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Financial conditions, business cycle fluctuations and growth at risk

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Abstract

We study the macroeconomic consequences of financial shocks and increase in economic risk using a quantile vector autoregression. Financial shocks have a negative, but asymmetric impact on the real economy: they substantially increase growth at risk, but have limited impact on upside potential. The impact of financial shocks is explained away after controlling for economic risk (measured by the interquantile range). The effects are economically relevant. Bad economic environment, characterized by negative real and financial shocks, has a highly skewed impact on business cycle fluctuations, leading to a peak reduction of monthly industrial production by more than 2%. In comparison, positive real and financial shocks in a good economic environment have limited effect on upside potential of the economy.

Keywords: Risk; uncertainty; financial conditions; quantile regression.

JEL classification: C32, C53, E32, E44.

Non-technical summary

Changes in the state of the financial system can provide powerful signals about risks to future growth. At the same time, economic uncertainty plays a key role in business cycle fluctuations. In this paper, we study the macroeconomic consequences of financial shocks and heightened economic uncertainty using a quantile vector autoregression (QVAR) model. This framework allows us to model the quantile forecast of an endogenous variable as a function of lags of all the endogenous variables.

We estimate the QVAR model on US data for industrial production and an indicator of financial stress. The results indicate that financial shocks have a negative but asymmetric impact on the real economy: specifically, they have a disproportionately larger effect on the left tail of the industrial production distribution, as compared to the right tail.

A byproduct of the QVAR is the simultaneous estimation of many quantiles. It is well known from the statistical and risk management literature that interquantile ranges are a robust proxy for volatility, which in turn is frequently used as a proxy for uncertainty. In our macro QVAR model of the US economy, we find that the industrial production 5-95% interquantile range is highly correlated with our indicator of financial stress. It makes therefore sense to ask whether the interquantile range helps explaining the risks to future growth.

We answer this question by augmenting our QVAR model with the industrial production interquantile range. We find that controlling for the interquantile range reduces by half the impact of the financial indicator and weakens substantially its asymmetric impact on industrial production. The asymmetric impact is absorbed by the interquantile range itself. In other words, an important channel through which financial conditions have an asymmetric impact on the real economy is by increasing economic uncertainty.

One possible narrative consistent with these findings is that worsening financial conditions lead to a contraction in the supply of credit and to an increase in the downside risk to growth, but have little effect on its upside potential. This, in turn, leads to an increase in economic uncertainty, making firms even more cautious in responding to business conditions, ultimately leading to lower investment and an even more pronounced downside risk to the economy.

We show that these effects are economically relevant by analysing how the system reacts in a good versus a bad environment. Specifically, we compute the forecast of the US industrial production under a scenario in which the system is hit by a sequence of negative real and financial shocks (bad environment), and compare its performance to positive real and financial shocks (good environment). Consistently with the theory, the bad environment is characterized by a much more pronounced downturn, relative to the expansion associated with the good environment.

1 Introduction

There is increasing empirical evidence that macroeconomic risk is bad for growth (Bloom, 2014). At the same time, there are strong theoretical and empirical arguments to think that a deterioration of financial conditions have also a negative impact on the economy (Gilchrist and Zakrajsek, 2012). More recently, empirical evidence is mounting that shocks to financial conditions have a disproportional impact on the downside risks to the economy, as compared to upside potential (Adrian, Boyarchenko and Giannone, 2019, Chavleishvili and Manganelli, 2019, Carriero, Clark and Marcellino, 2020). This paper makes two main contributions. First, it shows how to endogenously embed macroeconomic risk in a quantile vector autoregressive model. Second, it finds that – once controlling for it – it is macroeconomic risk, rather than financial conditions, that has an asymmetric impact on the real economy.

We work with the quantile vector autoregressive (QVAR) model recently introduced by Chavleishvili and Manganelli (2019). The QVAR allows one to model the quantile forecast of an endogenous variable as a function of lags of all the endogenous variables. We consider a bivariate QVAR model with US industrial production and excess bond premium. 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.

We first show that the excess bond premium has a strong asymmetric effect on the distribution of the US industrial production: an increase in the excess bond premium has a disproportionately larger effect on the left tail and little effect on the right tail of the forecast distribution of industrial production.

This result is in line with the recent findings of Adrian et al. (2019) and qualifies those of Gilchrist and Zakrajsek (2012), who show that the excess bond premium has a negative impact on the mean of US GDP.

One advantage of QVAR is the simultaneous estimation of many quantiles. It is well known from the statistical and risk management literature that interquantile ranges are a robust proxy for volatility (Taylor, 2005). Volatility, in turn, is frequently used as a proxy for uncertainty (Bloom, 2014).[1] When applied to our macro QVAR model of the US economy, we find that the industrial production 5-95% interquantile range is highly correlated with the excess bond premium. We can therefore ask the question: what is the relative importance of financial conditions and economic risk in affecting the US economy?

We answer this question by augmenting our QVAR model with the interquantile range. The new model combines the economic intuition of the ARCH-M model of Engle, Lilien and Robbins (1987) with the econometric framework of the VAR for VaR of White, Kim and Manganelli (2015), which in turn is the multivariate extension of the CAViaR model of Engle and Manganelli (2004). We find that augmenting the QVAR model with the industrial production interquantile range reduces by half the impact of the excess bond premium. It also drives away the asymmetric impact of the excess bond premium on the forecast distribution of the industrial production, as this role is replaced by the interquantile range itself.

