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Financial conditions, business cycle fluctuations and growth-at-risk ☆

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ABSTRACT

We augment a quantile vector autoregressive model with the interquartile range of economic growth, a robust proxy for volatility, to assess the relative importance of financial conditions and economic risk in affecting the business cycle. We find that economic risk displays an asymmetric effect on economic growth distribution, very much similar to financial conditions: they substantially increase growth-at-risk, but have limited impact on upside potential. We also document that the asymmetric impact of economic risk depends on the state of the economy and is substantially amplified in times of high economic risk, while remaining subdued in tranquil times.

1. Introduction

There is robust empirical evidence and sound theoretical justification that financial conditions and economic risk are important drivers of the business cycle. Under a wide variety of definitions, adverse financial conditions have consistently been shown to negatively affect expected economic growth (Gilchrist and Zakrajsek (2012)). More recently, a more refined empirical analysis has shown that the impact on first moments masks an important asymmetric impact on the entire growth distribution: a sharp deterioration in financial conditions has an overwhelming effect on downside risks, but little impact on upside potential (Adrian et al. (2019)). The research on economic risk,[1] instead, has remained focused on the average impact it has on growth (Fernandez-Villaverde and Guerron-Quintana (2020)), with little attention given to whether its impact is asymmetric as for financial conditions, with the recent exceptions of Huang et al. (2024) and Keijsers and van Dijk (2025).

This paper makes three main contributions. First, it develops an econometric framework to endogenously embed economic risk and financial conditions in a semi-parametric quantile vector autoregressive (QVAR) model that can account for asymmetric impacts of all the variables under study. Second, it finds that economic risk displays an asymmetric effect on economic growth distribution, very much similar to financial conditions. Third, it uncovers that the asymmetric impact of economic risk is substantially amplified in times of high economic risk, while remaining subdued in tranquil times.

☆ The views expressed in this paper are those of the authors and do not necessarily reflect those of the European Central Bank. We thank an anonymous referee for useful comments and suggestions. All errors remain our own.

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[1] Most of the literature refers to uncertainty, rather than risk. Here we follow the convention from the decision theory literature, which defines uncertainty as a situation where the randomness cannot be quantified by probabilities (Knight (1921)). Volatilities and similar estimates of dispersion, on the other hand, are measures of risk, because they can be derived from the underlying probability distribution.

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Let us elaborate on each of these findings, starting from the novel econometric contribution of this paper. The concept of economic risk is intrinsically linked to the second moment of the growth distribution. The claim that economic risk has an impact on growth can therefore be cast econometrically in terms of second moments of an endogenous variable entering the specification of its first moment, an intuition reminiscent of the ARCH-M model of Engle et al. (1987). Such a modelling strategy, however, makes it difficult to study asymmetric effects, as we explain in the discussion of the model.

An econometric set up that lends itself to address potential asymmetries is the quantile vector autoregressive (QVAR) model recently introduced by Chavleishvili and Manganelli (2024). Within the QVAR framework, any quantile of the distribution of the endogenous variables can be modelled as a function of all lagged endogenous variables. It is well known from the statistical and risk management literature that interquartile ranges are a robust proxy for volatility (Pearson and Tukey (1965) and Taylor (2005)). Volatility, in turn, is frequently used as a proxy for risk (Bloom (2014)). Since the interquartile range of economic growth is a byproduct of the QVAR estimation, it is possible to augment the QVAR with the interquartile range to assess the relative importance of financial conditions and economic risk in affecting economic growth. We show how this requires that the QVAR model is estimated jointly, as it can no longer be estimated equation by equation and quantile by quantile as in Chavleishvili and Manganelli (2024), since the quantile of each random variable may depend on different quantiles of other random variables. In practice, the joint estimation is obtained by using as initial conditions the quantile estimates under some zero restrictions, which can be easily and efficiently computed.

We next bring the model to the data, estimating a bivariate QVAR model with US industrial production and an indicator of financial conditions, the Composite Indicator of Systemic Stress (CISS, introduced by Hollo et al. (2012)). We identify the model by assuming that the financial variable can simultaneously react to the real variable, but the real variable can react only with a lag to shocks in the financial variable. This brings us to the second main contribution of the paper. We find that the interquartile range has a counter-cyclical behaviour similar to that of other indicators of economic risk. As for many other proxies (ranging from VIX, disagreement among professional forecasters, to simple word counts of *uncertain* in newspaper articles), the interquartile range increases during recession and decreases during expansions. Furthermore, once the industrial production interquartile range is endogenously incorporated in the QVAR model, we find that economic risk exhibits a substantial asymmetric impact on the real economy. As already observed for financial conditions, an increase in economic risk has a large and negative impact on the left part of the distribution of industrial production and little impact on its upside potential.

The downside risks for the economy associated with financial frictions have been widely studied (see Bernanke (2023) for a review). At times of financial distress, an increase in the cost of credit makes it increasingly difficult for consumers and firms to obtain financing. This in turn reduces the net worth of banks and borrowers, which further increases intermediation costs and limits the supply of credit to the economy, depressing spending and investment (see, for instance, Bernanke et al. (1996), Christiano et al. (2014), Gertler and Karadi (2015)). A simple intuition to understand why both financial conditions and economic risk have an asymmetric impact on the growth distribution is that the upside potential is limited in the short run by the production factors available in the economy. The downside risks, instead, are virtually unlimited (think of wars, financial crises, or pandemics). There is an emerging literature that studies the impact of disaster risk, building on this intuition that most increases in risks imply one-sided negative impact for the macroeconomy (Baker et al. (2023), Gabaix (2012)). A more widely studied channel is that agents react to an increase in risk by displaying a precautionary behaviour. Precautionary behaviour leads to an increase in precautionary savings and at an aggregate level a reduction in investment and consumption. Several macroeconomic models have formalized the precise channels through which this may happen (see Fernandez-Villaverde and Guerron-Quintana (2020) for a recent review of the literature).

Our empirical evidence of an asymmetric impact of economic risk on growth is consistent with the findings of the recent paper by Keijsers and van Dijk (2025), who however use a different econometric methodology and a different data set. Keijsers and van Dijk (2025) take a real-time out-of-sample forecasting perspective and adopt a two-stage estimation strategy. They first model economic growth using an autoregressive process and next apply quantile regression to the residuals obtained from the first stage. Multi-step forecasts are obtained by direct estimation, as in Adrian et al. (2019). In our econometric framework, instead, everything is endogenous and the multi-step forecast is coherently derived from the one-step estimated model. While in the presence of mis-specification there are no theoretical reasons to prefer one modelling strategy over the other, it is reassuring that the two methodologies produce qualitatively similar results in terms of asymmetric impact of risk on the distribution of growth. Another related paper is Huang et al. (2024), who add a macroeconomic uncertainty index as an additional conditioning variable in the quantile regression specified by Adrian et al. (2019), so following again a direct estimation strategy. They find that tight financial conditions decrease all conditional quantiles of output growth of the same magnitude, while high macroeconomic risk raises the upper quantiles and decreases the lower ones.

Our third contribution is to provide empirical evidence that, in situations of high macroeconomic risk, the economy is particularly vulnerable to downside risks, when endogenously taking into account the macroeconomic risk itself. Our set up is similar in spirit to Bekaert and Engstrom (2017). In a bad scenario, defined as the economy being hit by a series of consecutive negative shocks, accounting for the impact of economic risk brings down the median of the distribution of industrial production, but even more so the left part of the distribution. In situations when macroeconomic risk is moderate, macroeconomic risk itself is much less important. There is therefore evidence of an amplification mechanism at play.

