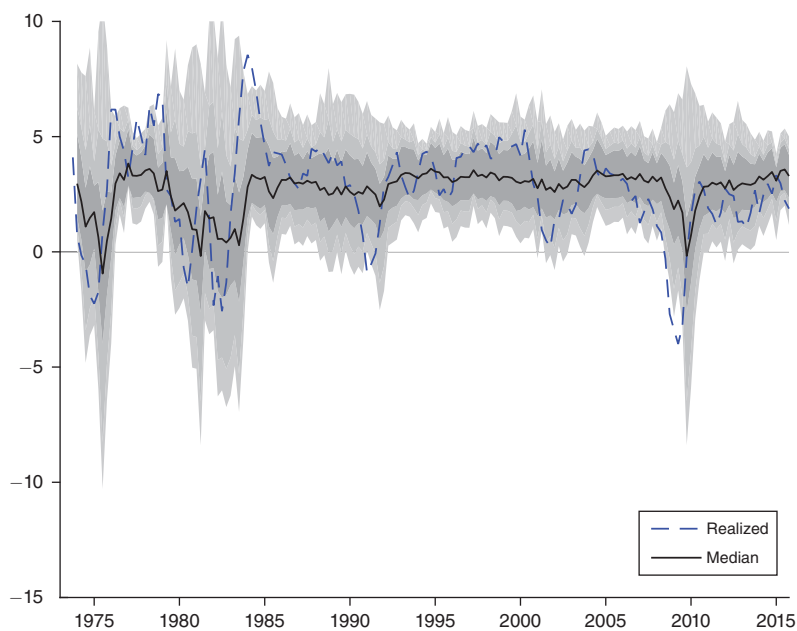
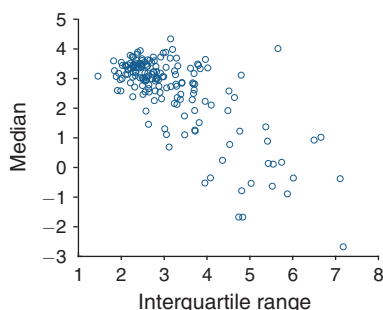


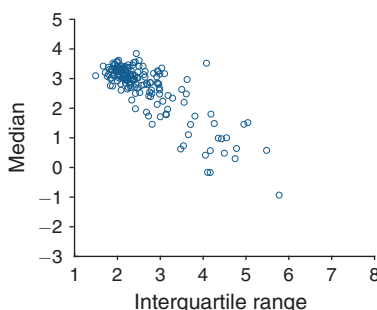
FIGURE 5. PREDICTED DISTRIBUTIONS

Note: The figure shows the time series evolution of the predicted distribution of one-quarter-ahead (panel A) and four-quarters-ahead (panel B) real GDP growth.

Panel A. Median and interquartile range one quarter ahead

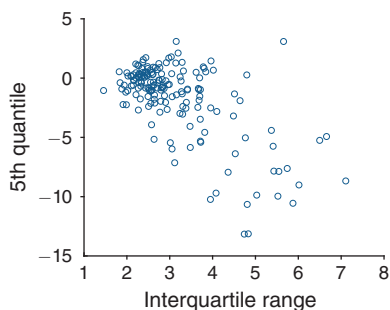


Panel B. Median and interquartile range one year ahead



high IQR
means data
very spread

Panel C. Q5 and interquartile range one quarter ahead



Panel D. Q5 and interquartile range one year ahead

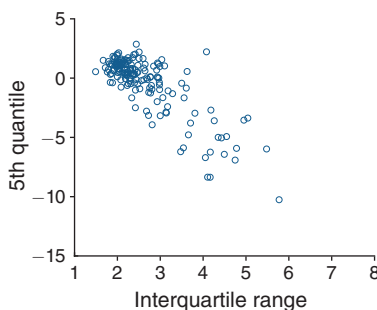


FIGURE 6. MEDIAN, INTERQUARTILE RANGE, AND 5 PERCENT QUANTILE OF THE PREDICTED DISTRIBUTION

Note: The figure shows scatter plots of the median versus the interquartile range (panels A and B) and the 5 percent quantile versus the interquartile range (panels C and D).

II. Quantifying GDP Vulnerability

A. The Conditional GDP Distribution

The quantile regression (2) provides us with approximate estimates of the quantile function, an inverse cumulative distribution function. In practice, these estimates are difficult to map into a probability distribution function because of approximation error and estimation noise. We fit the skewed t -distribution developed by Azzalini and Capitanio (2003) in order to smooth the quantile function and recover a probability density function:⁶

$$(3) \quad f(y; \mu, \sigma, \alpha, \nu) = \frac{2}{\sigma} t\left(\frac{y - \mu}{\sigma}; \nu\right) T\left(\alpha \frac{y - \mu}{\sigma} \sqrt{\frac{\nu + 1}{\nu + \left(\frac{y - \mu}{\sigma}\right)^2}}; \nu + 1\right),$$

⁶ An alternative approach to smoothing the quantile densities is to interpolate the quantile function using splines. Imposing monotonicity and smoothness requires additional modeling choices, as in, for example, Schmidt and Zhu (2016).

Given a probability p , the quantile function $Q(p)$ tells us the value x such that $\text{Prob}(X \leq x) = p$. I want to smooth it, obtaining a perfect CDF¹. I can then calculate the CDF and the n the PDF = d/dx CDF

where $t(\cdot)$ and $T(\cdot)$ respectively denote the PDF and CDF of the Student t -distribution. The four parameters of the distribution pin down the location μ , scale σ , fatness ν , and shape α . Relative to the t -distribution, the skewed t -distribution adds the shape parameter which regulates the skewing effect of the CDF on the PDF. The skewed t -distribution is part of a general class of mixed distributions proposed by Azzalini (1985) and further developed by Azzalini and Dalla Valle (1996). The intuition for the derivation is that a base probability distribution, in this case $t(\frac{y-\mu}{\sigma}; \nu)$, gets shaped by its cumulative distribution function, and rescaled by a shape parameter α . The notable special case is the traditional t -distribution when $\alpha = 0$. In the case of both $\alpha = 0$ and $\nu = \infty$, the distribution reduces to a Gaussian with mean μ and standard deviation σ . When $\nu = \infty$ and $\alpha \neq 0$, the distribution is a skewed normal.

For each quarter, we choose the four parameters $\{\mu_t, \sigma_t, \alpha_t, \nu_t\}$ of the skewed t -distribution f to minimize the squared distance between our estimated quantile function $Q_{y_{t+h}|x_t}(\tau)$ from (2) and the quantile function of the skewed t -distribution $F^{-1}(\tau; \mu_t, \sigma_t, \alpha_t, \nu_t)$ from (3) to match the 5, 25, 75, and 95 percent quantiles:

$$(4) \quad \{\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h}\} = \arg \min_{\mu, \sigma, \alpha, \nu} \sum_{\tau} \left(\hat{Q}_{y_{t+h}|x_t}(\tau|x_t) - F^{-1}(\tau; \mu, \sigma, \alpha, \nu) \right)^2,$$

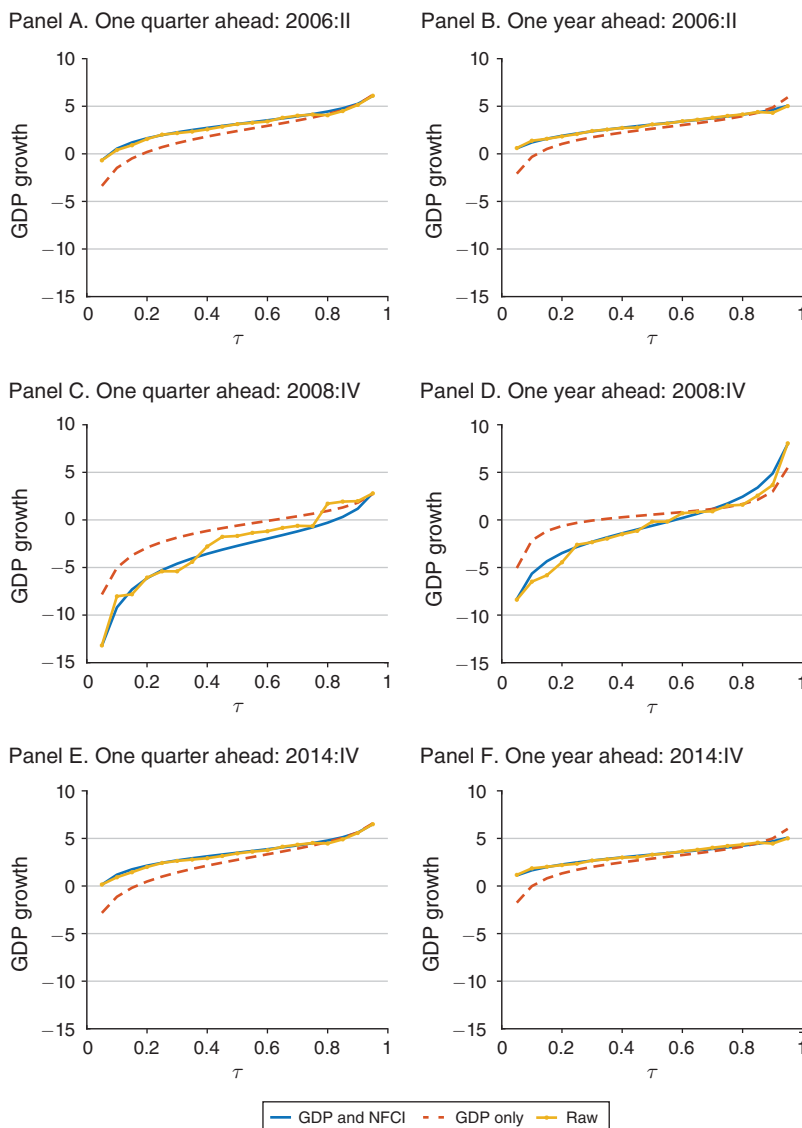
where $\hat{\mu}_{t+h} \in \mathbb{R}$, $\hat{\sigma}_{t+h} \in \mathbb{R}^+$, $\hat{\alpha}_{t+h} \in \mathbb{R}$, and $\hat{\nu}_{t+h} \in \mathbb{Z}^+$.⁷ This can be viewed as an exactly identified nonlinear cross sectional regression of the predicted quantiles on the quantiles of the skewed t -distribution.⁸

Figure 7 plots the estimated conditional quantile distribution $\hat{Q}_{y_{t+h}|x_t}(\tau|x_t)$ and two versions of the fitted inverse cumulative skewed t -distribution $F^{-1}(\tau; \hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h})$, one conditional on both GDP growth and NFCI and one conditional on GDP growth alone, for three sample dates at different points of the business cycle: 2006:II, which represented the end of the Federal Reserve's tightening cycle before the financial crisis; 2008:IV, when the zero lower bound was reached just after the failure of Lehman; and 2014:IV, which is the last in-sample date of our dataset. In all three cases, the skewed t -distribution is sufficiently flexible to smooth the estimated quantile function while passing through all four target quantiles for both the one-quarter-ahead and the four-quarters-ahead forecasts. Figure 7 also shows that the distribution conditional on both economic and financial conditions can deviate substantially from the distribution conditional on economic conditions only. While the full conditional distribution is above the distribution conditional only on economic conditions during expansions, it is significantly below the distribution the conditional only on economic conditions during recessions, especially in the left tail.

Figure 8 then plots the two versions of the fitted conditional probability density functions of GDP growth for the same three quarters. Comparing the conditional density across the three quarters, we see significant time variation in the density and

⁷Notice that these parameters are functions of the conditioning variables x_t . We drop the explicit dependence for notational convenience.

⁸An alternative approach would be to use the entire quantile function to pin down the parameters of f , and allow the parameters of the skewed t -distribution to be over-identified. We follow the more parsimonious exactly-identified approach here.



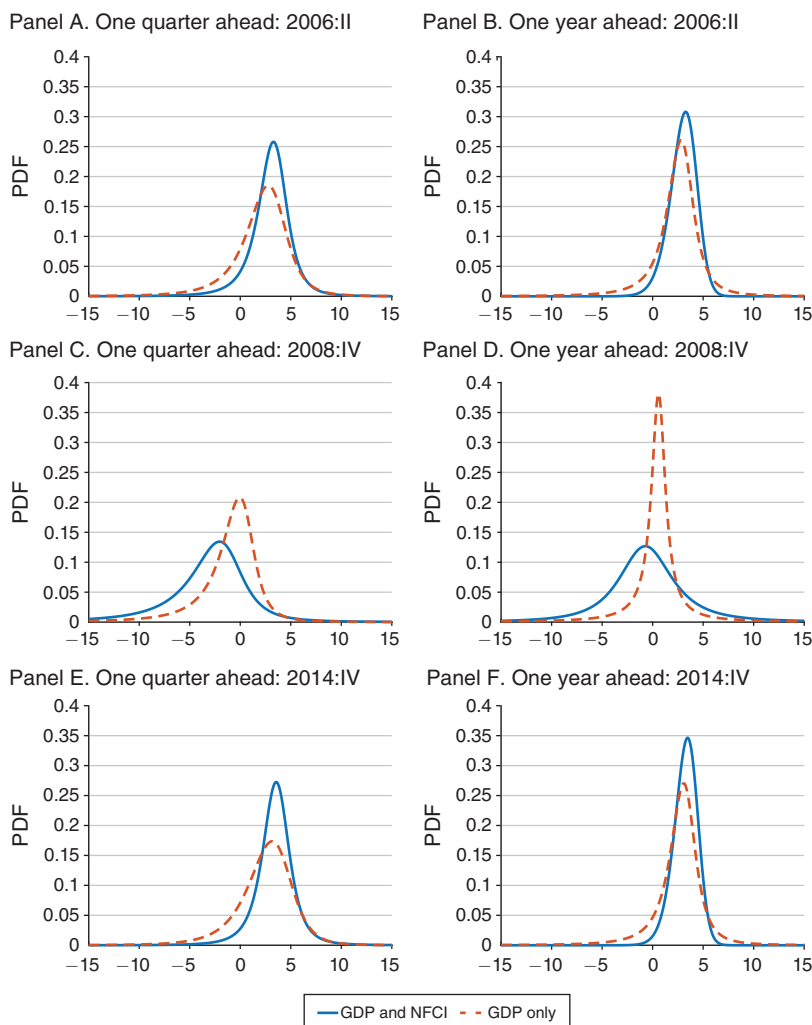
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in recessione, la coda sinistra si abbassa, indicando la possibilità di una crescita molto negativa

FIGURE 7. THE CONDITIONAL QUANTILES AND THE SKEWED t -DISTRIBUTION

Notes: The panels in this figure show the conditional quantiles together with the estimated skewed t -inverse cumulative distribution functions for one-quarter-ahead and one-year-ahead GDP growth. For comparison, we also report the skewed t -inverse cumulative distribution functions obtained by fitting the quantiles obtained by conditioning only on current real GDP growth.

that this time variation is primarily due to changes in the lower tail of the distribution. During business cycle upswings, such as in 2006:II and 2014:IV, the distribution conditional on both GDP growth and financial conditions has lower variance and greater positive skewness than the distribution conditional on GDP growth only. During downturns, such as 2008:IV, instead, the distribution conditional on both GDP growth and financial conditions has higher variance, greater negative skewness, and a lower mean than the distribution conditional on GDP growth only. These



mediana più
bassa e coda
sinistra pesante
in recessione!
come si voleva

FIGURE 8. PROBABILITY DENSITIES

Notes: The panels in this figure show the estimated skewed t -density functions for one-quarter-ahead and one-year-ahead real GDP growth, with the density estimated conditional on current real GDP growth and NFCI. For comparison, we also report the skewed t -density functions obtained by conditioning on current real GDP growth only.

results might seem to contradict the recent evidence on the unpredictability of GDP growth during the Great Moderation (see, e.g., D'Agostino, Giannone, and Surico 2006; Rossi and Sekhposyan 2010) and the weak and unstable predictive power of financial indicators (Stock and Watson 2003). However, those studies focused on point forecasts, while we investigate the ability of current economic and financial conditions to predict the entire distribution of GDP growth.

