Macroprudential policy stance assessment: the case of Croatia

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Abstract

This paper contributes to the literature on empirical macroprudential policy (MP) stance assessment. The main purpose of this framework is to evaluate the potential benefits and costs of MP tools and instruments that have been employed in a financial system. We focus on a country that has a fairly active macroprudential policy to establish the initial framework for assessing the effectiveness of macroprudential policy in Croatia. A quantile regression approach is used in order to evaluate the efficiency of the MP stance, on quarterly data ranging from the mid-1990s until 2022. It is shown that somewhat different results could have been obtained if a variable definition has been employed. Measurement of the MP stance is difficult, then, 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.

Keywords: systemic risk, macroprudential policy, financial stability, financial conditions, quantile regression, policy assessment, macroprudential stance

1 INTRODUCTION

Today, most European Union countries have a fairly active macroprudential policy (MP), which has received more attention since the Global Financial Crisis (GFC) (see Carstens, 2021; Ampudia et al., 2021; or Portes et al., 2020). In the last couple of years, empirical work started to focus on answering the question how effective this policy is, and how its stance is to be measured. Compared to monetary and fiscal, macroprudential policy is still relatively new, and much more work must be done to answer this question (ESRB, 2021). To measure the MP stance, we should first define it. In 2019, ESRB defined the MP 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 it establishes a relationship between macroprudential policy actions and the financial stability objectives (ESRB, 2019, 2021)[1]. This is a useful concept, as it could enable the policymakers to get a better understanding of MP effects, it could foster better policy decision-making, by reducing the policy inaction bias and would enable cross-country comparisons. Swedish authorities (2022) agreed that one of the problems in the EU context is the policy inaction bias, and that the European Systemic Risk Board (ESRB) should make regular assessments of the macroprudential policy stance across countries.

To measure the MP stance, literature[2] developed the Growth-at-Risk framework (GaR), as it relates current macro-financial conditions in the economy and MP measures to the entire distribution of the future GDP growth. One important aspect that is looked upon here is the so-called tail risk, i.e. what the worst possible outcomes of future real growth are. This is important, as financial stability risks lie in those tail risks, which we call systemic risk. Reducing these risks in the financial

[1] However, there is still no consensus on this, as found in Arslan and Upper (2017).

[2] Besides the papers mentioned below, see, e.g. Škrinjarić (2023d, 2024).

system could lead to a lower probability of a future crisis[3], and MP could increase the financial system's resilience (Sánchez and Röhn, 2016). Thus, utilizing the GaR approach to measure MP stance could help in obtaining information on how this policy affects real growth, and macroprudential instruments could be tailored accordingly. GaR framework can be used to estimate the inter-temporal trade-offs of the application of MP instruments, as we can estimate the "benefits" of limiting the extreme negative outcomes of future growth and compare them to the potential "costs" of limiting mean future growth (Škrinjarić, 2024). Several central banks already started 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 (2022a) for latest), ECB reports (ECB, 2019), and regular risk identification (see Banco de España, 2021). Besides this specific characteristic of the MP stance assessment, the *at-Risk* approach also has other benefits, such as better forecasting capabilities compared to linear models, and in generating scenarios, as well as calibrating them in stress testing (see IMF, 2020; Flament, Hurlin and Lajaunie, 2023). That is why empirical research[4] that utilizes this framework has significantly increased in the last couple of years.

The purpose of this paper is to construct a GaR framework and empirically evaluate MP effects and stance for the case of an active country with respect to this policy: Croatia. To evaluate the MP stance, we collected quarterly data on selected macrofinancial variables, and the MP index that captures all of the instruments and tools that have been used since the mid-90s to increase the resilience of the financial system. Then, we employ quantile regression as the methodological apparatus to estimate the GaR model for the Croatian case. There are two reasons why this single-country analysis could be interesting for an international audience. Firstly, GaR can be estimated either on a single-country basis, or in a panel quantile regression setting. The "one size fits all" approach in which countries are merged in a panel setting is not always the best[5]. Certain specificities characterize individual countries and their experiences over time, and a such information could be lost in

[3] Also, financial crises are costly. Reinhart and Rogoff (2009) estimate that crisis episodes are related to significant increases in government spending, as government debt increases on average by 86% for 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, Schularick and Taylor (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 "normal" recessions. Recoveries from financial crises are slower when compared to other types of crises, as found in Kannan, Scott and Terrones (2013). Other relevant findings about the costs of financial crises can be found in Koh et al. (2020), Jordá, Schularick and Taylor (2012), Claessens, Kose and Terrones (2012), and Papell and Prudan (2011). To avoid the costs caused by financial crises, systemic risk should be reduced, in which endeavour macroprudential policy plays an important role.

[4] Other interesting and important variables have been analysed, 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).

[5] E.g., Plagborg-Møller et al. (2020) found significant country heterogeneity in their results. After a battery of forecasts and estimations made, the authors found a couple of significant mean growth predictors, and fewer still for the volatility of growth, alongside different signs of results, and great cross-country heterogeneity in the results, which prompted the authors to conclude that some caution needs to be taken when one tries to build a theoretical model on empirical results.

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a panel setting. Ampudia et al. (2021) list some other drawbacks of panel settings, which include the high diversity in macroprudential measures across countries being truncated into simple indicators. 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[6] differences among countries that affect the GaR results is growing (O'Brien and Wosser, 2022; Gächter, Geiger and Hasler, 2022). Secondly, another reason is the unique experience of Croatia's macroprudential policy in the last 20 years: 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 MP employing different measures started in 2003 (Kraft and Galac, 2011). This means that the MP stance assessment of Croatia includes an interesting period in which both tightening and loosening measures were included. Not many countries have such data luxury.

The main findings of the paper show that it is actually difficult to evaluate the MP stance, due to several reasons. The variable that captures the MP instruments that are applied in practice has methodological challenges, as it captures many different tools policymakers apply. The source of data collection for this MP variable also matters, alongside how this variable is transformed and used in the model. The majority of the results turned out to be insignificant. There is somewhat indication that there could be positive effects of tighter MP today; however, the full results are still inconclusive, as the change of the model specification results in different overall interpretations. Future work should increase the number of observations to re-evaluate what was done in this study or try to conduct a panel analysis with countries in which MP was conducted in a similar way in the same period.

The rest of the paper is structured as follows. In section 2 we review literature that is related to the empirical approach of this study, whereas in section 3 we talk about some challenges in measuring macroprudential policy in practice. It is important to take this into consideration, as to measure the effects of MP, one needs to correctly define the variable. The fourth section describes the methodology and datasets used in this study and the empirical results are shown in the fifth section. The final, sixth section concludes the paper with some recommendations for future policy evaluation and empirical analyses.

[6] 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).

2 LITERATURE REVIEW[7]

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The main focus of this research is empirical evaluation of the macroprudential policy effects on future real growth, so in this section, we focus mostly on papers that are closely related. This stream of research is relatively new, and is still developing. Thus, before analysing the main findings, we briefly review some of the seminal papers that are important for this empirical framework. The size and scope of related literature has increased significantly in the last couple of years since then. Still, conclusions about the effectiveness of MP are that knowledge is still limited due to a high degree of uncertainty (Buch, Vogel and Weigert, 2018), and a short history of the policy itself (ESRB, 2019). Nevertheless, 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.

A few major conclusions emerge from the related work discussed below. Although the number of papers that employ a GaR framework has significantly increased in the last couple of years, only a small number of papers include the macroprudential policy variable to assess the stance of the policy. The reasoning could be found in the 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, MPI measurement problems could discourage some authors from undergoing such analysis, as different results can be obtained concerning the definition and transformation of the MPI variable. 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.

2.1 INITIAL CONTRIBUTIONS

Seminal papers that introduced the GaR concept within the macroprudential policymaking were actually focused on better GDP growth forecasting. The main motivation was to enhance the approach of obtaining forecasts of tail risks of GDP growth, as models applied in practice and empirical research did not take into consideration the non-linear relationships between the macro-financial variables. Besides the usual variables that can be used for GDP growth forecasts, specific financial variables were introduced to facilitate the short-term forecasting, such as the financial conditions, financial stress, and systemic risk indicators. All these measures have good short-term forecasting properties, but they do differ in their nature. Financial conditions measures can be defined as the ease with which finance can be accessed by non-financial corporations and households (BoE, 2021), systemic risk indicators can be defined as tools for identification of systemic events, defined as financial instabilities spreading to such an extent that they will spill over to economic growth (ECB, 2010); whereas financial stress indicators quantify the degree of aggregate stress in the financial system, and have been found to have short term predictability of an economic downturn (Chavleishvili and Kremer, 2023).

[7] Besides the works that are examined below, it is worth mentioning other preceding research that links financial conditions and financial vulnerabilities to the real economy. A comprehensive overview is given in Boyarchenko, Favara and Schularick (2022) and Škrinjarić (2022a, 2023a).