Our findings speak to the literature on uncertainty, financial conditions

[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. Volatilities and similar estimates of dispersion, on the other hand, are measures of risk, because they can be derived from the underlying probability distribution.

and growth at risk. The literature has shown that an increase in excess bond premium leads to a contraction in the supply of credit and to an increase in the downside risk to growth, but has little effect on its upside potential. The ensuing increase in economic risk makes firms even more cautious in responding to business conditions, ultimately leading to lower investment and an even more pronounced downside risk to the economy. We provide evidence that this financial-economic risk channel is not only statistically significant, but also economically important. We measure how the system reacts in a good versus a bad environment (Bekaert and Engstrom, 2017). We compute the forecast of the US industrial production under a scenario in which the system is hit by a sequence of negative real and financial shocks (bad environment), and compare its performance to a situation where the system is hit by symmetric positive real and financial shocks (good environment). The bad environment is characterized by a much more pronounced downturn, with a maximum contraction of monthly industrial production of more than 2%. This compares with an expansion of slightly more than 1% under the good environment.

The rest of the paper is structured as follows. Section 2 reviews the QVAR model and introduces the augmented QVAR with the interquantile range. Section 3 reports the statistical findings for the model of the US economy, while section 4 shows that our findings are also economically relevant. Section 5 concludes.

2 Econometric framework

We start by providing a concise exposition of the quantile vector autoregressive (QVAR) model of Chavleishvili and Manganelli (2019). We next show how the

QVAR model can be modified to allow for differential impact of positive and negative 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 variables $\{\tilde{Y}_t : t = 1, \cdots, T\}$, where $\tilde{Y}_t \in \mathbb{R}^n$ is an n-vector with i^{th} element denote by $\tilde{Y}_{it}$ for $i \in \{1, \cdots, n\}$ and $n \in \mathbb{N}$. We consider p distinct quantiles, $0 < \theta_1 < \cdots < \theta_p < 1$, for $p \in \mathbb{N}$. Define the vector stacking p times the dependent variables $\tilde{Y}_t$, $Y_t \equiv [\iota_p \otimes \tilde{Y}_t]$, where ι_p is a p-vector of ones, and the vector of structural quantile residuals $\epsilon_t \equiv [\epsilon_{1t}^{\theta_1}, \cdots, \epsilon_{nt}^{\theta_1}, \cdots, \epsilon_{1t}^{\theta_p}, \cdots, \epsilon_{nt}^{\theta_p}]'$. The structural quantile vector autoregressive model of order 1 is defined as:

$$Y_{t+1} = \omega + A_0 Y_{t+1} + A_1 Y_t + \epsilon_{t+1} \tag{1}$$

$$P(\epsilon_{i,t+1}^{\theta_j} < 0 | \Omega_{it}) = \theta_j, \quad \text{for } i = 1, \cdots, n, \quad j = 1, \cdots, p \tag{2}$$

where $\Omega_{1t} \equiv \{\tilde{Y}_t, \tilde{Y}_{t-1}, \cdots\}$ and $\Omega_{it} \equiv \{\tilde{Y}_{i-1,t+1}, \Omega_{i-1,t}\}$ for $i \in \{2, \cdots, n\}$, denote the recursive information set. The matrices A_0 and A_1 are block diagonal, and recursive identification is achieved by imposing that the diagonal blocks of A_0 are lower triangular matrices with zeros along the main diagonal.

Notice that, because of the way the recursive information set is defined, the quantile of each element of the vector Y_{t+1} at time t is a random variable, as, except for the first element, it depends on the contemporaneous shocks of the other variables. The trick to quantile forecasting is to recursively take the quantile of each of these quantiles (we refer to Chavleishvili and Manganelli, 2019, for a more elaborate exposition). Define $S_{j_{t+1}}$ the $n \times np$ matrix selecting specific quantile shocks from the vector ϵ_{t+1}, so that:

$$S_{j_{t+1}}\epsilon_{t+1} \equiv [\epsilon_{1,t+1}^{\theta_{j^1_{t+1}}}, \cdots, \epsilon_{n,t+1}^{\theta_{j^n_{t+1}}}]' \tag{3}$$

for $j^i_{t+1} \in \{1, \cdots, p\}$ and $i \in \{1, \cdots, n\}$. We assume that the quantile shocks identified by the matrix $S_{j_{t+1}}$ are set to zero. In words, the $S_{j_{t+1}}$ matrix is choosing a specific scenario, by imposing which quantile realization is occurring at time $t+1$ for each of the endogenous variables.

Under this scenario, by (1)-(2), the quantile forecast of $\tilde{Y}_{t+1}$ is:

$$\hat{\tilde{Y}}_{t+1}|S_{j_{t+1}} = C_{j_{t+1}}(\omega + A_1 Y_t) \tag{4}$$

where $C_{j_{t+1}} \equiv (I_n - S_{j_{t+1}}A_0\bar{S})^{-1}S_{j_{t+1}}$ and $\bar{S}$ is the $pn \times n$ duplication matrix such that $Y_{t+1} = \bar{S}S_{j_{t+1}}Y_{t+1}$.

