Improvements to the ESRB macroprudential stance framework

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ESRB
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Executive summary

The European Systemic Risk Board (ESRB) developed the macroprudential stance framework to compare systemic risks, macroprudential polices and resilience at country level. The purpose was to assess the macroprudential stance of member countries as either tight, neutral or loose, thus providing an overview of how countries' macroprudential policies compared with the policies of others.

The stance framework is based on a growth-at-risk (GaR) approach and indicator-based approaches. An indicator-based approach is used for both borrower-based measures (BBM) and for capital-based measures (CBM). The GaR and indicator-based approaches have their own perspectives, strengths and weaknesses and therefore complement each other (see Table A1 in Annex 1). The report of the expert group that operationalised the framework contains further information on each of the approaches.[1] As a third approach, the report contains a semi-structural micro-macro model known as the Banking Euro Area Stress Test (BEAST). BEAST is accessible to members via European Central Bank (ECB) groups and is therefore not maintained by the ESRB Secretariat.

The Contact Group on Macroprudential Stance (CGS) was set up to share experiences in using the framework and to propose improvements. The ESRB Secretariat shared the codes and data for the GaR and indicator-based approaches to enable members to apply the approaches at national level. The discussion on improvements was informed by members' learnings and by experiences in using the CBM approach gained by the ESRB Secretariat during the cross-country cyclical risk assessment carried out in 2022.

Besides sharing experience, the mandate of the CGS covers most notably approach robustness and consistency. This is measured through the use of consistency checks to propose refinements to the methodology and test alternative series and model specifications in order to arrive at consistent and stable results.

The stance assessments set out in this report illustrate the results of the methodological changes but are not the basis for policy proposals. Stance assessments are an input for ESRB risk and policy discussions, but are not the final outcome. Policy conclusions would be drawn based on quantitative results and discussions that also take expert judgement into account.

The ESRB stance framework was designed for cross-country comparison. This limits the possibility of data that are specific to a single country being included in the common framework. The reason is that under the indicator-based approach all observations are pooled across countries (and over time), meaning that it is necessary to use series that are available for all countries.

The framework will continue to benefit from ongoing use among members and the ESRB Secretariat and from further learnings. The improvements discussed in this report were informed by learnings from applying the framework. Moreover, once the improvements have been

[1] See "**Report of the Expert Group on Macroprudential Stance – Phase II (implementation)**", ESRB, December 2021.

incorporated and applied, users' experiences will provide valuable information on possible further room for improvement. The topics requiring further attention are outlined in Section 3 below.

Stance assessments under the GaR and indicator-based approaches complement each other. The approaches have different perspectives: the GaR approach is forward-looking and model-based, while the indicator-based approaches focus on BBM and CBM as policy measures and assess each country relative to all countries. Consequently, there may be plausible differences in the final stance assessments obtained. At the same time, inconsistent results will require further inspection (to give an extreme example, if a country's policy is assessed as loose in one approach but tight in the other).

This report takes stock of the group's learnings and describes methodological improvements. The results of the modifications made to the methodology are compared with the results of using the methodology described in the 2021 report. Data up to the same quarter, i.e. the same sample, are used to compare the differences between the original and improved methodologies.

The main improvements under the GaR approach:

- *Variable selection and back-testing*: addition of features to the model that allow the user to assess the quality of estimates and to select the optimal input variables.
- *Bias correction*: use of instrumental variable methods to correct for upward bias in estimating the model coefficients.
- Robustness to inclusion of the COVID-19 period in the sample tested: the coefficients are robust to the inclusion of the COVID-19 period.
- *Macroprudential policy index (MPI)*: entries of past macroprudential measures have been refined and new measures incorporated after having been classified as tightening, loosening or neutral.

The main improvements under the indicator-based approach:

- *Use of a cumulative distribution function,* instead of a bucketing approach with a four-level scale, to reduce jumps in the final stance assessment.
- *Refining of the thresholds* for the final stance assessment: the new thresholds are based on percentiles of the empirical cross-time, cross-country distribution of the final stance indicator.
- *Reduction of the complexity of the BBM approach:* the final stance is defined as a weighted sum of the inputs, thus making it easier to decompose the stance into its components.

For the GaR approach, the results differ from ESRB (2021) after correcting biases and revising the MPI. We sort the countries according to their median-to-tail distance and then compare them. Given that the estimation bias was corrected and the revised index improved based on members' expert judgement, the deviations are likely to stem from the correction of the estimation bias and the revision of the index.

Overall, the results for the indicator-based approach are in line with the methodology set out in ESRB (2021). For both BBM and CBM, the new proposal and the methodology under ESRB (2021) yield the same verbalised stance level – i.e. either loose, neutral, tight or in a grey zone, based on a numerical value – for roughly half of the observations. Only for a few observations does the assessment vary by more than one level, showing that the changes are largely limited.

1 Growth-at-risk approach

The growth-at-risk (GaR) approach estimates the impact of systemic risks, financial stress and macroprudential policy on the lower tail of the projected GDP growth distribution. The CGS took the model (i.e. code and data) used in ESRB (2021) as the starting point and improved the approach from there. Table 1 compares the specifications of ESRB (2021) with the findings of the CGS and shows the issue that was resolved in each case.

Table 1

Improvements to the GaR approach

Issue	Specification in ESRB (2021)	Specification by CGS
COVID-19 period not covered in estimation	Sample stopped before COVID-19 period	Updated model now includes the COVID-19 period
GaR may not fully reflect COVID-19 period volatility	Sample did not include COVID-19 period	GEOVOL index and dummies were proposed as additional variables upon necessity
Bias in quantile regression coefficients	Panel data fixed effects quantile regression (QR)	Bias-corrected panel QR with fixed effects and original QR for comparison
GaR back-testing methodology	Not available	Added in-sample testing methods
Incorrect entries in the Macroprudential Policies Evaluation Database (MaPPED)	-	Check of MaPPED entries
Discontinuation of MaPPED in 2018	Sample did not go beyond 2018	ESRB measures database appended to MaPPED
Measures from ESRB measures database are not classified as tightening/neutral/loosening	-	Classifications added based on rulebook
Verbalised stance assessment for GaR	Stance can be positive (loose) or negative (tight)	Five levels proposed as starting point (similar to indicator-based approach)

Source: Contact Group on Macroprudential Stance.

The CGS improved the GaR approach by refining the variables included in the model, simplifying the model code and developing a more granular verbal stance assessment. The group used annual logarithmic real GDP growth to calculate the stance metric for four and eight quarters ahead. In comparison, ESRB (2021) used the biannual real GDP growth rate for eight-quarters ahead calculations.

The MPI was error-corrected and new measures incorporated. Some members discovered inconsistencies between the entries in the Macroprudential Policies Evaluation Database (MaPPED) and the actual implementation of macroprudential measures in their countries. Therefore, all members checked the consistency of the MaPPED entries and revised them as necessary. Afterwards the ESRB measures database was appended to the improved MaPPED database. As the ESRB database lacks information on the direction of measures, the CGS developed a rulebook to allow regular, consistent updates of the MPI in the future.

To improve the quality of the GaR approach, a back-testing code was introduced. Back-testing allows model performance to be evaluated and enhances the credibility of the estimates obtained. It is also useful when choosing between different sets of factors.

The significant improvements made to the GaR model code are the product of bias corrections. The CGS identified two significant biases that need to be tackled. The first of these arises when estimates of quantile regression cause the quantiles to cross each other. Currently there is a code available to resolve this issue for single countries, which can also be developed for the panel setting. The second bias relates to the dynamic panel estimation and is resolved by using instrumental variables in the estimation.

The CGS also worked on improving the final stance assessment. Originally stance was assessed only as loose or tight, there was no neutral stance or a stance at any other point along the scale. The proposal of the CGS is to introduce five macroprudential stance levels, which would be similar to the indicator-based approach.

1.1 Treatment of the COVID-19 period

The highly volatile COVID-19 period challenges the robustness of the GaR framework. The volatility in the time series affects not only the models in themselves but also the way they are applied. Krygier and Vasi (2021) state two reasons why a GaR framework may not adequately reflect the risks prevalent through the COVID-19 period. First, the ensuing negative GDP growth rates were not caused by endogenous financial sector imbalances, but rather an exogenous shock. Second, such big drops in GDP have not been observed previously. Alessandri and Di Cesare (2021) also note that financial markets did not react fast enough to reliably indicate the impending slowdown.

Although GaR models may not fully reflect downside risks under unusual circumstances, the models nevertheless yield insights into the materialisation of financial stress. O'Brien and Wosser (2021) show that even during the COVID-19 period, a widening of the gap from the 5th percentile forecast growth rate to the median forecast can be observed. This widening suggests greater uncertainty overall regarding the forecast growth rate for GDP. As financial indicators alone cannot capture all shocks, several ways to assess the effect of the COVID-19 period on model results were studied.

To understand whether the COVID-19 period had a significant influence on GaR results, the group compared the quantile regression estimates with and without data covering the COVID-19 period. Both panel and country-level models showed similar quantile regression estimates in each case. Meanwhile, Szendrei and Varga (2023) show that the inclusion of the COVID-19 period does little to change the model results and the variables selected in each case are similar. In a similar vein, re-estimating GaR models for euro area countries, as per Lang et al (2023), via the inclusion of the COVID-19 period, yields largely stable parameters. However, standard errors are larger, and some coefficients (such as the Country-Level Indicator of Financial

Stress, or CLIFS) are affected more than others. Further, the inclusion of the COVID-19 period results in less stable coefficients for a model estimated on euro area aggregate variables. The CGS estimated GaR using pre-COVID-19 data (until the fourth quarter of 2019) and with COVID-19 period data (until the fourth quarter of 2021), choosing GaR four and eight-quarters ahead (the coefficients and their standard errors are given in Annex 7). The estimations use the revised MPI (see Section 1.4). For estimations eight-quarters ahead, the coefficient values and their standard errors do not differ much. One of the reasons is that the data available to us at present for estimating the coefficients capture only the fluctuations in GDP eight-quarters ahead, but not the chosen factors. This means that we cannot make any conclusive decisions regarding the estimation of GaR for longer-term periods in the future. However, for four-quarters ahead, some of the coefficients differ quite substantially and their standard errors in some cases are larger. Therefore, when using horizons or combinations of factors not yet tested, the CGS recommends careful evaluation of coefficient stability compared with models estimated on samples that do not include any COVID-19 period observations. In addition, the use of COVID-19 observations to evaluate GaR model performance or to select variables is not recommended, unless the excessive volatility of the COVID-19 period is specifically tackled.

Solutions to capture more of the COVID-19 period volatility include the use of dummies and specific variables. Several group members tested the GEOVOL index proposed by Engle and Campos-Martin (2020) in order to capture the effects of the pandemic and the war in Ukraine on GaR forecasts. In some countries, the GEOVOL index is a significant determinant of GaR and helps to characterise the lower tail of the growth distribution in a more realistic fashion. However, in certain other countries it is not significant. GEOVOL can be added to the regressor set and tested further. The group tested whether including COVID-19 dummies (for the second quarter of 2020 and the third quarter of 2020) yielded more plausible coefficient estimates in the case of four quarters ahead than using the whole dataset. For most variables, the coefficients in the specification with dummies over the full period were indeed closer to those estimated without the COVID-19 period than coefficients estimated in the specification without dummies over the full period. However, the inclusion of dummy variables did not improve the standard errors of the coefficients.

1.2 Variable selection and back-testing

1.2.1 Variable selection

An extension to the GaR approach tests the explanatory power of input variables and helps to choose the optimal model. Users of the code can compare the power of a variety of model specifications. The variable selection code has not been consolidated with the baseline code yet since it is a country-level model.

The variable selection approach is based on least absolute shrinkage and selection operator (Lasso) and involves a non-crossing constraint. The Lasso method places a penalty on the coefficients and shrinks to zero those coefficients which are small. The constraint prevents any crossing of fitted values across forecast percentiles. So far, the code can be applied only on a country-by-country basis and is therefore not merged with the baseline MATLAB code. It is separately available to users. We plan to develop a panel version of this code by the end of this year as further research on the topic. In the meantime, we will use the existing code for country-level investigation. Further details can be found in the Technical Appendix.

1.2.2 Back-testing the GaR model

The CGS complemented the baseline code with back-testing functions to evaluate the model's performance and enhance the credibility of the estimates. The purpose of back-testing is model validation, i.e. assessing if a model is working properly. Back-testing a risk measure involves testing forecasts against realisations. Each different specification of a GaR model generates a forecast distribution that encompasses a range of possible outcomes, including their values and corresponding probability of realisation. However, a full distribution does not materialise ex post: when the time comes, only one scenario materialises, which is one data point.[2] A risk measure is said to be back-testable if an observable test statistic exists that allows us to compare the actual value recorded versus the forecasts generated by the model. Ideally, we would take the full forecast distribution into account when comparing the actual versus the forecast values, because our aim is to produce forecasts that are as accurate as possible. Therefore, the test statistic allows us to decide whether predictions are over- or under-estimated as well as the extent of the forecast error on average. For example, the risk measure could be the Value at Risk (VaR), and the test variable the VaR breaches. Over time, we have a sequence of predictions of future realisations and our objective is to test ex post the quality of our predictions.

Back-testing functions to evaluate model performance have been added to the GaR toolbox. One of the key objectives of any GaR analysis is to make GDP growth forecasts. To unlock its full potential, such forecasts should be probabilistic. As outlined, this means using the probability distributions of a continuous variable, namely GDP growth. There is, therefore, an imperative to use well-established techniques when comparing and ranking density forecasts, so as to increase confidence in implementing this approach for stance evaluation purposes.

The CGS considers density forecasts in a time series context. This takes place in an expanding window setup consisting of the past m observations used to fit a density forecast for a future observation that lies k periods ahead. The comparison typically uses a proper scoring rule. A scoring rule is a loss function $S(f, y)$ with arguments that include the density forecast, f, and the realisation, y, of the future observation Y.

The CGS uses Akaike information criterion (AIC) and Bayesian information criterion (BIC) scores to quantify the in-sample fit in the back-testing methodology. Both scores are based on a penalised likelihood function. We use the quantile weighted continuous rank probability score (QWCRPS) for both in- and out-of-sample back-testing. All the scoring rules used involve negatively oriented penalties, meaning the lower the score, the better. Further details can be found in the Technical Appendix.

2 In the context of back-testing and limited data availability, bootstrap methods could be explored (e.g. residual-based wild bootstrap) in future work.

The CGS ran robustness checks. Comparing the performance of quantile regressions with other quantitative methods such as nearest neighbour, regression trees and ordinary least squares (OLS), it found that quantile regression is the most efficient technique (the comparison results can be found in the Technical Appendix).

The back-testing exercise showed that the Composite Indicator of Systemic Stress (CISS) marginally outperforms the Country-Level Index of Financial Stress (CLIFS) as a financial stress measure, though CLIFS is still used in the model due to its superior data availability relative to CISS.[3] The benchmark model from ESRB (2021) uses the CLIFS index. Empirical results show that CLIFS is not a significant determinant of GaR for all countries, particularly at forecast horizons beyond four quarters. The performance of both risk indicators in a GaR framework was assessed using the quantile weighted probability score as a metric. The CGS performed in-sample testing due to the shortness of the time series. The results show that CISS marginally outperformed CLIFS in the panel setting. However, CISS is only available for ten European countries and this limited coverage will not be extended during the period in which the CGS remains operational.

1.2.3 Bias correction in the coefficients

The estimation of unbalanced dynamic panel quantile regression (QR) with fixed effects and short time series has a significant bias in the coefficients. Vávra (2023) showed that GaR models have a sizeable bias of 30% for short samples, even for data history of T=100. The bias of the left tail is not only highly relevant but also is not in the favourable direction inasmuch as the model underestimates the left tail. Moreover, for panel linear models, the Nickell bias is of order beta/T where beta is the coefficient and T is the length of the shortest time series. Galvao (2011) shows that for panel QR this bias could be even larger.

Given the short length of our unbalanced panel (T=20), the theoretical findings should be sufficient to motivate the need for bias correction in the GaR approach. We created a bias-corrected panel QR with fixed effects MATLAB code based on Galvao (2011) and merged it with the baseline code. We have continued to investigate the properties of the bias-corrected panel QR, which also involves comparing it with the old code. When comparing the results of the non-corrected and bias-corrected codes, two features became obvious: first, for the bias-corrected code the coefficients of the CLIFS index are more significant and have more intuitive signs compared with the coefficients of the non-corrected code.[4] Second, during crisis periods the distance between the median and the left tail is more pronounced for the bias-corrected code. This is in line with the findings of Vávra (2023). Until the final results have been fully considered and a decision on whether or not to deploy has been made, we intend to retain the new bias-corrected code as research code for the present.

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3 See the **ECB Data Portal page on the Composite Indicator of Systemic Stress**.

4 Intuitively one would expect the tail percentile quantile regressions to reflect a negative coefficient for the CLIFS variable, implying that a deterioration in financial conditions (increase in CLIFS) leads to more adverse GDP left tail forecasts.

The bias-corrected panel QR presents significant crossings of fitted values belonging to different quantiles. This means the fitted value for the median or even for the 90th percentile can be smaller than that of the 10th percentile, which we find undesirable, although it is a well-known feature of baseline QR. This problem was solved by sorting the fitted values as in Chernozhukov et al. (2010). Some coefficients are quite different from the ones found in the old baseline code and the in-sample fit is better for the old code. It is important to note that the old code yields some counter-intuitive signs for certain important coefficients like CLIFS for the chosen horizon of eight quarters, and also for the old and new MPI index. In contrast, the coefficients of the bias-corrected code consistently yield intuitive signs for both CLIFS and the Systemic Risk Indicator (SRI) for both the four-quarter and the eight-quarter forecast horizon. For four quarters, the SRI is significant in the interaction term with CLIFS. For the eight quarter horizon, the SRI is significant in the interaction with CLIFS and the capital-based MPI. As such, further testing of the bias-corrected code will continue until a decision is made on whether to use the code as a new baseline. Charts 1 and 2 further below provide a comparison of the old code and the bias-corrected code for the old MPI. Charts 3 to 6 portray this comparison for the new MPI index for horizons equal to four and eight quarters. It is clear from the charts that for the new MPI there is a significant reordering of the countries when comparing the old code to the new one. Moreover, there are changes in the order if we keep the estimation method unchanged but switch from four quarters to eight. Unfortunately, the sample is too short for out-of-sample back-tests. A total of 50 datapoints are needed for the pre-sample fit and we only have 20 or so datapoints with which to calculate the average QWCRPS in the unbalanced panel.

As a solution to improve the in-sample fit for the new bias-corrected code, we are working on a coding refinement, in which the crossings of the fitted values are eliminated within the estimation procedure by applying a non-crossing constraint, as in Szendrei and Varga (2022). We have already tested the fit of this new refined bias-corrected code and the improvement in model fit is very significant. In particular, the left tail QWCRPS score is superior to the old code.

The SRI series are very short for Croatia, Estonia, Romania and Slovenia. The sample will become longer once the last five datapoints after 2020 have been added. Furthermore, the CGS discussed a data collection in countries with short series. These countries could extend their respective SRI series through the use of internal sources, especially if their methodology is consistent with the ECB methodology for computing the SRI.

The Technical Appendix provides a comparison between the old and new bias-corrected codes. We show the estimates of the coefficients with the error bounds and the in-sample model fit.

1.2.4 Discussion of results

So that readers can understand the magnitude of the coefficient bias, we show comparisons of reported coefficients between the old baseline code and the bias-corrected code. We also break these coefficients into groups relating to the old and the new versions of the MPI index (Table 2). In each case the coefficients relate to the 10th percentile (tail risk) quantile regression of the specification in question. The eight-quarter forecast horizon is the benchmark and is consistent with ESRB (2021). The four-quarter horizon is shown for information and comparison purposes.

