Thematic article on financial stability —— 2/2020

Vulnerable growth: Bayesian GDP-at-Risk

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VULNERABLE GROWTH: BAYESIAN GDP-AT-RISK

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This thematic article presents a new approach used by the CNB to try to quantify vulnerable real GDP growth risk. This risk is closely linked with the accumulated financial vulnerability in the economy, as the latter tends to deepen the trough of the economic cycle in the event of a sudden negative shock. The CNB's new approach uses Bayesian quantile regression to estimate the distribution of future real GDP growth. The estimate is conditional on the vulnerability of the financial system. The chosen approach makes it possible to link the distribution of real GDP growth for the Czech Republic to the growth forecast obtained from the CNB's official "g3+" structural model. This allows the CNB to obtain both more robust estimates of the distribution and a result coherent with its official forecast, despite the availability of only short time series. Quantifying vulnerable real GDP growth risk gives the CNB an additional financial stability indicator revealing the degree of vulnerability of the Czech financial system.

I. INTRODUCTION

The CNB maintains financial stability by monitoring the vulnerability of the financial system, among other things. It does so using a range of financial indicators, such as the absolute and relative levels of debt and resilience of the real and financial sectors and the overvaluation of prices of various types of assets. A highly vulnerable financial system not only has low resilience to adverse, often unexpected shocks, but can also amplify the impact of such shocks on the economy through the close links that exist between sectors. Shock materialisation in economies with vulnerable financial systems tends to result in a deep, long-lasting recession, with real GDP growth falling to levels in a very low quantile of its distribution.[2]

This thematic article presents a Bayesian quantile regression-based approach used by the CNB to try to quantify the distribution of future real GDP growth conditional on the accumulating vulnerability of the financial system. The approach builds on the traditionally applied GDP-at-Risk (GaR) model based on standard quantile regression, which is widely used by central banks to estimate the distribution of real GDP growth. The GaR model is usually employed to estimate future real GDP growth at the 5% quantile. Put simply, it quantifies the real GDP growth rate that can be expected with a probability of 0.05. An economy may get into such an adverse situation in conditions of accumulated vulnerability in its financial system. The logic of the approach is thus quite simple: the greater is the vulnerability of the financial system, the more fragile is the estimated future real GDP growth rate and the lower is the level it may reach in a recession.

The estimates obtained using this model, i.e. estimates from the left-hand end of the estimated distribution of real GDP growth, serve two main purposes for the CNB. First, they are useful as a communication tool, as the CNB can express the financial vulnerability of the system using macroeconomic variables the public is familiar with. Second, the conditional estimate of the distribution of future real GDP growth, and especially the estimate at the 5% quantile, can be used ad hoc to create an alternative adverse scenario for the CNB's stress tests.

We begin this article by describing the traditionally applied GaR model and its shortcomings. We then introduce the CNB's Bayesian quantile regression-based approach (the BGaR model) and explain its advantages. We conclude by estimating the distribution of Czech real GDP growth and briefly describing the results.[3]

II. ESTIMATING REAL GDP GROWTH USING QUANTILE REGRESSION

Real GDP growth forecasts are usually obtained using structural macroeconomic models and communicated in the form of fan charts showing the confidence intervals of the forecast (CNB, 2019b), i.e. the uncertainty surrounding the future GDP growth path. The distribution of future GDP growth presented using fan charts might seem to offer some room for illustrating the uncertainty regarding GDP growth associated with the build-up of financial risks in the economy, which would be expressed by a decrease in the lower confidence interval of the forecast.