The issue of amplification of economic risk is much less researched, but similar mechanisms to those of financial accelerator models may be at play. Another channel is the fact that an increase in risk may exhibit features similar to an aggregate demand shock (Leduc and Liu (2016)). The sharp asymmetric amplification in these models is driven by search frictions in the labour market that give rise to a new option-value channel. With search frictions, a job match represents a long-term employment relationship that is difficult or too inconvenient to break. Risk increases the option value of waiting and reduces the value of the match. Firms respond by reducing hiring, affecting aggregate economic activity, an effect which is reinforced by the presence of nominal rigidities. Building on wage rigidities, Cacciatore and Ravenna (2021) show how economic downturns may result in state-dependent amplification of risk shocks.

There is also an increasingly number of papers that study non-linearities in dynamic stochastic general equilibrium models, whose insights are consistent with the findings of our paper. Christiano et al. (2014) show that fluctuations in risk, as proxy for the idiosyncratic uncertainty experienced by entrepreneurs, represent an important shock driving the business cycle. Similarly, Bloom (2009) introduces time-varying second moments in an otherwise standard model of firms to show that uncertainty shocks can generate short sharp recessions and recoveries. Mendicino et al. (2025) develop a quantitative general equilibrium model where banks are exposed to non-diversifiable borrower default risk. The insights from this model are also consistent with our findings, by capturing the limited upside, but substantial downside risk of loan portfolios.

The rest of the paper is structured as follows. Section 2 reviews the QVAR model and introduces the augmented QVAR with the interquartile range. Section 3 reports the statistical findings for the model of the US economy, uncovering the asymmetric impact of both financial conditions and economic risk on the economy. Section 4 focuses on the strong amplification effects of economic risk. Section 5 provides robustness results and Section 6 concludes.

2. Econometric framework

We start by providing a concise exposition of the quantile vector autoregressive (QVAR) model of Chavleishvili and Manganelli (2024). We next show how the QVAR model can be modified to allow for differential impact of risk shocks. We conclude this section with a brief explanation of how to estimate and conduct inference with QVAR.

2.1. Quantile vector autoregression

We observe a series of random vectors $\{Y_t : t = 1, \ldots, T\}$, where $Y_t \in \mathbb{R}^n$ is an n-vector. A quantile vector autoregressive model of order 1 is defined as:

$$Q_\theta(Y_t|\Omega_t) = \omega(\theta) + A_0(\theta)Y_t + A_1(\theta)Y_{t-1} \tag{1}$$

where $\Omega_t \equiv \{\Omega_{1t}, \ldots, \Omega_{nt}\}$ is a recursive information set, defined as $\Omega_{1t} \equiv \{Y_t, Y_{t-1}, \ldots\}$ and $\Omega_{it} \equiv \{Y_{i-1,t+1}, \Omega_{i-1,t}\}$ for $i \in \{2, \ldots, n\}$. The vector $Q_\theta(Y_t|\Omega_t)$ is an $(n \times 1)$ vector, which stacks together the n quantiles corresponding to each element of n-vector $\theta \in (0,1)^n$. The matrix A_0 is lower diagonal, which implies a recursive identification.

The analogy with a standard VAR is clear. A VAR models the interaction among the conditional means of the random vector Y_t. A QVAR models the interaction among any arbitrary set of quantiles (as defined by the vector θ) of the same random vector. One important difference with VAR is that QVAR cannot be estimated in reduced form, but requires recursive estimation. The equivalence between recursive and reduced form in VAR models relies on the fact that the reduced form shocks are a linear combination of the structural shocks: application of the law of iterated expectations, which in turn relies on the fact that the expectation is a linear operator, ensures that the conditional expectation is zero for both the structural residuals and their linear combination. The quantile operator, instead, is nonlinear. When applied to each equation of the QVAR, it recovers the marginal distribution of each random variable, but it says nothing about their correlation. Writing the QVAR in recursive form allows one to decompose the joint distribution in the product of marginal and conditional distributions, thus taking care of any possible contemporaneous correlation across the endogenous variables.

Quantile forecasting can be obtained by simulation, by drawing a sequence of random vectors $u_t \in (0,1)^n$ and computing the corresponding quantile, $\hat{Q}_{u_t}(Y_t|\Omega_t) = \hat{\omega}(u_t) + \hat{A}_0(u_t)Y_t + \hat{A}_1(u_t)Y_{t-1}$, where hats denote estimated parameters. By repeating this calculation for an arbitrarily large number of random draws u_t and iterating it forward for any time $t+h$, it is possible to obtain the forecast distribution of Y_{t+h} for any $h > 0$. A byproduct of this forecasting strategy is scenario analysis, which is equivalent to choosing a specific path for the future quantiles.

We refer to Chavleishvili and Manganelli (2024) for a complete exposition of the model.

2.2. A macro VAR for VaR

The QVAR framework introduced above can be modified to estimate how increased volatility in one of the endogenous variables affects the distribution of the endogenous variables themselves. There is a thriving literature arguing that risk shocks play a significant role in explaining sharp economic downturns and more generally asymmetric drops in output (see, for instance, Bloom (2009), Bloom (2014), Jurado et al. (2015), Fernandez-Villaverde and Guerron-Quintana (2020), Ludvigson et al. (2021) and Castelnuovo (2023)). Growth dispersion is typically measured by volatility, but can be also measured by the interquartile distance (see Pearson and Tukey (1965), and, for recent applications, Taylor (2005)). These considerations motivate the following econometric specification.

$$\begin{aligned} Q_\theta(Y_t|\Omega_t) = \omega(\theta) &+ A_0(\theta)Y_t + A_1(\theta)Y_{t-1} + \\ &+ A_2(\theta)[Q_{\bar{\theta}}(Y_{t-1}|\Omega_{t-1}) - Q_{\underline{\theta}}(Y_{t-1}|\Omega_{t-1})] \end{aligned} \tag{2}$$

that is, we assume that the random variables are driven not only by Y_t and Y_{t-1}, but also by the difference between past high (denoted by $\bar{\theta}$) and low ($\underline{\theta}$) quantiles. For instance, by choosing $\bar{\theta} = 75\%$ and $\underline{\theta} = 25\%$ quantiles, this specification can be used to test the impact of dispersion. This modelling idea is similar to the ARCH-M model of Engle et al. (1987), where expected returns are modelled as a function of conditional volatility. Such a modelling strategy, however, makes it difficult to study asymmetric effects. Any scale-location model cannot by construction capture the type of asymmetries that we are studying. Any given variable may affect in a statistically significantly way the mean and/or the variance of a random variable. If it affects the mean, the whole distribution is shifted in parallel to the movement of the mean. If it affects the variance, the variance of the distribution is either increased or decreased, shifting the corresponding quantiles either outward or inward, but again in a symmetric way. Cases in which some variables (like economic risk or financial conditions) affect the left tail of the distribution, but not the right tail cannot generally be replicated by scale-location models.

Model (2) fits the VAR for VaR framework of White et al. (2015), so that the associated inference apparatus can be readily applied. One feature of this system, common to the GARCH, CAViaR and VAR for VaR models, is that the quantiles must be computed recursively, for a given initial condition. This can be easily implemented following the same strategy outlined in the previous subsection.

2.3. Estimation

Estimation and inference of model (2) can be obtained using the framework developed by White et al. (2015). Suppose the interest lies in estimating $J \in \mathbb{N}$ quantiles for n random variables. Denote the $\theta_i^j \in (0,1)$ quantile for the i^{th} random variable by $q_{it}^j(\beta)$, for $i = 1, \ldots, n$ and $j = 1, \ldots, J$, where β is the vector of all unknown parameters in the model.