Table 2

Model comparison (bias correction, forecast horizon, MPI)

Non-bias corrected model; old MPI; h=4q; perc 0.1

	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.217	-0.007	-0.140	-0.034	0.000	0.000	-0.003	0.012	0.001	-0.012
Significance	***	*	***				***	*		*
Standard error	0.037	0.004	0.021	0.022	0.001	0.001	0.001	0.007	0.001	0.007

Bias corrected model; old MPI; h=4q; perc 0.1

	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.995	0.009	-0.012	-0.350	-0.023	0.001	-0.002	-0.001	0.027	0.001
Significance	***			***	***				***	
Standard error	0.092	0.009	0.047	0.052	0.003	0.003	0.002	0.016	0.002	0.016

Non-bias corrected model; old MPI; h=8q; perc 0.1

	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.110	-0.041	0.085	0.084	-0.001	-0.002	-0.005	0.016	0.000	-0.027
Significance	***	***	***	***			***	**		***
Standard error	0.036	0.004	0.020	0.022	0.001	0.001	0.001	0.008	0.001	0.007

Bias corrected model; old MPI; h=8q; perc 0.1

	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.994	-0.043	-0.047	0.016	0.019	0.003	0.000	-0.004	0.014	0.003
Significance	***	***			***				***	
Standard error	0.100	0.010	0.057	0.056	0.003	0.003	0.002	0.019	0.003	0.019

Non-bias corrected model; new MPI; h=4q; perc 0.1

	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.276	-0.008	-0.161	0.004	0.000	-0.003	-0.004	0.016	-0.002	-0.002
Significance	***	**	***			**	***	**	*	
Standard error	0.034	0.004	0.020	0.022	0.001	0.001	0.001	0.008	0.001	0.007

Bias corrected model; new MPI; h=4q; perc 0.1

	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.996	0.011	-0.011	-0.368	-0.004	0.000	-0.001	-0.002	0.004	-0.001
Significance	***			***	*				*	
Standard error	0.086	0.009	0.048	0.048	0.002	0.002	0.002	0.016	0.002	0.016

Non-bias corrected model; new MPI; h=8q; perc 0.1

	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.126	-0.037	0.086	0.069	0.001	-0.001	-0.005	0.012	0.000	-0.021
Significance	***	***	***	***			***			***
Standard error	0.035	0.004	0.022	0.021	0.001	0.001	0.001	0.008	0.001	0.007

Bias corrected model; new MPI; h=8q; perc 0.1

	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.997	0.006	-0.033	-0.227	0.053	-0.002	-0.002	-0.002	0.033	-0.001
Significance	***			*	***				***	
Standard error	0.287	0.025	0.140	0.128	0.006	0.006	0.006	0.045	0.006	0.045

Source: Contact Group on Macroprudential Stance.

Some interesting results emerge from these comparisons. The coefficient for lagged GDP growth is much larger and retains its statistically significant negative value, regardless of which MPI index is used. This implies that the larger the GDP growth reported today, the more adverse the future output growth tail risk. The bias correction suggests that tail risk in the old specification may have been under-reported in the past, particularly so in the case of countries that may have experienced strong GDP growth rates. The CLIFS indicator is an important determinant of near-term tail risk to output. In the bias-corrected version of the code this variable appears to lose statistical significance at the shorter four quarters ahead horizon which, prima facie, might be considered problematic. Offsetting this, however, is the much more significantly important interaction term involving financial conditions (CLIFS) and the cyclical systemic risk measure (SRI). The CLIFS and SRI interaction coefficient is highly significant and negative, revealing that materialised stress is especially harmful when vulnerabilities are present. The coefficient of the CLIFS at the eight quarters ahead horizon is more meaningful in the case of the bias-corrected model. It is negative and insignificant, which is in line with expectations. Meanwhile, for the non-bias-corrected model this coefficient is positive and significant, which is counter-intuitive. The intertemporal trade-off for the SRI can also be better seen for the bias-corrected model. Its coefficient is positive and insignificant for the four quarters ahead horizon and non-significantly negative for the long-run, eight quarters ahead horizon. However, the SRI is significant in the interaction with CLIFS. The significant negative coefficient for the interaction term between SRI and CLIFS at the four and eight quarters ahead horizons, particularly in the presence of the updated MPI indices, implies that financial conditions shocks will have a materially adverse impact on GDP tail risk, and this effect will be further amplified as the financial cycle approaches its peak.

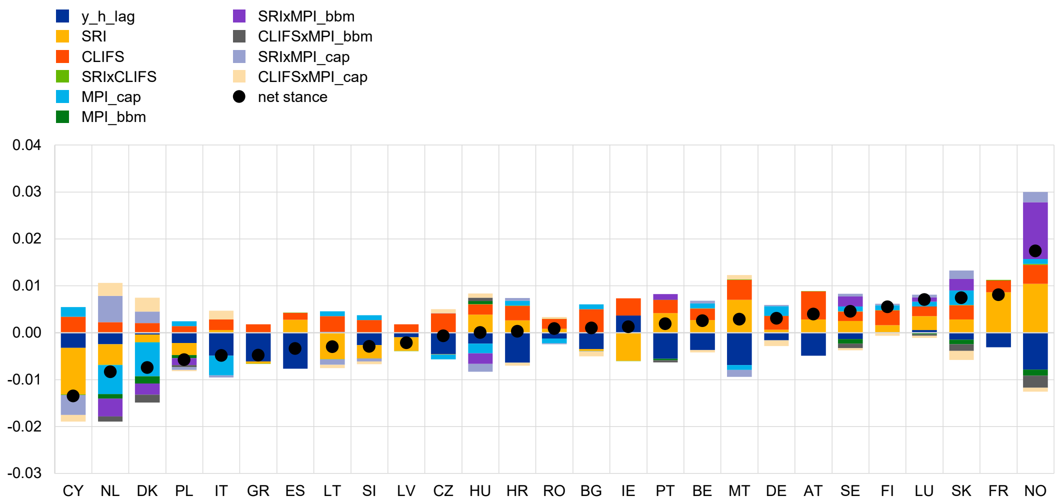
In terms of the macroprudential policy indicators themselves, the results are somewhat mixed. There appears to be no significant tail risk correlation between borrower-based measures (MPI_bbm) and future GDP tail risk, regardless of the forecasting horizon. However, the capital-based indicator measure (MPI_cap), at eight quarters ahead with a significantly positive coefficient, shows the tail risk benefits (reduction in tail risk) from higher bank capital requirements. This is something that the old model (pre-bias correction and MPI updates) failed to reflect. Indeed, the old model appeared to suggest that relatively tighter bank capital policies appeared to be correlated with more adverse near-term tail risk to GDP growth, a counter-intuitive result. As mentioned above, we are continuing to investigate the properties of the new model and associated results, though we are already encouraged by several of the enhanced results and more intuitive interpretations that the updated models appear to offer.

We also provide the visual comparison of net stance for the third quarter of 2021 using different versions of the code and MPI in Charts 1 to 6. In line with the changes in coefficients, we see a more pronounced, largely negative effect of lagged GDP growth on the net stance for both four and eight quarters ahead. We also see that CLIFS is no longer a visible determinant of the net stance in the bias-adjusted model in contrast to the non-adjusted model.

The use of the new MPI places somewhat more emphasis on borrower-based and capital-based measures alone, and somewhat less emphasis on their interactions with financial conditions or cyclical risk. Using the non-adjusted model, greater emphasis is placed on the borrower-based measures, which in most cases loosen the net stance. In the bias-adjusted model version, capital-based measures significantly tighten the net stance in most cases.

Chart 1

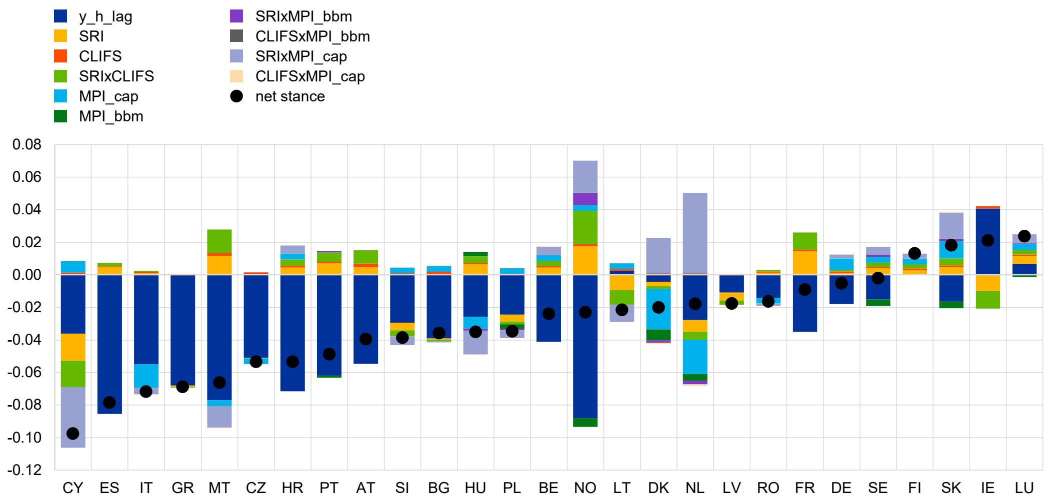
Contribution of variables ordered by the size of the net stance in the non-adjusted model using the old MPI for a four-quarter horizon from Q3 2021



Source: Contact Group on Macroprudential Stance.
Note: The y-axis shows the GDP growth rate gap from forecast median to forecast 10th percentile tail risk as of data for the third quarter of 2021. The net stance excludes country-level fixed effects from median and tail forecasts. A negative contribution (e.g. from SRI in the case of CY) implies that the current value of the variable reduces that country's tail risk as of the third quarter 2021. Larger gaps are suggestive of increased tail risk relative to median forecasts and that a tightening of macroprudential policy stance may be considered.

Chart 2

Contribution of variables ordered by the size of the net stance in the bias-adjusted model using the old MPI for a four-quarter horizon from Q3 2021

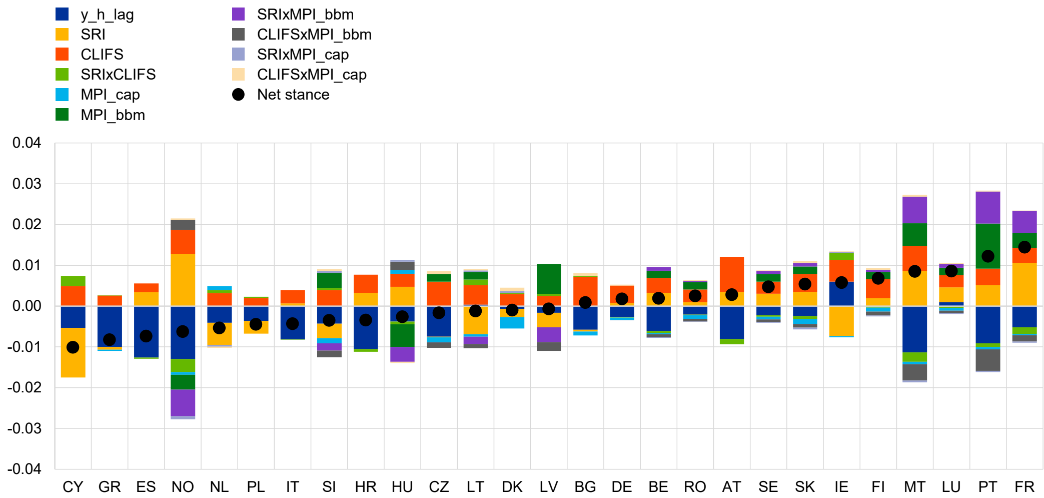


Source: Contact Group on Macroprudential Stance.
Note: The y-axis shows the GDP growth rate gap from forecast median to forecast 10th percentile tail risk as of data for the third quarter of 2021. The net stance excludes country-level fixed effects from median and tail forecasts. A negative contribution (e.g. from SRI in the case of CY) implies that the current value of the variable reduces that country's tail risk as of the third quarter

2021. Larger gaps are suggestive of increased tail risk relative to median forecasts and that a tightening of macroprudential policy stance may be considered.

Chart 3

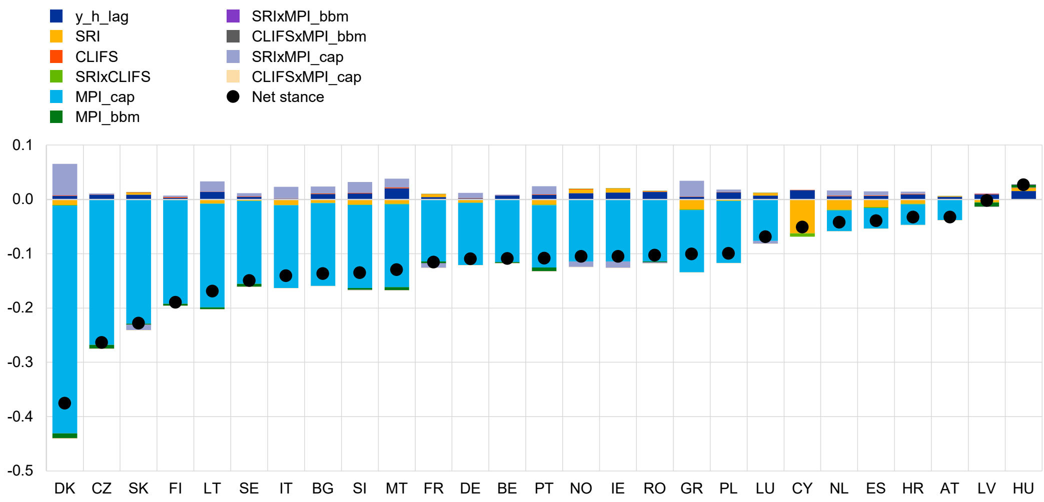
Contribution of variables ordered by the size of the net stance in the non-adjusted model using the new MPI for a four-quarter horizon from Q3 2021



Source: Contact Group on Macroprudential Stance.
Note: The y-axis shows the GDP growth rate gap from forecast median to forecast 10th percentile tail risk as of data for the third quarter of 2021. The net stance excludes country-level fixed effects from median and tail forecasts. A negative contribution (e.g. from SRI in the case of CY) implies that the current value of the variable reduces that country's tail risk as of the third quarter 2021. Larger gaps are suggestive of increased tail risk relative to median forecasts and that a tightening of macroprudential policy stance may be considered.

Chart 4

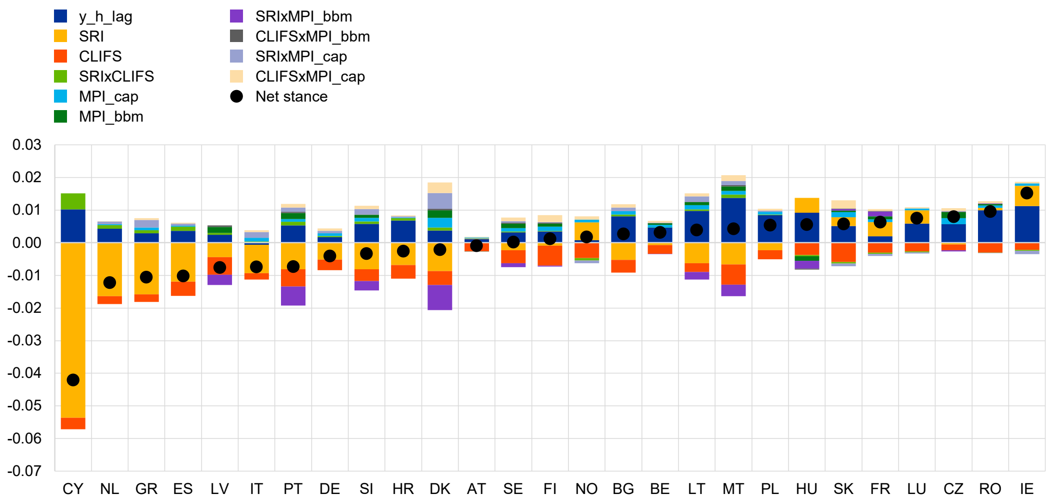
Contribution of variables ordered by the size of the net stance in the bias-adjusted model using the new MPI for a four-quarter horizon from Q3 2021



Source: Contact Group on Macroprudential Stance.
Note: The y-axis shows the GDP growth rate gap from forecast median to forecast 10th percentile tail risk as of data for the third quarter of 2021. The net stance excludes country-level fixed effects from median and tail forecasts. A negative contribution (e.g. from SRI in the case of CY) implies that the current value of the variable reduces that country's tail risk as of the third quarter 2021. Larger gaps are suggestive of increased tail risk relative to median forecasts and that a tightening of macroprudential policy stance may be considered.

Chart 5

Contribution of variables ordered by the size of the net stance in the non-adjusted model using the new MPI for an eight-quarter horizon from Q3 2021

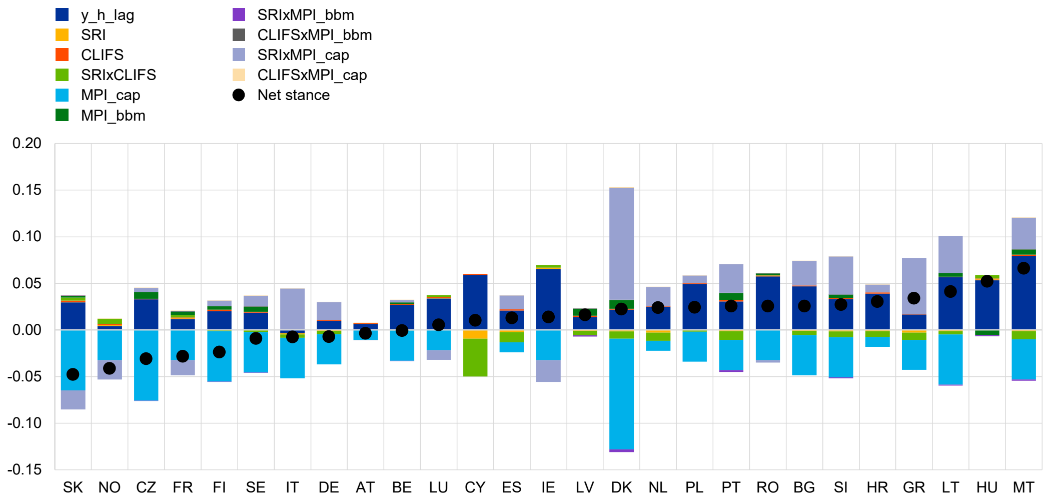


Source: Contact Group on Macroprudential Stance.
Note: The y-axis shows the GDP growth rate gap from forecast median to forecast 10th percentile tail risk as of data for the third quarter of 2021. The net stance excludes country-level fixed effects from median and tail forecasts. A negative contribution (e.g. from SRI in the case of CY) implies that the current value of the variable reduces that country's tail risk as of the third quarter

2021. Larger gaps are suggestive of increased tail risk relative to median forecasts and that a tightening of macroprudential policy stance may be considered.

Chart 6

Contribution of variables ordered by the size of the net stance in the bias-adjusted model using the new MPI for an eight-quarter horizon from Q3 2021

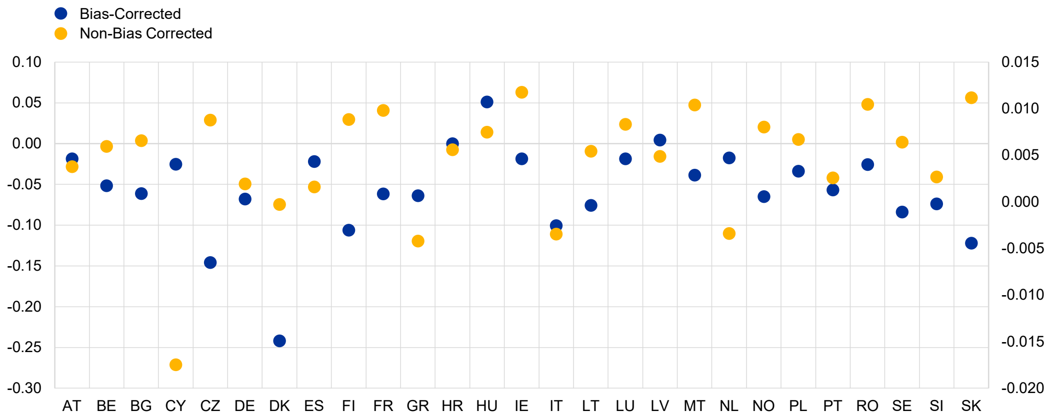


Source: Contact Group on Macroprudential Stance.
Note: The y-axis shows the GDP growth rate gap from forecast median to forecast 10th percentile tail risk as of data for the third quarter of 2021. The net stance excludes country-level fixed effects from median and tail forecasts. A negative contribution (e.g. from SRI in the case of CY) implies that the current value of the variable reduces that country's tail risk as of the third quarter 2021. Larger gaps are suggestive of increased tail risk relative to median forecasts and that a tightening of macroprudential policy stance may be considered.