Given any arbitrary sequence $\{S_{j_{t+h}}\}_{h=1}^{H}$, it is possible to iterate the system (4) forward to obtain the forecast of the dependent variables $\tilde{Y}_{t+H}$ at any future point H.

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. According to Bloom (2014), growth volatility affects growth itself. Growth dispersion is typically measured by volatility, but can be also measured by the interquantile distance (see Pearson and Tukey, 1965, and, for recent applications, Taylor, 2005). These considerations motivate the following econometric specification.

$$Y_{t+1} = q_{t+1} + \epsilon_{t+1}, \quad P(\epsilon_{i,t+1}^{\theta_j} < 0|\Omega_{it}) = \theta_j, \quad \text{for } i = 1, \cdots, n, \quad j = 1, \cdots, p \tag{5}$$

where

$$q_{t+1} = \omega + A_0 Y_{t+1} + A_1 Y_t + A_2 q_t \tag{6}$$

that is, we assume that the random variables are driven not only by the observables Y_{t+1} and Y_t, but also by some linear combination of past quantiles. Careful choice of the matrix A_2 allows us to test the theories about the impact of increased economic dispersion. For instance, by choosing the matrix so that it selects the difference between the 95% and 5% quantiles, this specification can be used to test the impact of dispersion. This modeling idea is similar to the ARCH-M model of Engle, Lilien and Robbins (1987), where expected returns are modeled as a function of conditional volatility.

System (6) 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.

Forecasts, conditional on the shocks identified by the matrix $S_{j_{t+1}}$ can be obtained in a similar fashion to the standard QVAR:

$$
\begin{aligned}
\hat{\hat{Y}}_{t+1}|S_{j_{t+1}} &= S_{j_{t+1}} Y_{t+1} \\
&= S_{j_{t+1}}(\omega + A_0 Y_{t+1} + A_1 Y_t + A_2 q_t) \\
&= S_{j_{t+1}} A_0 Y_{t+1} + S_{j_{t+1}}(\omega + A_1 Y_t + A_2 q_t) \\
&= S_{j_{t+1}} A_0 \bar{S} S_{j_{t+1}} Y_{t+1} + S_{j_{t+1}}(\omega + A_1 Y_t + A_2 q_t) \\
&= (I_n - S_{j_{t+1}} A_0 \bar{S} S_{j_{t+1}})^{-1} S_{j_{t+1}}(\omega + A_1 Y_t + A_2 q_t)
\end{aligned}
$$

This system can be updated recursively as system (4) for any given sequence $\{S_{j_{t+h}}\}_{h=1}^{H}$, by simply noting that:

$$
\hat{q}_{t+h} = \omega + A_0 \hat{Y}_{t+h} + A_1 \hat{Y}_{t+h-1} + A_2 \hat{q}_{t+h-1}
$$

for $h = 2, \cdots, H$ and where we have dropped the dependence of the forecasts on $\{S_{j_{t+h}}\}_{h=1}^{H}$ for notational convenience.

2.3 Estimation

Inference for the VAR for VaR model (6) can be obtained using the framework developed by White et al. (2015). Let $q_t(\beta) \equiv \omega + A_0 Y_t + A_1 Y_{t-1} + A_2 q_{t-1}(\beta)$ and $q_{it}^{j}(\beta)$ the j^{th} quantile of the i^{th} variable of the vector $q_t(\beta)$, where we have made explicit the dependence on β, the vector containing all the unknown parameters in ω, A_0, A_1, and A_2. Define the quasi-maximum likelihood estimator $\hat{\beta}$ as the solution of the optimization problem:

$$
\hat{\beta} = \arg\min_{\beta} T^{-1} \sum_{t=1}^{T} \left\{ \sum_{i=1}^{n} \sum_{j=1}^{p} \rho_j \left(\tilde{Y}_{it} - q_{it}^{j}(\beta) \right) \right\}, \tag{7}
$$

where $\rho_j(u) \equiv u(\theta_j - I(u < 0))$ 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:

$$\sqrt{T}(\hat{\beta} - \beta^*) \xrightarrow{d} N(0, Q^{-1}VQ^{-1}) \tag{8}$$

where

$$\begin{aligned}
Q &\equiv \sum_{i=1}^{n}\sum_{j=1}^{p} E[f_{it}^{j}(0)\nabla q_{it}^{j}(\beta^*)\nabla' q_{it}^{j}(\beta^*)] \\
V &\equiv E[\eta_t \eta_t'] \\
\eta_t &\equiv \sum_{i=1}^{n}\sum_{j=1}^{p} \nabla q_{it}^{j}(\beta^*)\psi^{j}(\epsilon_{it}^{\theta_j}) \\
{}^{j}(\epsilon_{it}^{\theta_j}) &\equiv \theta_j - I(\epsilon_{it}^{\theta_j} \leq 0) \\
\epsilon_{it}^{\theta_j} &\equiv \tilde{Y}_{it} - q_{it}^{j}(\beta^*)
\end{aligned}$$

and $f_{it}^{j}(0)$ is the conditional density function of $\epsilon_{it}^{\theta_j}$ evaluated at 0. The asymptotic variance-covariance matrix can be consistently estimated as suggested in theorems 3 and 4 of White et al. (2015), or using bootstrap based methods in the spirit of Buchinsky (1995).