By stacking all quantiles together, model (2) can be rewritten as $q_t(\beta) \equiv \bar{\omega}(\beta) + \bar{A}_0(\beta)Y_t + \bar{A}_1(\beta)Y_{t-1} + \bar{A}_2(\beta)q_{t-1}(\beta)$, where the vector $\bar{\omega}(\beta)$ and the matrices $\bar{A}_k(\beta)$ for $k = 0, 1, 2$ stack all the matrices of model (2) appropriately together and we have made explicit the dependence on β, the vector containing all the unknown parameters in the model. Define the estimator $\hat{\beta}$ as the solution of the optimization problem:

$$\hat{\beta} = \arg\min_{\beta} T^{-1} \sum_{t=1}^{T} \left\{ \sum_{i=1}^{n} \sum_{j=1}^{p} \rho_{\theta_i^j} \left(Y_{it} - q_{it}^j(\beta) \right) \right\}, \tag{3}$$

where $\rho_\theta(u) \equiv u(\theta - I(u < 0))$ is the standard check function of quantile regressions.

Under the assumptions of theorems 1 and 2 of White et al. (2015), $\hat{\beta}$ is consistent and asymptotically normally distributed. The asymptotic distribution is:

$$\sqrt{T}(\hat{\beta} - \beta^*) \xrightarrow{d} N(0, Q^{-1}VQ^{-1}) \tag{4}$$

where

$$Q \equiv \sum_{i=1}^{n} \sum_{j=1}^{p} E[f_{it}^j(0) \nabla q_{it}^j(\beta^*) \nabla' q_{it}^j(\beta^*)]$$

$$V \equiv E[\eta_t \eta_t']$$

$$\eta_t \equiv \sum_{i=1}^{n} \sum_{j=1}^{p} \nabla q_{it}^j(\beta^*) \psi^j(\epsilon_{it}^{\theta_i^j})$$

$$\psi^j(\epsilon_{it}^{\theta_i^j}) \equiv \theta_i^j - I(\epsilon_{it}^{\theta_i^j} \leq 0)$$

$$\epsilon_{it}^{\theta_i^j} \equiv Y_{it} - q_{it}^j(\beta^*)$$

and $f_{it}^j(0)$ is the conditional density function of $\epsilon_{it}^{\theta_i^j}$ evaluated at 0. The asymptotic variance-covariance matrix can be consistently estimated as suggested in theorems 3 and 4 of White et al. (2015).[2]

Equation (3) is minimised using the fminsearch optimisation function in Matlab, which is based on the Nelder-Mead simplex algorithm. The estimation is done with the following procedure. We use the QVAR model (1) to compute the difference between the 75% and 25% quantiles of industrial production. Then, we include the obtained interquartile range of industrial production as an exogenous variable in the QVAR and re-estimate it. Finally, we use the resulting QVAR estimates as starting values in the optimisation routine.

The different equations of the QVAR model are estimated independently from each other by regression quantiles, as introduced by Koenker and Bassett (1978). The relevant objective function, in this case, is minimised using the interior point (Frisch-Newton) algorithm. The Matlab package is available at Roger Koenker website: http://www.econ.uiuc.edu/~roger/research/rq/rq.html.

[2] Alternatively, standard errors can be computed using bootstrap based methods in the spirit of Buchinsky (1995).

3. The impact of financial stress and its interaction with economic risk

We start our analysis by estimating a simple structural QVAR(1) model, where risk plays no role. We next estimate the macro VAR for VaR model and compare its results with those of the simple QVAR. We highlight how the two models generate different dynamics, emphasising the role of risk.

Let Y_{1t} and Y_{2t} denote the economy's output and financial conditions, respectively. The model is estimated using the following two US monthly variables for the period from January 1980 to December 2022: the log-difference of industrial production (IP) and the Composite Indicator of Systemic Stress.[3] The latter is an aggregation of 15 stress indicators selected from five major segments of the US financial system: financial intermediaries sector, money markets, equity markets, bond markets, and foreign exchange markets. The CISS takes higher values when stress prevails in several market segments at the same time, capturing the idea that financial stress is more systemic and more dangerous for the economy whenever financial instability spreads widely across different segments of the financial system. The methodology for the CISS is described in Hollo et al. (2012) and Chavleishvili and Kremer (2023). Interacting CISS with IP captures the intuition that financial frictions in periods of credit market stress tend to produce deeper and more prolonged recessions (Bernanke (2023)).

We estimate the following model:

$$Y_{1,t+1} = \tilde{\omega}^{\theta} + \qquad a_{11}^{\theta} Y_{1t} + a_{12}^{\theta} Y_{2t} + \epsilon_{1,t+1}^{\theta} \tag{5}$$

$$Y_{2,t+1} = \tilde{\omega}^{\theta} + a_{01}^{\theta} Y_{1,t+1} + a_{21}^{\theta} Y_{1t} + a_{22}^{\theta} Y_{2t} + \epsilon_{2,t+1}^{\theta} \tag{6}$$

where $\tilde{\omega}_1^{\theta} = \omega_1^{\theta} + b_1^{\theta}(L) GMI_{t+1}$ and $\tilde{\omega}_2^{\theta} = \omega_2^{\theta} + b_2^{\theta}(L) GMI_{t+1}$. The term L is the lag operator, which in the empirical application is set equal to 3, as this is the value that minimizes the objective function. The term GMI_{t+1} is the Google Mobility Index for the US at time $t+1$, which measures the movement trends during the Covid pandemic across different categories of places such as retail and recreation, transit stations and workplaces. The GMI is available until October 2022: for November and December 2022 we assume no change compared to October.[4]

The role of GMI_{t+1} and its lags is to partial out the effects of Covid from the dependent variables. Controlling for the GMI does not affect the QVAR results, while it helps in obtaining VAR for VaR coefficients similar to those estimated pre-covid[5] and reducing their standard errors. Fernandez-Villaverde and Jones (2020) show that the GMI is highly correlated with GDP and unemployment rates during the Covid period. The idea of using pandemic indicators as exogenous controls to "de-covid" the data has been put forward by Ng (2021), showing that this makes it possible to recover impulse responses to economic shocks similar to the pre-covid ones.

The estimates of the cross equation regression quantile coefficients are reported in Fig. 1. Each dot corresponds to a different quantile estimate, whose probability can be read on the horizontal axis. The dashed lines represent the 95% confidence intervals.

The results show that there is no impact of real variables in the financial equation (6), neither contemporaneous nor lagged, as can be seen in the middle and bottom charts of the figure. However, the coefficient a_{12}^{θ} which measures the impact of financial stress on industrial production, exhibits a negative, statistically significant effect. More precisely, an increase in the CISS has a disproportionately larger effect on the left tail of the distribution of industrial production, but no effect on its right tail. These findings are in line with those of Adrian et al. (2019) for the U.S. and Chavleishvili and Manganelli (2024) for the euro area, and find theoretical support in the literature on the real impact of financial frictions in times of financial stress (see Bernanke (2023) and the references therein).

The asymmetric impact of financial stress is further illustrated in Fig. 2, which reports the one month ahead forecasts for the 10% and 90% quantile of the industrial production conditional on the CISS. It is evident from the plot that the Composite Indicator of Systemic Stress does not help predicting the upside potential of the U.S. economy, while it affects substantially its downside risks. Large drops of the 10% quantile of industrial production are clearly visible during the global financial crisis of 2008 and the Covid pandemic.

There is a substantial literature arguing that uncertainty has a negative impact on the economy. In particular, the literature on economic risk has highlighted both theoretically and empirically how financial variables interact with uncertainty about the real sector (Christiano et al. (2014), Alfaro et al. (2024), Bloom (2014), Caldara et al. (2016) and Ludvigson et al. (2021)). Several channels have been identified, such as postponement of investment and consumption in durable goods, or increase in precautionary behaviour (see, for reviews, Bloom (2014), Fernandez-Villaverde and Guerron-Quintana (2020) and Castelnuovo (2023)).

