Staff memo

Macrofinancial conditions, financial stability and economic growth in Sweden – evaluating the Growth-at-Risk framework

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Summary

Dominika Krygier and Tamás Vasi both work at the Financial Stability Department of the Riksbank. [1]

In this staff memo, we examine the extent to which macrofinancial conditions, represented by two composite indicators, can predict extreme negative economic outcomes in Sweden. Macrofinancial conditions are important because they can affect the functioning of the financial system, and thus financial stability, for example through the build-up of different risks and vulnerabilities. Any disruptions that may lead to a poorer functioning of the financial system might ultimately translate into lower economic growth.

To study the relationship between macrofinancial conditions and growth, we apply the recently popularised *Growth-at-Risk* (GaR) framework presented in Adrian et al. (2019). The GaR framework allows for a complete modelling of the distribution of expected outcomes of GDP growth, given current macrofinancial conditions. This means that we are able to map possible future states of the economy and assign probabilities to each outcome conditional on the current macrofinancial environment. In our case, macrofinancial conditions are represented, on the one hand, by a macrobased indicator capturing *systemic risk* and, on the other, by an indicator that captures *financial conditions*. A particular advantage of GaR is its ability to analyse downside risks to economic growth, also called tail-risks, in macroeconomic forecasting. Tracking the evolution of these risks is crucial from a financial stability perspective. In this way vulnerabilities and conditions with the potential to trigger a financial crisis (that is, leading to a materialisation of the downside risk) can be assessed and addressed continuously.

The main objective of this staff memo is to apply and evaluate the GaR framework in a Swedish context and, in that way, provide a basis for future policy work using the method. With the help of this framework, we assess two cases, the global financial crisis of 2008-2009 and the recent COVID-19 pandemic. We find that, in the short term, information about macrofinancial conditions is useful when assessing potential downside risks to growth. This suggests that the GaR framework may serve as a useful tool to spot early changes in vulnerabilities and conditions, and consequently to build resilience in the system. However, in line with previous studies by other central banks, we find that, while the GaR framework provides a useful description of tail dynamics for economic activity for both out-of- and in-sample predictions, its forecasts ought to be taken with caution when shocks, such as the COVID-19 pandemic, do not originate from the financial sector.

[1] The authors would like to thank Mattias Danielsson, Robert Emanuelsson, Jens Iversen, Kristian Jönsson, Calum McDonald, Ola Melander, Olof Sandstedt, Annika Svensson, Jakob Winstrand and Xin Zhang for their valuable input. The authors would also like to thank other colleagues at the Riksbank who shared their insights and thoughts with us during the working process. Any remaining mistakes are our own. The views in this staff memo are those of the authors and do not necessarily coincide with the views of the Executive Board or the staff of Sveriges Riksbank.

Sammanfattning

Dominika Krygier och Tamás Vasi är verksamma vid Riksbankens avdelning för finansiell stabilitet.

I detta staff memo undersöker vi i vilken utsträckning makrofinansiella förhållanden, enligt två olika sammansatta indikatorer, kan användas för att förutse extrema negativa ekonomiska utfall i Sverige. Makrofinansiella förhållanden är viktiga eftersom de kan påverka funktionen i det finansiella systemet, och därmed den finansiella stabiliteten, till exempel genom att risker och sårbarheter byggs upp i systemet. Störningar som leder till att det finansiella systemet fungerar sämre kan i slutändan leda till sämre ekonomisk tillväxt.

Vi använder oss av ramverket Growth-at-Risk (GaR) för att studera sambandet mellan makrofinansiella förhållanden och ekonomisk tillväxt (BNP-tillväxt). Ramverket utvecklades av Adrian et al. (2019) och går ut på att modellera fördelningen av förväntade utfall för BNP-tillväxten under nuvarande makrofinansiella förhållanden. I praktiken betyder detta att vi kan kartlägga möjliga framtida utfall för BNP-tillväxten och tilldela varje utfall en sannolikhet. I GaR representeras makrofinansiella förhållanden dels av en indikator som fångar systemrisker i det finansiella systemet, dels av en indikator för finansiella förhållanden. En fördel med GaR-ramverket är att vi kan studera risker för extrema negativa utfall i ekonomisk tillväxt, så kallade svansrisker, i samband med ekonomiska prognoser. Att följa hur dessa risker utvecklas är centralt utifrån ett finansiellt stabilitetsperspektiv, eftersom det skapar förutsättningar att bedöma och adressera sårbarheter och förhållanden som skulle kunna orsaka en finanskris.

I detta staff memo använder vi GaR baserad på svenska data och lägger på det sättet en grund för framtida policyarbete med ramverket. Med hjälp av ramverket analyserar vi två specifika fall: den globala finanskrisen 2008-2009 och coronapandemin. Våra resultat visar att information om makrofinansiella förhållanden kan vara användbar när man vill skatta riskerna kopplade till extrema negativa utfall för den ekonomiska tillväxten på kort och medellång sikt. Det innebär att GaR-ramverket kan vara ett lämpligt verktyg för att tidigt upptäcka förändringar i makrofinansiella sårbarheter och förhållanden och på det sättet hjälpa till för att bygga upp motståndskraft i systemet. Även om GaR-ramverket väl beskriver dynamiken kring den ekonomiska tillväxten, bör skattningarna användas med en viss försiktighet. Detta framför allt i fall där ekonomiska chocker, som i exemplet coronapandemin, inte härstammar inifrån det finansiella systemet. Detta resultat är i linje med tidigare empiriska studier som gjorts av andra centralbanker och institutioner.

1 Introduction

In recent years, there has been an increasing interest in understanding the relationship between financial stability and economic growth. This has motivated the development of tools to identify the build-up of macroeconomic risks ahead of time.[2] One such risk measure is called *Growth-at-Risk* (henceforth GaR), which links current macrofinancial conditions to future GDP growth.

The GaR framework was proposed in Adrian et al. (2019) and has been popularised by the International Monetary Fund (IMF) as a useful risk measure for economic growth. Several institutions, including central banks, currently publish GaR to track the evolution of expected growth outcomes given current macrofinancial conditions.[3] The appeal of the GaR framework in policy work is that it provides an intuitive method in which forecasting can be thought of as a risk management exercise (Plagborg-Møller et al. (2020)). Specifically, macrofinancial conditions today may affect growth tomorrow by contributing to the build-up of different risks and vulnerabilities. The GaR framework allows the policy maker to model the distribution of expected outcomes of GDP growth given these conditions. A particular usefulness of GaR is its ability to analyse downside risks to economic growth, or tail-risks, in macroeconomic forecasting. This may guide the policy maker regarding the trade-off between economic growth and its downside risks. Realisations of downside risks or 'lower tail outcomes' are also damaging to the economy. Given that central banks should act to promote financial stability, monitoring this trade-off is important.

The main objective of this staff memo is to apply and evaluate the GaR framework in a Swedish context and to serve as a basis for future policy analysis using the methodology. We measure the expected conditional GDP growth distribution in Sweden given current macrofinancial conditions. To represent macrofinancial conditions in Sweden, we estimate GaR using two composite indicators developed by Riksbank staff: the *systemic risk indicator* (SRI) and the *financial conditions index* (FCI).[4] The SRI tracks risks and vulnerabilities in different markets and sectors that are important from a financial stability perspective, while the FCI aims to reflect financial market dynamics and 'financial conditions' in the more traditional way. These indicators thus measure different aspects of the financial system by gauging macrofinancial conditions broadly.[5] Consequently, estimating GaR conditioned on *either* SRI or FCI allows us to obtain an extensive picture of whether macrofinancial conditions can help in predicting extreme macroeconomic outcomes in Sweden. We find evidence of the likelihood of future *weak* economic growth in Sweden *rising* when our indicators show increased risks and vulnerabilities in the financial system. In particular, the effect of the build-up of systemic or financial risk on potential one-quarter ahead predicted output growth points

[2] See for example López-Salido, Stein and Zakrajšek (2017), Mian, Sufi and Verner (2017) or Bordalo, Gennaioli and Shleifer (2018).

[3] See for example IMF (2017), Bank of Ireland (2020, 2021), ECB (2020), Bank of England (2019), Czech National Bank (2020), Bank of Canada (2020) and Bank of Italy (2021).

[4] See D. Krygier and P. van Santen (2020), "A new indicator of risks and vulnerabilities in the Swedish financial system", *staff memo*. Sveriges Riksbank and in Alsterlind et al. (2020), "An index for financial conditions in Sweden", staff memo, Sveriges Riksbank.

[5] See Section 4 for a more detailed explanation of the indicators.

to the short-term usefulness of the two macrofinancial condition indicators for forecasting future downside risks to growth. Moreover, this result also suggests that the GaR framework can guide policy makers to spot early financial risks and vulnerabilities and consequently to build resilience in the financial system. However, in line with previous studies by other central banks, we find that, while the GaR framework provides a useful description of tail dynamics for economic activity, its forecasts ought to be viewed with caution when distortions, such as the COVID-19 pandemic, do not originate from the financial sector.

1.1 Conceptual background

The GaR framework originates from the idea of Value-at-Risk (VaR), which estimates the maximum expected loss on an investment over a pre-defined time horizon given a certain confidence level. VaR may also be expressed in terms of probabilities and is technically defined as follows[6]:

(1) $$\Pr(x_{t+h} \leq VaR_{\alpha}) = 1 - \alpha$$

In the equation above, x_{t+h} is the variable, for example the return on an asset at *h* periods in the future, and $1 - \alpha$ is the confidence level, or probability that the VaR_{α} will not be exceeded at time $t + h$. Basically, we want to be able to say something about how much our asset may fall in value between time period t and $t + h$ with a pre-defined probability $1 - \alpha$.

To take a simple example, if our asset has a one week $VaR_{95\%}$ of -10%, it means that there is a 5% probability that the asset's price will *fall by more* than 10% over a one-week period. Or, the other way around, that there is a 95% probability that the asset's price will *not fall by more* than 10% over a one-week period. Another intuitive example would be to imagine that the asset, for example a stock, has been trading for 1,000 weeks. If our calculated $VaR_{95\%}$ for that stock is -10%, it means that, statistically, during $0.05 \cdot 1{,}000 = 50$ of those 1,000 weeks traded, the stock fell by more than 10% over a one-week period.[7]

Applying the VaR methodology to GDP growth rather than the price or return of an asset follows the same logic, and hence the term *growth* at risk. We may also call GaR 'GDP VaR', because it estimates how much GDP could fall in an extreme scenario, given a pre-defined time horizon (*h*), often one or four quarters, and a confidence level, often 95%. In other words, it estimates a rare, but possible, bad future macroeconomic outcome by taking into account current macrofinancial conditions. In a similar way, we can therefore define GaR as follows:

(2) $$\Pr(x_{t+h} \leq GaR_{\alpha} | \Omega_t) = 1 - \alpha$$

[6] When the distribution is a continuous function.

[7] This simple example corresponds to estimating VaR using the historical simulation method assuming that the asset's future and past returns follow the same distribution. VaR can also be estimated using other methods such as Monte Carlo simulations or different types of parametric estimations.

Now x_{t+h} instead denotes GDP growth at time $t + h$, with Ω_t denoting the information set available at time *t,* that is what we know about macrofinancial conditions at the present time. The GaR is hence the VaR of future GDP growth as a function of macrofinancial conditions (in whatever way we choose to define them).

2 Motivation

The relationship between macrofinancial conditions and economic growth has been studied extensively in the literature. Studying this relationship is motivated from both an academic and a policy perspective (see e.g. Minsky (1977), Mishkin (1999) and Hakkio & Keeton (2009)). From a central bank perspective, macrofinancial conditions are important because they affect the functioning of the financial system, which in turn affects financial stability through the build-up of different risks and vulnerabilities. Any disruptions that may lead to a poorer functioning of the financial system, making it *instable,* might hamper economic growth. In particular, financial instability typically rarely stays within the financial sector but may have extensive repercussions that propagate into the real economy and therefore affect economic growth prospects.

Empirical evidence shows that financial vulnerabilities also increase risks to growth.[8] In other words, once financial vulnerabilities are high, they can amplify and prolong the impact of different shocks and disruptions on growth. During a financial crisis, when large losses, or defaults, threaten the banking sector, the financial system is unable to support the real economy and propagates the shocks, rather than absorbing them (see e.g. Borio (2014), Brunnermeier & Sannikov (2014) and Krishnamurthy & Muir (2017)). Also, during a financial crisis, bank lending typically falls and not only directly affects borrowing by firms but also indirectly affects economic activity in the regions in which these firms operate (Huber (2016)). The 1990s crisis in Sweden is a typical example. Likewise, the global financial crisis of 2008-2009 revealed how stress in the financial system can affect real economic activity negatively. Therefore, financial stability seems to be an important contributor to sustainable economic growth.

