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Macroprudential stance assessment: problems of measurement, literature review and some comments for the case of Croatia

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The author state that the views presented in this paper are those of the author and do not represent the views of the institution the author works at or the views of Croatian National Bank.

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Ocjena karaktera makrobonitetne politike s pomoću pristupa rast-pri-riziku: problem mjerenja, pregled literature i komentari za Hrvatsku

Sažetak

Rad se bavi ocjenom karaktera makrobonitetne politike i pridonosi literaturi na dva načina. Prvo, daje sveobuhvatan pregled srodne literature kako bi se utvrdili rezultati dosadašnjih istraživanja i teorijskih doprinosa u tom području. Drugi dio rada posvećen je empirijskoj analizi i ocjeni karaktera makrobonitetne politike za Hrvatsku, pri čemu se razmatraju različiti problemi iz prakse. Budući da je empirijski dio rada usmjeren na zemlju koja je relativno aktivna u provođenju makrobonitetne politike, rezultati i zaključci mogu biti korisni i drugim zemljama za unapređivanje metodologije kojom se nastoje definirati i ocijeniti karakter i učinci makrobonitetne politike. Rezultati mogu biti različiti ovisno o odabiru i definiciji pojedinih varijabli. Radi se o zahtjevnom zadatku, s obzirom na to da rezultati ovise o definiciji indikatora makrobonitetne politike i određenih metodoloških aspekata koje treba razmotriti pri izračunu tih indikatora te o drugim metodološkim činiteljima.

Ključne riječi: sistemski rizik, makrobonitetna politika, financijska stabilnost, financijski uvjeti, kvantilna regresija, ocjena politike, karakter makrobonitetne politike

JEL klasifikacija: E32, E44, E58, G01, G28, C22

Macroprudential stance assessment: problems of measurement, literature review and some comments for the case of Croatia

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Abstract: This paper contributes to the literature on macroprudential stance assessment in two ways. Firstly, it gives a comprehensive review of related literature to see the current directions research and policy practice, alongside the problems. Secondly, it empirically evaluates different aspects and issues when assessing the macroprudential stance. The empirical part of the paper focuses on country that has a fairly active macroprudential policy to establish the initial framework for assessing the effectiveness of macroprudential policy in Croatia. Results show that somewhat different results could be obtained based on variable definition and selection. This means that measuring macroprudential stance is difficult, as it depends on the definition of the macroprudential policy variable, selection of other important variables in the analysis, as well as other methodological factors.

Key words: systemic risk, macroprudential policy, financial stability, financial conditions, quantile regression, policy assessment, macroprudential stance, Q-VAR, growth at risk

JEL classification: E32, E44, E58, G01, G28, C22

The author states that the views expressed in this paper do not represent the views of Bank of England. This paper was written at time the author was employed at Croatian National Bank.

Contents

1. INTRODUCTION

Today, most European Union countries have a fairly active macroprudential policy, which has received more attention after the GFC (Global Financial Crisis, see Carstens, 2021; Ampudia et al., 2021; or Portes et al., 2020). As some of the tasks of the macroprudential policy include tracking and mitigating systemic risk, it should be based on a carefully constructed and coherent framework (Cecchetti and Suarez, 2021). Compared to monetary and fiscal, macroprudential policy is still relatively new, and much more work must be done to identify and evaluate its transmission channels (ESRB, 2021). Villar (2017) found that up to 2017, there was no reliable direct method found to measure such issues. Araujo et al. (2020) conducted a meta-analysis on the effectiveness of the macroprudential policy, as the authors state that there is still limited consensus on it. Although the results of this analysis were promising, the conclusion says that more work needs to be done. This includes analysis of non-linearities in the models, the downturn phase of the financial cycle and other relevant issues. Knowledge about the effects of macroprudential policy is limited due to a high degree of uncertainty (Buch et al., 2018), a short history of the policy itself (ESRB, 2019), and a lack of consensus on what macroprudential stance is (see Arslan and Upper, 2017).

Financial crises are costly. Reinhart and Rogoff (2009) estimate that crises episodes are related to significant increases in government spending, as government debt increases on average by 86% during three years following a banking crisis. Laeven and Valencia (2012) estimated that the cumulative cost of banking crises is about 23% of GDP during the first four years of their duration, and fiscal costs amount to about 6.8% of GDP (Laeven and Valencia, 2013). Jordá et al. (2013) found that financial crises are costlier than other recessions, as after five years, the real GDP per capita is lower by 5% compared to other recessions. Recoveries from financial crises are slower when compared to other types of crises, as found in Kannan et al. (2013)[1]. Reducing systemic risks in the financial system could lead to a lower probability of a future crisis, and macroprudential policy could increase the system's resilience (Sánchez and Röhn, 2016).

As the link between financial conditions, financial stability, and the real economy has gained more attention in the last decade, tools and frameworks have been developed to analyse it[2]. The framework[3] of interest in this paper (Growth-at-Risk, GaR henceforward) is one way the analysis could be done, as it links current macro-financial conditions in the economy with future GDP growth. On the one hand, literature

[1] Other relevant findings about the costs of financial crises can be found in Koh et al. (2020), Jordá et al. (2012), Claessens et al. (2012), and Papell and Prudan (2011).

[2] One of the main approaches is to utilize the Early Warning Model (EWM) to evaluate the predictive capability of different systemic risk variables, see Aldaroso et al. (2018), Drehmann and Juselius (2013), Detken et al. (2014), Škrinjarić (2022, 2023), or Škrinjarić and Bukovšak (2022) for an introduction.

[3] Theoretical definitions are presented in the Appendix.

recognizes the importance of future growth forecasts due to the definition of financial stability. That is why empirical research on this topic has exploded in recent years. It is essential to obtain information on the effects of macroprudential policy on real growth and to tailor macroprudential instruments accordingly. On the other hand, some authors find that this policy should not be based on predictability (Gertler, 2020), and should be designed to respond to unpredictable shocks in the best way. Some find that their out-of-sample forecasts are not stable (Alessandri et al., 2019), others have significant volatility of real-time forecasts (Cucic et al., 2022) within this methodology. Some conclude that there exist limitations in predicting the capabilities of financial variables (Reichlin et al., 2020), with a recommendation that joint dynamics of real and financial variables should be monitored.

Nevertheless, the growing body of related literature has hopped on the bandwagon of forecasting the "at-risk" measures[4], with central banks already publishing this concept regularly in their financial stability reports (Bank of Japan, 2019; Banque centrale du Luxembourg, 2022; Deutsche Bundesbank, 2018; Central Bank of Ireland, 2022; ECB, 2019), regular IMF reports (e.g., see IMF, 2017 for earliest applications, or IMF 2022 for latest), ECB reports (ECB, 2019), and regular risk identification (see Banco de España, 2021). The European Systemic Risk Board (ESRB, 2019, 2021) started to develop a framework in which the macroprudential policy measures are related to future GDP growth, based on the definition of macroprudential policy and financial stability itself. ESRB (2011) defines that the ultimate objective of macroprudential policy is the stability of the financial system, by increasing its resilience, taming the build-up of vulnerabilities in the system and smoothing out the financial cycle, which should ultimately contribute to economic growth. In 2019, ESRB defined the macroprudential stance as "the balance between systemic risk and resilience relative to financial stability objectives, given implemented macroprudential policies; the stance metric represents residual systemic risk in the financial system, relative to a neutral level of risk considered sustainable in the long run", and establishes a relationship between macroprudential policy actions and the financial stability objectives (ESRB, 2019, 2021). This is a useful concept, as it could enable cross-country comparisons, and could foster better policy decision-making, by reducing the policy inaction bias. Swedish authorities (2022) agreed that one of the problems in the EU context is this bias, and ESRB should make regular assessments of the macroprudential stance across different countries. Thus, is not surprising that research on this topic has exploded in the last couple of years. However, there still exist many problems in practice, which make the operationalisation of this framework difficult. That is why the motivation of this research is to identify results of related literature, and extract important messages. Besides this, the paper provides an empirical analysis for the case of Croatia, to see what the challenges that occur in empirical studies are. The results are not near a complete picture on a stable measure of distance to tail, but provide initial basis for

[4] Such as inflation-at-risk (López-Salido and Loria, 2021), bank capital-at-risk (Lang and Forletta, 2019 2020), house-price-at-risk (Deghi et al., 2020), unemployment (Adams et al., 2020), or capital flows (Eguren-Martin et al., 2021, Gelos et al., 2022).

future work to improve on this to finally arrive at stable and usable measure that can help in macroprudential policy decision making.

Reasoning why this single-country analysis could be interesting for an international audience is two-fold. Firstly, the "one size fits all" approach in which countries are merged in a panel setting is not always the best[5]. As some specificities characterize individual countries and their experiences over time, such information could be lost in a panel setting. Ampudia et al. (2021) list some drawbacks of panel settings as well, which include high diversity in macroprudential measures across countries is truncated into simple indicators (that take values +1 and -1). Budnik et al. (2021) comment that panel GaR estimation could be biased if time-invariant country characteristics are omitted from the model. Moreover, research on the importance of structural differences between countries that affect the GaR results is growing (O'Brien and Wosser, 2022; Gächter et al., 2022). Secondly, another reason is the unique experience of Croatia's macroprudential policy in the last 20 years. Namely, even in the pre-GFC period, Croatia was among those countries that had a relatively active macroprudential policy (Vujčić and Dumičić, 2016). A lot of measures were employed to tackle credit growth (Bambulović and Valdec, 2020), and higher activity of macroprudential measures started in 2003 (Kraft and Galac, 2011). This means that the macroprudential stance assessment of Croatia includes an interesting period in which both tightening and loosening measures were included. Not many countries have such data luxury.

This research and its content can be helpful for policymakers not only in Croatia but in other countries, due to pointing out some issues, advantages, and challenges of existing frameworks and applications. The main results of the empirical part of the paper confirm that it is challenging to evaluate the macroprudential stance. Based on quarterly data from the mid-1990s to 2Q 2022, several models have been estimated based on different variable definitions and transformations. The macroprudential policy variable is difficult to define, as it consists of many measures with different intensities. The source of data collection also matters, alongside how this indicator is transformed. Although insignificant, the results of estimated coefficients of the effects of policy variables on future growth are of the correct sign. Greater positive coefficients are observed for the GaR growth compared to smaller values for the median case. The distance to tail (difference between the median and GaR values) provides general ideas on the tightness or looseness of the policy concerning other macro-financial conditions.

The rest of the paper is structured as follows. The second section gives a literature review, and afterward, the third section deals with issues of an important variable in this assessment - the macroprudential policy index. As this variable is significant for the stance assessment, it should be defined most accurately. For the empirical part of the paper, the methodology is described in the fourth section, with the empirical results given in the fifth section. The final section concludes the paper.

[5] E.g., Plagborg-Møller et al., 2020, found significant country heterogeneity in their results, see section 3 for more details.

2. LITERATURE REVIEW[6]

The size and scope of related literature has increased significantly in the last couple of years. First group of papers, the seminal ones, related GaR to financial conditions in the economy, for the purpose of better GDP growth forecasting. Here, Giglio et al. (2015, 2016) examine the predictive power of many systemic risk measures (like Covar, MES, SRISK, etc.) for the case of the USA and selected advanced economies. The main focus was to obtain information on which measures are successful in forecasting future GaR, with in- and out-of-sample comparisons. Probably the most famous papers in this group are the Adrian et al. (2016, 2019), who argue that most growth forecasts are point estimates and ignore the heterogeneity of different quantiles of growth distribution. The authors show that lower quantiles of future US GDP growth have greater volatility when compared to the upper ones, which are fairly stable over time. Deteriorating financial conditions are related to a decrease in future average GDP growth, with low upside risks regardless of today's financial conditions. This indicates a nonlinear relationship between financial conditions and future GDP growth distribution exists. These previous studies include only the financial stress in the analysis. For better tailoring of macroprudential measures, other variables are needed that are useful for medium-term forecasts of future GDP growth. Aikman et al. (2018) extended this to aggregated measures of financial vulnerabilities in the UK: leverage in the private nonfinancial sector, asset valuations in property markets, and credit terms, based on previous literature on early warning models and banking crises. The authors found different effects on future GDP growth across quantiles and when compared to the OLS (ordinary least squares) estimate. As the results are intuitive and straightforward to communicate, such an approach could be used within the macroprudential decision-making when looking at the results of such forecasting.

Then, the literature started to expand the number of exploratory variables that are important for the macroprudential policymaker. Financial vulnerability indicators are included in the analysis, as well as other macro-financial ones, that could help in forecasting GDP growth. One good example here is the paper of Plagborg-Møller et al. (2020). It is an extensive study of future GDP growth distribution forecasting of 13 advanced economies, based on several nonparametric and parametric approaches, a long list of GDP predictors for monthly and quarterly data from 1975[7] to 2019. The variable list had different economic and financial indicators among financial conditions included. This study covers a wide selection of in- and out-of-sample forecasts and nowcasts. General conclusions could have been more favorable, as a great degree of heterogeneity of results was found, not just between the countries, but between indicators that belong to the same category, such as financial variables (important for the macroprudential stance assessment afterward). These findings confirm the previous research of Reichlin et al. (2019), who utilized a semi-structural model for future GDP growth forecasting besides the quantile regression approach. Aikman et al. (2019 a, b) extend the Adrian et al. (2019) approach by looking at different variables of medium-term vulnerabilities in the financial system. The authors include credit growth information, house price growth, current account imbalances, etc. Another novelty is that the authors constructed a measure of banking sector leverage to see how the increase in capital requirements affects bank capital and the growth-at-risk. Using such a variable in the analysis can be observed somewhat as the macroprudential authority's stance correlates with future growth distribution.