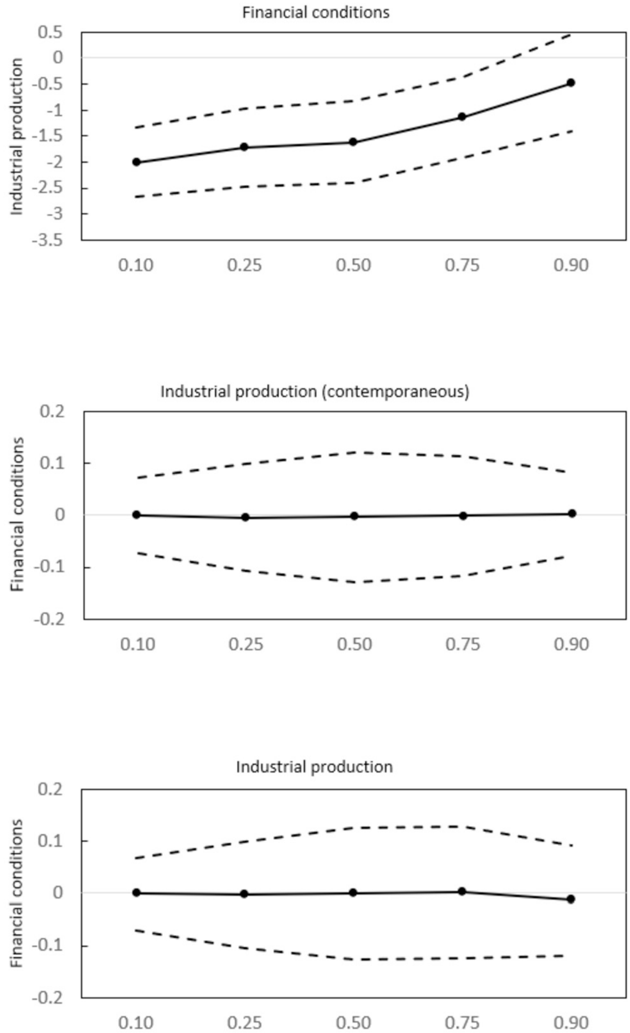
A widely used proxy for economic risk is volatility, which in turn can be proxied by the interquartile range. In Fig. 3, we report the difference between the 75% and 25% quantiles together with the CISS. The two series show correlation and in particular they tend to spike during recessions, although the CISS spikes more frequently outside of recession periods.[6] The interquartile range of

[3] We obtain industrial production data from https://fred.stlouisfed.org/ and the CISS from https://data.ecb.europa.eu/.

[4] We obtain GMI data from Haver Analytics, a time series data platform.

[5] Pre-covid results are available upon request.

[6] The Kendall and Spearman rank correlations between the interquartile range and the CISS series displayed in Fig. 3 are equal to 0.47 and 0.66, respectively. Rank correlation is also statistically significant, as in both cases the *p-value* for testing the hypothesis of no correlation is close to 0. We will return to the important question of the relative importance of economic risk and financial conditions in the discussion of our empirical application in Section 4.



Note: The figure reports the cross equation regression quantile coefficients associated with the system (5)-(6), from 10% to 90% confidence levels, together with 95% confidence bands. The label *Financial conditions* refers to the coefficient a_{12}^{θ}, the label *Industrial production (contemporaneous)* refers to the coefficient a_{01}^{θ} and the label *Industrial production* to the coefficient a_{21}^{θ}.

Fig. 1. QVAR estimates.

industrial production reaches extreme peaks between April and May 2020 attributable to the Covid pandemic, while the Composite Indicator of Systemic Stress reaches its largest value during the global financial crisis of 2008.[7]

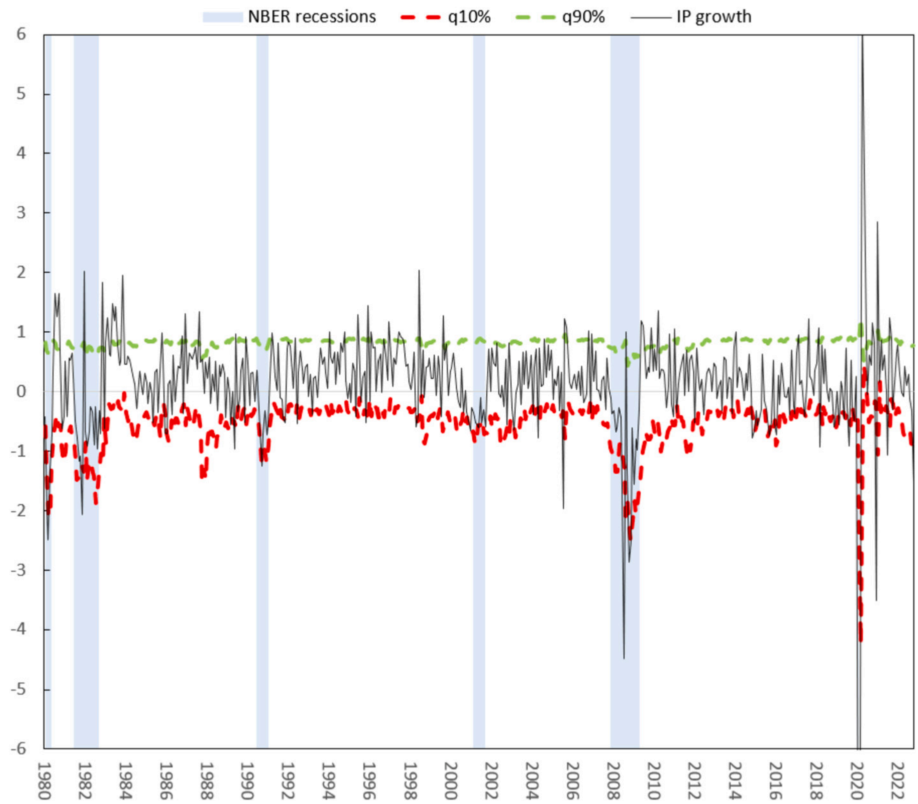
It makes sense therefore to ask whether the interquantile range helps explaining the rate of growth of industrial production, as suggested by the literature on uncertainty and business cycle. To answer this question, we estimate the following restricted VAR for VaR:

$$Y_{1,t+1} = \tilde{\omega}_1^{\theta} + a_{11}^{\theta} Y_{1t} + a_{12}^{\theta} Y_{2t} + a_3^{\theta}(q_{1t}^{0.75} - q_{1t}^{0.25}) + \epsilon_{1,t+1}^{\theta} \tag{7}$$

$$Y_{2,t+1} = \tilde{\omega}_2^{\theta} + a_{01}^{\theta} Y_{1,t+1} + a_{21}^{\theta} Y_{1t} + a_{22}^{\theta} Y_{2t} + \epsilon_{2,t+1}^{\theta} \tag{8}$$

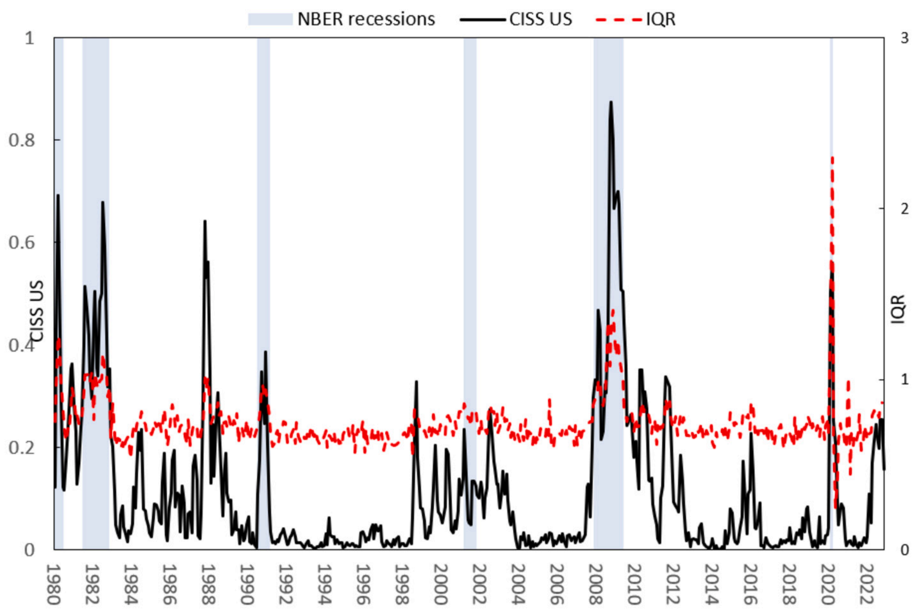
where again $\tilde{\omega}_1^{\theta} = \omega_1^{\theta} + b_1^{\theta}(L)GMI_{t+1}$ and $\tilde{\omega}_2^{\theta} = \omega_2^{\theta} + b_2^{\theta}(L)GMI_{t+1}$. We consider three lags for the GMI as this minimizes objective function (3). For consistency, the same number of GMI lags is selected for the QVAR system (5)-(6).

