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Protecting Growth

A Quantile Vector Autoregression to Evaluate the Power of Monetary Policy in Mitigating the Transmission of Financial Stress on GDP Growth

Author

Benedikt Kagerer (449639)

Supervisor: Prof. Dr. D.J.C. van Dijk

Second assessor: P.A. Opschoor, MSc.

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Abstract

This paper investigates the effectiveness of monetary policy in reducing Growth at Risk during financial stress scenarios. For this analysis a quantile vector autoregressive (QVAR) model is used due to its nonlinear properties. Using quantile regressions in a VAR setting allows to explore the dynamics between economic growth, monetary policy and financial stress in all parts of the distribution of the variables. The analysis shows that a loosening in monetary policy effectively reduces the risk to GDP growth caused by shocks in financial stress. Moreover, monetary policy seems to be more efficient in times of tight financial conditions. The results suggest nonlinear interactions along several dimensions between GDP growth, financial stress and the change in monetary policy. These findings indicate that not only linear VARs, but also frequently used threshold VARs might miss important features of the data. Including monetary policy uncertainty (MPU) leads to insignificantly better distribution predictions for GDP growth, which are, however, overshadowed by a reduced sample size.

Contents

1 Introduction

The effectiveness of monetary policy in times of high financial stress is disputed in scientific literature. Most prominently this discussion was led during the financial crisis in 2008. While the Federal Reserve aggressively lowered the Federal Funds Rate (FFR) from an initial 5.25% in 2007 down to nearly zero for the following seven years, the question whether this easing of monetary policy indeed translated into better access to capital in times of financial trouble was highly controversial in academia. Nobel laureate Paul Krugman expressed his doubt at the time in a column for the *New York Times*:

"We are already, however, well into the realm of what I call depression economics. By that I mean a state of affairs like that of the 1930s in which the usual tools of economic policy above all, the Federal Reserve's ability to pump up the economy by cutting interest rates have lost all traction. When depression economics prevails, the usual rules of economic policy no longer apply: virtue becomes vice, caution is risky and prudence is folly"(Krugman, 2008).

The main reason for monetary policy to act in a situation of a tight financial condition is the negative effect that financial stress has on the macroeconomy. Strains in financial markets can spill over to the real economy fuelling unemployment and hampering output. Moreover, financial insecurity creates uncertainty about the value of assets, increasing the risk of further financial turmoil, leading to a self enforcing vicious circle referred to as the financial accelerator (Mishkin, 2009). During the financial crisis the credit spreads, indicating liquidity in the interbank market, rose about tenfold despite the significant cut in policy rate. This raised the question whether lowering the refinancing rate for financial institutions induced liquidity into the market at all. Mishkin argues that in the absence of a loosening of monetary policy, the negative feedback loop would have been more severe, leading to further contractions in the real economy. He further suggests that monetary policy might be even more efficient under tight financial conditions due to the negative feedback loop. This paper, thus, helps to empirically clarify whether monetary policy can weaken the transmission of financial stress into the real economy, therefore, absorbing some of the damage caused by the self-enforcing downturn. The main research question this paper addresses is the following:

To what extent can monetary policy mitigate the negative effect of shocks in financial stress on GDP growth and how efficient is the policy instrument under different levels of economic and financial stress?

These two closely related parts of the main research question are answered separately in the second part of the paper. Moreover, the effectiveness of the policy instrument might further depend on the public uncertainty about its future path. Therefore, also the effect of uncertainty about the future monetary policy rate on the median and the distribution of GDP growth is analysed.

The relation between financial instability and economic risk is of great interest for policy makers especially since the financial crisis in 2008 (Creel, Hubert, & Labondance, 2015). Adding a policy component to the evaluation of this relationship might lead to fruitful insights into appropriate responses to such shocks. Similar to what has been suggested in the literature about incorporating credit spreads into the Taylor Rule (Taylor, 2008), the model implemented in this paper helps to quantify the benefits of incorporating financial stress in the monetary policy setting process. By establishing the effect of monetary policy under diverse economic and financial situations, central banks can take more accurate actions in line with their defined goals.

The formal analysis of the research question is performed by a multivariate quantile vector autoregression (QVAR), which allows to model different translation mechanisms for different parts of the distribution of economic growth. Even though this approach is more flexible than most alternatives, it has rarely been used in economic literature and has not yet been applied to evaluating the effectiveness of monetary policy. In particular, the possibility to investigate the relationship between variables at different parts of their distribution in the form of impulse response functions makes this approach a promising candidate model for the question at hand. The quantiles of all included variables can be chosen freely and independently. Ultimately, the model is used to construct impulse response functions depicting the reaction of different quantiles of GDP growth to two different shocks and under various monetary and financial circumstances. Firstly, the response of GDP growth at various parts of the distribution after an exogenous shock to financial stress is analysed. This exercise is performed under different monetary policy regimes. Secondly, the effect of an exogenous shock to the change of the main refinancing rate on different quantiles of GDP growth is discussed, while considering various financial stress levels. In that the paper contributes to the methodological use of QVARs by allowing control variables in the impulse response functions to be affected at different quantiles than the median.

This paper confirms the negative relationship between financial stress and downward risk to GDP growth especially at low quantiles. Furthermore, its results suggest that monetary policy plays an effective role in absorbing part of the transmission of financial shocks to the real economy. Also, the findings contradict the view as expressed by Krugman and indicate that monetary easing effectively supports the macroeconomy even more permanently in high stress scenarios. Additionally, this paper concludes that including the publicly perceived uncertainty in monetary policy (MPU) provides slightly more accurate distribution forecasts for GDP growth, these gains are, however, insignificant and overshadowed by a smaller sample size when including MPU.

The following part summarizes the state of the literature on the relationship between financial stress, monetary policy and economic growth and the appropriate empirical identification schemes. This is followed by a description of the data used for the analysis. Next, the empirical investigation then starts by confirming the link between financial stress and downward risk to growth in a static setting. This relationship is then translated into a dynamic multivariate model including the monetary policy rate to answer the main research question. Lastly, the information content of monetary policy uncertainty for measuring downward risk to GDP growth is investigated.

2 Theoretical Background

2.1 Financial Stability and Economic Growth

According to economic literature there are various links between financial stability and economic growth. On the one hand, the Schumpeterian view suggests that credit is necessary for entrepreneurs to finance innovation. From this perspective, the financial sector serves as facilitator. On the other hand, the real economy also affects the financial system as with increasing economic expansions the demand for financial services rises (Creel et al., 2015). More recent studies using panel data mainly confirmed the positive relationship between financial development and GDP growth (e.g. Beck and Levine (2004)). Beyond these well established positive connections also a possible adverse effect of financial instability on economic development has been researched. While the importance of financial liberalization for economic growth is disputed, the possible adverse effects of financial instability on economic outcomes have been well noticed before the financial crisis of 2008 by Stiglitz (2000), who argued for interventions in short-term capital flows.

This concern of financial instability for economic development voiced by Stiglitz has been at the attention of several empirical researchers too. Creel et al. (2015) empirically and theoretically derived the negative effect of financial instability on economic growth using a panel GMM with instrumental variables. In this tradition Adrian, Boyarchenko, and Giannone (2019) established a strong relationship between the state of financial conditions and downward risk to GDP growth in the USA by considering the effect on the complete distribution of GDP conditional on economic and financial circumstances. Many earlier studies have failed to establish such a clear relationship between GDP growth and financial stress due to their focus on the mean rather than the complete distribution (Adrian et al., 2019). In the style of the popular Value at Risk as measure for risk to financial investments, Adrian, Grinberg, Liang, and Malik (2018) define the 5^{th} percentile of the distribution of GDP growth equivalently as Growth at Risk and conclude that this downside risk is systematically underestimated as higher moments of the distribution of GDP growth besides the mean are often neglected. Given that coefficient estimates in quantile regressions are less precise for the tails of the distribution, this paper looks at effects for the 20 and 80 percent quantiles instead of investigating the 5 and 95 percent quantiles. By considering the distribution, this paper aims to replicate the significant effect of financial stress on the lower quantiles of GDP growth.

The quantile regression presented by Adrian et al. (2019) is a static estimation of the relationship between financial stress and different levels of GDP growth. A step towards a dynamic formulation of the problem as described by Adrian et al. has been taken by Chavleishvili and Manganelli (2019), who also transformed the static nonlinear relationship between financial stress and economic output into a dynamic model for the Euro Area. The main methodological difference between their approach and the approach taken by this study is that the analysis in this paper is multivariate and additionally incorporates the effects of money supply. In other words, the perspective taken is the main difference to the paper by Chavleishvili and Manganelli (2019): While the findings of Adrian et al. initiated Chavleishvili and Manganelli to construct a QVAR to create scenarios for stress testing exercises, the findings are used in this paper as a starting point for an investigation of the protection of GDP growth. According to Sánchez and Röhn (2016) macroprudential policies can contribute towards reducing the vulnerability of growth. At the same time, the authors find that stricter use of these policies is associated with a lower average growth rate. Hence, this paper focuses on the protective role of monetary policy.

2.2 The Role of Monetary Policy

The relation between monetary policy and financial stress seems to be a two-edged sword. On the one hand, a loose monetary policy contributes towards excessive risk taking in markets leading to financial vulnerabilities (Adrian & Liang, 2016). On the other hand, once these vulnerabilities translate into tight financial conditions, a loosening of monetary policy might contribute towards overcoming this stress period with less economic damage. Baxa, Horváth, and Vašíček (2013) find that central banks generally do respond to financial stress. Establishing increasing risks due to financial instability thus indicates that macroeconomic policy tools are not able or not used to completely counterbalance financial stress. This paper sheds light on the first option by investigating whether monetary policy is a suitable instrument to respond to financial stress.

Monetary policy models are conventionally estimated using vector autoregressive approaches (Smets & Wouters, 2003). Kremer (2016) investigates the effect of conventional and unconventional monetary policy on output growth, by also incorporating financial stress in a standard macro - financial multivariate time series model. This linear approach was already criticized by Evans, Kuttner, et al. (1998) as it rules out likely nonlinear responses such as the ones indicated by an "opportunistic disinflation policy", which describes the strategy of sustaining booms with low rates and increasing rates after recessions in order to reduce inflation and inflation expectations, sacrificing higher employment. In earlier empirical research first steps towards the problem of a nonlinear effect of monetary policy were often taken in the form of regime switching models, where the regime depends either on the money supply or the economy's position in the business cycle (Weise, 1999). More recently, Saldías (2017) estimated the nonlinearity of the effect of monetary policy using a similar threshold dependent model where the regime depends on the financial conditions and Aikman, Lehnert, Liang, and Modugno (2020) constructed a model in which the regime is determined by credit. Saldías (2017) finds that monetary policy is more effective in promoting output growth in regular times than in periods of high financial stress. Looking at the effect of unitary shocks in the change of the refinancing rate under different levels of financial stress he finds a stronger response of output under regular conditions than in stress scenarios in an impulse response analysis. Nonetheless, Saldías argues that monetary policy has a larger effect on financial conditions in situations of financial stress, indicating that there is a role for monetary policy in addressing stress once it materializes. The approach chosen for this research allows to additionally consider different levels of economic growth, adding a further nonlinear dimension in order to get a more differentiated picture of the relationship.

This paper presents a contribution to the literature not only by establishing nonlinear dynamics of monetary policy and financial and economic conditions but also by not requiring the setting of artificial regimes ex-ante. In this respect the QVAR allows for a more insightful analysis and for more freedom to consider nonlinear dynamics along several dimensions. This is the main advantage over threshold vector autoregression models as used by Weise (1999) or Saldías (2017). Using a quantile vector autoregression also allows for smooth transitions as the coefficients are allowed to float over the individual quantiles. Most closely this research resembles the evaluation of macroeconomic policy efficiency in the form of fiscal policy by Linnemann and Winkler (2016), who implemented a similar QVAR.

2.3 Monetary Policy Uncertainty as Risk to Growth

Besides the direct role of monetary policy, economic theory also suggests an indirect effect concerning monetary policy. Companies might postpone their investments or refrain from hiring in situations where future interest rates and inflation are uncertain. Monetary policy, especially in the US, aims to stabilize the economy, but this stabilizing effect depends on the credibility of the monetary policy institution and the expectations of economic agents (Boivin & Giannoni, 2006). High uncertainty about future interest rates and inflation might reduce the tractability of monetary policy leading to an increased risk to growth. The notion that monetary policy is less efficient under high economic uncertainty was investigated by Aastveit, Natvik, and Sola (2013), who showed that the transmission of monetary policy on investments is two to five times weaker when uncertainty is in its top percentiles.

Macroeconomic and financial uncertainty have played an increasingly important role in the macro-financial academic discussion over the past few years. Recent research indicates a predictive, exogenous role of financial uncertainty and a responsive, endogenous role of macroeconomic uncertainty (Ludvigson, Ma, & Ng, 2015). Jurado, Ludvigson, and Ng (2015) find that increases in uncertainty are followed by large decreases in economic output, but caution against whether this observation is a cause or a response. Irrespective of the causal chain, this paper will investigate whether including monetary policy uncertainty improves the conditional distribution of future GDP growth in the short run (one quarter ahead) and in the long run (one year ahead).

3 Data

For the analysis I follow to large parts the selection of data as done by Adrian et al. (2019). As a measure of financial stress I use the National Financial Conditions Index (NFCI) starting from January 1973. This composite index, constructed using 105 individual indicators, is a weekly measure that captures financial stress in money, debt and equity markets and in the banking system (Adrian et al., 2019). Because the index is updated weekly to have a mean of zero and a standard deviation of one, a positive NFCI indicates tighter than average monetary conditions. The second variable, namely GDP growth, is only available on a quarterly basis. To align the frequency of the data, the quarterly average of the NFCI is used for the analysis. Taking Adrian et al.'s work further, I extend the database to the first quarter of 2020. This leads to changes in earlier values of NFCI and GDP growth, due to the repetitive updating of the series (this holds specifically for the NFCI, which is changed constantly due to the fixed values for mean and variance).

Further, it is necessary to include a measure for the monetary policy tool. For this, I follow the convention and include the Federal Funds Rate (Saldías, 2017). Given that one of the main targets of monetary policy is to maintain price stability, the variable used to capture this is the consumer price index (CPI) for all items in the US measured on a quarterly basis. All four described variables are downloaded from the Federal Reserve Bank of St. Louis (FRED).