Below, we list two facts that motivate using the GaR framework for our analysis of macrofinancial conditions and economic growth.

Fact 1: *Economic fluctuations are asymmetric over the business cycle.* Chart 1 shows that the distribution of Swedish real GDP growth exhibits some skewness and fat tails.[9] The chart plots a histogram of annual real GDP growth over the sample period 1995Q2 – 2021Q2. As shown in the chart, most of the growth in the sample was between -0.5 and 1.5 per cent year-to-year. However, some events resulted in unusually large negative GDP growth outcomes. Such events happened during the financial crisis in 2008-2009 and at the beginning of the COVID-19 pandemic. Previous studies

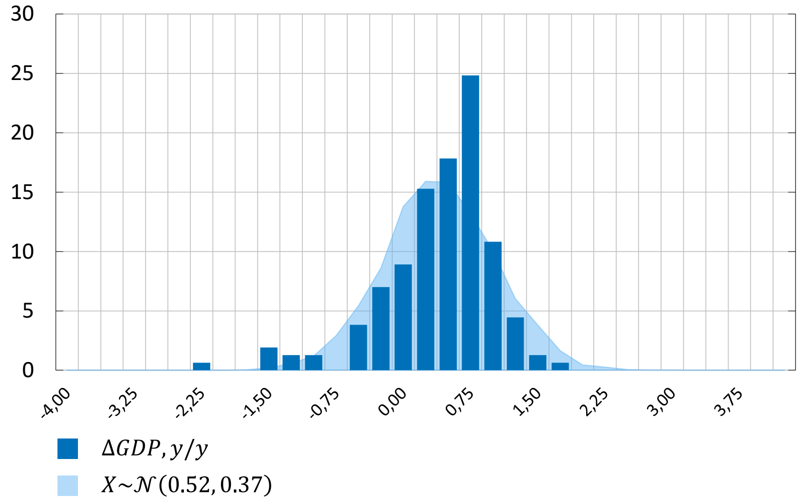
[8] Financial vulnerabilities are a part of overall financial conditions. See, for example, Kose, Claessens and Terrones (2011a, 2011b).

[9] Skewness and kurtosis (also called fat tailedness) are two statistical measures describing the third and fourth moments of the frequency distribution. Skewness measures (the lack of) symmetry, and kurtosis measures whether the variable is 'outlier prone' (i.e. has many outliers) as compared to the normal distribution.

have suggested that recessions can be described with high GDP volatility (see e.g. Bloom (2014)) leading to fatter tails and left-skewness (Bloom et al. (2019)) in the distribution. Therefore, the non-linear approach used in GaR seems appropriate given the skewed and fat-tailed nature of GDP growth.

Chart 1. Distribution of real GDP growth

Probability density



Note: Histogram of seasonally adjusted annualised GDP growth over the sample period 1995Q2-2021Q2. Each bar represents the probability (y-axis) of different values for realised real GDP growth (x-axis) during the stated period. The mean is around 0.5 per cent. The light blue area shows the distribution of a normally distributed variable with the same mean and variance as the seasonally adjusted annualised GDP growth rate.

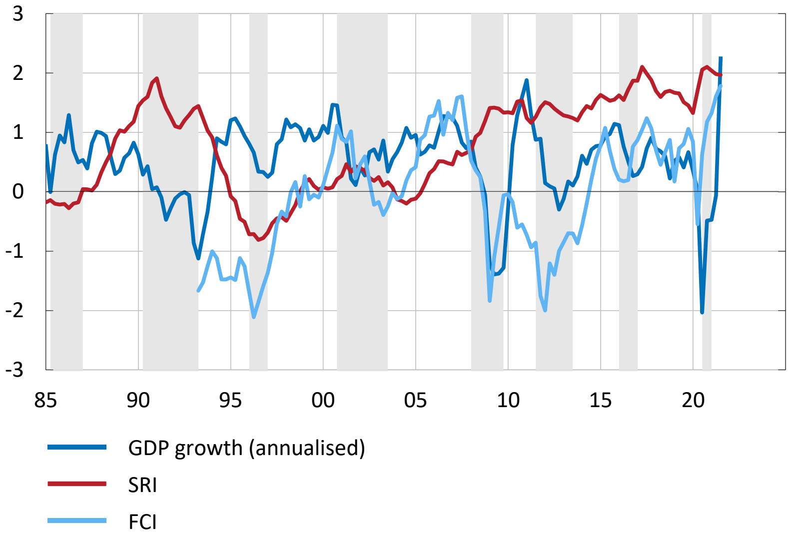
Sources: Statistics Sweden and authors' own calculations.

Fact 2: *Extreme negative outcomes of real GDP growth often coincide with adverse financial conditions and tend to be preceded by increasing levels of systemic risk.* Chart 2 shows two of the Riksbank's financial indicators – the *systemic risk indicator* (SRI) and the *financial conditions index* (FCI), plotted together with the year-to-year change in real GDP.[10] This chart, together with the results in Table A.1 (See Appendix A), suggests that the SRI is (statistically significantly) negatively correlated to future GDP growth. Hence, historically, a fall in GDP growth tends to be correlated with periods of rising financial risks and vulnerabilities. This is also the case for the FCI – movements in the FCI occur in line with economic growth as the state of financial markets affects financial decisions made by participants in the economy. In Chart 2, we observe that declines in GDP growth tend to coincide with large negative outcomes in the FCI. The empirical point that extreme negative outcomes of real GDP growth often coincide with adverse financial conditions and preceding rising levels of systemic risk has also been established by a number of studies, see for example Aikman et al. (2019), Gertler & Gilchrist (2018) and Schularick & Taylor (2012).

[10] The indicators SRI and FCI are explained in more detail in section 4.

Chart 2. GDP growth and macrofinancial conditions

Per cent, standard deviation



Note: Seasonally adjusted annualised GDP growth. The unit of interpretation is standard deviations for the SRI and FCI. The grey areas correspond to recession periods as defined by the OECD recession indicator for Sweden.

Sources: Statistics Sweden, OECD and the Riksbank.

3 An overview of related literature

GaR was conceptualised by Adrian, Boyarchenko and Giannone (2017) in a Federal Reserve Bank of New York staff report titled *Vulnerable growth*[11]. The main argument for GaR in the paper is that policy makers are often concerned with the downside and upside risk to GDP forecasts (or any type of macro forecast, essentially) and how sensitive the forecasts are to unexpected shocks. However, standard economic forecasts usually only provide us with point estimates of the conditional mean. By only looking at the point forecast, we might ignore risks building up around this forecast that ultimately affect the point forecast over time. As a central bank and given our task of safeguarding financial stability, we are interested in the tail risks, which is to say identifying the worst thing that could happen to economic growth in the future given current developments in the financial sector. In other words, we want to estimate the downside risks to the economy. The GaR therefore focuses its attention on the lower tail of the distribution of forecasted growth, because the lower tail is typically more sensitive to shocks and to changes in conditions.

Adrian, Boyarchenko and Giannone (2019) model the full distribution of future real GDP growth as a function of current financial and economic conditions and find that the estimated lower quantiles of the distribution exhibit strong variation with current *financial conditions*, while the upper quantiles are more stable over time. In addition, current *economic conditions* forecast the median of the distribution, but do not contain information about the other quantiles of the distribution.[12] By fitting a distribution to smooth out the estimated quantile distribution estimates, they obtain the estimated conditional distribution of GDP growth over time (see Figure 1 “Distribution of GDP growth over time” on page 1265 in Adrian et al. (2019)). Two apparent conclusions from their results are as follows. First, the whole distribution evolves over time, that is to say the distribution of future GDP growth varies over time in line with varying financial and economic conditions, and second, downside risks to GDP growth vary more strongly over time than upside risks.

Moreover, building on the findings in Adrian, Boyarchenko and Giannone (2019), Adrian et al. (2018) examine the relationship between financial conditions and the distribution of future real GDP growth for 22 countries. They confirm the forecasting ability of financial conditions for the distribution of expected GDP growth but also that the effect of financial conditions changes over the forecasting horizon. In the short run, loose financial conditions are found to forecast high growth and low volatility, while, in the medium run, growth is lowered and volatility increases. The findings are also in agreement with the extensive literature on volatility dynamics and financial crises. For example, the ‘volatility paradox’ (Brunnermeier and Sannikov (2014)) states that periods of low volatility tend to be followed by large macroeconomic contractions in the future.

[11] Also later published in the American Economic Review (April 2019).

[12] In the paper, the authors differentiate between *financial* conditions and *economic* conditions. Financial conditions are represented by the National Financial Conditions Index (NFCI) provided by the Federal Reserve Bank of Chicago, whereas economic conditions are represented by real GDP growth.

De Santis and Van der Veken (2020) analyse the great recession and show that financial variables improve the forecast of GDP growth and that weakened economic activity is not necessarily manifested by a change in the conditional mean of real GDP growth but is also, or instead, manifested in the higher moments of the distribution. Likewise, in a setting similar to ours, staff at the Central Bank of Ireland examine the extent to which future Irish output growth is shaped by current financial conditions as well as financial vulnerabilities. Near-term risks to economic growth are found to be significantly influenced by prevailing financial conditions, whereas medium term risks are more dependent on the development of financial vulnerabilities, such as excessive credit growth over a longer period (O'Brien and Wossner (2021)).

In another recent paper, Plagborg-Møller et al. (2020) critically evaluate the non-linear relationship between financial indicators and the distribution of future GDP growth in the United States. The study finds that the higher moments of the forecasted growth distribution are poorly estimated and thus none of the financial indicators considered by the authors provides robust and precise advance warnings of tail risks. Moreover, the authors find that, even if financial information may help in real time to predict the GDP growth distribution, financial markets do not seem to contain a large amount of forward-looking information about GDP growth beyond the current quarter.

More recent publications concerning the GaR framework have appeared in response to the COVID-19 pandemic. Barro et al. (2020) apply the GaR framework to quantify expected output losses due to the Spanish flu in 1918-1920 and use the results to gain a deeper understanding of COVID-19 and the associated expected macroeconomic risks. Alessandri and Di Cesare (2021) use GaR to study the first outbreak of COVID-19 as a case study. Similarly to our results, as we will see further on in this staff memo, they find that financial markets reacted too late, even at relatively short horizons, and made it difficult to register the increase in downside risk that the pandemic would later cause. The shock of COVID-19 is indeed rare and, as noted by the authors, probably ranks among the least predictable events in recent decades, which makes any forecasting exercise challenging.

Last, Brownlees and Souza (2020) conduct an out-of-sample backtesting exercise of GaR forecasts. Their backtesting results show that both GaR and GARCH forecasts have similar performances to each other. This suggests that standard volatility models such as the GARCH(1,1) are more accurate, even though the GARCH(1,1) uses no information other than GDP growth. The authors argue that, where forecasting is concerned, their results suggest caution should be exercised against relying too heavily on the GaR technique. Overall, opinions concerning the usability of the GaR technique as a tool to forecast downside risks to GDP growth, given current macrofinancial conditions and risks, are mixed in the empirical literature.

4 Method and data

4.1 Estimation

A large body of studies has examined the extent to which different financial variables can be used to predict economic activity. However, this literature often focuses on improving point forecasts.[13] The GaR framework instead measures the expected GDP growth distribution conditional on current macrofinancial conditions. In particular, the GaR focuses on the lower tail of the distribution of forecasted growth, because the lower tail is typically more sensitive to shocks and to changes in conditions than the mean and because realisations of lower tail outcomes are damaging to the economy (Adrian et al. (2019)).

We follow the GaR analysis proposed by Adrian et al. (2019) and proceed in two steps. The first step corresponds to estimating quantile regressions.[14] Let y_{t+h} denote the annualised growth rate of GDP between *t* and *t+h* where *h* is quarter. Moreover, let x_t denote the conditioning variables. In our case, these are variables representing macrofinancial conditions (either SRI or FCI), as well as the one period lagged real GDP growth.[15] The lagged real GDP growth is included to control for possible time dependencies.