Chart 7 shows an expansion in both positive and negative direction between the bias-corrected and the non-corrected results. This means that the scale is larger in both directions for the corrected results compared with the non-corrected results. Apart from that, the stance assessments are rather similar.

Chart 7

Net stance as of Q3 2021



Source: Contact Group on Macroprudential Stance.
Note: Left-hand scale: Bias-corrected, Right-hand scale: Non-bias-corrected.

1.3 Refining of the MATLAB code

The CGS added new functionality to the baseline MATLAB code and made the code more user-friendly. The code was restructured to make it easier to understand and follow. The new functionality includes a bias correction for the coefficients and for the fitted values and back-testing features, as described earlier. The CGS improved the statistical properties of the panel quantile regression with fixed effects by incorporating cutting-edge research on GaR models. It also made minor changes when calculating growth rates and in the new code it switched to log growth, which is commonly used in the literature. Log growth is preferred over the standard growth rate because of its additivity over quarters. For the eight-quarter ahead estimates, we changed from eight quarters ahead biannual growth to eight quarters ahead annual growth. There were two main reasons for this, the first being that the shortest time series in the panel is T=20, which is comparable to the length of the difference in the biannual growth term. Secondly, biannual growth has very low variation and for the 12 countries with a short history it could be close to the long-term growth rate, which is not a proper choice for a dependent variable.

A new panel QR with a fixed effects function corrects the bias in the coefficients. The user can use both corrected and non-corrected (old) estimations and compare the results, coefficients and fitted values. An in-sample test can be made to assess the performance of the estimations.

For back-testing, we complemented the calculations with in-sample testing methods. The functions quantify the performance and fit our panel QR with a fixed effects estimation. This approach is based on Gneiting and Ranjan (2011) and Gneiting and Raftery (2007).

The Technical Appendix gives mathematical/statistical details for all new codes of the consolidated and added functions.

1.4 Macroprudential policy index

The GaR approach to macroprudential stance contains a macroprudential index (MPI) that measures how ESRB members have made use of macroprudential instruments. More specifically, the GaR framework considers three macroprudential indices – for CBM, for BBM and an aggregate index. These macroprudential indices were constructed by building on the Macroprudential Policies Evaluation Database (MaPPED[5]; see Budnik and Kleibl, 2018). The construction of the "dummy-type", i.e. the net changes indices that were used for ESRB (2021), was based on the direction of the policy (tightening/loosening) from the database.[6]

The ESRB measures database will be used to fill observations following the discontinuation of MaPPED. MaPPED contains detailed descriptions of macroprudential policy actions (or "policies of a macroprudential nature") taken in the European Union between 1995 and 2018. Now that it has been discontinued, the only other source that systematically collects information on policy action in the EU is the ESRB notifications database.[7] Therefore, the CGS appended the ESRB notifications database to the MaPPED database as of 2018 to construct updated series of the macroprudential indices. However, the notifications that ESRB members send to the ESRB Secretariat are not as detailed as MaPPED entries. For example, they do not include the direction of the policy. The steps taken to address this issue are described below.

The CGS classified the direction of measures in the ESRB notifications. First, measures were categorised as tightening, loosening or neutral.[8] Second, the legal status was classified as recommendation, legally binding, or other. Third, the classification took a first step towards weighting macroprudential measures by their intensity. Intensity was assessed on the basis of the length of the phase-in and the scope of the loosening during the COVID-19 period (see Annex 3). For example, the total weight of one of the capital conservation buffer comprises the several stepwise weights of its phase-in.

To help ensure the consistency of future classifications of the measures contained in the ESRB database, the CGS drafted a general rulebook. The rulebook contains the principles that guided the CGS when classifying the measures (see Annex 3). Table 3 shows a summary of the various classification aspects considered. There were no significant comments from members regarding the proposed classification rules or the classifications of the measures in the ESRB database prepared by the CGS.

5 See **a description of the MaPPED database on the ECB's website**.

6 The construction of the macroprudential indices is described in more detail in ESRB (2021).

7 See **an overview of macroprudential measures on the ESRB's website.**

8 The measures that were taken into account are the entries in the sheets CCoB, CCyB, G-SII, O-SII, SyRB, BBM, and Other measures of the ESRB notification database.

Table 3

Classification aspects and corresponding values for each of the selected measures from the ESRB notification database

Classification aspect	Values/macroprudential measure					
	CCoB	G-SII	O-SII	SyRB	BBM	Other measures
Legal status	legally binding	legally binding	legally binding	legally binding	legally binding recommendatio n other	legally binding recommendatio n
Direction of policy	tightening loosening neutral	tightening neutral	tightening loosening neutral	tightening loosening neutral	tightening loosening neutral	tightening loosening neutral
Stepwise quantification of the effect	stepwise (4 steps) N/A	stepwise (2 steps) stepwise (4 steps) N/A	partial loosening (weight 1/5) partial loosening (weight 1/3) stepwise (3 steps) N/A	stepwise (2 steps) stepwise (3 steps) partial loosening (weight 1/2) N/A	stepwise (2 steps) stepwise (3 steps) stepwise (4 steps) stepwise (7 steps) N/A	stepwise (2 steps) stepwise (4 steps) N/A

Source: Contact Group on Macroprudential Stance.
Note: CCoB: capital conservation buffer; G-SII: global systemically important institutions; O-SII: other systemically important institutions; SyRB: systemic risk buffer; BBM: borrower-based measures.

The CGS reached out to the ESRB members to check their MaPPED entries. Several members signalled inconsistencies between the most widely used macroprudential data sources. For example, information taken from the International Monetary Fund's integrated macroprudential policy database diverged from the MaPPED entries for countries such as Croatia and Slovenia. The MaPPED entries were then revised.

The Stata package for the MPI construction has been modified to include the classified measures from the ESRB database and extend the MPI series. The package that had been written by the previous expert group included procedures for constructing the index until the fourth quarter of 2020, using MaPPED (see ESRB, 2021). The new Stata package has been extended to construct the MPI on the basis of the revised MaPPED database and the appended classified measures from the ESRB notification database. The CGS made several conceptual improvements to the MPI constructed in ESRB (2021). First, CGS uses the revised version of the MaPPED database. The revisions were proposed by the relevant national authorities and involved adding or reclassifying certain macroprudential measures. Second, the CGS dates the policy changes according to the announcement date, thus helping to reduce the endogeneity bias in the GaR regressions. By contrast, the ESRB (2021) used implementation dates. Third, BBM as defined by the CGS no longer include the MaPPED category "Limits on credit growth and volume".[9] Lastly, the macroprudential measures that were not included in ESRB (2021), i.e. after 2018, have been classified to include their direction of change – tightening, loosening or neutral – and are included in the construction of the new MPI.

Endogeneity

Macroprudential policy, as is true with many other policy areas, must contend with the challenge of policy endogeneity. The problem of policy endogeneity in causal inference involving policy evaluation modelling is discussed by Buch et al. (2018). The authors argue that because policymakers react to the (expected) economic outlook, the macroprudential polices that they introduce are endogenous. The authors argue that "observed policy changes cannot be used at face value to identify exogenous changes." The endogeneity of the MPI in the GaR setting has been discussed in Galán (2020) and Suarez (2021). Suarez points out that if we want to interpret the relationship between MPI and future growth as causal, we need to address the potential endogeneity issues of the MPI before including it in the GaR framework.

The CGS investigated the literature to address endogeneity of the MPI. The most common approaches can each be allocated to one of three broad categories. The first advocates a two-step solution to obtain and use the non-systematic policy components of the MPI within the GaR model. Initially, the effects of business and financial cycles are purged from the MPI. Boar et al. (2017) and Galán (2020) apply a regression approach; Forbes and Klein (2015), Gelos et al. (2019) and Brandao-Marques et al. (2020) opt for an ordered probit specification, while propensity score matching is used in the work of Duprey and Ueberfeldt (2020). The second strand of literature considers the dates of announcements and enforcements of measures to solve the endogeneity issue (for example, De Schryder and Opitz (2019) exclude policy actions from the sample when the two dates do not fall in the same quarter). In a third strand of literature, the papers use various variable lags in the model (for example, Cerutti et al. (2015) use lagged values for the macroprudential policy variable).

The work undertaken by the CGS follows the first strand of literature, which addresses MPI endogeneity by obtaining non-systematic policy shocks. This approach is discussed in Boar et al. (2017), who suggest obtaining these components either in terms of residuals of the Taylor rule or residuals of fiscal policy rules related to changes in GDP (as put forward in Fatás and Mihov, 2012). The first step in the country-specific exercises that the CGS members conducted involved regressing the MPI on the most common variables that are considered when making macroprudential decisions, such as GDP growth, the credit cycle, and financial stress.[10]

$$\Delta^{(16)}MPI_t = MPI_t - MPI_{t-16} = \alpha + \sum_{i=1}^{3}\left(\beta_{1,i}\Delta^{(16)}GDP_{t-i} + \beta_{2,i}stress_{t-i} + \beta_{3,i}SRI_{t-i}\right) + u_t$$

[9] Limits on credit growth and volume is a different category as it targets institutions rather than households. See Table 5 in Olszak, M., Godlewski, C.J., Roszkowska S. and Skala, D. (2023), "Macroprudential policy tightening, loan loss provisioning and income smoothing: empirical evidence from European Economic Area banks", Working Papers of LaRGE Research Center, 2023-02, Laboratoire de Recherche en Gestion et Economie (LaRGE), Université de Strasbourg, March.

[10] For robustness we ran the regressions with four different type of stress indicators – VIX, Vstoxx, CLIFS, and CISS.

where MPI is either the capital-based MPI, the borrower-based MPI or the aggregate MPI; GDP stands for real gross domestic product; $stress$ takes the value of the CLIFS indicator, while the SRI is the systemic risk indicator.

The CGS examined the expected reactions of the macroprudential policy to the business and financial cycle indicators and assessed how comparable those are among macroprudential authorities. Expected interactions between the business and financial cycles with the macroprudential measures are drawn from the ultimate objective of macroprudential policy, which is to contribute to financial stability by counteracting the build-up of systemic risks. In that sense, a tightening of macroprudential policy (+) would follow an upswing in the business and the credit cycle and a loosening (-) upon risk materialisation (increased stress). For illustrative purposes, Table 4 summarises the type of sign that is expected when "purging" the MPI of the effects of the macro-financial aspects.

Table 4

Expected signs of the independent variables during the stage of obtaining non-systematic policy shocks

Independent variable	Expected sign
lagged GDP	+
lagged stress indicator	-
lagged SRI	+

Source: Contact Group on Macroprudential Stance.

We define the long-run propensities as: $\beta_\ell = \beta_{\ell,1} + \beta_{\ell,2} + \beta_{\ell,2},\ \ell = 1{,}2{,}3$ and test the following hypothesis using the F-test.

H_0: $\beta_{\ell,1} = \beta_{\ell,2} = \beta_{\ell,2} = 0$, for $\ell = 1{,}2{,}3$ against the alternative

H_1: $\beta_{\ell,i} \neq 0$, for at least one i=1,2,3 for each $\ell = 1{,}2{,}3$

The country-specific preliminary results show an interaction between macroprudential policy and the observed variables measuring the real and financial cycles three quarters earlier. Results among countries vary somewhat, which can be attributed to the length of the observed sample and also to the different variables to which the macroprudential policy reacts. In the case of Slovenia and Greece, the policy seems to react to the real cycle (as measured by real GDP growth). Notably, the Greek macroprudential authority seems to adhere even more so to the dynamics of the credit cycle (as measured by the country's SRI). Ultimately, macroprudential reactions can also be advised by the level of systemic stress present in the financial sector. In this sense, authorities either prioritise building buffers when the economy is performing well or tighten policy as and when they observe a build-up of vulnerabilities in the financial system with the upswing of the credit cycle. The results of the three F-tests for Slovenia and Greece are shown in Table 5 and are only illustrative of the chosen approach to obtain macroprudential policy shocks for their inclusion in further analyses.

Table 5
Obtaining non-systematic policy components of the MPI

	SI	GR
GDP β_1	20.09 (0.004)	36.98 (0.055)
$stress_{t-1}$ β_2	16.08 (0.007)	12.01 (0.627)
SRI_{t-1} β_3	-2.74 (0.000)	5.65 (0.004)
n	81	38
R^2	**0.77**	**0.31**

Source: Contact Group on Macroprudential Stance.
Notes: The values shown in parentheses are the p-values of the three F-tests: GDP, stress and SRI. The samples cover the period from the third quarter of 2000 to the fourth quarter of 2022 for Slovenia, and from the third quarter of 2012 to the fourth quarter of 2022 for Greece, but with two outliers. The regression uses the variables transformed into 16-quarter differences. The results shown in the table are from the regression where CLIFS was used as a stress variable, although comparable results are obtained when using the CISS indicator for the euro area).

1.5 The GaR stance metric

The CGS discussed refinements of the median-to-tail distance (MTD). The GaR approach proposes the MTD as a measure of macroprudential stance. However, the operationalisation of this metric needs further refinement. After the conditional GDP growth quantile regressions at the median and the 10th percentile were estimated, the computation of their distance was found to be a desirable measure of the macroprudential stance (see ESRB, 2021; Suarez, 2022). The MTD has the advantage of focusing on the importance of risks embedded in the lower tail of the growth distribution relative to its median. In particular, low MTD implies reduced downside risks relative to expected growth, which would indicate a tight stance. Meanwhile, high MTD indicates large downside risks relative to central tendency, and consequently a loose macroprudential stance. Although variations in this distance provide evidence on the direction of stance, the MTD does not by itself provide guidance on the level of stance that could be compared for individual countries and across them. In this regard, ESRB (2021) proposes to compute the MTD after purging fixed effects in the model. Thus, the MTD measure is expressed as its deviation from its long-run distance, which is represented by the fixed effects. Although this provides a metric capable of recognising country-specific MTD references, it also comes with certain constraints.

Deviations from the reference long-term MTD differ widely across countries. Differences in the dispersion of the MTD over the cycle hinder the task of comparing levels of stance between countries, and lead to the stance being over or under-estimated for some countries. In particular, in countries with high MTD variation, the range of deviations from the long-run reference MTD over the cycle can be several times larger than in countries with low MTD variation. This may pose difficulties when comparing stance across countries, because it may systematically under or over-estimate the level of the macroprudential stance for a given country. In this context, a straightforward solution would be to compute percentiles based on historical country-specific MTD values, which would result in consistent and comparable stance levels across countries.[11]

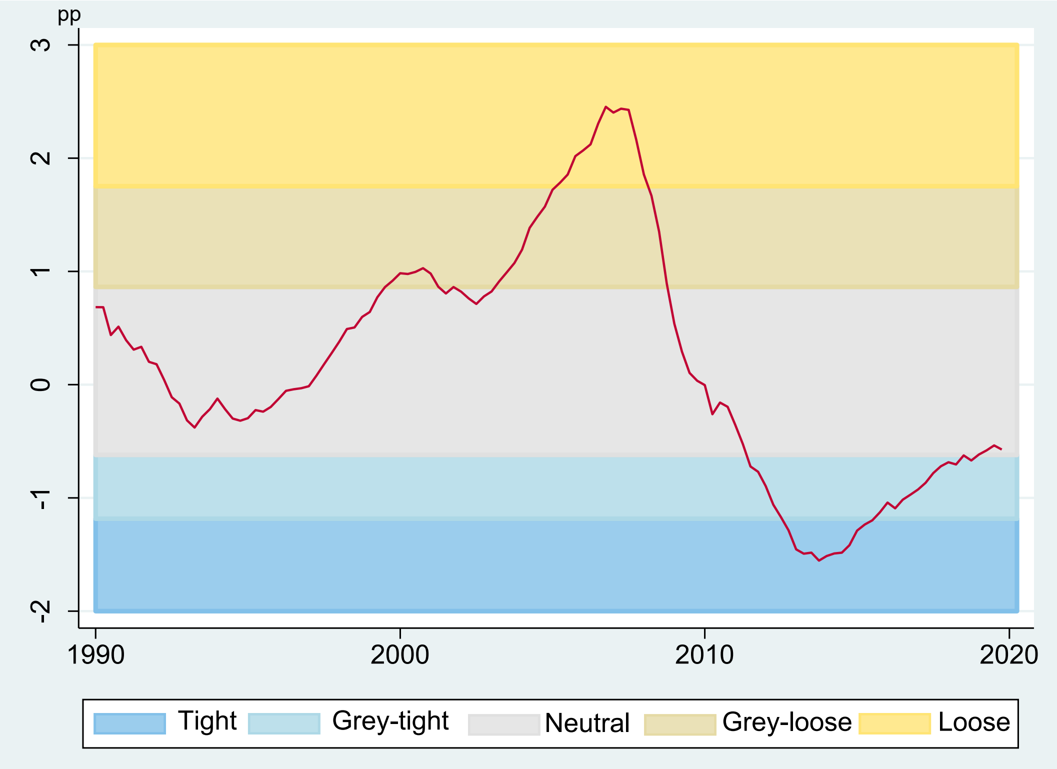
Given the uncertainty surrounding point estimates of the MTD and the lack of previous references on MTD values that could be associated with different stance levels, providing a metric defined as a range of values is more desirable. Aside from the comparability issues, in the current GaR approach, the stance can be classified into just two levels: loose or tight. This fails to recognise uncertainty around point estimates of the MTD and does not allow a neutral zone. In this context, using thresholds would allow us to devise a classification of the stance associated with ranges within certain thresholds, while also accounting for uncertainty around point estimates. The ranges may include a neutral zone around a zero MTD deviation from the long-run reference, as well as stance levels that are distinguished by the intensity of any corresponding tightness or looseness.

In line with the indicator-based approach, grey zones for the stance assessment would prevent too abrupt a change in the stance assessment. The indicator-based approach, allows five classification levels (loose, grey-loose, neutral, tight and grey-tight). This does not only account for uncertainty around MTD values, but also ensures a smoother transition towards different stance levels. These levels can also be associated with ranges based on percentiles of the country-specific historical distribution of the MTD. Chart 8 presents an example of the stance classification for one country. The example uses the same classification as the indicator-based approach. More precisely, the stance would be classified into one of five categories that reflect the intensity of the tightness or looseness of policy stance and include a neutral stance category around the long-run MTD reference.

[11] While this could also be done by pooling the MTD estimates, it would not solve the problem associated with the heterogeneity of this metric between countries. In particular, in countries where the MTD estimates have low variability, certain percentile ranges would hardly be reached, causing those countries to have a very low probability of presenting a loose or a tight stance. Conversely, in countries with a large dispersion of MTD values, the stance would always be over-estimated, resulting in a very low probability of it being around a neutral zone.

Chart 8
Stance classification based on the MTD

(pp)



Source: Contact Group on Macroprudential Stance.
Notes: The stance classification shown in the example is based on percentiles of the MTD series. The 10th, 30th, 70th and 90th percentiles have been selected as thresholds.

The stance verbalisation requires sufficient observations to be able to compute thresholds in a robust way, which would ideally include a complete financial cycle. It is worth noting that setting reliable thresholds based on percentiles of distributions of historical stance values requires as many observations as possible. More precisely, stance estimations over a complete financial cycle would be needed to reduce biases towards the phase of the cycle with available data. However, only around half of the countries included in the sample currently meet this requirement. Thus, the lack of data for long periods of time on some variables included in the model pre-empts carrying out these calculations for a relevant group of countries. This happens to be the main reason frustrating the computation of these thresholds using the stance estimations under the proposed model. However, if and when more data becomes available and the challenges associated with historical data are overcome, the proposed classification could be made operational for more countries.

2 Indicator-based approaches

The indicator-based approaches allow an intuitive comparison of risks, resilience and policy. There is an approach for BBM for residential real estate risks and an approach for CBM. Both approaches assess stance relating to the underlying macroprudential instruments (BBM or CBM) and are based on broadly accessible and available (for all countries) standard indicators. As such, the indicator-based approach allows an assessment of stance that is easy to communicate to audiences such as financial sector experts, academia, economic journalists, the general public and also policymakers. Note also that indicator-based approaches are not model-based.