Giglio, Kelly and Pruitt (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 those of Adrian, Boyarchenko and Giannone (2016, 2019), who argue that most growth forecasts are point estimates and ignore the heterogeneity of different quantiles of future 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.

2.2 EXTENDING THE FRAMEWORK

These previous studies include only the financial stress/systemic risk measures/financial condition indicators in the analysis, with short-term forecasting capabilities. In order to talk about macroprudential policy stance, other indicators and variables need to be included in the modelling process. This also will have consequences on tailoring macroprudential measures. The inclusion of other important indicators that are able to capture the policy itself could facilitate the analysis of the timing of the MP effects. Aikman et al. (2018) thus provide one of first extensions towards this way. The study used aggregated measures of financial vulnerabilities in the UK (leverage in the private nonfinancial sector, asset valuations in property markets, and credit terms) in the GaR modelling. The process of the selection of the best variables drew on previous literature on early warning models and banking crises. The authors found different effects on future GDP growth across different parts of the growth distribution within the quantile regression approach, and the estimates were significantly different 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 macroprudential decision-making when looking at the results of such forecasting.

Other studies emerged afterwards, such as Plagborg-Møller et al. (2020), is an extensive study of future GDP growth distribution forecasting in 13 advanced economies, based on several nonparametric and parametric approaches, and a long list of GDP predictors for monthly and quarterly data from 1975[8] to 2019. This study covers a wide selection of in- and out-of-sample forecasts and nowcasts. The authors found a great degree of heterogeneity of results, not just between the countries, but between different indicators used within the same category for a given country. Aikman et al. (2019a, 2019b) extend the Adrian, Boyarchenko and Giannone (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 they constructed a measure of banking sector leverage to see how the increase in capital requirements affects bank capital and growth-at-risk. As capital requirements were

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

the main tool to build up the resilience of financial systems after the GFC, using an indicator that captures this could be observed as an indicator of macroprudential policy, whose effectiveness could be evaluated within the GaR setting. Here, the main results indicate that greater capital requirements led to a 0.9 p.p. cumulative improvement of GDP-at-risk over three years. This prompted the authors to make a CCyB (countercyclical capital buffer) simulation as an example of capital requirements being increased before the GFC hit. Not surprisingly, the results showed that such a requirement would offset the GDP-at-risk significantly.

2.3 INTRODUCING THE MACROPRUDENTIAL POLICY INDICATOR IN THE ANALYSIS

Macroprudential policy does not solely utilize capital requirements, but many other instruments as well. Thus, MP variable as a full set of measures and instruments has been introduced in the analysis, and, in some cases, the variable is divided among several categories, such as tools that are mostly borrower-based ones, or capital based, etc. (for policy tool description, please see Claessens, 2014; Lim et al., 2011). Several authors examined GaR model to evaluate the effectiveness of different tools. Sánchez and Röhn (2016) examine not only MP, but also other policies and their effects on future GDP growth via panel quantile regression for the case of OECD countries. Main findings regarding MP effectiveness include lowering future mean growth (costs), but also lowering potential losses (benefits, in the form of a decrease in the amount of future GDP losses). However, since this policy is new compared to others in the study, it is concluded that it should be explored more in the future. Other policies, such as monetary, have longer datasets and so its effectiveness was able to be evaluated in different phases of business cycles. MP on the other hand, for some countries includes only the tightening phases after the GFC. Another study that observes all MP tools is Duprey and Ueberfeldt (2018). This is a concise note about GaR forecasting, in which both monetary and macroprudential policies are considered. This work includes both theoretical considerations of tightening both policies and empirical results for the Canadian case and period 1992 to 2020. Results show that MP tightening is more effective for reducing downside risks of future growth than monetary policy tightening. It means that in practice a tighter MP policy could be more effective in strengthening the resilience of financial systems, as if a crisis happens in the future, it will have fewer negative effects on real growth than monetary policy.

Two years later, the same authors (Duprey and Ueberfeldt, 2020) published a paper with more details on their previous work. Here, the main results show that both policies reduce left tail risks by not affecting the median growth. This means that in the medium-term neither policy has significant negative effects on the real economy. Furthermore, if both policies are tighter, this can reduce the future tail risk by targeting credit growth, and if the monetary policy is loose, the impact of low interest rates on financial stability could be partially compensated with tighter MP. All of this implies that MP really was effective in the Canadian case. Finally, there is an interesting simulation made at the end of this study, where the authors show how much benefit would have been obtained if a tighter MP had been in place before 2018, leading to a reduction of central risk.

2.4 RECENT FINDINGS ON MACROPRUDENTIAL POLICY EFFECTIVENESS

As more data on MP indicator has become available, a richer analysis has been possible, as in Galán and Rodríguez-Moreno (2020), Galán (2020a, 2020b). Here, the authors observe the MP effects at different phases of the financial cycle. Interaction terms between the MP indicator and other variables were included in the analysis to account for different phases of the financial cycle and financial stress levels in economies. Studies looked at EU countries in the period 1970 to 2019 and applied the panel quantile regression approach. The MP indicator was observed on an aggregated level (i.e. including all MP tools and instruments), but also from the borrower-based versus capital-based perspective. Some of the main findings here include that MP in general in the medium-term does not have significant negative effects on the mean growth, but has positive effects on the tail risks by reducing it up to 1.5 p.p.

Other studies that could observe richer results are those of Brandao-Marques et al. (2020), in which the authors utilize the quantile regression approach to propose a cost-benefit approach to macroprudential policy. In a panel setting (period: 1990-2016), they evaluate the effects of different types of policies on future GDP growth and inflation. The authors found evidence of MP trade-offs regarding lowering mean future growth and increasing the GaR growth (i.e. reducing the future losses). In particular, benefits were the results of BBM (borrower-based measures), whereas CBM (capital-based measures) were found to be better for building the system's resilience. Cucic et al. (2022) is an empirical case study of Denmark's GaR in the period 1982-2022. Both GaR and HaR (House price-at-Risk) were examined, and the effectiveness of the BBM and CBM measures was compared. The authors conclude that BBM measures shift the entire growth distribution right, whereas CBM measures have a trade-off between GaR and median growth.

Franta and Gambacorta (2020) goes into more details regarding BBM measures, as the authors apply the GaR approach to a panel dataset of 56 countries in the period 1980 to 2012 to evaluate the LTV (loan to value) and loan loss provisioning effects. 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. Thus, LTV can be used to reduce the volatility of GDP growth, whereas loan loss provisioning decreases the GDP losses in the event of a crisis. Finally, as a last recent empirical work related to this research, we found Drenkovska and Volčjak (2022). It is a study of the Slovenian GaR case in the period 2003-2020. This paper is actually divided into two sections. In the first part, authors develop a financial stress indicator for the Slovenian case. Then, the second part uses this indicator alongside financial cycle and MP indicators to evaluate the MP stance. However, the authors did not find the MP indicator to be significant in the analysis. An explanation could be found in the utilisation of a single-country approach, with insufficient data being provided for the tail risk estimation part of the framework itself.

3 CHALLENGES WITH THE MACROPRUDENTIAL POLICY INDEX

Before moving on to the empirical part of the study, we wanted to comment on some of the challenges of using the MP variable in GaR analysis. To evaluate the MP stance, we need to include the MPI (macroprudential policy indicator) in the model. MPI is built upon information about (de)activating MP tools over time, and detailed information about them can be found in several popular databases: ECB (2018) or IMF (2022b). To construct the MP indicator, one has to have in mind that MP cannot be measured as monetary policy through policy rate. 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 the 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. Moreover, introduction of a measure for the first time has different effects compared to it being fine-tuned over time.

3.1 DEFINITION AND TRANSFORMATION OF THE MPI VARIABLE

First challenge is the definition of the MPI variable itself. One part of the research that uses the MP variable takes the MPI index (regardless of the form and transformation) and calls this the macroprudential policy stance. Examples include Akinci and Olmstead-Rumsey (2015): "... 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..."; and Ćehajić and Košak, 2021): "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 as used in the GaR literature. However, it introduces more complexity in comparison to 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.).