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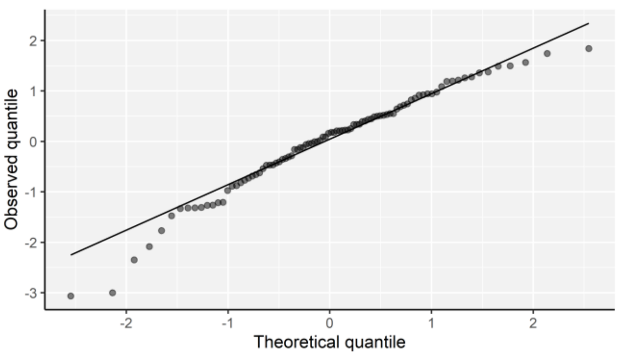
[2] See, for example, Borio and Lowe (2002), Schularick and Taylor (2012), Jorda et al. (2015), Adrian and Liang (2018), Mian et al. (2017) and Salido et al. (2017).

[3] Given the nature and scope of this article, we focus on describing the motivation for the approach and discussing its advantages. The technical side of the approach, along with other possible applications of the method, will be the subject of a CNB working paper currently under preparation.

However, when compiling fan charts it is usual to assume a symmetric normal distribution of future real GDP growth, with the variance derived from the past forecast error.[4] This, however, introduces three main limitations for the quantification of the future path of real GDP growth conditional on the evolution of systemic financial risk, and also causes some difficulties with subsequent communication. First, the existence of systemic financial risk means that the distribution of future GDP growth is skewed (Adrian et al., 2019). This is evident when one analyses the historical real GDP growth data in the Czech Republic (see Chart 1). Second, the length of the time period used in the fan charts to calculate the variance often does not match the length of the financial cycle in which systemic financial risks build up (Borio, 2014). Third, the confidence intervals of the forecast do not reflect the accumulation of measurable vulnerabilities in the economy.

Chart 1 Quantile-quantile plot for real GDP growth

(%)



Source: CNB ARAD, authors' calculations.

Note: Quantile-quantile plot for the test of normality of real annual GDP growth in the Czech Republic for the period of 2004 Q1–2019 Q4. In the case of normality, the points should lie on the 45° line, i.e. the observed quantiles should be equal to the theoretical quantiles of the normal distribution. The plot shows that GDP growth is skewed to the left.

These limitations mean it is more appropriate to use GaR models to make conditional estimates of the distribution of future GDP growth. In these models, the emphasis is on "tail" risk (such as the estimate of GDP growth at the 5% quantile of the distribution). The modelling of the growth estimate is conditional on the build-up of financial vulnerability in the economy. The results of GaR models indicate that when the measurable risks to financial stability in the economy are elevated, the estimates of future GDP growth in lower quantiles lie at lower levels (Adrian et al., 2019) than the results assuming a symmetric distribution.

Cecchetti and Li (2008) are usually credited as the originators of GaR models. Such models were popularised mainly through their use by central banks[5] and international institutions to communicate the uncertainty surrounding future GDP growth (IMF, 2017; Prasad et al., 2019). The usual GaR approach uses traditional "frequentist" quantile regression to estimate annual real GDP growth (Koenker and Hallock, 2001). This statistical method answers the question: "*How will the τ quantile of the response variable change if the conditioning variable X changes by one unit?".*[6]