In times where the FFR is stuck at the zero lower bound (ZLB) the effect of monetary policy is difficult to evaluate. Earlier research has therefore often only considered a subperiod analysis. Wu and Xia (2016) have proposed a measure which allows using all available data by using a shadow rate instead of the FFR from the year 2009 onwards. This influential measure also incorporates the summarized effect of unconventional monetary policy and is a tractable approximation of a nonlinear term structure model near the zero lower bound. Using this rate overcomes the problem of the structural break in the funds rate, while retaining the same relationship to macroeconomic variables as before the ZLB period (Wu & Xia, 2016). Hence, this shadow rate enables a continuous use of data for monetary policy evaluation, for example in VAR analyses, and is identical to the funds rate if the rate is at at least 25 basis points. This choice only affects the period between the first quarter of 2009 and the third quarter of 2015. The data is downloaded from the website of the Federal Reserve Bank of Atlanta. As the shadow rate is model dependent, there are opposing views in the academic discussion whether it can be used to fill the gap of the zero lower bound period. Therefore, my results have to be interpreted in light of this choice. For the entire following analysis, the variable denoted as FFR includes the shadow rate.

For the investigation of the effect of monetary policy uncertainty, the US monetary policy uncertainty (MPU) index developed by Husted, Rogers, and Sun (2019) is used. This index is calculated based on uncertainty expressed in newspapers relating to Federal Reserve monetary policy decisions. More specifically, the measure is computed based on the frequency of specific keywords related to uncertainty about the monetary policy tools in the selected newspapers. It is constructed from 1985 onwards and available for download on Husted et al.'s website. For the investigation the index is scaled by $\frac{1}{100}$ for coefficient visualization purposes. More information and summary statistics for the used variables are provided in the Appendix.

A first graphical analysis justifies the approach chosen. Figure 1 shows that the NFCI spikes at times where the economy is in a recession. Until 1990 the GDP growth seemed to stagnate in times where the FFR was at its peak, forcing the Fed to set lower rates thereafter. A good example of this feature is the recession in the early 1980s, where the Fed was forced to fight high inflation. Once the Fed lowered the rate, the economy was able to temporarily recover until another rate increase was implemented. Note that the rate crosses the ZLB as a result of my choice to use the shadow rate in the period 2009 Q1 to 2015 Q3. Lastly, the NFCI and the refinancing rate are depicted together. Figure 1 shows that periods of high financial stress, indicating tight credit conditions, correspond to periods with a high FFR. A tight monetary stance translates directly into tighter credit conditions.

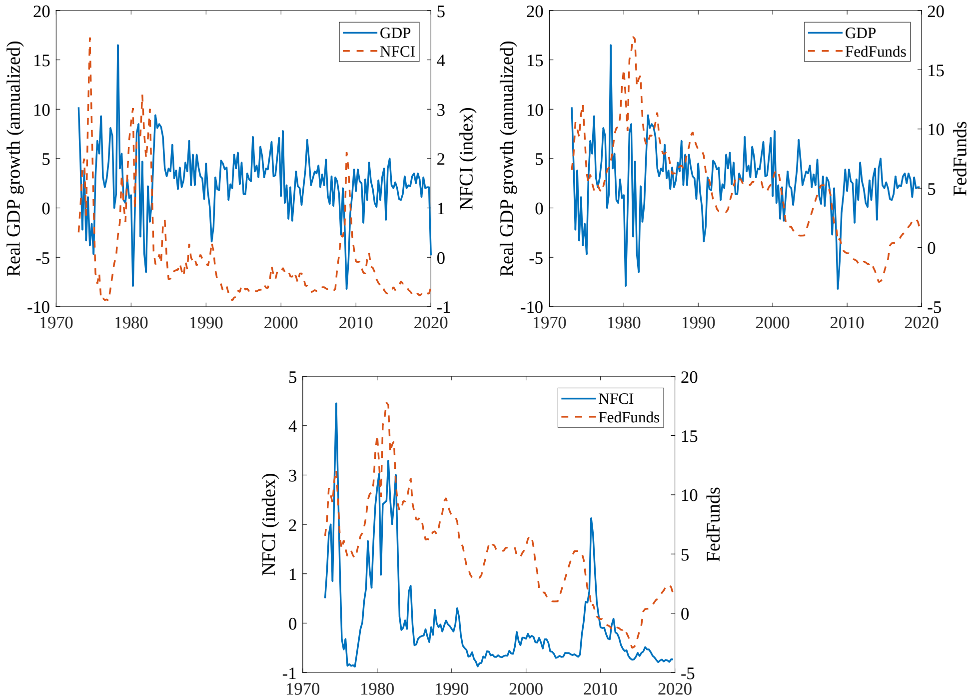

Figure 1: Plot of GDP growth against the NFCI (top left), GDP growth against the FFR (top right) and NFCI against the FFR (bottom)

The plot of the individual series reveals a trend in some of the additional variables (e.g. FFR). In order to avoid ordering in quantiles according to time but instead, to obtain the order according to the position in the business cycle, first differences are used for the FFR (ΔFFR) and the inflation (Δ^2CPI) in the QVAR analysis. The analysis, thus, focuses on the implemented action of the central bank (loosening or tightening of FFR) rather than on the level. Another advantage of using differenced variables is the potential nonstationarity of individual quantiles, which would lead to permanent shocks in the dynamic analysis. As the regression is calculated for different quantiles of the dependent variable, the autoregressive coefficient for some quantiles might exceed one. Although this option cannot be ruled out by the transformation, the likelihood can be reduced nonetheless. Nonstationarity can be significantly rejected for the chosen transformed series but might still occur for individual quantiles. The transformation of inflation and the FFR is in line with previous literature (Schüler, 2014), where the two series were incorporated in a similar fashion.

4 Downward Risk to GDP and Financial Stress

4.1 Methodology - Static Quantile Regression

In the first part of the paper, the procedure outlined by Adrian et al. (2019) with the data updated until the first quarter of 2020 is applied. This method allows to reconfirm the nonlinear relationship between financial stability and future GDP growth. For the analysis a quantile regression is used. This method was developed by Koenker and Bassett Jr (1978) and allows for an investigation of the complete distribution of the dependent variable. While OLS is bound to estimating effects on the mean of a given variable conditional on the vector of regressors, the approach chosen for this paper allows estimating different effects for different quantiles of the dependent variable. The quantile regression estimates the effect of a vector of explanatory variables x_t on a quantile θ of the dependent variable y_t. $Q_\theta(y_t|x_t)$, as defined below, is a consistent estimator of the quantile function of y_t conditional on the variables incorporated in x_t (Koenker & Bassett Jr, 1978).

$$Q_\theta(y_t|x_t) = x_t\hat{\beta}_\theta \tag{1}$$

In this application y_{t+h} is the average growth of GDP between time t and t+h and x_t contains financial stress in the form of the NFCI and the current GDP growth together with an intercept. The coefficients $\hat{\beta}_\theta$ in the quantile regression investigating the relation between future GDP growth and current economic and financial conditions are determined in the following way:

$$\hat{\beta}_\theta = \underset{\beta_\theta \in \mathbb{R}^k}{argmin} \sum_{t=1}^{T-h} (\theta * I_{(y_{t+h} \geq x_t\beta)}|y_{t+h} - x_t\beta_\theta| + (1-\theta) * I_{(y_{t+h} < x_t\beta)}|y_{t+h} - x_t\beta_\theta|) \tag{2}$$

where I is the indicator function and θ represents the individual quantiles. The coefficients β_θ are estimated by minimizing a quantile weighted sum of absolute errors. If the error is positive, an observation will be weighted by θ and if the error is negative it will be weighted by $1-\theta$, where θ gives the quantile of interest of the dependent variable. In this fashion, various coefficients belonging to the different quantiles of the target variable can be estimated. Estimations at the tails of the distribution, however, become less precise due to a large weight to a small fraction of observations.

4.2 Results - Static Quantile Regression

When performing this analysis with GDP growth over the next quarter and next year as dependent variable and a constant and the stress index as independent variable for the complete sample period from 1973 Q1 to 2020 Q1, we obtain various regression lines corresponding to the estimated coefficients for the 5^{th}, 50^{th} and 95^{th} quantile.[1] These are depicted in the top part of Figure 2 together with the OLS estimate. The fact that the slopes differ widely across the quantiles is a first indication of a nonlinear relationship. Financial stress seems to exhibit a large negative effect on the lower parts of the conditional distribution of GDP growth and a slightly positive effect on the top parts. This is confirmed by the bottom part of Figure 2, which shows the coefficients at different quantiles of GDP growth for NFCI obtained by a regression also including current GDP growth. The coefficients are plotted together with bootstrapped 68%, 90% and 95% confidence intervals constructed by fitting a linear VAR model. If the coefficients lie outside the confidence interval this indicates a nonlinear behaviour. The observed pattern of negative effects on low quantiles and positive effects on high ones is similarly observed for both the short- and long-run. Moreover, the fact that the nonlinear effect of NFCI does not disappear when also including the current GDP growth into the regression (bottom part) suggests that indeed financial and not economic factors lead to the observed nonlinearity.

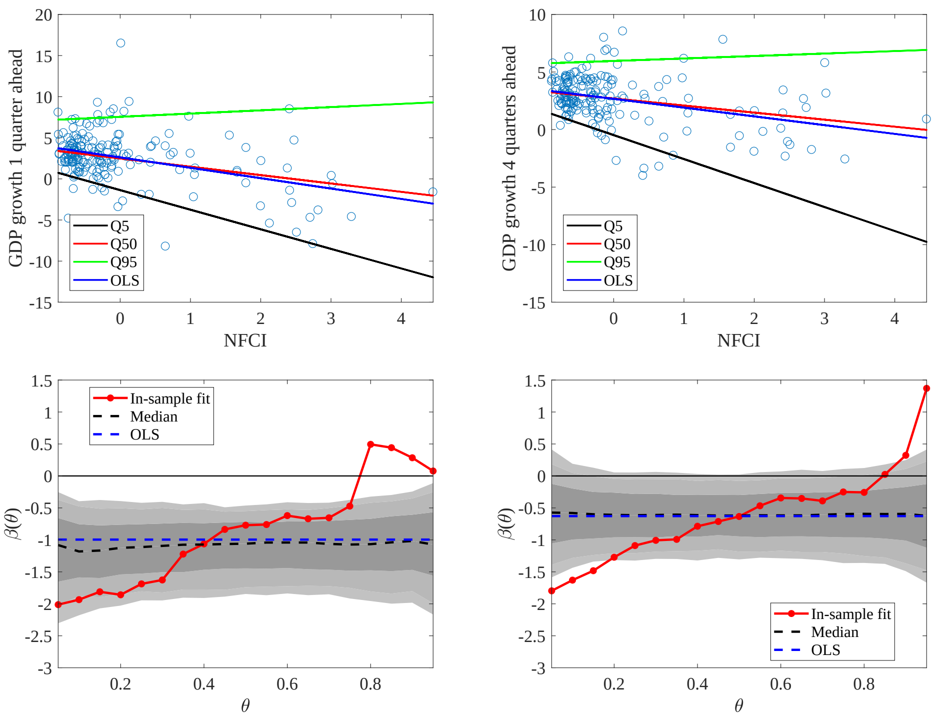

Figure 2: The top figures show the univariate quantile regression lines of real GDP growth on a constant and NFCI for one quarter ahead on the left and one year ahead on the right. The bottom figures depict the coefficients for the NFCI of the quantile regression of one quarter ahead (left) and one year ahead (right) GDP growth on a constant, current GDP and the NFCI together with the OLS estimate and the bootstrapped median obtained by a fitted linear VAR. Additionally, the 68%, 90% and 95% confidence intervals obtained by the linear VAR are depicted.

After estimating the individual coefficients, these can be used to construct one quarter and

[1]These and the following results are obtained by using the replication code provided by Adrian et al. (2019). The results of the following sections are obtained by adaptions and extensions of the provided code. URL: https://www.aeaweb.org/articles?id=10.1257/aer.20161923

one year ahead forecasts for the complete conditional distribution of GDP growth based on current economic and financial conditions. The predicted time series development of the conditional median and the 5, 25, 75, and 95 percent quantile is presented in Figure 3. The left figure depicts the continuously changing downward risk to GDP growth for quarterly forecasts. The variation in downward risk conditional on financial stress and the current state of the economy is considerably higher than risk to the upper quantiles, where the forecasted distribution is relatively stable. This feature is also reflected in the one year ahead conditional distribution visualized on the right. The pronounced downward spikes of the distribution highlight the asymmetric feature of the conditional distribution. Again, frequent changes in the downward risk are observable, while the upward risk remains more stable.

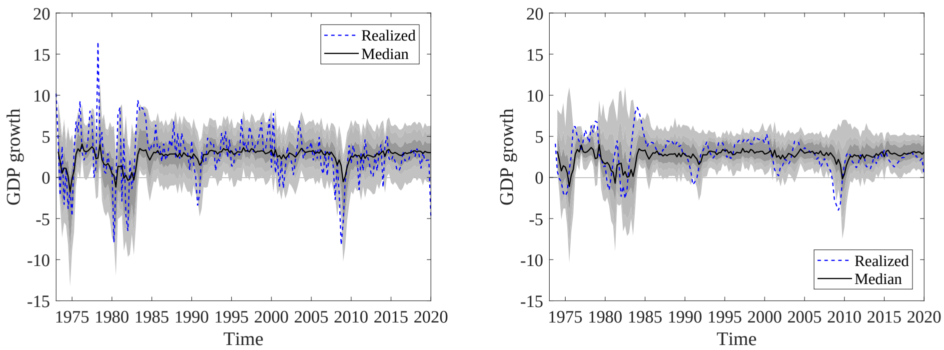

Figure 3: One quarter ahead (left) and one year ahead (right) predicted distribution of real GDP growth using current GDP and NFCI. Depicted are the conditional median and the 5, 25, 75, and 95 percent quantiles as well as realized GDP growth.

The added period between 2016 and 2020 is, besides the last observation, a relatively stable time period and updating the two variables did not change any part of the results. The same patterns remain visible for the coefficients as well as the conditional distribution. These results suggest that financial stress might be especially harmful for GDP development at the lower parts of the distribution and therefore increases the Growth at Risk. This relationship might, however, be non-causal in that financial stress could function as an indicator for other underlying developments.

Adrian et al. (2019) continue their analysis by quantifying the Growth at Risk using various measures. If financial stress indeed poses a risk to GDP growth in the way the previous analysis suggests, the logical next step is to investigate means by which this effect can be reduced in order to protect growth. On the one hand, regulatory guidelines such as the Single Supervisory Mechanism in the Euro Area, might reduce the risk of severe financial stress in the first place. On the other hand, monetary policy tools might be able to absorb some of the negative effects by easing financial conditions. Monetary policy might even be more effective because of the limited reach of macroprudential regulation also due to shadow banking opposed to the worldwide effect of monetary policy (Adrian & Liang, 2016).

5 The Role of Monetary Policy

In order to investigate whether it is indeed necessary to consider the effect of monetary policy on GDP growth in a nonlinear fashion as often suggested in academic literature, a similar regression as in the first part of the paper is performed and extended by the first difference of the FFR as regressor besides current GDP growth and NFCI. The figures below are a first step towards exploring the dynamics between financial stress, monetary policy and GDP growth.