[6] Besides the works that are examined below, it is worth mentioning other preceding research that link financial conditions and financial vulnerabilities to the real economy. A comprehensive overview is given in Boyarchenko et al. (2022) and Škrinjarić (2022, 2023). Moreover, a lot of related papers not mentioned in this section are summarized in the Appendix in Tables A1 and A2.

[7] For the US case, and 1980 for other countries.

Here, the main results indicate that greater capital requirements led to a 0.9 p.p. cumulative improvement of the GDP-at-risk over three years. This prompted the authors to make a CCyB (countercyclical capital buffer) simulation as an example of increasing the capital requirements before the GFC hit. Not surprisingly, the results showed that such a requirement would offset the GDP-at-risk significantly.

Third group of papers focuses more on some methodological aspects of the modelling, and introduces different measures of goodness-of-fit, such as De Lorenzo Buratta et al. (2022), who focused on Portugal's GaR from 1991 to 2019. The authors estimate a wide range of results in terms of expected shortfall (ES), longrise (EL), probabilities of entering a recession, and entropy, and robustness checking of the results. As many variables were included in the analysis to see what performs best, one part of the research also looks at PCA results. The paper concludes that the proposed measures of ES and EL should be complementary to the GaR approach. Others focused on specific corrections of some variables so that the analysis is more robust. O'Brien and Wosser (2021) is an example of such paper, where authors utilized quarterly data from 1990 until Q3 2020 for 27 OECD countries. For the case of Ireland, GNI was used instead of GDP for the growth forecast and the credit-to-GDP gap, based on the panel quantile regression results. This paper's main purpose was to evaluate how current financial conditions and systemic cyclical risks shape future Irish GNI growth. The results of the forecasts are in line with previous literature on short-term results of stress indicators, with medium-term significant results for the cyclical risks variable. Thus, the authors concluded that such an approach is useful for policy instrument calibration, as the distribution of future real growth is differently affected by today's increases in financial imbalances or systemic risk.

Fourth group introduces the macroprudential policy variable in the analysis. One important thing to note here is the issue of endogeneity, as Deutsche Bundesbank (2021) warns about majority of research on this topic actually looks at correlations and not causality (see section 3.3.). Sánchez and Röhn (2016) examine various policies and their effects on future GDP growth via panel quantile regression for the case of OECD countries. The authors address the problem of policy endogeneity; all policy variables were lagged by four quarters. When focusing on macroprudential policy, the main results show that mean output growth is reduced, but the tail risk is also. However, due to this policy being relatively new compared to others, it is concluded that this should be explored more in the future. Duprey and Ueberfeldt (2018) is a short but concise note about GaR forecasting, in which both monetary and macroprudential policies are considered. This work is a mix of theoretical considerations of tightening both policies and empirical results. The authors showed that macroprudential tightening is more effective for reducing downside risks of future growth than monetary policy tightening for the Canadian case. When focusing on an estimation of quantile regression for the period from 1992 to 2020, the results indicate that macroprudential policy effectively reduces the GaR. Two years later, the same authors (Duprey and Ueberfeldt, 2020) published a paper with more details on their previous work. Here, the authors include both monetary and macroprudential policies in the analysis when focusing on the empirical part of the paper. The main results show that both policies reduce left tail risks by not affecting the median growth, whereas increasing the 5th percentile growth via the credit channel of banks. Afterward, simulations are made for the choice set of the macroprudential policymaker, showing how the benefits would be achieved if a tighter stance was taken, which was in line with real activity in 2018.

Finally, some other related empirical papers that deal with GaR topics are as follows. Galán and Rodríguez-Moreno (2020) is a study that comments on "at-risk" measures and their usefulness in macroprudential policy decision-making. Empirical analysis shows an application of house price-at-risk and GaR. A panel of 27 EU countries, with quarterly data from 1970 to 2019, has been employed to estimate GaR, with the MPI variable included in the analysis. Interaction terms between MPI and other variables were included in the study to account for different phases of the financial cycle and financial stress levels in economies. Heterogeneity of results in terms of the effects of MPI on different growth quantiles was found. However, one problem here is the endogeneity of the MPI variable (please see section 3.3.). Galán (2020a) extended the Adrian et al. (2019) approach with macroprudential measures for 28 EU countries from 1970-2018. Moreover, this research is related to Sánchez and Röhn (2016), who did not include macro-financial controls in their study, but Galán (2020a) did, as these variables are the ones most related research started to connect with future GDP growth in the first place. The study enables a cost-benefit analysis due to observing the entire future growth distribution alongside the term structure of such effects. One of the key findings is that the position of the financial cycle is an important fact when observing the effects of macroprudential policy. The study also considers endogeneity issues of MPI as a robustness check, and the results confirm the ones without considering this. The same author, Galán (2020b), reused the same data and refined the models from his previous publication. Different variable definitions, model specifications, and robustness checking were made. However, the conclusions stayed the same.

Brandao-Marques et al. (2020) utilize the quantile regression approach to propose the cost-benefit approach of macroprudential policy. In a panel setting (period: 1990-2016), authors observe the effects of different policies, including macroprudential, on future GDP growth and inflation. This includes policy surprises by looking at deviations of policy variables from estimated policy rules. The authors found evidence of policy trade-offs regarding lowering mean growth and increasing the GaR growth. In particular, benefits were pronounced regarding BBM (borrower-based measures), whereas CBM (capital-based measures) were found to be better for building the system's resilience. Franta and Gambacorta (2020) is a concise paper on the concept of GaR, with an application to 56 countries and the period 1980-2012. Although the MPI variable is included in this approach, other variables that entered the analysis were inflation and monetary policy interest rate. Other control variables are not found, but the authors focused on LTV (loan to value) and loan loss provisioning aspects in MPI to see their effects on future GDP growth. The results show that LTV narrows the whole future distribution of the growth, whereas loan loss provisions only move the left tail of the distribution upward.

Drenkovska and Volčjak (2022) is a recent study of the Slovenian GaR case. The authors are motivated to develop a macroprudential policy framework in which the MPI is included in the GaR analysis. The Slovenian FCI (financial conditions index) has been constructed in the first step. Afterward, for the period 2003-2020, GaR is estimated, where additional variables are included besides the FCI and systemic risk one (e.g., industrial confidence indicators). Although the results regarding FCI and systemic risk align with related literature, the MPI variable was not significant in the analysis. Thus, the authors comment that this analysis should be improved in future work and practice. Cucic et al. (2022) give a good short introduction to macroprudential stance assessment and GaR framework before moving on to the empirical case study of Denmark in the period 1982-2022. GaR and HaR (House pice-at-Risk) are estimated, and BBM and CBM indices are included in the modelling process. The authors conclude that BBM measures shift the entire growth distribution right, whereas CBM measures have a trade-off between GaR and median. However, no comments are found on whether endogeneity issues were solved. Distance between the median and tail is presented to measure the macroprudential stance. This is the first (known to the author) empirical study besides the ESRB (2021) report that tries to measure such a stance. As there are no other similar studies in this sense, the authors observe the historical distribution of the Danish macroprudential stance.

A few major conclusions emerge from the related work in the subsections above. A small number of papers include the macroprudential policy variable in the analysis to assess the stance of the policy. The reasoning could be found in a relatively short time series of the macroprudential policy indicator for some countries and problems defining and measuring this variable. On the one hand, some countries only have a couple of years of MPI data, which disables a single-country analysis. On the other hand, measurement problems of MPI could discourage some authors from undergoing such analysis, as different results can be obtained concerning the definition and transformation of the MPI variable.

Approximately a third of the literature utilizes panel data, and the rest focuses on a single-country analysis. This finding is surprising, as many would think that most of the papers would focus on panel analysis. On the one hand, panel analysis enables using more data and obtaining reliable results. However, on the other hand, differences in definitions of variables and their usefulness for specific countries warn that the "one size fits all" approach may not always be the best. As an example, a credit-to-GNI (Gross National Income) gap and y-o-y GNI growth rates are used for the case of Ireland instead of GDP (Gross Domestic Product), as GNI is a better representation for this case, as well as ICSI (Irish Composite Stress Index) instead of CLIFS (Country-Level Index of Financial Stress) in O'Brien and Wosser (2021). Another good example is Plagborg-Møller et al. (2020), where a comprehensive analysis of future GDP growth forecasting of 13 advanced economies was done[8]. After a battery of carried-out forecasts and estimations, the authors found a few significant mean growth predictors,

[8] In the vein of the quantile regression approach, most of the empirical research is related to this one.

less for the volatility of growth, alongside different signs of results, and great cross-country heterogeneity in the results, which prompt the authors to conclude that some caution needs to be taken when one tries to build a theoretical model based on empirical results. A lot of reviewed literature introduces country-specific financial conditions or financial vulnerability indicators. Authors are motivated by some specific dynamics, characteristics, and/or problems of a single country, and to account for this, variables are modified to reflect this in the best possible way.

Part of the literature talks about forecasting growth distribution, and this terminology is acceptable. However, some problems occur when discussing macroprudential policy's effects on future GDP growth if endogeneity issues are not mitigated, especially in a single equation setting (see section 3.3.). If one wants to talk about macroprudential stance assessment, the best approach is to evaluate the effects of the MPI variable on future growth. Such models are different from those that only focus on forecasting. Therefore, it should be evident in the analysis what the researcher is aiming for. As the MPI variable is very important for accurate macroprudential stance assessment, issues regarding this indicator are reviewed in the next section.

3. ISSUES WITH MACROPRUDENTIAL POLICY INDEX

Macroprudential stance assessment includes the MPI as a crucial variable in the analysis. Usual sources of this indicator include ECB (2018) and IMF (2022). However, there are some things that need to be considered when doing empirical analysis. First and foremost, macroprudential policy is not measured via a policy rate as monetary policy is. Rather, it is measured through counting the number of measures over time, by constructing indices based on a binary variable, or a variable that takes a couple of values (e.g., -1, 0, or 1). This alone introduces a challenge of aggregation of heterogeneous measures, and on top of that, the intensity of different measures imposes an additional problem. First introduction of a measure, which is classified as a capital one, could have completely different effects to a borrower-based measure that is, e.g., fine-tuned. Macroprudential policy is endogenous, and if GaR literature wants to talk about the effects of policy on future growth, this challenge needs to be considered. Even sourcing of MPI data also has some problems. These problems are commented in the following sub-sections.

3.1. Definition and transformation of the MPI variable

First issue is the definition of the MPI variable itself. Part of the literature that utilizes the macroprudential variable in any analysis takes the MPI index (regardless of the form and transformation) and calls this the macroprudential policy stance. Examples include Akinci and Olmstead-Rumsey (2015), where authors state, "... These cumulative variables sum the dummy variables (tightening net of easing) to get an idea of a country's "macroprudential policy stance" in a given quarter..."; or Ćehajić and Košak (2019), where authors state "we design our main macroprudential measures by summing all policy changes over time, both tightening and easing. This allows us to capture the overall macroprudential stance in a given country and time period.". Although this is not wrong, such an approach is not in line with the definitions of macroprudential stance in the GaR literature. However, it introduces more complexity in comparison of results across studies. Another issue is that some papers do not explicitly describe in which form the MPI indicator enters the analysis (net values, cumulative, etc.).

The first step in collecting and defining the MPI variable is to collect the data from established database, such as the ECB (2018) or the IMF (2022) one. As all measures in such databases are given in a descriptive form, MPI is defined as a simple binary variable, where the +1 value indicates a tightening measure that took place in a given quarter and -1 is a loosening one. Usually, ambiguous and absence of measures are given a value of 0. More details can be found in Cerutti et al. (2017), Budnik and Kleibl (2018), Garcia Revelo et al. (2019), etc. As an initial MPI definition, it could be calculated by first looking at individual instruments (measures) within every quarter:

$$mpi_i = \begin{cases} 1, & \text{if a measure } i \text{ is tightening} \\ 0, & \text{absence of measure } i \\ -1, & \text{if a measure } i \text{ is loosening} \end{cases} \tag{3}$$

and adding up the values in (3):

$$\mathrm{MPI}_1 = \sum_{i=1}^{N} mpi_i\,, \tag{4}$$

where N is the total number of instruments. This is a starting point in a lot of research, reflecting a general policy direction. If MPI1 is positive, more tightening measures were activated in a given quarter than loosening ones. Zero value could indicate either no actions or the number of tightening and loosening ones were equal.

Based on Garcia Revelo et al. (2020), several other variants of MPI can be defined as follows. The first variant represents quarterly MPI with three values: -1, 0, and 1, based on tightening, loosening, or absence of all measures:

$$\mathrm{MPI}_2 = \begin{cases} 1, & \text{if } \mathrm{MPI}_1 > 0 \\ 0, & \text{if } \mathrm{MPI}_1 = 0 \\ -1, & \text{if } \mathrm{MPI}_1 < 0 \end{cases} \tag{5}$$

This means that regardless of the overall sum in each quarter being +1 or more, it will be rescaled to +1, and similar is true for negative values. Thus, this transformation looks only at the information if the macroprudential policy is tightening or loosening, regardless of the number of measures. A second measure is to divide the original MPI_1 (formula 4) by the number of measures in each quarter. This is suitable for cross-country analyses.

Several other specifications on a single-country analysis are found in Ćehajić and Košak (2021) as follows:

$$\mathrm{MPI}_3 = \begin{cases} 1, & \text{if sum of all measures is positive} \\ 0, & \text{othervise} \end{cases} \quad (6)$$

and

$$\mathrm{MPI}_4 = \begin{cases} 1, & \text{if sum of all measures is negative} \\ 0, & \text{othervise} \end{cases} \quad (7)$$

and they take into consideration only tightening or loosening of the policy. A potential problem with these last two measures is found if there is not much data on one type of policy, usually loosening.