A country's stance assessment evaluates the risk-resilience policy situation of a country relative to other countries. The indicator-based approach pools all data across time and across countries. Therefore, the stance of a country is derived relative to other countries. As information for new quarters is added, the sample with which we compare a given country increases, though not significantly.[12] Hence, changes in a country stance from one quarter to the next are driven almost entirely by changes in the country itself.[13]

Table 6 compares the issues that were identified under ESRB (2021) and shows how the CGS addresses them. The main changes are the standardisation methodology, a simplified approach for BBM, how new observations are included, and the thresholds for verbalised stance.

[12] In the calculations performed in this report, the whole sample is used to evaluate the stance at every point, so as to avoid using a small sample for the initial quarters. Thus, the stance at, say, the first quarter of 2017 is relative to the whole sample from the first quarter of 2016 to the third quarter of 2022. Moving forward, data pertaining to new quarters will affect only the stance assessments of new quarters (i.e. the stance at the fourth quarter of 2023 will be based on the sample from the first quarter of 2016 to the fourth quarter of 2023, while the stance at the fourth quarter of 2024 will be based on the sample from the first quarter of 2016 to the fourth quarter of 2024). For this reason, adding a new quarter will increase the sample size by one over the number of quarters previously included, which is no more than 1/31 (1/27 for BBM, where the initial sample considered here is the first quarter of 2016 to the third quarter of 2021).

[13] Since there is only a relatively small increase in the sample when a new quarter is added, the change in the stance of a country from one quarter to the next will by driven mostly by changes in the country itself. If it is considered desirable to compute the change in stance driven exclusively by changes in the country itself, this can be calculated by excluding the updates for the other countries from the comparison sample.

Table 6

Improvements to the indicator-based approaches

Issue	Specification in ESRB (2021)	Specification by CGS
Indicator standardisation	Bucketing.	Cumulative distribution function (CDF) approach.
Assessments change abruptly	Few discrete levels, based on thresholds, to describe the range of risk, resilience, policy.	Indicator values are comparable within the indicator set without losing their continuous properties.
Assessment changes with new observations	All assessments change if percentile-based thresholds change with new observations.	Pseudo-real-time approach – past assessments are fixed.
End-level problem	Further increases in risk/resilience/policy effects are not represented if their assessment is already in the highest bucket.	Further risk/resilience/policy effects are represented on the continuous scale.
Complex methodology and decomposition of BBM stance	The stance is the weighted sum of two sub-segments (value and income-based). Not all inputs into the final stance are additive, and bucketing is applied at different levels. This complicates stance decomposition.	A simplified approach similar to that used for CBM is used. All components of the stance are additive and decomposition of the stance is straightforward.
Final stance difficult to explain	Percentile-based bucketing of indicators, their subsequent aggregation and a further bucketing of the final stance.	Simple weighted sum of all CDF-transformed indicators.
Thresholds for verbalised assessment are somewhat arbitrary and not symmetric	The range of the overall stance indicator is divided on the basis of expert judgement.	Percentiles of a fixed sample (Q1 2016-Q3 2021 for BBM; Q1 2016-Q3 2022 for CBM).

Source: Contact Group on Macroprudential Stance.

In ESRB (2021) the indicator-based approaches for both BBM and CBM used a bucketing transformation for the standardisation of each indicator/component. This concept involved bucketing observations for each indicator into a four-level scale, based on the indicator distribution percentiles across time and across countries. The three main drawbacks of bucketing are (i) the relative dearth of levels to assess risk/resilience/policy indicators, which could lead to an abrupt change in the assessment if indicators were close to a threshold, with the potential to induce/increase volatility in the stance metric; (ii) further increases in risk/resilience/policy are not captured if the indicator is already in the highest bucket; and (iii) it is relatively complicated to explain. A further concern with the bucketing approach is that, as thresholds are based on the entire historical indicator distribution and only four buckets are defined, new observations that change the distribution can also lead to a review of the buckets and possibly significant reviews of previous assessments.

The BBM approach was based on a complex aggregation methodology. Complexity comes from the definition of two sub-segments (value- and income-based), a multiplicative term for systemic importance/spillovers and the application of bucketing at different levels. Therefore, the task of decomposing final stance into components was not straightforward and nor was it easy to communicate the drivers of the assessment.

The thresholds for verbalisation of the stance were based on expert judgement. The output of the approach is a number for the overall stance. To convert the number into a verbalised stance, thresholds were defined. They were based on expert judgement and are not symmetric.

Old stance assessments are frozen when a new quarter is added. The stance framework is a cross-country-cross-time comparison. Therefore, past stance assessments could change with hindsight when new quarters are added, the reason being that the distribution changes. From a policy perspective, past stance assessments reflect the stance at that time and should not be "overwritten" when new information becomes available (the new information is reflected in the most recent assessment).

2.1 Benefits of the cumulative distribution function

In the previous report, the indicator-based approaches for both BBM and CBM used a bucketing transformation for the standardisation of each indicator/component. This involved, for each indicator, bucketing observations into a four-level scale, based on distribution percentiles of the indicator across time and across countries (the 70th, 80th and 90th percentiles of the pooled distribution) and on thresholds defined in previous work[14].

To standardise the indicators, the group introduced an approach based on the cumulative distribution function (CDF) instead of (discrete) bucketing. Raw indicators are standardised by transforming the values of each indicator into the corresponding value of their empirical CDF, as in Holló, Kremer and Lo Duca (2012). This implies the computation of order statistics of each indicator x_t as follows:

$$z_t = \begin{cases} \frac{r}{n} \; for \; x_{[r]} \leq x_t < x_{[r+1]}, \quad r = 1,2,\dots,n-1 \\ 1 \; for \; x_t \geq x_{[n]} \end{cases} \tag{1}$$

for $t = 1,2,\dots,n$.

In this way, for all indicators each observation is assigned a value of between 0 and 1, indicating its position in the overall distribution and it is no longer necessary to rescale indicators through the use of discrete buckets.

The "real-time" version, where this same standardisation is done recursively over expanding samples, will be used in the future.[15] The benefits of this standardisation are its robustness to new observations, which yields a more detailed understanding of risk/resilience/policy at each time period. Both features (CDF and "real time") mitigate the reclassification of past stance assessments.

[14] In the case of BBM, a main reference point for the thresholds was the work carried out by the ESRB Working Group on Real Estate Methodologies (WG-REM).

[15] As noted above, in the calculations performed in this report we use the whole sample from the beginning (the stance of, say, the first quarter of 2017 is evaluated by comparing it with the entire sample from the first quarter of 2016 to the third quarter of 2022), so as to avoid using a very small sample for the initial quarters.

2.2 Indicator-based approach for capital-based measures

2.2.1 Modification of the Resilience measure for CBM stance

In the Resilience measure, capital is replaced by own funds. In ESRB (2021), Resilience was defined as capital minus combined buffer requirements (CBR), scaled by banking sector assets. CBR are subtracted to avoid double-counting, as CBR also enter the Policy variable. Initially, the definition of resilience relied on the time series of capital, which is a component of total equity. Since capital does not contain retained earnings, which was considered an important component of banks' resilience, the group decided to choose a broader definition. Therefore, total equity was used to calculate CBM for the 2022 internal ESRB report on cyclical risks across countries. Total equity (as capital) is more an accounting/balance sheet concept than a measure used for regulatory reporting purposes. The CGS investigated the series available for all countries and decided to use own funds. The advantages of own funds over capital are that firstly, own funds series comes from a regulatory reporting concept and secondly, own funds series are rather more stable over time. Moreover, using own funds is consistent with CBR, as both measures are prudential concepts, in contrast to total equity and capital. Table 7 provides the definitions of capital and own funds and gives some further details on the relative time series. Meanwhile, Chart 9 shows the time series for capital and own funds for selected countries. The time series of own funds appears less volatile and more stable over time compared to capital measures. For example, the capital series for Germany and Portugal display a break in late 2018, while own funds appear to remain stable across the period considered. The advantage of using own funds ahead of capital becomes clear if we look at the French series. The capital series peaks in mid-2016 and displays a break in late 2020, while the own funds series remains stable at all times over the time period considered.

Table 7

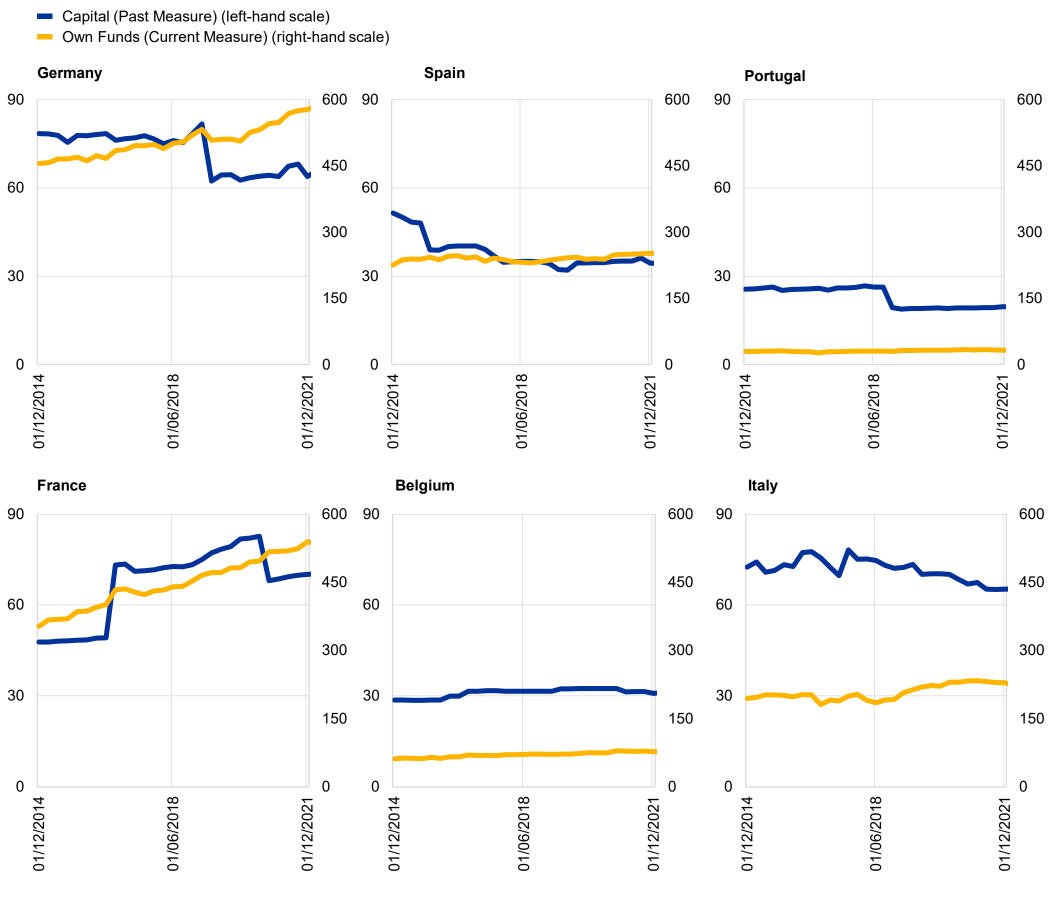
Definition of capital (past measure) and own funds (revised measure)

Row	Capital: FINREP Table F01.03	Row	Own funds: COREP Table C.01
0010	Capital	0010	OWN FUNDS
0020	Paid up capital	0015	TIER 1 CAPITAL
0030	Unpaid capital which has been called up	0020	COMMON EQUITY TIER 1 CAPITAL
0040	Share premium	0030	Capital instruments eligible as CET1 Capital
0050	Equity instruments issued other than capital	0130	Retained earnings
0060	Equity component of compound financial instruments		….
0070	Other equity instruments issued	0530	ADDITIONAL TIER 1 CAPITAL
0080	Other equity	0750	TIER 2 CAPITAL
0090	Accumulated other comprehensive income		
0095	Items that will not be reclassified to profit or loss		
0128	Items that may be reclassified to profit or loss		
0190	Retained earnings		
0200	Revaluation reserves		
0210	Other reserves		
0240	(-) Treasury shares		
0250	Profit or loss attributable to owners of the parent		
0260	(-) Interim dividends		
0270	Minority interests [Non-controlling interests]		
0300	TOTAL EQUITY		
0310	TOTAL EQUITY AND TOTAL LIABILITIES		

Sources: Contact Group on Macroprudential Stance, ECB Statistical Data Warehouse (SDW), consolidated banking data (CBD).
Notes: The capital definition is taken from FINREP (balance sheet statement: equity, Table F 01.03, row 010, column 010) while own funds are defined based on COREP (prudential requirements, Table C 01.00, row 010, column 010). The SDW code for capital is CBD2.A.?.W0.67._Z._Z.A.I.LE110._X.ALL.CA._Z.LE._T.EUR, whereas the code for own funds is CBD2.A.?.W0.67._Z._Z.A.A.O0000._X.ALL.CM._Z.LE._T.EUR.

Chart 9
Comparison between capital (past measure) and own funds (revised measure) for selected countries

(EUR billions)



Sources: Contact Group on Macroprudential Stance, ECB Statistical Data Warehouse (SDW), consolidated banking data (CBD).

Box 1 in the Annexes section of this report shows the results when Resilience is scaled by risk-weighted assets (RWA) rather than total banking sector assets. The results are presented as a robustness check for information purposes. The CGS decided to stick to scaling by banking sector assets. This follows the reasoning of ESRB (2021): as policymakers vary their risk weights, scaling by RWA would introduce a direct effect of policies upon Resilience.

2.2.2 Revised thresholds for CBM stance

The overall CBM stance indicator is mapped into a verbalised stance assessment. This provides a clear interpretation for policymakers and helps to assess the variation of stance across time and across countries. The verbalised assessment has five zones: tight, grey-tight, neutral, grey-loose and loose. The two grey zones prevent excessive oscillation between loose and tight to neutral. They can also be interpreted as warning signs, in the sense that policymakers might want to take action to avoid falling into a tight or loose assessment. The mapping is defined on the basis of thresholds computed as percentiles of the overall CBM stance indicator. The sample ranges from the first quarter of 2016 to the third quarter of 2022. All countries are pooled, and there are no country-specific thresholds. The numerical thresholds corresponding to these percentiles are then fixed, so that the thresholds are the same for subsequent assessments. The percentiles chosen are the 10th, 30th, 70th and 90th.[16] In this way, the verbalised stance has a clear and direct interpretation. For example, a loose verbalised assessment corresponds to a stance looser than 90% of all observations in the sample from the first quarter of 2016 to the third quarter of 2022. A grey-loose assessment is looser than 70%, but tighter than 10% of all assessments. Note that the resulting stance metric is ordinal rather than cardinal.[17]

The thresholds may be re-evaluated in the future, particularly if developments have materially affected the indicator distributions. The sample period is still short relative to the average length of financial cycles. New observations will be added to the sample approximately twice a year. In a threshold re-evaluation, an immediate option would be to use the same percentiles as described above for the extended sample.

2.2.3 Comparison with results under the ESRB (2021) methodology

The revised approach yields a more principle-based threshold definition and more directly interpretable verbalised assessments. In ESRB (2021) thresholds were chosen based on expert judgement and lacked tight-loose symmetry and a clear interpretation.[18] The revised approach makes improvements in both directions and also offers a guide for possible future threshold updates (using the same percentiles but applied to a more up-to-date distribution).

The numerical thresholds used in ESRB (2021) lead to the 7th, 17th, 80th and 80th percentiles for CBM.[19] For BBM, they are the 14th, 46th, 81st and 82nd percentiles. We could obtain thresholds that are the same for CBM and BBM by averaging the respective percentiles over the two approaches. Symmetry between loose and tight could be achieved by averaging the interval lengths (in percentile space) of the tight and loose zones as well as both grey zones. This procedure would lead to thresholds that deviate the least from those of the previous assessment, while also obtaining symmetry. The thresholds under this alternative approach are the 15th, 26th, 75th and 86th percentiles, which are relatively close to the 10th, 30th, 70th and 90th proposed

16 The 10th, 30th, 70th and 90th percentiles lead to the following thresholds for tight, grey-tight, neutral and grey-loose: -1.03, -0.612, -0.299 and -0.075.

17 The approach is similar to the one used in other-cross country analyses where heat maps and summary indicators are defined. This choice of approach is also motivated by the fact that is difficult to identify appropriate thresholds independently from the distribution. Moreover, most available time series are short, especially for some countries, making country-specific thresholds difficult to calculate.

18 Symmetry occurs where the loose zone has the same size as the tight zone, and where the grey-loose zone is equal in size to the grey-tight zone. Zones size can be measured in the range of the percentiles, or in percentile space. Here we ensure that the thresholds are the same in percentile space, so that, in the initial sample, we have the same number of country-quarters in loose as in tight, and in grey-loose as in grey-tight.

19 When the ESRB (2021) methodology is applied to the updated data, there are zero observations in the grey-loose zone, so the grey-loose and loose zones are both bounded by the 80th percentile.

here. We favour this latter proposal because the numerical values are simpler. Also, larger grey zones can lead to more stable assessments over time, as well as provide earlier warning signals when the stance is starting to become too loose or too tight.

The overall results for the verbalised CBM assessment are similar to those obtained under the ESRB (2021) methodology. Table 8 below compares the overall stance obtained under the revised formulation of the CBM approach with the results obtained by applying the ESRB (2021) methodology to the updated dataset.

Table 8

CBM transition matrix comparing the revised verbalised assessment with that obtained using the ESRB (2021) methodology

		CDF approach (current)					
		Loose	Grey-loose	Neutral	Grey-tight	Tight	
Bucketing approach (ESRB 2021)	Loose	59	66	39	1		165
	Grey-loose						0
	Neutral	16	83	252	112	10	473
	Grey-tight		1	11	37	11	60
	Tight					54	54
	Total	75	150	302	150	75	752

Source: Contact Group on Macroprudential Stance.
Notes: Each cell indicates the number of country-quarters where the verbalised assessment using the ESRB (2021) methodology is as indicated in the first column and the verbalised assessment proposed in this document is as indicated in the first row. Green cells correspond to matching verbalised assessments under the two approaches, yellow cells to verbalised assessments differing by one zone, red cells to assessments differing by two zones, and brown cells to assessments differing by three zones.

In 53% of the observations the two approaches yield the same verbalised stance level (sum of the green cells divided by the total). In 38% of cases, the verbalised assessment differs by one zone (of those, 73% lie between neutral and grey-loose or grey-tight), while in 9% of cases, the difference is two zones (tight or loose to neutral). In a single case (0.1%) the difference is three zones. Since the overall population of the zones has changed notably, and is now more symmetric, these differences are to be expected. Importantly, the share of grey-loose observations increases from 0% to 20%, of which a majority (55%) were classified as neutral under the previous approach. The absence of grey-loose observations in the initial assessment called for the thresholds to be adjusted to cover the full spectrum of verbalised assessments and avoid abrupt changes between the neutral and loose zones. The fact that in only 9% of the cases is the change more than one zone indicates that the changes are largely limited.

Table 9 below displays the heat map of the stance assessment for all countries considered in the first quarter of 2016 to the third quarter of 2022 period. The results are similar to those achieved using the ESRB (2021) methodology, which is included for reference in the annexes section of this report. However, the verbalised assessment is now smoother: changes from quarter to quarter are now limited to a single zone (with one exception: LU from the first quarter of 2016 to the second quarter of 2016), while the ESRB (2021) approach yields several direct changes from neutral to tight or loose without entering the grey zones.