Equation (7) is minimised using the fminsearch optimisation function in Matlab, which is based on the Nelder-Mead simplex algorithm. The estimation is done using as starting values in the optimisation routine the QVAR estimates and initialising the remaining parameters at zero. 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: www.econ.uiuc.edu/∼roger/research/rq/rq.html

3 The impact of excess bond premium and its interaction with economic risk

We start our analysis by estimating a simple structural QVAR(1) model. Let Y_{1t} and Y_{2t} denote the US industrial production and excess bond premium, respectively. The dataset consists of the following two US monthly variables covering the period from January 1973 to June 2016: the log-difference of industrial production and the excess bond premium. The latter is the component of the Gilchrist and Zakrajsek (2012) corporate bond credit spread index that is left after the component due to default risk is removed. It is interpreted as a measure of the spread between yields on private versus public debt that is due to financial market frictions.

We estimate the following model:

$$Y_{1,t+1} = \omega_1^\theta + \qquad\qquad a_{11}^\theta Y_{1t} + a_{12}^\theta Y_{2t} + \epsilon_{1,t+1} ^\theta \tag{9}$$

$$Y_{2,t+1} = \omega_2^\theta + a_{01}^\theta Y_{1,t+1} + a_{21}^\theta Y_{1t} + a_{22}^\theta Y_{2t} + \epsilon_{2,t+1}^\theta \tag{10}$$

The estimates of the cross equation regression quantile coefficients are reported in figure 1. Each dot corresponds to a different quantile estimate, whose probability can be read on the horizontal axis. The dashed lines represent the 90% confidence intervals, while the straight red line gives the OLS estimate of the corresponding VAR model.