We also show the time series evolution of the fitted parameters in online Appendix Figures A.1 and A.2. The time series pattern of the scale parameter σ_t resembles the financial conditions index most closely. The parameters $\hat{\alpha}_{t+h}, \nu_{t+h}$ that govern the shape and fatness of the distribution exhibit time series patterns that have

low correlations with either the economic or the financial conditions index. This is because our fitting procedure is very nonlinear, thus giving rise to a time series pattern that would be difficult to detect using linear regressions or correlations. Furthermore, the α_{t+h} , ν_{t+h} parameters are relatively stable.

The picture that emerges is one where changes in location and scale are the most important determinants of the shifts in the conditional distribution. The strong time-variation in the lower quantiles of the distribution reflects the strong negative correlation between the location and scale. Deteriorations in financial conditions coincide with declines in the location and increases in the scale of the distribution, and thus with a leftward shift of the distribution.

B. Measuring Vulnerability

The median of the predicted density provides the modal forecast for GDP growth next quarter and four quarters ahead. However, policymakers are often concerned with the downside and upside risks to the forecast or, in other words, how vulnerable the predicted path of GDP growth is to unexpected shocks. In this paper, we quantify upside and downside vulnerability of future GDP growth as the “extra” probability mass that the conditional density assigns to extreme right and left tail outcomes, relative to the probability of these outcomes under the unconditional density. By comparing the probability assigned to extreme outcomes by the conditional density to the probability assigned to the same outcomes by the unconditional density, we evaluate whether the predicted GDP distribution in a given quarter implies greater vulnerability around the modal forecast than the unconditional distribution.

More formally, we denote by $\hat{g}_{y_{t+h}}$ the unconditional density computed by matching the unconditional empirical distribution of GDP growth⁹ and by $\hat{f}_{y_{t+h}|x_t}(y|x_t) = f(y; \hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h})$ the estimated skewed t -distribution. We define the upside, \mathcal{L}_t^U , and downside, \mathcal{L}_t^D , entropy of $\hat{g}_{y_{t+h}}(y)$ relative to $\hat{f}_{y_{t+h}|x_t}(y|x_t)$ as

$$(5) \quad \mathcal{L}_t^D(\hat{f}_{y_{t+h}|x_t}; \hat{g}_{y_{t+h}}) = - \int_{-\infty}^{\hat{F}_{y_{t+h}|x_t}^{-1}(0.5|x_t)} (\log \hat{g}_{y_{t+h}}(y) - \log \hat{f}_{y_{t+h}|x_t}(y|x_t)) \hat{f}_{y_{t+h}|x_t}(y|x_t) dy,$$

$$(6) \quad \mathcal{L}_t^U(\hat{f}_{y_{t+h}|x_t}; \hat{g}_{y_{t+h}}) = - \int_{\hat{F}_{y_{t+h}|x_t}^{-1}(0.5|x_t)}^{\infty} (\log \hat{g}_{y_{t+h}}(y) - \log \hat{f}_{y_{t+h}|x_t}(y|x_t)) \hat{f}_{y_{t+h}|x_t}(y|x_t) dy,$$

where $\hat{F}_{y_{t+h}|x_t}(y|x_t)$ is the cumulative distribution associated with $\hat{f}_{y_{t+h}|x_t}(y|x_t)$ and $\hat{F}_{y_{t+h}|x_t}^{-1}(0.5|x_t)$ is the conditional median. Intuitively, downside entropy measures the divergence between the unconditional density and the conditional density that occurs below the median of the conditional density. When downside entropy is high, the conditional density assigns positive probability to more extreme left tail growth outcomes than the unconditional density. Similarly, upside entropy measures the divergence between the unconditional density and the conditional density that

⁹ The unconditional density is time invariant and can be computed by performing the two-step procedure where only the constant term is included in the quantile regression of the first step.

occurs above the median of the conditional density. When upside entropy is high, the conditional density assigns positive probability to more extreme right tail growth outcomes than the unconditional density. It is important to note that, unlike the full relative entropy between two distributions, upside and downside entropy can be negative, though not at the same time. That is, while the overall divergence between two distributions is positive, one density can put more mass in one tail of the distribution while the other puts more mass in another tail.

In online Appendix A.1, we illustrate the properties of downside and upside entropies using two examples: one where GDP growth evolves according to a first-order autoregressive (AR(1)) process with normal innovations and the second in which GDP growth evolves according to an AR(1) process with innovations drawn from a mixture of normal distributions. When both the conditional and unconditional distributions of GDP growth are Gaussian, downside entropy is high when the median of the conditional distribution is lower than the median of the unconditional distribution. If the conditional and unconditional medians coincide, downside entropy equals upside entropy. Instead, when innovations to the conditional distribution are drawn from a mixture of truncated normals, the volatility conditional on GDP growth falling below the median is higher than the volatility conditional on GDP growth falling above the median, and upside entropy exceeds downside entropy even when the conditional and unconditional median of the GDP growth distribution coincide.

An alternative way of characterizing downside and upside risks to GDP growth is in terms of expected shortfall and its upper tail counterpart, which we term the expected longrise. For a chosen target probability π , the shortfall and longrise are defined, respectively, as

$$SF_{t+h} = \frac{1}{\pi} \int_0^\pi \hat{F}_{y_{t+h}|x_t}^{-1}(\tau|x_t) d\tau;$$

queste due guardano solo la conditional distribution, le altre due il rapporto tra cond e uncond

$$LR_{t+h} = \frac{1}{\pi} \int_{1-\pi}^1 \hat{F}_{y_{t+h}|x_t}^{-1}(\tau|x_t) d\tau.$$

The information content of the relative entropy and the expected shortfall measures is distinct. While shortfall and longrise summarize the tail behavior of the conditional distribution in absolute terms, downside and upside entropy measure the tail behavior of the conditional distribution in excess of the tail behavior exhibited by the unconditional distribution. Thus, if both the unconditional and conditional distributions are negatively skewed, downside entropy will be low while expected shortfall will be high.

Panels A and B of Figure 9 show the evolution of GDP upside and downside entropy one and four quarters ahead. Panels C and D plot the 5 percent expected shortfall and the 95 percent expected longrise. Despite differences in the information content of the two measures, they exhibit a surprising degree of similarity, indicating that the non-Gaussian features of the conditional distribution are largely absent from the unconditional distribution. It is also noteworthy that, while the upside and downside entropy measures do comove, downside entropy is more volatile and has much more pronounced nonlinearities. Similarly, the expected shortfall and longrise measures are positively correlated but expected shortfall is significantly more volatile.

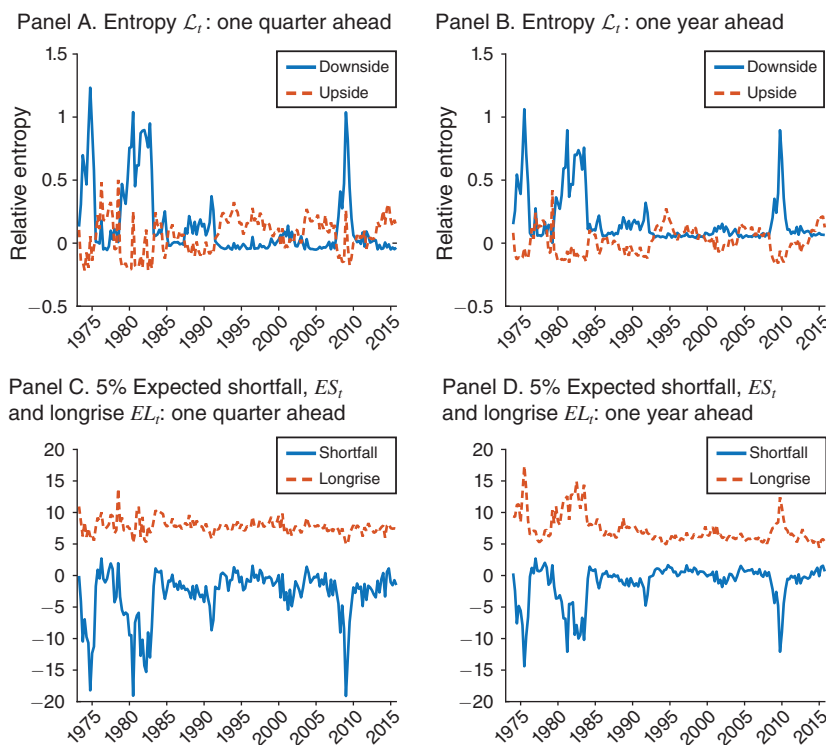


FIGURE 9. GROWTH ENTROPY AND EXPECTED SHORTFALL OVER TIME

Note: The figure shows the time series evolution of relative downside and upside entropy \mathcal{L}_t^D and \mathcal{L}_t^U together with the 5 percent expected shortfall ES_t .

III. Out-of-Sample Evidence and Alternative Approaches

A. Out-of-Sample Evidence

In this section, we evaluate the out-of-sample performances of the methods. We back-test the model by replicating the analysis that an economist would have done by using the proposed methodology in real time, with the caveat that we use final revised data only.¹⁰

We produce predictive distributions recursively for two horizons (one and four quarters), starting with the estimation sample that ranges from 1973:I to 1992:IV. More precisely, using data from 1973:I to 1992:IV, we estimate the predictive distribution for 1993:I (one quarter ahead) and 1993:IV (one year ahead). We then iterate the same procedure, expanding the estimation sample, one quarter at a time, until the end of the sample (2015:IV). At each iteration, we repeat the estimation steps of Sections I and II, estimating quantile regressions, matching the skewed t -distribution, and computing downside and upside entropy. The outcome of this procedure is

¹⁰Real-time data for the NCFI are only available for the recent past.

a 20-year time-series of out-of-sample density forecasts for each of the two forecast horizons.

We perform two types of out-of-sample analyses. First, we study the robustness of the results shown so far by comparing the in-sample measures of vulnerability with their real-time counterparts. Second, we evaluate the out-of-sample accuracy and calibration of the density forecasts by analyzing the predictive score and the probability integral transform (PIT), that is, the predictive density and cumulative distribution evaluated at the out-turn, respectively.

Results for the first exercise are presented in Figure 10. We report selected quantiles and downside entropy computed using the full sample (in-sample) and recursively (out-of-sample). The figure illustrates that the in-sample and out-of-sample estimates of the quantiles are virtually indistinguishable. The similarities are more striking as the financial crisis of 2007–2009 is a significant tail event that is not in the data when estimating the out-of-sample quantiles. The stability of the recursive estimates thus shows that downside vulnerability can be detected in real time.

To assess the reliability of the predictive distribution, we measure the accuracy of a density forecast using the predictive score, computed as the predictive distribution generated by a model and evaluated at the realized value of the time series. Higher predictive scores indicate more accurate predictions because they show that outcomes that the model considers more likely are closer to the ex post realization. Panels A and B of Figure 11 plot the scores of the predictive distribution conditional on both financial and economic conditions together with the scores of the predictive distribution conditional on economic conditions alone. The predictive score for the distribution conditional on both financial and economic conditions is frequently above that of the distribution conditional economic conditions only. Thus, the full conditional distribution is often more accurate, and rarely less accurate, than the one that conditions on economic conditions only, and the information contained in the conditioning variables is a robust and genuine feature of the data.

We conclude the out-of-sample evaluation by analyzing the calibration of the predictive distribution. We compute the empirical cumulative distribution of the PITs, which measures the percentage of observations that are below any given quantile. The model is better calibrated the closer the empirical cumulative distribution of the PITs is to the 45-degree line. In a perfectly calibrated model, the cumulative distribution of the PITs is a 45-degree line, so that the fraction of realizations below any given quantile $Q_{y_{t+h}|x_t}(\tau)$ of the predictive distribution is exactly equal to τ . Results are presented in panels C and D of Figure 11 for both the conditional and unconditional distribution. Following Rossi and Sekhposyan (2017), we report confidence bands around the 45-degree line to account for sample uncertainty.¹¹ For both the full conditional predictive distribution and the predictive distribution that conditions on economic conditions only, the empirical distribution of the PITs is well within the confidence bands for the lower quantiles, though the empirical distribution falls outside the confidence band in the center of the distribution. Overall, Figure 11

¹¹ The confidence bands should be taken as general guidance since they are derived for forecasts computed using a rolling scheme, i.e., with a constant length of the estimation sample, while we use an expanding estimation window. For the one-quarter-ahead, the bands are based on the critical values derived under the null of uniformity and independence of the PIT. For the PITs of the one-year-ahead predictive distributions, bands are computed by bootstrapping under the assumption of uniformity only.