We estimate the following quantile regression:

$$\text{(3)} \qquad \widehat{\beta_q} = \underset{\beta_q}{\operatorname{argmin}} \sum_{t=1}^{T-h} \left(q \cdot \mathbf{1}_{y_{t+h} \geq x_t \beta} \left| y_{t+h} - x_t \beta_q \right| + (1-q) \cdot \mathbf{1}_{y_{t+h} < x_t \beta} \left| y_{t+h} - x_t \beta_q \right| \right)$$

where $\mathbf{1}_{(.)}$ denotes the indicator function. The predicted values for these quantile regressions are:

$$\text{(4)} \qquad \hat{Q}_{y_{t+h|x_t}}(q|x_t) = x_t \hat{\beta}_q$$

Equation (4) corresponds to the quantiles *q* of the predictive distribution of y_{t+h} conditional on the financial indicators. This method allows us to take a non-linear approach to capture the skewed and fat-tailed nature of GDP growth as discussed in Sections 2 and 3.

In the second step, the conditional predictive density function is estimated for future GDP growth. It is derived by fitting a skewed t-distribution on the predicted values of the estimated conditional quantile regressions, following the approach by Adrian et al. (2019). See APPENDIX B – Step 2 in GaR for further explanation and technical details.

[13] See, for example, Stock and Watson (2003), Forni et al. (2003).

[14] For more details on quantile regressions, see Koenker and Bassett (1978) or Adrian et al. (2019).

[15] Because the variables in the two indicators can overlap, we separately estimate our GaR model conditioned on SRI or FCI.

4.2 Data

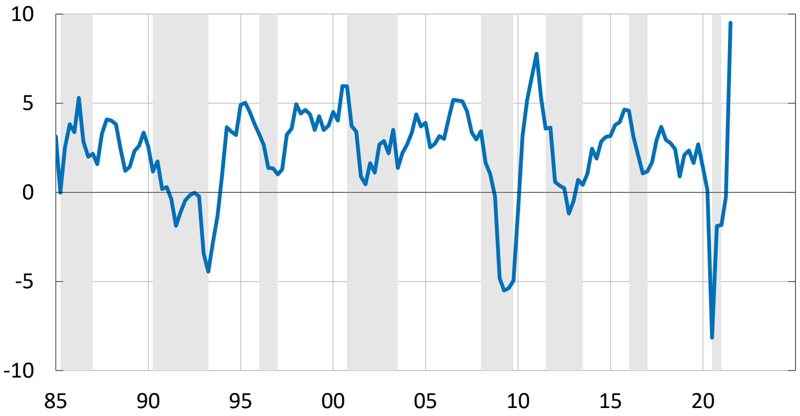
In line with previous studies, we use data on annualised GDP growth (the dependent variable) and two financial indicators, the *systemic risk indicator* (SRI) and the *financial conditions index* (FCI) as explanatory variables, both representing macrofinancial conditions in the Swedish economy.[16] Riksbank staff have developed both indicators. Below we explain, in more detail, the data used in this study.

Real GDP growth

Chart 3 shows seasonally adjusted annualised real GDP growth in Sweden between 1995Q2-2021Q2. The shaded areas indicate recessions in Sweden as defined by the OECD based recession indicator. 'Recession' is defined as the period between the peak and trough of the economic cycle, and both the peak and trough are local extrema.

Chart 3. Seasonally adjusted annualised GDP growth in Sweden

Per cent



Note: The last observation is Q2 2021. Light grey areas refer to the OECD based recession indicator for Sweden.

Sources: Statistics Sweden and OECD.

Financial indicators

First, we forecast the conditional distribution of annualised GDP growth based on information reflecting *systemic risk* in the economy. The indicator we use is the *systemic risk indicator* (SRI), which captures household, bank and non-financial companies' leverage as well as other variables that are important for the risk assessment (see Chart 4).[17] Broadly, the SRI tracks risks and vulnerabilities in different sectors and markets that are important from a financial stability perspective. It combines a large amount of information from several different parts of the financial system and can therefore provide a composite picture of risks to financial stability and their development over time. Typically, the prior build-up of imbalances, for example through excessive credit

[16] An alternative way would be to estimate the GaR model with Statistics Sweden's estimation of monthly GDP growth conditioned on FCI (both available on monthly frequency). The general conclusion of this Staff Memo did not change when we estimated the model with this alternative method.

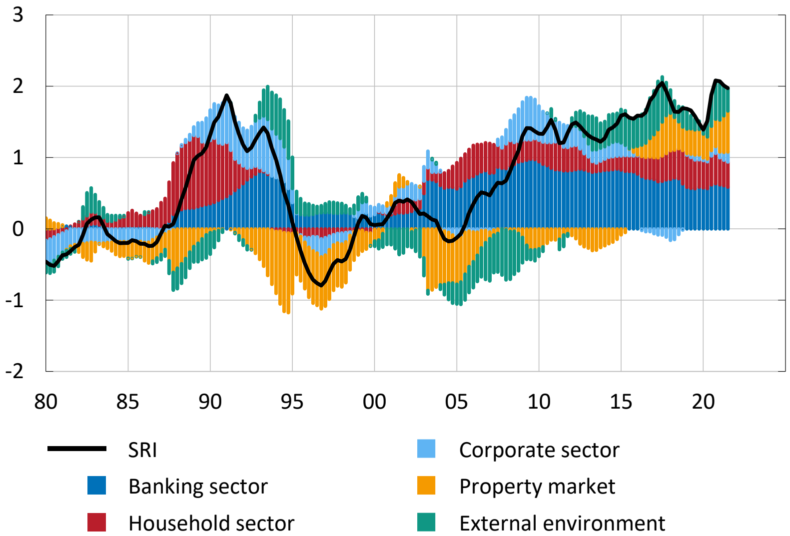
[17] Published as a Riksbank staff memo by Krygier, D. and van Santen, P. (2020), "A new indicator of risks and vulnerabilities in the Swedish financial system", *Staff memo,* Sveriges Riksbank.

growth in different parts of the economy, has been shown to matter when it comes to the length and depth of financial crises. The systemic risk indicator is an aggregation of underlying sectoral indicators and is available on a quarterly frequency since 1980.

Second, we re-estimate the model conditioned on the *FCI (financial conditions index)*, which corresponds to combinations of key domestic financial market asset returns, funding spreads and volatility (see Chart 5). The FCI aims to reflect financial conditions by summarising the status of a number of indicators representing important submarkets in the Swedish financial market. The FCI is available on a monthly frequency since 1993. The indicator is aggregated on a quarterly level before entering the model.

Chart 4. Systemic risk indicator for the Swedish financial system

Standard deviation

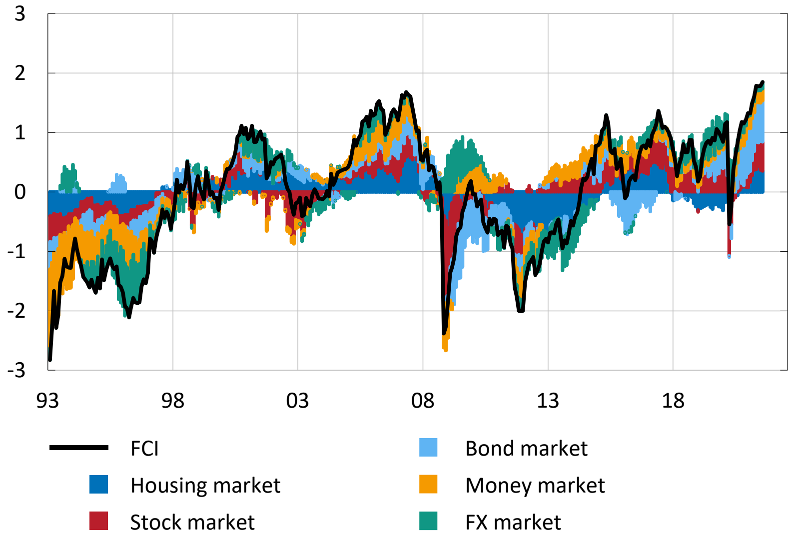


Note: A higher value means higher risks and vulnerabilities. For all series included, see D. Krygier and P. van Santen (2020), "A new indicator of risks and vulnerabilities in the Swedish financial system", *Staff memo*, Sveriges Riksbank.

Source: The Riksbank.

Chart 5. Index for financial conditions in Sweden

Standard deviation



Note: A higher value indicates more expansionary financial conditions. For all series included, see J. Alsterlind, M. Lindskog and T. von Brömsen (2020), "An index for financial conditions in Sweden", *Staff memo*, Sveriges Riksbank.

Source: The Riksbank.

Macrofinancial conditions and financial vulnerabilities

The FCI and SRI used in this study are both indicators that try to capture the development of different factors that matter for the functioning of the financial system. In a broader sense, for example, financial conditions affect the monetary policy transmission mechanism, and conversely, monetary policy works through affecting financial conditions. At the same time, financial conditions ultimately have an effect on financial stability, by affecting financial vulnerability dynamics. For example, the low interest rate environment that has been inherent in our economy over the last decade has enabled favourable funding conditions for, for example, households and firms. At the same time, the build-up of leverage has been substantial, making households and firms vulnerable for higher interest rates. Hence, on the one hand, accommodative monetary policy is needed to stimulate the economy, while, on the other, a lower interest rate environment spurs increased risk-taking and rising asset prices, contributing to vulnerabilities. The two indicators, FCI and SRI, are hence integrated but ultimately measure somewhat different aspects of the financial system and overall macrofinancial conditions. Furthermore, central banks are faced with the challenge of adapting financial conditions without compromising short-term growth, while also simultaneously trying to address the build-up of vulnerabilities and their effect on growth in the medium term and long term.

5 Results

In this section, we first present the *in-sample* estimated conditional probability functions for real GDP growth for periods during the *global financial crisis* (GFC) (2007Q2–2008Q4) and for periods during the *COVID-19 pandemic* (2020Q2-2020Q4), which is to say that we show the entire estimated distributions of expected outcomes of GDP growth given macrofinancial conditions.[18] Specifically, we employ two models in which the dependent variable is always annualised GDP growth one- or four-quarters ahead, while the conditioning variables are:

Model 1: GDP growth at time $t-1$ and the SRI at time t

Model 2: GDP growth at time $t-1$ and the FCI at time t

The aim is to evaluate the way in which the GaR framework provides useful information about risks to growth during times of financial distress and during periods when the economy is hit by shocks not originating from the financial sector (COVID-19). Our analysis covers short-term impacts from adverse financial conditions, as well as medium-term impacts from systemic risk, to capture the growth distribution.

Second, we try to answer whether it is possible to predict an increase in GDP growth vulnerability *out-of-sample* by analysing the forecasting ability of the two for the Swedish financial crisis in the early 90s and the global financial crisis.

5.1 Intuition

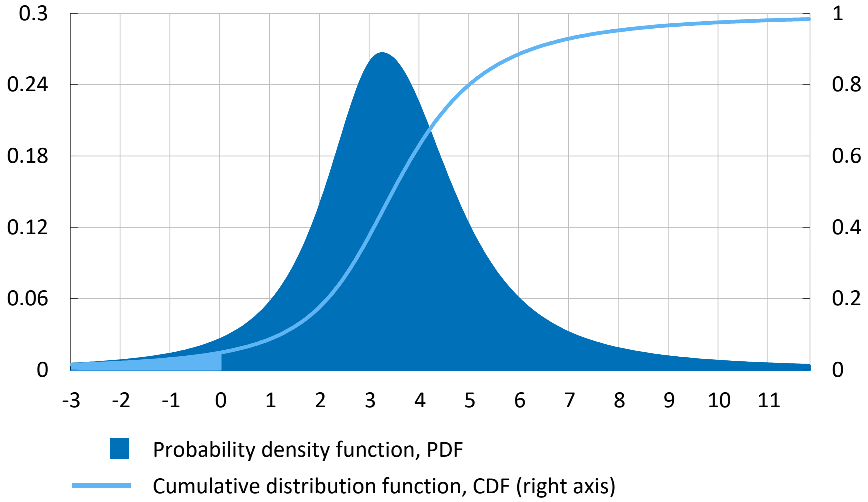
Before proceeding to the results, Chart 6 below aims to give an intuitive description on how to understand the conditional probability functions displayed in sections 5.3 and 5.4. The chart shows the estimated probability density function derived from the models for Swedish GDP growth for the fourth quarter of 2007 in dark blue, and the corresponding cumulative distribution function in light blue.[19] These functions are derived from estimating a quantile regression (see Equation 3 in section 4) where GDP growth is the dependent variable and current macrofinancial conditions are the explanatory variable. By estimating such a quantile regression and using the estimated parameters to forecast the next period GDP growth (see Equation 4 in section 4), we may, after completing a few more steps (see APPENDIX B), obtain the two density functions below.