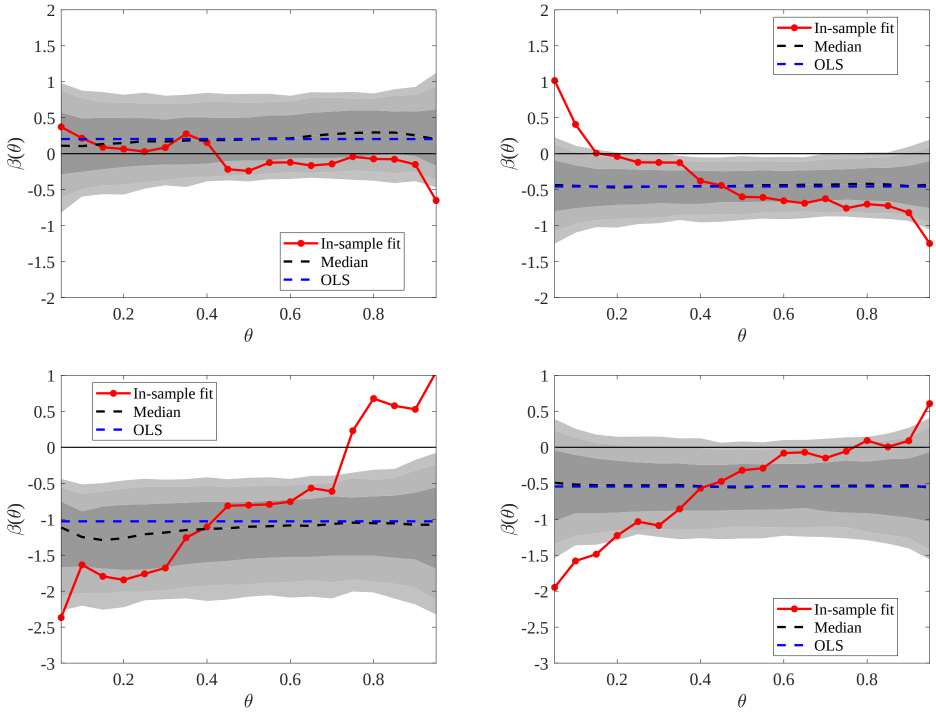

Figure 4: The top figures depict the coefficients for ΔFFR of the quantile regression of one quarter ahead (left) and one year ahead (right) GDP growth on a constant, current GDP, the first differenced FFR and NFCI. The bottom figure depicts the coefficients of NFCI for the same regression. Coefficients are plotted together with the OLS estimate and bootstrapped quantiles obtained by a fitted linear VAR.

As can be seen in the lower part of Figure 4, the effect of NFCI remains nonlinear and affects GDP growth in a similar way as in the previous analysis. The first differenced FFR is negatively related with GDP growth for most parts of the distribution and exhibits nonlinearity especially in the long run (top part). However, such a static analysis might not give an appropriate picture of the true dynamics at work between the selected variables. Therefore, instead of investigating the distribution of GDP growth conditional on the monetary policy rate similar to the first part, this part of the paper explores the role of monetary policy in determining the path of GDP growth in a dynamic setting. For that reason a QVAR model including GDP growth, the NFCI, ΔFFR and Δ^2CPI is constructed.

5.1 Methodology - Dynamic QVAR

The equation estimated for financial stress in the first section can also be expressed in a different fashion:

$$\tilde{Y}_{1,t+1} = \omega_1^{\theta} + \alpha_{11}^{\theta}\tilde{Y}_{1,t} + \alpha_{12}^{\theta}\tilde{Y}_{2,t} + \epsilon_{t+1}^{\theta} \tag{3}$$

In this formulation, the future GDP growth ($\tilde{Y}_{1,t+1}$) depends on the current GDP growth ($\tilde{Y}_{1,t}$) and the current financial condition ($\tilde{Y}_{2,t}$). This formulation can be interpreted as the first line of a quantile vector autoregression for different quantiles θ. By augmenting the equation by the monetary policy tool and the measure for price stability and by adding the equations below, a structural QVAR can be estimated for GDP growth, financial condition, change in inflation and the first differenced Federal Funds Rate. In structural VARs, the included variables are allowed to be contemporaneously related in order to gain insights into the structure of an economy. This makes restrictions, such as an economically motivated choice for the ordering of the variables, necessary in order to be able to identify the system of equations. According to the imposed order, due to the selected zero restrictions, the GDP growth is denoted as $\tilde{Y}_{1,t}$, the change in price level growth as $\tilde{Y}_{2,t}$, financial conditions as $\tilde{Y}_{3,t}$ and ΔFFR is written as $\tilde{Y}_{4,t}$ in the following.

This ordering of the formulation leads to several structural identification assumptions. The design of the proposed structural QVAR is mostly in line with conventional identification design (Christiano, Eichenbaum, & Evans, 1999). Firstly, the real variables GDP growth and Δ^2CPI do not respond contemporaneously to changes in the financial or monetary conditions but rather with a lag of one quarter. Secondly, GDP growth is ordered before Δ^2CPI allowing for a contemporaneous effect of GDP growth on inflation growth (Mojon & Peersman, 2001). Thirdly, the financial variable is allowed to directly react to changes in the real variables, which can be understood by the speed with which financial markets react to economic news. Lastly, as in Kremer (2016), the monetary policy tool is allowed to react instantaneously to both the economic and the financial variables. Using quantile regressions different coefficients $\alpha_i^{\theta_i}$ are obtained for different quantiles θ_i of the dependent variable $\tilde{Y}_{i,t+1}$, where $i = 1, 2, 3, 4$.

$$\tilde{Y}_{1,t+1} = \omega_1^{\theta_1} + \alpha_{11}^{\theta_1}\tilde{Y}_{1,t} + \alpha_{12}^{\theta_1}\tilde{Y}_{2,t} + \alpha_{13}^{\theta_1}\tilde{Y}_{3,t} + \alpha_{14}^{\theta_1}\tilde{Y}_{4,t} + \epsilon_{1,t+1}^{\theta_1} \tag{4}$$

$$\tilde{Y}_{2,t+1} = \omega_2^{\theta_2} + \alpha_{021}^{\theta_2}\tilde{Y}_{1,t+1} + \alpha_{21}^{\theta_2}\tilde{Y}_{1,t} + \alpha_{22}^{\theta_2}\tilde{Y}_{2,t} + \alpha_{23}^{\theta_2}\tilde{Y}_{3,t} + \alpha_{24}^{\theta_2}\tilde{Y}_{4,t} + \epsilon_{2,t+1}^{\theta_2} \tag{5}$$

$$\tilde{Y}_{3,t+1} = \omega_3^{\theta_3} + \alpha_{031}^{\theta_3}\tilde{Y}_{1,t+1} + \alpha_{032}^{\theta_3}\tilde{Y}_{2,t+1} + \alpha_{31}^{\theta_3}\tilde{Y}_{1,t} + \alpha_{32}^{\theta_3}\tilde{Y}_{2,t} + \alpha_{33}^{\theta_3}\tilde{Y}_{3,t} + \alpha_{34}^{\theta_3}\tilde{Y}_{4,t} + \epsilon_{3,t+1}^{\theta_3} \tag{6}$$

$$\tilde{Y}_{4,t+1} = \omega_4^{\theta_4} + \alpha_{041}^{\theta_4}\tilde{Y}_{1,t+1} + \alpha_{042}^{\theta_4}\tilde{Y}_{2,t+1} + \alpha_{043}^{\theta_4}\tilde{Y}_{3,t+1} + \alpha_{41}^{\theta_4}\tilde{Y}_{1,t} + \alpha_{42}^{\theta_4}\tilde{Y}_{2,t} + \alpha_{43}^{\theta_4}\tilde{Y}_{3,t} + \alpha_{44}^{\theta_4}\tilde{Y}_{4,t} + \epsilon_{4,t+1}^{\theta_4} \quad (7)$$

This model formulation encompasses a large range of QVARs as every variable $\tilde{Y}_{i,t+1}$ is allowed to be affected at different quantiles θ_i and therefore by different coefficients $\alpha_i^{\theta_i}$. For all considered quantiles the model is estimated by using equation-by-equation quantile regressions. The model formulation allows to answer a wide range of interesting questions: For instance from a monetary policy model point of view the effect of an increase in the median of ΔFFR ($\theta_4 = 0.5$) on lower quantiles of GDP growth ($\theta_1 = 0.2$) under adverse financial conditions ($\theta_3 = 0.8$), regular conditions ($\theta_3 = 0.5$) and beneficial conditions ($\theta_3 = 0.2$) can be investigated. From a stress testing point of view, the formulation can be used to model the adverse effect of a negative shock to financial conditions on the growth of GDP under various monetary policy regimes. This highlights the goal of this paper to combine recent literature on macro-financial links with monetary policy models.

When using the QVAR as defined in the system of equations (4-7) for forecasting purposes or for constructing impulse response functions, a choice for θ has to be made for every dependent variable independently ($\theta = [\theta_1, \theta_2, \theta_3, \theta_4]$). This choice depends on the question at hand and should either give insight into the relationship between variables at a certain part of the distribution (impulse response functions) or should be a reasonable image of the truth (forecasting). The quantiles considered for the individual variables do not need to be the same. By selecting a certain quantile θ_i for every dependent variable $\tilde{Y}_{i,t+1}$ the corresponding coefficients $\alpha_i^{\theta_i}$ are determined and allow to model the effect of the remaining variables on the dependent variable as if the variable was at the selected quantile. The variables, thus, are not forced to be at a certain quantile in forecasting or impulse response analysis, but rather are related to the remaining variables as if they were at a given quantile. To also make the independent choice of quantiles explicit in the mathematical notation, I rewrite the general model for a QVAR with p lags and k variables in the following form:

$$\tilde{Y}_{t+1} = A_0(\theta) + \sum_{j=0}^{p} A_{j+1}(\theta)\tilde{Y}_{t+1-j} + \epsilon_{t+1}(\theta) \quad (8)$$

where

$$A_0(\theta) = \begin{bmatrix} \alpha_1(\theta_1) \\ \alpha_2(\theta_2) \\ ... \\ \alpha_k(\theta_k) \end{bmatrix}, A_{i+1}(\theta) = \begin{bmatrix} \alpha_{j,11}(\theta_1)...\alpha_{j,1k}(\theta_1) \\ \alpha_{j,21}(\theta_2)...\alpha_{j,2k}(\theta_2) \\ ... \\ \alpha_{j,k1}(\theta_k)...\alpha_{j,kk}(\theta_k) \end{bmatrix}, \epsilon_{t+1}(\theta) = \begin{bmatrix} \epsilon_{1,t+1}(\theta_1) \\ \epsilon_{2,t+1}(\theta_2) \\ ... \\ \epsilon_{k,t+1}(\theta_k) \end{bmatrix} \quad (9)$$

Essentially, this can be simplified to the following equation when using one lag:

$$\tilde{Y}_{t+1} = A_0(\theta) + A_1(\theta)\tilde{Y}_{t+1} + A_2(\theta)\tilde{Y}_t + \epsilon_{t+1}(\theta) \tag{10}$$

The coefficient $\alpha_{j,in}(\theta_i)$ gives the effect of the j'th lag of variable n on the θ_i - quantile of the conditional distribution of variable $Y_{i,t+1}$ (Linnemann & Winkler, 2016). An explicit example of the matrix formulation we get for a selected vector of quantiles $\theta = [\theta_1, \theta_2, \theta_3, \theta_4]$ is given in the following:

$$\begin{bmatrix} \tilde{Y}_{1,t+1} \\ \tilde{Y}_{2,t+1} \\ \tilde{Y}_{3,t+1} \\ \tilde{Y}_{4,t+1} \end{bmatrix} = \begin{bmatrix} \omega_1^{\theta_1} \\ \omega_2^{\theta_2} \\ \omega_3^{\theta_3} \\ \omega_4^{\theta_4} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 \\ \alpha_{021}^{\theta_2} & 0 & 0 & 0 \\ \alpha_{031}^{\theta_3} & \alpha_{032}^{\theta_3} & 0 & 0 \\ \alpha_{041}^{\theta_4} & \alpha_{042}^{\theta_4} & \alpha_{043}^{\theta_4} & 0 \end{bmatrix} \begin{bmatrix} \tilde{Y}_{1,t+1} \\ \tilde{Y}_{2,t+1} \\ \tilde{Y}_{3,t+1} \\ \tilde{Y}_{4,t+1} \end{bmatrix} + \begin{bmatrix} \alpha_{11}^{\theta_1} & \alpha_{12}^{\theta_1} & \alpha_{13}^{\theta_1} & \alpha_{14}^{\theta_1} \\ \alpha_{21}^{\theta_2} & \alpha_{22}^{\theta_2} & \alpha_{23}^{\theta_2} & \alpha_{24}^{\theta_2} \\ \alpha_{31}^{\theta_3} & \alpha_{32}^{\theta_3} & \alpha_{33}^{\theta_3} & \alpha_{34}^{\theta_3} \\ \alpha_{41}^{\theta_4} & \alpha_{42}^{\theta_4} & \alpha_{43}^{\theta_4} & \alpha_{44}^{\theta_4} \end{bmatrix} \begin{bmatrix} \tilde{Y}_{1,t} \\ \tilde{Y}_{2,t} \\ \tilde{Y}_{3,t} \\ \tilde{Y}_{4,t} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t+1}^{\theta_1} \\ \epsilon_{2,t+1}^{\theta_2} \\ \epsilon_{3,t+1}^{\theta_3} \\ \epsilon_{4,t+1}^{\theta_4} \end{bmatrix}$$

Designing the matrix A_1 for a set of quantiles in the given lower triangular fashion with 0 entries on the main diagonal is equivalent to a Cholesky decomposition of the residual variance-covariance matrix in standard reduced form VARs (Lütkepohl, (2005) as described in Chavleishvili and Manganelli, (2019)). The main motivation for using a structual QVAR is the possibility to investigate the relationships between the variables at hand at different quantiles. Impulse response functions can be created from these estimates in a similar fashion as for regular structural VARs. Depending on the question to answer, a choice for $\theta = [\theta_1, \theta_2, \theta_3, \theta_4]$ has to be made. Once this choice is made, the matrices described in equation (9) can be constructed for the $k = 4$ variables. The structural system can be rewritten as regular QVAR in the following form:

$$B(\theta)\tilde{Y}_{t+1} = A_0(\theta) + A_2(\theta)\tilde{Y}_t + \epsilon_{t+1}(\theta) \tag{11}$$

$$\tilde{Y}_{t+1} = B(\theta)^{-1}A_0(\theta) + B(\theta)^{-1}A_2(\theta)\tilde{Y}_t + B(\theta)^{-1}\epsilon_{t+1}(\theta) \tag{12}$$

$$\tilde{Y}_{t+1} = A_0^*(\theta) + A_2^*(\theta)\tilde{Y}_t + u_{t+1}(\theta) \tag{13}$$

where $B(\theta) = I_n - A_1(\theta)$, $A_0^*(\theta) = B(\theta)^{-1}A_0(\theta)$, $A_2^*(\theta) = B(\theta)^{-1}A_2(\theta)$ and $u_{t+1}(\theta) = B(\theta)^{-1}\epsilon_{t+1}(\theta)$. This formulation allows for constructing stress testing scenarios or for forecasting exercises. Impulse response functions, which are of high interest for this paper's research question, trace the development in the selected quantiles of the variables after an initial exogenous shock in the error term of one of the variables. In this application impulse response analysis is used to trace the development of quantile specific GDP growth in the presence of an initial unit shock to financial stress and the change in the monetary policy rate. The impulse response functions are obtained in the following way:

$$\frac{\delta E_t(\tilde{Y}_{\theta,t+H})}{\delta \epsilon_t} = (B(\theta)^{-1} A_2(\theta))^H B(\theta)^{-1} \;\; for\, H \geq 1 \tag{14}$$

The derivation of the formulation of the impulse response function can be found in the Appendix. From this 4-by-4 matrix, the column belonging to the shocked variable has to be selected. The impulse response functions obtained in equation 14 above constitute the main result of the paper.