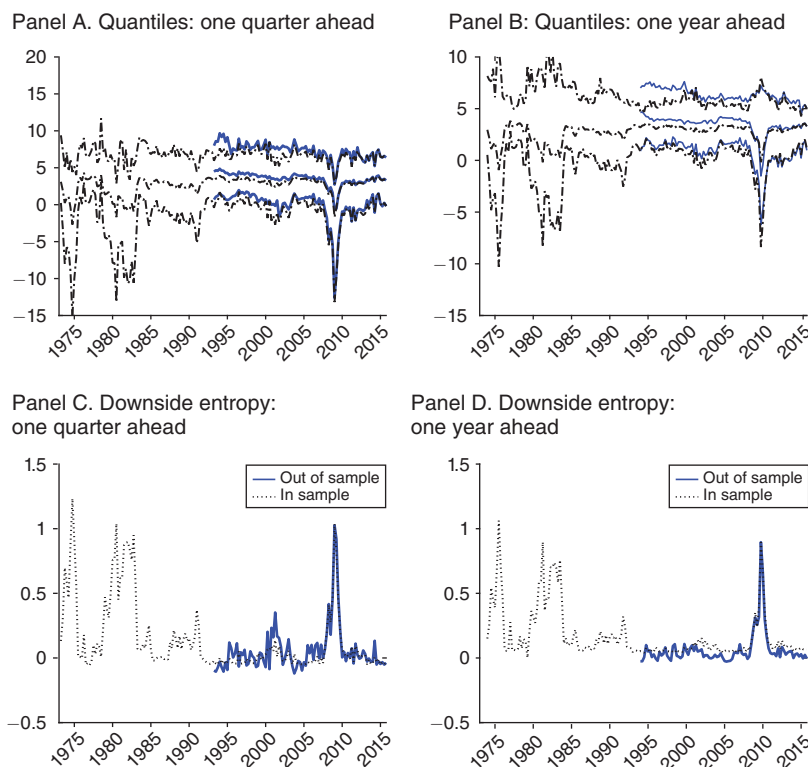


FIGURE 10. OUT-OF-SAMPLE PREDICTIONS

Notes: The figure compares out-of-sample and in-sample predictive densities for GDP growth one and four quarters ahead. Panels A and B show the 5, 50, and 95 percent quantiles. Panels C and D show downside entropy.

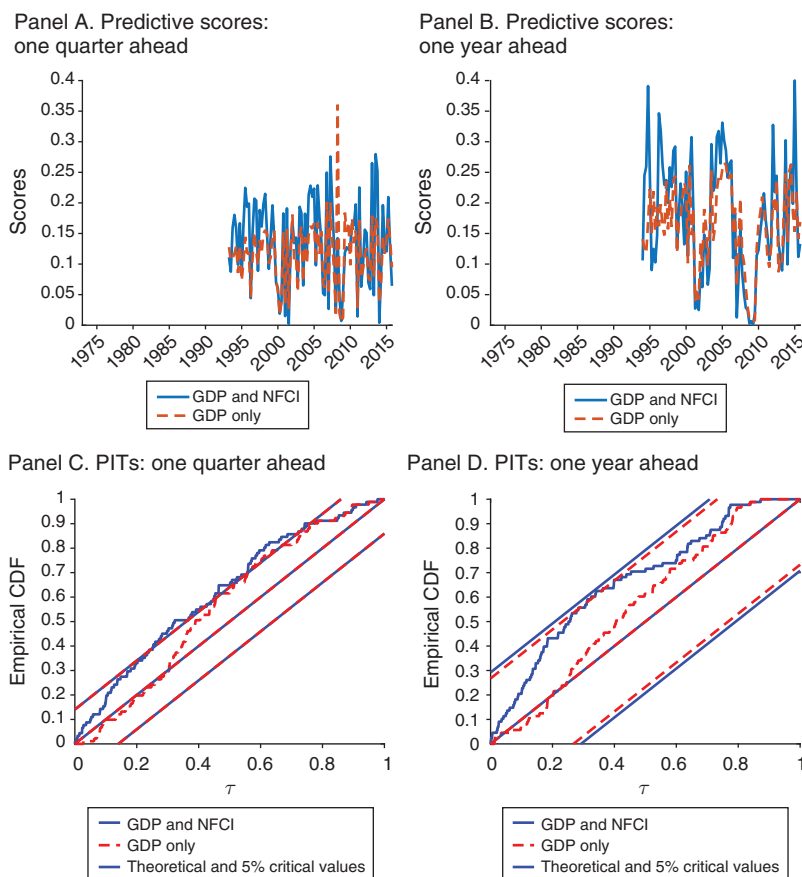
illustrates that the quantile regression approach generates robust predictive distributions, and is able to capture downside vulnerabilities particularly well.

B. Alternative Econometric Approaches

We view our two-step estimation procedure of fitting quantile regressions in the time series, and then the distribution across quantiles, as a methodological contribution of the paper. Our two-step procedure is straightforward to estimate both in- and out-of-sample and is very flexible. In the online Appendix, we further show that the procedure is robust to including alternative measures of financial conditions. In this subsection, we investigate two alternative econometric approaches: a fully parametric approach that estimates the conditional distribution of GDP growth via maximum likelihood and a fully nonparametric approach.

We begin with the fully parametric approach. Consider the following model:

$$(7) \quad y_{t+1} = \gamma_0 + \gamma_1 x_t + \sigma_t \varepsilon_{t+1}; \quad \ln(\sigma_t^2) = \delta_0 + \delta_1 x_t,$$



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FIGURE 11. OUT-OF-SAMPLE ACCURACY

Notes: The figure reports the predictive scores and the cumulative distribution of the probability integral transform. Panels A and B compare the out-of-sample predictive scores of the predictive distribution conditional on both NFCI and real GDP growth, and the predictive distribution conditional on real GDP growth only. Panels C and D report the empirical cumulative distribution of the probability integral transform (PITs). Critical values are obtained as in Rossi and Sekhposyan (2017).

where $\varepsilon_{t+1} \sim N(0, 1)$ and x_t are conditioning variables. The model is estimated via maximum likelihood.¹² Panel A of Figure 12 plots the conditional mean and the conditional lower and upper fifth quantiles for one-quarter-ahead GDP growth implied by the model in equation (7). The simple conditionally heteroskedastic model is able to reproduce the strongly skewed conditional GDP distribution by simply shifting the mean and volatility of GDP as a function of economic and financial conditions.

Both the quantile regression and the conditionally heteroskedastic model are linear in the conditioning variables, a condition which might seem restrictive. We

¹²We have also estimated the model with autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) components of Engle (1982), but it turns out that in quarterly data, the conditioning variables drive out those effects.

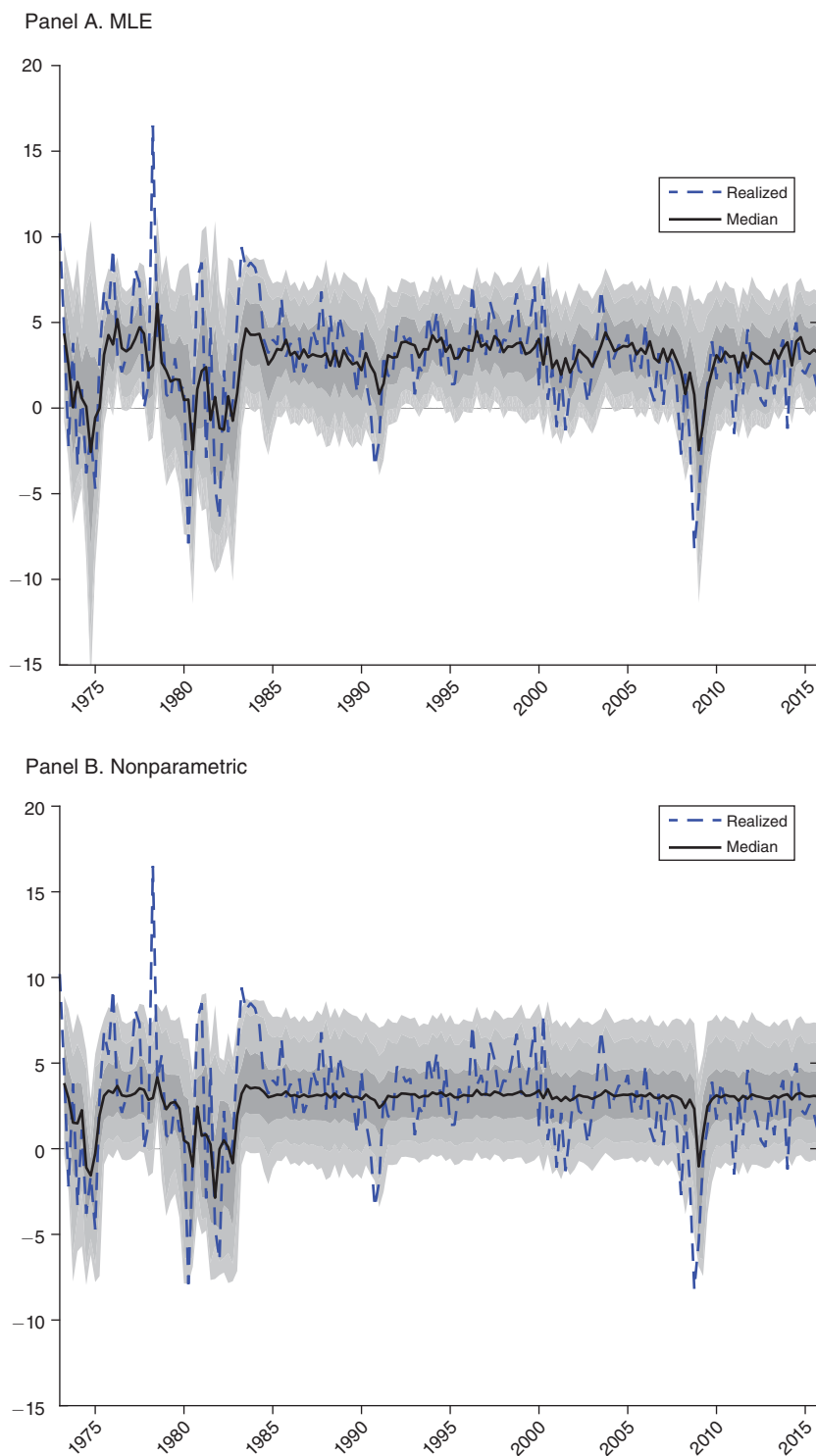


FIGURE 12. ALTERNATIVE ECONOMETRIC APPROACHES: PREDICTED DISTRIBUTIONS

Notes: The figure shows the conditional mean, and the 95 percent and 5 percent standard error bands for GDP growth one-quarter-ahead. In panel A, the distributions are estimated with a conditionally Gaussian model with conditioning variables in the mean equation and the volatility equations. In panel B, the distributions are estimated nonparametrically.

obtain the same qualitative results more directly (less parametrically) allowing for general dependence of the quantiles on the conditioning variables. In particular, following Li, Lin, and Racine (2013) we estimate the conditional cumulative density function of one-quarter-ahead GDP growth y_{t+1} as a function of current quarter conditioning variables $x_t = (x_{1,t}, \dots, x_{n,t})'$ as

$$(8) \quad \hat{F}_{y_{t+1}|x_t}(y|x) = \frac{\frac{1}{T-1} \sum_{t=1}^{T-1} \Phi\left(\frac{y - y_{t+1}}{\omega_0}\right) K_\omega(x_t, x)}{\frac{1}{T-1} \sum_{t=1}^{T-1} K_\omega(x_t, x)},$$

where

$$K_\omega(x_t, x) = \prod_{i=1}^n \frac{1}{\omega_i} \phi\left(\frac{x_i - x_{i,t}}{\omega_i}\right),$$

and $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal PDF and CDF, respectively; T is the number of observations; and $\omega_0, \omega_1, \dots, \omega_n$ are bandwidths chosen by cross-validation, as described in Li, Lin, and Racine (2013).¹³

Panel B of Figure 12 plots the conditional mean and the conditional lower and upper fifth quantiles for one-quarter-ahead GDP growth implied by the model in equation (8). As with the maximum likelihood (ML) estimates, the conditional quantiles obtained using the less parametric estimation procedure produce the general feature that the right tail of the distribution is stable while the left tail moves with financial conditions. However, the fluctuations of the left tail are smoother, due to a conservative bandwidth selection that is necessary to counteract the tendency of the very flexible model to overfit the data.¹⁴

Overall, the results for both the fully parametric and the fully nonparametric models confirm that our main findings are not an artifact of the two-step quantile regression procedure but reflect a robust property of the distribution of GDP growth conditional on financial conditions.

Alternative ways to estimate conditional GDP distributions have been proposed in the literature, such as the two-state Markov chain of Hamilton (1989). Hamilton's model could be augmented to include financial conditioning variables that shift the transition probabilities between the two states using the estimation method of Filardo (1994). More generally, Chen, Fan, and Tsyrennikov (2006) present a semiparametric estimator of multivariate copula models that would allow the mixing between distributions as a function of financial condition variables (see Smith and Vahey 2016 for an application to modeling GDP growth). Another strand of the macroeconomic literature introduces time-varying volatility into macroeconomic dynamics following the Bayesian vector autoregression of Primiceri (2005). For example, Clark (2011) features an exogenously time-varying stochastic volatility

¹³The authors establish optimality of this data-driven selection method under the assumption of independence. Although serial dependence might be a concern in our application, recent work by Li, Ouyang, and Racine (2009) on nonparametric regression with weakly dependent data suggests that these optimality results may still be valid.

¹⁴In online Appendix Figure A.8, we further show that both the ML approach and the nonparametric approach perform well out-of-sample, though slightly less so than the semiparametric conditional quantile approach. Indeed, the scores of the predictive distributions are somewhat smaller.

process in a Bayesian vector autoregression. The incorporation of financial conditions in the volatility process in such Bayesian vector autoregressions might give rise to conditional density forecasts similar to the ones we obtain. Finally, alternative semiparametric and nonparametric methods could be used, including the sieve regressions of Chen, Liao, and Sun (2014) or the efficient nonparametric methods of Li and Racine (2007) and Norets and Pati (2017).

IV. Implications for Theories of Macroeconomic Dynamics

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Our main finding is that, while economic conditions forecast median GDP growth, downside risks to GDP growth are predicted by financial conditions and upside risks are stable over time. This finding presents challenges to traditional macroeconomic modeling because it points to the importance of financial conditions above economic conditions in predicting the future evolution of GDP growth. Measures of financial conditions may help forecast downside risks to GDP growth because they capture frictions in either the supply of or the demand for credit in the economy, or because financial conditions represent a more informative signal about potential future risks. In this section, we discuss these theoretical alternatives.

We begin with the literature on the credit channel of monetary policy (see the overviews by Bernanke and Gertler 1995; Boivin, Kiley, and Mishkin 2010; and Brunnermeier, Eisenbach, and Sannikov 2013), which emphasizes the role that frictions play in the *demand* for credit. In these models, which rely on asymmetric information between lenders and borrowers and moral hazard on the part of borrowers, a tightening in the stance of monetary policy leads to a decrease in the net worth of productive firms, causing adverse selection and moral hazard problems to worsen. This generates an asymmetry in the business cycle, with tighter financial conditions preceding economic downturns. However, this literature has the drawback that, in the most common DSGE implementations of the credit channel, models are only solved up to first-order, so that financial vulnerability does not play a role in equilibrium (see, in particular, Bernanke, Gertler, and Gilchrist 1999 and Del Negro et al. 2013). In contrast, we find that financial conditions are particularly correlated with the higher moments of GDP growth, suggesting that nonlinear approximations to the solutions of such models may be more appropriate for capturing the empirical distribution of GDP growth.