[7] Estimating the model with a wider interquantile range (10%-90% or 5%-95%) produces qualitatively similar results. There are limits, of course, to how far in the tails the model can be estimated. In particular, extreme quantile estimation requires a different inference procedure, as illustrated, for instance, by Chernozhukov (2005).



Note: The figure reports the one month ahead forecast of the 10% and 90% quantiles of US industrial production (IP) obtained with the QVAR.

Fig. 2. QVAR growth-at-risk. (For interpretation of the colours in the figure(s), the reader is referred to the web version of this article.)



Note: The figure reports the difference between the 75% and 25% quantiles forecasts of industrial production, together with the CISS for the United States.

Fig. 3. Interquartile range and US CISS.

Including the lag quantiles is a parsimonious form of controlling for an infinite number of lagged dependent variables, very much like in ARMA or GARCH models. Fig. 4 reports the regression quantile estimates of the coefficients a_{12} and a_3.[8] A comparison with the top panel of Fig. 1 reveals that after controlling for the interquartile range, the CISS has still a larger negative effect on the left tail and little impact on the right tail of the industrial production forecast distribution. But, at the same time, the interquartile range is also significant and has a negative asymmetric impact on the real economy (see bottom panel of Fig. 4). In other words, it is not only the financial condition index that matters for the downside risks to economic growth, but also macroeconomic risk. Keijsers and van Dijk (2025) obtain similar findings using different data and different methodology.

Fig. 5 compares the one month ahead forecasts for the 10% quantile of industrial production obtained with the macro VAR for VaR framework (blue dashed line) and the QVAR model (red dotted line). It is interesting to note that including the interquartile range substantially increases the estimated downside risks to the US economy during the Covid pandemic recession in 2020. This can be explained by the different behaviour of CISS and interquartile range during the Covid crisis displayed in Fig. 3: specifically, financial stress is not particularly high, while our proxy for macroeconomic risk reaches extreme peaks.

Our findings are consistent with the literature on disaster risks (Gabaix (2012)), whereby the Covid pandemic crisis can be interpreted as a rare disaster risk shock. One way to model a change in rare disaster probability is to consider skewness shocks to the underlying endogenous variables. Modelling time-varying skewness, however, is extremely challenging, as illustrated by White et al. (2008). Our QVAR framework, instead, oversteps the challenge of modelling higher order time-varying models by modelling directly the different quantiles of the distributions and subsequently aggregating them to shed light on any part of the distribution of interest. We will further investigate the impact of large asymmetric shocks in the next section.

Our results are also in line with previous and recent research analyzing the interaction between economic risk and financial frictions. Christiano et al. (2014) include cross-sectional economic risk in a financial accelerator model and show that economic risk plays a key role in driving the business cycle, but this depends crucially on including financial variables in the model. Gilchrist et al. (2014) study the relationships between uncertainty, investment, and credit spreads and find that financial frictions significantly amplify the effects of uncertainty through changes in credit spreads. Arellano et al. (2019) argue that hiring inputs is risky because financial frictions limit firm's ability to insure against shocks. Therefore, an increase in risk induces firms to reduce their inputs to reduce such risk, with a consequent economic downturn. More recently, Alfaro et al. (2024) propose a general equilibrium heterogeneous firms model with real and financial frictions, showing that financial frictions amplify risk shocks by doubling their impact on output, increase persistence by doubling the duration of the drop and propagate risk shocks by spreading their impact on financial variables. For additional references, see Castelnuovo (2023).

4. Bad environment - good environment

The macro VAR for VaR allows us to quantify over time the asymmetric effects of positive and negative shocks to the economic and financial system. This section shows that the results of the previous section are not only statistically significant, but also economically meaningful.

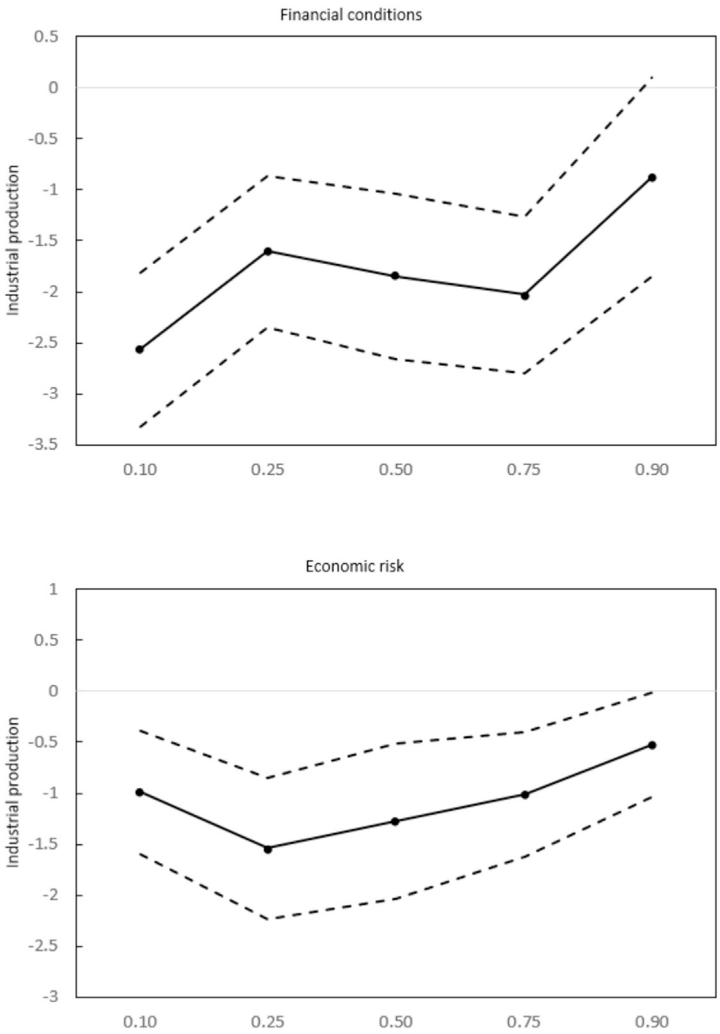
We compute the quantile forecasts of the macro VAR for VaR, associated with the scenarios reported in Table 1. The good environment is characterized by a sequence of right tail realizations for the real variable and of left tail realizations for the financial variable. More precisely, Table 1 assumes that in the good environment the US economy is hit by a sequence of six consecutive 90% quantile realizations for the industrial production and six consecutive 10% realizations of the CISS. This corresponds to two quarters of extremely good economic outcomes and low financial stress. The bad environment is defined symmetrically, as a sequence of six consecutive 10% and 90% quantile realizations of industrial production and CISS, that is, bad economic outcomes and high financial stress.[9] From the seventh month onward, we assume that the economy follows its median evolution. Other (more or less severe) scenarios could be considered or calibrated to mimic any past crisis. The scenario we consider is similar in terms of severity of industrial production contraction to the one observed during the Great Financial Crisis around October 2008.