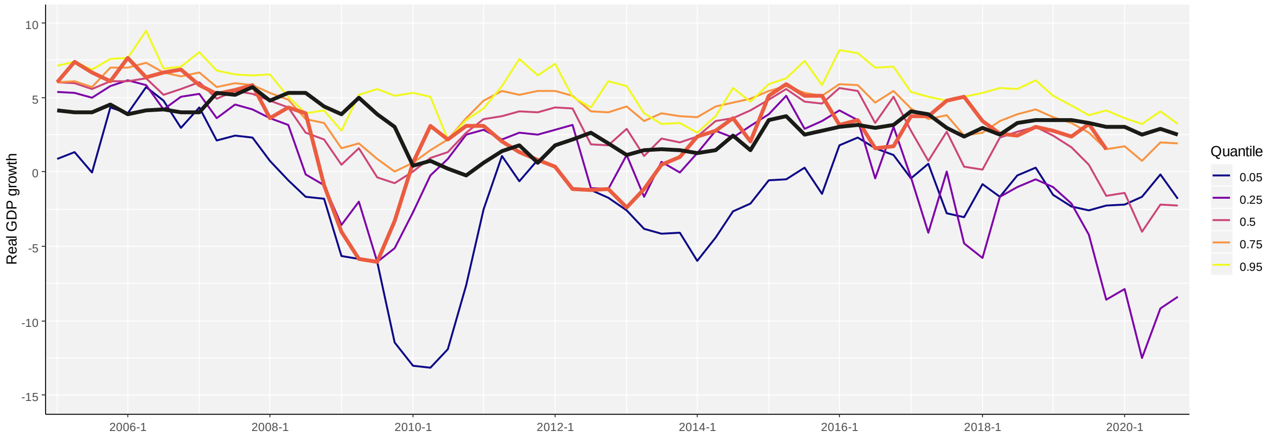
For illustration, we used quantile regression to estimate Czech annual real GDP growth one year ahead, employing data for the period 2004 Q1–2019 Q4 for the individual quantiles (see Chart 2). The choice of model variables is described in more detail in the next section (see equation 1). The chart also plots the CNB's official forecast as published in its Inflation Report, shifted one year back. Looking at the results, it is clear at first glance that the usual GaR modelling approach is imperfect, as the quantiles cross each other. This arises because the parameters for the individual quantiles are estimated separately in this approach. In other words, median real GDP growth is estimated independently of real GDP growth at the 25% quantile, and so on. This results in lower future real GDP growth at, say, the 25% quantile than the 5% quantile, an outcome that is difficult to interpret. In our case, the quantiles cross particularly frequently in the key out-of-sample predictions,[7] where it is the 25% quantile that attains the lowest values. In addition, the quantiles cross much more often for closer quantiles such as 10% and 5%.

Another significant imperfection of the usual approach is that the modelled estimates of real annual GDP growth at the individual quantiles can deviate in an unintuitive way from the forecasts obtained using the main structural macroeconomic models. Comparing the Czech real GDP growth estimates made using quantile regression with the CNB's official forecasts,[8] such deviations are apparent during 2008 and mainly outside the period on which the model was estimated, see development in 2020 (see Chart 2). The plot of the estimates at the individual quantiles in 2020 versus the official forecast could thus be interpreted as meaning that the official real GDP growth forecasts are over-optimistic and lie close to the estimates at the 95% quantile. During 2008, the official real GDP growth forecasts are even higher than the estimates modelled at the 95% quantile. However, the main focus is on the out-of-samples.

[4] This is the approach used at many central banks, the CNB included (CNB, 2008; Franta et al., 2014).
[5] For example, the Banca d'Italia (Piergiorgio et al., 2019), the Bank of England (Aikman et al., 2018), the Deutsche Bundesbank (2018), the Bank of Lithuania (2019) and the ECB (Deghi et al., 2018).
[6] For example, τ equal to 0.5 represents the conditional median of the response variable, i.e. the median of annual real GDP growth.
[7] The model parameters are estimated on the basis of the observed situation at the end of 2019. The forecast for 2019 and 2020 is therefore an out-of-sample prediction, as the model is forecasting outside the period that was used to estimate the model parameters. Out-of-sample predictions are usually employed to test the predictive power of a model.
[8] The official forecasts are obtained until 2008 using the semi-structural QPM model (Beneš et al., 2002) and from 2008 on using the fully structural DSGE "g3" model, which has been refined over time (Andrle et al., 2009; CNB, 2019a).

Chart 2 Estimated distributions of Czech real GDP growth – GaR model

(y-axis in %; quarterly data)



Source: CNB, authors' calculations.

Note: Modelling of individual quantiles of Czech annual real GDP growth four quarters ahead. The specification of the model variables is the same as in section IV. The bold red line is historical real GDP growth. The bold black line is the CNB's official forecast for the given year and quarter, as published a year earlier in the quarterly Inflation Report. The model is estimated on the 2019 Q4 data. Out-of-sample predictions for 2020 Q1–2020 Q4 are also shown. The remaining lines show the paths of the estimated quantiles (see the key) of annual real GDP growth.