As many countries have a lot of zero values in the above MPI specifications, some authors (see Akinci and Olmstead-Rumsey, 2015) try to overcome this by using a cumulative MPI index:

$$\mathrm{MPI}_{\text{cumulative}} = \sum_{t=1}^{T} \mathrm{MPI}_{1t} , \quad (8)$$

where MPI_1 from equation (4) is cumulated over time, up until the end of the sample T. However, Plagborg-Møller et al. (2020) and McCracken and Ng (2016) comment that it is better to utilize stationary variables if possible. MPI defined in (3) is often not stationary, especially in macroprudential active countries. That is why more research is looking at year-on-year changes in the cumulative index (4):

$$\mathrm{MPI}_5 = \mathrm{MPI}_{\text{cumulative}, t} - \mathrm{MPI}_{\text{cumulative}, t\text{-}4} , \quad (9)$$

as found in Galán (2020 a, b), Vandenbussche et al. (2015), Cerutti et al. (2017), Alam et al. (2019). Finally, the ESRB (2021) Report utilized 20-quarter change of the cumulative MPI indicator. This could be especially problematic, as the quantile regressions are estimated for growth up to 16 quarters ahead. It makes difficult to interpret measures that were put into force 20 quarters ago, and their effects 16 quarters in future (i.e., 9 years in total).

3.2. Intensity issues

Another important issue when using the MPI variable as defined in the previous sub-section is that the values of +1, 0, and -1 only reflect if a measure is a tightening or loosening one (or the absence of it for zero values). These values do not reflect the intensity of a measure and its relative importance, e.g., the introduction of a measure could have more significant effects on financial stability when compared to its fine-tuning. It was different when capital buffer requirements were introduced in a country and when their values were adjusted over time. Another example comes to mind regarding the CCyB (countercyclical capital buffer): two countries could introduce this buffer at the same time. If one country introduces this buffer in one quarter and then gradually increases it over three quarters, the MPI indicator will have +1 values in 4 quarters, accumulating to +4. However, if another country immediately introduces the value of CCyB that is equal to the accumulated version of the first country, this second country would only get a +1 value, which would be constant in other subsequent quarters.

Thus, one has to have this in mind when using the MPI indicator in empirical research. These indicators reflect the frequency of macroprudential measures, not the magnitudes. A couple of papers emerged in the last couple of years that try to adjust the intensity of MPI indicators. Eller et al. (2020), Vandenbussche et al. (2015), and Richter et al. (2018, 2019) have been working on this. Fernandez-Gallardo and Paya (2020) follow Meuleman and Vander Vennet (2020), and assign a positive value for tightening actions, opposite for loosening, and zero for ambiguous impact or no measures. For the intensity adjusting part, policy actions that are activated for the first time receive the highest weights, a lower value for changes in the level, even lower for changes in the scope, and maintaining a level and scope is given the lowest weight. When a measure is deactivated, the cumulative index gets value zero. Galán (2020b) besides the usual analysis (see the literature review section), includes one section of robustness checking, in which the author looks at the intensity of the LTV ratio and its effect on GaR. Since the iMaPP database that author uses in the study includes mean regulatory LTV ratios, author opted to test its effectiveness during the upswing and downturn of the financial cycle, and obtained results that are consistent to the main ones in the first part of the study.

Unfortunately, a consensus on how to solve this problem has not yet been found because research states that "we assign a higher weight to policy actions we consider to be more important", as in Meuleman and Vander Vennet (2020), a paper that Fernandez-Gallardo and Paya (2020) follow. This is something future research needs to work on, trying to find an objective way to define such adjustments.

3.3. Endogeneity issues

Endogeneity characteristic of macroprudential variable is probably the biggest issue in related research. It is well known that regulators and policymakers take into consideration some typical variables such as credit growth, debt burden, etc., when making decisions about its instruments. As Akinci and Olmstead-Rumsey (2018) explain, those countries that experienced rapid credit growth have a greater probability of a tighter macroprudential policy. Buch et al. (2018) explicitly state that this policy is endogenous: the policymaker reacts to expected economic environment, and in that form cannot be used to identify exogenous changes. This is not restricted only to macroprudential policy; other two policies have this problem as well, which has been tackled for many decades now. The main motivation is always the same: to identify the non-systematic monetary policy movements so one can estimate causal effects of policy on macroeconomic variables. Some earlier approaches are reviewed in Christiano et al. (1999), whereas newer approaches are reviewed in a comprehensive chapter Ramey (2016), and include narrative identification, regime switching approach, and many others, both for monetary and fiscal policy specifications. That is why it is surprising why some related research here does not deal with this issue.

Prasad et al. (2019), as one of the earlier GaR studies, comments that GaR is not a structural model, and cannot be used to talk about causality. However, there still exist papers today that talk about causality, but endogeneity issues were not solved. Richter et al. (2018, 2019) define the following criteria in order to talk about causality: policy actions need to be exogenous with respect to the current and lagged variables; these actions have to be uncorrelated with other shocks, and have to be unexpected. There are several approaches that tackle this, by using one approach or the other, as presented below

3.3.1. Obtaining non-systematic policy shocks

If the aim of the analysis is to talk about causality, then non-systematic policy shocks should be used. They can be defined as random, i.e. portion of the policy that is not related to the state of the economy (McCallum, 1999). Future research on the effects of macroprudential policy should probably consider this approach. Non-systematic monetary policy shocks have been considered in empirical literature for a long time now, especially since the Lucas (1972) critique, who claimed that the non-systematic component of monetary policy is the part that is important for conducing the policy itself. One popular approach to obtain non-systematic shocks when doing a single-equation analysis is to do the following two steps. In the first step, MPI is estimated on a set of variables that should affect macroprudential policy decision making: financial vulnerabilities, measured through credit-to-GDP gap, composite indicators of systemic risk, house price dynamics, and other variables found in early warning models literature (see Tölö et al., 2018, and Škrinjarić, 2022a, for an exhaustive list).

Brandao-Marques et al. (2020) estimate an ordered probit regression for the MPI variable, as it takes values[9] {-2, -1, 0, 1, 2}. Previous quarter credit-to-GDP gap, house price gap and previous year cumulative value of MPI itself are used as explanatory variables in the regression, and the estimated residuals are extracted and interpreted as true policy shocks. This study compared monetary and macroprudential policy shocks in affecting future growth. With the approach of extracting the "true" random shocks for both policies, the results were in favour of macroprudential policy, i.e. stronger and significant effects on growth were found, especially for the borrower based measures, and if combined with looser monetary policy. Similar appraoch was done in Gelos et al. (2019), where different policies were contrasted in how much they are effective in taming the capital inflows for selected countries, and macroprudential tools were found to be effective in mitigating risk of large inflows in the medium term. Galán (2020a) uses the four-quarter moving sum of original MPI values in the analysis and utilizes regression to extract residuals from a model that includes all other regressors that enter the GaR equation. Here, however, all of the variables are assumed to affect MPI in the

[9] See section 4.1.2. for MPI values definition.

same quarter. This could be questionable, due to knowledge that in practice, data collection and decision making takes some time. Lagged values of explanatory variables should be considered in explaining macroprudential decisions today. However, the results in this study showed little difference in the results when the macroprudential policy variable was purged from specific effects from macro-financial variables to the results without any "cleaning" of the data. Reasoning could be as already mentioned challenge of regressing the MPI on variables from the same quarter. Boar et al. (2017) have a similar definition of MPI as in Brandao-Marques et al. (2020). However, the former does not have a probit regression approach. Instead, the regular panel regression is used to obtain MPI residuals. Again, as the previous reference, authors do not lag the variables[10] in the analysis, but the results indicated a negative correlation between the macroprudential policy residual and GDP per capita growth, which authors interpreted those countries with a wider macroprudential gap experienced worse performance (lower growth) in the observed sample, i.e., the more active a country is in the use of macroprudential measures, the higher and less volatile is its per capita GDP growth. Duprey and Ueberfeldt (2020) also have an interesting approach, due to MPI variable taking values -1, 0 and 1. Authors opted to use propensity score matching, such that the probability of MPI variable taking positive or negative values depends on the lags of other variables that are considered in the GaR part of the analysis. It can be concluded that the type of the model that is used to obtain non-systematic policy shocks is important, based on the MPI definition: if the MPI is defined as a cumulative index over time, regression approach could be used. On the other side, if values of -1, 0 and 1 are used, then multinomial models should be used instead. Another important issue is the definition of the model in terms of using lagged values of explanatory variables. As macroprudential policy reacts to macro-financial environment with a lag, this should be taken into consideration when doing this part of the analysis.

3.3.2. Considering dates of announcements and enforcements of measures

Some authors have a narrative approach for identifying macroprudential shocks, such as De Schryder and Opitz (2019, 2021). In this study, the authors look at MPI effects on credit dynamics, but the main interest here is how authors address endogeneity issues. The focus is made on announcement and implementation dates. Some measures were introduced and implemented in the same quarter, and those that did not have the same quarter of both introducing and implementing them, were excluded in MPI construction. Authors rationale that banks could prepare themselves more if the announcement date is far away from the implementation date, which is not in line with definition of unexpected shocks. Authors give an example of introduction of the LTV (loan to value) ratio as to why they observe announcement and implementation dates in the same quarter or not: banks could expand their lending when anticipating future credit restrictions, and the enforcement dates of a measure goes against unexpected nature of shock. The results of this approach indicate that macroprudential shocks have persistent and sizeable effects of the credit cycle in advanced EU economies, and

[10] Change of credit-to-GDP ratio, capital inflows and GDP growth are included in as explanatory variables.

authors conclude that macroprudential tools in those countries have desired effects in curbing the credit cycle. Something similar is done in Duprey and Ueberfeldt (2020). Here, authors estimate the model with MPI values that are based both on announcement and dates when measures were put in force (for the results, please see literature review section).

Since not many papers are found who have this approach in extracting a macroprudential shock on the basis of announcement versus enforcement dates, it remains a question of the effectiveness of it. Namely, when some macroprudential measures are introduced in an economy, the procedure is quite lengthy, as the policymaker firstly analyses some issues that are accumulating in the system, tries to give warnings via official publications, and financial stability reports are filled with boxes that specifically analyse some problems that are starting to emerge. This could prepare banks to change their behavior over time, and when a formal measure is announced, it could have the same effect as for the case of observing the measure from the formal date it was put in force. Thus, future work should try to gauge if some change in bank behavior has preceded even the formal announcement dates of a macroprudential measure

3.3.3. Lagging values in models

Some authors decide to include lagged values of MPI indicator in the single-equation approach, such as Ossandon Busch et al. (2022), who only state that *„causality concerns can be addressed, for instance, by lagging the variable policy* (referring to MPI) *in order to separate the policy decisions from current macro trends*.“; and Gelos et al. (2022), who add one year of lagged MPI data in the model, without explaining on the reasoning. The only thing that comes to mind is the following. In modeling, in order to include effects of variables that are not explicitly included in the model (due to, e.g., data unavailability), one can include a lagged value of the dependent variable, as it is influenced with such factors. Thus, by including it in that way, one could say that previous quarter values of important variables that affect the variable of interest are included indirectly in the current value of the same variable.
However, others do the opposite: Cerutti et al. (2017) state that greater number of lags of other variables should be included in the model. This is something more common in other literature that tries to deal with endogeneity of a variable. If we assume that MPI is affected by previous values of, e.g., financial vulnerabilities in the system, it is an obvious choice to include previous lags of the latter variable in a model.

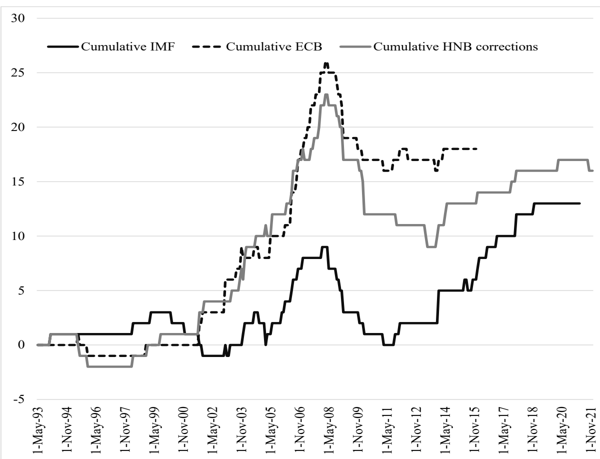
Some papers include lags of both the MPI and other variables, such as Eller et al. (2020), who decide on the lags selection based on the BIC (Bayes information criterion). Ćehajić and Košak (2021) talk about panel setting possibilities of estimation a GMM based model to tackle endogeneity. Authors interested in such setting can refer to this paper, and references there.

It is still not completely clear on which of these approaches are correct, as sometimes they do the opposite things (lagging MPI versus lagging variables that affect MPI), which leads to different economic interpretations, alongside having econometric consequences. As endogenity has been examined for monetary and fiscal policy for some time now, future work that focuses on macroprudential policy should try to compare these approaches to see what should done next.

3.4. Different sources of MPI data issues

Different databases have been developed in the last couple of years, in which a systematic overview of the type of the measure was put into place (or revoked), description of the measure and general reasoning on why the measure was used. The ECB (2018) and IMF (2022) ones are commonly used ones. The ECB database, called MaPPED, is a comprehensive dataset, with probably 1500 hundred policy actions for EU countries since 1995. Supervisory authorities have submitted measures, their descriptions and other information on measures, and since macroprudential policy has somewhat formalized after the GFC, other measures before it has been retroactively categorized to fit macroprudential measures, or microprudential that had macroprudential character. It also includes changes in measures, i.e., if fine tuning was done, so it presents a good starting point to use in analysis. The IMF database, iMaPP, combines information from various sources, including Macroprudential Policy Survey, and the IMF member countries that submit information on a yearly basis. This database also has a detailed description of each submitted measure, alongside detailed classification, but some caveats are that not every measure is included (those that were introduced before the sample period started), and only those measures that were cross checked with official documents were included (this means that earlier measures that were not publicly announced in English language were probably not included in the database).

