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Growth-at-Risk and Financial Stability: Concept and Application for Slovenia*

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Abstract

This paper explores the information that measures of increased vulnerabilities and cyclical systemic risk in the financial system contain about the downside risk in the real economy. The connection between macrofinancial conditions and economic activity in this paper is assessed using the growth-at-risk (GaR) approach on Slovenian macrofinancial data. We show that the prevailing financial conditions influence the tail risks regardless of the time horizon, and the medium horizon risks are more dependent upon systemic financial vulnerabilities, such as when credit growth is excessive. These results have significant potential to inform macroprudential policy, the conduct of which implies managing risks for real economic activity stemming from financial imbalances in a forward-looking manner.

Keywords: growth-at-risk, macroprudential policy, systemic risk, financial conditions, financial stability, probability distribution
JEL Classification: E44, E47, E58, E66.

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Povzetek

Analiza obravnava informacije, ki jih vsebujejo merila povečane ranljivosti in cikličnega sistemskega tveganja v finančnem sistemu o tveganju padca aktivnosti realnega sektorja gospodarstva. Povezava med makrofinančnimi pogoji in gospodarsko aktivnostjo je v prispevku ocenjena z uporabo metode tvegane rasti (growth-at-risk) na slovenskih makrofinančnih podatkih. Prikazano je, da prevladujoče finančne razmere vplivajo na repna tveganja ne glede na časovno obdobje ter da so srednjeročna tveganja bolj odvisna od sistemskih finančnih ranljivosti, kot je to na primer prekomerna rast kreditov. Z dobljenimi rezultati se lahko zelo obogati informacijska baza za makrobonitetno politiko, ki vključuje v prihodnost usmerjeno obvladovanje tveganj, ki izhajajo iz finančnih neravnovesij, za realno gospodarsko aktivnost.

1 Interaction between the financial system and real activity (tail-growth)

The experiences of the global financial crisis have reignited the academic and policy debate on the relationship between the imbalances of the financial sector and the severe downturns in the real economy. At the heart of this debate was the realization that financial stability has a critical bearing on macroeconomic outcomes (Blanchard et al., 2010). Theoretical studies have already confirmed that the evolution of macrofinancial vulnerabilities carries important signals about evolving risks to future economic activity.

There are two main causes of tail events i.e. severe downturns with a low probability of occurrence, such as the 2008 global financial crisis. One is carried in the information that is embedded in the state of the financial conditions prior to the crisis, while the other is the systemic risk that is reflected in the position in the credit cycle. The link between financial structure (i.e. credit cycles) and macroeconomic activity has been long established in the literature.[1] In times when the economy is expanding and investment opportunities appear ample and easy to finance, macro-financial vulnerabilities build up and consequently the risk of accelerated and prolonged effects of the potential shocks to the economy increases. In the case of such shock, financial imbalances – such as excessive leverage and overpriced assets – may result in unfavourable interactions between the financial system and the real economy. The built-up macro-financial imbalances are often followed by severe recessions and financial crises.[2] In that sense, economic growth responds non-linearly to adverse shocks, which can further lead to a significant reduction in financial stability and consequently amplify the adverse macroeconomic situation.

The sources of the non-linear response of economic growth are the constraints that economic agents face when financing their activities, or so called financial frictions.[3] These amplify the relationships (transmission mechanism) between the real economy and the financial system. This amplifying mechanism works through the ease of financing in upturns of the cycle when asset prices are high. At the same time the risk premia are low, as the volatility on the financial markets is also low. However, should a shock hit such a vulnerable, highly leveraged economy, the asset prices would be among the first to strongly (and negatively) react to it, where even small changes

[1] Gertler (1988) in his work thoroughly surveys the early works and discussion on this macrofinancial link, while Bernanke (1993) has extensively discussed the macroeconomic role of the credit aggregates.

[2] See, for example, Kaminsky and Reinhart (1999), Claessens et al. (2011), Gourinchas and Obstfeld (2012), Schularick and Taylor (2012), and Mian et al. (2017).

[3] Works that incorporate models in which financial intermediaries face financial constraints in the financial sector include, among others Gertler and Kiyotaki (2010) and Gertler and Karadi (2011).

can lead to major equity losses. As pointed out by Deutsche Bundesbank (2021),[4] the initial shock may be amplified in a non-linear way by a self-reinforcing interaction between asset prices and financial and market liquidity frictions in the economy. Experience and empirical evidence support the view that financial vulnerabilities increase risks to growth and that recessions accompanied by financial crises are typically much more severe and protracted than ordinary recessions.[5] The powerful feedback effect between financial imbalances and the real economy has also been corroborated by Nalban and Smădu (2022) who show that "when financial uncertainty shocks hit the economy, the effects are significantly larger, with output responding about ten times stronger compared to both productivity and preference uncertainty shocks of a comparable magnitude."

In the context of the financial market's agents, the asymmetric response of the real economy can also be observed in its recovery after a financial shock. While a downturn is, as Minsky (1975) noted, triggered by a collapse in confidence of either borrowers or lenders, the beginning of an upturn is conditioned by the solid confidence of both sides, which experience has shown to be restored in a slow and cautious manner.

The financial and economic crisis of 2008-09 revealed the need for a re-examination of the financial regulation and brought forward a renewed focus on macroprudential policy, which aims to address systemic risk, that is, "the risk of developments that threaten the stability of the financial system as a whole and consequently the broader economy" (Bernanke, 2009. In times of expansion the decisions made by market players may certainly make sense at the micro level, but they more often than not neglect the potential negative implications for the stability of the financial system as a whole. In the context of the financial stability, macroprudential policy is mandated to prevent and reduce the accumulation of systemic risks by strengthening the resilience of the financial system. That is to say, the policies of macroprudential authorities must be designed in such a way as to counteract the build-up of financial vulnerabilities, which is expected to eventually lead to reduced downside risks in the real economy. Although managing economic growth is not the direct objective of macroprudential policy, an absence of financial stability manifests itself in a higher likelihood of deep recessions.

In this regard, there has been a growing need in the past years for the development of a quantitative framework for macroprudential policy assessment and design. Past attempts to do this have faced several challenges. From one side, there are a variety of tools – including many that are still in developmental phases – which face problems with either data limitations or the relatively short historical experience with their use. Yet another set of challenges reflects the non-integrated way the separate

[4]Please see their report for a more detailed discussion on the amplification mechanism.

[5]See for example, Claessens et al. (2011a, 2011b)

risk assessment tools have been used in informing macroprudential policy decisions. Additionally, certain challenges may be also identified in the vaguely defined concepts and measures of systemic risk and vulnerabilities that are used in this concept.

An important line of thinking proposes the use of macroprudential policy to manage real GDP growth distribution, in particular downside risks.[6] The following sections offers a short conceptual background of growth-at-risk (GaR) and an overview of the relevant work based on the GaR approach. Section 3 sets out the methodological approach used in the estimation of the GaR for Slovenia and Section 4 presents the results of the analysis. Section 5 discusses the usefulness of the GaR tool as an important part of a wider framework that can provide substantial information to macroprudential authorities in managing the risks to real economic activity that arise from financial imbalances in a forward-looking manner. Section 6 concludes and sets the stage for further work.

2 Growth-at-risk – conceptual background

The concept of growth-at-risk has received an increased attention in recent years from assessments of impact of systemic risk on economic output growth, to identifying macroprudential policy options for managing tail risk. The term itself was first used by Wang and Yao (2001), who proposed an assessment of financial systemic risk by extending the idea of value-at-risk, a popular risk management concept. The growth-at-risk concept and methods were later popularized by the seminal paper of Adrian et al. (2019a)[7] and the subsequent generation of growth-at-risk models and applications. In this literature, and by analogy with value-at-risk (VaR), the growth-at-risk (GaR) corresponds to the probability that future real GDP growth will fall below a predetermined threshold. In statistical terminology, the GaR of an economy over a given horizon is a certain chosen low quantile of the distribution of the (projected) GDP growth rate over such a horizon.