This inconsistency between the results of the GaR model and the CNB's structural model can be explained as follows: (i) the estimates at the individual quantiles were made independently of the CNB's forecasts, and (ii) the two models are very different in nature. The GaR model is based on simple linear relationships where the estimates of real GDP growth at the individual quantiles are conditional on the prior growth rates and the measured vulnerability of the financial system. The DSGE model is a structural model based on economic linkages but abstracting from the financial sector and the financial cycle (Ehrenbergerová and Malovaná, 2019). It is also very important to point out that the official forecast is an out-of-sample prediction, i.e. with no knowledge of the future values, over the entire time series length, whereas the quantiles estimated using the GaR model were obtained with knowledge of the entire time series till 2018.

For the reasons set out above, it is not desirable to use the well-known quantile regression-based approach to produce estimates of the distribution of future Czech real GDP growth conditional on systemic financial risks.

The CNB uses an innovative approach to Bayesian quantile regression to estimate the distribution of future real GDP growth (Feng et al., 2015). This Bayesian (BGaR) approach makes it possible to estimate all the quantiles at once, thereby eliminating the problem of crossing quantiles. Simultaneous quantile estimation is also crucial for linking the BGaR model to the CNB's official forecast using "system priors" (for more details, see, for example, Anderle and Plašil, 2016). Priors are incorporated into the BGaR model in such a way that the median annual real GDP growth estimated is regulated close to the value obtained from the CNB's official forecast published a year earlier. This is done over the entire time horizon of the estimate, including the most recently published official outlook. The link between the models makes it possible to provide information derived from modelled structural relationships that cannot be otherwise incorporated into conventional GaR models. The chosen alternative approach gives the CNB a more informed, more robust, more coherent and therefore more reliable estimate of the distribution of future real GDP growth.

III. ESTIMATING CZECH REAL GDP GROWTH USING BGaR

The version of the BGaR model used for this article incorporates the financial vulnerability measures the CNB currently uses and monitors (equation 1).[9] The conditional estimates of annual real GDP growth one year ahead at the individual quantiles are thus modelled in relation to the following variables: the composite indicator of systemic stress (CISS) for the Czech financial market, the financial cycle indicator (FCI), the banking prudence indicator (BPI) and annual real GDP growth. The BGaR model also contains a variable describing global uncertainty based on the occurrence of the combination of terms *economy*, *policy* and *uncertainty* in the international media (Baker et al., 2016).

[9] The specification of the model, and especially the number and type of input variables, may change over time and is presented here solely for the purposes of demonstrating the model. The construction of BGaR models will be examined in more detail in a working paper currently under preparation.

The FCI measures systemic financial risk across the financial cycle using input sub-indicators such as excessive growth in property prices, loans to the real sector and debt of the real sector, and also captures the correlations between them (Plašil et al., 2015). The construction of the CISS is based on the method of Holló et al. (2012). The CISS expresses the uncertainty on the Czech financial market using the spreads and volatilities of interbank interest rates, interest rate swap rates, government bond prices, equity prices and the exchange rate. In simple terms, the CISS reflects a worsening ability to intermediate market financing and diversify financial risks in the market. Given the significance of the banking sector in the Czech financial system, the variables also include the BPI, measured as the ratio of the interest margin to loss provisions per unit of loans to households and firms (Pfeifer and Hodula, 2018). The presence of annual GDP growth for the last year is motivated by evidence that business cycle recessions are deeper when they coincide with contractions in the financial cycle (Drehmann et al., 2012).