The Great Recession prompted the literature on credit frictions to also consider the role that financial conditions play in the *supply* of credit in the economy. Brunnermeier and Sannikov (2014), He and Krishnamurthy (2012), and Adrian and Boyarchenko (2012) consider production economies where the productive sector relies on a financial sector for the supply of credit. In these models, changes in the vulnerability of the financial sector lead to decreases in the supply of credit to the economy, potentially causing a downturn in GDP growth. The simplicity of the production sector considered allows these models to be solved analytically without relying on (log-)linearization and to instead emphasize the nonlinear amplification channel created by constraints on the intermediary sector. This literature also shows that, in the presence of leverage constraints on intermediary capital, a volatility paradox arises, in which times of low volatility of output growth coincide with high average output growth and foreshadow times of low average output growth.

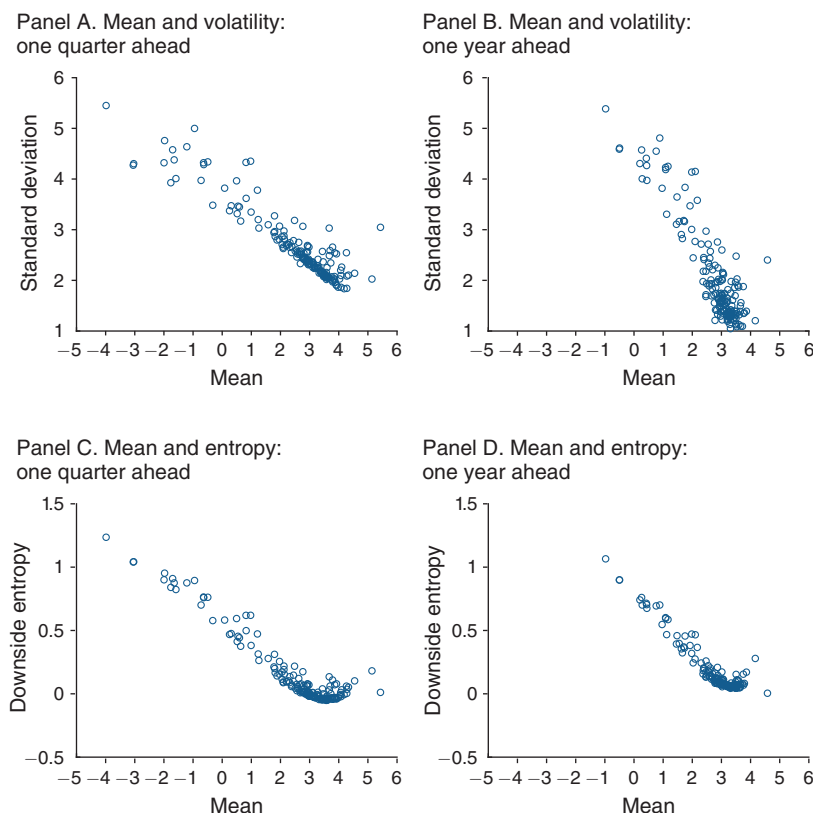


FIGURE 13. MEAN, VOLATILITY, AND ENTROPY

Notes: The figure shows scatter plots of the mean versus the volatility (panels A and B) and downside entropy versus the mean (panels C and D) of the one-quarter-ahead and the one-year-ahead distributions of real GDP growth.

The conditional distribution of GDP growth we construct is consistent with these predictions. Figure 13 shows that, contemporaneously, high realizations of the conditional mean of GDP growth are associated with both low volatility and low downside entropy. This negative relationship between the conditional mean and measures of growth vulnerability is present at both the one-quarter and four-quarter horizons. These two effects combined generate a negatively skewed unconditional distribution, as downward shifts in the growth outlook are associated with an increase in risk.

Figure 14 further shows that the negative relationship between the conditional mean and measures of vulnerability is present at multiple leads and lags of the vulnerability measures. In particular, the negative correlation between the conditional mean and volatility is statistically significant for two years leads and two years lags of volatility. Thus, the negative association between risk and return is a robust feature at multiple horizons. At the one-quarter horizon, a 1 standard deviation increase in the conditional volatility is associated with a 0.8 standard deviation decrease in the next quarter's predicted conditional mean of GDP growth.

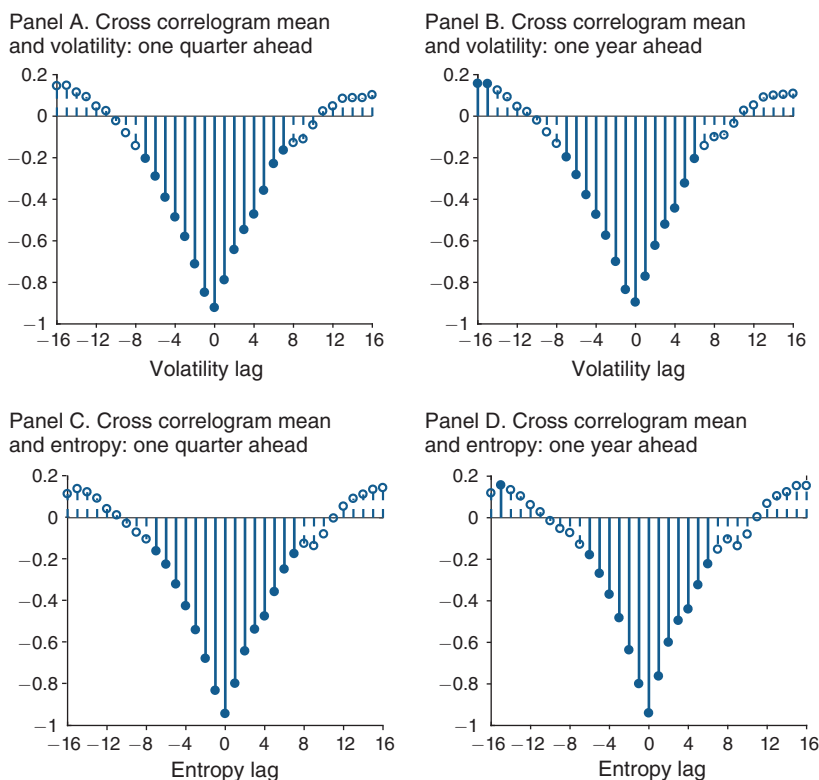


FIGURE 14. MEDIAN, INTERQUARTILE RANGE, AND 5 PERCENT QUANTILE

Notes: The figure shows the cross correlograms between the mean and volatility, and mean and downside entropy.

Finally, financial conditions may predict downside risk to GDP growth because financial conditions may provide a better signal of non-normal shocks to the economy. Models of the impact of Bayesian learning on aggregate outcomes (see, e.g., Orlik and Veldkamp 2014 and Johannes, Lochstoer, and Mou 2016) do have the potential to generate a negative correlation between the conditional mean and the conditional volatility of GDP growth. However, our results emphasize the importance of allowing agents to use financial conditions as a signal in forming their beliefs, as we find conditional volatility to be predicted by financial, not economic, conditions.

One possible source of non-normal shocks that could be captured by financial rather than economic conditions is disaster risk. Catastrophic tail events, such as the Great Depression or the 2008 financial crisis, can be used to generate a large equity risk premium (see, e.g., Barro 2009, Gabaix 2012, Wachter 2013, and Barro and Ursúa 2012). In turn, risk and uncertainty aversion to extreme tail events impact macroeconomic dynamics in equilibrium (see, e.g., Gourio 2012). In contrast, our evidence suggests that GDP vulnerability changes at relatively high frequencies and is thus unlikely to be driven by changes in the exposure to disaster risk. However, higher frequency changes in downside GDP vulnerability are consistent with the

more recent evidence from the term structure of asset prices: the slopes of term structures of risk premia across multiple asset classes suggest that the equilibrium pricing kernel reflects nonlinear shocks occurring at intermediate frequencies (see, e.g., van Binsbergen et al. 2013; Backus, Boyarchenko, and Chernov 2018).

V. Conclusion

The financial crisis of 2007–2009 and the ensuing Great Recession reignited academic interest in the volatility of GDP growth. In this paper, we argue that the entire distribution of GDP growth evolves over time, with the left tail of the distribution positively correlated with slack in financial conditions. We measure the vulnerability of GDP growth to downside risks as relative entropy of the unconditional relative to conditional predictive distribution, and show that growth vulnerability is correlated with financial conditions.

The strong relationship between GDP vulnerability and financial conditions rationalizes the FOMC's increased emphasis on the notion of financial conditions. Peek, Rosengren, and Tootell (2015) document the increased frequency of the mention of financial conditions in FOMC statements, and show that financial conditions are a significant explanatory variable in augmented Taylor rules. Caldara and Herbst (2016) argue that monetary policy can be characterized by a direct and economically significant reaction to changes in credit spreads. Monetary policy models that feature frictions in the financial intermediary sector rationalize these findings, as optimal Taylor rules are augmented by financial variables that can be interpreted as measures of GDP vulnerability (see Cúrdia and Woodford 2010, Gambacorta and Signoretti 2014). Adrian and Liang (2016) point out that monetary policy impacts financial conditions as well as vulnerabilities, thus producing an intertemporal trade-off for monetary policy between present macroeconomic objectives and risks to objectives in the future. Measuring downside growth vulnerability helps quantify the cost side of that trade-off.

REFERENCES

- Adrian, Tobias, and Nina Boyarchenko. 2012. "Intermediary Leverage Cycles and Financial Stability." Federal Reserve Bank of New York Staff Report.
- Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone. 2019. "Vulnerable Growth: Dataset." *American Economic Review*. <https://doi.org/10.1257/aer.20161923>.
- Adrian, Tobias, and Nellie Liang. 2016. "Monetary Policy, Financial Conditions, and Financial Stability." Federal Reserve Bank of New York Staff Report.
- Azzalini, Adelchi. 1985. "A Class of Distributions Which Includes the Normal Ones." *Scandinavian Journal of Statistics* 12 (2): 171–78.
- Azzalini, Adelchi, and Antonella Capitanio. 2003. "Distributions Generated by Perturbation of Symmetry with Emphasis on a Multivariate Skew t -Distribution." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 65 (2): 367–89.
- Azzalini, Adelchi, and A. Dalla Valle. 1996. "The Multivariate Skew-Normal Distribution." *Biometrika* 83 (4): 715–26.
- Backus, David, Nina Boyarchenko, and Mikhail Chernov. 2018. "Term Structures of Asset Prices and Returns." *Journal of Financial Economics* 129 (1): 1–23.
- Baker, Scott R., Nicholas Bloom and Steven J. Davis. 2016. "Measuring Economic Policy Uncertainty." *Quarterly Journal of Economics* 131 (4): 1593–636.
- Barro, Robert J. 2009. "Rare Disasters, Asset Prices, and Welfare Costs." *American Economic Review* 99 (1): 243–64.

- Barro, Robert J., and José F. Ursúa.** 2012. "Rare Macroeconomic Disasters." *Annual Review of Economics* 4: 83–109.
- Bernanke, Ben.** 2012. "The Great Moderation." In *The Taylor Rule and the Transformation of Monetary Policy*, edited by Evan F. Koenig, Robert Leeson, and George A. Kahn. Stanford, CA: Hoover Institution Press.
- Bernanke, Ben S., and Mark Gertler.** 1995. "Inside the Black Box: The Credit Channel of Monetary Policy Transmission." *Journal of Economic Perspectives* 9 (4): 27–48.
- Bernanke, Ben S., Mark Gertler, and Simon Gilchrist.** 1999. "The Financial Accelerator in a Quantitative Business Cycle Framework." In *Handbook of Macroeconomics*, Vol. 1, edited by John B. Taylor and Michael Woodford, 1305–40. Amsterdam: Elsevier.
- Blanchard, Olivier, and John Simon.** 2001. "The Long and Large Decline in U.S. Output Volatility." *Brookings Papers on Economic Activity* 1: 135–64.
- Boivin, Jean, Michael T. Kiley, and Frederic S. Mishkin.** 2010. "How Has the Monetary Transmission Mechanism Evolved over Time?" In *Handbook of Monetary Economics*, Vol. 3, edited by Benjamin M. Friedman and Michael Woodford, 369–422. Amsterdam: Elsevier.
- Brave, Scott, and R. Andrew Butters.** 2012. "Diagnosing the Financial System: Financial Conditions and Financial Stress." *International Journal of Central Banking* 8 (2): 191–239.
- Brunnermeier, Markus K., Thomas M. Eisenbach, and Yuliy Sannikov.** 2013. "Macroeconomics with Financial Frictions: A Survey." In *Advances in Economics and Econometrics: Tenth World Congress, Volume II, Applied Economics*, edited by Daron Acemoglu, Manuel Arellano, and Eddie Dekel. Cambridge: Cambridge University Press.
- Brunnermeier, Markus K. and Yuliy Sannikov.** 2014. "A Macroeconomic Model with a Financial Sector." *American Economic Review* 104 (2): 379–421.
- Caldara, Dario, and Edward Herbst.** 2016. "Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs." FRB Finance and Economics Discussion Paper 2016–049.
- Chen, Xiaohong, Yanqin Fan, and Viktor Tsyrennikov.** 2006. "Efficient Estimation of Semiparametric Multivariate Copula Models." *Journal of the American Statistical Association* 101 (475): 1228–40.
- Chen, Xiaohong, Zhipeng Liao, and Yixiao Sun.** 2014. "Sieve Inference on Possibly Misspecified Semi-Nonparametric Time Series Models." *Journal of Econometrics* 178 (1): 639–58.
- Clark, Todd E.** 2011. "Real-Time Density Forecasts from Bayesian Vector Autoregressions with Stochastic Volatility." *Journal of Business & Economic Statistics* 29 (3): 327–41.
- Clark, Todd E., Andrea Carriero, and Marcellino Massimiliano.** 2016. "Measuring Uncertainty and Its Impact on the Economy." Federal Reserve Bank of Cleveland Working Paper 1622.
- Cogley, Timothy, Sergei Morozov, and Thomas J. Sargent.** 2005. "Bayesian Fan Charts for U.K. Inflation: Forecasting and Sources of Uncertainty in an Evolving Monetary System." *Journal of Economic Dynamics and Control* 29 (11): 1893–925.
- Cúrdia, Vasco, and Michael Woodford.** 2010. "Credit Spreads and Monetary Policy." *Journal of Money, Credit, and Banking* 42: 3–35.
- D'Agostino, Antonello, Luca Gambetti, and Domenico Giannone.** 2013. "Macroeconomic Forecasting and Structural Change." *Journal of Applied Econometrics* 28 (1): 82–101.
- D'Agostino, Antonello, Domenico Giannone, and Paolo Surico.** 2006. "(Un)Predictability and Macroeconomic Stability." European Central Bank Working Paper 605.
- Del Negro, Marco, Stefano Eusepi, Marc Giannoni, Argia Sbordone, Andrea Tambalotti, Matthew Cocci, Raiden Hasegawa, and M. Henry Linder.** 2013. "The FRBNY DSGE Model." Federal Reserve Bank of New York Staff Report.
- Doz, Catherine, Domenico Giannone, and Lucrezia Reichlin.** 2012. "A Quasi-Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models." *Review of Economics and Statistics* 94 (4): 1014–24.
- Engle, Robert F.** 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica* 50 (4): 987–1007.
- Filardo, Andrew J.** 1994. "Business-Cycle Phases and Their Transitional Dynamics." *Journal of Business and Economic Statistics* 12 (3): 299–308.
- Gabaix, Xavier.** 2012. "Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance." *Quarterly Journal of Economics* 127 (2): 645–700.
- Gambacorta, Leonardo, and Federico M. Signoretti.** 2014. "Should Monetary Policy Lean against the Wind?" *Journal of Economic Dynamics and Control* 43: 146–74.
- Ghysels, Eric.** 2014. "Conditional Skewness with Quantile Regression Models: SoFiE Presidential Address and a Tribute to Hal White." *Journal of Financial Econometrics* 12 (4): 620–44.
- Giannone, Domenico, Michele Lenza, and Lucrezia Reichlin.** 2008. "Explaining the Great Moderation: It Is Not the Shocks." *Journal of the European Economic Association* 6 (2–3): 621–33.