Unlike the standard macroeconomic forecasting practices, where the focus is usually on the expected value of GDP growth, the GaR approach takes into account the overall distribution of the growth. By focusing on the low quantiles of future growth (a conventional practice in risk management) the GaR measure provides a foundation for assessing the severity of potential adverse outcomes and their implications. Additional to this measure, and perhaps more important from a macroprudential authority

[6] See for example Brandao-Marques et al. (2020), Carney (2020), Duprey and Ueberfeldt (2020), Galán (2020), Cechetti and Suarez (2020), and Suarez (2020).

[7] Throughout this paper, the work of Adrian et al. (2019a) is interchangeably referenced as Adrian et al. (2016) as it was originally published as a Federal Reserve Bank of New York Staff Report, before being published by the American Economic Review in 2019.

perspective, the GaR approach can provide information on the variables that determine the probability or severity of bad outcomes, including policy variables that may then be used to address such aggregate risk. It provides an assessment of their relative importance, which, expectedly, varies along the probabilistic distribution of growth and according to the forecast horizon.

Earlier works based on the GaR approach introduce a new macroeconomic measure of financial stability by linking financial conditions (Adrian et al., 2016; IMF, 2017), financial gap (Bank of Japan, 2018) or asset price booms (Ceccheti, 2008) to the probability distribution of future GDP growth. These studies point to strong variation of the lower quantiles of the distribution of future GDP growth, while the upper quantiles remain stable over time. Subsequent research based on GaR models introduces the credit aggregates as an additional measure and assesses the impact of credit cycle risks on future growth distribution (Aikman et al., 2018; Aikman et al., 2019; Duprey et al., 2018a; Duprey et al., 2018b; Duprey and Ueberfeldt, 2018; Galan, 2020). Some of these works already place the focus on operationalization of the growth-at-risk approach and incorporating it into a holistic macroprudential policy framework. The works of Duprey and Ueberfeldt (2018) and Galan (2020) emphasise the feasibility of the GaR approach in evaluating the effects of macroprudential policies on low probability tail events.

Finally, there is the current ongoing work at national authorities level and at the ESRB (2021) Expert Group on Macroprudential Stance, whose aim is to offer operational methods for assessing the macroprudential stance. They see the macroprudential policy as "a risk management approach to safeguarding financial stability, in which policymakers assess the level of systemic risk compatible with financial stability and adjust their policies accordingly to achieve a neutral stance." The GaR approach is one of the several in the toolkit they propose for regular monitoring and providing input in broader policy deliberations. The stance metric proposed in the related report and obtained by the GaR approach provides quantification of the future impacts from current vulnerabilities and conditions of the financial system by focusing on the downside risks to growth distribution.

The current analysis follows the methodology proposed by Adrian et al. (2016) and the IMF (2017), and benefits greatly from the work done by the ESRB (2021) regarding the inclusion of additional measures and setting the GaR approach in a holistic macroprudential policy framework, which is currently under development at Banka Slovenije.

3 Estimating growth-at-risk for Slovenia – theoretical and empirical background

Growth-at-risk is measured as a pre-defined quantile at the lower end of the distribution of the growth rate of a real economic variable of choice. In the related literature, the quantile of the chosen variable that corresponds with a tail risk is usually set at 5% or 10% of its distribution. The tail risk is thus estimated conditionally on selected explanatory variables, and for quarterly estimation procedures the real GDP is usually the key metric for economic activity, as financial crises manifest themselves in large GDP losses.

3.1 The quantile regression approach

The estimation of the GaR is based on the estimation of a quantile regression, which is used to capture the effects of the explanatory variables on the forecasted GDP growth distribution. The concept of "quantile regression" has been developed by Koenker and Bassett (1978) and widely used in the GaR literature for identifying the effects of cyclical vulnerabilities and financial conditions on the tail risk of real economic growth.[8] The quantile regression seeks to assess how much would a change in a conditioning variable in a multivariate regression affect the shape of the lower or upper tail of the distribution of the dependent variable. In terms of quantiles, the quantile regression tells us what happens to the τ^{th} quantile of the distribution of Y_t when the k^{th} conditioning variable $X_t^{(k)}$ changes.

As opposed to linear regressions, the quantile regression can be used for estimating severe adverse outcomes in the tails of the real economic variable growth distribution, which can help us in the assessment of the transmission of financial conditions to the real economy. In contrast to linear regression, the quantile regression coefficients are estimated by linear programming. More specifically, the conditional quantiles of a dependent variable in a quantile regression are expressed as a linear function of the explanatory variables.

In order to arrive at the estimation of the quantiles in the quantile regression, let us first look at the way a quantile can be found using linear programming. The τ^{th} quantile of a discrete variable X is any number q_τ such that $\Pr(Y < q_\tau) \leq \tau \leq \Pr(Y \geq q_\tau)$. It can be shown that $\hat{q}_\tau$ is the solution to the following optimization problem,[9]

[8] See, for example, *inter alia* Cecchetti and Li (2008) and Adrian et al. (2019a.)

[9] The relation between a given quantile (τ) and a selected explanatory variable impact on y occurs through a minimization process of the sum of absolute residuals (compared to the sum of squares in multiple regression). Positive residuals are given a weight of τ and negative residuals a weight of $(1-\tau)$. The problem here is postulated as a non-linear optimization problem, but by reformulating the absolute values in a linear fashion we can arrive at a linear optimization problem.

presented in equation (1):

$$\arg\min_{q\in\mathrm{R}} \frac{1}{T}\left\{\sum_{y_t\geq q}\tau\left|y_t-q\right|+\sum_{y_t<q}(1-\tau)\left|y_t-q\right|\right\} \tag{1}$$

or

$$\arg\min_{q} \frac{1}{T}\sum_{i=0}^{n}\rho_\tau\left(y_i-q\right) \tag{2}$$

where the function ρ_τ is the absolute value function.

For a case where $\tau = 0.5$, the problem becomes

$$\arg\min_{m} \frac{1}{T}\sum_{t=1}^{T}\left|y_t-q\right| \tag{3}$$

and is solved by the sample median, $q_{\tau=0.5}$. In that sense, the equation (1) is essentially a weighted version of the median model, with weights τ and $(1-\tau)$.[10] When $\tau = 0.5$ we have a symmetric weighting of observations with positive and negative residuals, otherwise ($\tau \neq 0.5$) the weighting is asymmetric.

To obtain the *quantile regression* linear problem, we can simply replace the q in (1) with $X_t'\beta$ in the definition of the quantile estimator, as Koenker and Basset (1978) suggest:

$$\hat{q}_\tau = \arg\min_{\beta} \sum_{y_t\geq X_t'\beta}\tau\left|y_t-X_t'\beta\right|+\sum_{y_t<X_t'\beta}(1-\tau)\left|y_t-X_t'\beta\right| = \sum_{\varepsilon_t\geq 0}\tau\left|\varepsilon_t\right|+\sum_{\varepsilon_t<0}(1-\tau)\left|\varepsilon_t\right| \tag{4}$$

This reflects the assumption that we make in quantile regression for the τ^{th} quantile, which is that: the τ^{th} conditional quantile is given as a linear function of the explanatory variables. For each quantile τ, the solution to the minimization problem yields a distinct set of regression coefficients. In that respect, the $\tau = 0.5$ corresponds to the median regression and $2\rho_{0.5}$ is the absolute value function.