Figure 1. Cumulative MPI values for Croatia, different sources



Source: ECB (2018), IMF (2022), HNB corrections is based on reports at Croatian National Bank.

When doing research on this topic, something peculiar was found. The two mentioned databases have, differences, at least for the case of Croatia. All of the measures were compared, revised, and based on internal reports of the Croatian National Bank, the dates and data were adjusted to reflect the most accurate dynamics of MPI measures. To depict the differences, a cumulative index was calculated based on formula (6) for the ECB, IMF and a combined revised version, and are shown in Figure 1. The ECB database is not updated anymore, and that is why this index stopped in 2018. However, it is striking to see the differences between the two databases. Reasoning is found in different classification of some measures, i.e., IMF does not take into consideration some measures that could be broadly classified as "other", but which had macroprudential character, whereas ECB did.

Up until writing this research, no comments were found in related literature on this problem. Authors usually collect the MPI data without manipulating it additionally. However, one need to have this in mind, that based on different sources, the estimation of final results could be very different, especially for active countries such as the example shown in Figure 1. One future research direction should tackle this issue.

4. METHODOLOGY DESCRIPTION

This section describes the methodology used in this paper in order to estimate GaR for the Croatian case. Quantile regression and related topics are described as follows.

4.1. Quantile regression[11]

This approach is fairly familiar in related research. Thus, a brief overview is given below. A linear quantile regression (QR) model can be defined as:

$$y_t(\theta) = \beta_0(\theta) + \sum_{k=1}^{K} x_{t,k}\beta_k(\theta) + \varepsilon_t(\theta), \tag{10}$$

where y_t is the dependent variable, θ is the quantile, betas are parameters that need to be estimated at each quantile, $x_{t,k}$ are conditional variables, ε_t is the error term. To estimate model (1), for every quantile $Q_\theta(y|X)$, $0 < \theta < 1$, a minimization problem is solved:

$$\arg\min_{\beta_k(\theta)} \sum_{t:y_t \geq \hat{y}_t} \theta\left|y_t - \beta_0(\theta) - \sum_{k=1}^{K} x_{t,k}\,\beta_k(\theta)\right| + \sum_{t:y_t < \hat{y}_t} (1-\theta)\left|y_t - \beta_0(\theta) - \sum_{k=1}^{K} x_{t,k}\,\beta_k(\theta)\right|, \tag{11}$$

where $\hat{y}$ is the estimated value of y. For the case of forecasting real GDP growth, y is defined $t+h$ quarters ahead:

$$y_{t+h} = 100\% \cdot \left(\frac{r\_GDP_{t+h}}{r\_GDP_t} - 1\right) / \frac{h}{4}\,, \tag{12}$$

[11] Introduction to quantile regression, alongside advantages to other approaches, such as being robust to outliers, heteroskedasticity, non-normality, etc. can be found in Koenker (2005), Davino et al. (2013), or Koenker and Bassett (1978).

where usually $h = 1, ..., 16$. A basic specification of a QR model that describes y_{t+h} could be the following one:

$$y_{t+h}(\theta) = \beta_0(\theta) + \beta_1(\theta)MPI_t + \beta_2(\theta)y_t + \beta_3(\theta)Stress_t + \beta_4(\theta)FV_t + \varepsilon_t(\theta),\ \theta = 0.05, \dots, 0.95, \tag{13}$$

where *MPI* is the macroprudential policy indicator, *Stress* denotes indicator of financial stress, and *FV* is financial vulnerabilities variable.

Goodness of fit of a QR model can be measured with pseudo-R squared, evaluated at each quantile θ:

$$R_\theta^2 = 1 - \frac{RASW_\theta}{TASW_\theta}, \tag{14}$$

where $RASW_\theta$ is the residual absolute sum of weighted deviations of real values to the estimated ones, and $TASW_\theta$ is the total absolute sum of weighted deviations.

4.2. Fitting the conditional distribution of estimated growth

The usual procedure after the QR estimation is to fit the skewed t-distribution of Azzalini and Capitanio (2003):

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

where $t(\cdot)$ and $T(\cdot)$ are the probability density function and cumulative density function respectively, μ is the location parameter, σ is scale, υ fatness, and α the shape parameter. Function (13) is used to smooth out the quantile function. In that way, the probability density function is obtained:

$$\underset{\mu,\sigma,\alpha,\upsilon}{\arg\min} \sum_\theta \left(\hat{Q}_{y_{t+h}} - F(\theta;\ \mu,\sigma,\alpha,\upsilon)\right)^2, \tag{16}$$

by matching the quantiles of the skewed t-distribution to the empirical quantiles obtained from the estimation. The empirical quantiles are usually the 5th, 25th, 75th and 95th. Some exceptions can be made to the 10th and 90th, when dealing with fewer data. Although the QR model obtains more estimated percentiles, Adrian et al. (2019) opt to have fewer quantiles for (16) to avoid over-parametrisation. Another approach is found in Lloyd et al. (2022) and Mitchell et al. (2021), where a non-parametric approach is used: conditional quantiles are mapped to conditional density, and interpolations across adjacent quantiles are made to smooth out the density. This papers uses measures[12] that are applied in the empirical research: unconditional coverage (UC) test of Kupiec (1995), usually called back-testing technique to evaluate the quality of the model. The UC test null hypothesis assumes that, on average, the

[12] For details, please refer to Dumitrescu et al. (2012).

conditional quantile is a correct coverage of the selected percentile of the forecasted distribution.

5. EMPIRICAL APPLICATION – CROATIAN CASE

5.1. Data description and stylized facts

For the empirical analysis, quarterly data on real[13] GDP for Croatia was collected from CNB (2023) for Q1 1991 to Q2 2022. Figure 2 depicts the dynamics of year-on-year growth in the entire period, where the consequences of the Croatian War of Independence at the beginning of the sample are visible, the banking crisis of 1998, the GFC, and the COVID-19 crisis are seen. The unconditional distribution of real growth is depicted in Figure 3 (left panel), and it is evident that it is not a Normal distribution, with a more significant left-sided skewness, which is corroborated in the right panel of Figure 3. Quantiles of Normal distribution are contrasted to the empirical quantiles of real growth, and significant departure is apparent. This is in line with related literature (Acemoglu et al., 2015; Sánchez and Röhn, 2016).

The second important variable in the analysis is the macroprudential policy index. The issue of different sources has already been discussed in section 4.3. Based on the discussion, the MPI observed in this study is based on the combination of the ECB and IMF databases, with needed corrections. The starting date for this variable is Q1 1994. Croatia has a relatively active macroprudential policy, so during the 2000s, due to enormous credit growth (due to financial deepening and general increase before the GFC hit), among other factors, tightening measures were made more often compared to loosening ones. Figure 4 depicts the number of tightening and loosening measures (panel a), whereas their signs are taken into consideration in panel b.

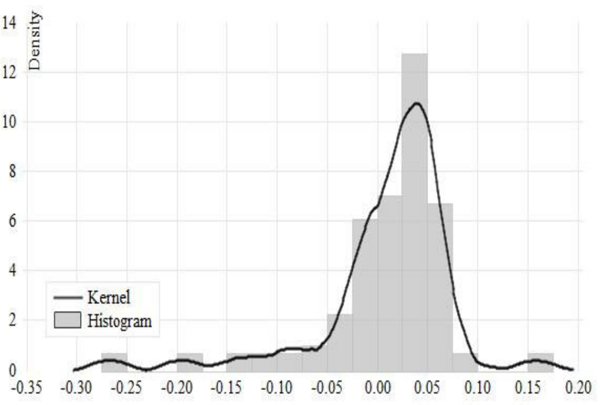
Figure 2. Real GDP growth, year-on-year, in %

Source: HNB (2023), author's calculation.

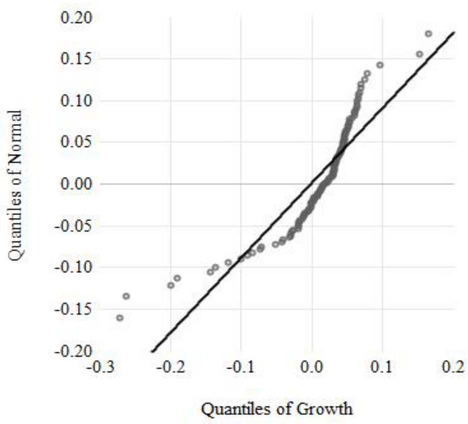
Figure 3. Histogram, kernel density and QQ plot for y-o-y real GDP growth rate

[13] GDP deflator was used to deflate the data.

Panel a. Histogram and kernel density of y-o-y real GDP growth rate



Panel b. QQ plot for y-o-y real GDP growth rate



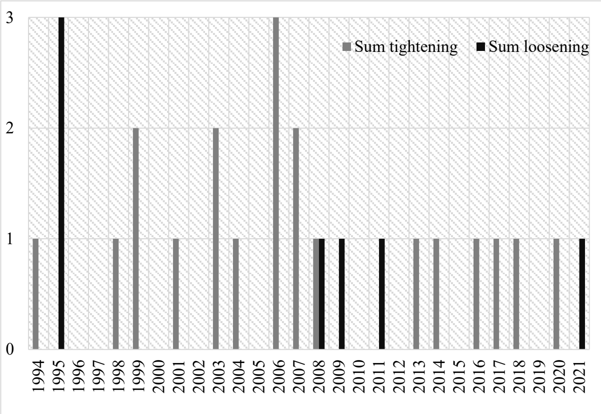
Source: author's calculation.

Another relevant variable in the GaR approach is financial vulnerability. This variable is also problematic as well, as different authors utilize a wide range of variables that capture credit dynamics, house price dynamics, credit institutions vulnerabilities, etc. ESRB (2021) uses the d-SRI indicator as it is based on panel estimation and is more comparable across countries. Individual studies focusing on a single-country analysis often substitute this indicator for one better suited for that country. This study will do the same. Besides the usual[14] credit dynamics variables and d-SRI, this study observes ICSR (Indicator of Cyclical Systemic Risks) as a Croatian version[15] of the composite indicator. Table 1 gives a brief overview of financial vulnerability measures, with Figure 5 showing their dynamics (more details on these measures for the case of Croatia can be seen in Škrinjarić and Bukovšak, 2022, Škrinjarić 2022b, 2023c). As one-year changes and growth rates are more volatile, two-year transformations are sometimes considered. Dynamics in Figure 5 shows that the credit growth was substantial in the 2000s due to financial deepening. Composite indicators of cyclical systemic risks increased during the 2000s, reflecting not only the rising credit dynamics but other relevant categories of financial vulnerabilities, such as house price dynamics, external imbalances, private sector debt burden, mispricing of risk, etc. Indicators reached their maximal values in 2007 and dropped fast when the crisis hit. The prolonged recession lasted for a few years, and in 2017 a mild recovery started. Finally, something to keep in mind is the problem of the non-stationarity of the data. White et al. (2015) assume that data for this analysis is stationary. The best option would be to have all variables transformed in a way that they are somewhat stationary. The d-SRI indicator is the commonly used variable, but it does not satisfy this assumption. All of the specifications in Figure 5 will be tested in section 5.2.1. to find which variable definition is the best in terms of model performance.

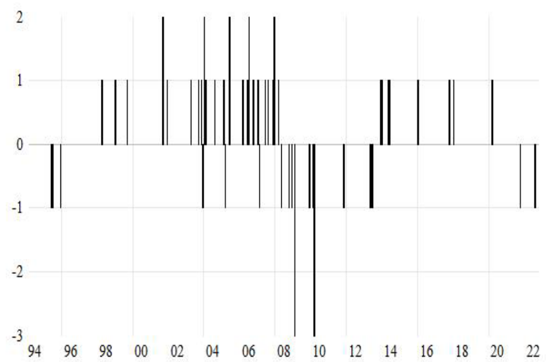
Figure 4. MPI (macroprudential policy index) dynamics

[14] See Škrinjarić and Bukovšak (2022) for Croatia's best individual credit dynamics indicators.
[15] See Škrinjarić (2022, 2023) for the composite indicator for Croatia.

Panel a. Number of tightening and loosening measures in one year



Panel b. MPI index dynamics every quarter



Source: ECB (2018), IMF (2022), author's calculation.

Table 1. Financial vulnerabilities variables

Abbreviation	Description	Transformation
C2GDP gap	Credit to GDP gap	Hodrick-Prescott filter gap, smoothing parameter for (narrow) credit series is 125K, for GDP is 1.600
Diff C2GDP ratio	Differenced credit to GDP ratio	One year difference of the (narrow) credit to GDP ratio
Diff Narrow credit	Differenced values of narrow credit	One year difference
d-SRI (ECB)	Domestic systemic risk indicator	See Lang et al. (2019)
ICSR (HR)	Indicator of Cyclical Systemic Risks	See Škrinjarić (2022, 2023a)
2y Diff Narrow credit	2-year differenced narrow credit	-
2y Diff C2GDP ratio	2-year differenced credit to GDP ratio	-
Diff ICSR (HR)	Differenced ICSR	-
Growth rate Narrow credit	One year growth rate of narrow credit	-

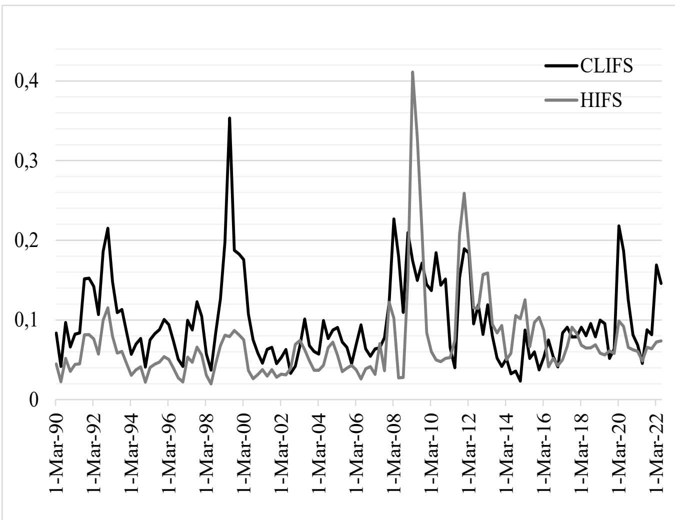
Source: author's calculation.