- Giglio, Stefano, Bryan Kelly, and Seth Pruitt. 2016. "Systemic Risk and the Macroeconomy: An Empirical Evaluation." *Journal of Financial Economics* 119 (3): 457–71.
- Gourio, François. 2012. "Disaster Risk and Business Cycles." *American Economic Review* 102 (6): 2734–66.
- Hamilton, James D. 1989. "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle." *Econometrica* 57 (2): 357–84.
- He, Zhiguo, and Arvind Krishnamurthy. 2012. "A Model of Capital and Crises." *Review of Economic Studies* 79 (2): 735–77.
- Johannes, Michael, Lars A. Lochstoer, and Yiqun Mou. 2016. "Learning About Consumption Dynamics." *Journal of Finance* 71 (2): 551–600.
- Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng. 2015. "Measuring Uncertainty." *American Economic Review* 105 (3): 1177–216.
- Kim, Chang-Jin, and Charles R. Nelson. 1999. "Has the U.S. Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle." *Review of Economics and Statistics* 81 (4): 608–16.
- Koenker, Roger W., and Gilbert Bassett, Jr. 1978. "Regression Quantiles." *Econometrica* 46 (1): 33–50.
- Li, Cong, Desheng Ouyang, and Jeffrey S. Racine. 2009. "Nonparametric Regression with Weakly Dependent Data: The Discrete and Continuous Regressor Case." *Journal of Nonparametric Statistics* 21 (6): 697–711.
- Li, Qi, Juan Lin, and Jeffrey Scott Racine. 2013. "Optimal Bandwidth Selection for Nonparametric Conditional Distribution and Quantile Functions." *Journal of Business and Economic Statistics* 31 (1): 57–65.
- Li, Qi, and Jeffrey Scott Racine. 2007. *Nonparametric Econometrics: Theory and Practice*. Princeton, NJ: Princeton University Press.
- McConnell, Margaret M., and Gabriel Perez-Quiros. 2000. "Output Fluctuations in the United States: What Has Changed Since the Early 1980s?" *American Economic Review* 90 (5): 1464–76.
- Norets, Andriy, and Debdeep Pati. 2017. "Adaptive Bayesian Estimation of Conditional Densities." *Econometric Theory* 33 (4): 980–1012.
- Orlik, Anna, and Laura Veldkamp. 2014. "Understanding Uncertainty Shocks and the Role of Black Swans." NBER Working Paper 20445.
- Peek, Joe, Eric S. Rosengren, and Geoffrey M. B. Tootell. 2015. "Should U.S. Monetary Policy Have a Ternary Mandate?" Paper presented at Federal Reserve Bank of Boston 59th Economic Conference: Macroprudential Monetary Policy, Boston.
- Primiceri, Giorgio E. 2005. "Time Varying Structural Vector Autoregressions and Monetary Policy." *Review of Economic Studies* 72 (3): 821–52.
- Rossi, Barbara, and Tatevik Sekhposyan. 2010. "Have Economic Models' Forecasting Performance for US Output Growth and Inflation Changed over Time, and When?" *International Journal of Forecasting* 26 (4): 808–35.
- Rossi, Barbara, and Tatevik Sekhposyan. 2017. "Alternative Tests for Correct Specification of Conditional Predictive Densities." Unpublished.
- Schmidt, Lawrence D. W., and Yinchu Zhu. 2016. "Quantile Spacings: A Simple Method for the Joint Estimation of Multiple Quantiles without Crossing." Unpublished.
- Smith, Michael S., and Shaun P. Vahey. 2016. "Asymmetric Forecast Densities for U.S. Macroeconomic Variables from a Gaussian Copula Model of Cross-Sectional and Serial Dependence." *Journal of Business and Economic Statistics* 34 (3): 416–34.
- Stock, James H., and Mark W. Watson. 2003. "Forecasting Output and Inflation: The Role of Asset Prices." *Journal of Economic Literature* 41 (3): 788–829.
- van Binsbergen, Jules H., Wouter Hueskes, Ralph Koijen, and Evert Vrugt. 2013. "Equity Yields." *Journal of Financial Economics* 110 (3): 503–19.
- Wachter, Jessica A. 2013. "Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility?" *Journal of Finance* 68 (3): 987–1035.

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1. Kristina Bluwstein, Marcus Buckmann, Andreas Joseph, Sujit Kapadia, Özgür Şimşek. 2023. Credit growth, the yield curve and financial crisis prediction: Evidence from a machine learning approach. *Journal of International Economics* **145**, 103773. [[Crossref](#)]
2. Valentina Corradi, Jack Fosten, Daniel Gutknecht. 2023. Out-of-sample tests for conditional quantile coverage an application to Growth-at-Risk. *Journal of Econometrics* **236**:2, 105490. [[Crossref](#)]
3. Tingguo Zheng, Lu Gong, Shiqi Ye. 2023. Global energy market connectedness and inflation at risk. *Energy Economics* **126**, 106975. [[Crossref](#)]
4. MICHAEL BAUER, MIKHAIL CHERNOV. 2023. Interest Rate Skewness and Biased Beliefs. *The Journal of Finance* **109**. . [[Crossref](#)]
5. Rui C. Mano, Silvia Sgherri. 2023. One Shock, Many Policy Responses. *Open Economies Review* **109**. . [[Crossref](#)]
6. Philipp Heimberger. 2023. Public debt and r-g risks in advanced economies: Eurozone versus stand-alone. *Journal of International Money and Finance* **136**, 102877. [[Crossref](#)]
7. Michael Anthonisz. 2023. Nowcasting Key Australian Macroeconomic Variables. *Australian Economic Review* **56**:3, 371-380. [[Crossref](#)]
8. Inmaculada Jimeno García, Anne Marie Garvey, Carlos Mir Fernández, Rocío Flores Jimeno. 2023. The financial vulnerability of non-profit entities: A theoretical framework proposal. *REVESCO. Revista de Estudios Cooperativos* **144**, e88655. [[Crossref](#)]
9. George Dotsis, Panagiotis Petris, Dimitris Psychoyios. 2023. Assessing Housing Market Crashes over the Past 150 years. *The Journal of Real Estate Finance and Economics* **109**. . [[Crossref](#)]
10. William Gatt. 2023. Housing Boom-Bust Cycles and Asymmetric Macroprudential Policy. *Journal of Money, Credit and Banking* **109**. . [[Crossref](#)]
11. Todd E. Clark, Florian Huber, Gary Koop, Massimiliano Marcellino, Michael Pfarrhofer. 2023. TAIL FORECASTING WITH MULTIVARIATE BAYESIAN ADDITIVE REGRESSION TREES. *International Economic Review* **64**:3, 979-1022. [[Crossref](#)]
12. Qifa Xu, Mengnan Xu, Cuixia Jiang, Weizhong Fu. 2023. Mixed-frequency Growth-at-Risk with the MIDAS-QR method: Evidence from China. *Economic Systems* **32**, 101131. [[Crossref](#)]
13. Sudipto Karmakar, Diogo Lima. 2023. Global capital flows and the role of macroprudential policy. *Journal of Financial Stability* **67**, 101137. [[Crossref](#)]
14. Luca Barbaglia, Sergio Consoli, Sebastiano Manzan. 2023. Forecasting with Economic News. *Journal of Business & Economic Statistics* **41**:3, 708-719. [[Crossref](#)]
15. Mengnan Xu, Qifa Xu, Shixiang Lu, Cuixia Jiang, Cheng Wang. 2023. High-frequency monitoring of China's green growth-at-risk. *Environmental Science and Pollution Research* **37**. . [[Crossref](#)]
16. Mariusz Górajski, Zbigniew Kuchta. 2023. Coordination and non-coordination risks of monetary and macroprudential authorities: A robust welfare analysis. *The North American Journal of Economics and Finance* **67**, 101922. [[Crossref](#)]
17. Martin Gächter, Elias Hasler, Johann Scharler. 2023. Kicking the can down the road: A historical growth-at-risk perspective. *Economics Letters* **228**, 111133. [[Crossref](#)]
18. Steven A. Sharpe, Nitish R. Sinha, Christopher A. Hollrah. 2023. The power of narrative sentiment in economic forecasts. *International Journal of Forecasting* **39**:3, 1097-1121. [[Crossref](#)]
19. Sercan Eraslan, Maximilian Schröder. 2023. Nowcasting GDP with a pool of factor models and a fast estimation algorithm. *International Journal of Forecasting* **39**:3, 1460-1476. [[Crossref](#)]

20. Efrem Castelnuovo. 2023. Uncertainty before and during COVID-19: A survey. *Journal of Economic Surveys* **37**:3, 821-864. [[Crossref](#)]
21. Graziano Moramarco. 2023. Financial-cycle ratios and medium-term predictions of GDP: Evidence from the United States. *International Journal of Forecasting* **7**. . [[Crossref](#)]
22. Yan Carrière-Swallow, José Marzluf. 2023. Macroeconomic Causes of Optimism in Growth Forecasts. *IMF Economic Review* **71**:2, 509-537. [[Crossref](#)]
23. Danilo Cascaldi-Garcia, Cibil Sarisoy, Juan M. Londono, Bo Sun, Deepa D. Datta, Thiago Ferreira, Olesya Grishchenko, Mohammad R. Jahan-Parvar, Francesca Loria, Sai Ma, Marius Rodriguez, Ilknur Zer, John Rogers. 2023. What is Certain about Uncertainty?. *Journal of Economic Literature* **61**:2, 624-654. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
24. Harendra Behera, Iman Gunadi, Badri Narayan Rath. 2023. COVID-19 uncertainty, financial markets and monetary policy effects in case of two emerging Asian countries. *Economic Analysis and Policy* **78**, 173-189. [[Crossref](#)]
25. Helena Chuliá, Ignacio Garrón, Jorge M. Uribe. 2023. Daily growth at risk: Financial or real drivers? The answer is not always the same. *International Journal of Forecasting* **109**. . [[Crossref](#)]
26. Matthias Rottner. 2023. Financial crises and shadow banks: A quantitative analysis. *Journal of Monetary Economics* **109**. . [[Crossref](#)]
27. Luke Hartigan, Michelle Wright. 2023. Monitoring Financial Conditions and Downside Risk to Economic Activity in Australia*. *Economic Record* **99**:325, 253-287. [[Crossref](#)]
28. Chuang Deng, Jian Wu. 2023. Macroeconomic downside risk and the effect of monetary policy. *Finance Research Letters* **54**, 103803. [[Crossref](#)]
29. Tobias Fissler, Yannick Hoga. 2023. Backtesting Systemic Risk Forecasts Using Multi-Objective Elicitability. *Journal of Business & Economic Statistics* **13**, 1-14. [[Crossref](#)]
30. Zhihong Jian, Haisong Lu, Zhican Zhu. 2023. Are systemic risk measures effective? Evidence from macroeconomic downside risk prediction. *Applied Economics Letters* 1-8. [[Crossref](#)]
31. Martín Harding, Jesper Lindé, Mathias Trabandt. 2023. Understanding Post-COVID Inflation Dynamics. *Journal of Monetary Economics* **38**. . [[Crossref](#)]
32. Antonin Aviat, Frédérique Bec, Claude Diebolt, Catherine Doz, Denis Ferrand, Laurent Ferrara, Éric Heyer, Valérie Mignon, Pierre-Alain Pionnier. 2023. Les cycles économiques de la France : une datation de référence. *Revue économique* **Vol. 74**:2, 5-52. [[Crossref](#)]
33. Yannick Hoga, Timo Dimitriadis. 2023. On Testing Equal Conditional Predictive Ability Under Measurement Error. *Journal of Business & Economic Statistics* **41**:2, 364-376. [[Crossref](#)]
34. Anthony Garratt, Timo Henckel, Shaun P. Vahey. 2023. Empirically-transformed linear opinion pools. *International Journal of Forecasting* **39**:2, 736-753. [[Crossref](#)]
35. Bram van Os, Dick van Dijk. 2023. Accelerating peak dating in a dynamic factor Markov-switching model. *International Journal of Forecasting* **35**. . [[Crossref](#)]
36. Ambili G. Kamalamma, Mukand S. Babel, Venkataramana Sridhar, Geethalakshmi Vellingiri. 2023. A novel approach to vulnerability assessment for adaptation planning in agriculture: An application to the Lower Bhavani Irrigation Project, India. *Climate Services* **30**, 100358. [[Crossref](#)]
37. James Mitchell, Martin Weale. 2023. Censored density forecasts: Production and evaluation. *Journal of Applied Econometrics* **18**. . [[Crossref](#)]
38. Tilmann Gneiting, Daniel Wolfrum, Johannes Resin, Kristof Kraus, Johannes Bracher, Timo Dimitriadis, Veit Hagenmeyer, Alexander I. Jordan, Sebastian Lerch, Kaleb Phipps, Melanie Schienle. 2023. Model Diagnostics and Forecast Evaluation for Quantiles. *Annual Review of Statistics and Its Application* **10**:1, 597-621. [[Crossref](#)]