When collecting data from established databases, one needs to assign numerical outcomes. This is because all measures in such databases are given in a descriptive form, whereas MPI is defined as a simple binary variable. Positive unit value indicates a tightening measure that took place in a given quarter and negative unit value indicates a loosening one. Finally, a zero value is assigned to ambiguous and/or absent measures (see formula 1). Descriptions on how the researcher can assign these values to different tools can be found in Cerutti, Claessens and Laeven (2017), Budnik and Kleibl (2018), Garcia Revelo, Lucotte and Pradines-Jobet (2020), etc. In a given quarter, we can define a measure mpi_i:

$$mpi_{i,t} = \begin{cases} 1, \text{if a measure } i \text{ is tightening} \\ 0, \text{absence of measure } i \\ -1, \text{if a measure } i \text{ is loosening} \end{cases} \quad (1)$$

and by adding up the values in (1) over time, we obtain the cumulative value as follows:

$$MPI_{i,t} = \sum_{t=1}^{T} mpi_{i,t} \tag{2}$$

Usually, values in (1) are counted for a group or all MP tools. Thus, formula (2) can present the cumulative value of all MP actions. This is a starting point in a lot of research, reflecting a general policy direction. Based on Garcia Revelo, Lucotte and Pradines-Jobet (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:

$$\widetilde{MPI}_{i,t} = \begin{cases} 1, \text{if } MPI_{i,t} > 0 \\ 0, \text{if } MPI_{i,t} = 0 \\ -1, \text{if } MPI_{i,t} < 0 \end{cases} \tag{3}$$

This means that regardless of the overall sum in each quarter being +1 or more, it will be rescaled to +1, and something 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 $mpi_{i,t}$ 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:

$$\overline{MPI}_t = \begin{cases} 1, \text{if sum of all measures is positive} \\ 0, \text{otherwise} \end{cases} \tag{4}$$

and

$$\overline{\overline{MPI}}_t = \begin{cases} 1, \text{if sum of all measures is negative} \\ 0, \text{otherwise} \end{cases} \tag{5}$$

and they take into consideration only the 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 as defined in (2). 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 (2) is often not stationary, especially in MP active countries. That is why more research is looking at year-on-year changes in the cumulative index:

$$d\_MPI_{i,t} = MPI_{i,t} - MPI_{i,t-4} \tag{6}$$

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

3.2 INTENSITY ISSUES

Another important challenge when using the MPI variable as defined in the previous sub-section is that the values of positive unit, zero or negative unit only reflect whether a measure is tightening or loosening. 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 than fine-tuning events. As an example, we focus on capital buffer requirements. Introduction of these requirements had different effects on the banking systems, compared to fine tuning, i.e. their subsequent additional increases. Values were adjusted over time[9]. This means that in the majority of cases, the MP indicator does not reflect the magnitude of a measure, only the frequency of it.

A couple of papers emerged in the last couple of years that try to adjust the intensity of MPIs. Eller et al. (2020), Vandenbussche, Vogel and Detragiache (2015), and Richter et al. (2018, 2019) have been working on this. Fernandez-Gallardo and Paya (2020) follow Meuleman and Vander Vennet (2020), and in the first step assign a positive value for tightening actions, the 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 maintenance of both 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 (Integrated Macroprudential Policy) database that author uses in the study includes mean regulatory LTV ratios, the 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: in the expansion phase of the cycle, tightening of LTV limits would improve GaR by approximately 0.5 p.p. Negative effects on the median growth are also significant but negative.

[9] As explained in Škrinjarić (2024), another example of different effects could be that when comparing the countercyclical buffer (CCyB) actions, one country could immediately introduce a value of 2% to take place in a given banking system. This country would get +1 value in the quarter when this action is taken. If the country does not change CCyB in the next few quarters, the value remains at +1. On the other hand, if another country decides to introduce 0.5% CCyB value, and in each subsequent quarter increase it by 0.5 p.p., it will get positive unit value every quarter and could have a cumulative indicator greater than the first country.

Unfortunately, a consensus on how to solve this important challenge 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). This is something future research needs to work on, trying to find an objective way to define such adjustments, and some solutions are summarized in Škrinjarić (2024).

3.3 ENDOGENEITY ISSUES

When policymakers and regulators make decisions about their tools and instruments, they take into consideration some typical variables such as credit growth or debt burden. Countries that experienced rapid credit growth (pre-GFC) have higher probability of having tighter MP (Akinci and Olmstead-Rumsey, 2018). The endogeneity characteristic of macroprudential variable is probably the biggest challenge in research that tries to evaluate MP effectiveness, regardless of the underlying methodological approach. As the MP policymaker reacts to the expected economic environment, MP cannot be used in the form described in the previous subsections to identify exogenous changes (Buch, Vogel and Weigert, 2018). However, the endogenous nature of MP is not new, and there have been different approaches to tackle this concern regarding monetary and fiscal policy. 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 to solution of the endogeneity issue are reviewed in Christiano, Eichenbaum and Evans (1999). Ramey (2016) on the other hand reviewed some newer approaches, such as narrative identification, regime switching approach, and many others, both for monetary and fiscal policy specifications. Prasad et al. (2019), one of the earlier GaR studies, comments that GaR is not a structural model, and cannot be used to talk about causality. Richter et al. (2018, 2019) define the following criteria in order to talk about causality: policy actions need to be uncorrelated with other possible shocks in the model, these policy shocks need to be unexpected, and they also need to be exogenous in reference to the current and lagged variables. Thus, there are a couple of ways to deal with this, explained below.

3.3.1 Obtaining non-systematic policy shocks

If the aim of the analysis is to discuss causality, then non-systematic policy shocks should be used. They can be defined as a random portion of the policy not related to the state of the economy (McCallum, 1999). Ever since the Lucas (1972) critique of monetary policy, in which the non-systematic component is the only component to be used when policy effects are evaluated, this part of the monetary policy has been evaluated in empirical research. To obtain non-systematic policy shocks, the procedure can be done in two steps. The first step observes the MPI as the dependent variable, and it is regressed on a set of specific variables that are important in MP decision making. Some examples include credit to GDP gap, house price dynamics, and other variables found in early warning literature (see Tölö, Laakkonen and Kalatie, 2018, and Škrinjarić, 2022a, for an exhaustive list). Residual values from the estimated model are collected and are observed as those policy actions that are not explained with the variables that were used in the model, and should be non-systematic shocks. In the second step, these residuals are used within the GaR model to talk about causality.

Some examples of using this within MP stance assessment are the following. Brandao-Marques et al. (2020) utilized ordered probit regression to obtain the non-systematic MPI shock[10]. 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. There was a similar approach in Gelos et al. (2022). Galán (2020a) 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 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. Duprey and Ueberfeldt (2020) also have an interesting approach, due to the MPI variable taking values -1, 0 and 1. The 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.

Two important things to consider in this two-step approach are the variable selection to regress the MPI on and the lags of these variables. The model in the first step should be correctly defined, i.e. the chosen variables should reflect what the MP policy maker is actually considering when making decisions. Also, as MP 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). This approach asks from the researcher to read all of the policy tool announcements in order to distinguish those that are a true shock compared to those that are reactions to the financial environment. 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 for introduction and implementation were excluded in MPI construction. The authors argue that banks can prepare themselves more if the announcement date is far away from the implementation date, which is not in line with the definition of unexpected shocks. These 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. Something similar is done in Duprey and Ueberfeldt (2020). Here, the authors estimate the model with MPI values that are based both on announcement and dates when measures were put in force.

[10] As it takes values {-2, -1, 0, 1, 2}.

This approach is challenging in practice, as policymakers make decisions on some MP tools by analysing the risks that are accumulating over some time. Sometimes, before a new tightening measure is introduced, the policymaker could issue warnings or recommendations for certain behaviour. Financial stability reports often have special sections/boxes that analyse certain challenges to the financial stability of a system. This could prepare banks to change their behaviour 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 is put in force. Thus, future work should try to gauge if some change in bank behaviour has preceded even the formal announcement dates of a macroprudential measure.

3.3.3 Lagging values in models

Another approach is including the lagged values of some variables in the underlying GaR regression. Some authors lag the explanatory variables in the GaR regression, whereas others lag the dependent one (i.e. the MPI variable). Lagging the macro-financial variables that are used in the GaR regression is based on the explanation that the macroprudential policymaker makes decisions about tools with respect to tracking those variables. It takes some time to evaluate the dynamics of those variables. Thus, these variables are lagged in the GaR model specification, as 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. Cerutti, Claessens and Laeven (2017) state that a greater number of lags of these variables should be included in the model. The question remains what a greater number is, and if we do not have long time series (usually a problem for MP empirical analyses), we cannot "afford" to include a great number of lags in the model itself. The second approach of lagging the dependent variable is found in 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." A similar approach is used in Gelos et al. (2022), who add one year of lagged MPI data in the model, without explaining the reasoning. The only thing that comes to mind is the following. In modelling, 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 includes in itself the effects of all factors, although data cannot be collected on some of them or else they are not directly measurable.

Furthermore, there are also some papers that lag both the MPI indicator and the rest of the macro-financials that are used in the GaR setting, such as Eller et al. (2020). Authors decide on the lag selection based on the BIC (Bayes information criterion). This is a purely statistical approach to the definition of the best model and should be complemented with MP knowledge from practice. It is still not completely clear 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 endogeneity 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), with a description of the measure and a general explanation of why the measure was used. The ECB (2018) and IMF (2022a) are commonly used[11]. The ECB database, called MaPPED (Macroprudential Policies Evaluation Database), is a comprehensive dataset, with 1925 hundred policy actions for EU countries since 1995 until 2017[12]. Supervisory authorities have submitted measures, their descriptions and other information on measures, and since macroprudential policy was somewhat formalized after the GFC, other measures before it have been retroactively categorized to fit macroprudential measures, or microprudential measures that had a macroprudential character. It also includes changes in measures, i.e. if fine tuning was done, so it presents a good starting point for an analysis.