The financial conditions indicator for the Croatian case is somewhat problematic, as the ECB (2023) version has a very different dynamic compared to the one that HNB developed (the period for this variable is Q1 1990 to 2Q 2022). Figure 6 contrasts the two indicators, where it is seen that during the GFC and the sovereign bond crises, the ECB version does not capture the stress, whereas the COVID-19 crisis and war in Ukraine are not much reflected in the HNB version. CLIFS is constructed based on three markets: equity, bond and foreign exchange market (see Duprey et al., 2015), whereas HIFS is the tweaked version of CISS (Holló et al., 2012), in which some minor things are changed based on data unavailability, and includes all five markets (besides the aforementioned ones in HIFS, money and bank markets).

Figure 5. Financial vulnerabilities in Croatia, different measures

Note: C2GPD – credit to GDP, Diff – difference, i.e., year-on-year (y-o-y) difference, d-SRI – domestic systemic risk indicator, ICSR – indicator of cyclical systemic risk, 2y Diff – two-year difference. Growth rate of narrow credit is y-o-y.
Source: HNB (2023), author's calculation

Figure 6. Comparison of CLIFS (ECB version) to the HIFS (HNB version) of financial stress



Source: ECB (2023) and HNB (2023)

5.1.1. Trying to reduce endogeneity of MPI

Following the references in section 3.3.1., we obtain non-systematic shocks of MPI_1 (the non-cumulative version) and MPI_2 (takes values of +1, 0, and -1) via ordered logistic regression, as the order of the MPI values matters. MPI_1 was calculated based on formula (4) in each quarter, i.e., where the tightening measures were given value +1 by each measure, loosening measures were given value -1 per measure, and absence of any measure or ambiguous ones were given value 0. Then, the net MPI is calculated by reducing the total amount of loosening measure from the total amount of tightening ones. MPI_2 was calculated based on formula (5), where the MPI_1 was translated into values -1, 0 or 1, i.e., if the overall net MPI in a quarter is negative, it was given value of -1, and the opposite is true for the overall initial positive value.

As previously commented, the macroprudential policy cannot immediately react to macro-financial surroundings due to data lags, legislation bounds, etc. That is why we compare several model specifications, in which lagged values of real growth, financial stress (HIFS, the HR version), and financial vulnerabilities (yoy change of credit-to-GDP ratio) are used. We are interested in talking about causal effects, and since there exist a bulk of literature on monetary and fiscal policy that does this approach in extracting policy shocks to talk about these effects, currently we opted to take this approach (see Ramey 2016).

Table 2 lists AIC values[16] for both MPI specifications, where models M1 to M4 refer to how many lags of other variables are included[17]. Models with three lags of other variables have the lowest AIC value, so they will be used to obtain residuals of the macroprudential policy variable.

Table 2. AIC values of several model specifications.

Model	M1	M2	M3	M4
AIC MPI_1	241.23	236.14	**234.02**	234.88
AIC MPI_2	175.57	171.90	**169.65**	171.36

Source: author's calculation.

5.2. Quantile regression results

Results onwards include the following variables and transformations:

[16] SIC values resulted with the same ordering. As these are just ordinary regressions, the idea is to see the trade-off between the explanatory power of the model versus the number of parameters included in the model. Information criteria give us this information.

[17] I.e., we compare four models M_*i*, where *i* stands for how many lags of all variables on the right hand side (RHS) of the ordered probit equation symbol were included. The explanatory variables included lagged value of the real growth itself, as it is usually put in GaR modelling, and the other variables included were: HIFS and YoY change of the credit-to-GDP ratio. E.g., M_3 means that all variables on the RHS were included with lags 1, 2 and 3 to regress the MPI dynamics on.

- Real GDP growth, forecasting horizons $h = 4$ and 12 to contrast short- and medium-term results in models,
- Residuals from models (M_3) in Table 2 for MPI_1 and MPI_2,
- All nine financial vulnerabilities indicators from Figure 5,
- Original values of MPI_1 and MPI_2 for models where lagged variables are included.

As many combinations of variables could be observed, to reduce their number, individual quantile regressions are estimated for the case of MPI and financial vulnerabilities. Finally, the best ones are selected for further analysis as follows.

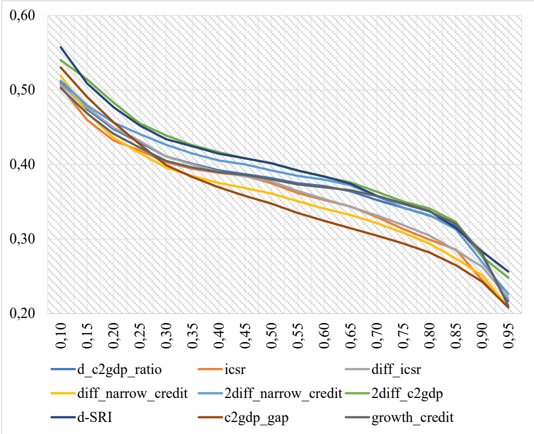
5.2.1. Selecting best variables for each indicator category

The selection criteria for the best models onwards are the following ones: we compare the value of pseudo R-squares on each quantile, ranging from 10^{th} until 95^{th}, firstly between all possible candidates of financial vulnerabilities. Then, the same is done for the financial stress variables (HIFS and CLIFS), and finally for the MPI 1 versus 2 (after purging effects of other variables in them from the previous subsections). These comparisons are done for $h = 4$ and 12 quarters ahead, to get an idea of the performance both in the short and medium run. Then, we try to select variables that have an overall better performance over all quantiles over both time horizons. For the comparisons, we estimate a quantile regression on an individual variable basis.

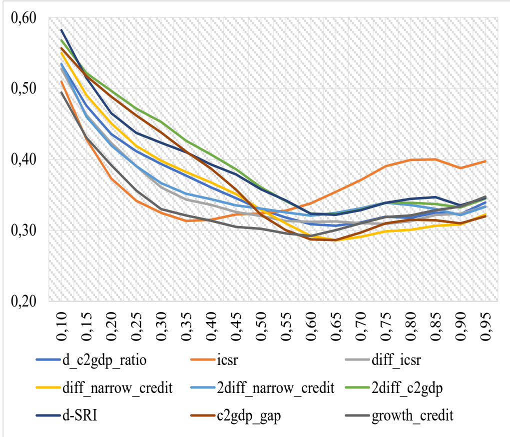
Individual QR models have been estimated for growth 4 and 12 quarters ahead, and financial vulnerability variables from Figure 5. Pseudo R-squares are shown in panels a. and b. in Figure 7. It takes work to select the best indicator. As for the case of $h = 12$, the best ones are the non-stationary variables: ICSR, d-SRI, and credit-to-GDP gap. They are followed by stationary ones: yoy and 2-year change of credit-to-GDP ratio. We opt to use stationary variables over the non-stationary ones, as the rest of the variables in the model exhibit stationary behaviour. Moreover, this is a single country analysis, so it is better to have as many as possible observations, so the YoY change of credit-to-GDP ratio is preferable over the two-year change. Panels c. and d. compare the MPI variables, and here the picture is a bit clearer: MPI_1 has better performance.

Figure 7. Comparing pseudo-R squares of individual variables

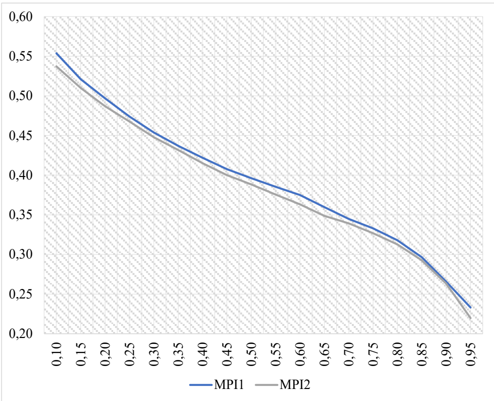
Panel a. $h = 4$, financial vulnerabilities



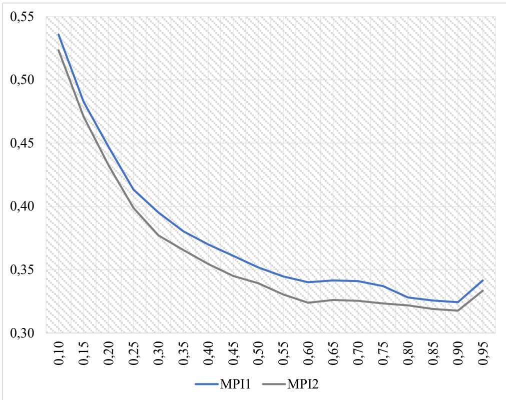
Panel b. $h = 12$, financial vulnerabilities



Panel c. $h = 4$, MPI



Panel d. $h = 12$, MPI



Source: author's calculation.

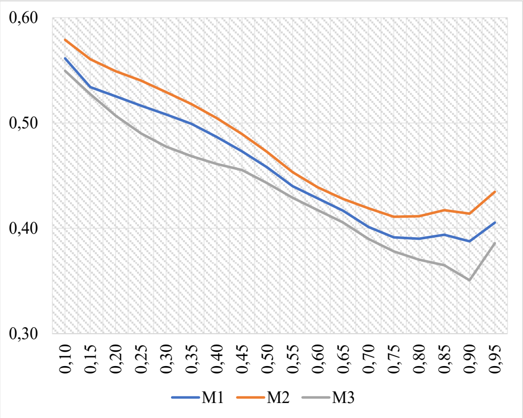
5.2.2. Selected models result

Based on previous discussions, the following variable variants are compared:

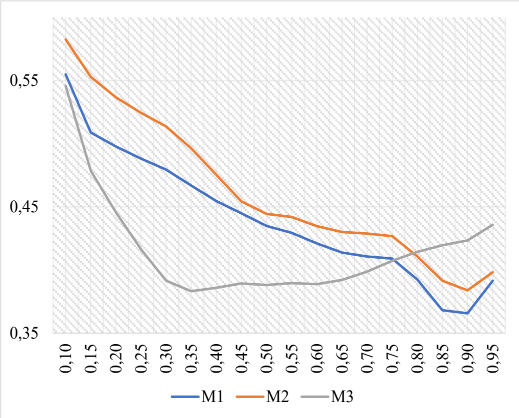
- Model (1): yoy change of credit-to-GDP ratio, HIFS, residuals of MPI_1
- Model (2): 2-year change of credit-to-GDP ratio, HIFS, residuals of MPI_1
- Model (3): ICSR, HIFS, residuals of MPI_1

Figure 8. Pseudo R-squares for models (1) to (3)

Panel a. $h = 4$



Panel b. $h = 12$



Source: author's calculation.

Figure 8 shows pseudo-R squares for all three models, for 4Q and 12Q ahead growth forecast. There are small differences between M1 and M2, whereas M3 is the-worst performing one. When looking at p-values of UC tests (see section 5.4.), all three models perform well (the null hypothesis cannot be rejected in all cases), i.e., the estimated 10th percentile and median correctly cover the 10th percentile and median of the true growth realisations.

When comparing the effects of MPI variables in models (1) to (3), Figure 9[18] shows the estimated coefficients for $h = 4$ for the QR case (dotted curve), which is contrasted to the OLS results (red dashed line). In all three cases, the MPI QR estimates differ over quantiles and are different compared to the OLS lines. At first glance, the effects on the lower tail of the growth distribution are positive and greater than the median (central) value. This is in line with previous research that tighter macroprudential policy positively affects the future lower tail of GDP growth distribution. However, positive, albeit almost nonsignificant, results regarding the effect on the median could also be explained. When the times are good, in terms of economic growth and the upward phase of the financial cycle, imposing higher reasonable macroprudential requirements cannot hurt future average growth, especially when credit institutions have fairly high own voluntary buffers.