39. Thierry U. Kame Babilla. 2023. Digital innovation and financial access for small and medium-sized enterprises in a currency union. *Economic Modelling* **120**, 106182. [[Crossref](#)]
40. Galina Potjagailo, Maik H. Wolters. 2023. Global financial cycles since 1880. *Journal of International Money and Finance* **131**, 102801. [[Crossref](#)]
41. Martin Iseringhausen. 2023. A time-varying skewness model for Growth-at-Risk. *International Journal of Forecasting* **37**. . [[Crossref](#)]
42. Tamás Kiss, Stepan Mazur, Hoang Nguyen, Pär Österholm. 2023. Modeling the relation between the US real economy and the corporate bond-yield spread in Bayesian VARs with non-Gaussian innovations. *Journal of Forecasting* **42**:2, 347-368. [[Crossref](#)]
43. Aaron J. Amburgey, Michael W. McCracken. 2023. On the real-time predictive content of financial condition indices for growth. *Journal of Applied Econometrics* **38**:2, 137-163. [[Crossref](#)]
44. Tony Chernis, Patrick J. Coe, Shaun P. Vahey. 2023. Reassessing the dependence between economic growth and financial conditions since 1973. *Journal of Applied Econometrics* **38**:2, 260-267. [[Crossref](#)]
45. Simon Lloyd, Ed Manuel, Konstantin Panchev. 2023. Foreign Vulnerabilities, Domestic Risks: The Global Drivers of GDP-at-Risk. *IMF Economic Review* **109**. . [[Crossref](#)]
46. Anil K Kashyap, Jeremy C. Stein. 2023. Monetary Policy When the Central Bank Shapes Financial-Market Sentiment. *Journal of Economic Perspectives* **37**:1, 53-75. [[Crossref](#)]
47. Tibor Szendrei, Katalin Varga. 2023. Revisiting vulnerable growth in the Euro Area: Identifying the role of financial conditions in the distribution. *Economics Letters* **223**, 110990. [[Crossref](#)]
48. William Gatt. 2023. Loan-to-value limits as a macroprudential policy tool: Developments in theory and practice. *Journal of Economic Surveys* **79**. . [[Crossref](#)]
49. Florian Huber, Gary Koop, Luca Onorante, Michael Pfarrhofer, Josef Schreiner. 2023. Nowcasting in a pandemic using non-parametric mixed frequency VARs. *Journal of Econometrics* **232**:1, 52-69. [[Crossref](#)]
50. Federico Bassetti, Roberto Casarin, Marco Del Negro. Inference on probabilistic surveys in macroeconomics with an application to the evolution of uncertainty in the survey of professional forecasters during the COVID pandemic 443-476. [[Crossref](#)]
51. Malte Knäuper, Fabian Krüger, Marc-Oliver Pöhle. 2023. Score-Based Calibration Testing for Multivariate Forecast Distributions. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
52. Jesús Fernández-Villaverde, Samuel Hurtado, Galo Nuño. 2023. Financial Frictions and the Wealth Distribution. *Econometrica* **91**:3, 869-901. [[Crossref](#)]
53. Kosmas Kaprinis. The Macroprudential Shift: A Policy Pillar in the Making 21-41. [[Crossref](#)]
54. Mario Bellia, Ludovic Calès. 2023. Bank Profitability and Central Bank Digital Currency. *SSRN Electronic Journal* **26**. . [[Crossref](#)]
55. Philipp Adämmer, Jan Prüser, Rainer Alexander Schüssler. 2023. Forecasting Macroeconomic Tail Risk in Real Time: Do Textual Data Add Value?. *SSRN Electronic Journal* **24**. . [[Crossref](#)]
56. Michele Lenza, Inès Moutachaker, Joan Paredes. 2023. Density Forecasts of Inflation: A Quantile Regression Forest Approach. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
57. Menzie David Chinn, Baptiste Meunier, Sebastian Stumpner. 2023. Nowcasting World Trade with Machine Learning: A Three-Step Approach. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
58. Menzie David Chinn, Baptiste Meunier, Sebastian Stumpner. 2023. Nowcasting World Trade with Machine Learning: a Three-Step Approach. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
59. Luiz Renato Lima, Lucas Godeiro. 2023. Quantile Forecasting with Textual Data. *SSRN Electronic Journal* . [[Crossref](#)]

60. Manfred M. Fischer, Niko Hauzenberger, Florian Huber, Michael Pfarrhofer. 2023. General Bayesian time-varying parameter vector autoregressions for modeling government bond yields. *Journal of Applied Econometrics* **38**:1, 69-87. [[Crossref](#)]
61. Farrukh Javed, Tamás Kiss, Pär Österholm. 2022. Performance analysis of nowcasting of GDP growth when allowing for conditional heteroscedasticity and non-Gaussianity. *Applied Economics* **54**:58, 6669-6686. [[Crossref](#)]
62. Piergiorgio Alessandri, Pierluigi Bologna, Maddalena Galardo. 2022. Financial Crises, Macroprudential Policy and the Reliability of Credit-to-GDP Gaps. *IMF Economic Review* **70**:4, 625-667. [[Crossref](#)]
63. Simone Arrigoni, Alina Bobasu, Fabrizio Venditti. 2022. Measuring Financial Conditions using Equal Weights Combination. *IMF Economic Review* **70**:4, 668-697. [[Crossref](#)]
64. Marcin Pietrzak. 2022. Can financial sector distress be detected early?. *Borsa Istanbul Review* **22**:6, 1132-1144. [[Crossref](#)]
65. Pietro Dindo, Andrea Modena, Loriana Pelizzon. 2022. Risk pooling, intermediation efficiency, and the business cycle. *Journal of Economic Dynamics and Control* **144**, 104500. [[Crossref](#)]
66. Ana Beatriz Galvão, Michael Owyang. 2022. Forecasting low-frequency macroeconomic events with high-frequency data. *Journal of Applied Econometrics* **37**:7, 1314-1333. [[Crossref](#)]
67. Alexander Foltas, Christian Pierdzioch. 2022. On the efficiency of German growth forecasts: an empirical analysis using quantile random forests and density forecasts. *Applied Economics Letters* **29**:17, 1644-1653. [[Crossref](#)]
68. Matthias Thiemann. 2022. Growth at risk: Boundary walkers, stylized facts and the legitimacy of countercyclical interventions. *Economy and Society* **51**:4, 630-654. [[Crossref](#)]
69. Chokri Zehri. 2022. The Time-Varying Effects of Policies: Evidence from Capital Flows to Emerging Markets. *International Economic Journal* **36**:4, 569-595. [[Crossref](#)]
70. Jing Lian Suah. 2022. Impact of uncertainty and exchange rate shocks: Theory and global empirics. *Journal of Asian Economics* **82**, 101510. [[Crossref](#)]
71. Michael Pfarrhofer. 2022. Modeling tail risks of inflation using unobserved component quantile regressions. *Journal of Economic Dynamics and Control* **143**, 104493. [[Crossref](#)]
72. Nima Nonejad. 2022. Predicting equity premium out-of-sample by conditioning on newspaper-based uncertainty measures: A comparative study. *International Review of Financial Analysis* **83**, 102251. [[Crossref](#)]
73. Afees A. Salisu, Christian Pierdzioch, Rangan Gupta, David Gabauer. 2022. Forecasting stock-market tail risk and connectedness in advanced economies over a century: The role of gold-to-silver and gold-to-platinum price ratios. *International Review of Financial Analysis* **83**, 102300. [[Crossref](#)]
74. Òscar Jordà, Martin Kornejew, Moritz Schularick, Alan M Taylor. 2022. Zombies at Large? Corporate Debt Overhang and the Macroeconomy. *The Review of Financial Studies* **35**:10, 4561-4586. [[Crossref](#)]
75. Matias Ossandon Busch, José Manuel Sánchez-Martínez, Anahí Rodríguez-Martínez, Ricardo Montañez-Enríquez, Serafin Martínez-Jaramillo. 2022. Growth at risk: Methodology and applications in an open-source platform. *Latin American Journal of Central Banking* **3**:3, 100068. [[Crossref](#)]
76. Fernando Eguren-Martin, Andrej Sokol. 2022. Attention to the Tail(s): Global Financial Conditions and Exchange Rate Risks. *IMF Economic Review* **70**:3, 487-519. [[Crossref](#)]
77. Rodrigo Hizmeri, Marwan Izzeldin, Ingmar Nolte, Vasileios Pappas. 2022. A generalized heterogeneous autoregressive model using market information. *Quantitative Finance* **22**:8, 1513-1534. [[Crossref](#)]
78. Laurent Ferrara, Joseph Yapi. 2022. Measuring exchange rate risks during periods of uncertainty. *International Economics* **170**, 202-212. [[Crossref](#)]

79. Andrea Carriero, Todd E. Clark, Massimiliano Marcellino. 2022. Nowcasting tail risk to economic activity at a weekly frequency. *Journal of Applied Econometrics* 37:5, 843-866. [[Crossref](#)]
80. Philippe Goulet Coulombe, Maxime Leroux, Dalibor Stevanovic, Stéphane Surprenant. 2022. How is machine learning useful for macroeconomic forecasting?. *Journal of Applied Econometrics* 37:5, 920-964. [[Crossref](#)]
81. MICHAEL T. KILEY. 2022. Unemployment Risk. *Journal of Money, Credit and Banking* 54:5, 1407-1424. [[Crossref](#)]
82. Michael Funke, Rongrong Sun, Linxu Zhu. 2022. The credit risk of Chinese households: A micro-level assessment. *Pacific Economic Review* 27:3, 254-276. [[Crossref](#)]
83. Toni Ahnert, Christoph Bertsch. 2022. A Wake-Up Call Theory of Contagion. *Review of Finance* 26:4, 829-854. [[Crossref](#)]
84. Tobias Adrian, Federico Grinberg, Nellie Liang, Sheheryar Malik, Jie Yu. 2022. The Term Structure of Growth-at-Risk. *American Economic Journal: Macroeconomics* 14:3, 283-323. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
85. Luis Brandão-Marques, Qianying Chen, Claudio Raddatz, Jérôme Vandenbussche, Peichu Xie. 2022. The riskiness of credit allocation and financial stability. *Journal of Financial Intermediation* 51, 100980. [[Crossref](#)]
86. Fabrizio Ferriani, Andrea Gazzani. 2022. Financial condition indices for emerging market economies: Can Google help?. *Economics Letters* 216, 110528. [[Crossref](#)]
87. Daniel Soques. 2022. TIMING AND SIGNALS OF MONETARY REGIME SWITCHING. *Macroeconomic Dynamics* 26:4, 885-919. [[Crossref](#)]
88. Javier Suarez. 2022. Growth-at-risk and macroprudential policy design. *Journal of Financial Stability* 60, 101008. [[Crossref](#)]
89. Mikhail Stolbov, Maria Shchepeleva. 2022. Modeling global real economic activity: Evidence from variable selection across quantiles. *The Journal of Economic Asymmetries* 25, e00238. [[Crossref](#)]
90. Anusha Chari, Karlye Dilts-Stedman, Kristin Forbes. 2022. Spillovers at the extremes: The macroprudential stance and vulnerability to the global financial cycle. *Journal of International Economics* 136, 103582. [[Crossref](#)]
91. Yuejiao Duan, John W. Goodell, Haoran Li, Xinming Li. 2022. Assessing machine learning for forecasting economic risk: Evidence from an expanded Chinese financial information set. *Finance Research Letters* 46, 102273. [[Crossref](#)]
92. Yuya Sasaki, Yulong Wang. 2022. Fixed- k Inference for Conditional Extremal Quantiles. *Journal of Business & Economic Statistics* 40:2, 829-837. [[Crossref](#)]
93. Ozge Akinci, Albert Queralto. 2022. Credit Spreads, Financial Crises, and Macroprudential Policy. *American Economic Journal: Macroeconomics* 14:2, 469-507. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
94. Stéphane Lhuissier. 2022. Financial conditions and macroeconomic downside risks in the euro area. *European Economic Review* 143, 104046. [[Crossref](#)]
95. Claudia Foroni, Massimiliano Marcellino, Dalibor Stevanovic. 2022. Forecasting the Covid-19 recession and recovery: Lessons from the financial crisis. *International Journal of Forecasting* 38:2, 596-612. [[Crossref](#)]
96. Laurent Ferrara, Xuguang Simon Sheng. 2022. Guest editorial: Economic forecasting in times of COVID-19. *International Journal of Forecasting* 38:2, 527-528. [[Crossref](#)]
97. Boyan Jovanovic, Sai Ma. 2022. Uncertainty and growth disasters. *Review of Economic Dynamics* 44, 33-64. [[Crossref](#)]

98. Laurent Ferrara, Matteo Mogliani, Jean-Guillaume Sahuc. 2022. High-frequency monitoring of growth at risk. *International Journal of Forecasting* **38**:2, 582-595. [[Crossref](#)]
99. ROBIN GREENWOOD, SAMUEL G. HANSON, ANDREI SHLEIFER, JAKOB AHM SØRENSEN. 2022. Predictable Financial Crises. *The Journal of Finance* **77**:2, 863-921. [[Crossref](#)]
100. Tim Bollerslev. 2022. Realized Semi(co)variation: Signs That All Volatilities are Not Created Equal. *Journal of Financial Econometrics* **20**:2, 219-252. [[Crossref](#)]
101. Shujie Wu, Haichun Ye. 2022. FIEs and the Transmission of Global Financial Uncertainty: Evidence from China. *Journal of Financial and Quantitative Analysis* **19**, 1-28. [[Crossref](#)]
102. Michael Pfarrhofer. 2022. Measuring International Uncertainty Using Global Vector Autoregressions with Drifting Parameters. *Macroeconomic Dynamics* 1-24. [[Crossref](#)]
103. Nina Boyarchenko, Giovanni Favara, Moritz Schularick. 2022. Financial Stability Considerations for Monetary Policy: Empirical Evidence and Challenges. *Finance and Economics Discussion Series* **2022**:005, 1-33. [[Crossref](#)]
104. Wenbo Jia, Yingce Yang. Growth at Risk of Oil Price Based on Quantile Regression 906-913. [[Crossref](#)]
105. Marco Gross. 2022. Beautiful cycles: A theory and a model implying a curious role for interest. *Economic Modelling* **106**, 105678. [[Crossref](#)]
106. Zhanna Chupina, Irina Abanina, Valery Abramov, Kira Artamonova, Oksana Yurchenko, Irina Osipova, Pavel Stroev. 2022. Management of Monetary Policy in the Framework of Decision Making on Setting Interest Rates for Sustainable Social System: Example of the Russian Federation. *Sustainability* **14**:1, 79. [[Crossref](#)]
107. Gaston Gelos, Lucyna Gornicka, Robin Koepke, Ratna Sahay, Silvia Sgherri. 2022. Capital flows at risk: Taming the ebbs and flows. *Journal of International Economics* **134**, 103555. [[Crossref](#)]
108. David Lopez-Salido, Francesca Loria. 2022. Inflation at Risk. *SSRN Electronic Journal* **37**. . [[Crossref](#)]
109. Anusha Chari, Karlye Dilts Stedman, Kristin J. Forbes. 2022. Spillovers at the Extremes: The Macroprudential Stance and Vulnerability to the Global Financial Cycle. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
110. Philippe Goulet Coulombe. 2022. A Neural Phillips Curve and a Deep Output Gap. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
111. Afees A. Salisu, Rangan Gupta, Christian Pierdzioch. 2022. Predictability of tail risks of Canada and the U.S. Over a Century: The role of spillovers and oil tail Risks#. *The North American Journal of Economics and Finance* **59**, 101620. [[Crossref](#)]
112. Tony Chernis, Patrick J. Coe, Shaun P. Vahey. 2022. Reassessing the Dependence Between Economic Growth and Financial Conditions Since 1973. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
113. Toni Ahnert, Christoph Bertsch. 2022. A Wake-Up Call Theory of Contagion. *SSRN Electronic Journal* **40**. . [[Crossref](#)]
114. Benjamin King, James Semark. 2022. Reducing Liquidity Mismatch in Open-Ended Funds: A Cost-Benefit Analysis. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
115. Whayoung JUNG. 2022. Tightening Financial Conditions and Implications for the Housing Market in Korea. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
116. Aleksey Kipriyanov. 2022. Comparison of Models for Growth-at-Risk Forecasting. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
117. Giovanni Covi, James Brookes, Charumathi Raja. 2022. Measuring Capital at Risk in the Uk Banking Sector: A Microstructural Network Approach. *SSRN Electronic Journal* **71**. . [[Crossref](#)]