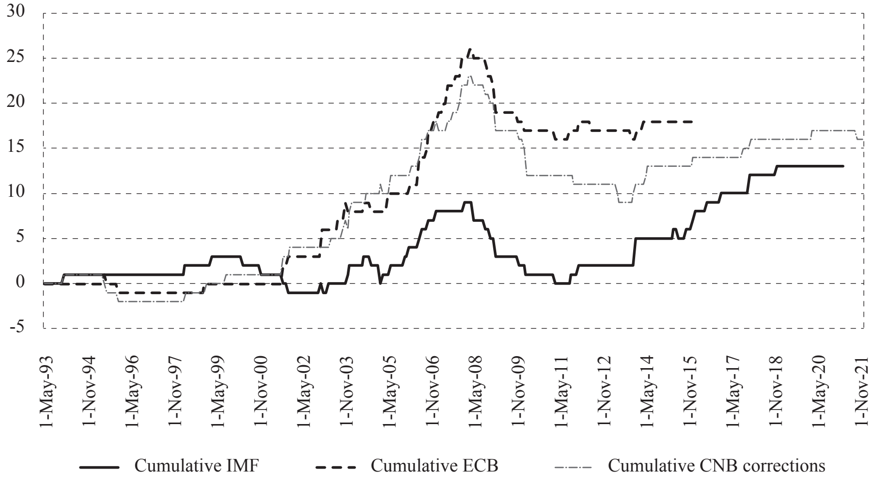
The IMF database, iMaPP (Integrated Macroprudential Policy), combines information from various sources, including the Macroprudential Policy Survey, and the IMF member countries that submit information on a yearly basis. This database also has a detailed description of each submitted measure, alongside 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. However, the tools described in the IMF database are very different to those in the ECB version, as when we found something peculiar when doing research on this topic. 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 graph 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. The explanation is to be found in the different classifications of some measures; the IMF does not take into consideration some measures that could be broadly classified as "other" for the Croatian case, but which had macroprudential character, whereas the ECB did. The main differences, then, for the case of Croatia inhere in the ECB having a broader base of different tools that have not been strictly classified as macroprudential measures, but as having macroprudential purpose. On the other hand, the IMF did not include these measures, as we have seen when sifting through both datasets and reconciling them to obtain one final "clean" MPI dataset.

[11] Others include the ESRB database for EU countries: https://www.esrb.europa.eu/national_policy/html/index.en.html, or Cerutti, Claessens and Laeven (2015). Some other sources are listed and commented in Alam et al. (2019), in appendix I, table 4.

[12] This number comes from counting the total number of all tools in the Excel sheet provided in Budnik and Kleibl (2018).

Graph 1
Cumulative MPI values for Croatia, different sources



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

Up until the writing of this research, no comments were found in related literature on this problem. Authors usually collect the MPI data without manipulating it additionally. However, one needs to bear it in mind if different sources are used, the estimation of final results can be very different, especially for active countries such as the example shown in graph 1. One future research direction would be to tackle this issue.

4 METHODOLOGY AND DATA 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. After that, we describe the data used in this study for the empirical work done in the next section.

4.1 QUANTILE REGRESSION[13]

A linear quantile regression (QR) model can be defined as:

$$y_t(\theta) = \beta_0(\theta) + \sum_{k=1}^{K} x_{t,k}\beta_k(\theta) + \varepsilon_t(\theta) \tag{7}$$

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:

[13] 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, Furno and Vistocco (2013), or Koenker and Bassett (1978).

$$\underset{\beta_k(\theta)}{\arg\min} \sum_{t:y_t \geq \hat{y}_t} \theta \left| y_t - \beta_0(\theta) - \sum_{k=1}^{K} x_{t,k}\beta_k(\theta) \right| + \sum_{t:y_t < \hat{y}_t} (1-\theta) \left| y_t - \beta_0(\theta) - \sum_{k=1}^{K} x_{t,k}\beta_k(\theta) \right| \tag{8}$$

where $\hat{y}$ is the estimated value of y. For the case of evaluating MP effects on future real growth y, the real growth is defined $t+h$ quarters ahead:

$$y_{t+h} = 100\% \times \left(\frac{r\_GDP_{t+h}}{r\_GDP_t} - 1 \right) / \frac{h}{4} \tag{9}$$

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

$$y_{t+h}(\theta) = \beta_0(\theta) + \beta_1(\theta) MPI_t + \beta_2(\theta) y_t + \beta_3(\theta) Stress_t + \beta_4(\theta) FV_t + \varepsilon_t(\theta), \quad \theta = 0.05, \ldots, 0.95 \tag{10}$$

where *MPI* is the macroprudential policy indicator, *Stress* denotes indicator of financial stress, and *FV* is a financial vulnerabilities variable. Mentioned variables are an example of which variables are usually used in this modelling. In other words, the GaR model in (10) usually includes the autoregressive term y, the MPI indicator in some form as commented on in section 3.1., and then a variable that corresponds to financial conditions, stress or systemic risk indicators, with a final variable of financial vulnerabilities or financial cycle indicator. This work will look into financial stress and several financial cycle indicators in the empirical section. To evaluate the values of coefficients at different forecast horizons h, the dependent variable on the left-hand side of equation (10) is changed, such that the h quarter growth from equation (9) is regressed on the same set of variables in equation (10). This is the local projection approach, as often used in macroeconomic literature and the plotted reaction of GDP growth to changes in explanatory variables is considered as the impulse response (see Jordà, 2023).

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

$$R_\theta^2 = 1 - \frac{RASW_\theta}{TASW_\theta} \tag{11}$$

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.

Rationales on why the MP effectiveness changes across the growth distribution and alongside different coefficients are in place both for financial conditions/stress and financial cycle indicators is as follows. The early warning methodology literature (see Tölö, Laakkonen and Kalatie, 2018) on which variables forecast financial crises has shown that financial cycle indicators have good predictive power of not only financial crises, but also subsequent economic downturns. This means that the

OLS estimates cannot capture those tail risks. If one used the threshold regression approach, the usual assumptions that hold for OLS should also hold here, which would not capture the heteroskedasticity in the data that is present, alongside other assumptions regarding the error term. Moreover, by applying threshold regression, one would need to sub select the dataset into more regions for which the model is estimated above and below a certain threshold, which would result in an insufficient number of datapoints for the tail risk. Moreover, one would also need to test for more than one threshold, which is not feasible for such a short time series. Furthermore, if one opted for time varying parameters, same assumptions on the error term need to be imposed as for OLS, which is again not satisfied in practice. Quantile regression does not rely on any assumption on the distribution of the datasets that are used, or about the error term. Next, the seminal contribution of Adrian, Boyarchenko and Giannone (2019) has shown that there is almost no effect on mean growth when the usual set of variables that are used is complemented with a financial stress indicator. On the opposite side, there is a significant negative effect on the downside growth risk. This was empirically tested on other economies in the following research, thus it made a stepping stone by which to move from linear models to the quantile regression approach. From the economic point of view, the reason on why the MPI would have different effects on GDP growth at different parts of the distribution is that if done properly, increases of MPI value (which means that the policy is tightening) in good times should increase the resilience of the financial system, which would prepare it to deal with a future crisis better by avoiding huge losses. However, increasing the resilience does come at a cost, by, e.g. banks having greater capital requirements would perhaps decide to reduce lending in some capacity, which would decrease the investment in the economy and thus, the mean growth would be reduced as a consequence.

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):

$$f(y;\mu,\sigma,\alpha,\upsilon)=\frac{2}{\sigma}t\left(\frac{y-\mu}{\sigma};\upsilon\right)T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{\upsilon+1}{\upsilon\left(\frac{y-\mu}{\sigma}\right)^{2}}};\upsilon+1\right) \tag{12}$$

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:

$$\underset{\mu,\sigma,\alpha,\upsilon}{\arg\min}\sum\nolimits_{\theta}\left(\hat{Q}_{y_{t+h}}-F\left(\theta;\mu,\sigma,\alpha,\upsilon\right)\right)^{2} \tag{13}$$

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, Boyarchenko and Giannone (2019) opt to have fewer quantiles for (13) to avoid over-parametrization. Another approach is found in Lloyd, Manuel and Panchev (2022) and Mitchell, Poon and Zhu (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. These papers use a measure of model accuracy, the unconditional coverage (UC) test of Kupiec (1995), usually called a back-testing technique, to evaluate the quality of the model. The UC test null hypothesis assumes that, on average, the conditional quantile is a correct coverage of the selected percentile of the forecasted distribution.