Table 9
CBM heat map

	2016				2017				2018				2019			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
BE			0.14	0.09	0.05	0.07	0.02	-0.08	-0.23	-0.25	-0.27	-0.35	-0.31	-0.29	-0.26	-0.35
BG	-1.24	-1.25	-1.24	-1.18	-1.18	-1.19	-1.37	-1.33	-1.29	-1.27	-1.20	-1.20	-1.16	-1.24	-1.20	-1.18
CZ	-0.41	-0.47	-0.41	-0.48	-0.39	-0.40	-0.40	-0.44	-0.40	-0.37	-0.43	-0.49	-0.48	-0.51	-0.54	-0.60
DK	0.02	0.02	0.02	-0.07	-0.07	-0.14	-0.16	-0.19	-0.36	-0.32	-0.33	-0.44	-0.55	-0.53	-0.53	-0.58
DE	-0.17	-0.18	-0.20	-0.21	-0.21	-0.24	-0.26	-0.29	-0.33	-0.35	-0.34	-0.36	-0.47	-0.44	-0.42	-0.49
EE	-1.19	-1.14	-1.21	-1.18	-1.24	-1.26	-1.26	-1.24	-1.27	-1.31	-1.42	-1.40	-1.34	-1.36	-1.32	-1.36
IE	-0.70	-0.72	-0.72	-0.75	-0.78	-0.70	-0.71	-0.70	-0.85	-0.93	-0.93	-0.95	-0.98	-0.81	-1.01	-0.84
GR	-0.50	-0.54	-0.54	-0.53	-0.58	-0.60	-0.64	-0.64	-0.73	-0.72	-0.67	-0.61	-0.62	-0.67	-0.67	-0.71
ES	-0.18	-0.19	-0.23	-0.20	-0.22	-0.20	-0.25	-0.22	-0.18	-0.17	-0.16	-0.18	-0.31	-0.31	-0.32	-0.34
FR	0.30	0.35	0.30	0.19	0.19	0.18	0.19	0.14	0.11	0.12	0.14	0.04	-0.09	-0.08	-0.04	-0.15
HR	-0.83	-0.82	-0.80	-0.83	-0.86	-1.52	-1.46	-1.52	-1.52	-1.48	-1.43	-1.44	-1.42	-1.44	-1.43	-1.53
IT	-0.27	-0.30	-0.32	-0.19	-0.23	-0.27	-0.33	-0.34	-0.34	-0.28	-0.29	-0.30	-0.35	-0.38	-0.37	-0.43
CY	-0.49	-0.56	-0.60	-0.57	-0.56	-0.49	-0.49	-0.48	-0.50	-0.48	-0.40	-0.37	-0.59	-0.55	-0.61	-0.68
LV	-0.52	-0.49	-0.53	-0.56	-0.52	-0.65	-0.80	-0.74	-0.82	-1.01	-1.09	-1.10	-0.96	-0.84	-0.86	-0.87
LT	-0.22	-0.20	-0.15	-0.43	-0.51	-0.51	-0.67	-0.61	-0.82	-0.74	-0.76	-0.79	-0.47	-0.53	-0.55	-0.54
LU	-0.92	0.01	0.01	-0.07	-0.14	-0.07	-0.07	-0.08	-0.07	0.03	-0.05	0.04	0.02	-0.08	-0.07	0.10
HU	-0.40	-0.40	-0.35	-0.39	-0.35	-0.29	-0.21	-0.13	-0.36	-0.33	-0.30	-0.42	-0.57	-0.62	-0.60	-0.68
MT		-0.02	0.04	0.07	0.03	0.00	0.00	-0.05	-0.21	-0.26	-0.26	-0.37	-0.58	-0.58	-0.53	-0.59
NL	0.03	0.00	-0.07	-0.16	-0.22	-0.27	-0.25	-0.23	-0.44	-0.47	-0.47	-0.54	-0.69	-0.70	-0.71	-0.78
AT	-0.30	-0.36	-0.40	-0.38	-0.34	-0.39	-0.35	-0.38	-0.40	-0.41	-0.36	-0.40	-0.63	-0.64	-0.63	-0.67
PL	-0.48	-0.52	-0.51	-0.53	-0.54	-0.54	-0.58	-0.59	-1.01	-1.03	-1.05	-0.97	-1.00	-1.01	-1.00	-1.05
PT	-0.27	-0.25	-0.26	-0.19	-0.26	-0.30	-0.29	-0.30	-0.36	-0.36	-0.34	-0.30	-0.37	-0.35	-0.36	-0.37
RO	-0.50	-0.48	-0.43	-0.46	-0.47	-0.49	-0.47	-0.50	-0.52	-0.69	-0.68	-0.71	-0.86	-0.85	-0.82	-0.93
SI	-0.64	-0.64	-0.64	-0.61	-0.63	-0.62	-0.61	-0.61	-0.70	-0.72	-0.65	-0.67	-0.78	-0.77	-0.79	-0.82
SK	-0.13	-0.12	-0.11	-0.10	-0.40	-0.43	-0.48	-0.50	-0.49	-0.52	-0.56	-0.55	-0.60	-0.61	-0.59	-0.60
FI	-0.12	-0.13	-0.14	-0.21	-0.21	-0.23	-0.25	-0.28	-0.11	-0.07	-0.05	-0.13	-0.29	-0.31	-0.41	-0.44
SE	-0.35	-0.37	-0.36	-0.40	-0.37	-0.39	-0.38	-0.45	-0.47	-0.48	-0.49	-0.49	-0.48		-0.53	-0.57
NO	-0.33	-0.30	-0.34	-0.44	-0.38	-0.42	-0.47	-0.51	-0.57	-0.45	-0.57	-0.53	-0.50	-0.48	-0.51	-0.70

	2020				2021				2022		
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3
BE	-0.30	-0.17	-0.21	-0.25	-0.19	-0.20	-0.25	-0.26	-0.21	-0.37	-0.38
BG	-1.24	-1.39	-1.31	-1.25	-1.20	-1.23	-1.24	-1.24	-1.20	-1.23	-1.19
CZ	-0.59	-0.57	-0.58	-0.66	-0.50	-0.53	-0.42	-0.42	-0.24	-0.20	-0.25
DK	-0.42	-0.40	-0.34	-0.32	-0.30	-0.36	-0.39	-0.50	-0.49	-0.61	-0.71
DE	-0.38	-0.33	-0.33	-0.29	-0.20	-0.28	-0.25	-0.26	-0.24	-0.28	-0.23
EE	-1.37	-1.12	-1.06	-0.93	-0.90	-0.88	-0.90	-0.76	-0.91	-0.96	-0.98
IE	-0.62	-0.53	-0.69	-0.96	-1.02	-1.03	-1.07	-1.13	-1.05	-1.06	-0.99
GR	-0.67	-0.44	-0.33	-0.31	-0.20	-0.04	-0.01	-0.03	-0.02	-0.20	-0.32
ES	-0.25	0.02	0.02	-0.01	0.03	-0.01	-0.03	-0.03	-0.06	-0.19	-0.23
FR	-0.02	0.07	0.07	0.00	0.03	0.01	0.01	-0.05	-0.02	-0.10	-0.09
HR	-1.48	-1.40	-1.02	-1.03	-1.03	-1.02	-1.33	-1.45	-1.31	-1.40	-1.33
IT	-0.42	-0.30	-0.29	-0.26	-0.24	-0.24	-0.23	-0.20	-0.24	-0.33	-0.36
CY	-0.76	-0.54	-0.48	-0.36	-0.30	-0.27	-0.28	-0.28	-0.31	-0.53	-0.63
LV	-0.99	-0.85	-0.82	-0.90	-0.86	-0.82	-0.72	-0.49	-0.82	-0.56	-0.58
LT	-0.66	-0.51	-0.47	-0.42	-0.46	-0.41	-0.38	-0.33	-0.31	-0.20	-0.19
LU	0.22	0.19	0.13	-0.04	-0.08	-0.16	-0.15	-0.08	-0.06	-0.06	-0.04
HU	-0.58	-0.53	-0.31	-0.26	-0.28	-0.28	-0.19	-0.25	-0.24	-0.26	-0.24
MT	-0.60	-0.37	-0.34	-0.34	-0.32	-0.31	-0.34	-0.31	-0.30	-0.34	-0.39
NL	-0.62	-0.56	-0.54	-0.54	-0.43	-0.46	-0.42	-0.48	-0.45	-0.48	-0.48
AT	-0.64	-0.50	-0.54	-0.54	-0.47	-0.49	-0.48	-0.50	-0.45	-0.52	-0.55
PL	-0.61	-0.56	-0.63	-0.64	-0.63	-0.54	-0.49	-0.46	-0.42	-0.44	-0.41
PT	-0.39	-0.22	-0.19	-0.20	-0.15	-0.15	-0.12	-0.09	-0.13	-0.24	-0.28
RO	-0.82	-0.84	-0.82	-0.90	-0.82	-0.77	-0.71	-0.62	-0.64	-0.67	-0.64
SI	-0.77	-0.76	-0.81	-0.77	-0.73	-0.75	-0.77	-0.72	-0.67	-0.68	-0.67
SK	-0.63	-0.61	-0.59	-0.60	-0.54	-0.52	-0.46	-0.41	-0.40	-0.39	-0.36
FI	-0.32	-0.14	-0.11	-0.18	-0.11	-0.14	-0.15	-0.17	-0.20	-0.22	-0.27
SE	-0.34	-0.23	-0.28	-0.34	-0.31	-0.32	-0.33	-0.35	-0.35	-0.46	-0.54
NO	-0.57	-0.64	-0.65	-0.68	-0.60	-0.60	-0.67	-0.77	-0.79	-0.78	-0.87

Source: Contact Group on Macroprudential Stance.
Notes: The numbers show the numerical stance assessment for the corresponding country-quarter. Colours indicate the

verbalised assessment: orange corresponds to loose, light orange to grey-loose, white to neutral, light blue to grey-tight and blue to tight.. The upper bounds of the verbalised assessment zones are -1.03, -0.612, -0.299 and -0.075.

2.3 Indicator-based approach for borrower-based measures

2.3.1 Revised stance measure for BBM

The revised BBM stance metric uses a streamlined aggregation methodology. The first change is to reduce the number of standardisation steps to (i) improve levels of transparency, (ii) make the decomposition into main drivers easier to understand, and (iii) provide a stance equation similar to the one used for CBM. In ESRB (2021), four-level buckets are used first to standardise the initial variables and then to standardise residual risks for the value-based and income-based segments. However, this makes the relationship between the initial input variables and the final indicator less transparent. In the revised approach, only the input variables are standardised. Their aggregation across the risk, resilience and policy dimensions mirrors the approach used for the CBM stance. The second revision is that the systemic/spillover component enters the equation additively, instead of multiplicatively, thus allowing the final stance to be decomposed into the contributions from risk, resilience and policy, again similar to the CBM approach. A drawback of the multiplicative specification used in ESRB (2021) was that this decomposition was too complex. A consequence of the additive form is that a country with low risk and high spillover term has a non-zero Risk component. Even so, the CGS considered the simpler decomposition as the most desirable feature and, in order to reduce the impact of the spillover component on total risk, a lower weight is assigned to it with respect to the risk component. The third revision is to assign equal weights to the risk, resilience and policy variables of the value-based and income-based segments. The differentiated weights in the initial approach lack empirical grounding and may impede readability. These improvements ultimately make it easier to communicate results to policymakers.

The equation for the BBM overall stance indicator is:

$$STANCE_{RRE}^{BBM} = Risk - Resilience - Policy \tag{2}$$

$Risk$ is an average of risks associated with the value-based segment (R1), the income-based segment (R2) and spillovers (S):

Risks in the value-based segment: R1= $\frac{C1+C2+C3+C4}{4}$ (3)

Risks in the income-based segment: R2= $\frac{F1+F2+F3}{3}$ (4)

Spillover risks: S= $\frac{S1+S2+S3}{3}$ (5)

where the single variables are reported in Table 10.

$Risk$ is defined as:

$$Risk = 0.8 * \left(\frac{R1 + R2}{2}\right) + 0.2 * S \quad (6)$$

A smaller weight is assigned to the S component in order to limit the impact of the spillover dimension on the Risk component.

$Resilience$ is an average of the resilience indicators identified in ESRB (2021) for both the value-based (C5) and income-based segments (H1, H2), i.e. $Resilience = 0.5C5 + 0.5\left(\frac{H1+H2}{2}\right)$[20].

The $Policy$ indicator is a simple average of the defined effects of loan-to-value (LTV) and debt-service-to-income (DSTI) limits as in the initial approach. These two variables are scaled linearly to map the effects identified in the initial bucketing approach. More specifically, for the LTV limit, ESRB (2021) identified a minimal policy effect for an LTV limit above 100% (i.e. bucket value equal to 0.5). The maximal effect was for an LTV limit below 80% (bucket value equal to 3). In the revised approach, these effects (P1) are mapped using the following system:

$$P1 = \begin{cases} -4 * \mathrm{LTV} + 4.2 \;\; if \; 0.8 \le \mathrm{LTV} \le 1 \\ 0.2 \; if \; LTV > 1 \\ 1 \; else \end{cases} \quad (7)$$

Where the LTV limit is lower than 0.8, the policy is considered tight and the maximum value of policy is assigned to the country. Conversely, for an LTV limit greater than 1, a minimum policy value of 0.2 is assigned. If there is no policy limit, a value of 0 is assigned.

Similarly, the effect of DSTI limits (P2) is defined using:

$$P2 = \begin{cases} -4 * \mathrm{DSTI} + 2.2 \; if \; 0.3 \le \mathrm{DSTI} \le 0.5 \\ 0.2 \; if \; 0.5 < \mathrm{DSTI} \\ 1 \; else \end{cases} \quad (8)$$

[20] In the standardisation of C5, H1 and H2 we assign to each of them one minus the corresponding percentile, so that lower values of LTI, DTI and DSTI correspond to higher resilience.

Table 10
Risk and resilience indicators

Collateral (C)	Funding (F)	Household (H)	Systemic importance/spillovers (S)
C1 **RRE price growth**	**F1** Mortgage credit growth	**H1** HH sector DTI	**S1** Housing investment-to-GDP
C2 **RRE price gap**	**F2** Mortgage credit-to-GDP ratio	**H2** HH sector DSR	**S2** Bank exposure to RRE in relation to capital
C3 **Price-to-income ratio**	**F3** HH credit-to-GDP gap		**S3** Bank exposure to construction in relation to capital
C4 **Price-to-rent ratio**			
C5 **LTV (observed on the market)**			

Source: ESRB (2021).
Note: Blue denotes risk indicators. Green denotes resilience indicators. Red denotes risk amplification indicators. RRE: residential real estate; LTV: loan-to-value ratio; HH: xxx; DTI: debt-to-income ratio; DSR: debt service ratio.

2.3.2 Revised thresholds for BBM stance

The overall BBM stance indicator is mapped into a verbalised stance assessment. The procedure mirrors the CBM approach, in that the numerical thresholds are calculated in the overall BBM stance indicator corresponding to the 10th, 30th, 70th and 90th percentiles. As more observations are now available than under ESRB (2021), the numerical thresholds for BBM are based on the sample from the first quarter of 2016 to the third quarter of 2021.[21]

2.3.3 Decomposition

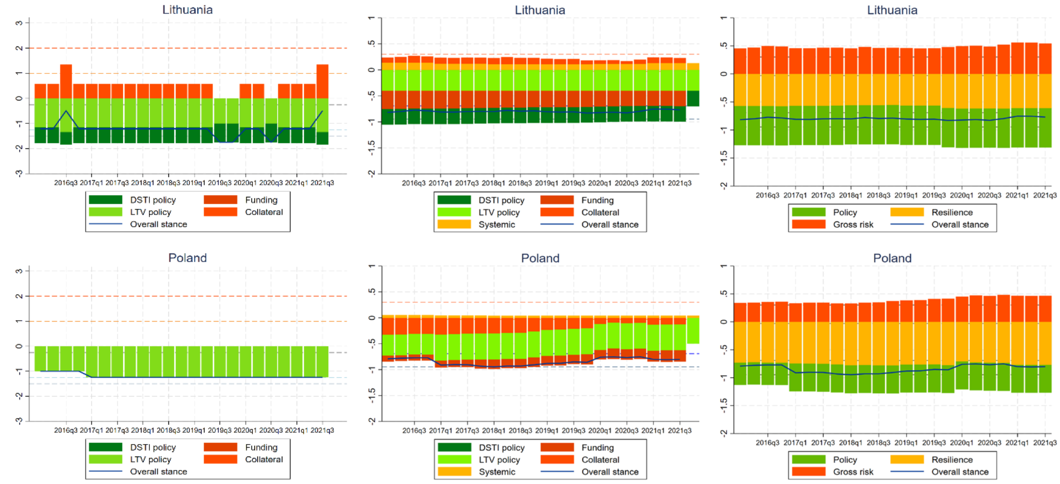
The revised BBM stance metric allows a simpler decomposition into its component drivers. As the overall BBM assessment is now calculated using simply the formula of Risk – Resilience – Policy, as in the case of CBM, a decomposition into these components is straightforward. In regard to the overall stance, the change in the components can be seen to be smoother and more gradual (see Chart 10, right panels). Only significant policy changes introduce sharper modifications in the corresponding component. While the risk and resilience components seem less volatile, clear trending can be observed in various cases. Compared with ESRB (2021), the revision introduces the Systemic/Spillover component additively, hence its relatively stable contribution to the calculation across time periods can be shown a further stacked column section on the bar charts (compare the left panels with the middle panels of Chart 10). We can also observe an increased contribution from the resilience variables due to the changes made to the stance calculation, and in some cases it outweighs the funding and collateral components in the risk type decomposition (see

[21] The values corresponding to the 10th, 30th, 70th and 90th percentiles are -0.947, -0.692, -0.0306 and 0.301.

the funding and collateral components in the negative range in the middle panels of Chart 10). Under the proposed new approach, the components are always present to some degree, thus avoiding the issue where certain components are entirely absent under the bucketing approach. Lastly, note, that below the level of the overall stance, it should not be expected that the sum of the components of the two different types of decomposition of the revision equals a component of the other type; rather, they capture different perspectives on breaking down the stance measurements.

Chart 10

Decomposition of BBM stance by component and calculation method, for selected countries



Source: Contact Group on Macroprudential Stance.
Note: Left: Decomposition by funding and collateral risk minus resilience and corresponding policy calculated using ESRB (2021) methodology; Middle: Decomposition by funding and collateral risk minus resilience and corresponding policy calculated using the revised method; Right: Decomposition by risk, resilience and policy calculated using the revised method. Note that where the blue line representing the overall stance is not illustrated, certain data are missing for the calculation.

2.3.4 Comparison with results using the ESRB (2021) methodology

The overall results for the verbalised BBM assessment are similar to those obtained using the ESRB (2021) methodology. Table 11 compares the revised overall BBM stance with the results obtained by applying the ESRB (2021) methodology to the updated dataset.

Table 11
BBM transition matrix comparing the revised verbalised assessment with that obtained using the ESRB (2021) methodology

		CDF approach (current)					
		Loose	**Grey-loose**	**Neutral**	**Grey-tight**	**Tight**	**Total**
Bucketing approach (ESRB 2021)	Loose	41	36	20			97
	Grey-loose	2	4				6
	Neutral	10	66	98	10		184
	Grey-tight			93	73	1	167
	Tight			1	23	52	76
	Total	**53**	**106**	**212**	**106**	**53**	**530**

Source: Contact Group on Macroprudential Stance.
Notes: Each cell indicates the number of country-quarters where the verbalised assessment obtained using the ESRB (2021)

methodology is as indicated in the first column and the verbalised assessment proposed in this document is as indicated in the first row. Green cells correspond to matching verbalised assessments under the two approaches, yellow cells to verbalised assessments differing by one zone, and red cells to verbalised assessments differing by two zones.

In 51% of the observations, the two approaches yield the same verbalised stance zone. In 44% of cases, the verbalised assessment differs by one zone, while in 6%, the difference is of two zones (tight or loose to neutral).[22] Since the overall population of the levels has changed notably, and is now more symmetric, these differences are to be expected. The fact that in only 6% of the cases is the change more than one zone indicates that the changes are largely limited. Further information on comparing the results of the revised approach with respect to the results published in ESRB (2021) can be found in Annex 2 of this report (Tables A4 and A5).

Table 12 below displays the heat map of the stance assessment for all countries considered in the period from the first quarter of 2016 to the third quarter of 2021. The results are similar to those achieved using the ESRB (2021) methodology, which is included for reference in Annex 2 (Table A3). However, the verbalised assessment is now smoother: changes from quarter to quarter are now always limited to a single zone, while the ESRB (2021) approach yields several direct changes from neutral to tight or loose without entering the grey zones.

[22] The difference versus 100% is due to rounding.