5.2 Results - Dynamic QVAR

5.2.1 Impulse Response Analysis

The results presented in the following section depict the response of GDP growth to a unitary shock in NFCI and ΔFFR, corresponding closely to one standard deviation for both variables (NFCI: SD = 0.99, ΔFFR: SD = 0.95). Whereas in previous applications (e.g. Linnemann and Winkler (2016), Schüler (2014)) only the shocked variable and the dependent variable were considered at different quantiles, this paper's research question requires to further consider the control variable at various quantiles. Only then, the first part of the research question, whether monetary policy is able to absorb part of the negative spill-over effects of financial stress, can be answered. This new feature makes the QVAR the appropriate choice for the problem at hand and underlines the flexibility of the model to answer different kinds of research questions.

By analysing the path of GDP growth after shocks to financial stress under various monetary policy settings, insights into the effectiveness of these measures in times of financial instability can be obtained. Figure 5 shows this development of GDP growth at different quantiles after a shock to financial stress. GDP growth and the NFCI are depicted below for 20 quarters following the initial shock. The impulse response functions are calculated as shown in equation 14 in the previous section.

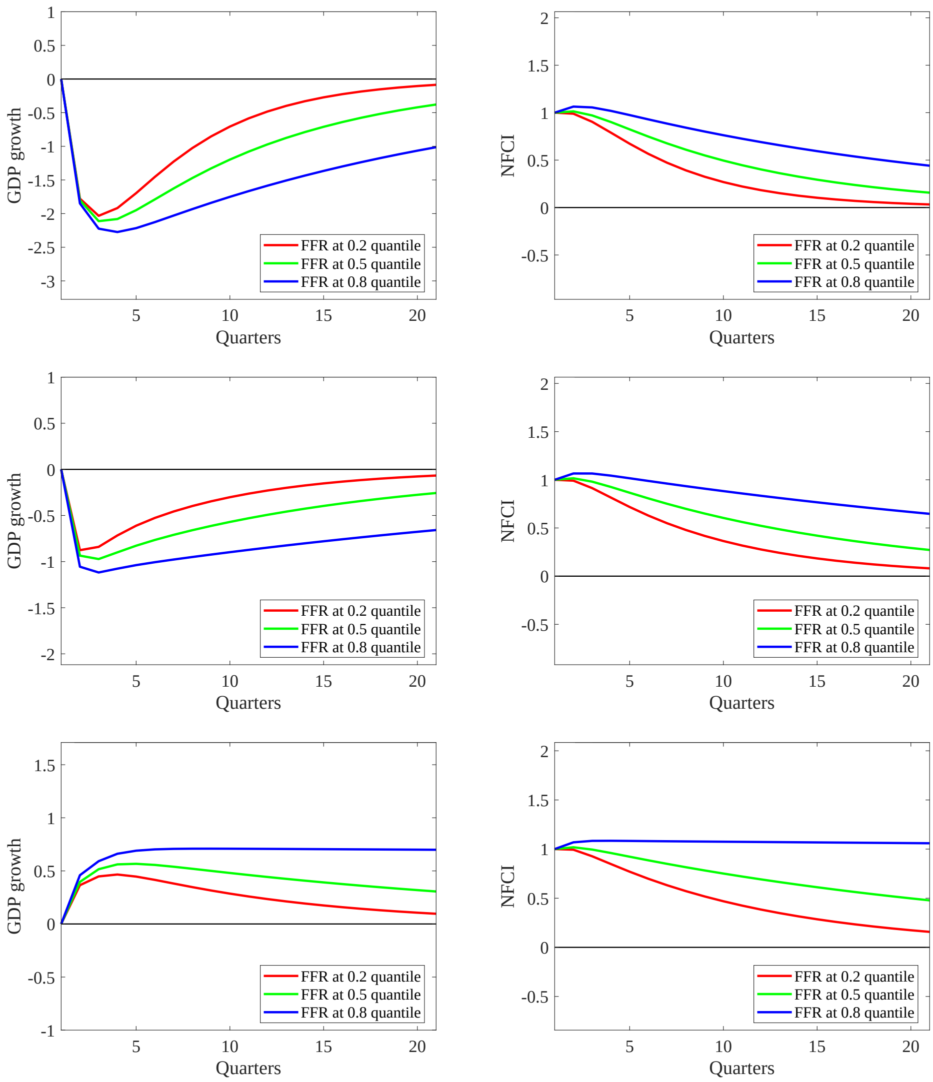

Figure 5: Development of GDP growth in percentage points for the 20th (top), 50th (center) and 80th (bottom) quantile after an initial unitary shock to NFCI (NFCI and Δ^2CPI affected at the median).

The results indicate a clear nonlinear response of GDP growth to a unitary financial shock. GDP initially declines by around 2% for the lowest quantile of GDP growth, by around 1% at the median and increases by an initial 0.5% for the highest quantile (Figure 5). This is in line with the previous analysis, which suggested a particularly pronounced risk in the lower parts of the distribution of GDP growth. Moreover, the monetary policy regime seems to be able to partly counter the effects of financial stress. Especially in the lower parts of the distribution of GDP we see that when changes in FFR in percentage points are lowest (e.g. a reduction of the rate), the negative effect can be substantially reduced and a quicker recovery follows. This path is shown by the red line. The peak negative effect of a shock to NFCI on GDP growth materializes within the first year for low and median quantiles of growth. For high levels of GDP growth on the contrary, tightening of monetary policy seems desirable in the presence of financial shocks. These results are in line with standard economic theory and support the view that monetary policy is effective in positively influencing the feedback loop.

The bottom right figure suggests a persistent shock of NFCI at the 80^{th} quantile of FFR and GDP growth. Especially the higher quantiles of the variables considered are on the verge to being nonstationary. As long as an economic interpretation is ensured, first differences as chosen in this paper can reduce this problem but can not rule out the possibility of nonstationarity completely. The impulse response functions indicate that the interactions between monetary policy, financial stress and GDP growth are nonlinear along several dimensions. Not only do the stress effects vary depending on the state of GDP growth, but, moreover, they also vary depending on the level of change in the FFR. This highlights that threshold VARs, which are often used in monetary policy evaluation, miss important features of the interaction.

This model is, besides the stress testing perspective taken in the previous analysis, also related to classic monetary policy models. To answer the second part of the research question, the efficiency of monetary policy tools under different economic and financial stress scenarios is considered. The design of the model allows to trace the effect of a shock to the change in FFR on different quantiles of GDP growth under several financial stress levels. As shocks to ΔFFR are non-stationary at the highest quantiles of financial stress, the 70^{th} quantile of financial stress is considered the high stress scenario in the following results.

The results depicted in Figure 6 show that a shock in the first differenced FFR has comparable effects on GDP growth across quantiles. At all quantiles, GDP deteriorates for the consecutive quarters. This contraction is largest for the lowest quantile of GDP growth and decreases with the considered quantile. The lower the level of financial stress, the faster the recovery of GDP growth for all considered quantiles. Under high levels of stress an increase in ΔFFR leads to a permanent negative GDP growth. These results support the view proposed by Mishkin (2009), suggesting that monetary policy might even be more effective during times of financial stress, and oppose the findings of Saldías (2017). Similarly to Saldías (2017), the results suggest a stronger effect of monetary policy shocks on financial conditions when the financial system is already in a stress situation (Appendix, Figure 18).

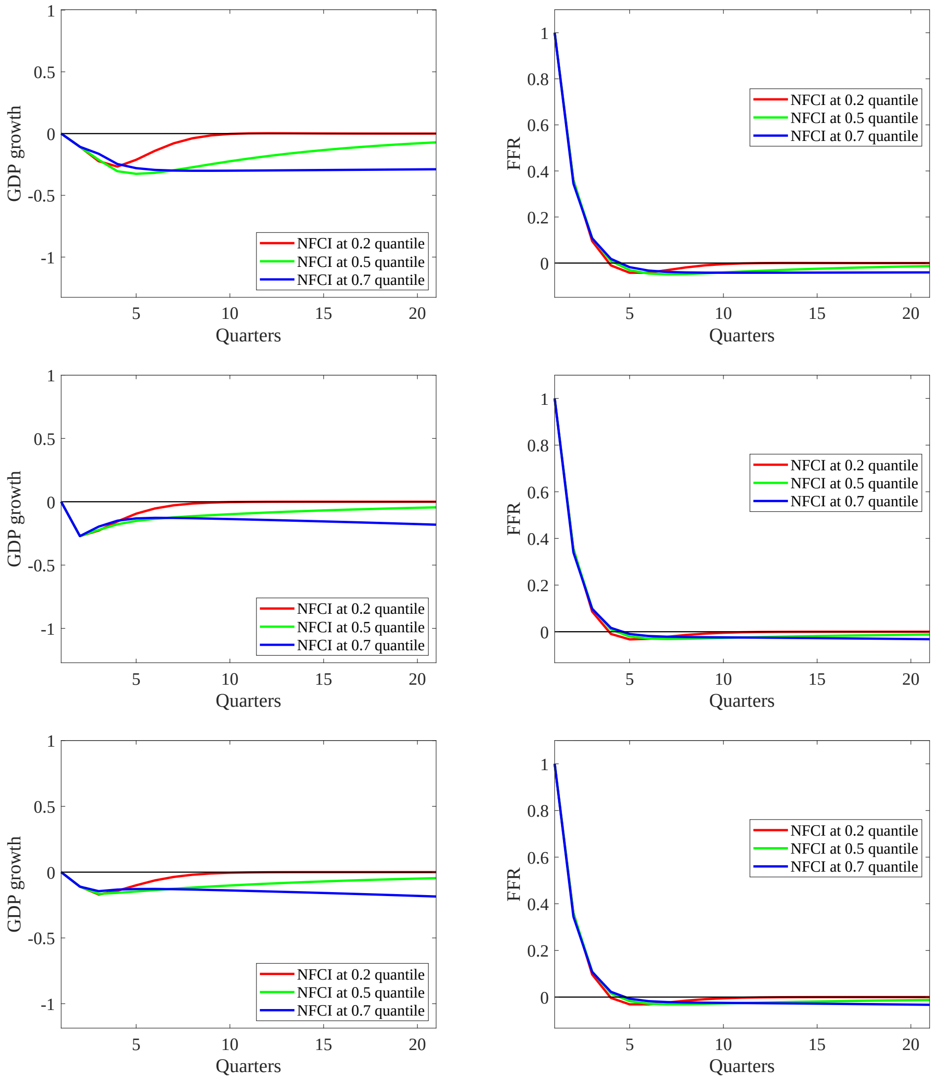

Figure 6: Development of GDP growth in percentage points for the 20th (top), 50th (center) and 70th (bottom) quantile after an initial shock to ΔFFR (NFCI and Δ^2CPI affected at the median).

In summary, the previous analysis shows that a loose monetary policy reduces the transmission of financial stress on the real economy, indicates that monetary policy is more efficient under high financial and economic stress and suggests an especially strong role for expansionary monetary policy in addressing tight financial conditions once stress materializes. The remaining impulse responses for the Δ^2CPI and the ΔFFR (in case of a shock to NFCI) and the NFCI (in case of a shock to ΔFFR) are given in the Appendix.

The two previously shown impulse response functions for the median of GDP growth when affected by a shock in NFCI (left) and ΔFFR (right) are depicted in Figure 7 below (all other variables are also affected at the median). In this figure, bootstrapped 90% confidence intervals are added, which indicate that under both scenarios, the response of GDP growth is significant for many of the following quarters.

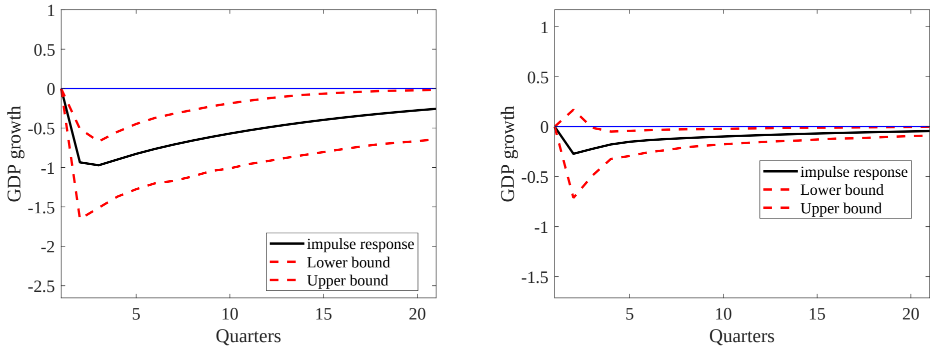

Figure 7: Development of GDP growth for the median in percentage points after an initial shock to NFCI (left) and ΔFFR (right) (NFCI, Δ^2CPI and ΔFFR also affected at the median). The impulse response is depicted with a bootstrapped 90% confidence interval.

The obtained impulse response functions are robust to different ordering and sample choices. The main uncertainty in academia is whether the monetary policy measure should be determined before or after the financial variables. When interchanging the position of the two variables, the main results remain unchanged, but impulse response functions become more spiky. The graphs corresponding to Figures 5 and 6 in the analysis provided above are depicted in the Appendix in Figures 19 and 20 for the changed order. The path of GDP growth remains similar for the considered shocks when the Federal Reserve is not allowed to contemporaneously respond to financial stress, whereas financial stress is directly affected by the change in FFR.

Moreover, the results are not driven by the choice of using a shadow rate for the ZLB period. When restricting the sample to the pre-ZLB subperiod from 1973 Q2 to 2008 Q4, similar results as for the complete dataset are obtained. The graphs corresponding to Figures 5 and 6 in the previous analysis are shown in Figures 21 and 22 in the Appendix for the reduced sample.