4.3 DISTANCE TO TAIL CONCEPT

Once the full model is estimated, one could calculate a measure called distance to tail (DTT), as a measure of downside risks, captured by the difference between the median and GaR value (ESRB, 2021). Thus, the policymaker could observe additional information from DTT in the following way. When evaluating the results of MPI effects on the median and GaR growth, the difference between two can also be looked at, as the value should decrease if the MP does not have negative effects on the mean growth, and positive effects on the lower tail risk at the same time. This is due to the "pushing" of the left tail of future GDP growth distribution towards the mean outcome. The economic rationale behind this is that if the policymaker imposes tighter restrictions on the financial system in "good" times, i.e. when the economy is in the upward phase of the business cycle, it should not be burdensome to financial institutions to increase their resilience. Afterwards, if a crisis or another negative shock happens that will affect the real economy in the future, the increased resilience today would prevent an even greater crisis at the end, i.e. the GaR value should be in better shape than if we did not impose tightening before the shock. Thus, a tighter stance is characterized with a lower DTT compared to a reference distance. The question remains of what reference value is to be compared to the empirical DTT values we obtain in the analyses. No consensus exists today; thus, in the empirical part we compare the empirical DTT values to the average in the historical sample (something similar was done in Cucic et al., 2022).

4.4 DATA DESCRIPTION AND STYLIZED FACTS

For the empirical analysis, quarterly data on real[14] GDP for Croatia was collected from CNB (2023) for Q1 1991 to Q2 2022. Graph 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 graph 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

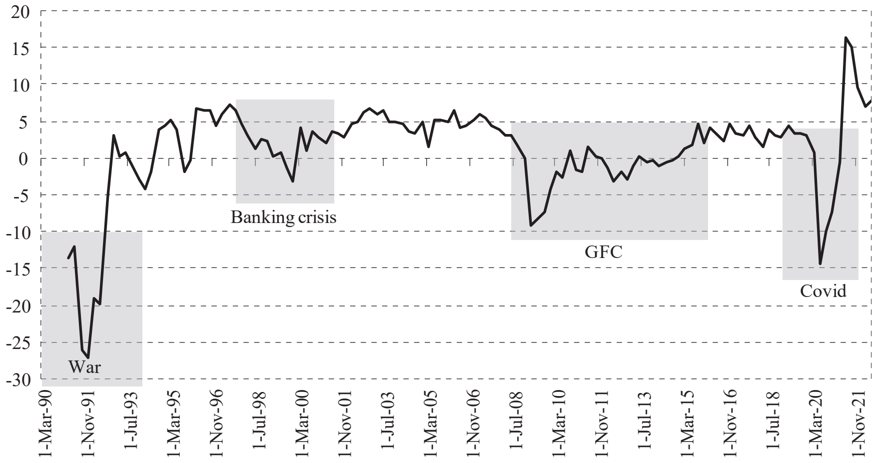
[14] GDP deflator was used to deflate the original nominal GDP series.

of graph 3. Quantiles of Normal distribution are contrasted to the empirical quantiles of real growth, and a significant departure is apparent. This is in line with related literature (Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015; Sánchez and Röhn, 2016).

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

Graph 2

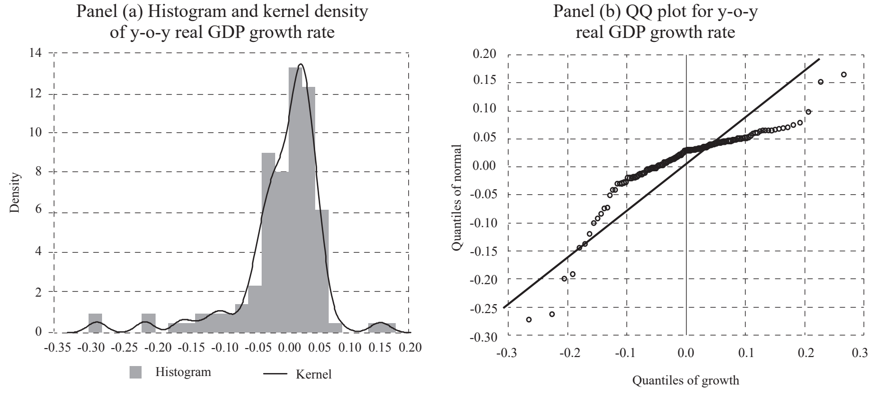
Real GDP growth, year-on-year, in %



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

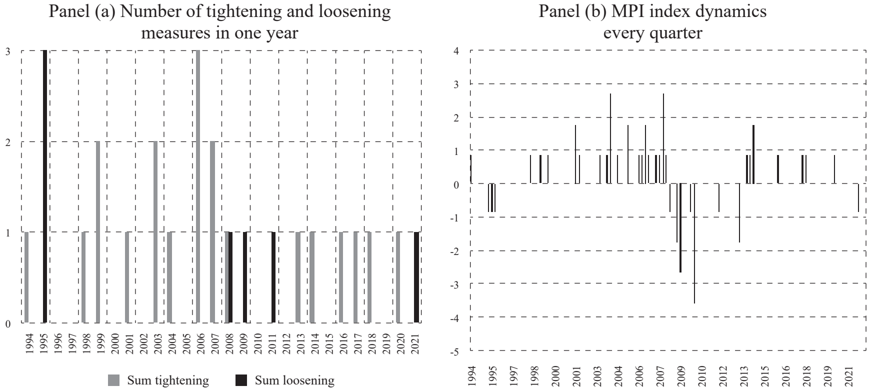
Graph 3

Histogram, kernel density and QQ plot for year-on-year real GDP growth rate



Source: Author's calculation.

Graph 4
Macroprudential policy index dynamics



Source: ECB (2018), IMF (2022), 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 institution vulnerabilities, etc. ESRB (2021) uses d-SRI (domestic systemic risk 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[15] credit dynamics variables and d-SRI, this study observes ICSR (Indicator of Cyclical Systemic Risks) as a Croatian version[16] of the composite indicator.

Table 1 gives a brief overview of financial vulnerability measures tested in this study, with graph 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). Dynamics in graph 5 shows that the credit growth was substantial in the 2000s due to financial deepening. Value of 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. (see Škrinjarić, 2023a). 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, Kim and Manganelli (2015a, 2015b) assume that data for this analysis are stationary. The best option would be to have all variables transformed in such a way that they are stationary, as the predictability of time series is mostly based on the stationarity of the series itself. The d-SRI indicator is the variable commonly used, but it does not satisfy this assumption. All of the specifications in table 1 and graph 5 will be tested in section 5.2.1. to find which variable definition is the best in terms of model performance.

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

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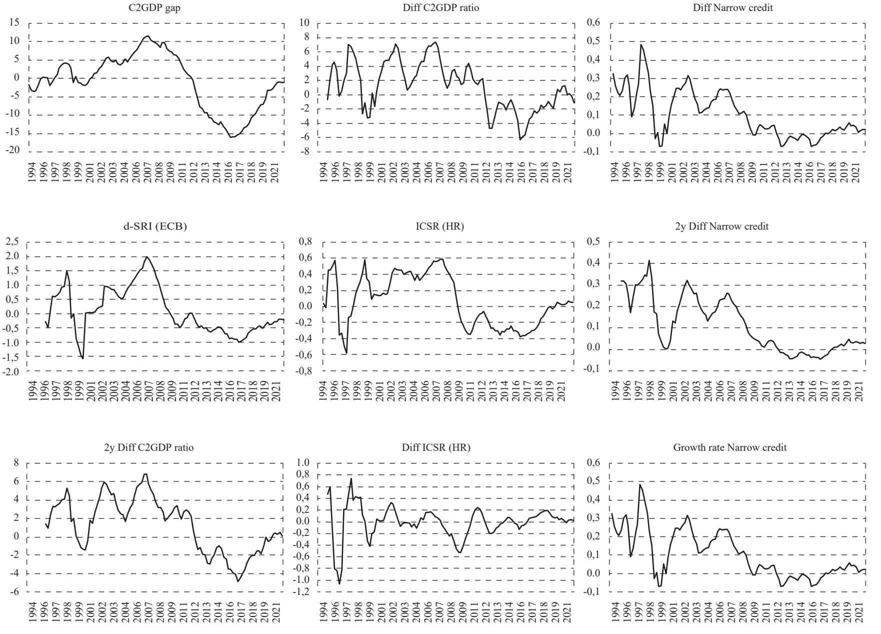
Table 1
Financial vulnerabilities variables

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.

The financial stress indicator for the Croatian case is somewhat problematic, as the ECB (2023) version has a very different dynamic compared to the one that the CNB developed (the period for this variable is Q1 1990 to 2Q 2022). Graph 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 CNB 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, Kremer and Lo Duca, 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).