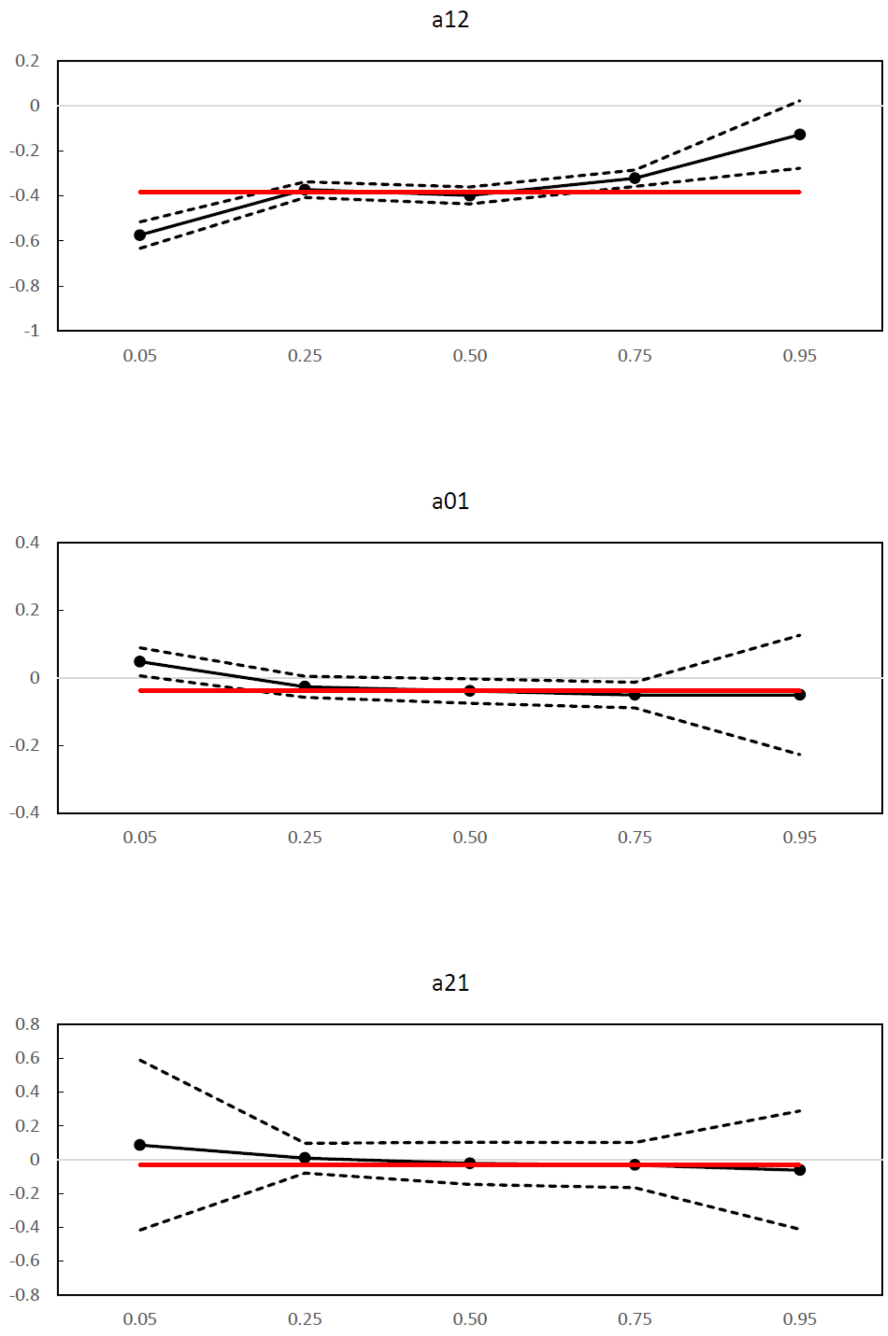


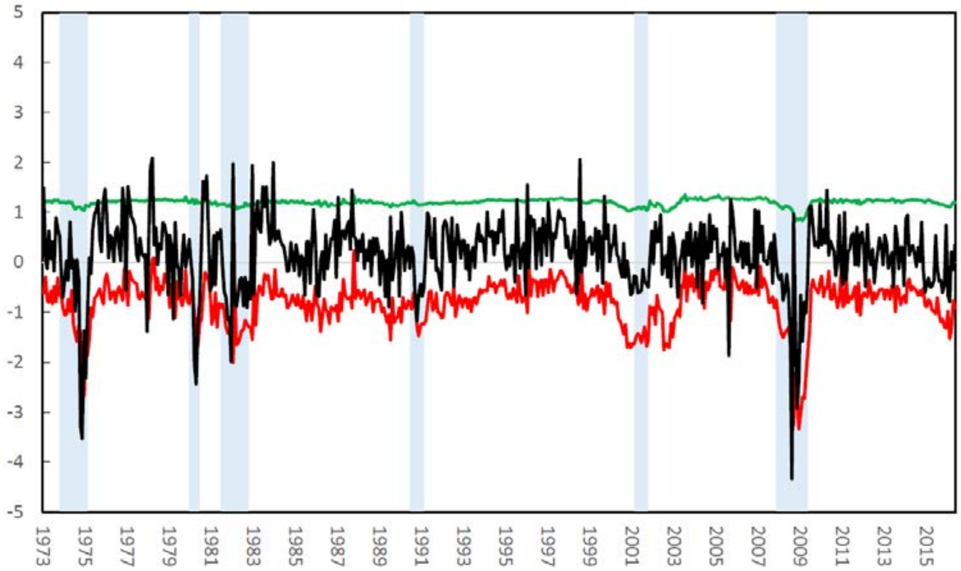
Figure 1: Regression quantile coefficients of the QVAR system 9-10

Note: The figure reports the cross equation regression quantile coefficients associated with the system 9-10, from 5% to 95% confidence levels, together with 90% confidence bands. The straight red line is the corresponding OLS coefficient.

The results show that there is little impact of real variables in the financial equation (10), as can be seen in the middle and bottom charts of the figure. However, the coefficient a^{θ}_{12} which measures the impact of the excess bond premium on the industrial production, exhibits a negative, statistically significant effect. More precisely, an increase in the excess bond premium 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) and Chavleishvili and Manganelli (2019). They also qualify those of Gilchrist and Zakrajsek (2012), showing that the excess bond premium has a negative impact on the central and left part of industrial production, but limited impact on the upside potential (the coefficient of the excess bond premium is not significantly different from zero at the 95% quantile). The intuition about the asymmetric impact of the excess bond premium is further illustrated in figure 2, which reports the one month ahead forecasts for the 5% and 95% quantile of the industrial production conditional on the excess bond premium. It is evident from the plot that the excess bond premium does not help predicting the upside potential of the U.S. economy, while it affects substantially its downside risks.

There is a substantial literature arguing that economic risk has a negative impact on the economy, as it induces agents to postpone investment and consumption in durable goods (see, for instance, Bloom, 2014). One proxy for economic risk is volatility, which in turn can be proxied by the interquantile range. In figure 3, we report the difference between the 95% and 5% quantiles together with the excess bond premium. The two series are highly correlated and they tend to spike during recessions. In fact, this is not surprising, in the light of the estimated coefficients reported in figure 1, since

Figure 2: Conditional forecast of industrial production



Note: The figure reports the one month ahead forecast of the 5% and 95% quantiles of industrial production, conditional on the excess bond premium.

$q_{1t}^{0.95} - q_{1t}^{0.05} = \omega_1^{0.95} - \omega_1^{0.05} + (a_{11}^{0.95} - a_{11}^{0.05})Y_{1,t-1} + (a_{12}^{0.95} - a_{12}^{0.05})Y_{2,t-1}$. Therefore, as long as $a_{12}^{0.95} \neq a_{12}^{0.05}$ (and the top panel of figure 1 shows that this is the case) the interquantile range is correlated with the excess bond premium. This finding is also consistent with the empirical evidence provided by Bekaert and Engstrom (2017), who show that the conditional variance of consumption growth peaks around the time of economic recessions.