Table 12
BBM heat map

	2016				2017				2018			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
BE												
BG					-0.35	-0.33	-0.32	-0.33	-0.18	-0.16	-0.16	-0.12
CZ	-0.42	-0.41	-0.39	-0.35	-0.44	-0.63	-0.62	-0.63	-0.66	-0.64	-0.63	-0.84
DK	0.05	0.05	0.07	0.06	0.10	0.11	0.11	0.10	0.07	0.07	0.06	0.05
DE	0.14	0.15	0.17	0.17	0.20	0.21	0.22	0.22	0.28	0.29	0.30	0.31
EE	-0.67	-0.65	-0.63	-0.62	-0.59	-0.63	-0.59	-0.58	-0.55	-0.57	-0.61	-0.59
IE	-1.03	-1.04	-1.03	-1.02	-0.99	-0.98	-0.96	-0.96	-0.97	-0.97	-0.97	-0.97
GR												
ES	-0.10	-0.10	-0.10	-0.10	-0.09	-0.08	-0.07	-0.08	-0.06	-0.05	-0.05	-0.05
FR	0.21	0.20	0.22	0.22	0.25	0.27	0.27	0.28	0.30	0.31	0.32	0.34
HR												
IT	-0.36	-0.36	-0.36	-0.37	-0.34	-0.34	-0.35	-0.35	-0.34	-0.35	-0.35	-0.35
CY												
LV	-0.81	-0.79	-0.78	-0.79	-0.70	-0.68	-0.68	-0.66	-0.58	-0.59	-0.62	-0.61
LT	-0.82	-0.80	-0.77	-0.79	-0.81	-0.81	-0.80	-0.80	-0.80	-0.78	-0.80	-0.79
LU									0.26	0.25	0.26	0.32
HU	-1.18	-1.17	-1.16	-1.16	-1.14	-1.14	-1.13	-1.13	-1.11	-1.10	-1.09	-1.07
MT						0.04	0.05	0.05	0.02	0.04	0.03	0.05
NL	0.30	0.30	0.32	0.36	0.35	0.36	0.38	0.38	0.36	0.36	0.38	0.38
AT												
PL	-0.79	-0.78	-0.77	-0.77	-0.91	-0.90	-0.91	-0.93	-0.95	-0.93	-0.93	-0.91
PT									0.23	0.23	-0.55	-0.54
RO	-0.62	-0.60	-0.61	-0.60	-0.60	-0.57	-0.59	-0.60	-0.50	-0.49	-0.50	-0.51
SI	-0.26	-0.25	-0.23	-0.82	-0.82	-0.78	-0.78	-0.78	-0.83	-0.83	-0.80	-0.80
SK	-0.07	-0.03	0.00	0.04	0.04	-0.04	-0.44	-0.45	-0.48	-0.47	-0.82	-0.81
FI	0.30	0.32	0.02	0.00	-0.02	-0.02	-0.02	-0.02	0.02	0.02	-0.08	-0.09
SE	-0.02	-0.01	-0.01	-0.01	-0.02	-0.02	-0.03	-0.05	-0.06	-0.08	-0.10	-0.11
NO	-0.22	-0.20	-0.17	-0.15	-0.64	-0.65	-0.67	-0.69	-0.69	-0.69	-0.70	-0.72

	2019				2020				2021		
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3
BE					-0.61	-0.56	-0.55	-0.51	-0.55	-0.57	-0.59
BG	-0.03	-0.03	-0.01	0.00	0.00	0.01	0.03	0.05	-0.06	-0.06	-0.04
CZ	-0.82	-0.82	-0.84	-0.87	-0.87	-0.66	-0.40	-0.38	-0.40	-0.39	-0.38
DK	0.04	0.05	0.05	0.04	0.15	0.17	0.19	0.21	0.20	0.20	
DE	0.32	0.33	0.35	0.36	0.38	0.41	0.44	0.46	0.49	0.49	0.50
EE	-0.52	-0.54	-0.51	-0.49	-0.50	-0.44	-0.44	-0.38	-0.36	-0.38	
IE	-0.97	-0.98	-0.99	-1.01	-1.02	-1.02	-1.04	-1.05	-1.12	-1.13	
GR									-0.21	-0.19	-0.20
ES	-0.06	-0.06	-0.06	-0.07	-0.07	-0.02	-0.03	-0.02	-0.03	-0.02	-0.04
FR	0.34	0.35	0.37	0.39	-0.02	0.03	0.06	0.08	0.09	0.08	0.09
HR					0.10	0.15	0.16	0.16	0.16	0.17	
IT	-0.36	-0.35	-0.34	-0.34	-0.32	-0.25	-0.26	-0.24	-0.22	-0.23	-0.23
CY					-0.79	-0.73	-0.75	-0.76	-0.72	-0.73	-0.72
LV	-0.57	-0.57	-0.54	-0.54	-0.35	-0.35	-0.83	-0.83	-0.85	-0.83	-0.80
LT	-0.81	-0.81	-0.81	-0.83	-0.82	-0.81	-0.83	-0.80	-0.75	-0.76	-0.77
LU	0.35	0.37	0.42	0.43	0.41	0.45	0.48	0.48	0.10	0.06	0.05
HU	-1.03	-1.02	-1.02	-1.01	-0.98	-0.95	-0.95	-0.94	-1.00	-0.99	-0.98
MT	0.14	0.17	-0.42	-0.41	-0.47	-0.45	-0.42	-0.38	-0.36	-0.37	-0.37
NL	0.43	0.44	0.43	0.42	0.37	0.39	0.39	0.40	0.37	0.39	0.41
AT					-0.91	-0.86	-0.82	-0.81	-0.80	-0.81	-0.82
PL	-0.88	-0.88	-0.85	-0.86	-0.76	-0.75	-0.77	-0.75	-0.80	-0.81	-0.80
PT	-0.55	-0.55	-0.55	-0.55	-0.54	-0.53	-0.52	-0.50	-0.52	-0.53	-0.51
RO	-0.57	-0.58	-0.56	-0.57	-0.62	-0.62	-0.63	-0.63	-0.58	-0.59	-0.59
SI	-0.97	-0.98	-0.97	-0.97	-0.95	-0.92	-0.92	-0.91	-0.97	-0.97	
SK	-0.92	-0.95	-0.93	-0.94	-0.95	-0.90	-0.89	-0.87	-0.86	-0.48	-0.48
FI	-0.07	-0.07	-0.08	-0.08	-0.07	-0.04	0.08	0.11	0.12	0.12	0.11
SE	-0.13	-0.12	-0.13	-0.14	-0.10	-0.08	-0.06	-0.04	-0.06	-0.06	-0.07
NO	-0.70	-0.69	-0.70	-0.72	-0.71	-0.70	-0.68	-0.66	-0.65	-0.65	-0.68

Source: Contact Group on Macroprudential Stance.
Notes: The numbers show the numerical stance assessment for the corresponding country-quarter. Colours indicate the verbalised assessment: orange corresponds to loose, light orange to grey-loose, white to neutral, light blue to grey-tight and blue to tight. The upper bounds for the zones are -0.947, -0.692, -0.0306 and 0.301.

3 Topics for further work

This section describes topics that the CGS was unable to address, but that might warrant further investigation.

Overall stance

The final stance assessments from all approaches could be combined into an overall stance. Currently the stance framework results in three final stance metrics: GaR, BBM and CBM. Follow-up work could first combine the BBM and CBM stance to create a joint indicator-based approach stance. Next, the GaR stance and the indicator-based stance could be combined to yield an overall stance for each country. For instance, one could test whether the indicator-based stance assessments would be a useful explanatory variable in the quantile regressions.

Stance for the European Union

A stance assessment at EU level could provide a useful benchmark for members to compare their respective positions. Currently there is no framework in place for computing an EU-wide stance. A simple starting point for the indicator-based approach might be a simple average of the numerical stance.

Refinements of the Macroprudential policy index

A further step to intensity measurement can be taken by weighting the CBM. The CGS took a first step by weighting the capital conservation buffer (CCoB) by the phase-in steps. In addition, other buffers could be weighted by their increment. A countercyclical capital buffer (CCyB) increase of 0.25 percentage points could, for example, be weighted as 1/10, taking the 2.5% ceiling for automatic reciprocity as a reference point. An alternative would be to estimate the coefficients of changes, rather than assigning +1 / 0 / +1.

Buffer shortfall to arrive at neutral stance

A back-of-the-envelope calculation could yield the buffer change that is needed to arrive at a neutral stance. The CBM indicator-based approach reveals how much risk is not covered by resilience and policy measures. However, if the stance is loose, it is unclear by how much CBM would need to be tightened to result in a neutral stance.

This calculation could be designed as a ceteris paribus analysis where the indicators of all other countries are kept equal. The effect of changing the CBR in a single country could thereby be isolated.

Incorporation of country-specific data

Further work could be carried out to explore how to incorporate more country-specific data that are not available and/or relevant for all countries. Currently there are certain constraints when attempting to incorporate country-specific series in the models. Given the heterogeneity of countries and differences in structural features, exploring ways to adjust the model to these circumstances would improve the fit and explanatory power of the approaches. One option might be to investigate whether differentiating between country regions (Western Europe, Central Eastern Europe, etc.) would improve the fit of the models. For instance, not all countries experienced financial deepening to the same extent.

Isolation of country-specific drivers of stance assessments

Future work could explore the merits of isolating country-specific drivers of stance assessments. One option would be to investigate whether changes in the stance for a given country are driven by changes in its own risks and policies (i.e. its own data) or reflect a change in its relative position compared with other countries. For instance, one idea would be to keep the observations for all countries (except the country under investigation) constant from one quarter to another, and to use “real” observations of that country for assessing its stance. This approach would isolate the effect of the change in that country’s risk and policy positions in the resulting stance. However, the country would still be assessed on the basis of the pooled distribution across countries as a reference for standardisation. The use of reliable country-specific distributions is useful in exploring country-specific aspects. However, owing to data limitation issues, percentile-based thresholds for stance assessments currently hinge on pooled distributions that make use of all available observations.

Further robustness checks

Additional robustness checks might warrant further investigation, while being mindful of data limitations. Although the CGS did perform robustness checks in the most relevant areas, more could be done to improve the framework. This would also consistent with the idea of continuously using and improving the framework. For instance, the BBM indicator-based approach does not yet contain income-based risk indicators, owing to data constraints and a lack of homogenous definitions across countries. For the GaR approach, for example, different ways to compute GDP growth rates and their impact on the results could be explored.

Policy use of the GaR approach

Next steps for making the GaR approach fit for policy use include further investigation into thresholds and verbalised assessments. Section 1.5 of this report describes how thresholds might be defined to classify a country’s net stance. The GaR approach does not currently have verbalised final stance assessments as available inputs for the indicator-based approach (loose/neutral/tight and grey zones). Deriving those is more challenging under the GaR approach owing to increased heterogeneity in the data across countries and the short time series involved.

Therefore, further work is needed to expand upon the reflections contained in this report and to establish distribution-based thresholds, similar to the indicator-based approach.

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Annexes

A.1 Overview material

Table A1

Comparison of GaR and indicator-based approach

Growth-at-risk approach	Indicator-based approach
Forward-looking, examines the impact of current macroprudential policy, distinguishing between CBM and BBM, financial conditions (SRI, CLIFS), and past GDP realisations, on future growth distributions.	Looks at current (and past) economic environment.
Fully data-driven results, providing a risk-return-type trade-off between macroprudential policy and future growth that depends on the preferences of policymakers.	Incorporates widely used indicators for risk and resilience. Thresholds for the final stance are based on the empirical distribution.
Looks at the economy on aggregate and produces a country-specific result comparing the current stance assessment with a historical benchmark, using fixed effects.	Distinguishes between borrower-based measures and capital-based measures and does not look at the economy on aggregate. It functions on a relative scale, and evaluates the risk-resilience-policy position of a country compared with the current and past period values of other countries and itself.
Answers the questions: “How high is the uncertainty regarding the possible materialisation of a left tail event in the real GDP growth distribution?” and “To what extent do current financial conditions contribute to this this uncertainty?” [Uncertainty is measured as the distance between expected growth and left tail.]	Answers the question: “To what extent are a country’s risks covered by resilience and policy compared with the other countries in the sample?”

Source: Contact Group on Macroprudential Stance.

A.2 Additional material for the indicator-based approach

Heat maps from ESRB (2021)

Table A2

CBM approach under ESRB (2021)

	2016				2017				2018				2019			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
BE			1	1	1	1	1	2	0	1	1	1	0	0	0	0
BG	-4	-4	-4	-4	-4	-4	-4	-4	-5	-4	-2	-5	-5	-4	-4	-4
CZ	-1	-2	-2	-2	-1	-1	-2	-2	-2	-1	-2	-2	-2	-2	-3	-3
DK	0	0	0	0	0	0	0	0	-1	0	0	-1	-1	-1	-2	-2
DE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EE	-3	-3	-4	-4	-4	-4	-3	-3	-3	-4	-5	-5	-5	-5	-5	-5
IE	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-2
GR	0	-1	-2	-2	-2	-2	-2	-3	-1	-1	-1	-1	-1	-1	-1	-1
ES	-1	-1	-1	-1	-1	0	0	0	0	0	0	0	0	0	0	0
FR	1	2	1	1	1	1	1	1	1	1	1	1	0	0	0	0
HR	-3	-3	-3	-3	-3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
IT	0	0	-1	0	0	0	-1	-1	0	0	0	0	0	0	0	0
CY	-2	-2	-2	-1	0	0	0	0	0	1	1	1	1	1	1	0
LV	-1	-1	-1	-1	-1	0	-1	-2	-1	-3	-4	-4	-2	-2	-2	-2
LT	0	0	2	-1	0	0	-1	-1	-2	-1	-1	-2	-1	-2	-2	-2
LU	-1	2	2	-1	0	0	2	2	2	2	2	2	2	0	0	2
HU	-1	-2	-2	-2	0	0	-1	-1	0	0	0	0	-1	-1	-1	-1
MT		0	1	1	1	1	1	0	1	1	1	0	0	0	0	-1
NL	1	1	1	0	0	0	0	0	-1	-1	-1	-1	-2	-2	-2	-2
AT	-1	-1	-1	-1	-1	-1	0	0	0	0	0	0	-1	-1	-1	-2
PL	-1	-2	-2	-2	-2	-1	-2	-2	-1	-2	-2	-2	-2	-3	-3	-3
PT	-1	-1	-1	-1	-2	-3	-3	-3	-1	-1	-1	-1	-1	-1	-1	-1
RO	-2	-2	-2	-2	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1
SI	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-2	-2	-2	-2
SK	1	1	1	1	1	1	1	1	1	1	1	-2	-2	-2	-2	-2

	2016				2017				2018				2019			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
FI	1	1	1	1	0	0	0	0	-1	0	1	1	0	0	-1	-1
SE	-1	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-3	-3		-3	-3
NO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	2020				2021				2022		
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3
BE	0	0	0	0	0	0	0	0	0	-1	-1
BG	-4	-5	-4	-3	-3	-3	-3	-4	-4	-4	-4
CZ	-2	-1	0	0	0	0	1	1	1	1	2
DK	-1	-1	-1	0	0	0	0	-1	-1	-1	-2
DE	0	0	1	1	1	1	1	1	1	0	0
EE	-5	-4	-2	-1	0	0	-1	0	-1	-2	-2
IE	0	0	0	-2	-2	-2	-2	-2	-2	-2	-2
GR	0	3	3	3	3	3	3	3	3	2	1
ES	0	1	1	3	3	3	1	1	1	0	0
FR	0	2	2	2	2	2	2	2	2	0	0
HR	-4	-4	-1	-1	-1	-1	-4	-4	-5	-4	-3
IT	0	1	1	1	1	1	1	1	1	0	0
CY	1	1	2	3	3	3	2	2	2	0	0
LV	-2	-2	-2	-2	-2	-2	-1	0	-2	-1	-1
LT	-2	-1	-1	-1	-1	-1	-1	1	1	1	1
LU	3	3	3	2	2	0	0	2	0	0	0
HU	-1	1	0	2	2	2	2	2	2	2	2
MT	-1	0	1	1	1	1	1	0	1	1	0
NL	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
AT	-1	-1	-1	-2	1	0	0	0	1	0	-1
PL	-1	0	-1	-1	-1	-1	-1	0	0	0	0
PT	-1	0	0	2	2	2	2	2	1	1	0
RO	-1	-1	-1	-1	-1	-2	-1	0	0	-1	-1
SI	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

	2020				2021				2022		
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3
SK	-2	-1	-1	-1	-1	-1	0	0	0	0	0
FI	0	1	1	1	1	1	1	1	1	1	-1
SE	-1	-1	-1	-2	-2	-2	-2	-2	-2	-2	-3
NO	-2	-2	-1	0	0	0	0	-2	-3	-3	-3

Source: Contact Group on Macroprudential Stance. Based on the ESRB (2021) methodology.
Notes: The numbers show the numerical stance assessment for the corresponding country-quarter. Colours indicate the verbalised assessment: orange corresponds to loose, light orange to grey-loose, white to neutral, light blue to grey-tight and blue to tight. The upper bounds of the verbalised assessment zones are -4.00, -2.25, 0.00 and 0.75.

Table A3

BBM approach under ESRB (2021)

	2016				2017				2018			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
BE												
BG					0.00	0.00	0.00	0.00	0.58	0.58	0.58	0.58
CZ	-0.29	-0.29	-0.29	-0.29	-0.75	-1.25	-0.87	-1.25	-0.87	-0.87	-0.87	-1.50
DK	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.01	2.00	2.00
DE	0.58	0.58	0.58	0.58	1.34	1.34	1.34	2.25	2.25	2.25	2.25	2.25
EE	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25	-0.79	-0.79	-1.25	-1.25	-1.25	-1.25
IE	-2.21	-2.21	-2.21	-2.21	-1.75	-1.75	-1.75	-1.75	-2.21	-2.21	-2.21	-2.21
GR												
ES	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
FR	0.00	0.00	0.00	0.00	0.58	0.58	0.58	0.58	0.58	0.58	1.00	1.00
HR												
IT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CY												
LV	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75
LT	-1.21	-1.21	-0.50	-1.21	-1.21	-1.21	-1.21	-1.21	-1.21	-1.21	-1.21	-1.21
LU									1.58	1.00	1.00	1.58
HU	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50
MT						0.58	0.58	0.58	0.58	0.58	0.58	0.58
NL	1.18	1.18	1.18	2.13	2.13	2.13	2.17	2.17	1.75	1.75	1.75	1.75
AT												
PL	-1.00	-1.00	-1.00	-1.00	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25
PT									1.00	1.00	-1.00	-1.00
RO	-1.00	-1.00	-1.00	-1.00	-1.00	-0.58	-0.58	-1.00	-1.00	-1.00	-1.00	-1.00
SI	0.00	0.00	0.00	-1.50	-1.50	-1.50	-1.50	-1.08	-1.08	-1.50	-1.08	-1.08
SK	-0.25	-0.25	-0.25	0.29	0.29	0.08	-1.08	-1.08	-1.08	-1.08	-1.92	-1.16
FI	0.58	0.58	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.26	-0.26
SE	2.00	2.00	2.00	2.00	1.74	1.74	1.74	1.68	2.00	2.00	1.74	1.74
NO	1.75	1.75	1.75	1.75	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50

	2019				2020				2021		
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3
BE					-1.50	-1.00	-1.25	-0.55	-0.55	-0.55	-0.55
BG	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
CZ	-1.50	-1.50	-1.50	-1.50	-0.83	-0.16	0.34	0.34	-0.29	-0.29	-0.29
DK	2.00	2.01	2.01	2.01	2.16	2.50	2.50	2.50	2.50	2.50	
DE	2.25	2.25	2.25	2.25	2.25	2.25	2.25	2.25	2.34	2.25	2.25
EE	-0.79	-0.79	-0.17	-0.17	-0.17	0.63	0.63	0.63	0.63	0.63	
IE	-1.75	-1.75	-1.75	-1.75	-1.75	-2.21	-2.21	-2.21	-2.21	-2.21	
GR									0.58	0.58	0.58
ES	0.00	0.00	0.00	0.00	0.58	0.58	0.58	0.58	0.58	1.00	0.00
FR	1.00	1.00	1.00	1.00	0.53	0.53	0.53	0.53	1.51	1.51	1.51
HR					0.58	0.58	0.58	0.58	0.58	0.58	
IT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CY					-0.76	-0.76	-0.76	-0.76	-0.76	-0.76	-0.76
LV	-0.75	-0.75	-0.75	-0.29	-0.29	-0.29	-1.55	-1.55	-0.65	0.38	0.38
LT	-1.21	-1.21	-1.75	-1.75	-1.21	-1.21	-1.75	-1.21	-1.21	-1.21	-0.50
LU	1.00	1.58	1.58	1.58	1.58	1.58	1.58	1.58	0.71	0.71	0.71
HU	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50	-1.50
MT	1.00	1.00	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50
NL	1.75	2.29	2.29	2.29	2.75	2.75	2.75	2.75	2.29	2.29	2.29
AT					-1.16	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25
PL	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25
PT	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-0.34	-0.34	-0.34	-0.34
RO	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00
SI	-1.50	-1.50	-1.50	-1.50	-1.50	-1.08	-1.50	-1.08	-1.50	-1.50	
SK	-2.50	-2.50	-2.50	-2.50	-1.92	-1.16	-1.92	-1.16	-1.16	-0.50	-0.50
FI	-0.26	-0.26	-0.26	-0.26	-0.26	-0.26	-0.05	-0.05	-0.05	0.25	0.25
SE	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68	2.00	2.00	2.00
NO	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50

Sources: Contact Group on Macroprudential Stance. Based on the ESRB (2021) methodology
Notes: The numbers show the numerical stance assessment for the corresponding country-quarter. Colours indicate the verbalised assessment: orange corresponds to loose, light orange to grey-loose, white to neutral, light blue to grey-tight and blue to tight.. The upper bounds of the verbalised assessment zones are -1.50, -0.50, 1.00 and 1.50.