Fig. 6 (left column) shows the forecasts of US industrial production obtained with the macro VAR for VaR framework associated with the two scenarios, together with the median forecast. We perform the exercise in three different periods, to highlight the different dynamics when the system is subject to more or less economic risk and financial stress. The top chart reports the forecasts as of December 2021, when macroeconomic risk (as measured by the interquartile range) was higher than the CISS. The middle chart shows the forecasts as of December 2018, when both the interquartile range and the CISS were relatively low. The bottom chart reports the forecast as of July 2008, right before the great financial crisis, when the CISS was substantially higher than economic risk.

The blue line in the middle represents the median forecasting path. The top-left chart shows an immediate decline by about -1.2%, with the system moving to positive growth only after 9 months. The lower red line with dots is the forecast associated with a sequence of bad environment quantile realizations. Similarly to the median, the bad environment produces a significant and persistent downturn of the economy. The peak monthly contraction of about -2.5% is reached after six months. This contrasts with the behaviour in the tranquil period (December 2018), where the immediate drop in industrial production is absent. Completely different in terms of magnitude is the behaviour of the economy at the time of the great financial crisis. A substantial increase in financial stress at a time when the financial conditions are already deteriorating produces a large increase in the downside risk to the economy (reaching -5%),

[8] In calculating the standard errors, we have set the bandwidth to 1.

[9] We borrow the terminology for the description of our scenarios from Bekaert and Engstrom (2017), who have introduced the *bad environment-good environment* framework. In their model, consumption growth features bad and good volatility, with shocks to bad (good) volatility decreasing (increasing) skewness in consumption growth. This framework has been then further developed by Bekaert et al. (2021) and Bekaert et al. (2023).



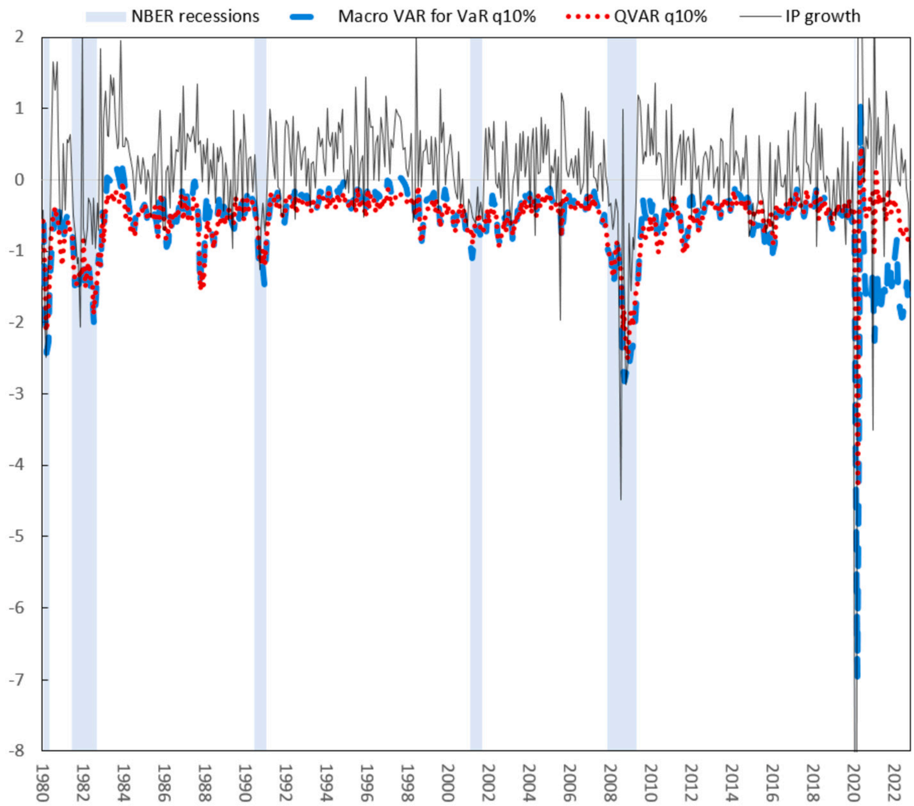
Note: The figure reports selected regression quantile coefficients associated with equation (7), from 10% to 90% confidence levels, together with 95% confidence bands. The label *Financial conditions* refers to the coefficient a_{12}^{θ} and the label *Economic risk* to the coefficient a_{3}^{θ}.

Fig. 4. Macro VAR for VaR estimates.

Table 1
Alternative scenarios.

	Good Environment	Bad Environment
t+1	{90%, 10%}	{10%, 90%}
t+2	{90%, 10%}	{10%, 90%}
t+3	{90%, 10%}	{10%, 90%}
t+4	{90%, 10%}	{10%, 90%}
t+5	{90%, 10%}	{10%, 90%}
t+6	{90%, 10%}	{10%, 90%}
t+7	{50%, 50%}	{50%, 50%}
…	…	…

Note: The table contains the sequence of quantile realizations associated with the alternative scenarios. For each couple, the first and second probabilities refer to the US industrial production and CISS quantile realizations, respectively.



Note: The figure reports the one month ahead forecast of the 10% quantile of US industrial production (IP) obtained with the macro VAR for VaR framework and the QVAR model.

Fig. 5. Macro VAR for VaR and QVAR downside risk.

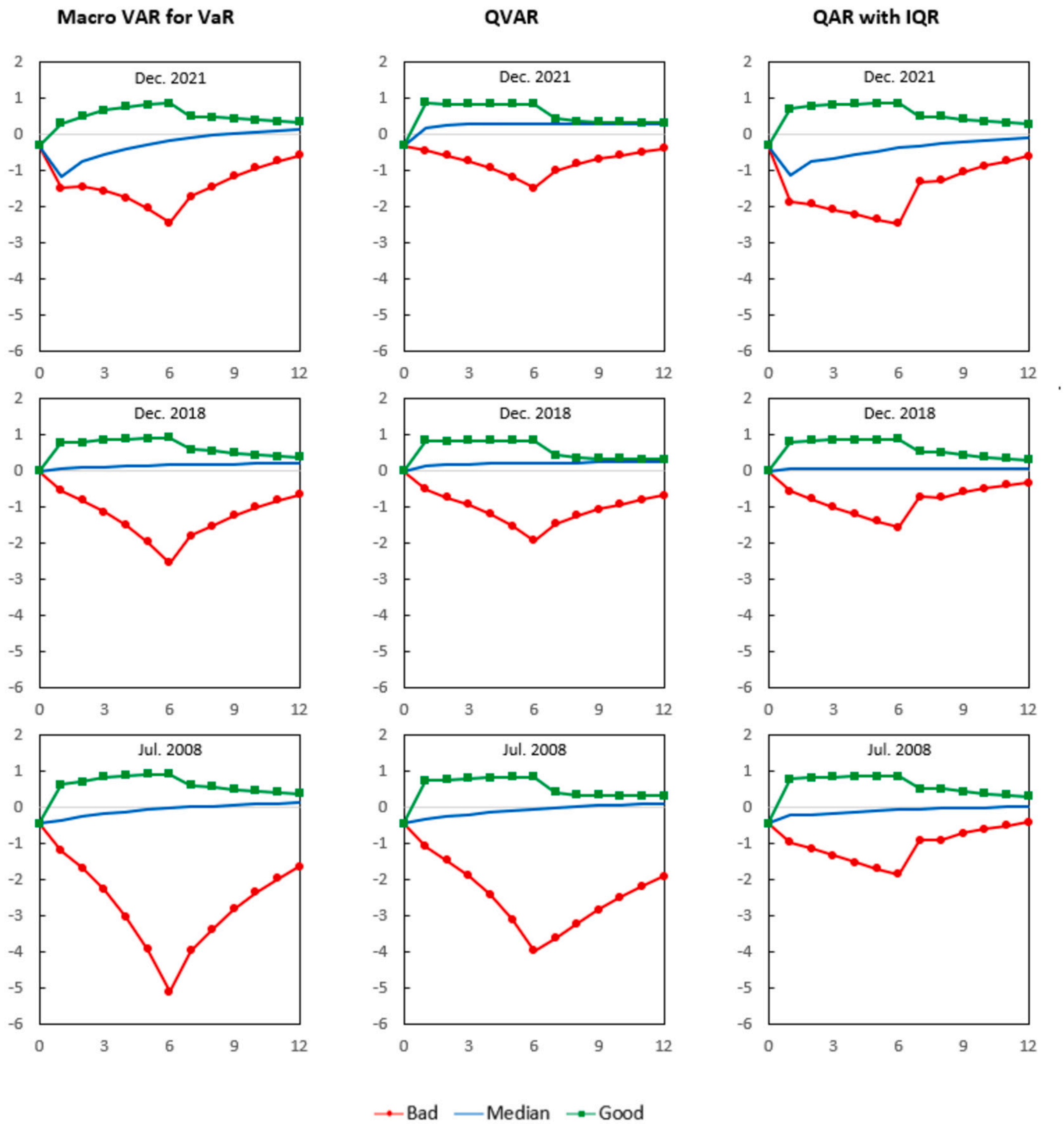
while leaving the upper part of the distribution substantially unaffected. This has clear and important implications for policy makers, who should exercise extreme caution in periods of poor financial conditions for the economy, to avoid that additional financial stress sends the economy into a downward spiral.