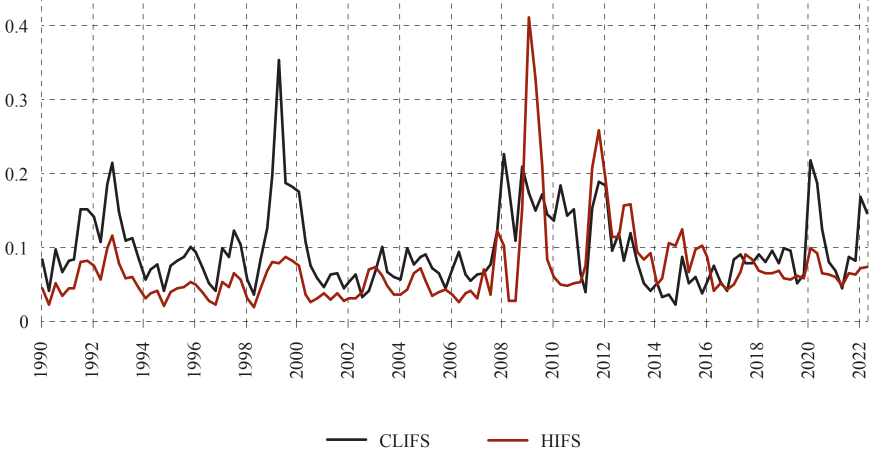
Graph 5
Financial vulnerabilities in Croatia, different measures



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: CNB (2023), author's calculation.

Graph 6
Comparison of CLIFS (ECB version) to the HIFS (CNB version) of financial stress



Source: ECB (2023) and CNB (2023).

5 EMPIRICAL APPLICATION: CROATIAN CASE

This section provides the main empirical analysis of the paper. We firstly comment on reducing the endogeneity of the policy variable itself. Afterwards, we compare the goodness of fit with respect to different variables to measure financial cycle or vulnerability. When the best models are selected, we compare their results regarding the MPI effectiveness for the tail risk and median growth. Finally, we show how the distribution of GDP growth changes over time, and comment on the resulting distance to tail measure.

5.1 TRYING TO REDUCE ENDOGENEITY OF MACROPRUDENTIAL POLICY INDEX

Following the references in section 3.3.1., we obtain non-systematic shocks of non-cumulative MPI values (i.e. just counting the number of tightening or loosening measures) via ordered logistic regression, as the order of the MPI values matters. MPI was calculated based on formula (1) in each quarter, i.e. where the tightening measures were given the value +1 for each measure, loosening measures were given the value -1 per measure, and absence of any measure or ambiguous ones were given the value 0. Then, the net MPI is calculated by reducing the total amount of loosening from the total amount of tightening measures. $\widetilde{MPI}$ was calculated according to formula (3).

As previously remarked, 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 to obtain the non-systematic policy shock in the first step, in which lagged values of real growth, financial stress (HIFS, the HR version), and financial vulnerabilities (y-o-y change of credit-to-GDP ratio) are used. We are interested in talking about causal effects, and since there exists a bulk of literature on monetary and fiscal policy that takes 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[17] for both MPI specifications, where models M1 to M4 refer to how many lags of other variables are included[18]. 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.

[17] SIC values resulted in 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.

[18] 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.

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Table 2
AIC values of several model specifications

Model	M1	M2	M3	M4
AIC MPI	241.23	236.14	**234.02**	234.88
AIC $\widetilde{MPI}$	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:

– 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 and $\widetilde{MPI}$.
– All nine financial vulnerabilities indicators from graph 5.
– Original values of MPI and $\widetilde{MPI}$ for models where lagged variables are included.

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

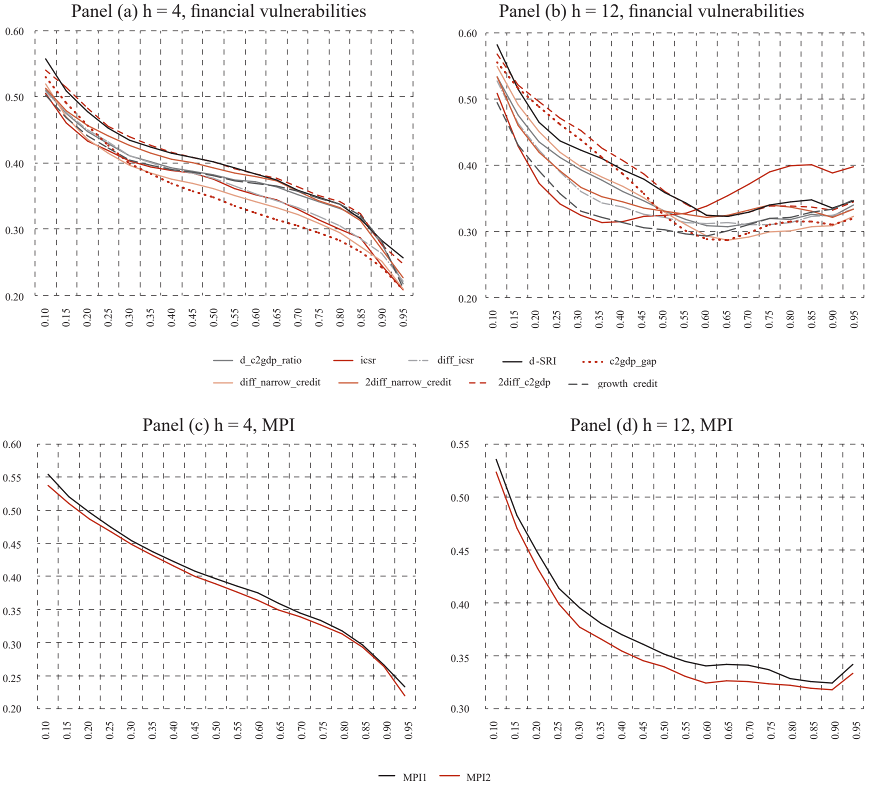
5.2.1 Selecting best variables for each indicator category

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.

Pseudo R-squares are shown in panels (a) and (b) in graph 7. It is visible that selection of the best indicator is not straightforward, as some indicators are better at certain quantiles, but worse at others. Also, at one horizon one variable is better performing, but worse at another horizon. When comparing all the variables in panels (a) and (b), the best ones are the non-stationary variables: ICSR, d-SRI, and credit-to-GDP gap. They are followed by stationary ones: y-o-y 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. Panels (c) and (d) compare the MPI variables, and here the picture is a bit clearer: MPI has better performance.

Graph 7

Comparing pseudo-R squares of individual variables



Note: MPI1 is the MPI variable, whereas MPI2 is defined in formula (4).

Source: Author's calculation.

5.2.2 Selected models' results

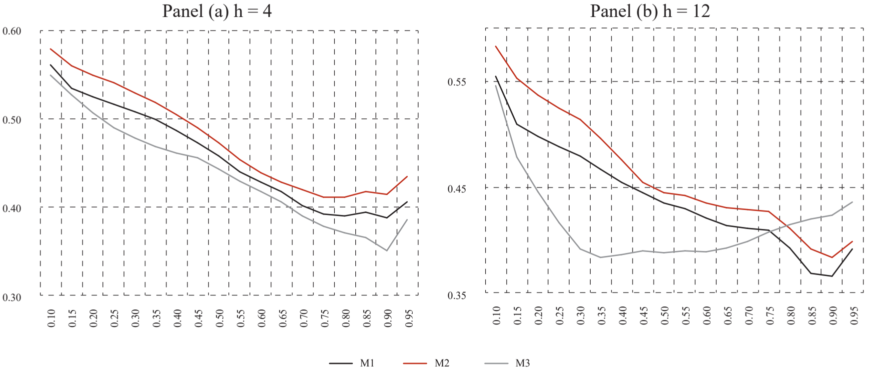
Based on previous discussions, the following variants of the model are compared:

– Model (1): y-o-y change of credit-to-GDP ratio, HIFS, residuals of MPI

– Model (2): 2-year change of credit-to-GDP ratio, HIFS, residuals of MPI

– Model (3): ICSR, HIFS, residuals of MPI.

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



Source: Author's calculation.

Graph 8 shows pseudo-R squares for all three models, for $h = 4$ and 12 quarter ahead growth forecast. There are small differences between M (1) and M (2), whereas M (3) is the worst performing one, as the overall pseudo R-squared is the worst. When looking at p-values of UC tests (see table 3), 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 realizations.

Table 3
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.

When comparing the effects of MPI variables in models (1) to (3), graph 9[19] 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 showing that tighter macroprudential policy positively affects the future lower tail of GDP growth distribution (see Galán, 2020a, 2020b; or Galán and Rodríguez-Moreno, 2020). However, positive, albeit almost nonsignificant, results regarding the effect on the median could also be explained. When 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.