3.2 Model specification and data

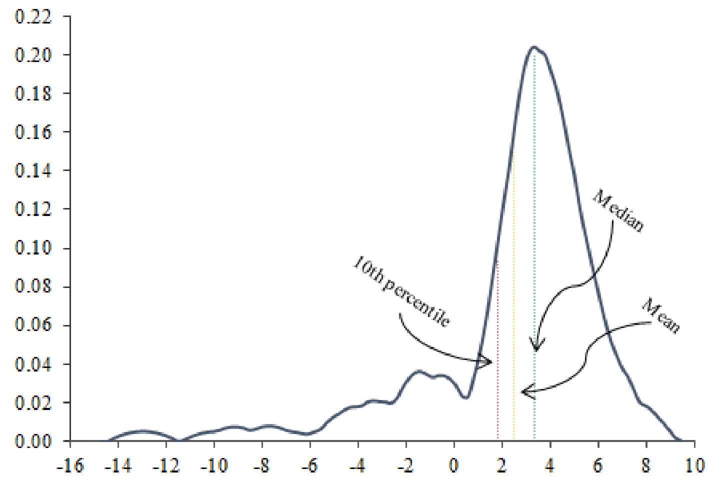
In the estimation of GaR for Slovenia approach, the metric we use for measuring economic activity is real GDP growth, as financial crises usually manifest in large falls

[10] Sum of absolute residuals is said to be minimized when an equal number of positive and negative residuals lies above and below the median line. Similarly, other quantile functions can be obtained by giving different weights to the negative and positive residuals, i.e., by minimizing the asymmetric weights of the residuals.

in GDP. In that sense, by focusing on the estimation of real GDP growth we remain consistent with the holistic approach to macroprudential policy (ESRB, 2021).

The (unconditional) historical average of the year-on-year real GDP growth rate for Slovenia between 1996 and 2020 was 2.5% and 1.8% for the 10th percentile (Figure 1). The graph of overall growth distribution reveals a stronger downward tail (left skewness), revealing downside risks to the Slovenian economy. Different factors and policies can influence the unconditional GDP growth left-tail distribution which may be identified as structural factors, factors stemming from the financial system, and policy-related factors.

Figure 1: Unconditional distribution of y-o-y growth GDP (1996 – 2020)



Note: The density is estimated using a kernel density estimator with a normal kernel function. The Jarque-Berra test statistics for each density strongly rejects the null hypothesis of normality; the test statistic for the unconditional distribution is 63.28 (vs the critical value of 5.991).
Source: Authors' calculations.

The mandate of the macroprudential policy implies managing risks, in a *forward-looking manner*, for real economic activity that may arise from imbalances in the financial system. However, low growth rates in the tail of the distribution may be related to factors that are outside of the scope of macroprudential policy. For example, they may occur due to adverse productivity shocks, as was the case with the recent COVID-19 pandemic shock, which may shift the entire forecasted growth distribution. In light of this, it is important to identify the drivers of low tail real growth that are in the macroprudential realm.

The GaR approach provides for identification and quantification of the impacts on the growth distribution that are related to financial conditions, systemic risk and macroprudential policy. In the language of the quantile estimation, the goal of macro-prudential policy would imply effectively steering the downside tail of the distribution of the forecasted growth rate of a real economic variable in order to offset the potential undesired effects of financial imbalances.

As the goal of an effective macroprudential policy is to manage the systemic risk over the financial cycle (ESRB, 2021), i.e. in a forward-looking manner, we estimate the following baseline model[11] for Slovenia:

$$y_{t+h}^{q} = \beta_0^q + \sum_{i \in I} \beta_i^q \mathbf{X}_{i,t} + \varepsilon_{t+h}^{q} \tag{5}$$

where $q \in \{0.1, 0.25, 0.5, 0.75, 0.9\}$ is the chosen quantile, y_{t+h} is the growth rate of real GDP over the next h quarters ahead and $\mathbf{X}_{i,t}$ contains a set of macrofinancial indicators I including a lag of the explanatory variable, financial conditions indicator (FCI), systemic risk indicator (SRI), macroprudential indicator (MPI), and a economic sentiment indicator (CLI), β_0^q and ε_{t+h}^{q} denote a constant term and the residual, respectively.

The growth distribution that we derive under the GaR framework is largely determined by the prevailing macrofinancial conditions. Having in mind the critical importance of the choice of macrofinancial variables for explaining their relationship with future growth, in selecting them we rely heavily on the existing literature and practices.

The most common sample of macrofinancial indicators that are typically used in constructing financial condition indices, which are some of the key explanatory variables in GaR estimations, include credit growth, interest rates, asset prices, volatilities and exchange rates (Arrigoni et al., 2020). The present analysis, however, follows the notion of two main types of indicators that signal risks to the real economy contingent on the length of the horizon over which they affect future growth. For example, indicators related to fast-moving asset prices and volatility indicators tend to signal risks to growth over the near term, whereas credit aggregates and leverage indicators change gradually over time and may indicate risks over longer horizons (IMF, 2017).

In the context of macrofinancail metrics that contain risks for the near term growth, recent works based on the GaR approach typically use the financial composite indicators (FCI)favoured by the IMF (2017), which follows the definition by Hatzius et al. (2010) and is methodologically based on the work of Koop and Korobilis (2014). And while other authors use different empirical econometric methods for constructing FCIs that have been developed in the recent literature,[12] they all represent a function of various asset prices, quantity and price of credit in the economy, or volatility in-

[11] We estimate the linear specification of the model, following the example of Adrian et al. (2017) and Aikman et al. (2018).

[12] Among the most commonly used FCI estimation approaches are Primiceri's (2005) time-varying parameter vector autoregression model-based FCI and the dynamic factor models of Doz et al. (2011).

Table 1: FCI Slovenia metrics by category

Spreads and implied volatilities	**Yields and price indices**
VIX (Global Volatility Index)	SBITOP
VSTOXX (EA Volatility Index)	Real property price index SI
CLIFS SI (Country Level Index of Financial Stress)	Long-term interest rate Slovenia
Euro spread (EURIBOR3m-EONIA3m)	
government bond spread over German bund (10 year)	
lending spreads SI	

Note: Categories adapted from Arrigoni et al. (2020)

dicators. For the purposes of our analysis we develop a financial conditions indicator for Slovenia[13] following the procedure proposed by Prasad et al. (2019). There are many macrofinancial variables that are relevant for explaining GDP growth and many that tend to comove. Moreover, there is an asymmetry in the cross-correlation of the financial variables that is contingent on the business cycle. In other words, in normal times the financial variables are weakly correlated with each other while in periods when large amplification effects of financial conditions on economic activity are typically observed (expansionistic phases (bubbles) and/or crashes) their correlation is pronounced. The benefits of applying a data reduction method before estimating the quantile regressions are thus twofold. First, it can extract common trends among relevant macrofinancial phenomena and remove idiosyncratic noise, thereby improving the quality of the regressions. It also reduces the number of parameters that need to be estimated, thereby helping overcome the potential challenge of limited data availability. In developing the Slovenian FCI we consider both metrics for financial stress and volatility, that aggregate information from a number of financial markets, as well as simpler metrics on yields and price indices that feature regularly in the policy debate and/or have been found to have good leading properties in other studies (Table 1).

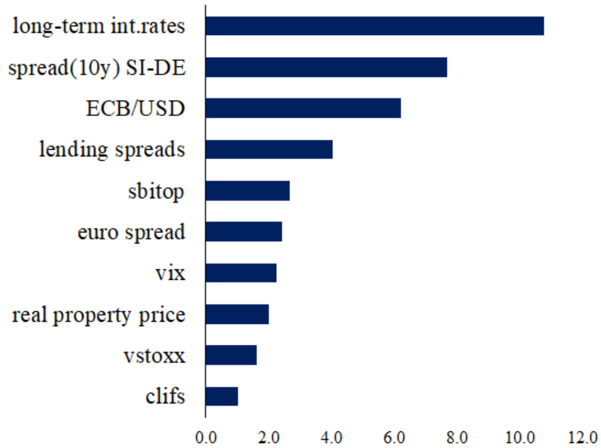
Although the existing literature often uses PCA-based methods to estimate FCIs,[14] we find the LDA the more suitable data dimension reduction method for this analysis. Compared to PCA, the LDA contains one additional step, the classification approach, which allows for linking of the financial variables with the historically low GDP growth in the data reduction process. In that sense, the loadings of each individual variable

[13]The FCI is estimated for 43 advanced and emerging market economies, but it is not available for some EU countries, including Slovenia. Other EU countries for which the indicator is not calculated include CY, EE, HR, LT, LU, LV, MT, RO, and SK.