118. James Mitchell, Dan Zhu, Aubrey Poon. 2022. Constructing Density Forecasts from Quantile Regressions: Multimodality in Macro-Financial Dynamics. *SSRN Electronic Journal* **109**. . [\[Crossref\]](#)
119. Ambili G. Kamalamma, Mukand S. Babel, Venkataramana Sridhar, Geethalakshmi Vellingiri. 2022. A Novel Approach to Vulnerability Assessment for Adaptation Planning in Agriculture: An Application to the Lower Bhavani Irrigation Project, India. *SSRN Electronic Journal* **11**. . [\[Crossref\]](#)
120. Matthias Rottner. 2022. Financial Crises and Shadow Banks: A Quantitative Analysis. *SSRN Electronic Journal* **19**. . [\[Crossref\]](#)
121. Silu Muduli, Harendra Kumar Behera, Michael Patra. 2022. Capital Flows at Risk: India's Experience. *SSRN Electronic Journal* **109**. . [\[Crossref\]](#)
122. Amir Sufi, Alan M. Taylor. Financial crises: a survey 291-340. [\[Crossref\]](#)
123. Seohyun Lee. 2022. Measuring Interdependence of Inflation Uncertainty. *SSRN Electronic Journal* **109**. . [\[Crossref\]](#)
124. Costanza Giannantoni, Valeria Patella, Massimiliano Tancioni. 2022. Secured and Unsecured Credit Cycles. *SSRN Electronic Journal* **109**. . [\[Crossref\]](#)
125. Francesca Loria, Christian Matthes, Donghai Zhang. 2022. Assessing Macroeconomic Tail Risk. *SSRN Electronic Journal* **109**. . [\[Crossref\]](#)
126. Martin Iseringhausen, Ivan Petrella, Konstantinos Theodoridis. 2022. Aggregate skewness and the business cycle. *SSRN Electronic Journal* **109**. . [\[Crossref\]](#)
127. Gábor Fukker, Michiel Kaijser, Luca Mingarelli, Matthias Sydow. 2022. Contagion from Market Price Impact: A Price-at-Risk Perspective. *SSRN Electronic Journal* **109**. . [\[Crossref\]](#)
128. Paul Bochmann, Paul Hiebert, Yves S. Schüler, Miguel Segoviano. 2022. Latent Fragility: Conditioning Banks' Joint Probability of Default on the Financial Cycle. *SSRN Electronic Journal* **109**. . [\[Crossref\]](#)
129. Pegah Mahdavi, Mohammad Ali Ehsani. 2022. Dynamic Causal Effects in Econometrics by Emphasizing the Non Parametric Method: Review Papers. *SSRN Electronic Journal* **74**. . [\[Crossref\]](#)
130. Seohyun Lee. 2022. Measuring Interdependence of Inflation Uncertainty. *SSRN Electronic Journal* **109**. . [\[Crossref\]](#)
131. J. Benson Durham. 2022. Nominal U.S. Treasuries Embed Liquidity Premiums, Too: An Affine Model of the Term Structure. *SSRN Electronic Journal* **84**. . [\[Crossref\]](#)
132. Malte Knüppel, Fabian Krüger. 2022. Forecast uncertainty, disagreement, and the linear pool. *Journal of Applied Econometrics* **37**:1, 23-41. [\[Crossref\]](#)
133. Florens Odendahl, Barbara Rossi, Tatevik Sekhposyan. 2022. Evaluating forecast performance with state dependence. *Journal of Econometrics* **109**, 105220. [\[Crossref\]](#)
134. Thiago Ramos Almeida. 2022. Macroeconomic Uncertainty Price and Investment Decisions. *SSRN Electronic Journal* . [\[Crossref\]](#)
135. Thiago Ramos Almeida. 2022. Interest Rate Uncertainty and Vulnerabilities in Stock Market Valuation. *SSRN Electronic Journal* **109**. . [\[Crossref\]](#)
136. Barbara Rossi. 2021. Forecasting in the Presence of Instabilities: How We Know Whether Models Predict Well and How to Improve Them. *Journal of Economic Literature* **59**:4, 1135-1190. [\[Abstract\]](#) [\[View PDF article\]](#) [\[PDF with links\]](#)
137. Adrian Alter, Elizabeth M. Mahoney. 2021. Local house-price vulnerability: Evidence from the U.S. and Canada. *Journal of Housing Economics* **54**, 101791. [\[Crossref\]](#)
138. Rangan Gupta, Xin Sheng, Christian Pierdzioch, Qiang Ji. 2021. Disaggregated oil shocks and stock-market tail risks: Evidence from a panel of 48 economics. *Research in International Business and Finance* **58**, 101515. [\[Crossref\]](#)

139. Tamás Kiss, Hoang Nguyen, Pär Österholm. 2021. Modelling Returns in US Housing Prices—You're the One for Me, Fat Tails. *Journal of Risk and Financial Management* **14**:11, 506. [[Crossref](#)]
140. Afees A. Salisu, Christian Pierdzioch, Rangan Gupta. 2021. Geopolitical risk and forecastability of tail risk in the oil market: Evidence from over a century of monthly data. *Energy* **235**, 121333. [[Crossref](#)]
141. Victor Pontines, Davaajargal Luvsannyam, Enkhjin Atarbaatar, Ulziikhutag Munkhtsetseg. 2021. The effectiveness of currency intervention: Evidence from Mongolia. *Journal of International Financial Markets, Institutions and Money* **75**, 101439. [[Crossref](#)]
142. Xiaojun Song, Abderrahim Taamouti. 2021. Measuring Granger Causality in Quantiles. *Journal of Business & Economic Statistics* **39**:4, 937-952. [[Crossref](#)]
143. John V. Duca, John Muellbauer, Anthony Murphy. 2021. What Drives House Price Cycles? International Experience and Policy Issues. *Journal of Economic Literature* **59**:3, 773-864. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
144. Kashif Yousuf, Serena Ng. 2021. Boosting high dimensional predictive regressions with time varying parameters. *Journal of Econometrics* **224**:1, 60-87. [[Crossref](#)]
145. Bo Wang, Haoran Li. 2021. Downside risk, financial conditions and systemic risk in China. *Pacific-Basin Finance Journal* **68**, 101356. [[Crossref](#)]
146. Benny Hartwig, Christoph Meinerding, Yves S. Schüler. 2021. Identifying indicators of systemic risk. *Journal of International Economics* **132**, 103512. [[Crossref](#)]
147. Guojin Chen, Yanzhen Liu, Yu Zhang. 2021. Systemic risk measures and distribution forecasting of macroeconomic shocks. *International Review of Economics & Finance* **75**, 178-196. [[Crossref](#)]
148. A. O. Ovcharov, V. A. Matveev. 2021. Financial Fear Index in the Digital Financial Assets Market. *Finance: Theory and Practice* **25**:4, 136-151. [[Crossref](#)]
149. Anna Cieslak, Annette Vissing-Jorgensen. 2021. The Economics of the Fed Put. *The Review of Financial Studies* **34**:9, 4045-4089. [[Crossref](#)]
150. Ji Hyung Lee, Youngki Shin. 2021. COMPLETE SUBSET AVERAGING FOR QUANTILE REGRESSIONS. *Econometric Theory* **78**, 1-43. [[Crossref](#)]
151. Michael T. Kiley. 2021. Growth at Risk From Climate Change. *Finance and Economics Discussion Series* **2021**:054, 1-19. [[Crossref](#)]
152. Fabio Busetti, Michele Caivano, Davide Delle Monache, Claudia Pacella. 2021. The time-varying risk of Italian GDP. *Economic Modelling* **101**, 105522. [[Crossref](#)]
153. Patrick A. Adams, Tobias Adrian, Nina Boyarchenko, Domenico Giannone. 2021. Forecasting macroeconomic risks. *International Journal of Forecasting* **37**:3, 1173-1191. [[Crossref](#)]
154. Ana Beatriz Galvão, Anthony Garratt, James Mitchell. 2021. Does judgment improve macroeconomic density forecasts?. *International Journal of Forecasting* **37**:3, 1247-1260. [[Crossref](#)]
155. Emanuele De Meo, Giacomo Tizzanini. 2021. GDP-network CoVaR: A tool for assessing growth-at-risk. *Economic Notes* **50**:2. . [[Crossref](#)]
156. Xin Gu, Xiang Cheng, Zixiang Zhu, Xiang Deng. 2021. Economic policy uncertainty and China's growth-at-risk. *Economic Analysis and Policy* **70**, 452-467. [[Crossref](#)]
157. Dong Jin Lee, Tae-Hwan Kim, Paul Mizen. 2021. Impulse response analysis in conditional quantile models with an application to monetary policy. *Journal of Economic Dynamics and Control* **127**, 104102. [[Crossref](#)]
158. Stephen S. Poloz. 2021. Technological progress and monetary policy: Managing the fourth industrial revolution. *Journal of International Money and Finance* **114**, 102373. [[Crossref](#)]
159. Tobias Adrian, Nina Boyarchenko, Domenico Giannone. 2021. MULTIMODALITY IN MACROFINANCIAL DYNAMICS. *International Economic Review* **62**:2, 861-886. [[Crossref](#)]

160. Robert J. Barro, Gordon Y. Liao. 2021. Rare disaster probability and options pricing. *Journal of Financial Economics* **139**:3, 750-769. [[Crossref](#)]
161. Christian Brownlees, André B.M. Souza. 2021. Backtesting global Growth-at-Risk. *Journal of Monetary Economics* **118**, 312-330. [[Crossref](#)]
162. Patrick Fève, Pablo Garcia Sanchez, Alban Moura, Olivier Pierrard. 2021. Costly default and skewed business cycles. *European Economic Review* **132**, 103630. [[Crossref](#)]
163. Charles Enoch. The Macroprudential Approach: A Strategy for All Seasons? 141-174. [[Crossref](#)]
164. Noh-Sun Kwark, Changhyun Lee. 2021. Asymmetric effects of financial conditions on GDP growth in Korea: A quantile regression analysis. *Economic Modelling* **94**, 351-369. [[Crossref](#)]
165. Diana Farrell, George Eckerd. 2021. The Stock Market and Household Financial Behavior. *SSRN Electronic Journal* . [[Crossref](#)]
166. Todd E. Clark, Florian Huber, Gary Koop, Massimiliano Marcellino, Michael Pfarrhofer. 2021. Tail Forecasting with Multivariate Bayesian Additive Regression Trees. *SSRN Electronic Journal* **36**. . [[Crossref](#)]
167. Bruno Albuquerque. 2021. Corporate credit booms, financial constraints, and the investment nexus. *SSRN Electronic Journal* **66**. . [[Crossref](#)]
168. Geert Bekaert, Eric C. Engstrom, Andrey Ermolov. 2021. Uncertainty and the Economy: The Evolving Distributions of Aggregate Supply and Demand Shocks. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
169. Daan Opschoor, Dick J.C. van Dijk, Philip Hans Franses. 2021. Heterogeneity in Manufacturing Growth Risk. *SSRN Electronic Journal* **80**. . [[Crossref](#)]
170. James Mitchell, Martin Weale. 2021. Censored Density Forecasts: Production and Evaluation. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
171. Tim Bollerslev. 2021. Realized Semi(Co)Variation: Signs that All Volatilities are Not Created Equal. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
172. Amir Sufi, Alan M. Taylor. 2021. Financial Crises: A Survey. *SSRN Electronic Journal* **69**. . [[Crossref](#)]
173. Bruno Albuquerque. 2021. Corporate debt booms, financial constraints and the investment nexus. *SSRN Electronic Journal* **66**. . [[Crossref](#)]
174. Maria T. Gonzalez-Perez. 2021. Lessons from Estimating the Average Option-implied Volatility Term Structure for the Spanish Banking Sector. *SSRN Electronic Journal* **25**. . [[Crossref](#)]
175. Simon Lloyd, Ed Manuel, Konstantin Panchev. 2021. Foreign Vulnerabilities, Domestic Risks: The Global Drivers of GDP-at-Risk. *SSRN Electronic Journal* **12**. . [[Crossref](#)]
176. Federic Holm-Hadulla, Alberto Musso, Thomas Vlassopoulos, Diego Rodriguez-Palenzuela. 2021. Evolution of the Ecb's Analytical Framework. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
177. Carmen Broto, José Alonso, Esther Cáceres García, Luis Gonzalo Fernandez Lafuerza, Jorge Galán, Matias Lamas, Jose Ramon Martinez Resano, Mariya Melnychuk, Silvia Merino, Patricia Stupariu, Maria Luisa Tejedor, Irma Alonso Alvarez, Mario Alloza, Pablo Burriel, Sandra Garcia, Maria Gil, Luis Molina, Maria Rodriguez-Moreno, Ernesto Villanueva, Andrés Alonso, Teresa Caminero, Clara I. Gonzalez, Maria T. Gonzalez-Perez, Maria Nalda Tomas, Pedro Javier Martínez-Valero. 2021. How Do Central Banks Identify Risks? A Survey of Indicators. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
178. Dimitris Korobilis, Bettina Landau, Alberto Musso, Anthoulla Phella. 2021. The Time-Varying Evolution of Inflation Risks. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
179. Sara B. Holland, Sergei Sarkissian, Michael J. Schill, Francis E. Warnock. 2021. Nonlinearities and a Pecking Order in Cross-border Investment. *SSRN Electronic Journal* **109**. . [[Crossref](#)]