5.2.2 Forecasting and Scenario Construction

The model presented has a range of applications besides impulse response functions. It can, for instance, be used for forecasting purposes. Depending on the expected quantile of each of the variables, different scenarios can be forecasted. Scenario based forecasting has increased in popularity in business as well as economic research applications. A simple calibration of the model provides insights into both favourable as well as unfavourable outcomes of economic developments. Especially in times of high uncertainty, scenario-based forecasting is necessary to obtain an overview over possible future paths of the variable of interest. As a performance check of the designed dynamic model, one step ahead forecasts for GDP growth are constructed using the estimation results over the complete sample. The following forecasts and scenarios are constructed using equation (13).

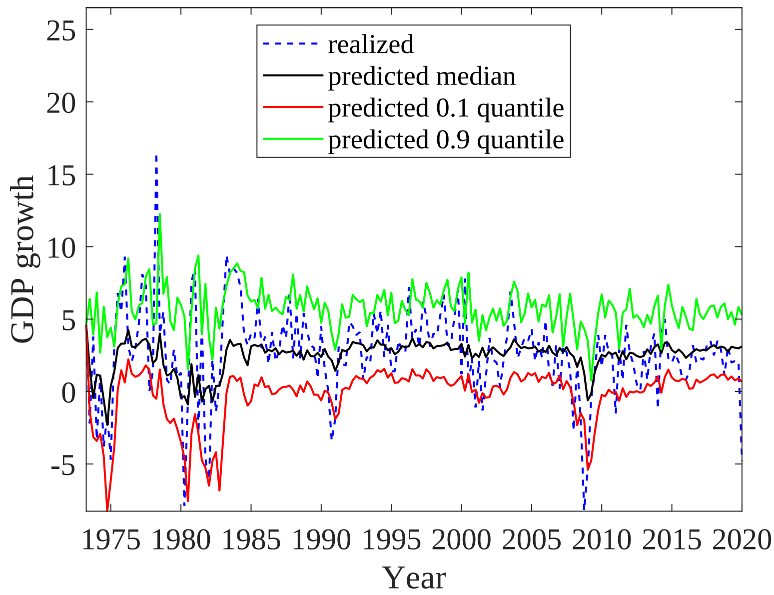

Figure 8: One step ahead forecasts of GDP growth for the 10th, 50th and 90th quantile of GDP growth plotted together with actual GDP growth. All other variables are estimated at the median.

Figure 8 shows that point forecasts such as the ones provided by the median might yield a poor forecasting performance in times of high uncertainty. Forecasting the complete distribution on the other hand gives a good indication of the bandwidth of possible future values. As expected, actual GDP growth lies outside the predicted distribution only in a small number of cases. This underlines the power of a quantile analysis compared to traditional linear models. Besides, the multivariate dynamic approach is significantly more flexible than the static method presented by Adrian et al. (2019). Firstly, the forecasts can be computed for different time horizons and are not limited to direct regression techniques. Secondly, the inclusion of several endogenous variables allows to construct countless scenarios of a possible future growth development. The results indicate that economic recessions caused by variables considered endogenously in the model such as financial stress can be more accurately forecasted in real time than recessions caused by exogenous factors. This becomes visible when comparing the instantaneous reaction of the model in the financial crisis of 2008 to its lagged reaction to today's recession caused by an exogenous virus. While in the figure presented above only GDP growth was considered at different quantiles, forecasts could theoretically be calibrated for all quantiles of all included variables. This freedom to choose quantiles requires a good economic understanding in order to construct meaningful forecasts based on reasonable future realisations.

As a concluding illustrative exercise, the presented model is used to forecast different scenarios of GDP development after the first quarter of 2020. The negative economic effects of the COVID-19 pandemic were already partly visible at that time, however, not to the extent to which it will impact the results of the second quarter. The constructed scenarios document both the strengths as well as the deficiencies of using the proposed method for forecasting purposes. An advantage is the wide range of scenarios that can be implemented leading to different paths of future GDP growth. Concerning the drawbacks, exogenous shocks such as a possible second wave of the Corona-crisis can not be modeled. In times where the economic behaviour deviates to a large extent from regular behaviour, forecasting based on past relationships will always be inadequate.

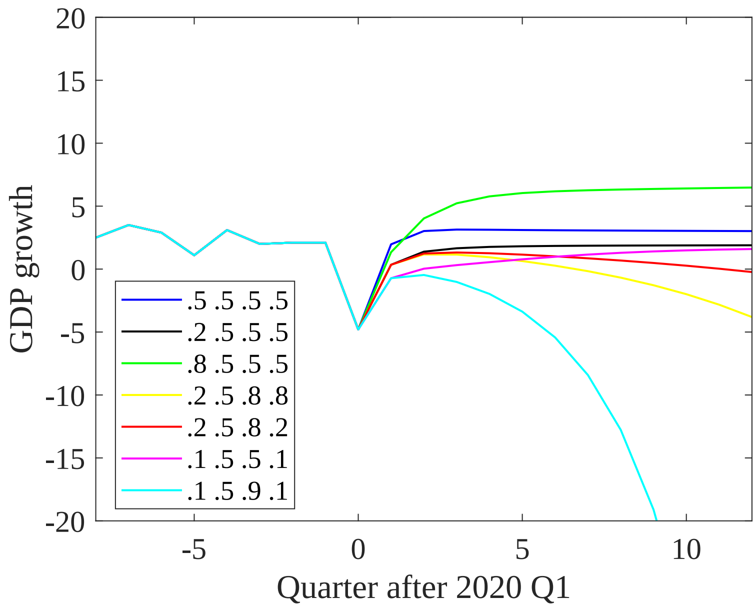

Figure 9: Scenarios constructed following the start of the COVID-19 pandemic. The labels correspond to the quantiles considered in the QVAR for GDP growth, ΔCPI, NFCI and ΔFFR respectively.

All scenarios constructed using the presented QVAR with different variations of quantiles predict an initial recovery of the growth rate and interpret the downward spike as a one-time occurrence (Figure 9). The most striking development is depicted by the light blue coloured path. However, for this path financial stress is related to the other variables as if it was at the 90 percent quantile for all quarters, which is a highly unrealistic scenario. Moreover, a less precise estimation at the tails of the distribution might contribute to the observed path. This highlights the importance to create reasonable scenarios. The base case scenario, which would similarly be obtained by a linear model, is the quick convergence to a "natural" growth rate as depicted by the dark blue line. Maybe the most realistic path in the short-term could be the one shown in magenta, which relies on the assumptions of GDP growth being for all quarters affected at low quantiles, the ΔFFR being low or negative and both other variables remain at their median levels. Many more scenarios can be investigated by the chosen design. This flexibility is especially useful for stress testing exercises, where the vulnerability of the future path of GDP growth depending on developments in the endogenous variables is measured. Moreover, the approach also allows for changing quantiles over time, which could increase the reasonability of the considered design. This option is neglected above for conciseness reasons. The goal of this illustration was not to argue for a best calibration of the model for forecasting, but rather to illustrate the features of scenario based forecasting with QVARs.

The previous analysis suggested that monetary policy can successfully contribute towards reducing the transmission of financial stress into economic stress. As Aastveit et al. (2013) have shown that monetary policy is less effective under high economic uncertainty, the risks to growth might be more accurately forecasted by including a measure for policy uncertainty. This will be investigated in the remaining part of the paper.

6 Monetary Policy Uncertainty and Downward risk to GDP

Beyond the role of monetary policy tools in overcoming scenarios of financial stress, monetary policy might also contribute indirectly to the downward risk to GDP growth. High public uncertainty about the future path of monetary policy might induce worries about inflation and interest rates, leading to delayed investments. These missing investments would directly translate into lower future GDP growth. By examining the properties of the distribution of GDP growth conditional on both monetary policy uncertainty, as measured by the newspaper based index by Husted et al. (2019), and financial stress, possible gains of including both variables when measuring Growth at Risk are evaluated. Especially after regulatory changes in the aftermath of the financial crises, economic downturns might not be accompanied by similarly high financial stress. Modelling downward risk to growth only based on previous financial and economic conditions might miss other possible factors leading to economic downturns. Depicted in Figure 10 are the coefficients obtained when including MPU, NFCI and current GDP growth. The effect of MPU as depicted in the top part exhibits some nonlinearity on the edge to being significant in the short run (left) and being slightly significant in the long run (right). At all quantiles MPU has a negative effect on GDP growth in the next quarter and for most quantiles also over the next year. Only at the highest quantiles, the long term effect seems to be somewhat positive.

The coefficients of NFCI are comparable to the previous analysis but are slightly more negative, suggesting an even higher downside risk to GDP, when correcting for the uncertainty in the monetary response. These coefficients and the conditional distribution of GDP growth remain similar when additionally including ΔFFR itself.

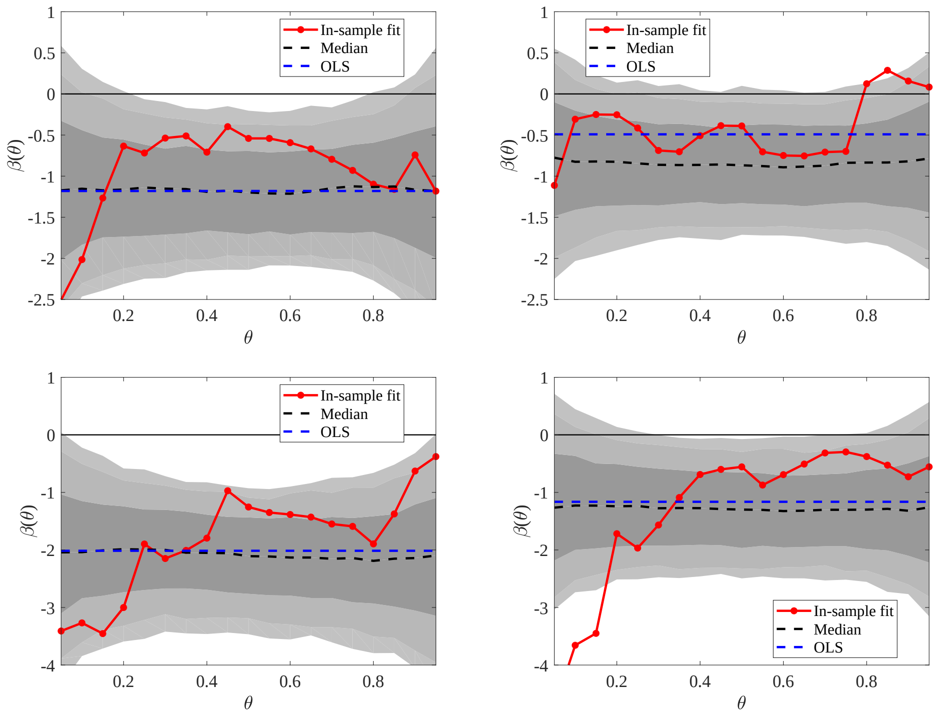

Figure 10: Coefficients of the quantile regression of GDP growth one quarter ahead (left) and one year ahead (right) on NFCI (bottom), MPU (top) and current growth together with a constant. Coefficients are plotted together with the OLS estimate and bootstrapped quantiles obtained by a fitted linear VAR.

6.1 Interpretational in-Sample Evaluation

The main goal of this part of the paper was to visualize the gains of including monetary policy uncertainty into the set of conditional variables for GDP growth. Therefore, the properties of the obtained distribution are compared in the following part.

The obtained distributions are very similar to a large extent (Figure 11). Both distributions exhibit larger volatility at lower quantiles. The main difference is that the monetary uncertainty index seems to additionally capture possible downward risks, which might be completely missed by financial stress. This becomes visible for the last few observations in the considered period, including the first quarter of the Corona crisis. The distribution based on only financial stress predicts no downward risk whatsoever, whereas the conditional distribution augmented by the MPU index clearly predicts the possibility of an economic downturn. It therefore seems to allow to predict risks, which are discussed in public debate but which do not directly lead to tight conditions on credit or money markets. While downward risks due to financial crises, as in 2008, can be modelled by only financial stress, economic downturns not preceded by tight financial conditions might be missed when neglecting monetary policy uncertainty.

The fact that the initial model is not able to capture the Growth at Risk in the first quarter of 2020, might be due to the quarterly perspective taken in this paper. When investigating the weekly NFCI data, increasing financial stress becomes visible, however, this hardly translates into a measureable increase when averaged over the complete first quarter of 2020. Hence, the model as presented by Adrian et al. underestimated the growth at risk significantly. This suggests that a quarterly perspective might be inappropriate for forecasting large crises, which are often unforeseeable. The fact that the model including MPU captures the downward risk to a certain extent is puzzling. The distribution of GDP growth in 2020 Q1 is based on monetary uncertainty and financial stress in 2019 Q4. In this quarter indeed the MPU spiked, but most likely for reasons unrelated to the COVID-19 outbreak, which only received media attention at the end of December 2019 (a graph of MPU and GDP growth is provided in the Appendix). Most likely, the increased risk was indicated by uncertainty related to the response of the Federal Reserve to the cash crunch in September 2019. Even though the presented graphs suggest otherwise, the accurate forecasting of the option of a decline in GDP due to the COVID-19 crisis might, thus, be just coincidental.

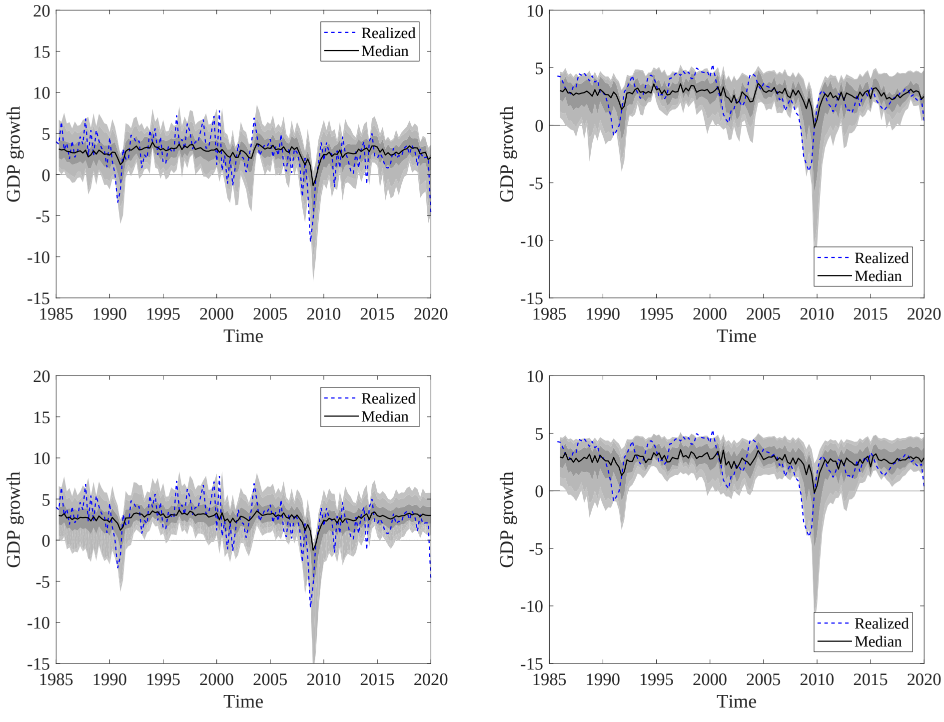

Figure 11: Distribution of GDP growth conditional on NFCI, current GDP growth and MPU (top) and conditional on only NFCI and current GDP growth (bottom) for one quarter ahead (left) and one year ahead (right). Depicted are the conditional median and the 5, 25, 75, and 95 percent quantiles as well as realized GDP growth.