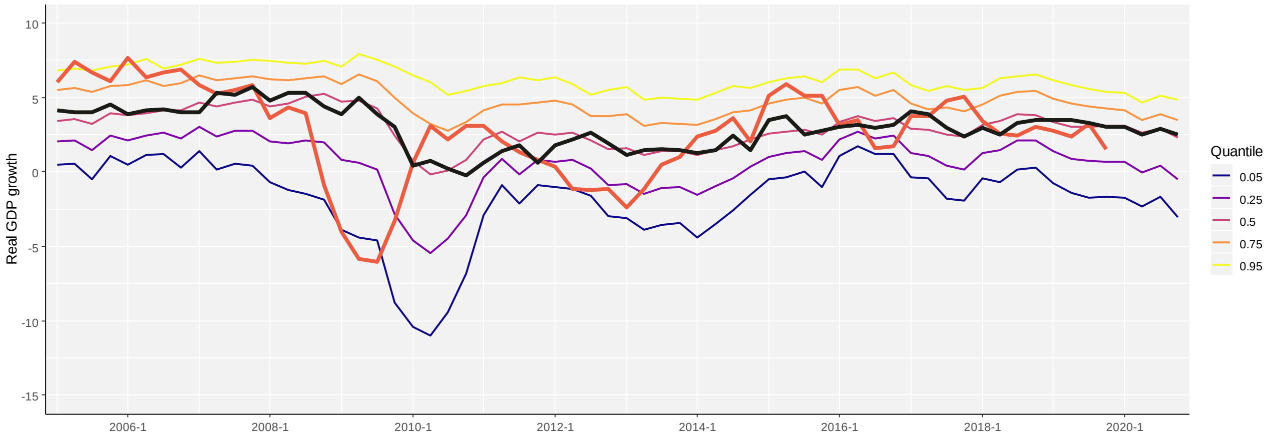
We used quarterly data for 2004 Q1–2019 Q4 to produce estimates using the BGaR model. The data for daily and monthly variables (the CISS and the uncertainty indicator respectively) were converted to quarterly frequency by including only the final observed value in the quarter. The GDP growth estimate at the 5% quartile between 2019 Q4 and 2020 Q4 can thus be viewed as a linear function of GDP growth between 2018 Q4 and 2019 Q4 and the remaining variables observed as of 2019 Q4. We also apply the above-mentioned link between the median and the official forecast for GDP growth between 2019 Q4 and 2020 Q4 published in 2019 Q4. The model therefore does not reflect events connected with the COVID-19 pandemic. The variables entering the estimation were the same for all quantiles, so – abstracting from quantile notation – the model can be described by the following equation:

$$GDP\_growth_{t;t+4} = \beta_0 + \beta_1 \cdot GDP_{growth_{t-4;t}} + \beta_2 \cdot CISS_t + \beta_3 \cdot FCI_t + \beta_4 \cdot BPI_t + \beta_5 \cdot uncertainty\_index_t \qquad (1)$$

Chart 3 shows the estimated distribution of Czech real GDP growth based on the BGaR model. The stronger link between the model estimates and the official CNB forecast is clear at first glance, given the frequent overlaps of the forecast values with the estimates at the 50% quantile. The estimates at the other quantiles are also affected via this link. The estimates at the individual quantiles do not cross and are also more stable for the out-of-sample estimates for 2020. The difference of the model is also apparent in a shift of the decline in real GDP growth (the bold red line) resulting from the global financial crisis below the 5% quantile compared with the model in Chart 1. The fact that the events of the global financial crisis represent a tail risk from a quantile lower than 5% is more realistic.