[14]The more advanced approach that the IMF employs for computing FCIs includes a FAVAR model (see Koop and Korobilis, 2004) that uses Kalman filtering, which tries to capture the joint dynamic of GDP and FCI, over 20 variables. However, FAVAR-derived and PCA-derived FCIs are very similar, as the correlation between the two across time for 43 countries has been found to be over 95% (IMF, 2019).

on the LDA component maximizes the separability between low and normal growth regimes[15] (see Figure 2) for the LDA loadings obtained for the metrics included in the construction of the FCI for Slovenia).

Figure 2: LDA loadings for the FCI



Note: The loadings represent the coefficients of the linear combination of variables used to generate the FCI. As such, they should be interpreted as a whole and not separately. Additionally the loading of a given variable will also depend on whether other variables are included or not.
Source: Authors' calculations.

A tightening of financial conditions, is a significant predictor of large macroeconomic downturns within a one-year horizon. In that sense, an increase in the FCI corresponds to tighter financial conditions, which are reflected in increased volatility in the financial markets and widening spreads (increasing price of risk) on one side and rapidly falling yields and price indices on the other.

Related to the more gradual risk transmission to the economy, one of the macrofinancial indicators that we include in our analysis is the domestic Systemic Risk Indicator (SRI) that captures the information that credit aggregates in the economy carry for future growth. The SRI used in the analysis is proposed in Lang et al. (2019) and composed of individual indicators that exhibit good early warning properties[16]

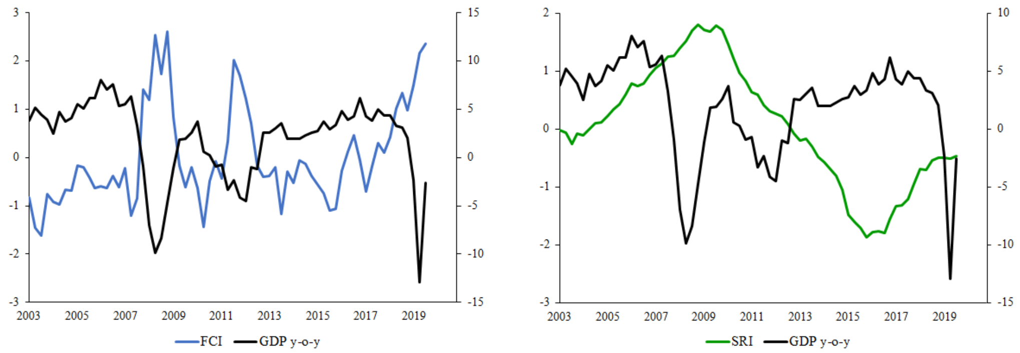
[15] One of the potential issues of the PCA approach is that data reduction is realized via a maximization variance principle among the set of individual variables, which might not be relevant information for predicting future GDP growth. On the other hand, the LDA maximizes the common variance among a set of variables $\mathbf{X}$ (similarly as the PCA), but it additionaly ensures that the linear combination of the variables $\mathbf{X}$ discriminates the class of a categorical variable, y. In the present case, the y variable is a dummy variable (which reflects a case of two classes), where y equals 1 when future GDP growth at the one-year level is below the 20$^{\text{th}}$ historical percentile and 0 otherwise. In other words, the loadings of each individual variables on the LDA component maximizes the separability between low and normal growth regimes (for more detailed discussion, see IMF, 2019).

[16] The SRI presents a composite indicator and is constructed as a weighted average of the six early warning indicators that include the two-year change in bank credit-to-GDP ratio (with a weight

and originate from an extensive set of ESRB risk categories that reflect credit developments, property prices, private sector debt burden, mispricing of risk and external imbalances.[17] The inclusion of this indicator follows the work of the ESRB (2021).

The Figure 3 shows the time series of real GDP growth and the Slovenian macrofinancial indicators, FCI and SRI. The time series plots already indicate the non-linear relationship between future GDP growth and macrofinancial conditions. In that sense, extreme negative outcomes in GDP growth tend to coincide with extreme positive outcomes of the FCI and the SRI.

Figure 3: Financial conditions, systemic risk, and real GDP growth



(a) FCI and GDP growth

(b) SRI and GDP growth

Source: Authors' calculations.

The forward-looking credit aggregates indicator (SRI) is expectedly less volatile and displays a wider cycle. The gradual build up of vulnerabilities over the medium term, as opposed to the FCI, can be illustrated with the following stylized example. In times of low leverage in the economy, increasing prices of assets may correspond, over the short term, to high expected growth. However, an environment such as that may give rise to the build-up of vulnerabilities over the medium term, which would ultimately increase the probability for tail outcomes (IMF, 2017).

The inclusion of the FCI and SRI builds on Adrian et al. (2019b), Prasad et al. (2019) and the ESRB (2021), which make a clear distinction between financial stress indicators that capture the materialization of the risk and systemic stress indicator, which develop endogenously[18] and act as potential amplifiers of shocks. In addition to these two basic metrics in the existing GaR estimation frameworks, in the analysis

of 36%), the current account-to-GDP ratio (20%), the three-year change in residential real estate (RRE) price-to-income ratio (17%), the three-year growth rate of real equity prices (17%), the two-year change in debt service ratio (5%), and the two-year growth rate of real total credit (5%).

[17]The SRI indicator is the one that ESRB recommends in the setting of the countercyclical buffer rates (Recommendation ESRB/2014/1) and the selection of the appropriate variables that indicate the build-up of system-wide risk associated with periods of excessive credit growth.

[18]The financial stress indicators capture the periods of the build-up of vulnerabilities in the system that can, in the presence of financial frictions, lead to materialization of the risk.

we include a macroprudential policy indicator (MPI) and also examine the inclusion of a metric of additional macroeconomic developments, a composite leading indicator (CLI). Both measures are constructed on the basis of several indicators by using the LDA approach in a similar way as with the FCI (Table 2).

The CLI is constructed from a vector of variables that include a domestic sentiment indicator and domestic industrial production on the one hand, and sentiment indicators of important trade partners (DE and IT) on the other. According to Sun and Samuel (2009), the importance of external real conditions is both plausible and consistent with the past literature, and weak external real conditions are associated with lower future growth both in the short- and medium-term, especially at the high quantiles of growth distribution (Komatsuzaki and Brito, 2019).

The macroprudential policy indexes that enter the LDA have been constructed building on the Macroprudential Policies Evaluation Database (MaPPED; Budnik and Kleibl, 2018) and they distinguish between capital-based and borrower-based measures (BBM). The two types of indices that can be constructed on the basis of the MaPPED database are the "dummy-type" indices that are obtained by assigning +1 for tightening and -1 for loosening policy decisions and the cumulative indices that are obtained by dynamically accumulating the net macroprudential changes m_t from tightening and loosening within each quarter[19]:

$$\mathrm{MPI}_t = \mathrm{MPI}_{t-1} + m_i \tag{6}$$

The MaPPED MPIs that are included in our LDA for constructing the MPI in our analysis are the dummy-type indices for capital- and borrower-based measures. The reasoning behind using the dummy-type indices is that the cumulative macroprudential indices tend to increase over time given that the number of policy "tightenings" is larger than that of "loosenings". Since the other variables entering the quantile regressions for GaR estimation are (close to) stationary, the upward trending evolution of the MPIs might bias the coefficient estimates.[20]

[19]There are several macroprudential indices that are used in the literature and constructed in a similar way. The MaPED MPI is constructed in such a way that, when several interventions occur within the same quarter, they are summed for that specific quarter. For example, if two tightening measures are implemented within one quarter, the MPI takes the value 2, if a tightening and a loosening measure are implemented the resulting MPI indicates no change. If the intervention is characterized in MaPPED as "other or with ambiguous impact" it is assigned the value of 0.