6.2 Empirical out-of-Sample Evaluation

A first empirical investigation into the one-quarter ahead predictive ability of both specifications is given in the following. The sample is divided into an estimation sample (1985 Q1 to 1999

Q4) and a forecasting sample (2000 Q1 to 2020 Q1). More specifically, an expanding window forecasting procedure is implemented, such that all previous realisations are used for a forecast (starting from the first quarter of 2000). This division ensures a sufficient sample size for the first forecast. However, the division also highlights the main drawback of including MPU, namely, its availability only from 1985 Q1 onwards. For comparison reasons we perform the same exercise with a limited sample starting from 1985 Q1 for the initial model without MPU. Based on these forecasts, predictive scores are calculated as the assigned density to the ex-post actual realisation (Adrian et al., 2019). Higher predictive scores indicate better forecasting performance, as a higher relative likelihood is given to the actual outcome.

In order to be able to compute these measures, a skewed t-distribution, which encompasses many other distributions, has to be fitted to the empirical quantile distribution. The skewed t-distribution proposed by Azzalini and Capitanio (2003) and used for measuring expected shortfall in Adrian et al. (2019) will be applied for this purpose. The distribution takes the following form:

$$f(y;\mu;\sigma;\alpha;\nu) = \frac{2}{\sigma}t(\frac{y-\mu}{\sigma};\nu)T(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{\nu+1}{\nu+(\frac{y-\mu}{\sigma})^2}};\nu+1) \tag{15}$$

For every quarter, the four parameters $[\mu_t;\sigma_t;\alpha_t;\nu_t]$ are fitted to minimize the squared distance between the quantile function provided by the quantile regression and the quantile function implied by the skewed t-distribution. The 5, 25, 75 and 95 percent quantiles are used for this purpose.

$$[\mu_{t+h};\sigma_{t+h};\alpha_{t+h};\nu_{t+h}] = arg\ min_{\mu,\sigma,\alpha,\nu}\sum_{\theta}(\hat{Q}_{y_{t+h}|x_t}(\theta|x_t) - F^{-1}(\theta;\mu,\sigma,\alpha,\nu))^2 \tag{16}$$

Once the parameters are specified for each quarter, it is possible to calculate the predictive scores and the probability integral transform. More information on the interpretation of the parameters and the applicability of the skewed t-distribution are provided in Adrian et al. (2019).

The predictive scores are reported in Figure 12 below for every quarter from 2000 onwards for both models together with the scores obtained by the unconditional distribution forecast. For the considered period, the gains of either of the two conditional models over the unconditional one are limited. This can be seen from the predictive scores, which are not consistently higher for the conditional models. The main reason for this is the small sample size, which leads to less precise quantile estimations of the conditional models. In comparing the two conditional models, the better performance of the MPU augmented model in the last quarters, where estimates are most precise, becomes apparent. Whether this observation is a consistent trend can not be determined due to the sample limitations. This better forecasting performance of the MPU augmented model at the end of the sample is not limited to the first quarter of 2020, but seems to already start in 2015 and is most prominent in 2019. The mean predictive score of the augmented model is slightly higher than the one of the original model. This slightly better performance is, however, not significant as shown by a Diebold-Mariano test for the assumption of equal predictive accuracy (Appendix, Table 3). The same pattern is also visible for the one-year ahead distribution forecasts as shown in Table 3 and Figure 15 in the Appendix.

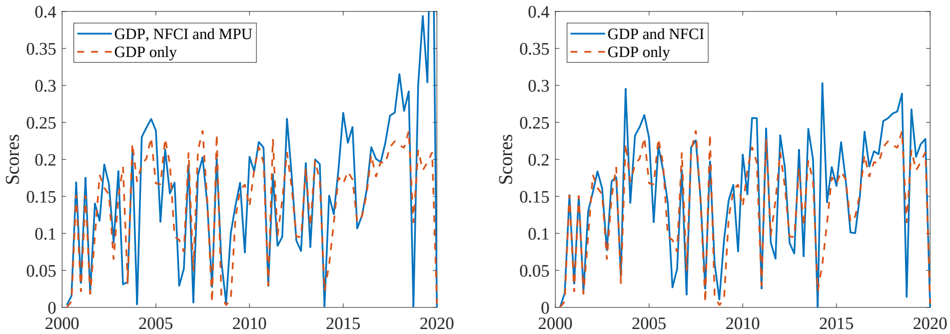

Figure 12: Predictive scores over forecasting period of the augmented model including monetary policy uncertainty (left) and of the initial model (right) for one quarter ahead distribution forecasts.

A slight preference towards the MPU augmented model also becomes apparent by the probability integral transform (PIT) method.[2] This method measures the percentage of realisations that is below a certain quantile. Considering the cumulative distribution of PITs, a model is better calibrated the closer the cumulative distribution is to the 45-degree line, suggesting that the fraction of outcomes below a certain quantile corresponds to the theoretical counterpart. The differences, however, are marginal, as both specifications cross the confidence interval for some observations (Figure 13). Besides the interpretational evaluation of the augmented model, the empirical evaluation also does not allow to draw a clear conclusion whether or not the MPU index improves forecasts of the distribution of GDP growth. The main drawback of including the MPU is the reduced sample size, which is not compensated by a significantly better estimation of downward risk.

[2]The PITs are calculated using the modified version of Rossi and Sekhposyan (2019) by Adrian et al. (2019)

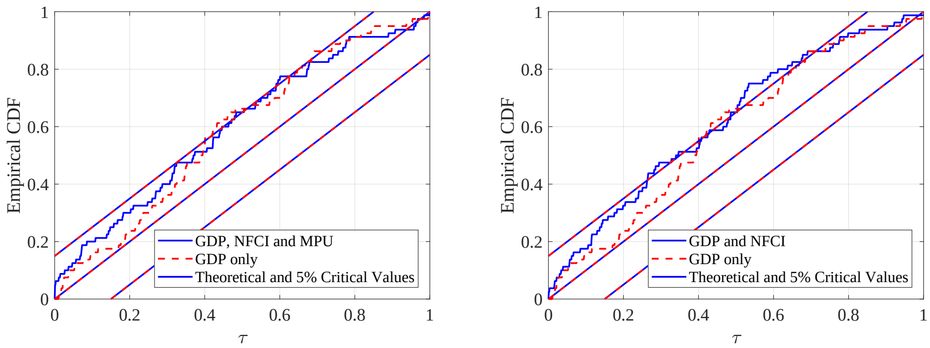

Figure 13: Empirical cumulative distribution of the Probability Integral Transform of the augmented model including monetary policy uncertainty (left) and of the initial model (right) for one quarter ahead distribution forecasts. Critical values computed as in Rossi and Sekhposyan (2019).

7 Conclusion

Adrian et al. (2019) established a pronounced risk to GDP growth due to financial stress. As recessions lead to unemployment and a decrease in the overall welfare of a society the goal of this paper was to investigate the power of one of the available tools to respond to this risk. This work provides a humble contribution towards the evaluation of the effectiveness of monetary policy under different scenarios of financial and economic stress.

The goal of this paper, as formulated in the research question, was to investigate the role of monetary policy in absorbing shocks of financial stress and to evaluate the efficiency of monetary policy under different levels of economic and financial stress. The impulse response functions obtained by a multivariate QVAR showed that monetary policy can absorb part of the negative effect a shock in NFCI has on GDP growth. This observation also holds for the lowest quantiles of GDP growth, suggesting that monetary policy is effective in reducing Growth at Risk in financial crisis times. Furthermore, monetary policy measures are especially effective for low quantiles of GDP growth and in high stress scenarios. These results contradict the findings of Saldías (2017) and the view expressed by Krugman (2008), but support Mishkin's (2009) claim of even more efficient monetary policy due to the financial accelerator principle.

Additionally, the analysis illustrates the power and limitations of scenario based forecasting. While the bandwidth of possible outcomes can be predicted with relative high certainty, large exogenous shocks and outstanding events can not be captured appropriately. Moreover, this paper investigated the benefits of introducing public monetary policy uncertainty into the quantification of downward risk to GDP growth to capture the risks of economic crises not preceded by tight financial conditions. While some results indicate slight benefits of including MPU, no clear advice on whether or not to include this economic uncertainty measure can be given.

The obtained results have to be interpreted in light of several choices made for the analysis. Firstly, the role of monetary policy to date was investigated using the shadow rate. The applicability of using the shadow rate as a substitute for the FFR in times of the ZLB is academically disputed. Further research should thus evaluate the robustness of the results for the complete sample to different shadow rates in order to verify that the observed relationships are still present in the period after the financial crisis. Secondly, scenarios and impulse response functions are based on a deliberate choice of quantiles for all variables included. The possible combinations are vast and other potentially more realistic scenarios can be proposed. Thirdly, the identification scheme imposes several constraints on the relations between the variables. The performed robustness check can only be considered a first step towards generally validating the obtained results. As the dynamic multivariate model might be a misrepresentation of the actual data generating process, further research could evaluate the robustness of the obtained impulse response functions by applying the local projection method developed by Jordà (2005). This method does not allow to investigate the dynamics as in the previous analysis where also the (endogenous) control variables were considered at different quantiles, but could be used to verify the general nonlinearity of GDP growth responses. Lastly, the analysis presented did not answer the question whether financial stress is sufficient for modeling downward risk to growth. Further research should evaluate whether the relationship between financial stress and risk to growth changed due to new stabilizing policies in the aftermath of the financial crisis. Moreover, the presented analysis indicated that a quarterly measurement of the vulnerability of GDP growth underestimates imminent risks to growth. Therefore, a more frequent measure might be desirable.

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8 Appendix

8.1 Abbreviation Overview

Table 1: Abbreviation Overview

Abbreviation	Meaning
CPI	Consumer Price Index
FFR	Federal Funds Rate
GDP	Gross Domestic Product
GMM	General Method of Moments
MPU	Monetary Policy Uncertainty
NFCI	National Financial Conditions Index
OLS	Ordinary Least Squares
(Q)VAR	(Quantile) Vector Autoregression
ZLB	Zero Lower Bound

Notes: This table summarizes and clarifies the abbreviations used in this paper.

8.2 Proof Impulse Response Function

The desired formulation for the impulse response function can be derived in a similar fashion as in Chavleishvili and Manganelli (2019) for the mean forecast.

$$\begin{aligned}\tilde{Y}_{\theta,t+1} &= B(\theta)^{-1}A_0(\theta) + B(\theta)^{-1}A_2(\theta)\tilde{Y}_{\theta,t} + B(\theta)^{-1}\epsilon_{t+1}(\theta)\\ &= \mu_t + B(\theta)^{-1}\epsilon_{t+1}(\theta)\end{aligned}$$

This separation into a deterministic and a shock component can be used in a repetitive manner:

$$\begin{aligned}E_{t+H}(\tilde{Y}_{\theta,t+H+1}) &= \mu_{t+H}\\ &= B(\theta)^{-1}A_0(\theta) + B(\theta)^{-1}A_2(\theta)\tilde{Y}_{\theta,t+H}\\ &= \sum_{h=0}^{H}(B(\theta)^{-1}A_2(\theta))^h B(\theta)^{-1}A_0(\theta) + (B(\theta)^{-1}A_2(\theta))^{H+1}\tilde{Y}_{\theta,t}\\ &\quad + \sum_{h=1}^{H}(B(\theta)^{-1}A_2(\theta))^{H-h+1}B(\theta)^{-1}\epsilon_{t+h}(\theta)\end{aligned}$$

Given that the expectation of future shocks is zero, the expectation of $\tilde{Y}_{\theta,t+H+1}$ conditional on time t can be written in the following way:

$$\begin{aligned}
E_t(\tilde{Y}_{\theta,t+H+1}) &= \sum_{h=0}^{H}(B(\theta)^{-1}A_2(\theta))^h B(\theta)^{-1}A_0(\theta) + (B(\theta)^{-1}A_2(\theta))^{H+1}\tilde{Y}_{\theta,t} \\
&= \sum_{h=0}^{H}(B(\theta)^{-1}A_2(\theta))^h B(\theta)^{-1}A_0(\theta) + (B(\theta)^{-1}A_2(\theta))^{H+1}(\mu_{t-1} + B(\theta)^{-1}\epsilon_t)
\end{aligned}$$

By taking the derivative the responses of the variables to unitary shocks in ϵ can be obtained.

$$\frac{\delta E_t(\tilde{Y}_{\theta,t+H+1})}{\delta \epsilon_t} = (B(\theta)^{-1}A_2(\theta))^{H+1}B(\theta)^{-1}$$

8.3 Data Overview

Table 2: Descriptive Statistics

	Time period	**Transformation**	**Average**	**SD**	**Max**	**Min**
GDP growth	1973Q1 - 2020Q1	none	2.64%	3.15%	16.50%	-8.20%
Δ^2CPI	1973Q2 - 2020Q1	first diff.	0.00	0.07	2.33	-3.99
NFCI	1973Q1 - 2020Q1	w. to q. (FRED convention)	-0.03	0.99	4.45	-0.88
ΔFFR	1973Q2 - 2020Q1	m. to q. and first diff.	-0.04	0.95	6.02	-3.99
MPU	1985Q1 - 2020Q1	scaled ($\frac{1}{100}$)	1.09	0.47	3.48	0.46

Notes: This table shows the available time period, the used transformation and a summary of the average, standard deviation, maximum and minimum values over the specific sample periods of all the used time series. According to FRED conventions, weeks belong to the quarter in which they end. The following initial series are used: A191RL1Q225SBEA (GDP growth), CPALTT01USQ657N (growth rate CPI), NFCI, FEDFUNDS, HRS_MPU_quarterly (MPU)

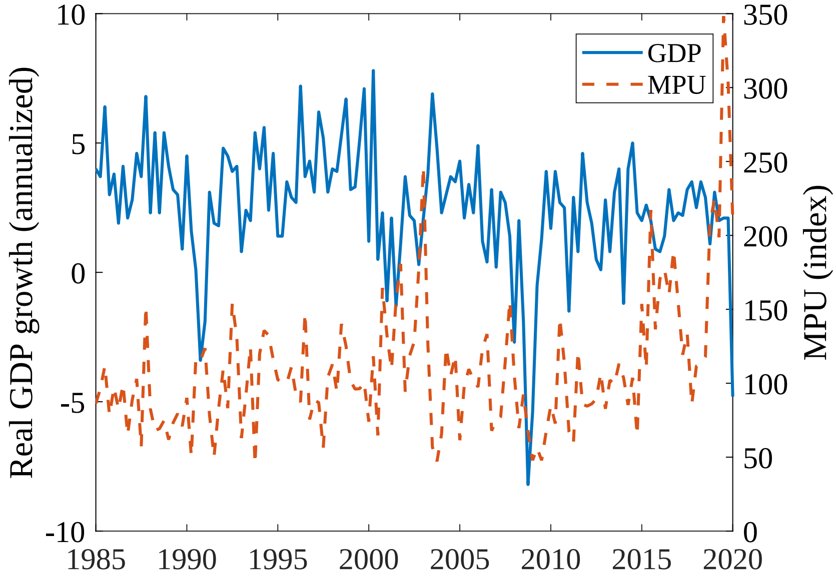

Figure 14: Development of US MPU and GDP growth.