[18] Macrofinancial conditions are represented by a systemic risk indicator (SRI) and a financial conditions index (FCI). See more details about the indicators in Section 4.

[19] This particular quarter was selected at random for illustrative purposes.

Chart 6. The PDF and CDF of GDP growth

Probability density, probability



Source: Authors' own calculations.

The PDF tells us something about how the next-period estimated outcomes of GDP growth are distributed. This is informative when assessing how the distribution changes over time, especially relating to the downside risks (the left tail of the distribution) to growth. The CDF instead tells us the probability of observing an outcome which is smaller than or equal to some value X, where X in this case is the estimated GDP growth rate *h* period(s) ahead. To find GaR, we therefore want to find the outcome of GDP growth that will satisfy Equation 2 in Section 1, as follows:

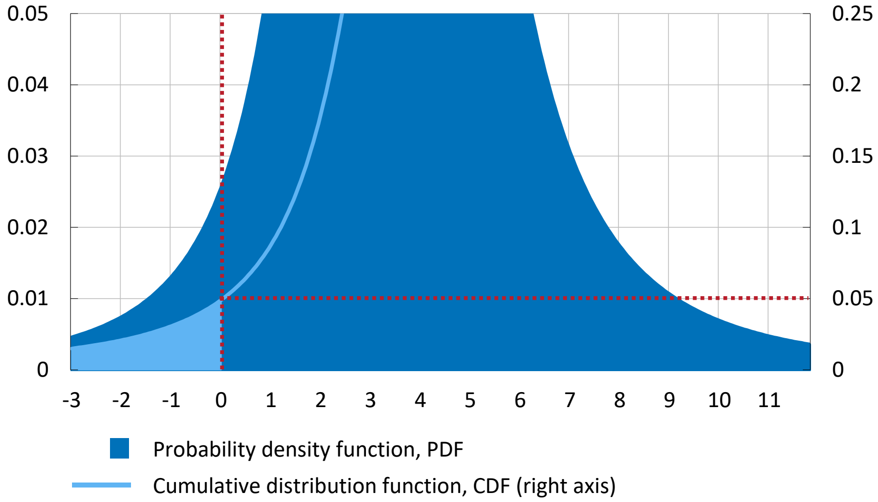
$$(5) \quad \Pr(GDP\ growth_{t+h} \leq GaR_{95\%} | macrofin.cond.) = 1 - 0.95 = 0.05$$

$$GaR_{95\%} = -0.4\ \%$$

By observing the CDF and examining what value corresponds to less than or equal to a probability of 5 per cent, we find GaR. This number is then interpreted as follows: there is a 5 per cent chance that the next (*h*) period GDP falls by more than 0.4 per cent, given current macrofinancial conditions. Observing the GaR over time thus tells us if downside risks to growth have increased or decreased, given the development of macrofinancial conditions.

Chart 7. The PDF and CDF of GDP growth zoomed in

Probability density, probability



Source: Authors' own calculations.

5.2 In-sample results

First, we examine the in-sample estimated coefficients in the quantile regressions of one- and four-quarter ahead GDP growth on lagged GDP growth and on either SRI or FCI.[20] For the one-quarter-ahead forecast, regardless of the predictors used, at the lower quantiles, the estimated coefficients are significant at the 10 percent level. This indicates that, in the short term, some explanatory power of future lower tail risks of GDP growth arises from the information content of our indicators representing macrofinancial conditions. Nevertheless, the statistically significant coefficients for previous quarter's GDP growth suggests that our short-term predictability of GDP distribution is mainly driven by previous quarter's GDP growth. On the other hand, the ability to predict future GDP vulnerabilities is more pronounced for both our indicators for the one-year-ahead forecast. Therefore, our results suggest that macrofinancial conditions are more informative for predicting tail outcomes for longer horizon forecasts.

Moreover, before we present our findings for the case studies (the global financial crisis 2008-2009 and the COVID-19 pandemic) and their corresponding probability density functions and estimated GaRs, we focus on the time evolution of key components of the predictive distributions – these are the upper and lower quantiles (5, 95), the mean, variance and skewness. Observing these components gives us information about the expected behaviour of the estimated GDP growth distribution conditioned on the information we have about macrofinancial conditions. We illustrate these components based on a GaR model that is conditioned on the SRI.[21]

[20] The estimated quantile regression coefficients are presented in Chart 17 and Chart 18 in APPENDIX D.

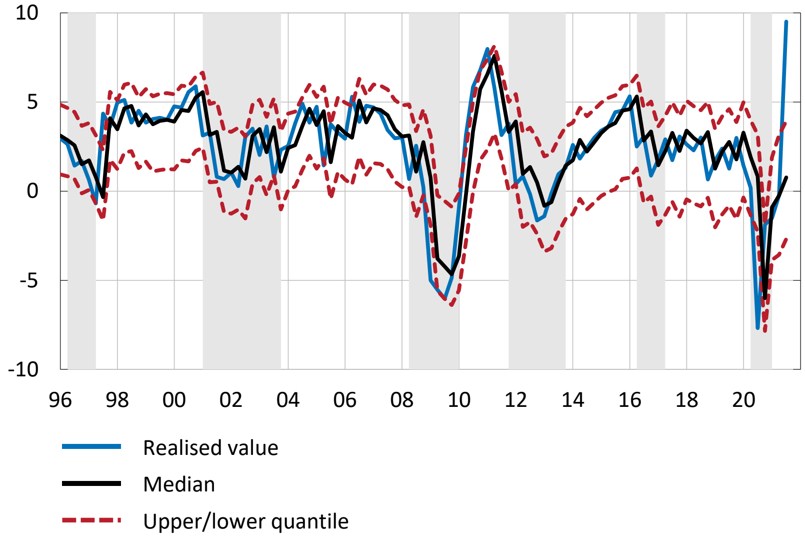
[21] We conduct two backtests in order to gauge the accuracy of the GaR model with either SRI or FCI as the explanatory variable. We find that the GaR forecast conditioned on SRI is the most accurate model of the

Chart 8 plots the in-sample one-quarter ahead forecasts (median) for annualised GDP growth throughout the sample period conditioned on SRI, together with the upper (95) and lower (5) percentiles. The forecast of the worst-case outcome (5th percentile of the future growth distribution, the lower red dashed line) and a good outcome (95th percentile of future growth distribution, the upper red dashed line) show that downside risks seem to be slightly more pronounced than upside risks. Moreover, from this information, we can also calculate the probability of annualised GDP growth being below zero (see Chart 9). We find that the model does well in capturing the probability of recession for both the GFC and the recent pandemic. Specifically, the probability of recession during the GFC was projected to be approximately 70 per cent, while it was close to 80 per cent in the first period of the pandemic.

Chart 8. Time-series plot of realised GDP growth and one- and four-quarter-ahead predictions of GDP growth using SRI as the main explanatory variable

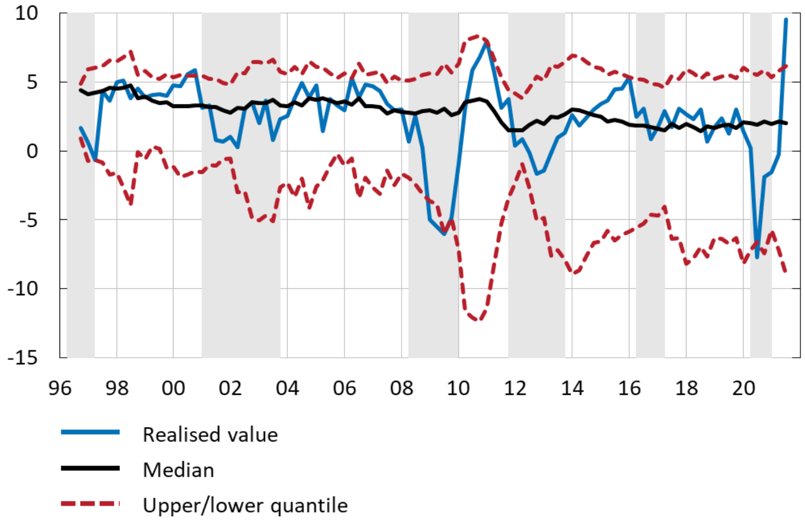
Per cent

h=1



two. The backtests are two common methodologies used in the VaR literature: Kupiec's (1995) proportion of failures (POF) test and Lopez's (1999) loss function based backtest. The POF test shows that, at 95% level of confidence, both models are successful in predicting actual growth. Considering the magnitude of the error when the actual outcome exceeds GaR(95), the model with SRI as explanatory variable has a lower loss function. See the Appendix for the backtesting results.

h=4



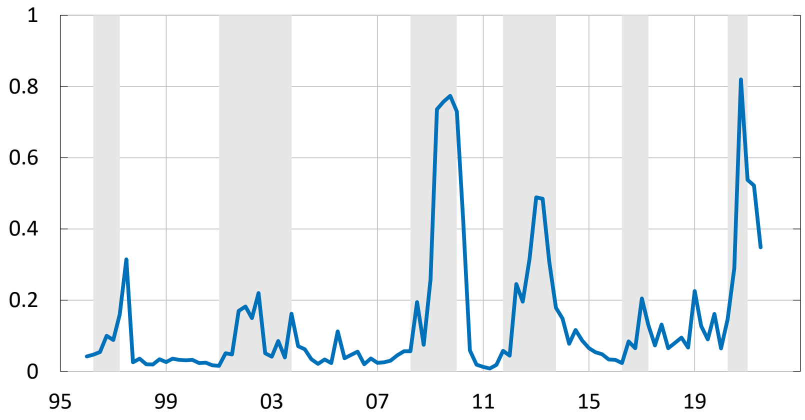
Note: One- and four-quarter ahead predictions of annualised real GDP growth (in per cent) using the model with SRI and one-quarter lag of real GDP as explanatory variables. The solid black line represents the median forecast, red dashed lines show the upper (95th) and lower (5th) percentiles and the solid blue line is the actual real GDP growth. Light grey areas refer to the OECD based recession indicator for Sweden. The predictions are made in-sample.

Sources: Statistics Sweden and authors' own calculations.

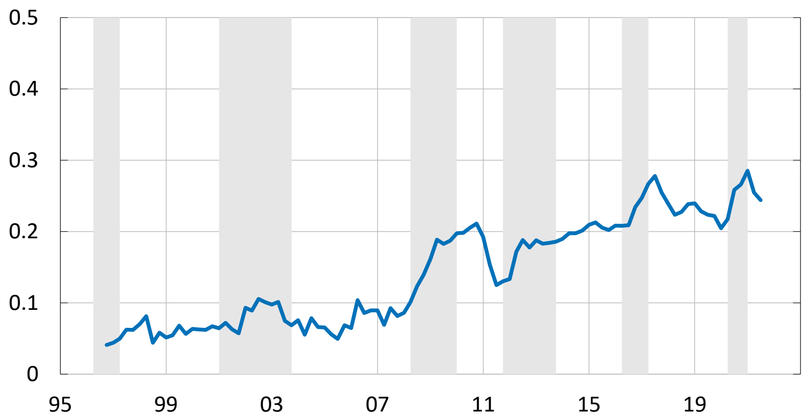
Chart 9. Probability of recession (in-sample forecast)

Probability

h=1



h=4



Note: The time series shows the probability of annualised GDP growth being below zero, as predicted by GaR based on the SRI as the explanatory variable with one quarter ahead forecast (h=1) and four quarter ahead forecast (h=4).

Source: Authors' own calculations.

Chart 10 shows the first three moments (mean, variance and skewness) of the forecasted distribution of real GDP growth at horizons *h*=1 and *h*=4, where *h* is quarter. The figures compare the models that condition on SRI (blue line) and FCI (red line).

Chart 10. In-sample forecasts: Time evolution of the predictive moments of real GDP growth

Note: Time evolution of the three moments of the one-quarter and four-quarter ahead predictive distribution of real GDP growth, from 1995Q1 to 2021Q2, for the models including SRI (blue) and FCI (red), with one-quarter lag of real GDP as explanatory variables. An increase in the skewness implies that the distribution becomes more skewed to the right, while a decrease in the skewness means that the distribution becomes more skewed to the left. Light grey areas refer to the OECD based recession indicator for Sweden.

Source: Authors' own calculations.