It makes sense therefore to ask whether the interquantile range helps explaining the rate of growth of industrial production. To answer this question, we estimate the following restricted VAR for VaR:

$$Y_{1,t+1} = \omega_1^\theta + \qquad a_{11}^\theta Y_{1t} + a_{12}^\theta Y_{2t} + a_3^\theta (q_{1t}^{0.95} - q_{1t}^{0.05}) + \epsilon_{1,t+1} \tag{11}$$

$$Y_{2,t+1} = \omega_2^\theta + a_{01}^\theta Y_{1,t+1} + a_{21}^\theta Y_{1t} + a_{22}^\theta Y_{2t} + \epsilon_{2,t+1}^\theta \tag{12}$$

Including the lag quantiles is a parsimonious form of controlling for an infinite

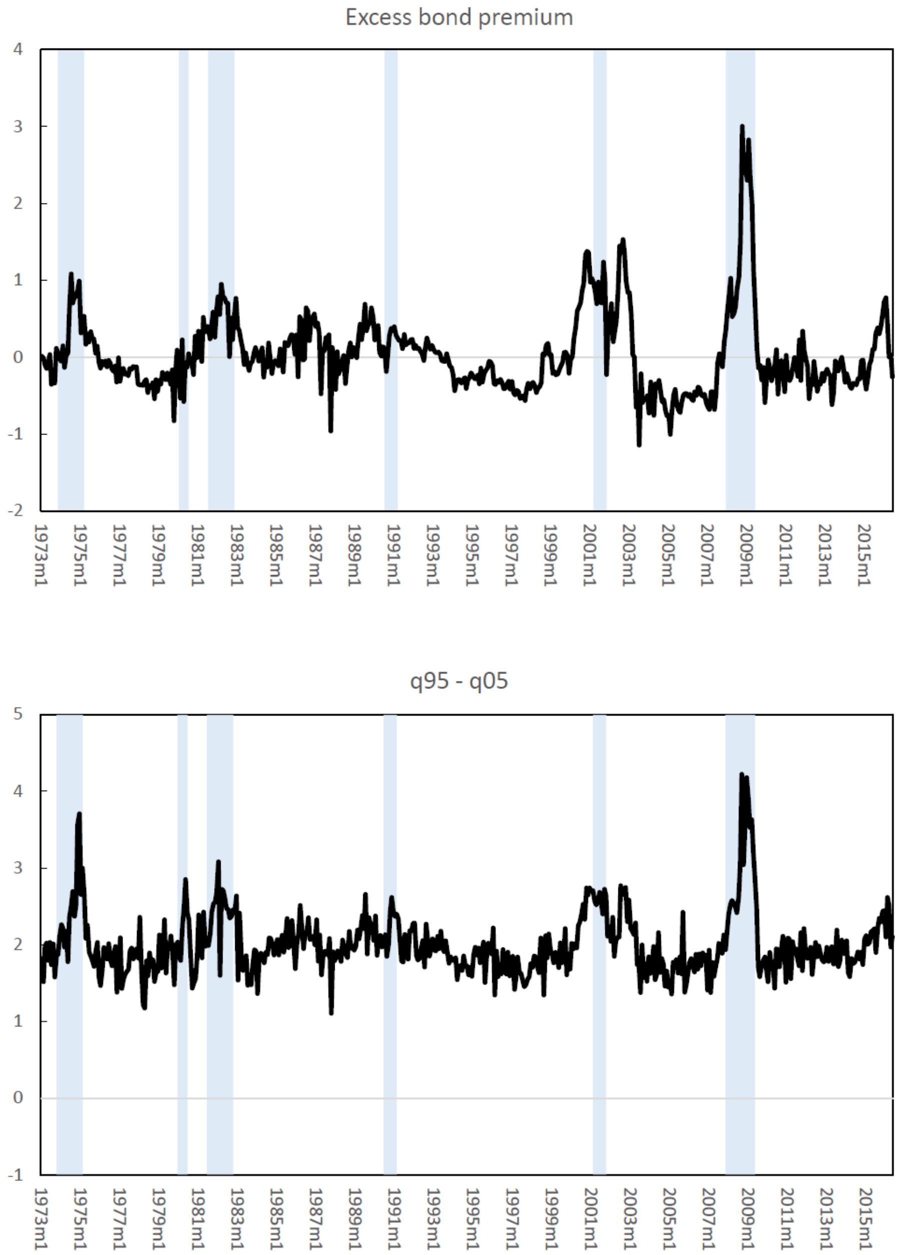


Figure 3: Interquantile range and the excess bond premium

Note: The figure reports the difference between the 95% and 5% quantiles forecasts of industrial production, together with the excess bond premium.

number of lagged dependent variables, very much like in ARMA or GARCH models. Figure 4 reports the regression quantile estimates of the coefficients a_{12} and a_3. A comparison with the top panel of figure 1 reveals that controlling for the interquantile range reduces by half the impact of the excess bond premium and weakens substantially its significance and asymmetric impact on the real variable. In particular, the impact on the left tail of industrial production is no longer significant. The asymmetric impact is absorbed by the interquantile range itself, as can be seen from the bottom panel of figure 4. These results further qualify the findings of Gilchrist and Zakrajsek (2012) and Adrian et al. (2019). The financial condition index by itself has little impact on the distribution of the real variable. It is the effect that it has through the impact on economic risk that matters the most.