Table 4. UC test results (p-values) for all three models

Model:	M1	M2	M3
10th percentile	0,54	0,81	0,43
Median	0,77	0,76	0,63

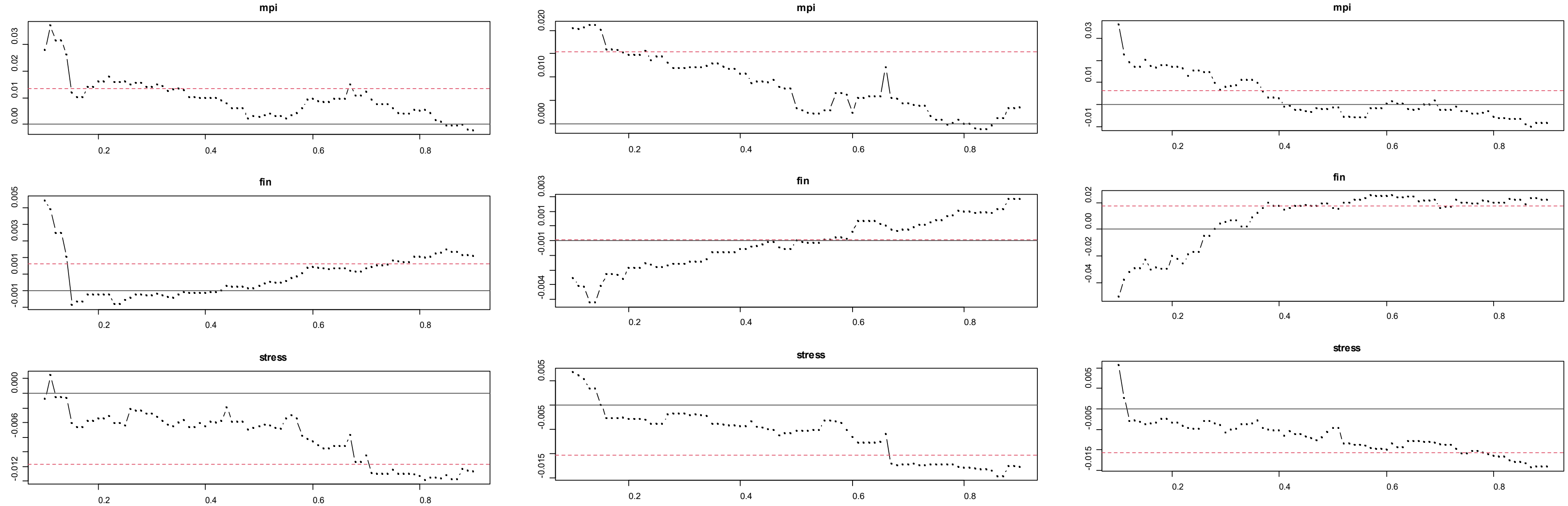
Source: author's calculation.

[18] Although we are mostly interested in comparing the median and the GaR value, i.e. calculating distance to tail, we are showing all quantiles in Figure 9 to get a better picture on the stability of the beta coefficients.

Figure 10 additionally examines confidence intervals for the MPI variables. Although the interval estimates include zero values in all cases, if the prudential authority thinks that the selected variables and model are reasonable, adding new data in the future could change these findings in favour of significant results. Some reasoning on why the results are not (yet) significant could be a relatively short time series for a single-country analysis, and the definition of the MPI variable itself, without intensity adjustment. Moreover, beta values for the median growth case are constant over all observed horizons, around 1%, but not significant. Suarez (2021) talks about effects on median growth being equal to zero and states that some nonlinearity exists or the policy variable has reached its upper limit. As the Croatian macroprudential policy is fairly active, the latter could be true. Moreover, Aikman et al. (2018) also found positive effects of higher bank capitalisation on GaR, with no significant reduction of median growth. Although not significant, the beta coefficients for the 10^{th} percentile start with the highest value for $h = 4$, and for each subsequent horizon decline. Due to the way MPI is defined, this is somewhat expected. When compared to previous related literature, the signs of the estimated parameters are in line with studies that include MPI variable in the analysis. However, the insignificance of the results could be also explained by the information that Croatia does not have borrower-based measures, which were found to be more effective in this analysis in previous related papers.

Figure 9. Estimated coefficients for models (1) – (3), $h = 4$ quarters ahead

Panel a. Model (1) Panel b. Model (2) Panel a. Model (3)



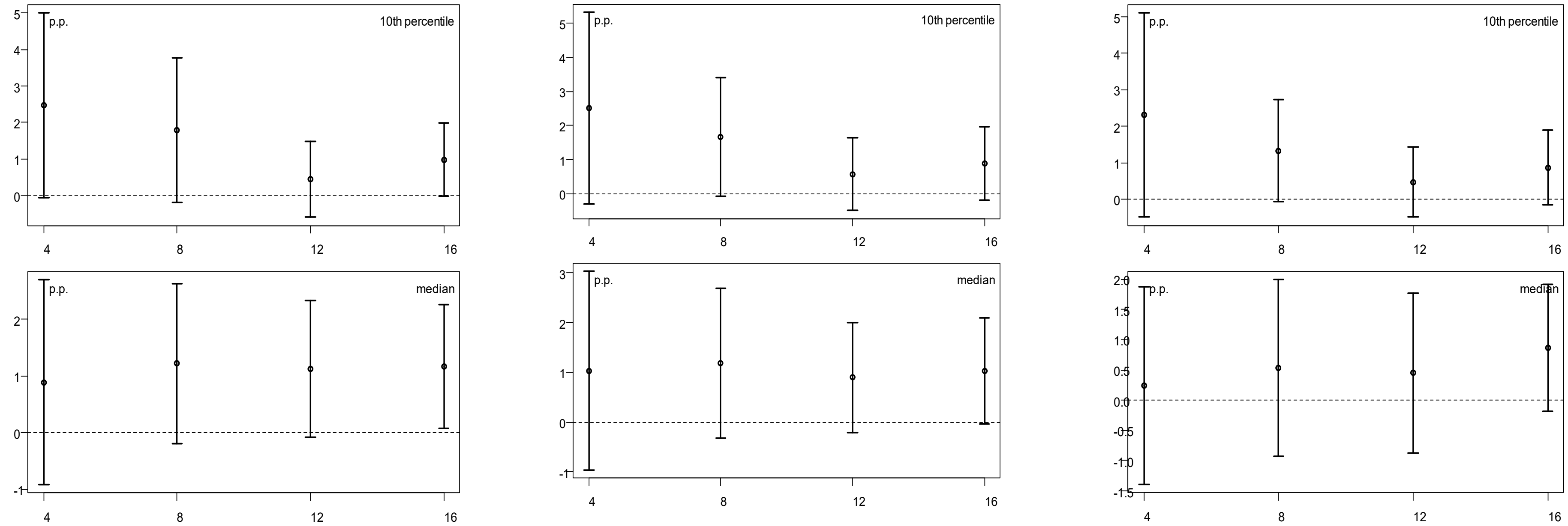
Note: y-axes values should be multiplied by 100% to get p.p. growth interpretations. mpi – variant of macroprudential policy variable, fin – financial vulnerabilities variable as described in main text.
Source: author's calculation.

Figure 10. Macroprudential policy effects on future growth

Panel a. Model (1)

Panel b. Model (2)

Panel c. Model (3)

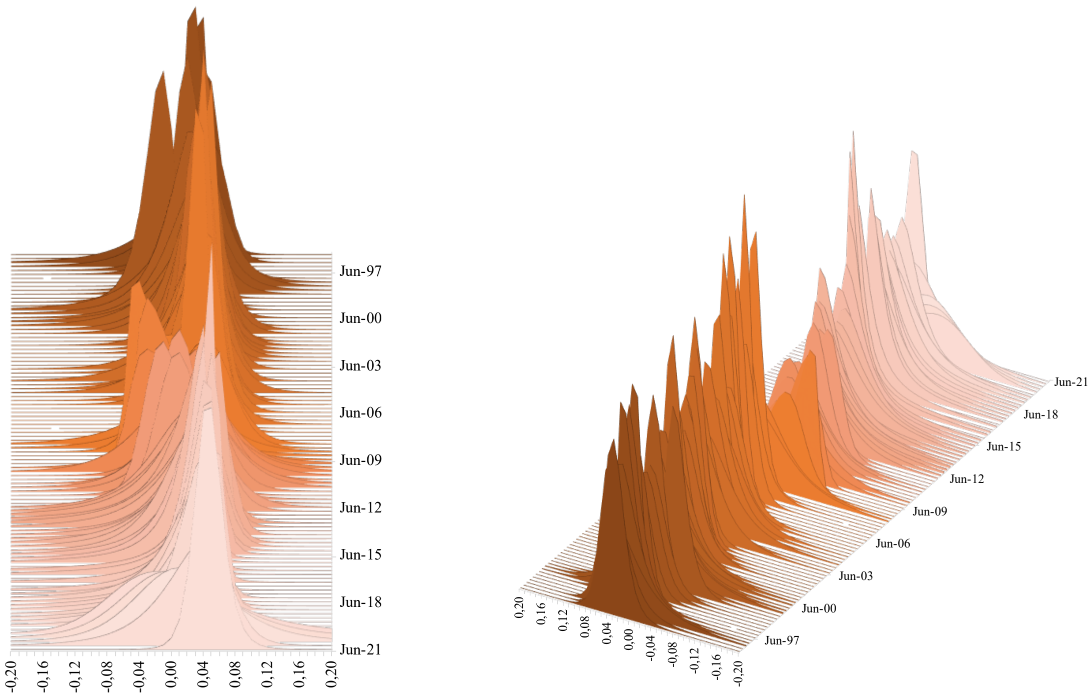


Note: confidence intervals obtained via block bootstrapping with 1000 replications.
Source: author's calculation.

5.2.3. Distribution fitting results

Next, skewed t-distributions for every quarter from the model (1) were fitted as described in section 5.2. Figure 11 shows the distribution changes over time (right panel is the left one but rotated so that older values can be seen better). The model captures specific dynamics very well, as the distribution becomes heavily titled to the left just before and during the GFC crisis; the prolonged recession afterward is also visible, as the distributions were more left tilted for a longer time. Finally, from 2015 onwards, the distributions became more compact until the COVID-19 shock shook it up again.

Figure 11. Fitted growth distributions from model (1), $h = 4$



Source: author's calculation.

5.2.4. Macroprudential stance measure (distance to tail)

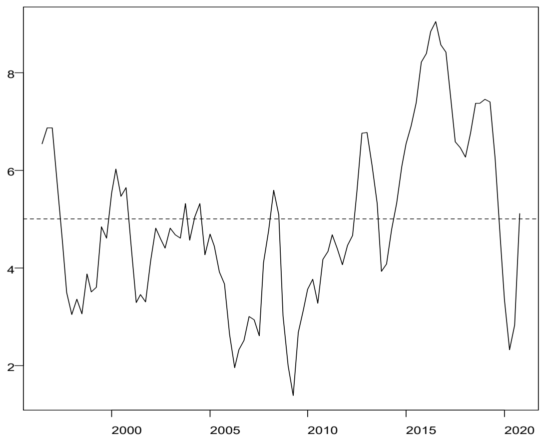
Using estimates from models (1) to (3), distance to tails (DTTs) have been calculated as the difference between the median and the 10th percentile growth for $h = 4$[19]. Results are shown in Figure 12. All estimated DTTs are volatile, and it is hard to tell a story from them. Panel a. shows that before GFC, majority of time, DTT was below the

[19] We use MPI “shocks” from a variable that was defined with values being equal to +1 or -1 (before purging out effects of other variables), and we are not using moving sums as some studies do, there is no reason to believe that a measure that takes +1 value in, e.g. 1Q 2019 should have effects 12Q ahead, as this is way overstretching the effects that macroprudential policy has. Using moving sums or similar transformations would include a greater autocorrelation i.e. memory of the variable and thus would make sense to look at a longer time horizon. But to observe effects 3 years in future is really overstretching and we don’t see central banks talking that the macroprudential measures have significant effects on the GDP growth or in general the real economy so long in the future.

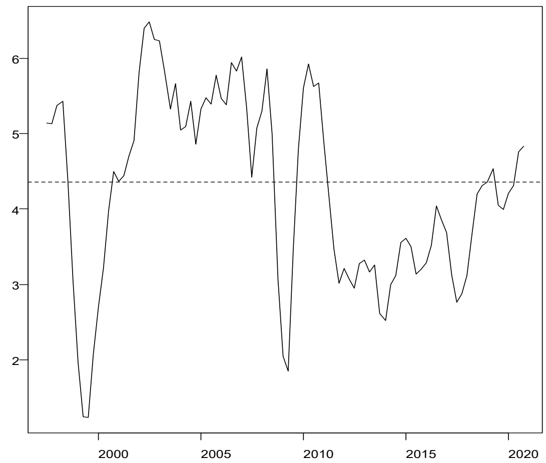
median value and was tighter compared to the period from 2015 to 2020. Covid-19 shock distorted the results at the end of the period, but the downward trend of DTT would likely continue without this shock, as the last observed value is lower than values before Covid hit. Moreover, this value is around the median[20] value, which could be a somewhat neutral level of macroprudential stance. Panels b. and c. tell completely different stories: in the pre-GFC period, the stance was looser due to higher DTT values, and in the second sub-period, the stance is tighter, with an increase of DTTs at the end of the observed periods. This cannot be true in practice. These results show how stance assessment is subject to data selection, transformation, and other relevant issues that were commented on in previous sections.

Figure 12. Distance to tail from models (1) to (3)

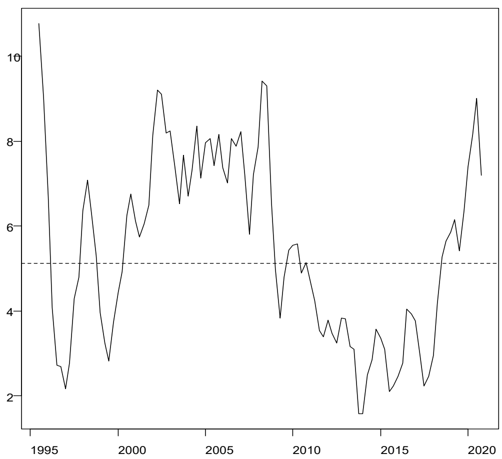
Panel a. Model (1)



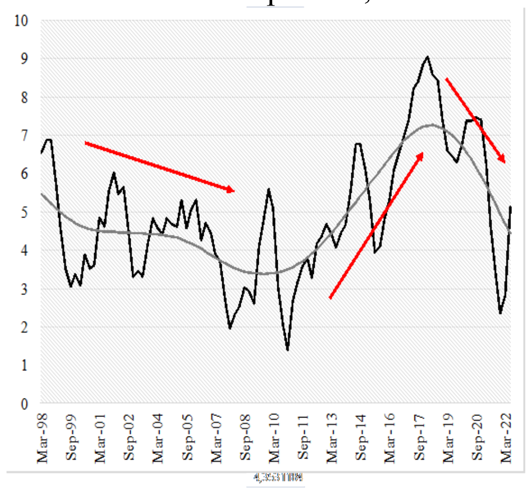
Panel b. Model (2)



Panel c. Model (3)



Panel d. DTT from panel a, more details



Note: dashed lines indicate median values of distance-to-tails
Source: author's calculation

[20] Here, we depict the median value of DTT as just a statistical value. It does not replace the theoretical „optimal" DTT value (see the Appendix).