One important question is whether it is possible to quantify the relevance of the impacts of economic risk and adverse financial conditions. Of particular interest is the question of which of these two sources of disruption is worst. We address this question by re-estimating our QVAR model in the three periods considered in Fig. 6 first by dropping the interquartile range (the second column of Fig. 6, labelled 'QVAR') and next by dropping the financial conditions (the third column, labelled 'QAR with IQR'). This last model is named QAR, quantile autogression, because by dropping the second variable the system is transformed into a univariate model with its own lags and interquartile range as explanatory variables.

The results shown in Fig. 6 are interesting and useful to answer the question of the relative importance. The behaviour of the system under the good scenario (given by the top green line with squares) remains largely unaffected, independently of the time period and model used. The upside potential of the economy in the short run is determined by the existing production capacity and it is reasonable to expect that it does not depend on financial and economic risks. The pictures change drastically when focusing on downside risks. In a tranquil period (December 2018), when both economic risk and financial conditions are within the normal range, the models without economic risk (the QVAR) and without financial conditions (the QAR with IQR) perform very similarly. However, when combined in the Macro VAR for VaR model, the downside effects are amplified, reaching a trough of -2.5% after 6 months, between 0.5% and 1% lower than the simpler models.

The situation appears to be completely different in crisis periods and the difference depends on the type of crisis affecting the economy. The COVID crisis (December 2021) was characterized by high economic uncertainty, as governments and central banks quickly intervened to stabilize financial markets. The model incorporating economic uncertainty (the top right chart of Fig. 6) exhibits dynamics very similar to the full model (the top left chart of Fig. 6). A model excluding economic risk and accounting only for financial conditions (the QVAR model in the top middle chart of Fig. 6) appears to miss most of the important left tail dynamics. The difference in behaviour is already striking when looking at the median, but it is further amplified in the bad scenario.

Periods of financial crisis, such as in July 2008, call for including financial conditions in the model. In this case (see the last row of Fig. 6), the situation is mirroring the one just described for the COVID crisis: It is now the inclusion of the financial conditions which appears to capture the relevant dynamics in the bad environment. Omitting the financial variables (the bottom right chart of Fig. 6) misses most of the downside risk in the bad scenario.

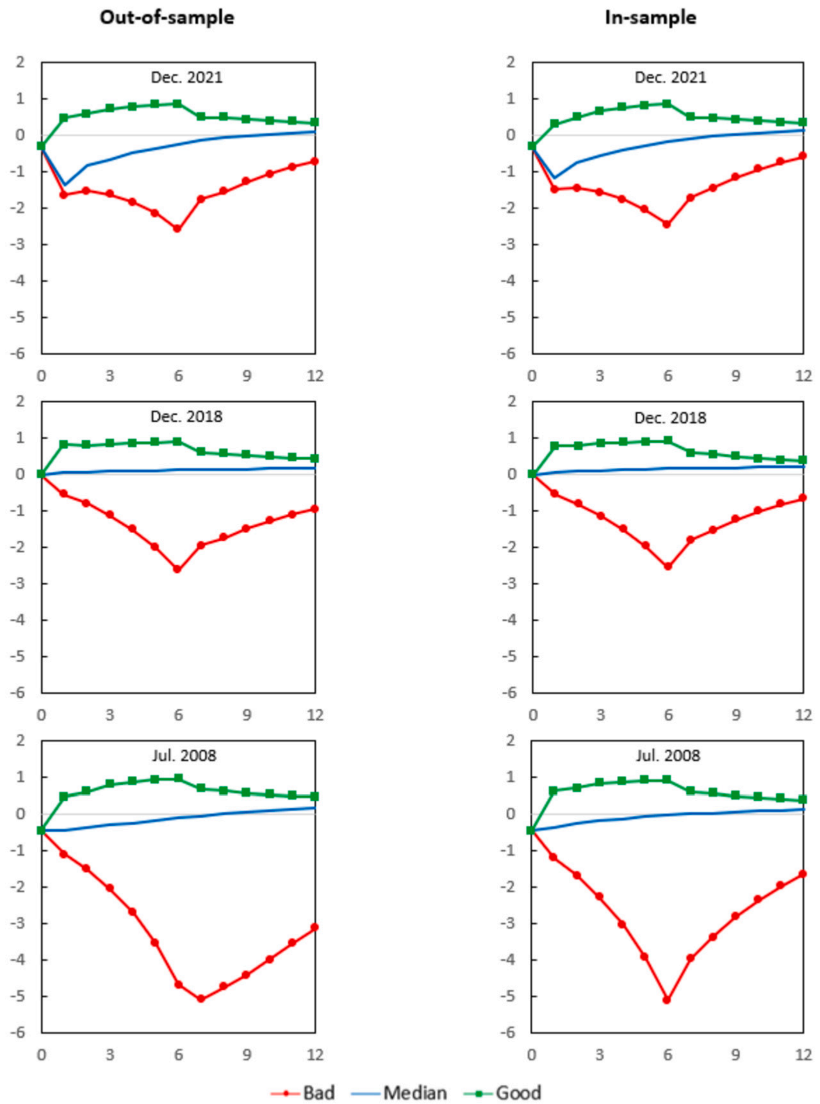


Note: The figure reports the US industrial production forecasts obtained with the macro VAR for VaR framework (left panel), the QVAR model (middle panel) and the QVAR model without financial conditions (right panel) under three alternative scenarios: the good and bad scenarios described in Table 1, as well as the median scenario. The top charts show the forecasts as of December 2021, the middle charts as of December 2018 and the bottom charts as of July 2008.

Fig. 6. Forecasting US industrial production.

Overall, our empirical results suggest that the relative importance of the variables capturing economic risk and adverse financial conditions is state dependent. When the economy appears to be more vulnerable to economic risk, it is the inclusion of economic risk that explains most of the downside dynamics in the system. When the economy instead is characterized by deteriorating financial conditions, it is financial conditions that drive downside risks to the economy. In general, including both variables in the system allows us to capture simultaneously both vulnerabilities, which may reinforce each other, as shown by the analysis of December 2018.