Chart 3 Estimated distributions of Czech real GDP growth – BGaR model

(y-axis in %; quarterly data)



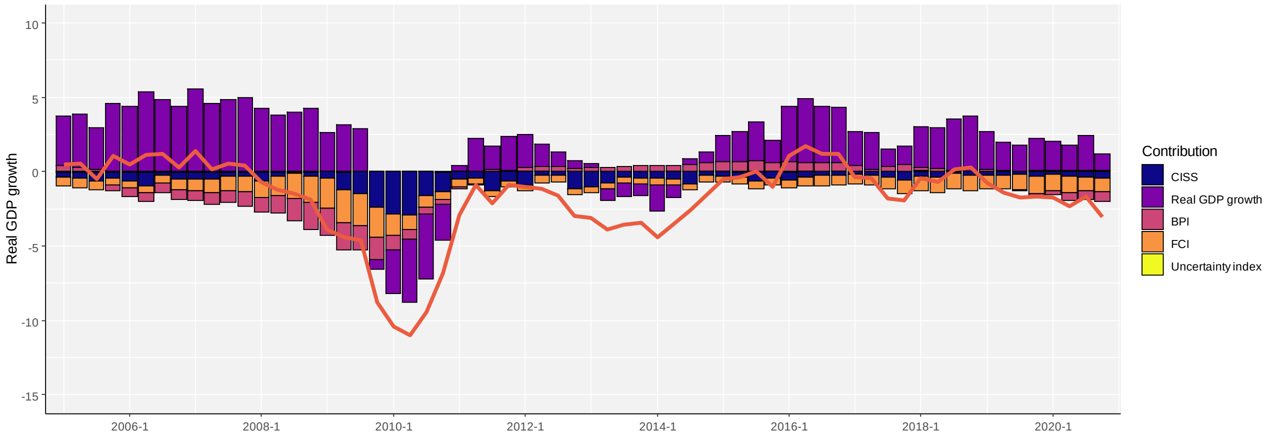
Source: CNB, authors' calculations.

Note: Estimate of individual quantiles of Czech annual real GDP growth four quarters ahead based on the BGaR model. The estimate of the median is regulated close to the official forecast. The bold red line is historical real GDP growth. The bold black line is the CNB's official forecast for the given year and quarter, as published a year earlier in the quarterly Inflation Report. The model is estimated on the 2019 Q4 data. Out-of-sample predictions for 2019 Q1–2020 Q4 are also shown. The remaining lines show the paths of the estimated quantiles (see the key) of annual real GDP growth.

Chart 5 shows another way of presenting the results of GaR models. It illustrates a shift of the entire estimated distribution of future real GDP growth to the left. It is apparent that at the 5% quantile the estimate of future real GDP growth has decreased from -1.7% to almost -3.2%. This shift occurred between 2019 Q4 and 2020 Q4, when the official GDP forecast was revised in terms of a slowdown of the Czech economy. However, the shift was also caused by increasing financial vulnerability in the economy, in particular growth in the ratio of the interest margin to loss provisions per unit of loans to households and firms and a slowdown in economic activity (see Chart 4).

Chart 4 Contributions of various vulnerability rates at the 5% quantile

(y-axis in %; quarterly data)



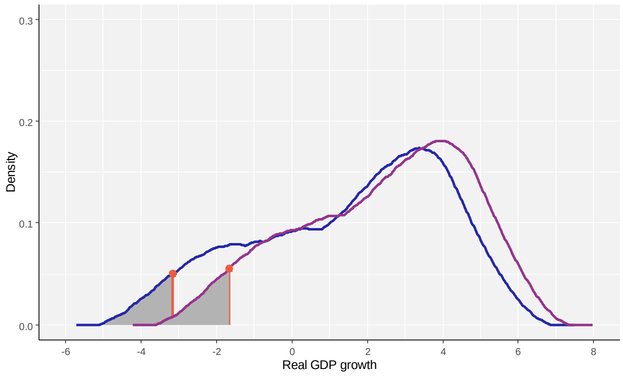
Source: CNB, authors' calculations.

Note: Contributions (excluding constant) to estimated GDP growth at the 5% quantile (red line) according to BGaR. The decrease in the 5% quantile for 2020 Q4 compared with 2019 Q4 is caused by a rising negative contribution of the BPI and a falling positive contribution of GDP growth. A rising negative contribution of the CISS can also be identified to a small extent. The uncertainty index does not have a significant effect at the 5% quantile of GDP growth in the Czech Republic.