8.4 Out-of-Sample Evaluation MPU

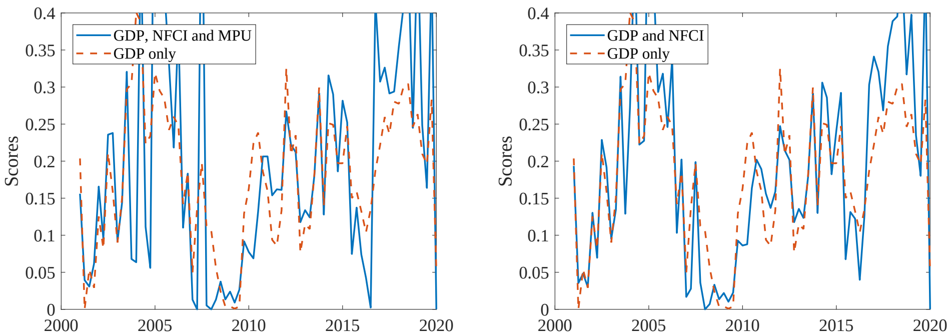

Figure 15: Predictive scores over forecasting period of the augmented model including monetary policy uncertainty (left) and of the initial model (right) for one year ahead forecasts.

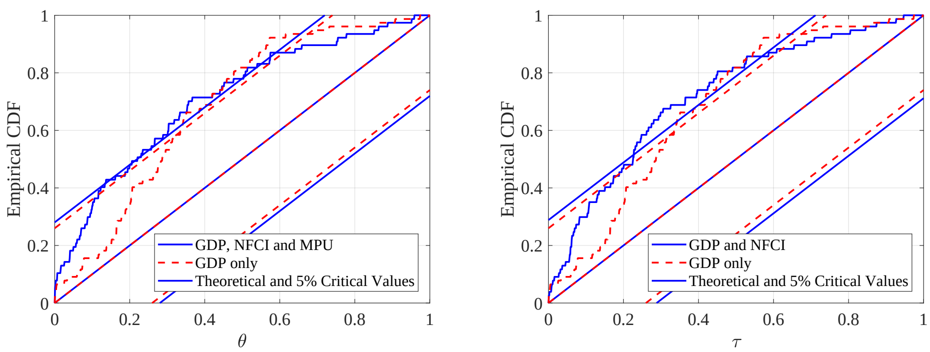

Figure 16: Empirical cumulative distribution of the Probability Integral Transform of the augmented model including monetary policy uncertainty (left) and of the initial model (right) for one year ahead predictions. Critical values computed as in Rossi and Sekhposyan (2019).

Table 3: Predictive Score DM-test

Horizon	**mean PS original model**	**mean PS MPU**	**DM-statistic**	**p-value**
H = 1	0.155	0.159	0.514	0.607
H = 4	0.193	0.197	0.482	0.630

Notes: This table shows the results of a Diebold Mariano test for the assumption of equal predictive accuracy. The original model based on GDP growth and NFCI is compared to the MPU augmented model.

8.5 Further Impulse Response Functions

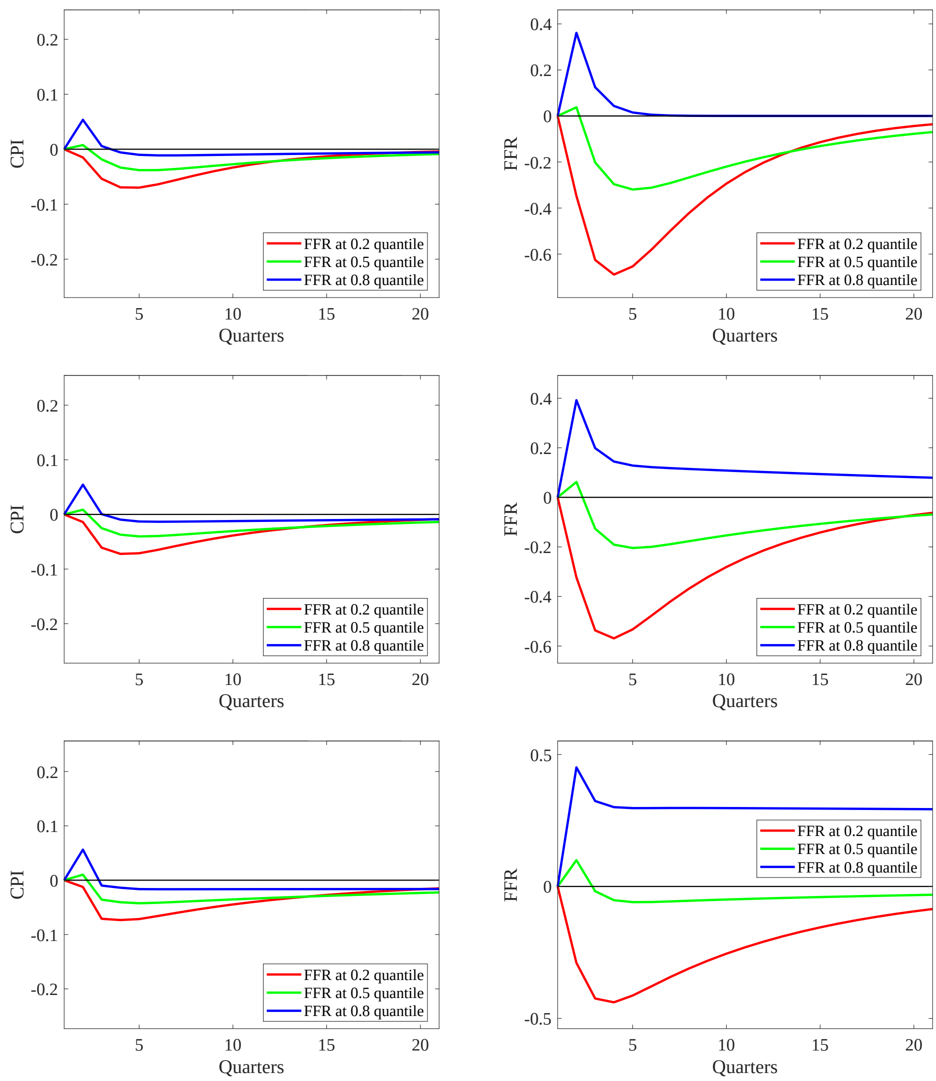

Figure 17: Development of Δ^2CPI and ΔFFR for the 20th (top), 50th (center) and 70th (bottom) quantile of GDP growth after an initial shock to NFCI (NFCI and Δ^2CPI affected at the median). This figure depicts the development of the remaining two variables not shown in Figure 5 for the different quantiles of GDP growth.

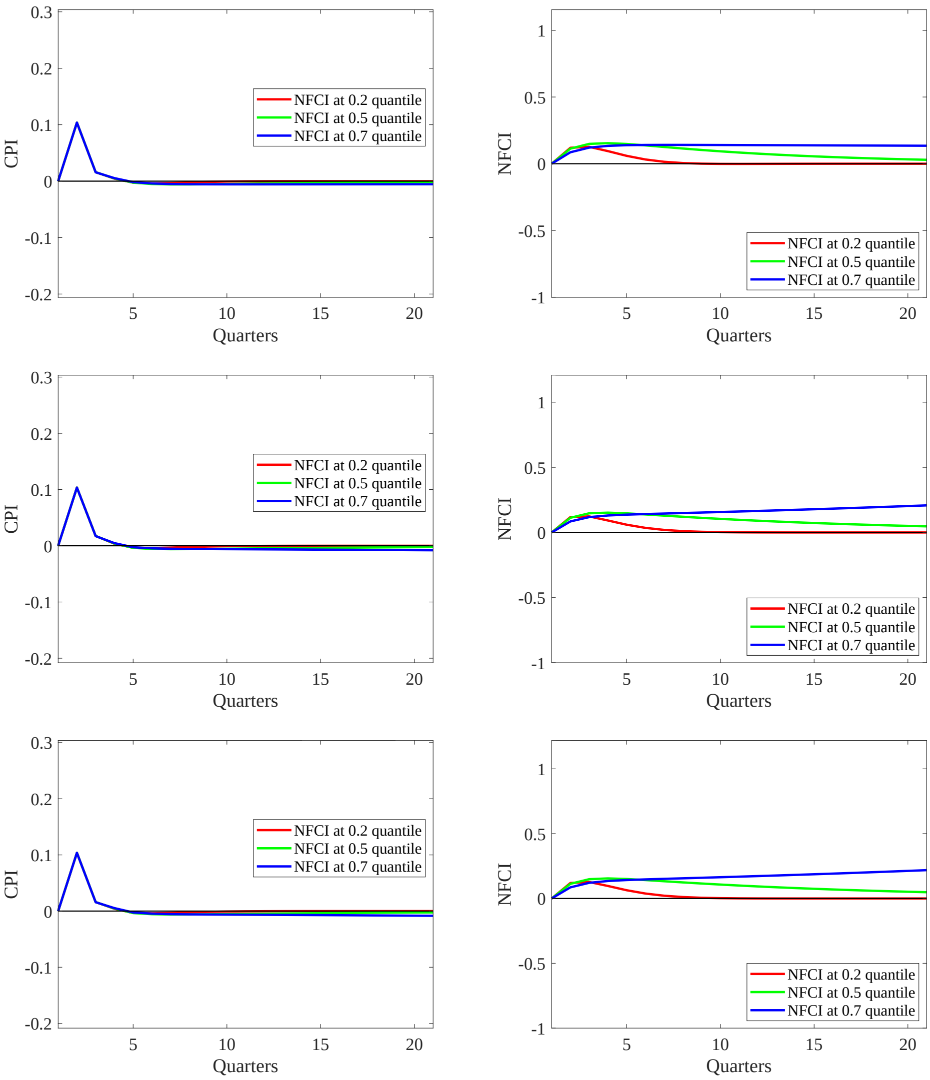

Figure 18: Development of Δ^2CPI and NFCI for the 20th (top), 50th (center) and 70th (bottom) quantile of GDP growth after an initial shock to ΔFFR (ΔFFR and Δ^2CPI affected at the median). This figure depicts the development of the remaining two variables not shown in Figure 6 for the different quantiles of GDP growth.

8.6 Robustness Checks

Robustness Ordering QVAR

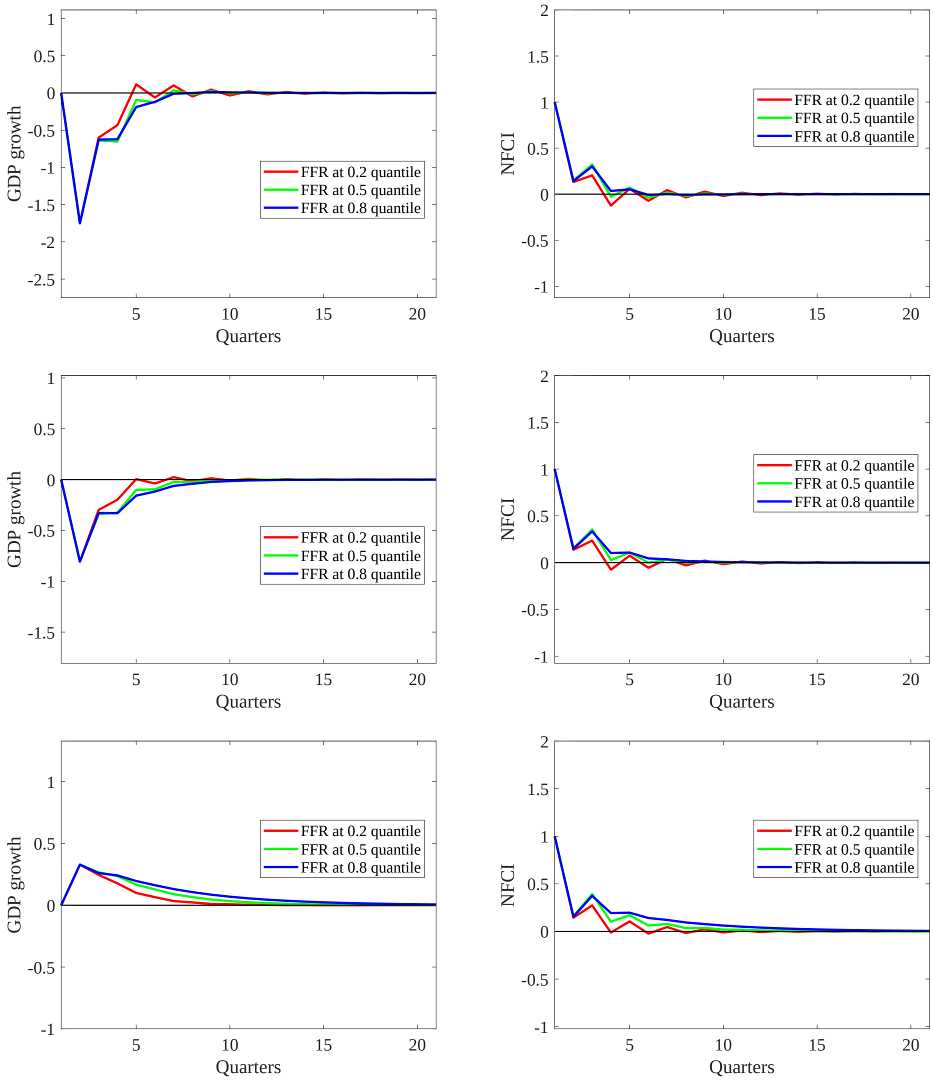

Figure 19: Development of GDP growth in percentage points for the 20th (top), 50th (center) and 80th (bottom) quantile after an initial unitary shock to NFCI (NFCI and Δ^2CPI affected at the median). ΔFFR ordered before NFCI.