Finally, to get a sense of how well the model performs out-of-sample, in Fig. 7 we compare the performance of the macro VAR for VaR model estimated using all the available observations (right column) with that of the model estimated using only the observations up to the month indicated in the figure (left column). There are no discernible differences between the out-of-sample and in-sample performances of the model in December 2021 and in December 2018. The differences start to be noticeable, but not dramatic, when the model is estimated using only the observations up to July 2008. The analysis therefore confirms that the model performance is robust for out-of-sample predictions.



Note: The figure reports the US industrial production forecasts obtained with the macro VAR for VaR framework out-of-sample (left panel) and in-sample (right panel) under three alternative scenarios: the good and bad scenarios described in Table 1, as well as the median scenario. The top charts show the forecasts as of December 2021, the middle charts as of December 2018 and the bottom charts as of July 2008.

Fig. 7. Macro VAR for VaR out-of-sample validation.

5. Alternative measures of financial conditions

We conclude the empirical investigation by showing that our findings are robust to alternative measures of financial conditions. We consider the National Financial Conditions Index (NFCI) produced by the Federal Reserve Bank of Chicago, the financial uncertainty index (FINUNC) by Ludvigson et al. (2021) and the excess bond premium (EBP) by Gilchrist and Zakrajsek (2012) for the US economy. The NFCI is an aggregation of 105 financial indicators relating to money markets, debt and equity markets and traditional and shadow banking systems (for more details on the methodology, see Brave and Butters (2012)). The financial uncertainty index by Ludvigson et al. (2021) measures the common component in the time-varying volatilities of 1 month-ahead forecast errors across 148 financial market time series. The EBP by Gilchrist and Zakrajsek (2012) is a residual corporate bond credit spread index orthogonal to firm specific information. It is interpreted as a measure of the spread between yields on private versus public debt that is due to financial market frictions.

Table 2
Quantile coefficients for alternative financial indicators.

	$q^{0.10}_{IP,t+1}$	$q^{0.25}_{IP,t+1}$	$q^{0.50}_{IP,t+1}$	$q^{0.75}_{IP,t+1}$	$q^{0.90}_{IP,t+1}$
Panel A: QVAR					
$NFCI_t$	-0.37*	-0.21*	-0.24*	-0.19*	-0.05
	(0.07)	(0.06)	(0.07)	(0.06)	(0.08)
$FINUNC_t$	-1.35*	-0.80*	-0.64	-0.38	-0.23
	(0.31)	(0.31)	(0.34)	(0.30)	(0.28)
EBP_t	-0.32*	-0.37*	-0.41*	-0.30*	-0.23*
	(0.10)	(0.10)	(0.10)	(0.09)	(0.08)
$EACISS_t$	-3.58*	-1.60*	-0.79	-0.73	-0.72
	(0.75)	(0.61)	(0.61)	(0.53)	(0.50)
$USCISS_t$ (baseline)	-2.01*	-1.72*	-1.62*	-1.15*	-0.49
	(0.34)	(0.38)	(0.40)	(0.40)	(0.48)
Panel B: Macro VAR for VaR					
$NFCI_t$	-0.39*	-0.22*	-0.27*	-0.26*	-0.09
	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)
$q^{0.75}_{IP,t} - q^{0.25}_{IP,t}$	-1.37*	-1.63*	-1.31*	-1.22*	-0.68*
	(0.31)	(0.55)	(0.43)	(0.33)	(0.32)
$FINUNC_t$	-0.33	-0.03	-0.07	0.08	-0.32
	(0.26)	(0.32)	(0.35)	(0.31)	(0.29)
$q^{0.75}_{IP,t} - q^{0.25}_{IP,t}$	-1.17*	-1.20*	-1.26*	-0.80*	-0.11
	(0.27)	(0.37)	(0.33)	(0.34)	(0.42)
EBP_t	-0.35*	-0.27*	-0.33*	-0.32*	-0.20*
	(0.08)	(0.10)	(0.10)	(0.08)	(0.09)
$q^{0.75}_{IP,t} - q^{0.25}_{IP,t}$	-1.08*	-1.26*	-1.18*	-0.81*	0.02
	(0.38)	(0.48)	(0.39)	(0.37)	(0.46)
$EACISS_t$	-2.86*	-1.09*	-0.57	-0.89	-0.67
	(0.80)	(0.55)	(0.58)	(0.55)	(0.48)
$q^{0.75}_{IP,t} - q^{0.25}_{IP,t}$	-0.42	-0.39*	-0.32	-0.05	-0.10
	(0.31)	(0.14)	(0.44)	(0.31)	(0.29)
$USCISS_t$ (baseline)	-2.57*	-1.60*	-1.85*	-2.03*	-0.88
	(0.38)	(0.38)	(0.41)	(0.39)	(0.50)
$q^{0.75}_{IP,t} - q^{0.25}_{IP,t}$ (baseline)	-0.99*	-1.54*	-1.27*	-1.01*	-0.53*
	(0.31)	(0.35)	(0.39)	(0.31)	(0.26)

Note: The table reports selected quantile coefficients for industrial production, estimated using the QVAR and the macro VAR for VaR model based on alternative financial indicators. Standard errors are reported in parentheses. Coefficients significant at 5% confidence level are denoted with *.

We also replicate the exercise for the euro area. We consider industrial production excluding Ireland.[10] To measure financial conditions, we focus on the Composite Indicator of Systemic Stress for the euro area (EA CISS) as Figueres and Jarocinski (2020) document that this is the most informative financial indicator for capturing the nonlinear relationship between financial conditions and output growth in the euro area. The EA CISS is built similarly to the US CISS, as described in Section 3.

Table 2 reports the quantile coefficients for the QVAR model (panel A) and the macro VAR for VaR (panel B), estimated using the different financial variables. Results in panel A overall confirm that shocks to financial conditions have an asymmetric impact on the distribution of real variables. The only exception is the excess bond premium, which shows a negative but flat relationship with the different quantiles of industrial production. This suggests that stress in the corporate bond market carries little information in estimating risks to growth. Adrian et al. (2019) and Figueres and Jarocinski (2020) find similar results using quarterly data for the US and euro area economy.

Panel B shows that also the results for the macro VAR for VaR are similar to those presented in Section 3: both macroeconomic risk and financial conditions have an asymmetric impact on the economy and, in this way, help explaining business cycle fluctuations. The quantile coefficients for the excess bond premium are similar to those reported in panel A, but at the same time the interquartile range has a nonlinear relationship with the real variable. The financial uncertainty index is not significant after controlling for macroeconomic risk, which continues to have an asymmetric impact on the growth distribution. This result differs from Ludvigson et al. (2021), who find that financial uncertainty is a key source of economic fluctuations while macroeconomic risk does not play a large role in causing lower economic activity.

[10] We obtain the data from Haver. The choice of excluding Ireland from the euro area industrial production is due to the abnormal seasonal patterns and volatility of the Irish industrial production figures from March 2020 onward. The Central Statistics Office is carrying out a review of the seasonal adjustment methodology for Irish industrial production to address these issues.

6. Conclusion

In this paper we augment a quantile vector autoregression model with the interquartile range of economic growth, a robust proxy for volatility, to assess the relative importance of financial conditions and economic risk in affecting the business cycle. We find that economic risk displays an asymmetric effect on economic growth distribution, very much similar to financial conditions: they substantially increase growth-at-risk, but have limited impact on upside potential. We also document that the asymmetric impact of economic risk is substantially amplified in times of high economic risk, while remaining subdued in tranquil times.

Our framework could potentially help policymakers design policy actions to respond in a timely manner to shocks to financial conditions and macroeconomic risk. Policymakers would be able to specify bad outcomes in terms of their risk tolerance and undertake appropriate actions based on the information provided by financial and macroeconomic risks. The evidence provided in this paper highlights how asymmetric macro-financial feedback effects can be properly taken into account.

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