One possible narrative consistent with these findings and those of the literature on credit spreads, economic risk and growth at risk, is that an increase in the excess bond premium, by potentially contracting the supply of credit, leads to an increase in the downside risks to growth, but has no effect on its upside potential. This, in turn, leads to an increase in economic risk (uncertainty, in the jargon of this literature), making firms more cautious in responding to business conditions, ultimately creating an even more pronounced downside risk to the economy.

These findings point to the importance of an economic uncertainty channel in the non-linear relationship between financial conditions and the conditional distribution of industrial production growth, suggesting that macroeconomic models with financial sector should allow for non-linear equilibrium relationships. Examples of non-linear DSGE models with financial frictions in the supply for credit include Brunnermeier and Sannikov (2014) and He and Krishnamurthy (2012). However, these models do not consider an economic uncertainty channel.

4 Bad environment - good environment analysis

The quantile VAR model 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 model described in section 2.2, associated with the scenarios reported in table 1. Recall from section 2.2 that scenarios are identified by a sequence of matrices $\{S_{j_{t+h}}\}_{h=1}^{H}$, which denote future quantile realizations of the endogenous variables. 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 economy is hit by a sequence of three consecutive 90% quantile realizations for the industrial production and three consecutive 10% realizations of the excess bond premium. This corresponds to a quarter of extremely good economic outcomes and compressed risk premia. The bad environment is defined symmetrically, as a sequence of three consecutive 10% and 90% quantile realizations of industrial production and excess bond premia, that is, bad economic outcomes and high risk premia. From the fourth month onward, we assume that the economy follows its median evolution. Of course, other (more or less severe) scenarios could be considered,

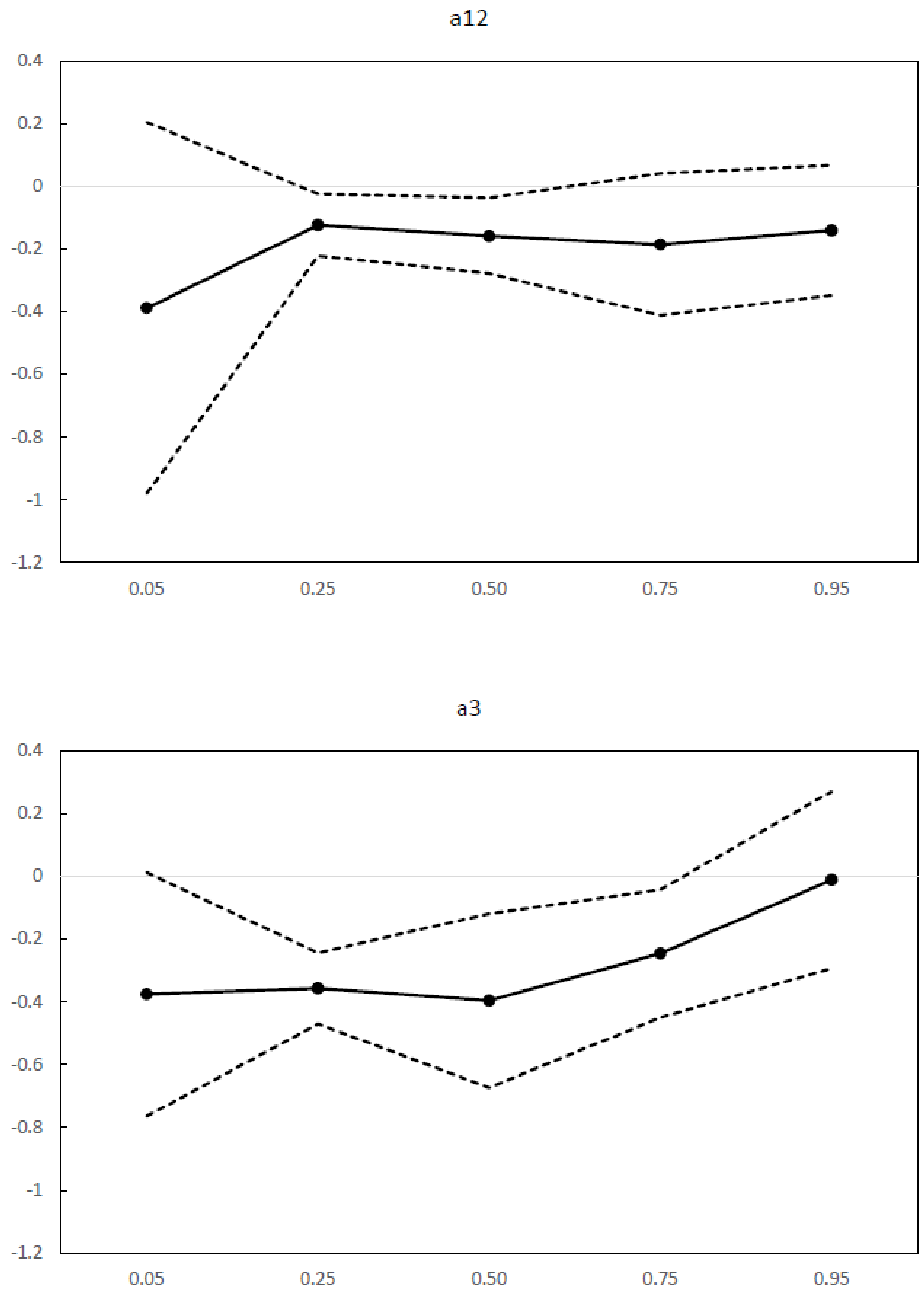


Figure 4: Regression quantile coefficients of equation 11

Note: The figure reports the regression quantile coefficients associated with equation (9), from 5% to 95% confidence levels, together with 90% confidence bands.