Moreover, suppose one would select, e.g., the panel a. DTT to be the true one, i.e., reflecting the actual effects of macroprudential policy on Croatian growth. In that case, the remaining question is how to evaluate this observed DTT to the neutral or optimal value? The second section of this paper gave an overview of theoretical definitions of these values, which is difficult to determine in reality. As the optimal DTT depends on macroprudential policymaker's preferences, alongside the relative effectiveness of this policy on GaR compared to median growth, it is evident that this is a difficult empirical task. Future work will probably include the calibration of utility function parameters based on policymakers' revealed preferences. Currently, we are left with observing the results with respect to the historical distribution of DTT in Figure 12, panel d. It takes the DTT from panel a. adds some additional information. Cucic et al. (2022) similarly observed DTT by looking at the median value. Red arrows show the general direction of DTT dynamics over time. Before GFC, the policy was introducing more measures as it was developing and trying to tackle enormous credit growth. This decreased DTT over time. During GFC, policy introduced loosening measures, which surely helped the DTT to decrease again after it spiked at the beginning of the crisis. A Croatia-specific situation afterward, the prolonged recession, could have affected the onward DTT, which was increasing until 2017. New tightening measures reduced the DTT onwards.

6. DISCUSSION AND CONCLUSION

Theoretical considerations about the effectiveness of macroprudential policy have been developing in the last couple of years, which includes great arguments on why this policy should work. However, the practice has mixed results that are affected by variable definition, selection, and transformation, probably due to the bird's eye approach to estimation. Micro-approach[21] of estimating the effects of macroprudential policy finds results more often compared to the macro-approach. The inconclusive results of this study are in line with the comments of Reichlin et al. (2019), who agree that the relationship between financial and real variables is difficult to model. This is proven in the empirical part of this paper, where it is shown that the results vary with respect to variable definition, transformation and model selection. One conclusion could be entirely different, if some of the changes are made. Such findings indicate that more work needs to be done before fully operationalising the DTT metric for regular use. This is one of many papers that find GaR modelling challenging. Alessandri and Di Cesare (2022) warn about the empirical problems and that instrument calibration based on such an approach should be very cautious.

An exhaustive literature overview in the first part of this paper sheds some light on the reasoning behind why the results are very mixed. In that way, when having all of that information, some better decisions could have been made for the empirical analysis of the Croatian case. This means that some problems detected in previous literature could be mitigated in the empirical part of the study. Some expectations were formed based on the literature review as well. They included that it would take more work to obtain

[21] Individual bank or banks' counterparties approach and similar.

concrete conclusions in this initial approach of designing a framework to assess the macroprudential stance in Croatia. The heterogeneity of data and variable definition, as well as results in previous papers, indicate that using such a framework still has issues.

Some drawbacks of the approach made in this research include the single equation approach, where only the future real growth is a dependent variable. Thus, in most cases, one can only talk about correlations between the variables or look at the results from the forecasting perspective. Furthermore, even though the endogeneity of the MPI variable was considered, future work should extend the analysis to the QVAR approach that is being developed at ECB. Such a framework would be better for solving the endogeneity issues.

Regarding the Croatian experience, the initial results obtained from this study need to be taken with some caution. Results, although still insignificant, show that the effect of tighter macroprudential policy is positive on the lower tail of the future GDP growth, without effects on the median growth. This means that the distribution is reshaped to lower the magnitude of downside risks. Tightening in normal times does not disturb future average growth, but it could have greater positive effects on reducing the downside risks when they materialize. This could be in line with those who say that macroprudential policy's primary role should be increasing the financial system's resilience. Less evidence is usually found for curbing the financial cycle. This could be an indication for the policymakers to focus more on those measures that increase the system's resilience, as it is much harder to reduce peaks and increase troughs of the financial cycle. Furthermore, the selected final model resulted in rather good distribution forecasting. This is seen in the dynamics of fitted growth distribution (see figure 13), which tells a reasonable story. Such an approach could be comparable or a complement to the official forecasting models. Finally, the distance to the tail (difference between the median and GaR growth) could tell us how effective some measures were and how the actual dynamics of the interaction and growth reaction are slow over time. Nevertheless, some fine-tuning of the results is still needed to obtain more robust and stable results. When compared to the results of the ESRB (2021) report, one needs to take into consideration a couple of things. Although it seems that the results in the report are stable and more usable than what was obtained here, there are caveats and challenges found in the ESRB approach. Two biggest ones refer to the definition of the MPI indicator and its transformation, whereas the other is the endogeneity issue. In the report, all measures are converted into +1 or -1, with the final MPI definition being calculated as a cumulative value of the indicator, and a 5 year change is the basis for the transformation. Since the local projections from the quantile regression are observed until 4 years ahead, this would mean that the effects of macroprudential policy could take place over a 9 year period, which is too long. Furthermore, a 5 year change has a long memory and often is not stationary for the case of countries like Croatia. Another issue, the endogeneity problem, is not resolved, as the 5 year change of MPI is used in the original form, without any other "cleaning" of the series. Moreover, in some cases, the report does the following. Financial stress and vulnerabilities indicators are regressed on the MPI variable, and their residuals are plugged in the quantile regression part. However, MPI is the variable whose dynamics depends on the financial vulnerabilities in the system (please see section 2 of this paper for more on this). So, the results in the mentioned report are not comparable to those obtained here.

In this paper, different results were shown, depending on many factors. However, based on the analysis, the MPI variable should be used as something other than a differenced cumulative indicator where the difference is some large time span. This ends up with even more delayed results in the impulse response functions of future GDP growth, where we already examine effects over four years ahead. Next, endogeneity problems should be solved as well. This could be done by trying to find a Taylor rule for macroprudential policy as a first step of the analysis. Although this was tried in this paper, one reason on why the results are still not satisfactory could be relatively short time series. If this is not solved when more data becomes available, it should be solved via the quantile VAR approach. Future work could also focus on how to deal with the COVID-19 period in the results. It is not easy to "clean" the data up, as the pandemic shock is present in the growth variable at both sides of the equation. With dynamic calculations for impulse response functions, it becomes even more challenging to tackle this problem. Although growth realisations in the pandemic period fall in the GaR territory, variables used to forecast growth are not constructed to track such shocks. Some bias in the results is present due to pandemic dynamics being included in the analysis.

Further research should solve some of the MPI problems from section 4, such as the intensity adjustment of the policy variable. Some initial steps have been done by Vandenbussche et al. (2015) and followed by Eller et al. (2020). But this could be problematic, as some authors assign weights based on their thinking of what is more important, such as Meuleman and Vander Vennet (2020). Such an approach should be as objective as possible. Some authors warn that the empirical research relies on quantile regressions too heavily and found that GARCH (generalized autoregressive conditional heteroskedasticity) models outperform the QR one (Brownlees and Souza, 2021). Other possible methodological directions could be MIDAS-QR (mixed data sampling), where higher frequency data could be used for forecasting purposes (Ferrara et al. 2022). Some authors are starting to focus on DSGE (Dynamic stochastic general equilibrium) modelling approach (Buch et al., 2018). However, others criticize this framework for not capturing tail risks (Blanchard, 2016), so an opportunity may exist to extend DSGE to GaR analysis. It is expected that the GaR framework will become more prevalent in climate change analysis. Bayoumi et al. (2021) and Kiley (2021) already provide an introduction. As climate disasters are becoming more frequent, it would not be surprising to see more and more applications to see the effects on financial stability.

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Appendix. MACROPRUDENTIAL STANCE DEFINITION

Surprisingly, there lacks a clear consensus on the definition of a macroprudential stance. It is essential to define this concept as empirical work is starting to measure it. Based on a questionnaire, Arslan and Upper (2017) found that measuring the objectives and the macroprudential policy stance is challenging in practice. Thus, up to that point, most countries did not measure their macroprudential stance at all, according to this questionnaire's results. That is why the authors conclude that policy inaction bias could result from a lack of such measurement and could be reduced if more rule-based approaches are defined.

The rest of the section and paper will define the macroprudential stance as in ESRB (2019) and Suarez (2020, 2021). Some other comments about what is also considered in practice will be commented on in section 4. Measuring macroprudential stance could be based on microeconomic theory (besides the mentioned two studies, seminal work includes Suarez, 2022; and Cecchetti and Suarez, 2021). The basis for the analysis is social preferences and welfare.

Suarez (2021) starts with a welfare function, where $w > 0$ is the measure of aversion for financial stability, $\bar{y}$ is the average or median growth, and y_c is the relevant growth quantile (GaR):

$$W = \bar{y} - 0{,}5w(\bar{y} - y_c)^2, \tag{1}$$

which is maximised with respect to risk level x. Median and quantile growth depend on x and z as a macroprudential policy variable (assumed to be exogenous). The main result is that an optimal policy keeps the gap between the median and the GaR constant at a certain target level. This level depends on two factors: the risk aversion w, and the relative impact of the policy z on the GaR compared to the median growth. The higher the risk aversion w is, the smaller the optimal distance between the median and GaR values. If the relative impact of policy z is much more significant on GaR than median growth, the optimal distance is smaller. Policy stance assessment is further developed in Cecchetti and Suarez (2021). The estimated distance between the median and GaR growth is compared to the optimal distance, which depends on three factors: benchmark probability of stress, risk aversion, and the relative impact of policy on GaR compared to median growth. If the probability of stress declines, risk aversion increases, or relative impact goes down the optimal distance increases. The authors implicitly define the macroprudential stance metrics by comparing the observed and optimal (*) distances:

$$stance = (\bar{y} - y_c)_{observed} - (\bar{y} - y_c)^{*} \tag{2}$$

If the observed distance is greater (smaller) than the optimal one, the policy is accommodative and should be tightened (loosened). The problem in practice is measuring the optimal level of distance, as it does not depend on empirical data. Rather, it should be based on preferences, as described in Suarez (2021).

Duprey and Ueberfeldt (2020) extended the analysis of utility function to observe monetary and macroprudential policies simultaneously. This paper is a mix of theory and empirical analysis. In a model of the economy's macroeconomic and financial stability, the central core is two market imperfections (principal-agent problem and limited liability with mispriced deposit insurance), which policymakers alleviate with tighter monetary and macroprudential policy. Tail risk is a gap between expected output and output realized in a bad state[22]. It is similar to the papers above and reflects financial stability concerns related to the risk-taking channel of monetary policy or loose regulatory requirements of the macroprudential policy. Moreover, from the derived indifference curves, results indicate that there exists a substitution effect between policies. When monetary policy rates are high (low), capital adequacy rations need to be relaxed (tightened).

It is obvious that such concept, although theoretically sound, is difficult to translate to empirical analysis. Namely, the observed distance in (2) is something that can be estimated in empirical approaches (although, as seen in the rest of this paper that this is very difficult). On the other side, the "optimal" distance is something that is extremely difficult to estimate, and needs to be included in future empirical studies. As mentioned, this distance depends on: i) risk aversion – meaning that each policymaker will have different value of w; ii) benchmark probability of stress – which is extremely difficult to forecast (see Škrinjarić, 2023b), and iii) relative impact of policy on median versus tail growth – which is estimated in empirics, but as mentioned, results greatly depend on the data, transformation, policy definition, etc. Thus, the majority of existing literature focuses on measuring the observed distance to tail, to at least solve problems of this part of the work first, before moving to the translation of theoretical concepts to the empirical.

[22] This is the theoretical definition. Empirically, the authors define the tail risk as others do, in terms of the difference between the median and the fifth percentile growth four quarters ahead.

Table A1. Summary of empirical research on Growth-at-Risk

Authors	Country, timeframe	Variables	Methodology	MPI included?	MPI definition/ transformation	Additional info	Conclusion
O'Brien and Wosser (2021)	27 OECD countries, 1990-2020	CLIFS, ISCR for Ireland; C2GDP gap	panel q-reg	No	-	GNI instead of GDP for Ireland (see main text); 5th percentile	Good for forecasting, advising to use for HaR and other applications
Plagborg-Møller et al. (2020)	13 AE, 1975(80) - 2019, focus on USA	A couple of dozens of individual variables that are grouped into categories via factor estimation	panel q-reg	No	-	Many forecasting and nowcasting exercises with a lot of predictor variables	Higher moments of the forecasted distribution are imprecise, no stable stylized facts are found in variable selection procedure, cross-country heterogeneity of results.
Ivanova et al. (2021)	Ukraine, 1996-2020	23 financial variables, grouped via PCA for forecasting purposes in the next step; GEPU	q-reg	No	-	Included variables that were good predictors of crises via EWM approach in previous literature	Results as previous literature on better growth predictability.
Sánchez and Röhn (2016)	OECD, 1970-2014 (differing over variables)	Several dozens of indicators for categories: financial market indicators, institutional quality, macroprudential indicators, labour market, external policies	panel q-reg	Yes	As in Cerutti et al. (2015): sum of individual measures in a quarter, ranging from 0 to 12	Endogeneity tackled with policy variable lags	Macroprudential policy lowers average growth, but decreases lower-tail risks, but newer data needs to confirm this.
Aikman et al. (2019a,b)	16 AE, 1908-2017	Different specifications of credit growth information, house price growth, current account imbalances	panel q-reg	No, but banking sector leverage included	-	Leverage included, to see how capital requirements affects bank capital, thus, a quasi MPI included.	Greater capitalisation would reduce downside risks, especially before GFC.
Krygier and Vasi (2021, 2022)	Sweden, 1995-2021	SRI, FCI (Swedish version)	q-reg	No	-	-	Results as previous literature on better growth predictability. Authors warn about problems of COVID-19 period predictability.
Alessandri et al. (2019)	Italy, 1970-2018	IIP and Itacoin alongside usual GDP, different financial conditions variables tested	q-reg	No	-	Forward looking recession probability, and uncertainty indicator defined, useful for future work on this topic.	OOS forecasting is not stable over time, and risk assessment framework could use GaR just as one aspect
Busetti et al. (2020)	Italy, 1970-2018	Besides the usual ones, EPU and PMI included	Expectile regression	No	-	Authors propose a decomposition of expected shortfall, for more insights about drivers of risk.	Financial conditions are useful for prediction, but deterioration of predictive power found at longer horizons.
Alessandri and Di Cesare (2021)	Italy, 1970-2020	Same as Alessandri et al. (2019)	q-reg	No	-	Continuation of Alessandri et al. (2019), to see performance over COVID-19 period	Historical descriptions are fine, but forecasts need to be scrutinized.