Box 1

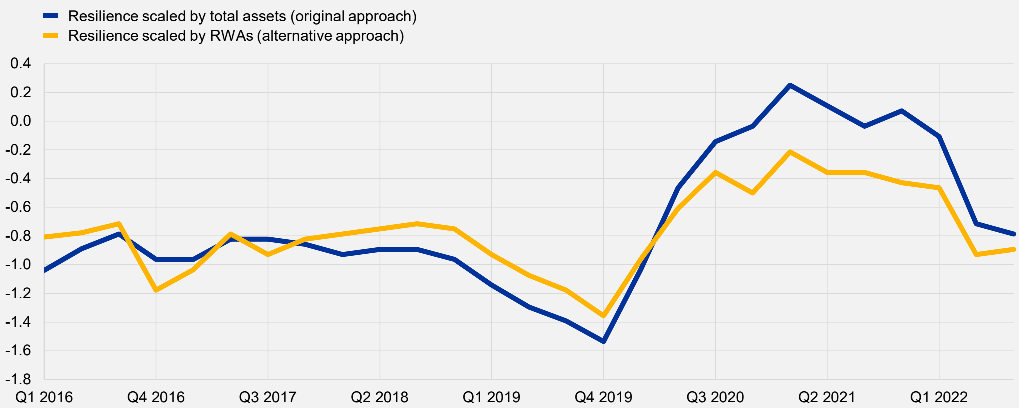
Robustness check: scaling Resilience by RWAs for the CBM stance

This box describes a robustness check for the CBM Resilience metric and explores whether the CBM stance assessment is sensitive to changes in the Resilience metric. We use the same numerator as in ESRB (2021), namely capital net of CBR, but scale by RWAs rather than total banking sector assets. This alternative scaling method offers insights from a prudential perspective based on regulatory reporting data. The level of risks present in banking system assets enters through the risk-weighting of assets. As in Section 2.2.1, capital is measured by looking at own funds. Therefore, the denominator and numerator are consistent, as both stem from the capital adequacy framework. For comparability with ESRB (2021), the check is performed using the bucketing methodology and the corresponding mapping of stance values to verbalised assessments.

The alternative Resilience quantification results in a tighter (i.e. lower numerical) stance on average since the onset of the COVID-19 pandemic (Chart A). For the third quarter of 2022, the stance stands at -0.79 in the original approach, compared with -0.89 under the alternative approach. The results of the alternative approach reflect higher numerical Resilience to the cyclical and structural risks that CBMs address (see Table 11 in ESRB (2021) for a list of those risks).

Chart A

Trend in average CBM numerical stance



Sources: ECB Statistical Data Warehouse and CGS calculations.

As a result of this alternate specification, CBM stance assessments tend to be relatively tighter. Over the past seven years, the number of countries in loose and grey zone loose (tight and grey-tight) stances is slightly lower (higher), compared to the original specification (Table A). Across both specifications, the assessment does not change for 46% of the observations. Moving from original to alternative specification, banking systems in countries with looser (tighter) assessments are characterised by higher (lower) risk-weight density on average, measured as total risk exposures divided by total assets. Hence, elevated risk-weight density appears to be positively associated with tighter assessments under the original approach, which uses a balance sheet-based denominator for Resilience. Overall, the definition of Resilience could be a contributing factor to the observed changes in stance assessments, as deduced in the alternative approach, which hinges on a complete regulatory reporting-based measure.

Table A

Transition matrix

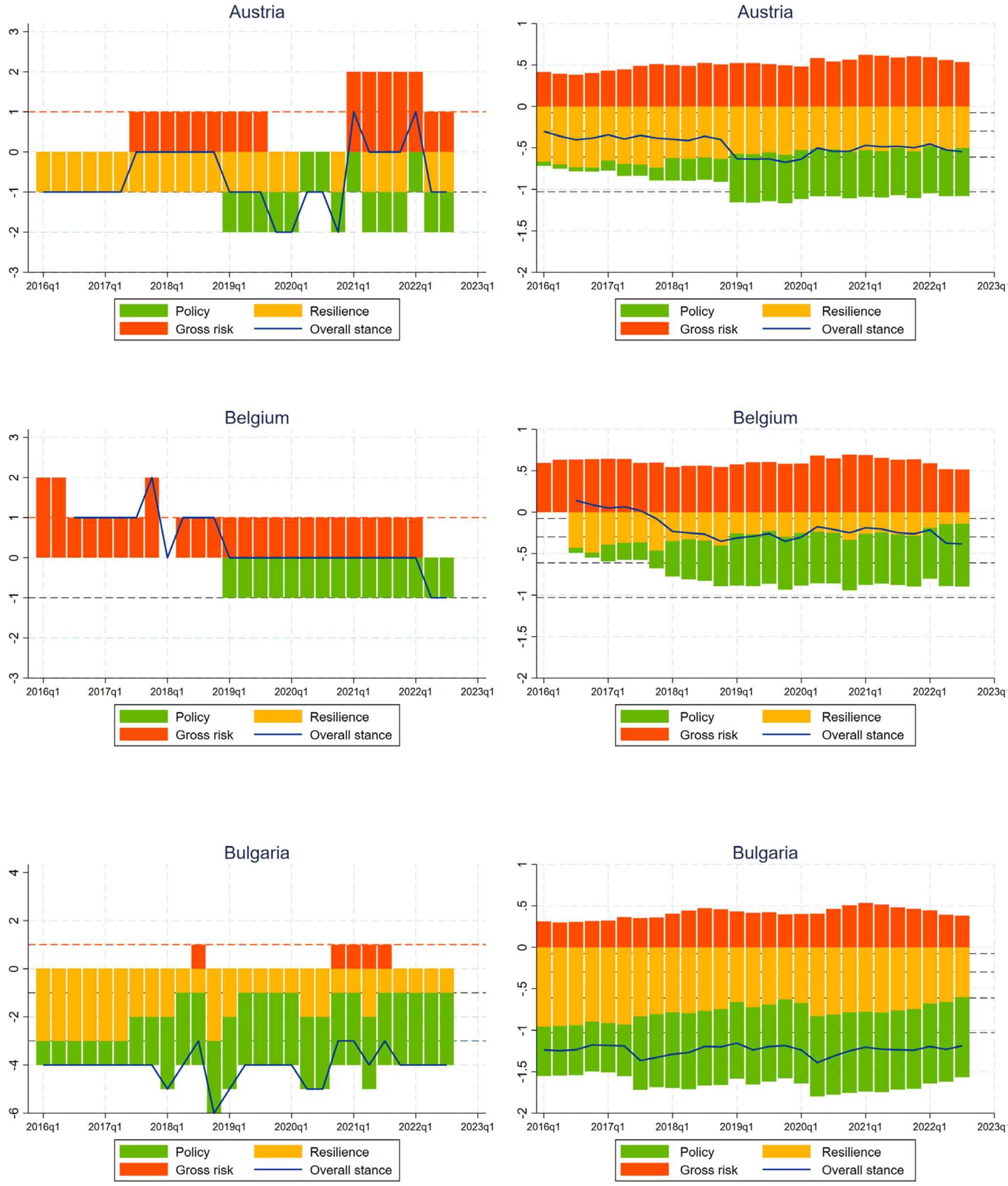
		Alternative approach					
		Tight	(Tight)	Neutral	(Loose)	Loose	Number of countries
Original approach	Tight	0	1	0	0	0	**1**
	(Tight)	0	2	1	0	0	**3**
	Neutral	0	3	8	2	2	**15**
	(Loose)	0	0	4	2	1	**7**
	Loose	0	0	1	0	1	**2**
	Number of countries	**0**	**6**	**14**	**4**	**4**	**28**

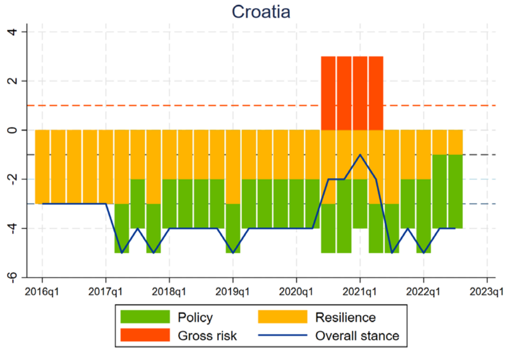
Period: First quarter of 2016 to the third quarter of 2022. Matrix based on verbalised assessments, associated with average numerical stance by country. For further details on the mapping of stance values to verbalised assessments, please refer to Table 12 in ESRB (2021).

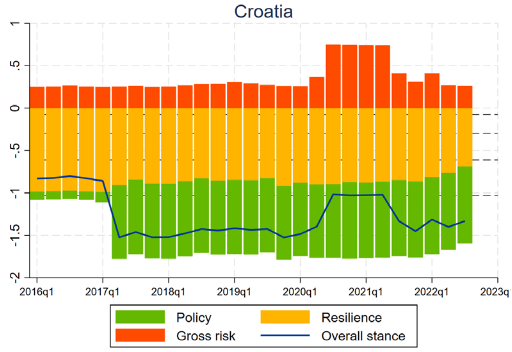
Decomposition charts for CBM approach

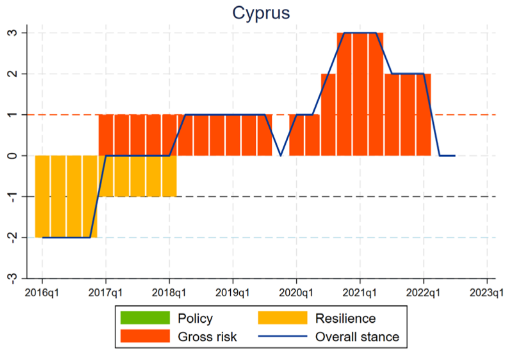
Chart A1

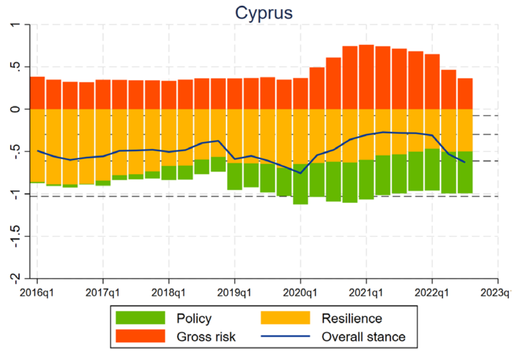
Decomposition of CBM stance by calculation method (left: ESRB (2021); right: revised method), for all countries