Chart 6 compares the estimate of the distribution of annual real GDP growth for 2020 Q4 obtained using the BGaR model with that published in the official CNB forecast in the Inflation Report issued at the end of 2019. A difference in the flexibility of the modelled distributions can be seen in the chart. The BGaR model makes it possible to reflect the build-up of financial vulnerability in the economy, as the distribution is skewed to the left and the left end is shifted to lower real GDP growth levels (of around -3% to -6%). At the same time, however, it keeps the main mass of the distribution close to the official forecast (around 3%). Unlike the results of the BGaR model, those from the official forecast do not capture the build-up of financial risk at all; the distribution of annual real GDP growth remains symmetric, with its variance governed "solely" by the past forecast error.

Chart 5 Shift of the distribution of Czech real GDP growth between 2019 Q4 and 2020 Q4

(x-axis in %)

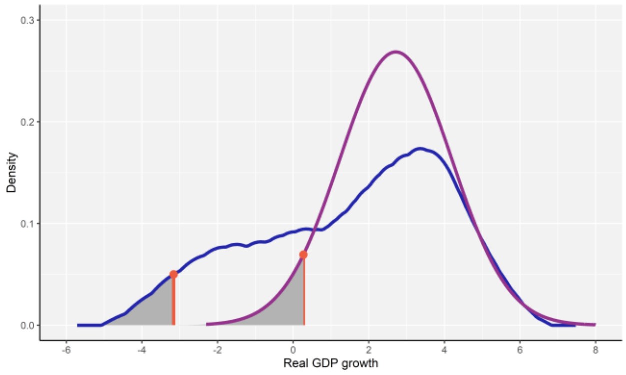


Source: CNB, authors' calculations.

Note: Estimated distribution for 2020 Q4 in blue and for 2019 Q4 in purple. 5% quantile in red. Estimated tail below 5% quantile in grey. Density obtained using Epanechnikov kernel.

Chart 6 Comparison of the BGaR results and the official CNB forecast for 2020 Q4

(x-axis in %)



Source: CNB, authors' calculations.

Note: Estimated distribution for 2020 Q4 based on BGaR in blue. Distribution from official forecast published in December Inflation Report 2019 in purple.

However, the results of the BGaR model should be viewed in the context of measurable risks reflecting financial stress and relaxed financial conditions. That Czech real GDP growth is at low levels at the 5% quantile gives satisfactory but only partial information on the extent to which the specific real GDP growth at any given time is fragile in relation to the vulnerability in the Czech financial system. This is mainly because the distribution of future real GDP growth is in fact determined by two components: measurable risk and (radical) unmeasurable uncertainty (Knight, 1921). An economy may face uncertainty quite often, including outside the financial system. One example is the current global spread of the coronavirus and its highly uncertain impacts. However, the impacts of such a shock may be amplified if the financial system is vulnerable.

IV. CONCLUSION

This article presented a BGaR model-based approach used by the CNB to estimate the distribution of future real GDP growth conditional on the vulnerability of the financial system in the Czech economy. The BGaR approach is more appropriate for the CNB than the usual approaches to estimating GaR models, especially as regards communication of the results, as it eliminates the traditional problem of crossing quantiles and allows the CNB to link the estimates of future real GDP growth at individual quantiles obtained using the BGaR model to the GDP growth forecast estimated using its principal "g3+" macroeconomic model. This makes the results obtained from the various models used by the CNB not only more consistent, but also more robust and more stable. The CNB's BGaR approach additionally allows it to communicate potential growth in the vulnerability of the financial sector not just using financial indicators (as, for example, in FSR 2019/2020), but also by means of easy-to-imagine macroeconomic variables such as GDP. The conditional estimate of the distribution of future real GDP growth, and especially the estimate at the 5% quantile, can also be used ad hoc to create an adverse scenario for the CNB's stress tests.

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