[20]Please see ESRB (2021) for the discussion on different approaches on the construction of the macroprudential policy indicators that deal with this econometric problem.

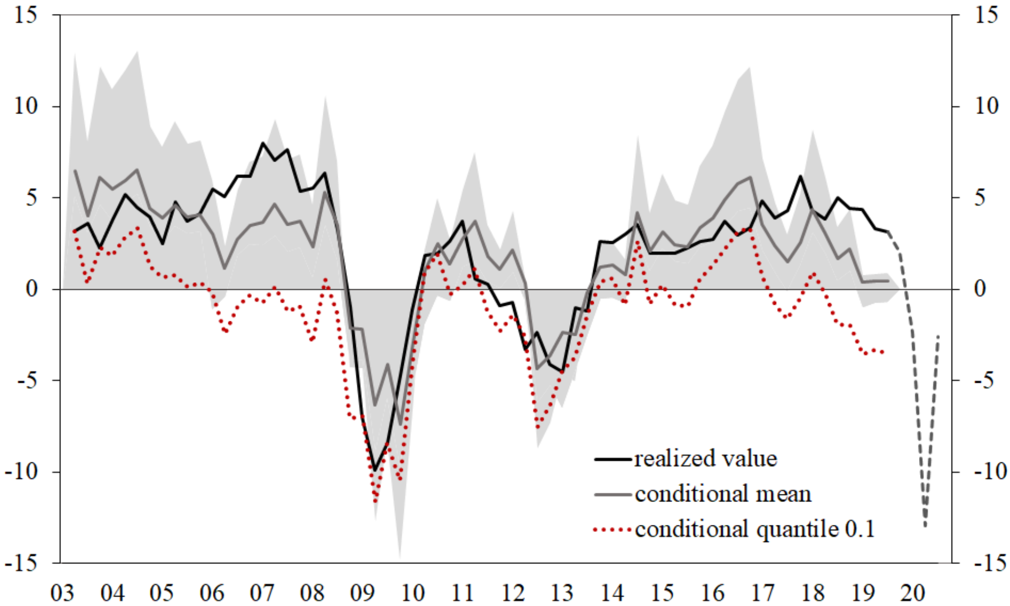
Table 2: Overview of the construction of the financial conditions index and the domestic systemic risk indicator

	Domestic systemic risk indicator (SRI)	**Financial conditions index (FCI)**	**External macroeconomic conditions (CLI)**	**Macroprudential policy (MPI)**
Aggregation method	*Weighted average of normalised indicators based on pooled median and standard deviation ranks*	*LDA, 20% threshold*	*LDA, 20% threshold*	*LDA, 20% threshold*
Metrics	Bank credit-to-GDP ratio (2-year change, 36%)	VIX (Global Volatility Index)	Industrial production SI (y-o-y)	MaPru Capital-based measures only, net (tightening minus loosening)
	Real total credit (2-year growth rate, 5%)	VSTOXX (EA Volatility Index)	Industrial confidence indicator – SI	MaPru Borrower-based measures only, net
	Debt-service-ratio (2-year change, 5%)	CLIFS SI (Country Level Index of Financial Stress)	Industrial confidence indicator – DE	
	RRE price-to-income ratio (3-year change, 17%)	Euro spread (EURIBOR3m-EONIA3m)	Industrial confidence indicator – IT	
	Real equity prices (2-year growth rate, 17%)	SBITOP		
	Current account-to-GDP ratio (20%)	Government bond spread over German bund (10 year)		
		Lending spreads SI		
		Long term interest rate Slovenia		
		Real property price index SI		

4 Estimation results

The quantile regressions are estimated at different points of the distribution of y^q_{t+h} and each coefficient β^q_i represents the macrofinancial linkage between the variable $X_{i,t}$ and future growth, at different points of the future growth distribution. Similarly as the OLS regression provides an estimation of a conditional mean, quantile regression estimates conditional quantiles of the dependent variable y_{t+h} conditional on financial variables $\mathbf{X}_{i,t}$, $\left(y_{t+h}, q \,|\, \{X_{i,t}\}_{i\in I}\right) = \hat{\beta}^q_0 + \sum_{i\in I} \hat{\beta}^q_i X_{i,t}$ for a given date t based on the point estimates of the coefficients $\hat{\beta}^q_0$ and $\hat{\beta}^q_i$. Figure 4 shows the estimated conditional quantiles for four quarters ahead (the baseline model).

Figure 4: Conditional quantiles (realization, mean, upper, lower, and GaR 10%)



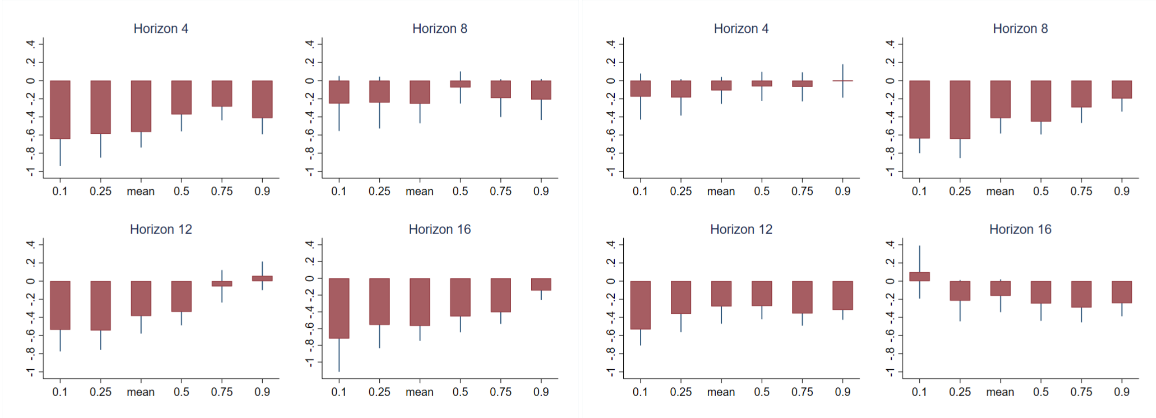
Note: The quantile regressions are estimated at different points of the distribution of y_{t+h} i.e. at 0.1, 0.25, 0.5, 0.75 and 0.9. Each beta coefficient represents the macrofinancial linkage between the variable and future growth, at different points of the distribution of GDP growth (basically, the business cycle). The confidence interval is reported at 10% level using heteroskedastic robust standard errors for quantile regression (Koenker 2005).
Source: Authors' calculations.

From the estimated baseline specification we can observe that there is a widening between the conditional mean and the GaR10%[21] before a significant drop in GDP growth. This corroborates the view that macrofinancial conditions contain predictive signals for increasing risks at the tail of the future GDP growth distribution. Based on the model estimation, we can also observe a widening gap in the period before the

[21] In this analysis we show the results for the 10$^{\text{th}}$ percentile of the future GDP growth distribution and denote the tail risk as GaR 10%.

COVID-19 crisis. Although this shock did not originate in the financial sector, the results indicate a phase of the build-up of financial vulnerabilities that is typical for later phases of a financial cycle.

Figure 5: Term-structure of the growth-at-risk



(a) Term structure FCI (b) Term structure SRI

Note: The vertical lines in the red bars denote confidence intervals at 10% and, when they cross the x-axis, this signals the absence of statistical significance of the predictor.
Source: Authors' calculations.