At the one-quarter-ahead horizon (*h*=1), the distributions of both models show a sharp decrease in the mean GDP growth around the period of the GFC. However, neither model captures the steep fall in GDP growth during the COVID-19 pandemic. This points to the fact that the recent crisis was not a financial crisis. Consequently, the models conditional on macrofinancial conditions do not capture it.

Moreover, for one quarter ahead forecast (h=1) movements in the second moment, the variances, are very similar during the entire sample period. Both models show a significant spike during the GFC, indicating a high uncertainty in growth around this period. Additionally, the ambiguity around future growth during the COVID-19 pandemic is captured well by both models, as the variances spike to their highest sample level.

Skewness – which represents the asymmetry of the distribution – for the one-quarter-ahead horizon (h=1) varies little over the sample period. The two models predict a distribution with a higher skewness during the GFC. The skewness of the predicted distribution conditioned on both models does not change noticeably during the COVID-19 pandemic.

At the four-quarter-ahead horizon (h=4), the findings are mostly in line with those discussed for h=1 but the fluctuations seem to be smaller and more volatile. Interestingly, both models do well in forecasting the substantial contractions in GDP at the four-quarter horizon around the GFC. Variance and skewness exhibit meaningful results around the GFC, but do not display interpretable patterns during the COVID-19 pandemic. The lack of predictability during the COVID-19 pandemic points to the pandemic being a rare event, which is unlikely to be captured by information in the historical data.

5.3 The Global Financial Crisis

The GaR framework was originally developed to assess the extent to which current macrofinancial conditions forecast downside risks to future GDP growth. Previous research has found that recessions are associated with left-skewed distributions while, during expansions, the conditional distribution is closer to being symmetric.[22] In other words, there is an asymmetric relationship between macrofinancial conditions and GDP growth. This means that, for example, if financial conditions deteriorate, the risk of weak future GDP growth (downside risk) increases more than the risk of strong future GDP growth (upside risk) increases, when financial conditions are favourable.[23] For this reason, we zoom in on the GFC of 2008-2009. Our focus is on the beginning of the crisis (2007Q4-2008Q1) and on the period when Swedish GDP fell the most (2008Q3-2008Q4). The forecasts of the growth distribution are made with the help of the SRI and FCI separately.

Chart 11 plots the *one*- and *four-quarter ahead* forecasts of the fitted conditional probability density function of GDP growth for the periods 2007Q4, 2008Q1 (A, B), 2008Q3 and 2008Q4 (C,D) using *SRI* as the explanatory variable. The estimated GaR is also plotted. Even if the realised annualised GDP growth in 2007Q4 was positive (1.12

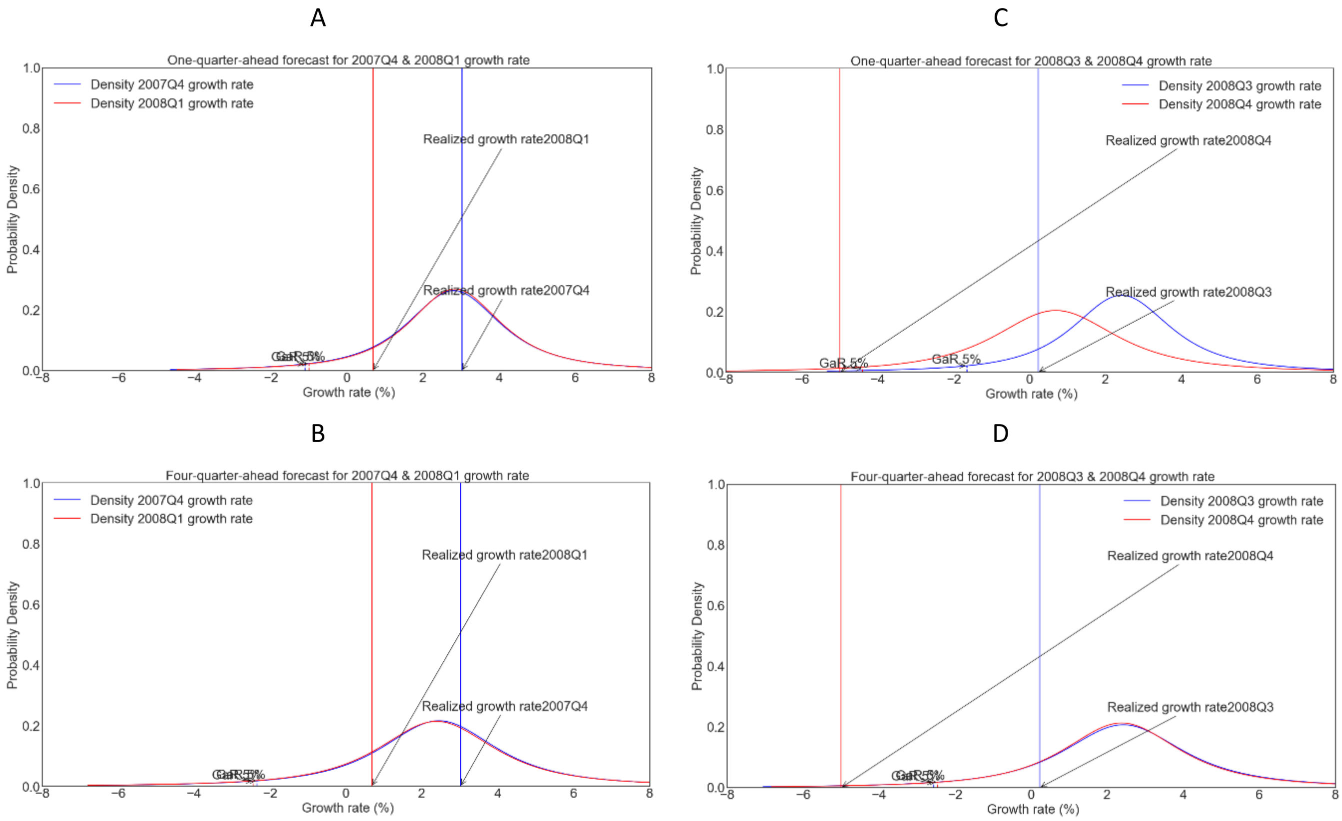
[22] See, for example, Adrian et al. (2019).

[23]GaR measures of downside risk of GDP growth increase with (tightened) financial conditions, while measures of upside risk are more stable over time.

per cent), the model shows a lower skewness of the conditional distribution for GDP growth, which is to say that the distribution is leaning more to the right indicating higher downside risk . Specifically, the one-quarter ahead forecast for 2007Q4, indicates a downside risk for GDP growth. The probability distributions for 2007Q4 and 2008Q1 are slightly flatter, with the four-quarter ahead forecast indicating that our systemic risk indicator predicted a more uncertain growth outlook for longer horizons. This is also observed by looking at the estimated GaR, which is further out in the left tail for the four-quarter ahead predictions. Nevertheless, given that the distribution does not shift, the model thus cannot predict a change in risk between the two periods, even though Swedish GDP had fallen.

It is interesting to note that, when Swedish GDP fell the most during the GFC (2008Q4), the change in the density compared to 2008Q3 was captured by a leftward shift in the distribution for the short-term forecasts. However, the forecasted distribution of GDP growth shows that the realised outcome for 2008Q4 was still an extreme event.

Chart 11. GFC - Probability densities of annualised GDP growth using SRI

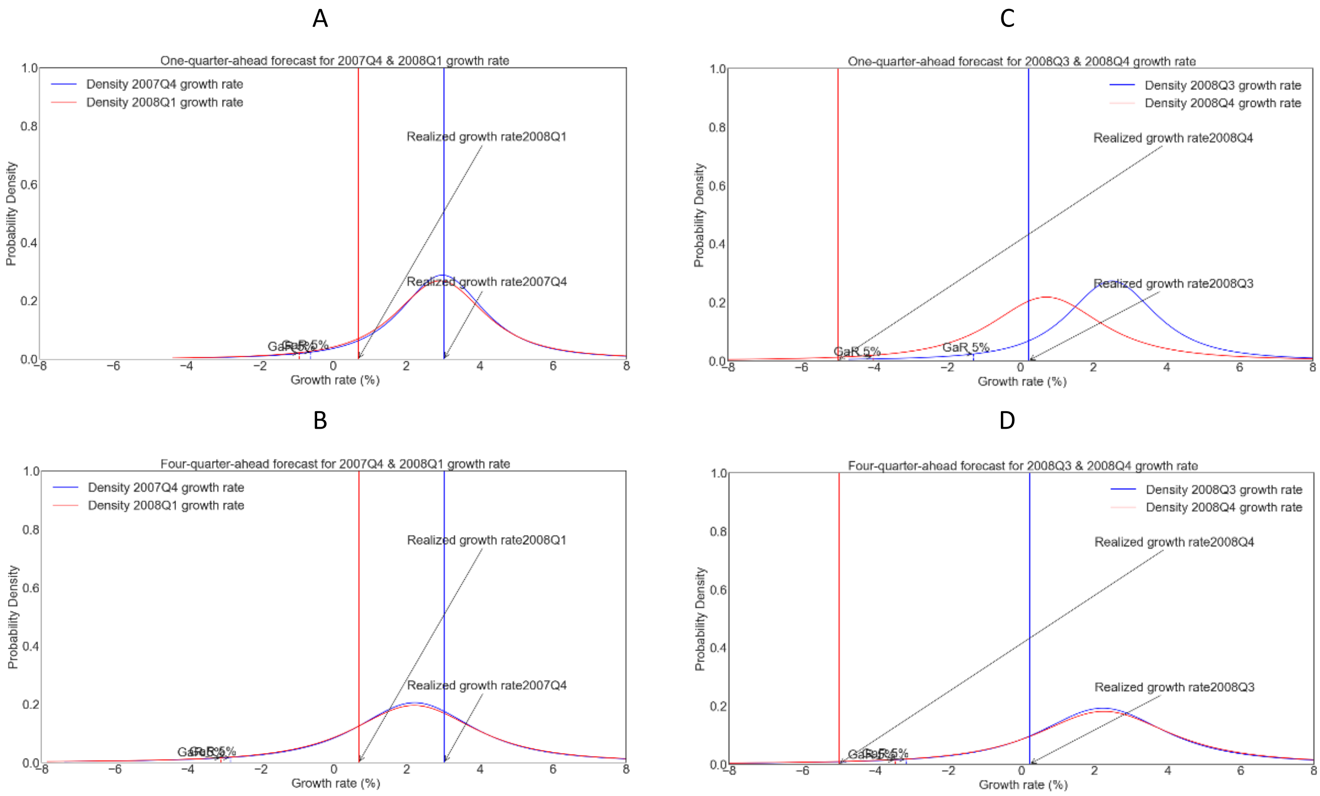


Note: One- and four-quarter ahead fitted conditional probability density functions of annualised real GDP growth for the GFC quarters. Each panel shows the skewed-t probability densities for our model with SRI and one-quarter lag of real GDP as explanatory variable. The vertical lines represent the realised real GDP growth.

Source: Authors' own calculations.

Chart 12 illustrates the *one-* and *four-quarter ahead* forecasts of the fitted conditional probability density function of real GDP growth for the GFC, now using FCI as the explanatory (conditioning) variable. As mentioned in the previous section, the drivers of the increase in the FCI correspond to higher spreads and volatility, lower asset prices and exchange rate depreciation. In contrast to the SRI, the FCI measures financial condition dynamics in Sweden. However, as shown in Chart 12, when financial stress spikes up in the fourth quarter of 2008, the conditional forecast of the model for both one- and four-quarter-ahead seem to do equally poorly in capturing the shift in the economy.

Chart 12. GFC - Probability densities of annualised GDP growth using FCI



Note: One- and four-quarter ahead fitted conditional probability density functions of annualised real GDP growth for the GFC quarters. Each panel shows the skewed-t probability densities for our model with FCI and one-quarter lag of real GDP as explanatory variables. The vertical lines represent the realised real GDP growth.