180. Sara B. Holland, Sergei Sarkissian, Michael J. Schill, Francis E. Warnock. 2021. Nonlinearities and a Pecking Order in Cross-Border Investment. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
181. Luca Rossi. 2021. Revisiting the Case for a Fiscal Union: the Federal Fiscal Channel of Downside-Risk Sharing in the United States. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
182. Kristina Bluwstein, Marcus Buckmann, Andreas Joseph, Sujit Kapadia, Özgür Simsek. 2021. Credit Growth, the Yield Curve and Financial Crisis Prediction: Evidence from a Machine Learning Approach. *SSRN Electronic Journal* **14**. . [[Crossref](#)]
183. Jonathan Bridges, Georgina Green, Mark Joy. 2021. Credit, Crises and Inequality. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
184. Andrej Sokol. 2021. Fan Charts 2.0: Flexible Forecast Distributions with Expert Judgement. *SSRN Electronic Journal* **37**. . [[Crossref](#)]
185. Anusha Chari, Karlye Dilts Stedman, Kristin J. Forbes. 2021. Spillovers at the Extremes: The Macroprudential Stance and Vulnerability to the Global Financial Cycles. *SSRN Electronic Journal* **140**. . [[Crossref](#)]
186. Dario Caldara, Danilo Cascaldi-Garcia, Pablo Cuba-Borda, Francesca Loria. 2021. Understanding Growth-at-Risk: A Markov Switching Approach. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
187. Yasin Mimir, Thore Kockerols, Erling Motzfeldt Kravik. 2021. Leaning Against Persistent Financial Cycles with Occasional Crises. *SSRN Electronic Journal* **12**. . [[Crossref](#)]
188. Valentina Aprigliano, Alessandro Borin, Francesco Paolo Conteduca, Simone Emiliozzi, Marco Flaccadoro, Sabina Marchetti, Stefania Villa. 2021. Forecasting Italian GDP Growth with Epidemiological Data. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
189. Maik Dierkes, Fabian Hollstein, Marcel Prokopczuk, Christoph Wuersig. 2021. Measuring Tail Risk. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
190. Elias Wolf. 2021. Estimating Growth at Risk with Skewed Stochastic Volatility Models. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
191. Stefano Cassella, Benjamin Golez, Huseyin Gulen, Peter Kelly. 2021. Horizon Bias in Expectations Formation. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
192. Leopoldo Catania, Alessandra Luati, Pierluigi Vallarino. 2021. Economic Vulnerability Is State Dependent. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
193. Matthew Baron, Emil Verner, Wei Xiong. 2020. Banking Crises Without Panics*. *The Quarterly Journal of Economics* **136**:1, 51-113. [[Crossref](#)]
194. Yi He, Yanxi Hou, Liang Peng, Haipeng Shen. 2020. Inference for conditional value-at-risk of a predictive regression. *The Annals of Statistics* **48**:6. . [[Crossref](#)]
195. Michael T. Kiley. 2020. Financial Conditions and Economic Activity: Insights from Machine Learning. *Finance and Economics Discussion Series* **2020**:095, 1-40. [[Crossref](#)]
196. Michal Franta, Leonardo Gambacorta. 2020. On the effects of macroprudential policies on Growth-at-Risk. *Economics Letters* **196**, 109501. [[Crossref](#)]
197. Selim Elekdag, Sheheryar Malik, Srobona Mitra. 2020. Breaking the Bank? A Probabilistic Assessment of Euro Area Bank Profitability. *Journal of Banking & Finance* **120**, 105949. [[Crossref](#)]
198. Jorge E. Galán. 2020. The benefits are at the tail: Uncovering the impact of macroprudential policy on growth-at-risk. *Journal of Financial Stability* **109**, 100831. [[Crossref](#)]
199. N. V. Suvorov, S. V. Treshchina, Yu. V. Beletskii. 2020. Design of Methods for Long-Term Forecasting of Development Trends in the Russian Economy (Methodology and Model Toolkit). *Studies on Russian Economic Development* **31**:6, 636-646. [[Crossref](#)]

200. Thibaut Duprey. 2020. Canadian Financial Stress and Macroeconomic Condition. *Canadian Public Policy* 46:s3, S236-S260. [[Crossref](#)]
201. ANIL K KASHYAP. 2020. My Reflections on the FPC's Strategy. *Journal of Money, Credit and Banking* 52:S1, 63-75. [[Crossref](#)]
202. Prachi Deuskar, Nitin Kumar, Jeramia Allan Poland. 2020. Signal on the Margin: Behavior of Levered Investors and Future Economic Conditions*. *Review of Finance* 24:5, 1039-1077. [[Crossref](#)]
203. Ding Liu, Weihong Sun, Xuan Zhang. 2020. Is the Chinese Economy Well Positioned to Fight the COVID-19 Pandemic? the Financial Cycle Perspective. *Emerging Markets Finance and Trade* 56:10, 2259-2276. [[Crossref](#)]
204. Matteo Mogliani, Anna Simoni. 2020. Bayesian MIDAS penalized regressions: Estimation, selection, and prediction. *Journal of Econometrics* 109. . [[Crossref](#)]
205. Juan Manuel Figueres, Marek Jarociński. 2020. Vulnerable growth in the euro area: Measuring the financial conditions. *Economics Letters* 191, 109126. [[Crossref](#)]
206. Tobias Adrian, Fernando Duarte, Nellie Liang, Pawel Zabczyk. 2020. NKV: A New Keynesian Model with Vulnerability. *AEA Papers and Proceedings* 110, 470-476. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
207. Alain Kabundi, Asithandile Mbelu. 2020. Estimating a time-varying financial conditions index for South Africa. *Empirical Economics* 109. . [[Crossref](#)]
208. Henrik Jensen, Ivan Petrella, Søren Hove Ravn, Emiliano Santoro. 2020. Leverage and Deepening Business-Cycle Skewness. *American Economic Journal: Macroeconomics* 12:1, 245-281. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
209. Andrea Carriero, Todd E. Clark, Massimiliano Marcellino. 2020. Capturing Macroeconomic Tail Risks with Bayesian Vector Autoregressions. *SSRN Electronic Journal* . [[Crossref](#)]
210. Pietro Dindo, Andrea Modena, Loriana Pelizzon. 2020. Risk Pooling, Leverage, and the Business Cycle. *SSRN Electronic Journal* . [[Crossref](#)]
211. Philippe Goulet Coulombe. 2020. The Macroeconomy as a Random Forest. *SSRN Electronic Journal* . [[Crossref](#)]
212. Nicolas Syrichas. 2020. Stress-Testing Net Trading Income: The Case of European Banks. *SSRN Electronic Journal* . [[Crossref](#)]
213. Roberto A. De Santis, Wouter Van der Veken. 2020. Macroeconomic Risks Across the Globe due to the Spanish Flu. *SSRN Electronic Journal* . [[Crossref](#)]
214. Alain Ntumba Kabundi, Francisco Nadal De Simone. 2020. Growth and Inflation Implications of Systemic Risk in the Euro Area Banking Industry: Lessons from the Financial Crisis. *SSRN Electronic Journal* 66. . [[Crossref](#)]
215. Johannes Beutel, Lorenz Emter, Norbert Metiu, Esteban Prieto, Yves S. Schüler. 2020. Dilemma in Mean, Trilemma in Tails: The International Transmission of Financial Shocks. *SSRN Electronic Journal* 48. . [[Crossref](#)]
216. Matthijs Breugem, Stefano Colonnello, Roberto Marfè, Francesca Zucchi. 2020. Dynamic Equity Slope. *SSRN Electronic Journal* 109. . [[Crossref](#)]
217. Anthony Saunders, Alessandro Spina, Sascha Steffen, Daniel Streitz. 2020. Corporate Loan Spreads and Economic Activity. *SSRN Electronic Journal* 33. . [[Crossref](#)]
218. Nina Boyarchenko, Domenico Giannone, Anna Kovner. 2020. Bank Capital and Real GDP Growth. *SSRN Electronic Journal* 567. . [[Crossref](#)]
219. Kirstin Hubrich, Daniel F. Waggoner. 2020. The Transmission of Financial Shocks and Leverage of Banks: An Endogenous Regime Switching Framework. *SSRN Electronic Journal* 109. . [[Crossref](#)]

220. Jakob Guldbæk Mikkelsen, Johannes Poeschl. 2020. Banking Panic Risk and Macroeconomic Uncertainty. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
221. Matthijs Breugem, Stefano Colonnello, Roberto Marfè, Francesca Zucchi. 2020. Dynamic Equity Slope. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
222. Marius Clemens, Stefan Gebauer, Tobias König. 2020. The Macroeconomic Effects of a European Deposit (Re-) Insurance Scheme. *SSRN Electronic Journal* . [[Crossref](#)]
223. Valentina Corradi, Jack Fosten, Daniel Gutknecht. 2020. Conditional Quantile Coverage: an Application to Growth-at-Risk. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
224. Yeow Hwee Chua, Zu Yao Hong. 2020. Tail Risk and Expectations. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
225. Geert Bekaert, Alexander Popov. 2019. On the Link Between the Volatility and Skewness of Growth. *IMF Economic Review* **67**:4, 746-790. [[Crossref](#)]
226. John Rogers, Jiawen Xu. 2019. How Well Does Economic Uncertainty Forecast Economic Activity?. *Finance and Economics Discussion Series* **2019**:085. . [[Crossref](#)]
227. Eleonora Granziera, Tatevik Sekhposyan. 2019. Predicting relative forecasting performance: An empirical investigation. *International Journal of Forecasting* **35**:4, 1636-1657. [[Crossref](#)]
228. Robert F. Engle, Tianyue Ruan. 2019. Measuring the probability of a financial crisis. *Proceedings of the National Academy of Sciences* **116**:37, 18341-18346. [[Crossref](#)]
229. Robert J. Barro, Gordon Y. Liao. 2019. Rare Disaster Probability and Options-Pricing. *Finance and Economics Discussion Series* **2019**:073. . [[Crossref](#)]
230. Gloria González-Rivera, Javier Maldonado, Esther Ruiz. 2019. Growth in stress. *International Journal of Forecasting* **35**:3, 948-966. [[Crossref](#)]
231. Francesca Loria, Christian Matthes, Donghai Zhang. 2019. Assessing Macroeconomic Tail Risk. *Finance and Economics Discussion Series* **2019**:026. . [[Crossref](#)]
232. Matteo Mogliani. 2019. Bayesian MIDAS Penalized Regressions: Estimation, Selection, and Prediction. *SSRN Electronic Journal* . [[Crossref](#)]
233. Pietro Dindo, Andrea Modena, Lorian Pelizzon. 2019. Risk Pooling, Leverage, and the Business Cycle. *SSRN Electronic Journal* . [[Crossref](#)]
234. Bastien Buchwalter. 2019. Contagious Volatility. *SSRN Electronic Journal* . [[Crossref](#)]
235. Jesús Fernández-Villaverde, Samuel Hurtado, Galo Nuno. 2019. Financial Frictions and the Wealth Distribution. *SSRN Electronic Journal* **903**. . [[Crossref](#)]
236. David Aikman, Jonathan Bridges, Sinem Hacioglu Hoke, Cian O'Neill, Akash Raja. 2019. How Do Financial Vulnerabilities and Bank Resilience Affect Medium-Term Macroeconomic Tail Risk?. *SSRN Electronic Journal* . [[Crossref](#)]
237. Christian T. Brownlees, Andre B.M. Souza. 2019. Backtesting Global Growth-at-Risk. *SSRN Electronic Journal* . [[Crossref](#)]
238. Tobias Adrian, Nina Boyarchenko, Domenico Giannone. 2019. Multimodality in Macro-Financial Dynamics. *SSRN Electronic Journal* . [[Crossref](#)]
239. Alessandro Graniero. 2019. The Macro and Asset Pricing Implications of Fluctuating Information Quality. *SSRN Electronic Journal* **65**. . [[Crossref](#)]
240. Caterina Mendicino, Kalin Nikolov, Juan Rubio Ramírez, Javier Suarez, Dominik Supera. 2019. Twin Default Crises. *SSRN Electronic Journal* . [[Crossref](#)]
241. Juan-Miguel Londono-Yarce, Nancy R. Xu. 2019. Variance Risk Premium Components and International Stock Return Predictability. *SSRN Electronic Journal* **109**. . [[Crossref](#)]

242. Yves Stephan Schüler. 2019. The Impact of Uncertainty and Certainty Shocks. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
243. Benny Hartwig, Christoph Meinerding, Yves Stephan Schüler. 2019. Identifying Indicators of Systemic Risk. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
244. Emanuele De Meo. 2019. Scenario Design for Macro-Financial Stress Testing. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
245. Rodrigo Hizmeri, Marwan Izzeldin, Ingmar Nolte, Vasileios Pappas. 2019. A Generalized Heterogeneous Autoregressive Model using the Market Index. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
246. Matthew Baron, Emil Verner, Wei Xiong. 2018. Identifying Banking Crises. *SSRN Electronic Journal* **93**. . [[Crossref](#)]
247. Daniele Bianchi, Kenichiro McAlinn. 2018. Large-Scale Dynamic Predictive Regressions. *SSRN Electronic Journal* **32**. . [[Crossref](#)]
248. Emanuele De Meo, Giacomo Tizzanini. 2018. GDP-Network CoVaR: A Tool for Assessing Growth-at-Risk. *SSRN Electronic Journal* . [[Crossref](#)]
249. Richard K. Crump, Domenico Giannone, Sean Hundtofte. 2018. Changing Risk-Return Profiles. *SSRN Electronic Journal* . [[Crossref](#)]
250. Eleonora Granziera, Tatevik Sekhposyan. 2018. Predicting Relative Forecasting Performance: An Empirical Investigation. *SSRN Electronic Journal* . [[Crossref](#)]
251. Wenhao Li. 2018. Public Liquidity Supply, Bank Run Risks, and Financial Crises. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
252. Geert Bekaert, Eric Engstrom, Nancy R. Xu. 2017. The Time Variation in Risk Appetite and Uncertainty. *SSRN Electronic Journal* . [[Crossref](#)]
253. Nancy Xu. 2017. Global Risk Aversion and International Return Comovements. *SSRN Electronic Journal* **109**. . [[Crossref](#)]
254. Roberto Marff, Julien Penasse. 2016. The Time-Varying Risk of Macroeconomic Disasters. *SSRN Electronic Journal* . [[Crossref](#)]
255. Christian Kubitza. 2016. Spillover Duration of Stock Returns and Systemic Risk. *SSRN Electronic Journal* **102**. . [[Crossref](#)]
256. Ye Li. 2015. Fragile New Economy. *SSRN Electronic Journal* **109**. . [[Crossref](#)]