Table 3 reports the key estimations results from the main specifications for four- and eight quarters ahead on a sample spanning 2003 – 2020. The first specification (1) includes all of the partitions mentioned above (lagged GDP growth, FCI, SRI, CLI, MPI), the second specification (2) includes only the financial conditions and systemic risk additional to the lagged GDP growth, the third and the fourth specifications (3,4)) – apart from the autocorrelated term) – contain only the FCI and SRI, respectively.

The negative coefficients on SRI and FCI indicate that higher systemic risk and financial stress lead to lower GDP growth at the 10th percentile of the GDP growth distribution, and thus generate lower forecasts for real GDP tail. As predicted by the literature, the FCI impacts the tail risk at four quarters ahead while it impacts the SRI in the medium to longer term. The intertemporal trade-offs associated with FCI and SRI are also captured in Figure 5 where the term-structure of the GaR for Slovenia is examined based on the estimation of the base model specification. The estimation is conducted for horizons ranging from four to 16 quarters. The estimation results reveal that while the FCI represents downside risks to growth regardless of the forecasting horizon, the SRI has the largest detrimental effects on the tail of the growth distribution around eight to 12 quarters ahead.

Table 3: Key estimation results from the main specifications for four- and eight quarters ahead

Dependent variable: average annualized real GDP over one quarter ahead at the 10^{th} percentile

	(1)		(2)		(3)		(4)	
	4q ahead	8q ahead	4q ahead	8q ahead	4q ahead	8q ahead	4q ahead	8q ahead
FCI	**-0.645*** **	-0.252	**-0.727*** **	**-0.470*** **	**-0.869*** **	-0.545		
SRI	-0.176	**-0.638*** **	**-0.211*** **	**-0.665*** **			-0.815	**-0.666*** **
CLI	-0.189	**-0.330*** **						
MPI	0.038	-0.172						
lagged GDP y-o-y	-0.302	-0.250	0.013	-0.422	-0.019	-0.239	-0.305	-0.507
Intercept	**-0.792*** **	**-0.648*** **	-0.806	**-0.792*** **	**-0.869*** **	**-1.157*** **	**-1.143*** **	**-0.969*** **
R^2	0.497	0.503	0.482	0.455	0.445	0.311	0.198	0.303

Source: Authors' calculations.

4.1 Areas for improvement

The estimated effects of the MPI are not significant and reveal the issues they present for the modeling process. These are typically related to the fact that the individual indices for single instruments represent rare events of changes. Modeling issues also arise as a consequence of the asymmetrically growing frequency of macroprudential policy actions after the global financial crisis, which introduces non-stationarity in the MPI series and thus calls for its transformation before entering the econometric analyses. The challenge of constructing a macroprudential index that would provide for improved estimation of the MPI's effect on the GaR in Slovenia is one of the areas for improvement in the future developments of the GaR framework.

The inclusion of the CLI in the quantile estimation of GaR similarly adds very limited information on the evolution of the tail risk of future growth. The reasons for this may be found in the fact that the variables included in the construction of the index are backward-looking, and therefore not strongly associated with future growth. An important step in the right direction has to do with ensuring that forecasting horizons are properly aligned. While forecasts of trading partner growth (expressed as growth in a real economic variable or an expectations metric) can be closely synchronized with future domestic GDP growth, using the current values of trading partner's growth in sentiment indicators could result in either a negative correlation or a distorted regression analysis. Additionally, Prasad et al. (2019) point out that the inclusion of the external economic conditions in the GaR estimation is reasonable in cases when domestic and external demand measures are highly asynchronous, which is less the case for Slovenia as an open-economy, one greatly integrated in the euro area economy. Future analyses should assess the relevance of including such additional indicators, and if included then forecasts or more forward-looking indicators should be included to ensure the alignment of forecasting horizons for future GDP growth.

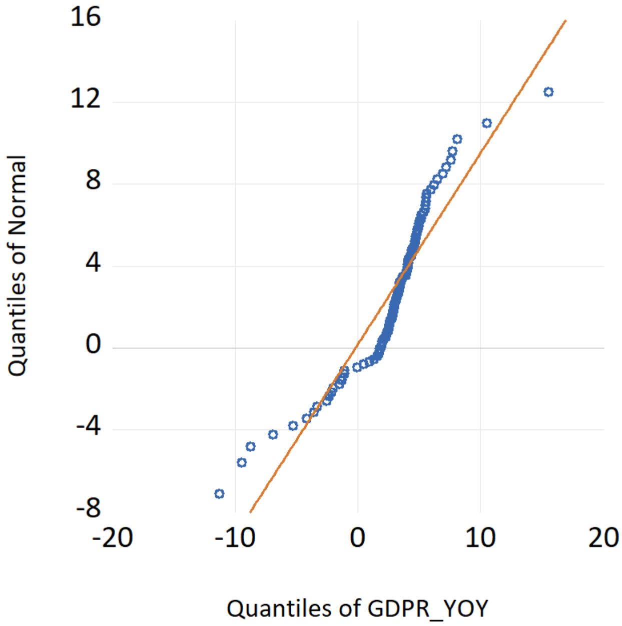
4.2 Generation of the future growth distribution (*t*-skew fit)

Upon estimating the various quantiles of the future real GDP growth, the entire conditional distribution can also be approximated.[22] The transformation of the empirical quantile distribution into an estimated conditional distribution of GDP growth is by fitting a skewed t distribution (following the approach advocated by Adrien et al. (2019a). The selection of the skewed t distribution, a flexible distribution function with four parameters put forward by Azzalini and Capitanio (2003), follows the ad-

[22]The conditional quantiles are a sufficient statistic for describing the conditional cumulative distribution function (cdf). From the cdf, we derive the probability distribution function (pdf) using parametric method to fit the conditional quantiles estimated in the regression. Following Adrian et al. (2010a), a parametric t-skew fit is used.

vice and practice in the existing literature.[23] Given that certain graphical techniques can reveal the presence or absence of symmetry in the data set with respect to the mean value, an additional indication that supports the application of the skewed t-distribution in the GaR estimation for Slovenia is shown in Figure 6.

Figure 6: Plotted quantiles of realized GDP growth rate against the theoretical values under the normal distribution (Q-Q plot)



Note: The vertical axis shows quantiles of the normal distribution while the horizontal shows the quantiles of the y-o-y growth rate for GDP for period 1996Q1 - 2020Q3. The deviations from the diagonal indicate deviations from the normal distribution. The values at the left tail reveal a higher density and justify the fitting of a different distribution than the one that would be used to fit the median or mean values.
Source: Authors' calculations.