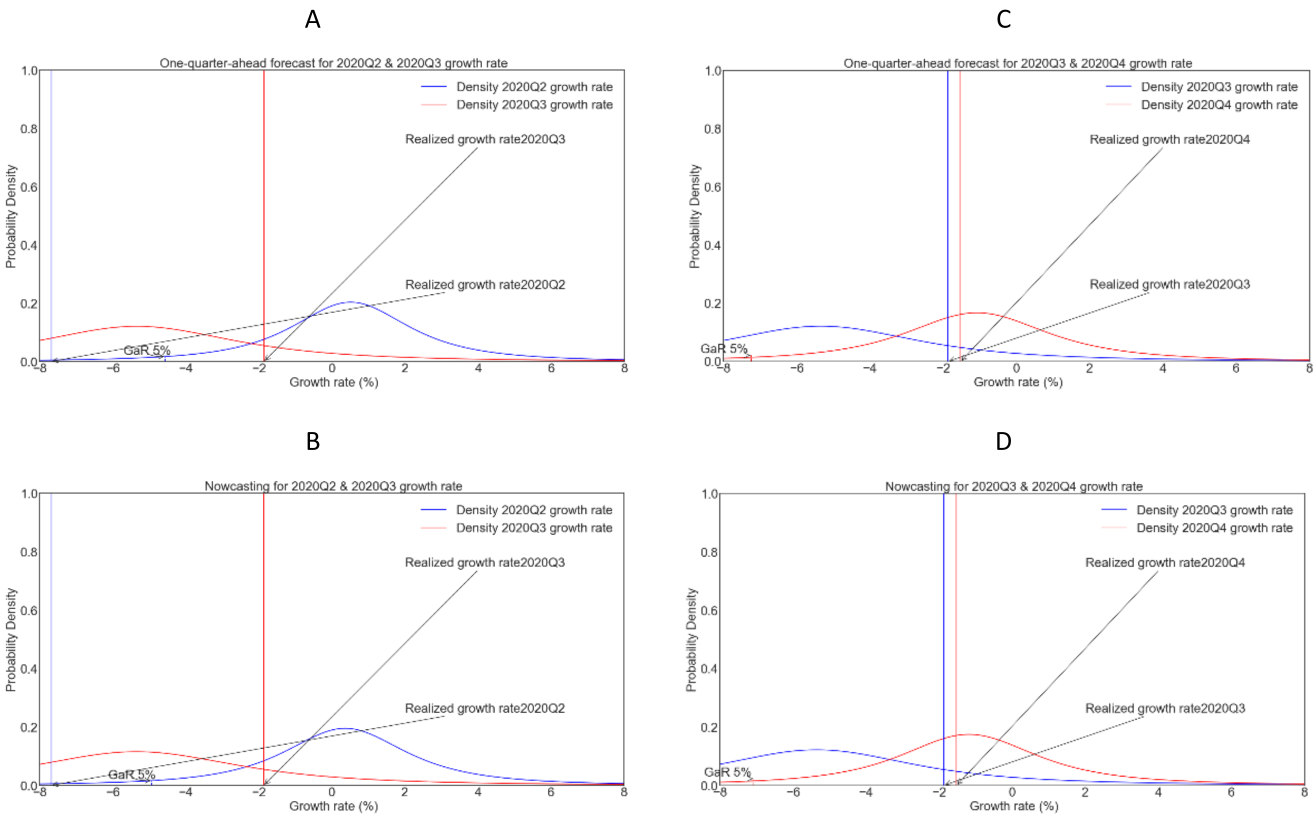
Source: Authors' own calculations.

5.4 The COVID-19 Pandemic

COVID-19 struck the world economy unexpectedly. The sharp fall in economic growth in Sweden, as in other parts of the world, was induced by governmental restrictions and lockdowns of a large part of the world economy with significant behavioural changes as a result. Given the delay in macroeconomic data, and the fact that the crisis started at the end of the first quarter of 2020, the fall in GDP growth only materialised in macro data in the second quarter of 2020. This provides a natural experiment for our analysis. Was the one-quarter-ahead forecast of the GaR accurate in forecasting the large changes in GDP growth during 2020?

The figures in the first rows (A, C) in Chart 13 and Chart 14 show that the one-quarter forecast distributions give a mixed picture of predicting economic growth during 2020. Conditioned on information available until the first quarter of 2020, not surprisingly both models fail to assign probability to the sharp downturn during the second quarter of 2020. Thus, financial variables prove not to be particularly valuable for forecasting this specific episode. First, the COVID-19 pandemic was not caused by growing imbalances in the financial sector, and second, such a steep fall in the growth of GDP has not been observed in the data on which we base the analysis. These two reasons together likely explain why the GaR, in this case, is not considered extreme enough, given the span of our data. Nevertheless, both models demonstrate a closer prediction of the upswing of GDP growth in 2020Q3 and 2020Q4 even if the uncertainty around the predictions increased, illustrated by rather flat distributions with fat tails.

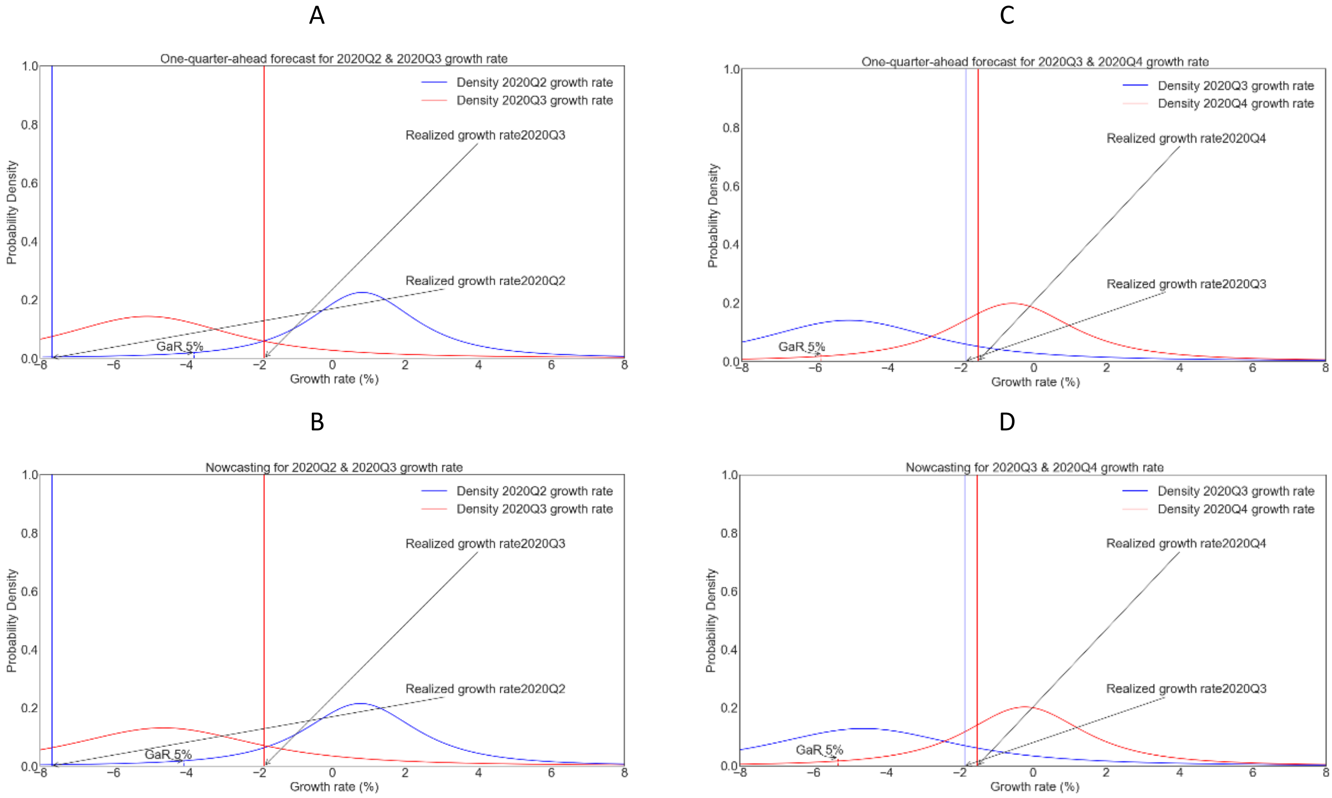
Chart 13. COVID-19 pandemic - Probability densities of GDP growth using SRI



Note: Nowcasting and one-quarter ahead fitted conditional probability density functions of real GDP growth for the COVID-19 pandemic. Each panel shows the skewed-t probability densities for the model with SRI and one-quarter lag of real GDP as explanatory variables. The vertical lines represent the realised real GDP growth.

Source: Authors' own calculations.

Chart 14. COVID-19 pandemic - Probability densities of GDP growth using FCI



Note: Nowcasting and one-quarter ahead fitted conditional probability density functions of real GDP growth for the COVID-19 pandemic. Each panel shows the skewed-t probability densities for our model with FCI and one-quarter lag of real GDP as explanatory variables. The vertical lines represent the realised real GDP growth.

Source: Authors' own calculations.

Above, we outlined that the predictive distributions of one-quarter ahead GDP growth for 2020 had mixed accuracy. Consequently, we also study whether the nowcasts (h=0, i.e. predicting the current-quarter GDP growth) in real time have been more accurate in our models. We re-estimate and compute the predictive distributions for the last three quarters of 2020 by conditioning on the financial indicators available at the same quarter as the forecasted GDP growth. The figures in the second row (B, D) of Chart 13 and Chart 14 show that the predicted distributions are similar to their one-quarter-ahead forecast equivalents (A, B). In particular, the steep fall in growth during the second quarter of 2020 is still not captured in the distributions, which is to say that the outcome is viewed as extremely unlikely. In conclusion, also when nowcasting, our financial indicators do not seem to add any additional predictive power in this case. However, we cannot be certain that they do not contain forward-looking information about growth. The weak results likely have to do with the fact that there is not enough variability on the quarterly level for the financial indicators, which may underestimate their level in times of sudden distress.

In summary, because the COVID-19 pandemic was not caused by financial imbalances, our COVID-19 case study suggests that financial variables are only useful to a limited extent at short horizons. While the financial indicators correctly hinted at the direction of real GDP growth for 2020Q3 and 2020Q4, the predictions for 2020Q2 were still very poor in this particular setting.

5.5 Out-of-sample results

So far, we assessed the behaviour of the models in-sample. In this section, we focus instead on the out-of-sample performance of the two models. First, we estimate the model conditioned on SRI for the periods 1995Q1-2021Q2, to predict the periods 1980Q1-1994Q4, covering the 1990s crisis in Sweden.[24] Specifically, can we predict the fall in GDP growth during the Swedish financial crisis in the early 90s? Compared to other recessions in our sample, the cause of this particular crisis originated from distortions in the Swedish financial system. Therefore, ideally, the Swedish financial crisis in the early 90s should be captured in our indicators reflecting macrofinancial conditions. Second, using the model conditioned on SRI from 1980Q1-2007Q4, we make another out-of-sample prediction for the period 2008Q1-2021Q2 in order to investigate whether this model can capture the increased downside risk during the Global Financial Crisis. Overall, in these exercises we try to answer whether it is possible to predict an increase in GDP growth vulnerability out of sample. Therefore, these exercises focus on short-to-medium horizons and try to gauge the overall ability of the model in assessing risks to GDP growth.

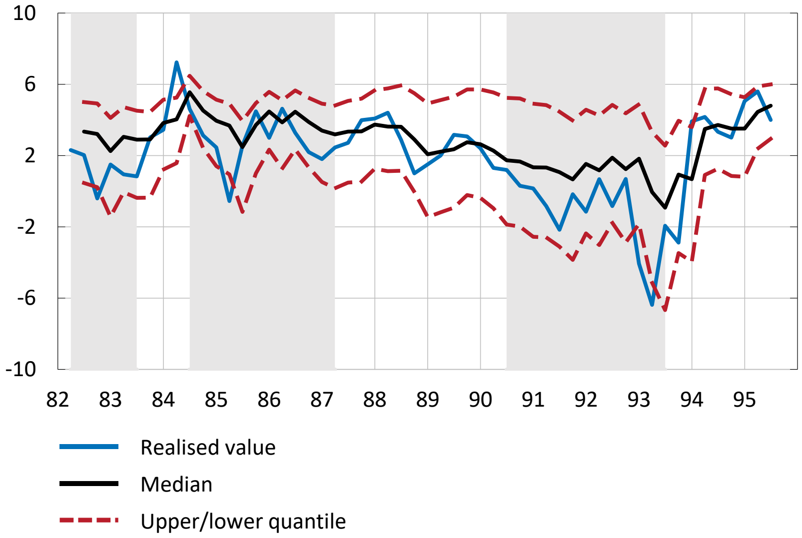
Chart 15 shows the one- and four-quarters ahead forecasts (median) for annualised GDP growth for the sample period 1982Q1-1995Q2 conditioned on SRI, together with the upper (95) and lower (5) percentiles. The model with short-term forecasting horizon (h=1) does well in capturing the Swedish financial crisis (1990-1994) while the one-year-ahead forecast indicates increased downside risk for falling GDP growth already from 1988.