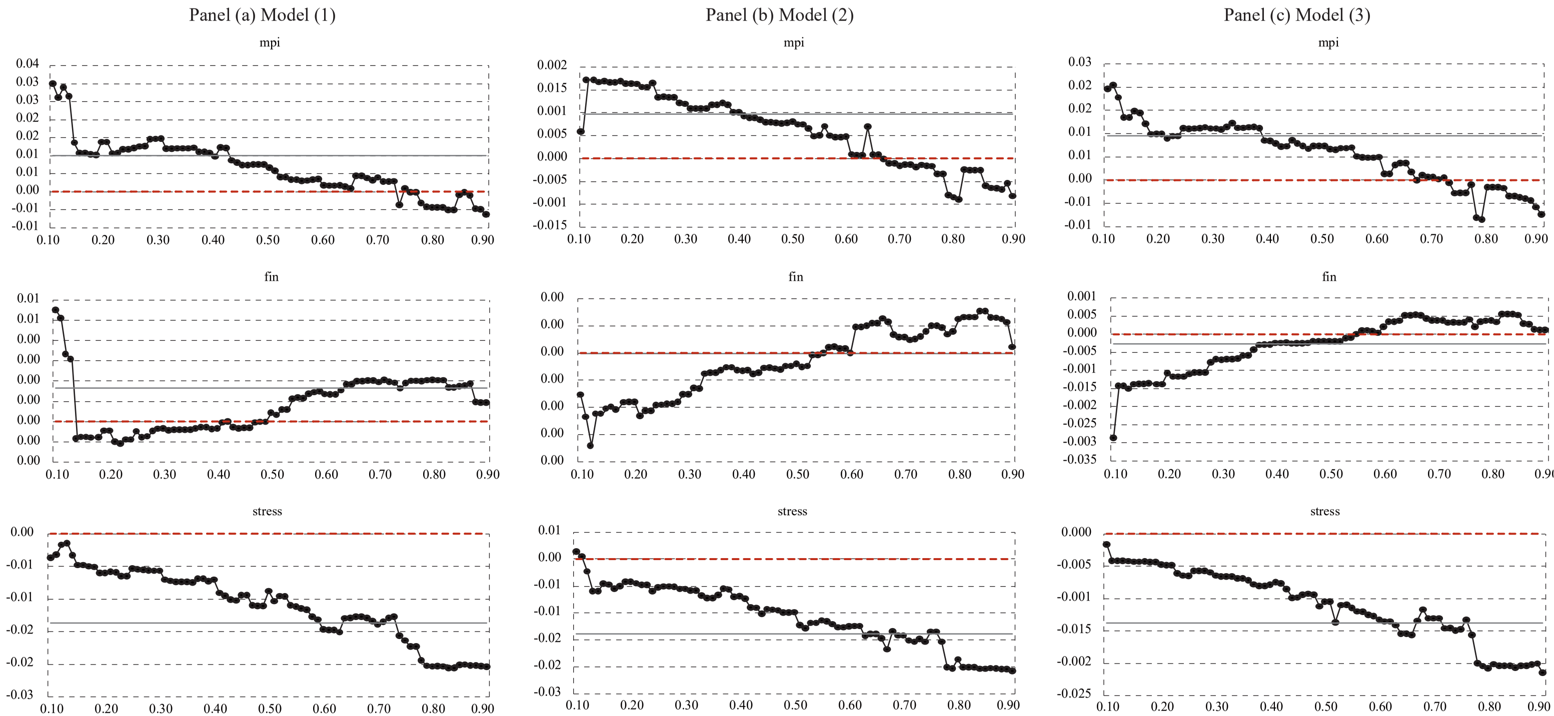
[19] Although we are mostly interested in comparing the median and the GaR value, i.e. calculating distance to tail, we are showing all quantiles in graph 9 to get a better picture on the stability of the beta coefficients.

Graph 10 additionally examines confidence intervals for the MPI variable, across different forecasting horizons. 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. From the literature review so far, one would expect to have positive significant results on the GaR value, with an either negative or an insignificant effect on the median growth. 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. Although we have time series that start in mid-90s which is fairly good for macroprudential policy, there are still not enough datapoints to cover the richer structure of the GDP growth distribution. Moreover, the GDP drops observed for this country in particular have different origins, and the magnitude varied. So far, the worst realizations refer to the Covid-19 shock and the GFC. The methodology applied in this type of research is not meant to capture Covid shocks. Thus, effectively, the GFC is the main driver of results regarding the tail risk. Moreover, the MPI in this paper is used to reflect the number of measures, not their adjusting or fine-tuning. So far, there is no consensus on how to adjust the MPI values in the best way, as it is dependent on specific country and general macroprudential policymaker experience If this were done, perhaps it could change the results obtained here.

Moreover, beta values for the median growth case are constant over all observed horizons, around 1%, but not significant. This is in line with Suarez (2021), where MP stance and effects on future growth are explained from a theoretical point of view: if no effects on median growth are found, this could indicate that there are still some non-linear MP effects on growth that are not captured in the GaR setting. Another explanation is that there exists a natural limit to some MP tools that being applied in practice did not have negative effects on economic growth. As the Croatian macroprudential policy is fairly active, the latter could be true. The Croatian banking system has been one of the highest capitalized in the EU since the capital requirements were introduced after the GFC. Thus, this affects the results as well, due to the frequency of increases made over time, and this is in line with Aikman et al. (2018) who found positive effects of higher bank capitalization on GaR, with no significant reduction of median growth. Although not significant, the beta coefficients for the 10th percentile start with the highest value for $h = 4$, and for each subsequent horizon decline. When compared to previous related literature (see literature review section), the signs of the estimated parameters are in line with related studies. 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 (Cucic et al., 2022).

Graph 9

Estimated coefficients for models (1) – (3), h = 4 quarters ahead

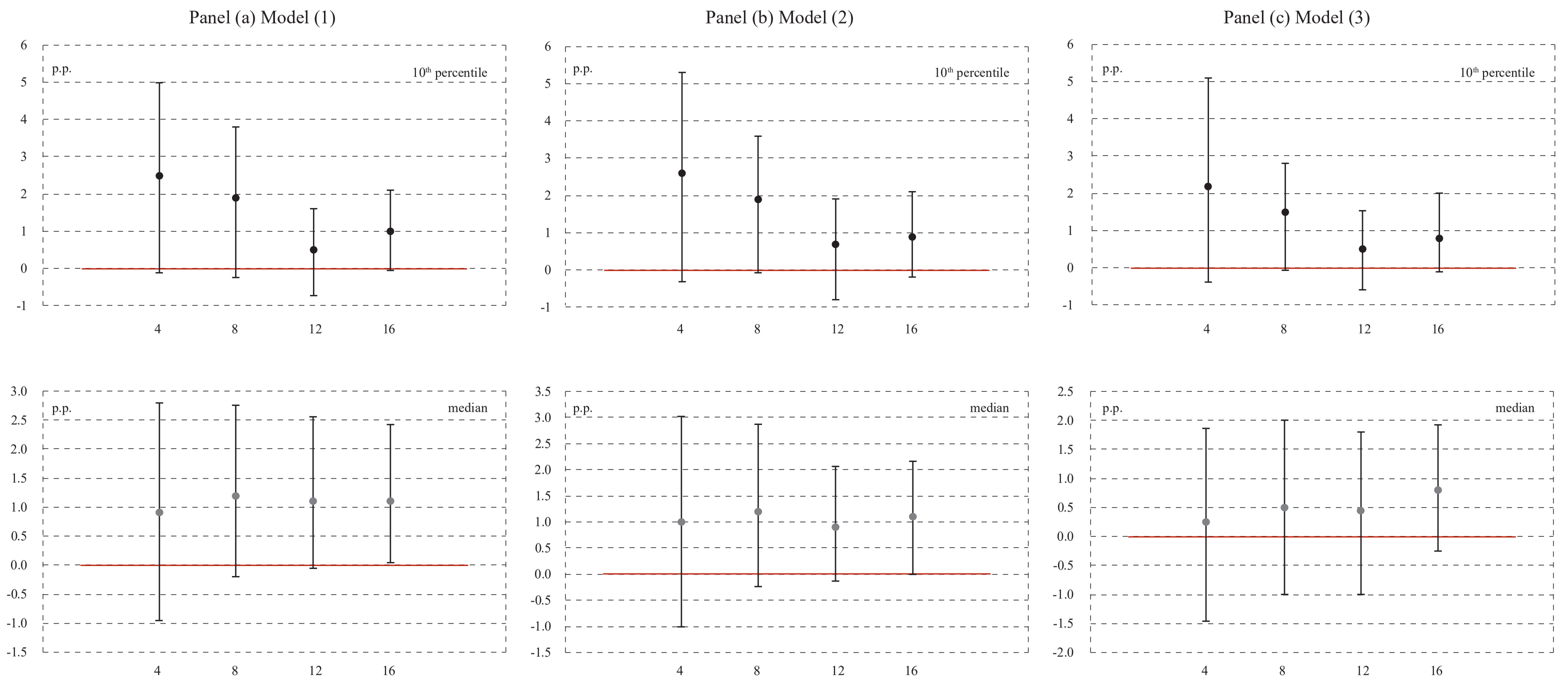


Note: y-axes values should be multiplied by 100% to get p.p. growth interpretations. mpi – variant of macroprudential policy variable, fin – financial vulnerabilities variable as described in main text.

Source: Author's calculation.