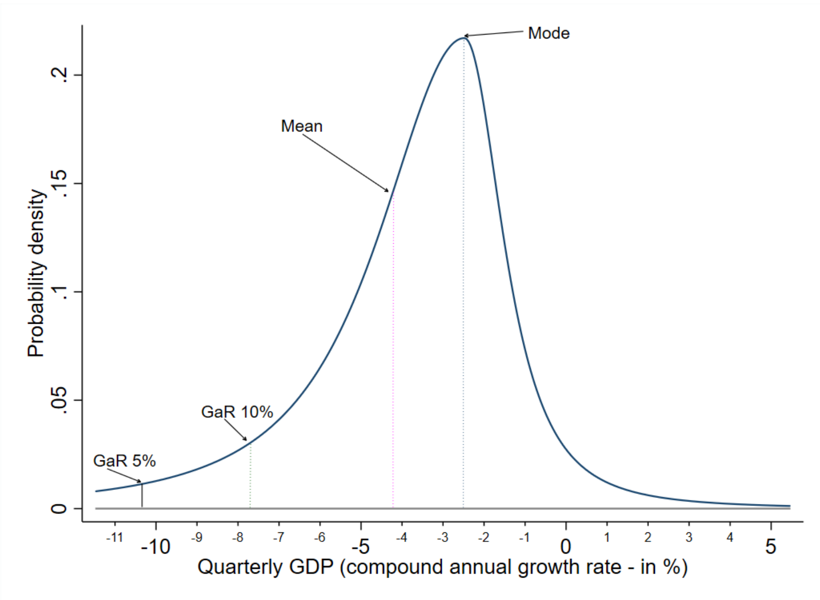
By fitting the skewed t-distribution the estimated quantile distribution is smoothed over the quarters by interpolating between the estimated quantiles. More precisely, for each quarter the following optimization problem is solved for the four parameters $\{\mu_t, \sigma_t, \alpha_t, \nu_t\}$ of the skewed t distribution f with the goal of minimizing the squared distance between the estimated quantile function y^q_{t+h} and the quantile function of the skewed t-distribution $F^{-1}(q;\, \mu_t, \sigma_t, \alpha_t, \nu_t)$ to match the 5%, 25%, 75%, and 95% quantiles.

$$\{\hat{\mu}_t, \hat{\sigma}_t, \hat{\alpha}_t, \hat{\nu}_t\} = \underset{\mu_t,\sigma_t,\alpha_t,\nu_t}{\operatorname{argmin}} \sum_q \left(\widehat{y^q_{t+h|x_t}} - F^{-1}(q;\, \mu_t, \sigma_t, \alpha_t, \nu_t) \right)^2 \tag{7}$$

[23]The skew version of the t-distribution has been proven useful to model tail events, as many distributions in finance are indeed skewed (please see, for example, Andersen et al. 2001).

This step allows us to obtain the complete distribution of future GDP growth conditional on the state of the macrofinancial variables and assess the likelihood of future economic activity at any level. A GaR of 10% corresponds to the value of GDP growth below which the area under the curve has a probability density of 0.1. Based on data from the analysed period, the GaR of 10% was estimated at -7.7% (Figure 7). In other words, the estimated probability that GDP growth will be lower than -7.7% is less than 10%.

Figure 7: *t*-skew fit GaR10%

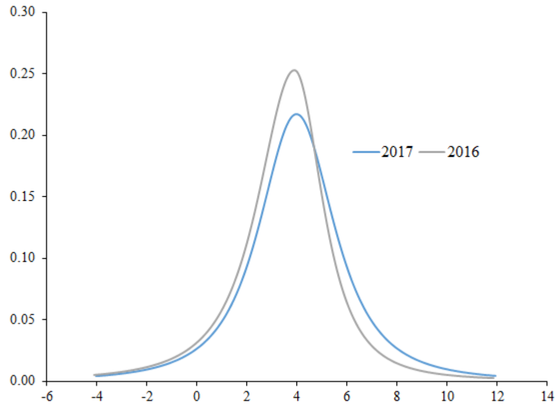


Date of input	**30.9.2020**
Horizon forward	4
Conditional mode	-2.5
Conditional median	-3.4
Conditional mean	-4.2
GaR5%	-10.3
GaR10%	**-7.7**
Growth below 0 probability	1.0
Skewness	0.7
Scale	1.5

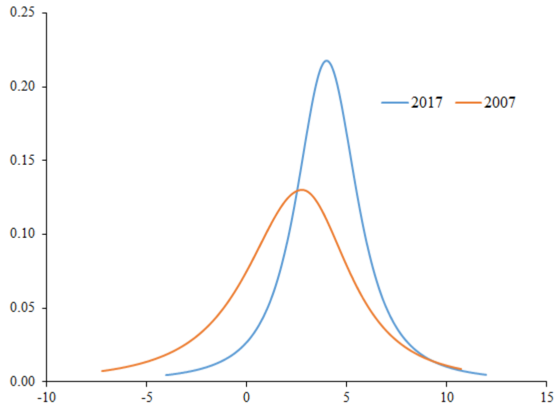
Source: Authors' calculations.

Adrien et al. (2019) show that the entire distribution, and not just the central tendency, evolves over time. Namely that recessions are associated with left-skewed distributions while, during expansions, the conditional distribution is closer to being symmetric. They additionally show that the probability distributions inherit the stability of the right tail from the estimated quantile distribution, while the median and left tail of the distribution exhibit strong time series variation. The comparison of the one-year ahead forecasts for the conditional density of Slovenian GDP growth at different points in the financial cycle is inline with the existing evidence. Namely, Figure 8 illustrates a more symmetrical distribution in the years that are generally recognized as an expansion period (2016 and 2017). By contrast, the left tail of the growth distribution in 2007 (pre-crisis period) is fatter and has a greater probability of recession (the area to the left of zero growth) compared with the year 2017.

Figure 8: The comparison of the one-year ahead forecasts for the conditional density of Slovenian GDP growth at different points in time



(a) Conditional density of GDP growth for years 2016 and 2017



(b) Conditional density of GDP growth for years 2007 and 2017

Source: Authors' calculations.

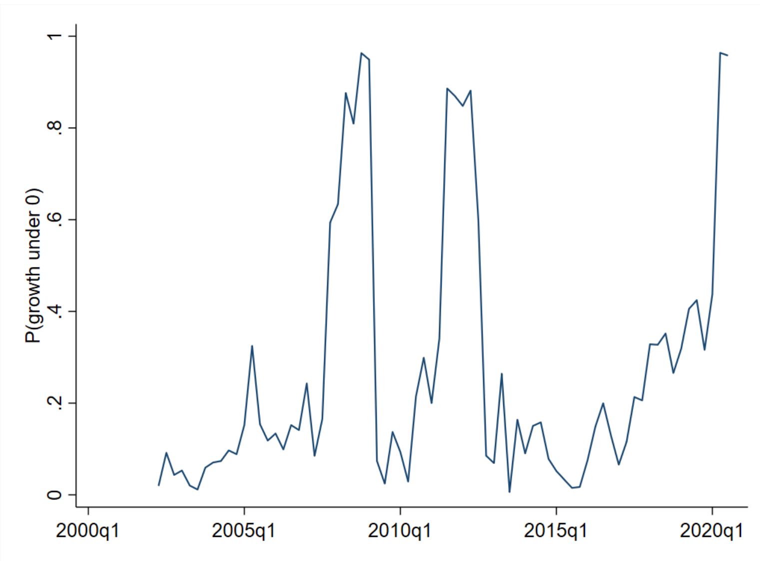
4.3 Historical distribution

To examine the historical distribution, the skewed t-distribution is fitted across the entire sample using the quantile coefficients that we estimate in the quantile regression (the baseline model). The derivation of the historical distribution (as well as certain parameters of interest, such as location, variance and skewness) is performed by rolling the estimation window and deriving the time series of the growth at risk for Slovenia. The assumption behind this analysis is that there are no structural breaks in the data, which ensures that the quantile estimator is asymptotically consistent. According to Adrien et al. (2019), this is a reasonable assumption given the limited sample size in macro time series. Such approach in deriving the historical distribution makes the GaR estimates easy to compare across time and avoids estimating quantile regressions on a very limited sample (especially at the beginning of the time series). As such, the only source of heterogeneity is the regressors.[24] Alternatively, by shortening the

[24]The conditional future growth density forecast depends on two sources of information: the beta coefficients from the quantile regression and the set of regressors from which the quantiles are computed (Prasad et al., 2019).

sample on which the coefficients are estimated to a particular point in time, the betas – as would be available to a forecaster in the past – can also be recovered. Figure 9 shows the probability of GDP realizing a negative growth rate.

Figure 9: Historical distribution of t-skew: probability of growth under 0%



Source: Authors' calculations.