[24] Due to lack of historical data for FCI, we do not estimate the model conditioned on FCI.

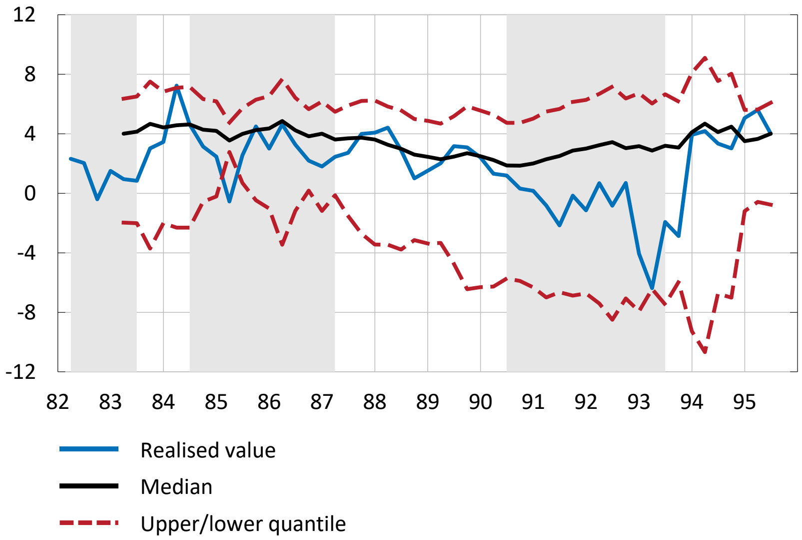
Chart 15. One- and four-quarters ahead out-of-sample predictions of annualised GDP growth using SRI as the main explanatory variable

Per cent

h=1



h=4



Note: One- and four-quarter ahead out-of-sample predictions of annualised real GDP growth (in per cent) for 1982Q1-1994Q4 using the model with SRI and one-quarter lag of real GDP as explanatory variables. The solid black line represents the median forecast, red dashed lines show the upper (95th) and lower (5th) percentiles and the solid blue line is the actual real GDP growth. Light grey areas refer to the OECD based recession indicator for Sweden.

Source: Authors' calculations.

Let us now turn to the predictability of risk vulnerability. We report the probability of GDP growth below zero in Chart 19 (APPENDIX E) for one- and four-quarters ahead. Both plots capture the Swedish financial crisis. However, the one-year-ahead (h=4) predicts approximately 20 per cent probability of a negative GDP growth, while the short-term forecast (h=1) assigns a 60 per cent probability. Nevertheless, the recessions in Sweden during the early- and mid-80s are well captured in the short-term forecast, but less so by the one-year-ahead.

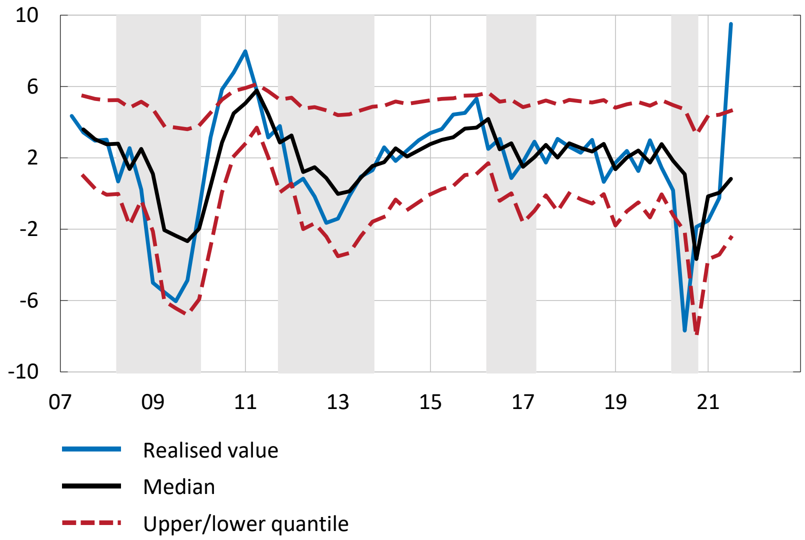
Next, we focus on the out-of-sample performance of the model conditioned on SRI by analysing whether our model predicts the increased downside risk of the Swedish GDP growth during the pre-phase of the Global Financial Crisis. To do that, we estimate the model during the period 1980Q1-2006Q4, and then predict the distribution of GDP growth from 2007Q1 to 2021Q2. The outcome of this procedure is a 14-year timeseries of out-of-sample density forecasts for each of the two forecast horizons.

The results for this exercise are presented in Chart 16 where we show the upper and lower quantiles plotted together with the realized GDP growth. The charts illustrate that the out-of-sample estimates do a somewhat good job of predicting the overall downside risk of GDP growth. However, the predictions of the immediate fall in GDP growth during the financial crisis in 2007-2008 are not fully captured by the model for neither one-quarter-ahead nor for one-year-ahead prediction. The explanation to this could perhaps be that the distortion in the financial market originated from the U.S. and was thus not reflected in the SRI.

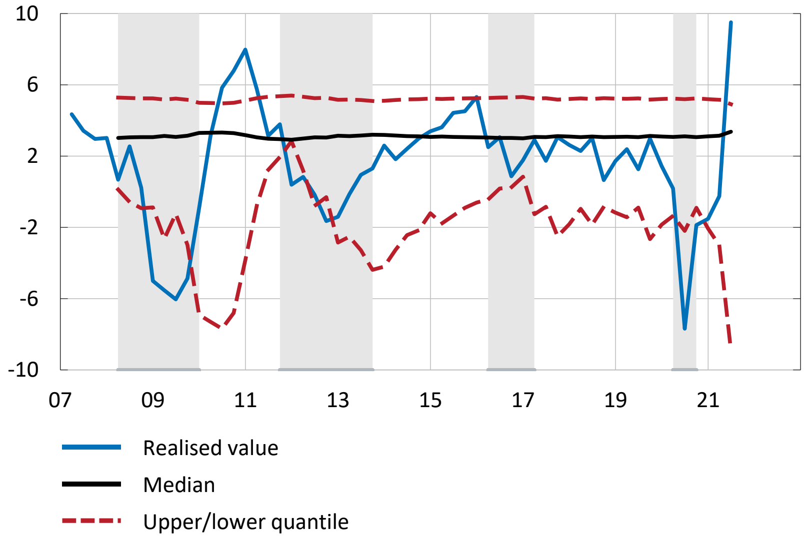
Chart 16. One- and four-quarters ahead out-of-sample predictions of annualised GDP growth using SRI as the main explanatory variable

Per cent

h=1



h=4



Note: One- and four-quarter ahead out-of-sample predictions of annualised real GDP growth (in per cent) for 2007Q1-2021Q2 using the model with SRI and one-quarter lag of real GDP as explanatory variables. The solid black line represents the median forecast, red dashed lines show the upper (95th) and lower (5th) percentiles and the solid blue line is the actual real GDP growth. Light grey areas refer to the OECD based recession indicator for Sweden.

Source: Authors' calculations.

We conclude the out-of-sample evaluation by analysing whether the one period lagged GDP growth is enough to explain the dynamics of the predicted GDP growth. In other words, we investigate if SRI contributes to the accuracy of out-of-sample growth distribution for the period 2007Q1-2021Q2. The results for this exercise are plotted in Chart 20 in APPENDIX F. We conclude that particularly for the medium forecast the predicted GDP growth distribution conditional on both GDP growth and macrofinancial conditions are more accurate than forecasting the distribution conditioned only on previous GDP growth.

6 Conclusions

A fundamental part of financial stability analysis concerns evaluating how macrofinancial conditions and vulnerabilities affect downside risks in the economy. Specifically, macrofinancial conditions are important because they can affect the functioning of the financial system, and thus financial stability, for example through the build-up of different risks and vulnerabilities. In the case of a crisis, were macrofinancial risks materialise, resulting output losses can be quite substantial.

The idea of linking current macrofinancial conditions to the distribution of future GDP growth enables an outlook on the expected distribution of economic growth – not only around the central forecast but also, more importantly, in the lower tail. Typically, macroeconomic forecasts focus on point forecasts of expected mean growth (first moment of the future GDP growth distribution). However, as Adrian et al. (2019) show, developments in higher moments also play a role, especially when assessing financial stability risks to economic growth.

Considering the entire distribution of expected conditional outcomes enables the policy maker to assess risks inherent in the financial system and their link to various states of the real economy. Specifically, the GaR framework can be used, for example, to assess policies that aim to enhance financial stability by quantifying the likelihood of different risk scenarios and their "costs" in terms of output losses. This can serve as a starting point for future preventive actions. Likewise, the framework can also be applied when evaluating actions already taken to improve the financial stability outlook. In this way, the GaR framework can provide a common metric for assessing downside risks to growth stemming from or related to developments in different financial variables and risk indicators, statically and over time. As discussed, for example, Adrian et al. (2019), a common metric promotes greater coordination of both financial stability risk assessment and the communication surrounding it.

The results based on Swedish data indicate that financial indicators representing macrofinancial conditions, such as the SRI and FCI, may have predictive power for the distribution of GDP growth. At times when shocks originate from the financial system, macrofinancial conditions can be helpful in predicting the distribution of growth. On the other hand, as our results based on the COVID-19 pandemic show, macrofinancial indicators have only a limited predictive ability when shocks do no originate from the financial sector or are not preceded by a build-up of macrofinancial imbalances.

The predictive power of macrofinancial indicators may also sometimes be limited because we use aggregated indicators. As Hasenzagl et al. (2020) show, aggregated indicators of macrofinancial conditions can mask heterogeneity across variables. A potential way to improve our indicators' ability to predict future growth distribution could therefore be to consider subcomponents of the indicators, or even individual variables. From a statistical point of view, financial crises and their impact on the real economy are ultimately hard to model empirically, due to financial crises being rare events. In addition, the main goal of indicators such as, for example, the SRI is not to predict crises but rather to say something about the expected loss in a crisis and to complement the financial stability analysis continuously. Crises tend to be deeper and more costly when they occur after a long period of rising vulnerabilities.

For policy purposes, the GaR framework can be used for further scenario analysis. In particular, the underlying financial variables can be shocked to assess how the shape of the entire growth distribution potentially changes. This analysis provides additional information about how the realisation of a risk scenario affects the overall risk of growth for future periods.

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APPENDIX A

Correlations

Table A.1 Pairwise correlations between GDP and SRI/FCI for different horizons h

Coefficient = $[-1,1]$

h	$\Delta gdp_t, SRI^q_{t-h}$	$\Delta gdp_t, FCI^q_{t-h}$
0	-0.367***	0.226**
1	-0.354***	0.268***
2	-0.325***	0.191**
4	-0.282***	-0.02
8	-0.327***	-0.349***
10	-0.328***	-0.341***
12	-0.297***	-0.320***

Note: Correlations are based on the whole sample period for each indicator: 1993q2-2021Q2 for the FCI and 1981q1-2021Q2 for the SRI. The stars indicate the significance level of the calculated Pearson correlation coefficient (* p<0.10, ** p<0.05 and *** p<0.01). h is quarter.

Sources: Statistics Sweden and the Riksbank.

APPENDIX B

Step 2 in GaR

As shown in Adrian et al. (2019), the conditional quantiles are a sufficient statistic for describing the conditional cumulative distribution function (CDF) and the probability density function (PDF). Following the authors, we use a parametric skewed t-distribution fit to derive the PDF from the CDF.

The skewed t-distribution, $F^{-1}(q|\mu, \sigma, \alpha, \upsilon)$, is governed by four parameters, location (μ), scale (σ), shape (α) and fatness of the distribution (υ). The parameters ($\mu, \sigma, \alpha, \upsilon$) are chosen for each quarter to solve the following minimisation problem:

A.1 $$\{\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\upsilon}_{t+h}\} = arg \min_{\mu,\sigma,\alpha,\upsilon} \sum \left(\hat{Q}_{y_{t+h|x_t}}(q|x_t) - F^{-1}(q|\mu, \sigma, \alpha, \upsilon) \right)^2$$

Once the optimal parameters are identified from A.1, it is straightforward to derive the fitted t-skewed CDF and PDF.

APPENDIX C

Backtesting results

Table A.2 Backtesting results

Backtesting method	GaR conditioned on SRI	GaR conditioned on FCI
***h*=1**		
Kupiec's POF	0.71	0.18
Lopez's average loss function	0.28	0.37
***h*=4**		
Kupiec's POF	0.24	0.84
Lopez's average loss function	0.05	0.05

Note: Backtesting for both one and four quarters ahead (h=1 and h=4). Kupiec's POF test is a test statistic asymptotically distributed as a chi-square variable with 1 degree of freedom (the critical value at 5% significance level is 3.841).