Drenkovska and Volčjak (2022)	Slovenia, 2003-2020	Usual variables, with external macroeconomic conditions	q-reg	Yes	Cumulative over time	Authors warn about shortfalls of using such defined MPI. Own version of financial conditions variable. Endogeneity issues not solved.	Usual conclusion about effects of financial conditions and vulnerabilities. MPI not significant.
De Lorenzo Buratta et al. (2022)	Portugal, 1991-2019	Usual variables	q-reg	No	-	In and oos forecasts, expected shortfall estimated, expected longrise, entropy, probability of entering recession	Proposed measures could be useful for forecasting, and complementary to GaR.
Duprey and Ueberfeldt (2018)	Canada, 1992-2020	Alongside the usual ones, inflation, overnight policy rate	q-reg and VAR	Yes	Number of measures in given quarter	Both monetary and macroprudential policies considered.	Macroprudential policy lowers tail risk.
Duprey and Ueberfeldt (2020)	Canada, 1982-2018	As in Duprey and Ueberfeldt (2018), and credit dynamics	q-reg and VAR	Yes	Number of measures in given quarter	Both monetary and macroprudential policies considered. Theoretical analysis alongside empirical. Endogeneity solved with propensity score method for MPI.	Macroprudential policy lowers tail risk.
Galán and Rodríguez-Moreno (2020)	27 EU, 1970-2019	Usual ones	panel q-reg	Yes	Cumulative over time	Robustness checked via replacing MPI with banks' solvency ratio (CET1 capital over RWA). HaR examined as well. Endogeneity issues not solved.	MPI increases GaR, decreases medium growth, i.e. trade-offs found.
Galán (2020a)	28 EU, 1970-2018	Instead of SRI, C2GDP 2y change, HPI 2y growth, CAB (%GDP)	panel q-reg	Yes	Cumulative over time	Endogeneity tackled with extracting non-systematic MPI by regressing it on other variables in the model. Problem here that the same period is used (MPI cannot react in the same period to these variables). Both financial cycle upswings and downswings included in the analysis. BBM and CBM measures observed separately.	Position of the financial cycle is important for MPI effectiveness.
Galán (2020b)	28 EU, 1970-2018	Instead of SRI, C2GDP 2y change, HPI 2y growth	panel q-reg	Yes	4-quarter net sum	Both financial cycle upswings and downswings included in the analysis. BBM and CBM measures observed separately. Robustness checking by dividing the sample to AE and EE). Endogeneity issue not	Similar conclusions to Galán (2020a)

						solved.	
Deutsche Bundesbank (2021)	Panel (44 countries), and Germany, 1970-2019(21)	Besides usual variables, US excess bond premium, inflation, interest rate	QVAR, panel q-reg	No	-	-	Publication finds it difficult to make real-time estimates of GaR with a longer lead time.
O'Brien and Wosser (2022)	27 OECD, 1090-2020	Structural: degree of trade, financial openness, FDI flows, and bank concentration	panel q-reg	No	-	Systemic banking crisis likelihood estimated as well.	Smaller, open economies with greater FDI flows are more vulnerable.
Franta and Gambacorta (2020)	56 countries, 1980-2012	Inflation, monetary policy interest rate	panel q-reg	Yes	No transformation, values take from -2 to 2	No financial stress and vulnerabilities included in the study.	LTV limits narrow the whole growth distribution.
Brandao-Marques et al. (2020)	37 countries, 1990-2016	Besides FCI, inflation and credit growth, exchange rates, capital flows	panel q-reg	Yes	Range from -2 to 2	Macroprudential policy endogeneity issue tackled with ordered probit regression residuals extraction. Proposition of estimation of loss-functions of different policies.	Estimated trade-offs are in favour of using macroprudential policy, whereas monetary policy alone is unfavourable.
Figueres and Jarocínski (2020a,b)	Euro area, 1986-2018	Different specifications of financial conditions	q-reg	No	-	-	Financial conditions predict shifts of the lower tail of future growth distribution
Ossandon Busch et al. (2022)	5 Latin American countries, 1990-2020	Financial conditions, VIX	panel q-reg	No	-	Paper popularizes the online platform developed for GaR estimation, and gives introduction to this topic.	-
Adams et al. (2020)	USA, 1971-2018	Unemployment, FCI, inflation	q-reg	No	-	Besides growth, inflation and unemployment are forecasted	Financial conditions predict growth and unemployment better than inflation
Cucic et al. (2022)	Denmark, 1982-2022	SRI, BBM MPI and CBM MPI	q-reg	Yes	Not specified	Financial conditions are not included in the analysis.	BBM measures shift the whole future distribution right, whereas CBM measures increase GaR, and lower median growth. However, nothing is stated about endogeneity of MPI variables.
Giglio et al. (2015, 2016)	USA and advanced economies, 1946(78,94)-2011	Financial stress indicators (a couple of dozen)	q-reg partial q-reg	No	-	Comparison of predictability of financial stress measures.	Financial sector stress predicts better future GaR, compared to other measures.
Aikman et al. (2018)	UK, 1987-2018	Financial vulnerabilities indicators	q-reg, BVAR	No	-	Indicators are grouped into three meaningful groups, the idea is to have alternative approach to EWM.	Authors propose such approach for macroprudential policy decision making, and communication with public.
Prasad et al.	Peru 1997-2017	Financial conditions, macro-	q-reg	No	-	Paper presents GaR	-

(2018)	Portugal Singapore 1992-2017	financial vulnerabilities				methodology, reasoning to use it, advantages	
Gächter et al. (2022)	24 European countries 1999-2019	Structural factors	Panel q-reg	No	-	-	Trade openness, financial sector size, public spending ratio and government effectiveness most important structural factors that determine differences between GaR levels and reactions to shocks in these variables.
Szabo (2020)	Czech 2004-2018	Financial conditions, financial cycle indicator, banking prudence indicator, GEPU	q-reg, Bayes q-reg	No	-	Focus on forecasting capabilities of models	Bayes model outperforms others
Landaberry et al. (2021)	Uruguay 1999-2019	FII	q-reg	No	-	-	Good forecasting capability of FII
Chavleishvili & Manganelli (2019/2020)	EA, 1999-2018	CISS and IIP	QVAR	No	-	Developed structural QVAR model, shown how to perform basic stress test scenarios	Different results over different quantiles and horizons.
Kwark & Lee (2021)	Korea, 1996-2018	FCI	q-reg	No	-	-	FCI have good forecasting properties
Álvarez et al. (2021)	Chile, 1994-2020	FCI	q-reg	No	-	-	FCI have good forecasting properties
Chicana & Nivin (2021)	Peru, 2005-2020	A couple of dozen variables from credit and financial markets, external financial conditions, financial strength	q-reg, VAR-X for counterfactual analysis	No	-	Several variations of empirical distribution fitting, and forecasting capability testing	Kernel density estimation and mixture of normal probability density functions best ones in forecasting.
Kipriyanov (2022)	USA, 1971-2020	Macro and financial variables: FCI, term spreads, stock returns, credit gap, inflation, etc.	q-reg, GARCH, quantile forest	No	-	Different model specifications contrasted to find best forecasting ones. Covid-19 period tested in recursive forecasts	Quantile regression found best, in sample and in out of sample forecasts of Covid-19 period.
Lloyd et al. (2022)	AE, 1981-2018	Domestic and foreign FCI and financial vulnerabilities	Panel q-reg	No, but capital ratio included	-	Capital ratio as a resilience variable included	Foreign factors have greater predictive power to domestic ones.

Note: real GDP growth is not stated as a variable, as it is the main dependent variable in studies. CLIFS – country level index of financial stress, ISCI – index of systemic cyclical risk, C2GDP – credit to GDP, GNI – gross national income, AE – advanced economies, EWM – early warning model, GEPU – geopolitical economic policy uncertainty, OECD – Organisation for Economic Cooperation and Development, MPI – macroprudential policy indicator, GFC – global financial crisis, SRI – systemic risk indicator, FCI – financial conditions index, IIP – index of industrial production, OOS – out of sample, EPU – economic policy uncertainty, PMI – purchasing managers index, CET – capital equity tier,

RWA – risk weighted assets, CAB – current account balance, BBM – borrower based measures, CBM – capital based measures, HPI – house price index, EU – European Union, EE- emerging economies, QVAR – quantile vector autoregression, FDI – foreign direct investment, LTV – loan to value, VIX – volatility index, BVAR – Bayesian VAR, FII – financial instability index, CISS – composite indicator of systemic stress, GARCH – generalized autoregressive conditional heteroskedasticity.
Source: author's compilation from mentioned sources.

Table A2. Summary of research with important findings related to Growth-at-Risk

Authors	Country, timeframe	Variables	Methodology	MPI included?	MPI definition/ transformation	Additional info	Conclusion
Chari et al. (2021)	66 countries (AE and EE)	Many variables, such as inflation, openness, policy rate, REER growth	Panel regression, panel q-reg	Yes	Different transformations based on type of policy	Endogeneity of policy tackled by regressing MPI on other variables in the model, with one period lag	Different policies have different impacts over the financial cycle.
Richter et al. (2018, 2019)	56 countries, 1990-2012	Inflation and policy rate changes. No financial conditions and vulnerabilities	Panel regression, local projections	Yes	LTV limits observed as MPI actions; no cumulation of values	Endogeneity of policy tackled by excluding those measures that had real activity as goals in announcements. Intensity adjusted MPI values as well. However, this could be subjective.	Tightening of LTV has greater effects on real activity, compared to loosening.
Belkhir et al. (2020)	100 countries, 2000-2017	Financial development index, GDP growth, debt-to-GDP, capital account openness, trade-to-GDP	Discrete dynamic panel regression, panel regression	Yes	Values of MPI from 0 to 12, based on Cerutti et al. (2017)	When data divided based on AE and EE, greater results obtained for EE.	Benefits of macroprudential policy outweighs costs. BBM measures more effective than financial-based tools.
Boar et al. (2017)	64 countries (AE and EE), 1990-2014	Financial development, openness, independence of supervisory authority	Dynamic panel	Yes	Log of 5y sum of number of changes of MPI measures in a given country.	GDP per capita growth it on a 5y non-overlapping basis. Interaction between some variables included. Endogeneity of MPI tackled with first-step regression of this variable (but no lags in the model).	The greater the macroprudential activity, the higher and less volatile GDP per capita growth is.
Beutel et al. (2022)	44 counties, 1980-2018	US financial conditions and interest rates	QVAR	No	-	Additional analysis on QIRFs based on country-specific characteristics to see what affects transmission of US	Both US financial conditions and monetary policy shocks are important in GaR forecasting of other countries in the study.

						shocks to other countries' GaRs.	
Ampudia et al. (2021)	11 EU countries, 1998-2017	GDP growth, inflation capital requirements, LTV ratios, other BBM measures	Panel VAR	Yes	MPI included in form of +1/-1	MPI not directly included in VAR, rather, policy shocks obtained from the proxy VAR approach	BBM measures more effective than CBM ones, longer lags for policy to have effect.
Kim & Mehrotra (2017,2018)	4 Asia Pacific 2000-2012	GDP, interest rates, consumer prices, stock of credit	Panel VAR	Yes	Cumulative MPI, as all other variables are in levels	-	Both policies (monetary and macroprudential) have negative effects on growth, inflation and credit dynamics

Note: Note: real GDP growth is not stated as a variable, as it is the main dependent variable in studies. CLIFS – country level index of financial stress, ISCI – index of systemic cyclical risk, C2GDP – credit to GDP, GNI – gross national income, AE – advanced economies, EWM – early warning model, GEPU – geopolitical economic policy uncertainty, OECD – Organisation for Economic Cooperation and Development, MPI – macroprudential policy indicator, GFC – global financial crisis, SRI – systemic risk indicator, FCI – financial conditions index, IIP – index of industrial production, OOS – out of sample, EPU – economic policy uncertainty, PMI – purchasing managers index, CET – capital equity tier, RWA – risk weighted assets, CAB – current account balance, BBM – borrower based measures, CBM – capital based measures, HPI – house price index, EU – European Union, EE- emerging economies, QVAR – quantile vector autoregression, FDI – foreign direct investment, LTV – loan to value, VIX – volatility index, BVAR – Bayesian VAR, FII – financial instability index, CISS – composite indicator of systemic stress, GARCH – generalized autoregressive conditional heteroskedasticity.
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