4.4 Scenario analysis

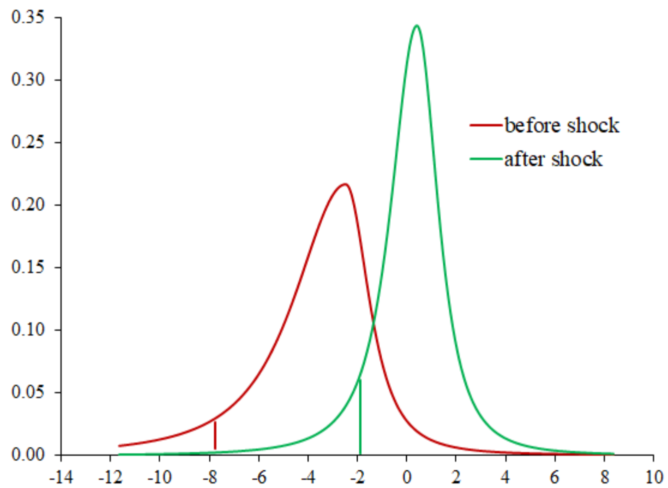
As a scenario analysis exercise, we perform a static counterfactual analysis by simulating the impact of a shock in a variable on the future GDP growth distribution. Such simulations could serve as a basis for pre-emptive action on the side of macroprudential policy. The scenario analysis is a static one in the sense that other variables are held constant and the shock happens ceteris paribus. By imposing a negative shock of two standard deviations on the FCI (which would imply loosening in the FCI), we obtain a shift of the entire distribution to the right. The after-shock distribution has a narrower left tail (is more symmetric) and a much lower probability of recession.

The conditional quantiles based on the new partition $\widetilde{x}_t = x_t * (1 + \text{shock})$ is re-estimated (using the estimated quantile regressions):

$$y^q_{t+h|\{\widetilde{x}_{i,t}\}_{i\in I}} = \widetilde{\beta}^q_0 + \sum_{i\in I} \widetilde{\beta}^q_t X_{i,t} \tag{8}$$

The estimated beta coefficients are the same as in the baseline regressions, which ensures comparable scenarios. The counterfactual (scenario) quantiles $y^q_{t+h|\{\widetilde{x}_{i,t}\}_{i\in I}}$ are, as before, the basis for deriving the skewed t-distribution (probability density).

Figure 10: Counterfactual scenario analysis – negative shock to FCI (loosening)



Note: The image reveals the impact of non-linearities (different beta for each quantile) on the future growth distribution: the shock propagates differently on different points of the distribution.
Source: Authors' calculations.

The interpretation of the results of the scenario analysis is that loose financial conditions are associated with substantial build-ups in leverage[25] and hence higher future growth.[26] However, the easy financial conditions fuel growth in the shorter term (which is shown in Figure 10, as it depicts the conditional probability distribution of one-year ahead GDP growth), but when those conditions are coupled with a build-up in leverage, risks to growth rise in the medium term (IMF, 2017).

5 Growth-at-risk based assessment of macroprudential stance

Important work has been done by the ESRB "identifying components of macroprudential stance and in establishing a link between the state of the financial system, macroprudential policies and its objectives" (ESRB, 2019 and ESRB, 2021). By definition, a stance in general sets up the relationship between actions and the objective one is set to achieve through these actions. In the case of the macroprudential stance, the stance is represented as a relationship between macroprudential authority's actions

[25]In times of low risk premia for risky investments, banks increase the loan supply. It is through rising asset prices, low financial market volatility and highly valued collateral that the capacity of the banks is expanded. See, for example, Adrian et al. (2010) and Adrian and Shin (2014).

[26]The theory draws a clear distinction between the impact of real-sector credit on GDP growth and that of the net build-up of debt in the economy. Among other works, please see Godley (1999), Werner (1997), Hudson (2006), Keen (2011) and others.

and the objective of supporting the financial stability by acting in the direction of preventing or mitigating systemic risk. A macroprudential stance assessment is aimed at explaining the extent to which macroprudential actions achieve the financial stability objective.

As macroprudential policy is multi-dimensional in terms of both intermediate/final objectives and instruments, it is demanding to point out clear and well-defined policy aims that are connected to metrics and potential target levels. The metric obtained from the estimations based on the GaR approach can be used for assessing the macroprudential policy stance. This metric refers to one of the stance metrics proposed by ESRB (2019 and 2021) that summarizes the impacts on expected and tail growth referring to the difference between the growth rate at the central tendency and in the tail. In that sense it is the objective of macroprudential policy to, based on the median-to-tail distance stance metric, act towards maintaining tail growth at a constant distance to the median growth. The objective is however limited only to factors that shape the forecasted growth distribution, which are in the domain of macroprudential policy.

Using the concept of GaR in the measurement of the downside risks that macroprudential policy targets opens the way for the use of empirical quantitative models in the design of macroprudential policies, and the development of concrete notions of macroprudential policy stance. The GaR approach enables the quantification of the effects of risk and policy variables on expected GDP growth, and the assessment of the risk of sufficiently adverse GDP growth outcomes. Due to the multiplicity of policy objectives or to the interaction of macroprudential policy objectives with the objectives of other policies, an inaction bias might arise.[27] Having a concept of policy stance, and a systematic and regularly updated framework for risk assessment can contribute significantly to better informed policy decisions and alleviate the risks of inaction bias.

The macroprudential policy design problem gives a quantitatively based macroprudential policy objective and a metric for the assessment of macroprudential policy stance similar to that of other macroeconomic policies. An important aspect that policymakers will need to consider is the implicit trade-off that will arise in managing the future growth distribution. While it will certainly depend on the underlying structural features of the economy and the financial system, as well as on the impact of macroprudential policy on the mean and tail growth rate of the real GDP growth distribution, it will also reflect the risk aversion of the policymaker.

[27] An inaction bias arises when policymakers may prefer to conduct deeper analysis and collect more data before activating policy measures.

6 Conclusion and the way forward

By definition, growth-at-risk analyses seek the linkages between macrofinancial conditions and the probability distribution of future real GDP growth. The GaR approach provides a methodology for understanding how financial conditions and the level of financial vulnerabilities contribute to the possibility of future episodes of weak economic growth. The approach applied in the present analysis provides for an assessment of the relative importance of the macrofinancial conditions and financial vulnerabilities, the importance of which varies along the probabilistic distribution of growth and according to the forecast horizon. As underlying financial risks cannot be directly observed and only have a direct impact on growth once they materialize, the macroprudential policy objective underpinning this tool is to manage moments of the forecasted growth distribution (ESRB, 2021).

The results obtained in this analysis confirm the expectation that the likelihood and severity of future weak or negative economic growth rises during periods where risks to financial stability are growing. In particular, by applying the GaR framework to Slovenia, we find that the prevailing financial conditions influence the tail risks regardless of the time horizon, and that medium horizon risks are more dependent on systemic financial vulnerabilities, such as when credit growth is excessive. In addition, for the purposes of the estimation of the GaR for Slovenia, we develop a financial conditions index (FCI) that can be used in future analyses for monitoring and assessing financial stability.

Further development of the framework should address data and specification issues, as indicated in Section 4.1. Additionally, the framework should be extended to be able to provide an assessment of the macroprudential stance, which as a metric represents the residual systemic risk in the financial system, relative to a neutral level of risk considered sustainable in the long run (ESRB, 2021). As the stance assessment of a country is a comparison to the other countries, the framework should be extended to panel estimation and include time series of other EU countries in the estimation procedure. Finally, the GaR approach to financial stability can be expanded by assessing the marginal effects of macroprudential policy on the growth-at-risk and the forward structure of its impact on tail growth. Its final aim is to provide beneficial information for the timing of macroprudential policy decisions over the cycle, and for a complete assessment of these policies in terms of GDP growth. It is by identifying, monitoring and assessing systemic risks to financial stability that macroprudential policy seeks to preserve the stability and enhance the resilience of the financial system, and consequently support its role in sustaining economic growth.

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