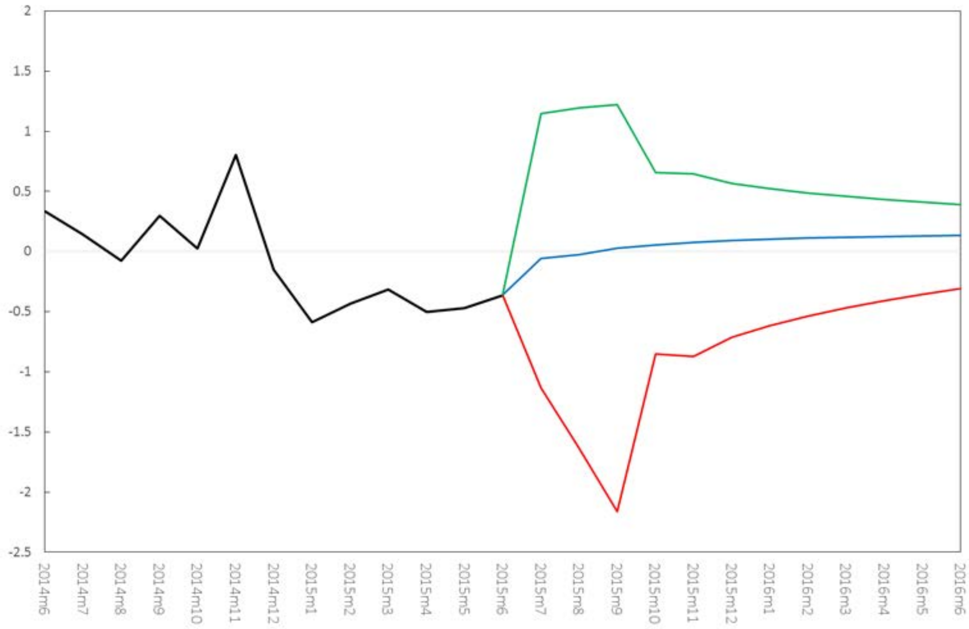


Figure 5: Forecasting US industrial production

Note: The figure reports the forecast of the US industrial production under three alternative scenarios: the good and bad scenarios described in table 1, as well as the median scenario.

but this one suffices to provide the empirical evidence of the asymmetric impact of bad and good environments.

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	{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 industrial production and excess bond premium quantile realizations, respectively.

The results are reported in figure 5. The scenarios are applied one year before the end of our sample. The figure reports the forecast of industrial production associated with the two scenarios, together with the median forecast.

The blue line in the middle represents the median forecasting path. It is similar to the mean forecast one would obtain with a standard VAR. The system is quickly reverting to its long run median forecast, which is around 0.2%. The lower red line is the forecast associated with a sequence of bad environment quantile realizations. This bad environment produces a significant and persistent downturn of the economy. The peak monthly contraction exceeds -2% and is reached after three months. The forecast associated with the symmetric sequence of good environment quantile realizations is given by the top green line. It is characterized by a much less pronounced and persistent expansion, as it is converging to the long run median forecast faster. The peak effect is also reached after three months, but at a lower level of slightly more than 1%.

These findings are consistent with those of Bekaert and Engstrom (2017), whose underlying theoretical framework predicts that an increase in financial risks leads to a negatively skewed distribution for the real variables. They extend the model of Campbell and Cochrane (1999) by assuming a stochastic process for macro variables that follows a time varying non-normal distribution. They refer to this as a *bad environoment-good environment* process, a terminology that we have borrowed for the description of our scenarios. In each period, consumption growth is hit by two types of shocks, characterized by positive and negative skewness. In their model, there are good times, in which the shocks drawn from the positively skewed distribution dominate, and bad times, when the negatively skewed shocks dominate and the recession risks are higher. They estimate the process using the univariate model proposed in Bekaert, Engstrom and Ermolov (2015), a GARCH model augmented with two gamma-distributed shocks that together imply a conditional shock distribution with time-varying heteroscedasticity, skewness and kurtosis. Our quantile VAR represents a semi-parametric alternative modeling approach, which can be easily extended to structural VAR analysis, as illustrated in this section.

5 Conclusion

We have estimated a quantile vector autoregressive model for the US economy with industrial production and excess bond premium as endogenous variables. Financial conditions have an asymmetric effect on the real economy, via the impact they have on economic risk. We measure economic risk as the interquantile range. Worsening financial conditions increase overall economic risk, which in turn increases growth at risk.

Our quantile VAR framework could potentially help policymakers design policy actions to respond in a timely manner to threats to financial stability indicated by changes in financial conditions. 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 conditions. The evidence provided in this paper highlights how asymmetric macro-financial feedback effects can be properly taken into account.

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