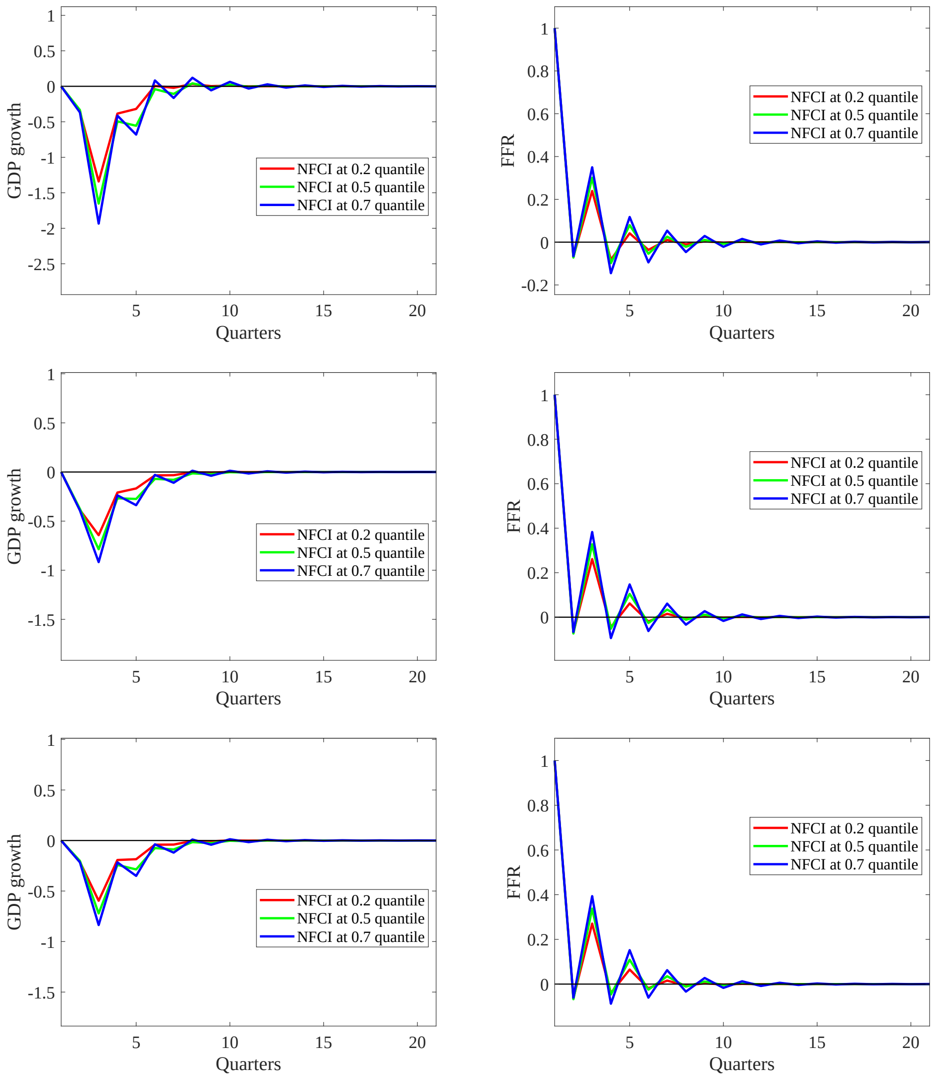

Figure 20: Development of GDP growth in percentage points for the 20th (top), 50th (center) and 70th (bottom) quantile after an initial shock to ΔFFR (NFCI and Δ^2CPI affected at the median). ΔFFR ordered before NFCI.

Robustness Shadow Rate Exclusion

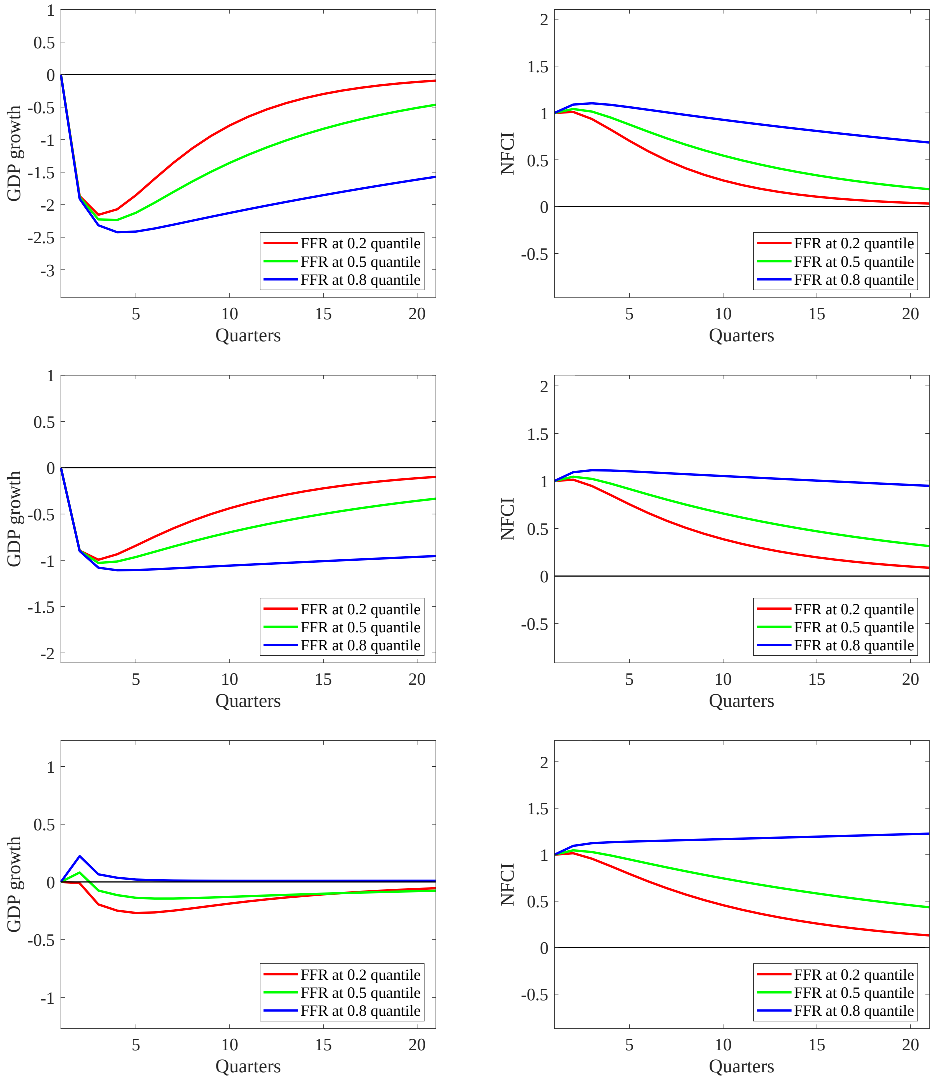

Figure 21: Development of GDP growth in percentage points for the 20th (top), 50th (center) and 80th (bottom) quantile after an initial unitary shock to NFCI (NFCI and Δ^2CPI affected at the median). Sample reduced to 1973 Q2 to 2008 Q4.

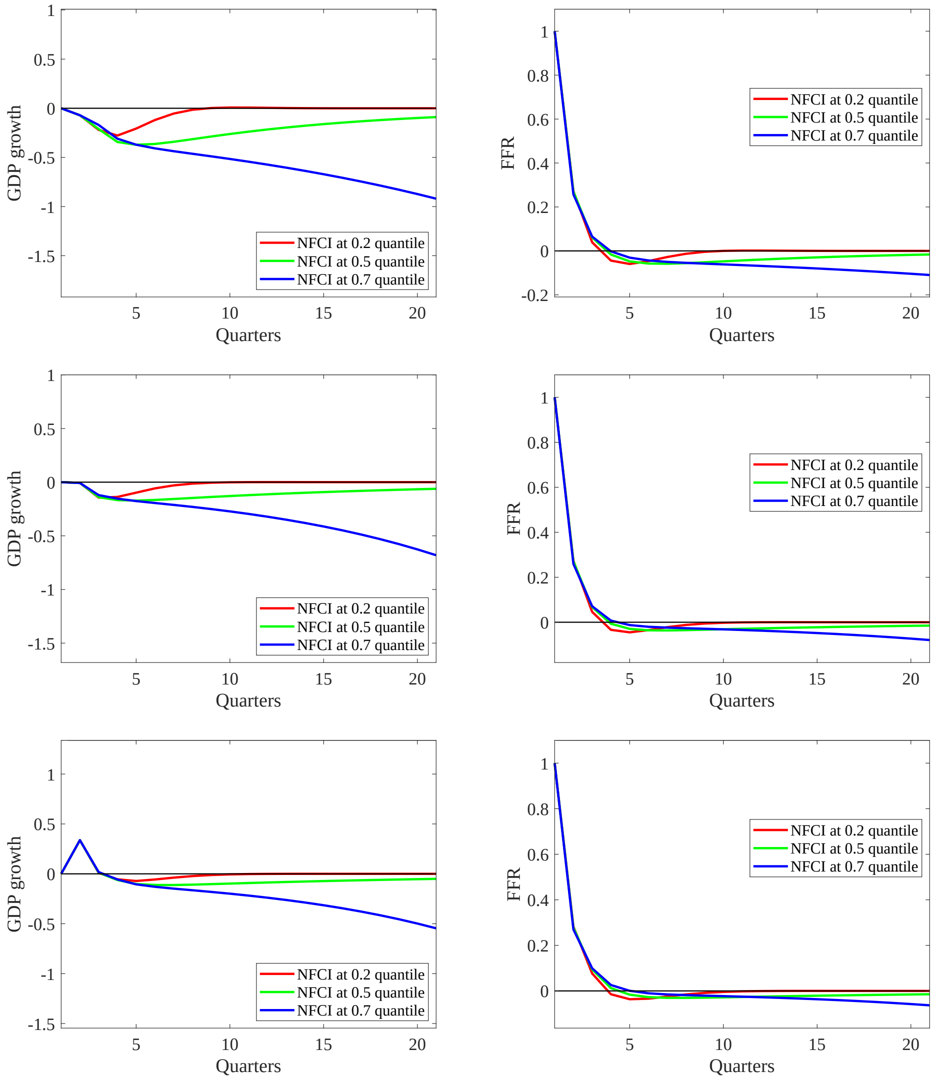

Figure 22: Development of GDP growth in percentage points for the 20th (top), 50th (center) and 70th (bottom) quantile after an initial shock to ΔFFR (NFCI and Δ^2CPI affected at the median). Sample reduced to 1973 Q2 to 2008 Q4.

8.7 Description Code

Original functions and relationship NFCI and GDP growth

- PlotPredictiveTS.m: This function plots the predictive time series of GDP growth for various quantiles based on the static quantile regression.
- PlotQRbands.m: This function plots the quantile coefficients with linearly bootstrapped bands.
- QRboot.m: This function carries out the quantile regression with optional bootstrapped confidence bands without contemporaneous regressors.
- VulnerabilityBands.m: This script produces charts of estimated quantile regression coeffi-

cients with bootstrapped confidence bands.

- VulnerabilityExploratory.m: This script plots raw data and creates scatterplots for univariate quantile regressions.
- VulnerabilityMain.m: This script estimates quantile regressions of future GDP on current values of GDP and the NFCI, and matches skewed t-distributions to the estimated quantiles.
- VulnerabilityReadData: This script reads in data from .xls files and saves it as .mat.
- VulnerabilityOutOfSample.m: This script estimates the models presented in the paper in psuedo real-time, and compares out-of-sample forecasting performance.

QVAR

- CompleteVAR_shadow.m: This script estimates a QVAR for GDP growth, NFCI, differenced CPI and differenced FFR. It provides impulse response functions after shocks to NFCI and Δ FFR. Moreover, bootstrapped confidence intervals are estimated for the results obtained at the median of all variables.
- CompleteVAR_shadowRobust.m: This script estimates a QVAR for GDP growth, NFCI, differenced CPI and differenced FFR. It provides impulse response functions after shocks to NFCI and Δ FFR. Δ FFR ordered before NFCI as robustness check.
- CompleteVAR_shadow_bands.m: This script produces figures of the coefficients obtained by quantile regressions together with confidence interval obtained by a linear VAR model indicating the significance of nonlinearity.
- CompleteVAR_shadow_exploratory.m: This script plots the time series of considered variables as well as univariate quantile regressions depicted in a scatter plot.
- CompleteVAR_shadow_forecast.m: This script estimates a QVAR for GDP growth, NFCI, differenced CPI and differenced FFR. It provides one quarter ahead forecasts for various quarters of GDP growth using estimates over the complete sample. Moreover, scenarios are constructed for the development of GDP growth in the Corona crisis.
- QRbootCont.m: This function carries out the quantile regression with optional bootstrapped confidence bands allowing for contemporaneous regressors.
- Forecastfct.m: Function creating one step ahead forecasts (step-by-step) for all variables included in a VAR

- IRFfct.m: This function creates matrices containing the time series development of all variables after an initial unitary shock to one of the variables.
- IRFfct_bounds.m: This function returns the impulse response of all variables after an initial shock to one of the variables together with bootstrapped 90% confidence bounds
- IRFfct_est_bounds.m: This function estimates the coefficients corresponding to a silumated sample based on the QVAR estimates without contemporaneous regressors.
- IRFfctRobust.m: This function creates matrices containing the time series development of all variables after an initial unitary shock to one of the variables for the robustness ordering of variables.
- IRFfct_estcont_bounds.m: This function estimates the coefficients corresponding to a silumated sample based on the QVAR estimates with contemporaneous regressors.
- sampleQVAR.m: This function simulates samples based on QVAR coefficient estimates for bootstrapping impulse response functions.
- IRFfct_matrices.m: This function returns the matrices containing the relevant coefficients as determined by input arguments for QVAR.
- PlotIRF.m: This function plots the impulse response functions
- PlotIRF_bounds.m: This function plots the impulse response function of one (quantile) scenario with bootstrapped confidence bounds
- Scenariofct.m: Function forecasting a future scenario based on current observation and specified quantiles.

Monetary Policy Uncertainty

- MPU_main.m: This script (adaption of VunerabilityMain) estimates quantile regressions of future GDP on current values of GDP, NFCI and the MPU, and matches skewed t-distributions to the estimated quantiles. It produces many of the charts presented in the paper by Adrian et al., now including MPU.
- MPUBands.m: This script (adaption of VunerabilityBands) produces charts of estimated quantile regression coefficients with bootstrapped confidence bands for MPU, NFCI and GDP growth.

- MPUExploratory.m: This script (adaption of VunerabilityExploratory) plots raw data, creates scatterplots for univariate quantile regressions with MPU.
- MPUOutOfSample.m: This script (adaption of VunerabilityOutOfSample) estimates the models presented in the paper in psuedo real-time, and compares out-of-sample forecasting performance.
- DMtest.m: This script calculates the Diebold-Mariano test statistic for the hypothesis of equal predictive accuracy in out-of-sample forecasting.