Graph 10

Macroprudential policy effects on future growth



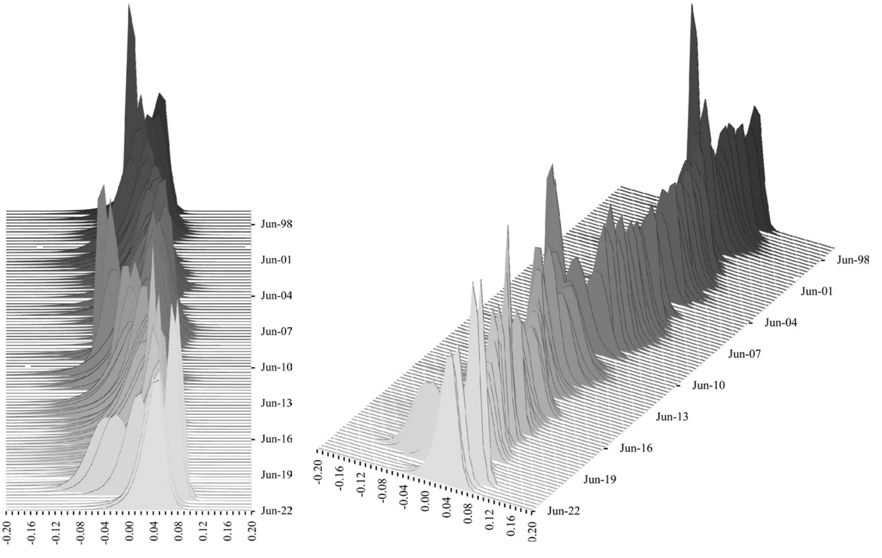
Note: Confidence intervals obtained via block bootstrapping with 1,000 replications. Block bootstrap is used to construct CIs as usual procedures like the xy-pair are not suited for the time series. The procedure applied here takes into consideration that time series exhibit autocorrelation and this should be included in the bootstrapping procedure, where the subsamples for the bootstrap are not constructed from random data picking. Rather, blocks are taken out as a time series. X-axis depicts the forecasting horizon of 4, 8, 12 and 16 quarters, whereas the y-axis shows the estimated coefficient besides the MPI variable in the GaR model specification.

Source: Author's calculation.

5.2.3 Distribution fitting results

Next, skewed t-distributions for every quarter from the GaR model were fitted as described in section 5.2. Graph 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 tilted to the left just before and during the GFC; 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.

Graph 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[20]. Results are shown in graph 12. All estimated DTTs are volatile, and it is hard to tell a story from them. Panel (a) shows that before the GFC, most of the time, DTT was below the median value and was tighter than in 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 have continued without this shock, as the rapid growth

[20] 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 as 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 it 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 hear central banks saying that the macroprudential measures have significant effects on the GDP growth or in general the real economy so long in the future.

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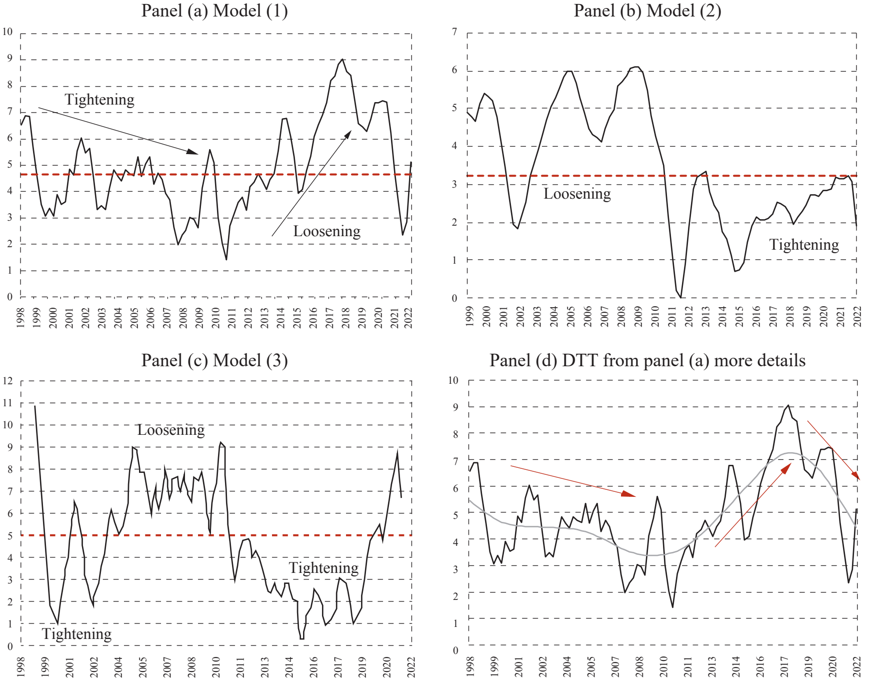
of consumer credit was in place before Covid hit. Moreover, this value is around the median[21] value, which could be a somewhat neutral level of macroprudential stance. Panels (b) and (c) tell completely different stories: in the pre-GFC period, the stance was looser due to higher DTT values, and in 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.

Graph 12

Distance to tail from models (1) to (3)



Note: Dashed lines indicate median values of distance-to-tails.

Source: Author's calculation.

Moreover, suppose one selected, 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? As the optimal DTT depends on the 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

[21] Here, we depict the median value of DTT as just a statistical value. It does not replace the theoretical "optimal" DTT value.

with respect to the historical distribution of DTT in graph 12, panel (d). It takes the DTT from panel (a) and adds a trend line (grey line). 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 the GFC, the policy was introducing more measures as it was developing and trying to tackle the enormous credit growth. This decreased DTT over time. During the 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, with explanations how this policy should work and affect future growth (see Suarez, 2021; and Checchetti and Suarez, 2021 as a starting point). However, practice so far has produced mixed results. An exhaustive literature overview in the first part of this paper sheds some light on the reasons why the results are very mixed. They could be different variable definition, selection, and transformation, and could also probably be due to the bird's eye approach to estimation (macro picture is observed, thus it is tough to capture some transmission mechanisms that way).

The inconclusive results of this study are in line with the comments of Reichlin, Ricco and Hasenzagl (2020), who agree that the relationship between financial and real variables is difficult to model. This is proven in this paper, where it is shown that the results vary with respect to variable definition, and model specification. 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 operationalizing the GaR approach to evaluate the MP stance on a regular basis. This is one of many papers that find GaR modelling challenging. This means that so far potential usage of this framework to tailor MP tools could be questionable. Alessandri and Di Cesare (2021) warn about the empirical problems and that MP instrument calibration based on such an approach should be very cautious. From this, we conclude that so far, MP tools should not be tailored according to the results obtained in this study. 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 when focusing on a one-year-ahead forecast. 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.

When comparing the approach and results to 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. In the mentioned report, the transformation of the MPI indicator is rather questionable. All MP tools are converted into +1 or -1, with the final MPI variable calculated as a cumulative value of all tools that were observed over time for a given country. Then, a 5-year change is the basis for the transformation of the cumulative indicator. This 5-year change is used as the main policy indicator in the GaR model where the forecasts are made up 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 countries like Croatia. The second challenge is the failure to solve the endogeneity issue of the policy variable. So, the results in the mentioned report are not comparable to those obtained here.

Some shortcomings of the approach taken in this research include the single equation approach. Future GDP growth is the only variable in this setting that is assumed to be endogenous. However, the interaction between the financial system and the real economy is two-sided. There has been some work on this that started emerging in the recent period: the ECB has been working on the quantile vector autoregression approach to deal with endogeneity of macro-financial variables and the feedback loops between the real and financial sector (Chavleishvili and Manganelli, 2020). In such a framework, one does not need to have a two-step procedure of purging the MP variable from macroeconomic shocks. Rather, the nature of vector autoregressive models can capture all interactions in one go.

Future work should mostly focus on resolving the MPI definition, i.e. how to translate different tools and their intensity into the final MPI value[22]; on solving the endogeneity challenge of the policy itself in order to talk about causality and measuring MP effectiveness. 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. Furthermore, as with other modelling, the recent COVID-19 shock has distorted some of the time series that are used in the empirical analysis. In this research, we did not do anything in this respect, i.e. the series were used without any "cleaning" beforehand. As GaR framework is not intended to capture such shocks, it is reasonable that the model used in this study could not forecast such shock in the GDP series. However, having this period in the dataset could affect the overall model results. Future work should try to see how to tackle this challenge.

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). Thus,

[22] Some initial steps have been done by Vandenbussche, Vogel and Detragiache (2015) and followed by Eller et al. (2020).

future work could consider other methodological directions, like the MIDAS-QR (mixed data sampling), where higher frequency data could be used for forecasting purposes (Ferrara, Mogliani and Sahuc, 2022). Some authors are starting to focus on the DSGE (dynamic stochastic general equilibrium) modelling approach (Buch, Vogel and Weigert, 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, Quayyum and Das (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 capable of visualising the effects on financial stability.

Disclosure statement
There are no financial or other potential conflicts of interest.

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