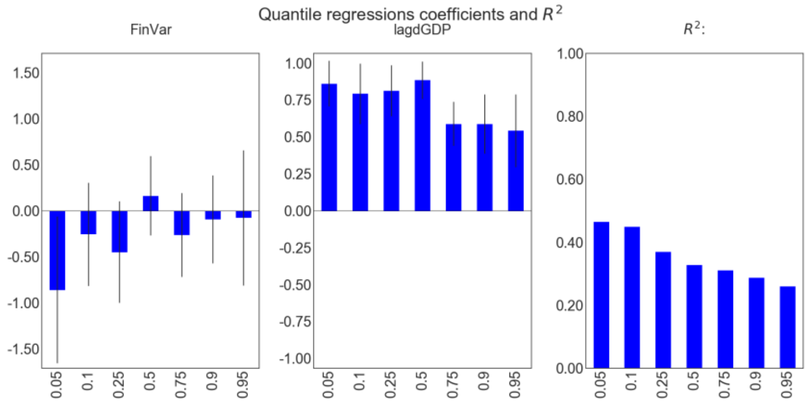
Sources: Kupiec, P. (1995) and Lopez, J.A. (1999).

APPENDIX D

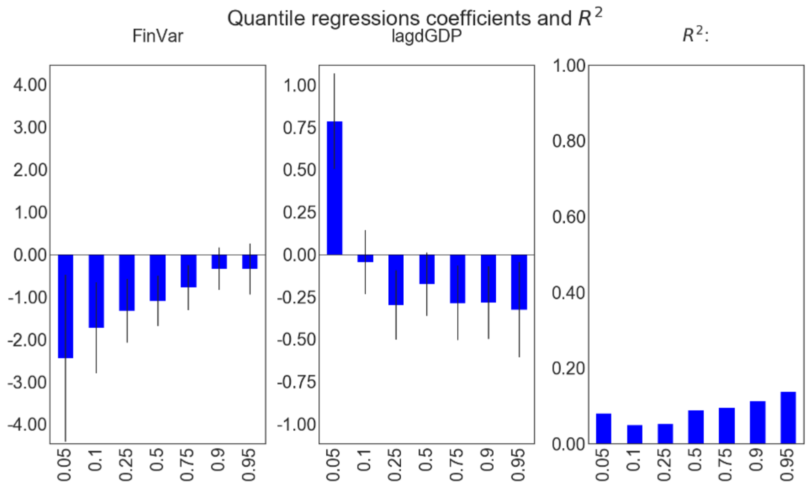
Quantile regression coefficients and R^2

Chart 17. In-sample Quantile Regression Coefficients and R-squared - SRI

h= 1



h=4

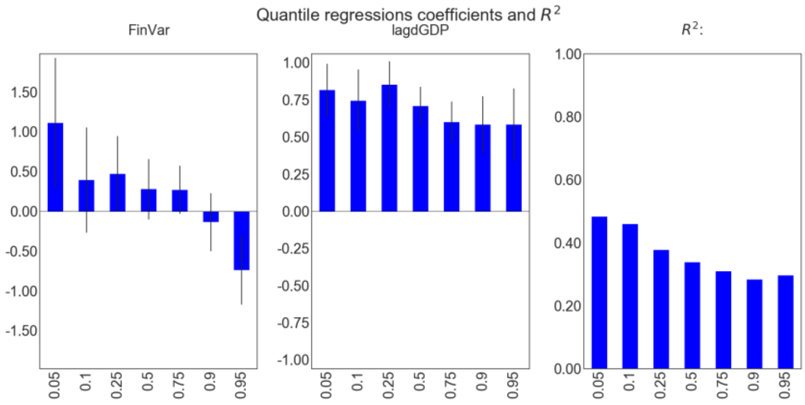


Note: In-sample quantile regression coefficient estimates for the model conditioned on SRI for both one- and four-quarters ahead projection of GDP growth. FinVar stands for financial variable (in this case SRI) at time t while lagdGDP is the lagged GDP growth at time t-1. The vertical black lines represent the coefficients' significant level at 10 per cent. Values on the x-axis represent quantiles.

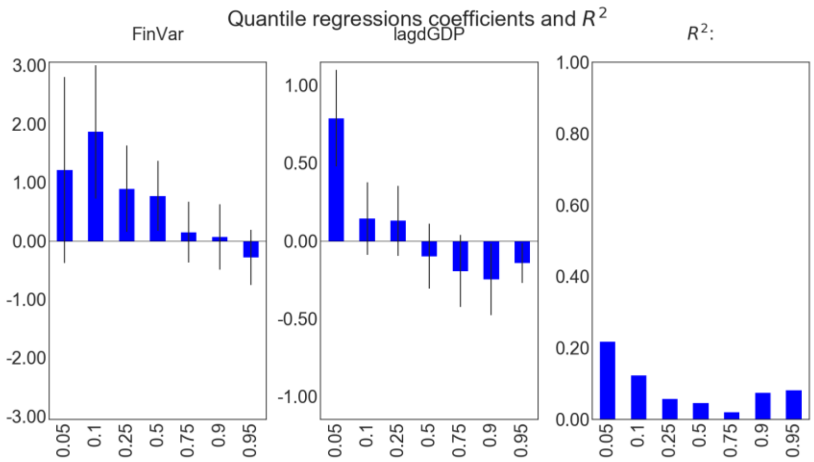
Source: Authors' calculations.

Chart 18. In-sample Quantile Regression Coefficients and R-squared - FCI

h=1



h=4



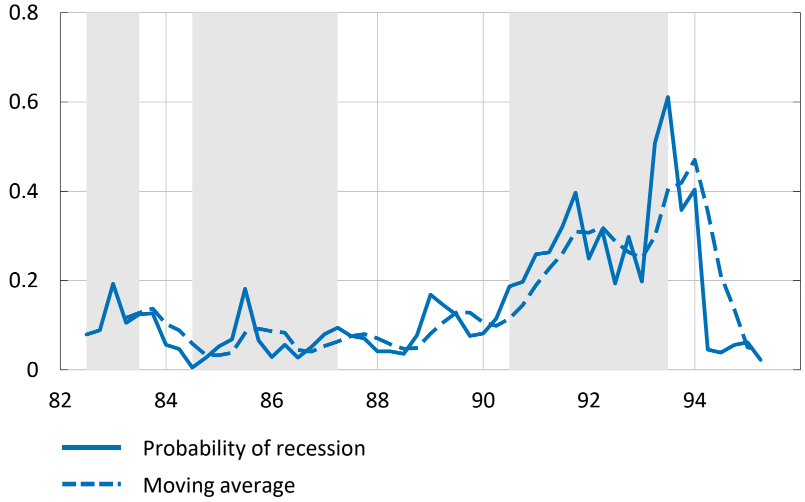
Note: In-sample quantile regression coefficient estimates for the model conditioned on FCI for both one- and four-quarters ahead projection of GDP growth. FinVar stands for financial variable (in this case FCI) at time t while lagdGDP is the lagged GDP growth at time t-1. The vertical black lines represent the coefficients' significant level at 10 per cent. Values on the x-axis represent quantiles.

Source: Authors' calculations.

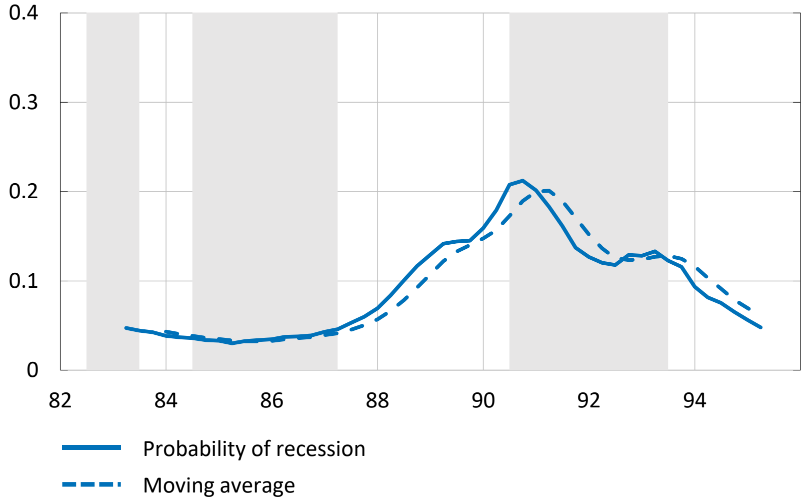
APPENDIX E

Chart 19. Probability of recession (out-of-sample prediction)

h=1



h=4



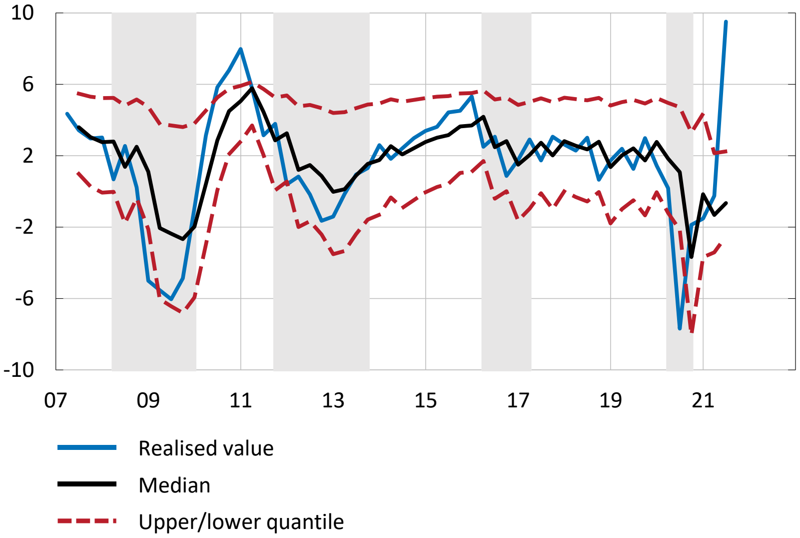
Note: The time series shows the probability of annualised GDP growth being below zero, as predicted by GaR based on the SRI as the explanatory variable with one quarter ahead forecast (h=1) and four quarter ahead forecast (h=4). For the period 1982Q1-1995.

Source: Authors' calculations.

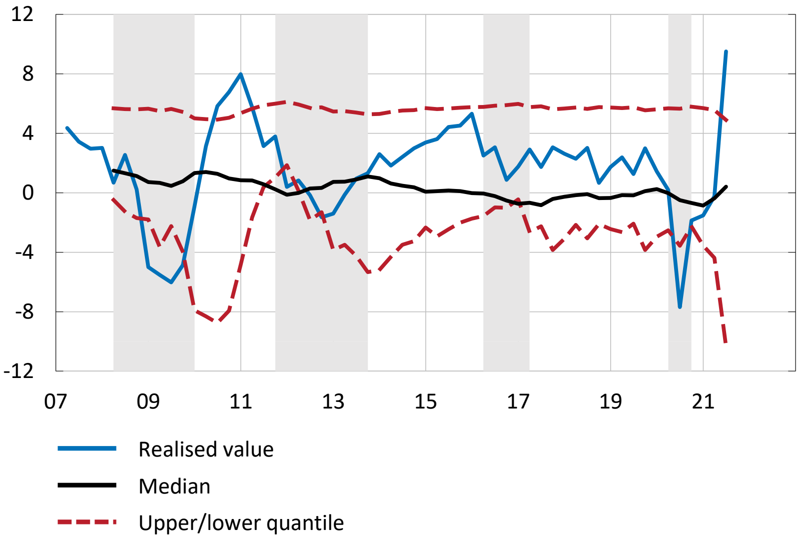
APPENDIX F

Chart 20. One- and four-quarters ahead out-of-sample predictions of annualised GDP growth using only previous quarters' GDP growth as explanatory variable

h=1



h=4



Note: One- and four-quarters ahead out-of-sample predictions of annualised real GDP growth (in per cent) for 2007Q1-2021Q2 using the model with only one-quarter lag of real GDP as explanatory variable. The solid black line represents the median forecast, red dashed lines show the upper (95th) and lower (5th) percentiles and the solid blue line is the actual real GDP growth. Light grey areas refer to the OECD based recession indicator for Sweden.

Sources: Statistics Sweden and authors' calculations.

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