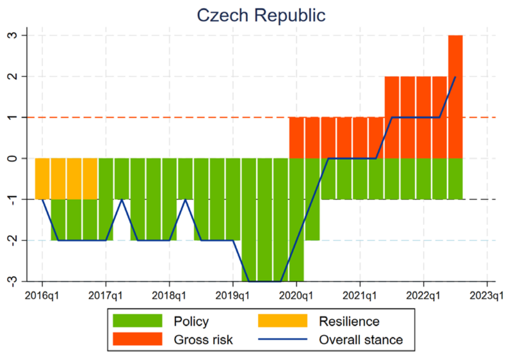


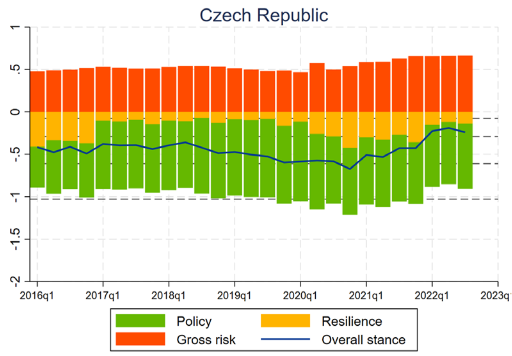

Croatia
Policy
Resilience
Gross risk
Overall stance

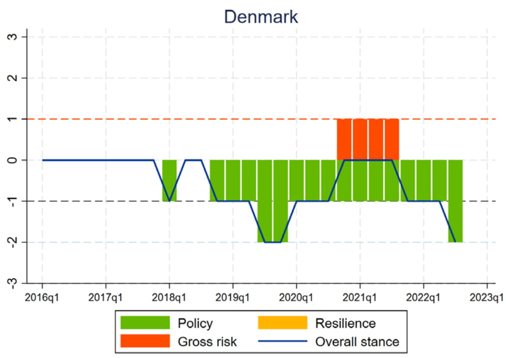

Croatia
Policy
Resilience
Gross risk
Overall stance

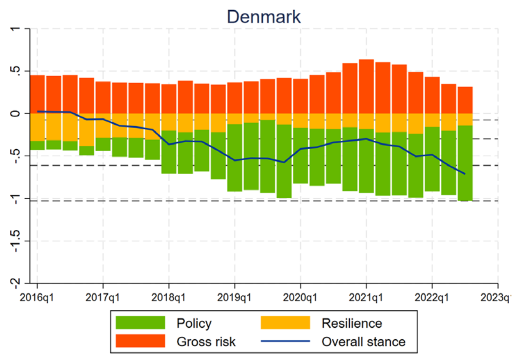

Cyprus
Policy
Resilience
Gross risk
Overall stance

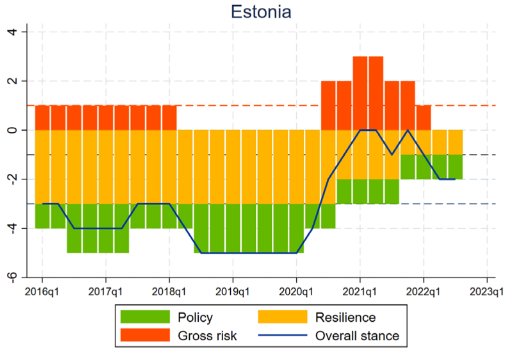

Cyprus
Policy
Resilience
Gross risk
Overall stance

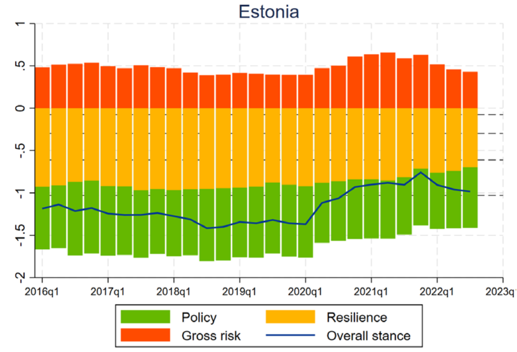

Czech Republic
Policy
Resilience
Gross risk
Overall stance

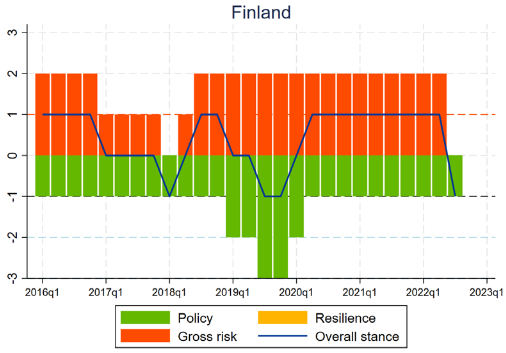

Czech Republic
Policy
Resilience
Gross risk
Overall stance

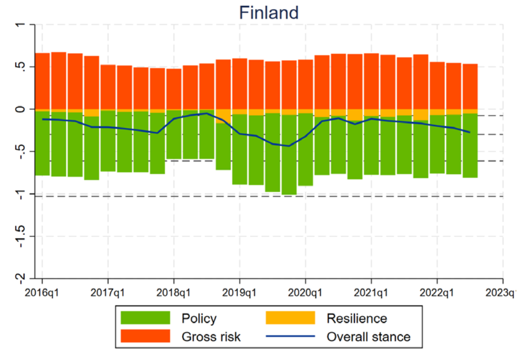

Denmark
Policy
Resilience
Gross risk
Overall stance

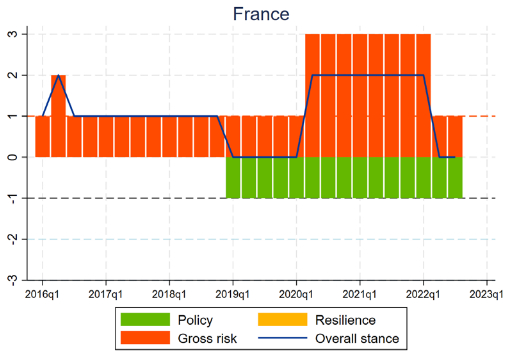

Denmark
Policy
Resilience
Gross risk
Overall stance

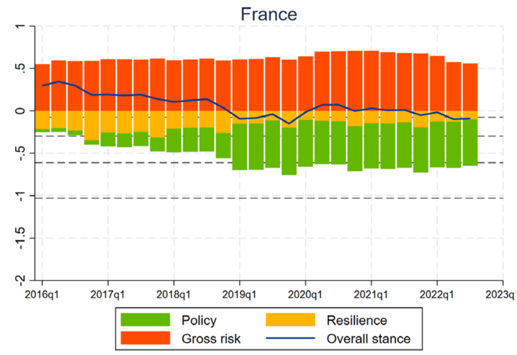

Estonia
Policy
Resilience
Gross risk
Overall stance

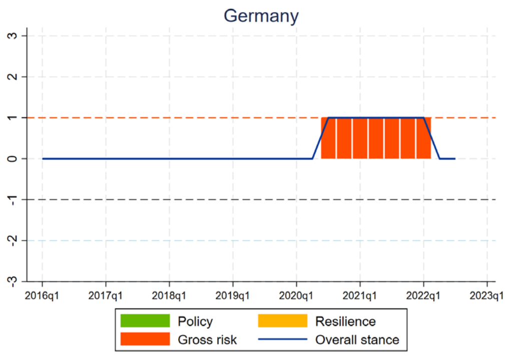

Estonia
Policy
Resilience
Gross risk
Overall stance

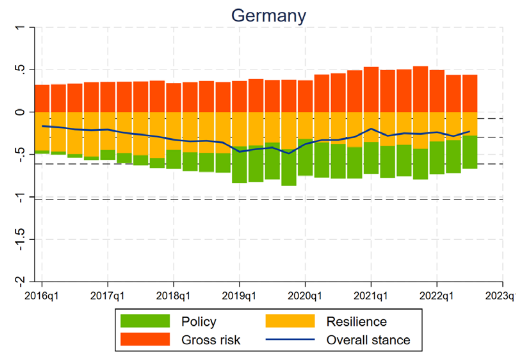

Finland
Policy
Resilience
Gross risk
Overall stance

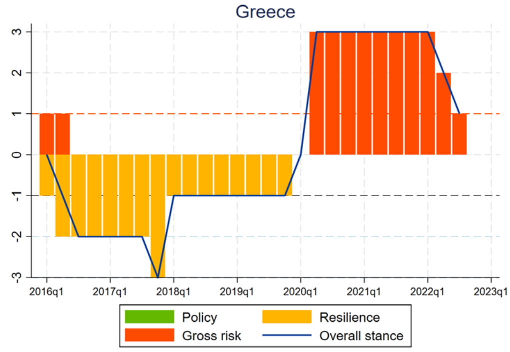

Finland
Policy
Resilience
Gross risk
Overall stance

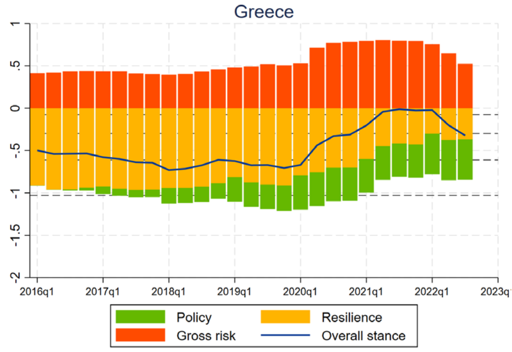

France
Policy
Resilience
Gross risk
Overall stance

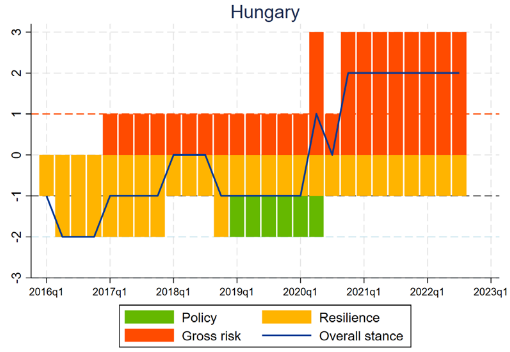

France
Policy
Resilience
Gross risk
Overall stance

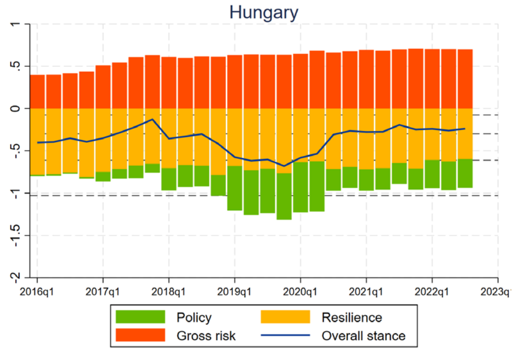

Germany
Policy
Resilience
Gross risk
Overall stance

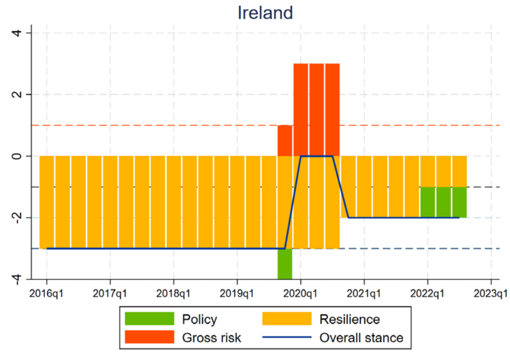

Germany
Policy
Resilience
Gross risk
Overall stance

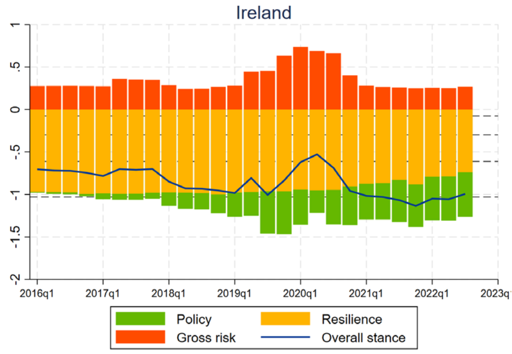

Greece
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

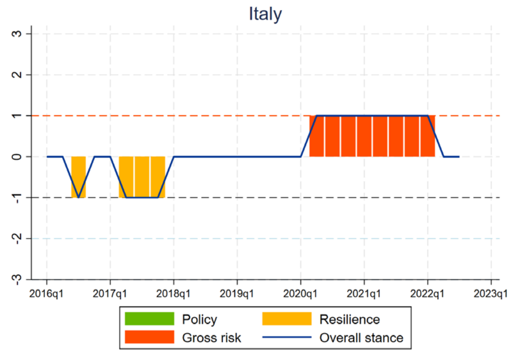

Greece
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

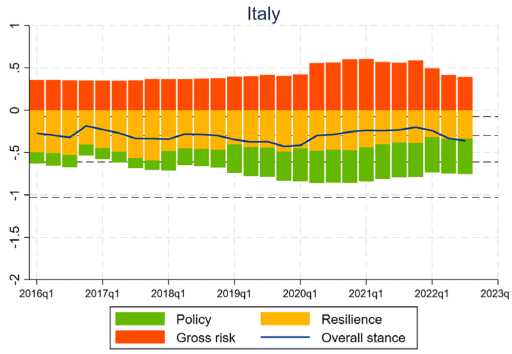

Hungary
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

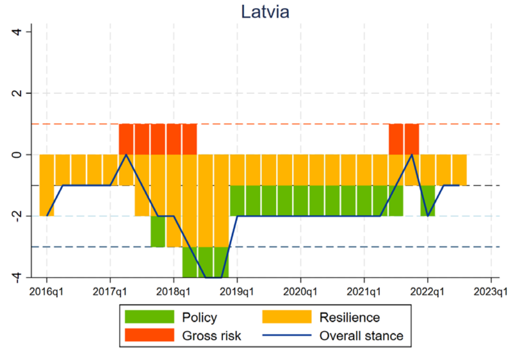

Hungary
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

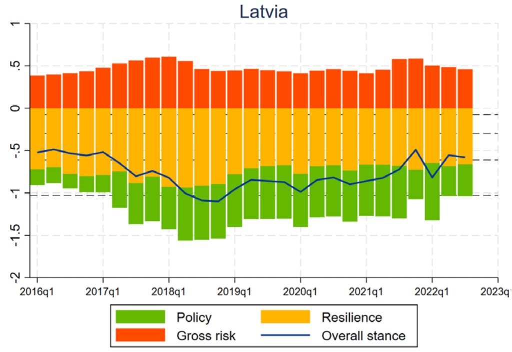

Ireland
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

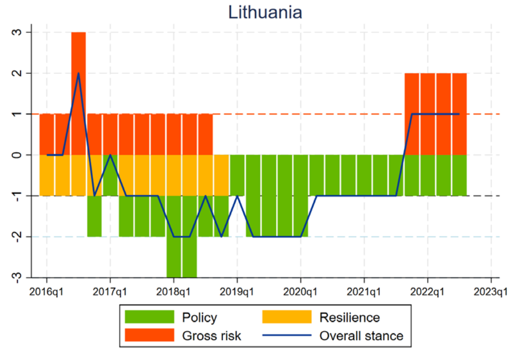

Ireland
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

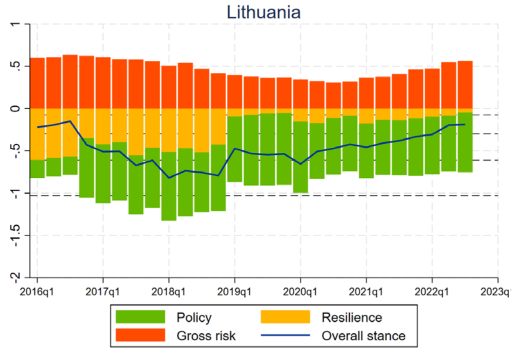

Italy
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

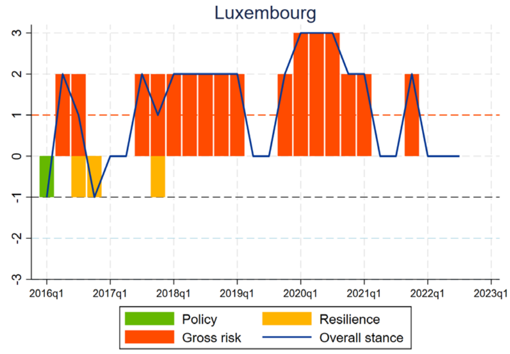

Italy
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

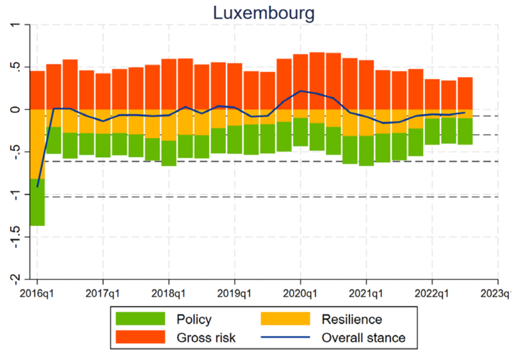

Latvia
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

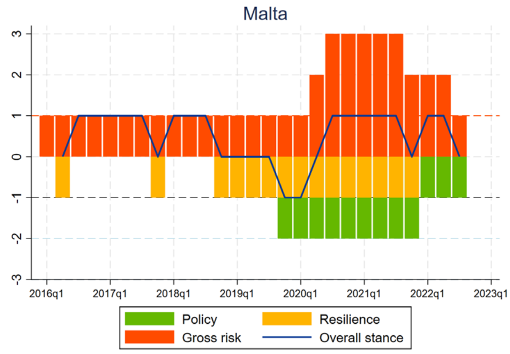

Latvia
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

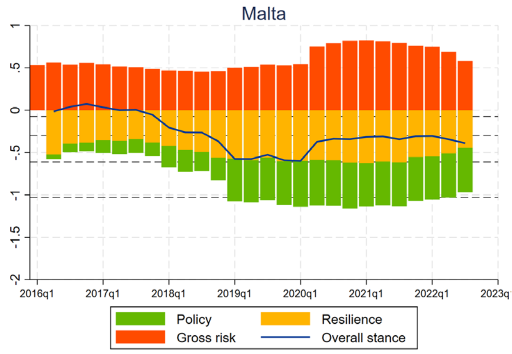

Lithuania
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

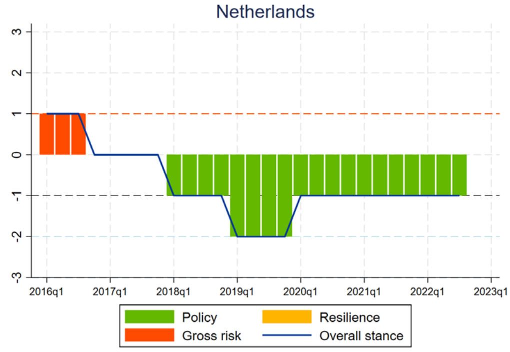

Lithuania
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

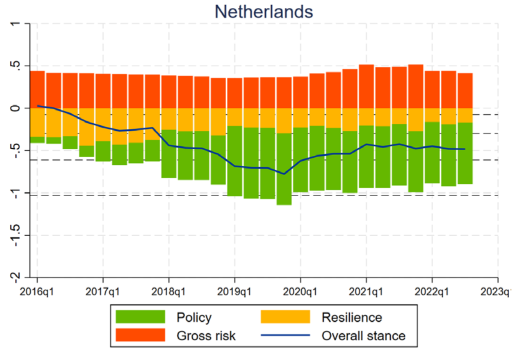

Luxembourg
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

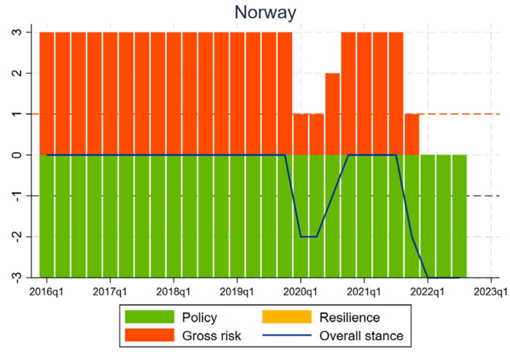

Luxembourg
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

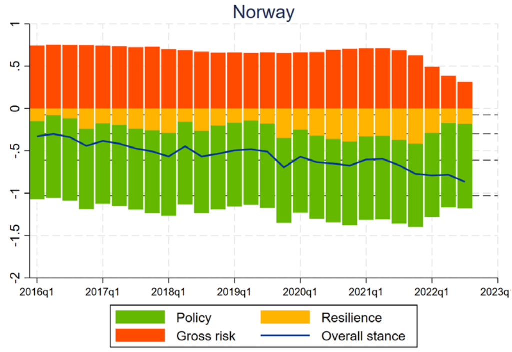

Malta
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

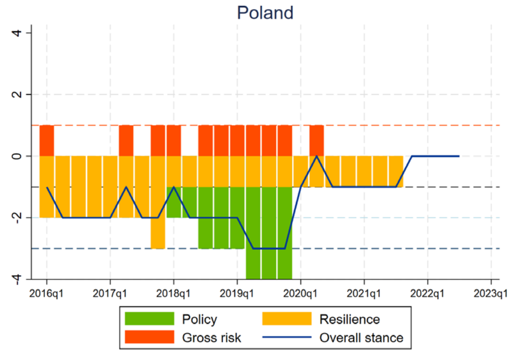

Malta
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

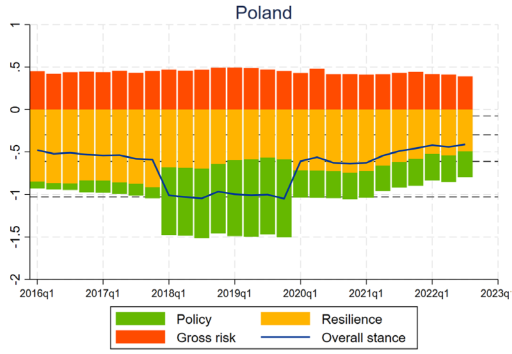

Netherlands
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

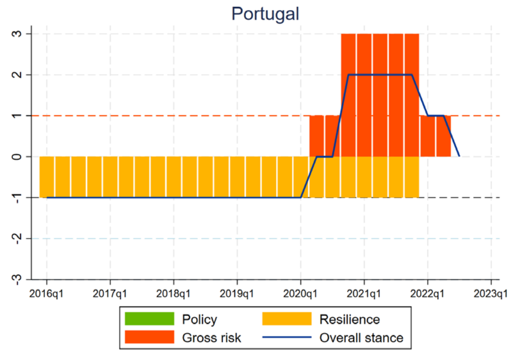

Netherlands
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

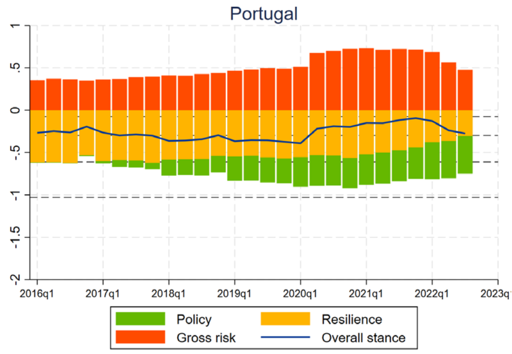

Norway
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

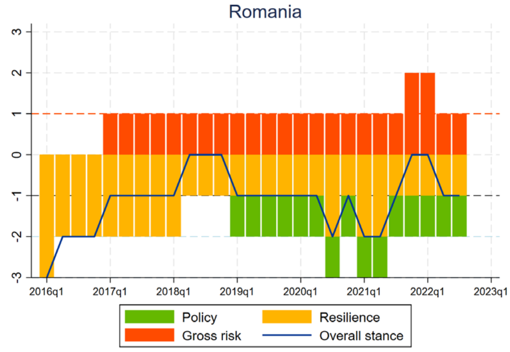

Norway
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

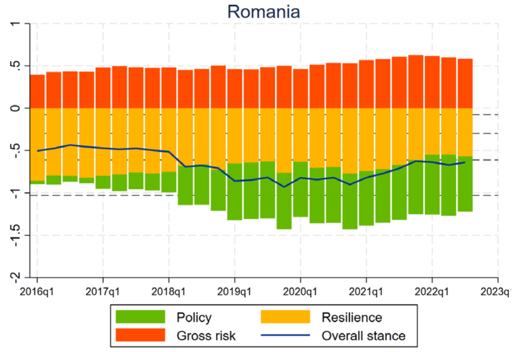

Poland
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

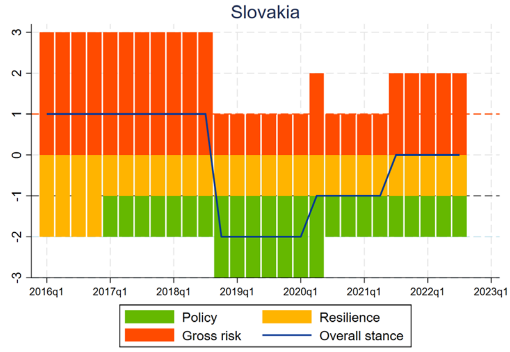

Poland
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

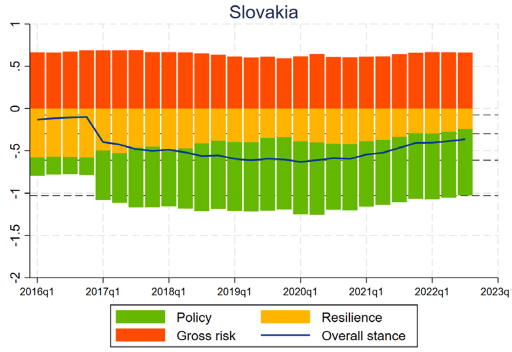

Portugal
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q1
Policy
Resilience
Gross risk
Overall stance

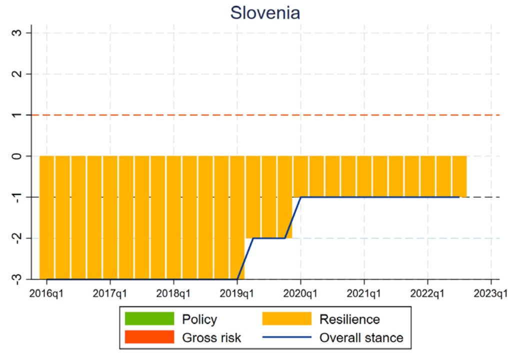

Portugal
2016q1 2017q1 2018q1 2019q1 2020q1 2021q1 2022q1 2023q
Policy
Resilience
Gross risk
Overall stance

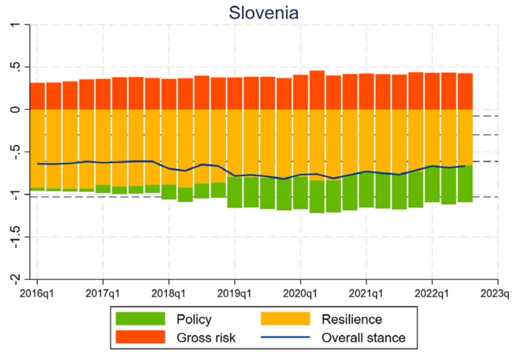

Romania
Policy
Resilience
Gross risk
Overall stance

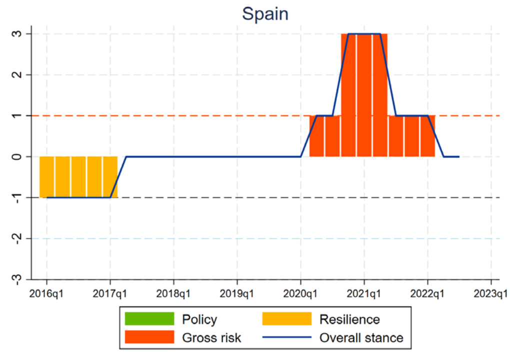

Romania
Policy
Resilience
Gross risk
Overall stance

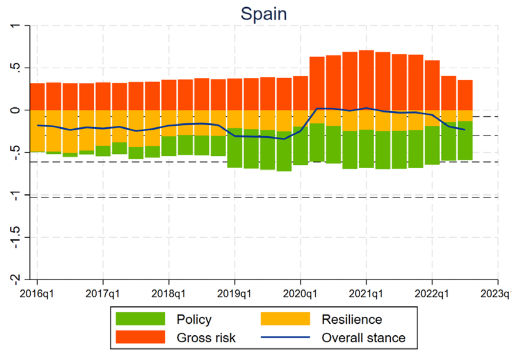

Slovakia
Policy
Resilience
Gross risk
Overall stance

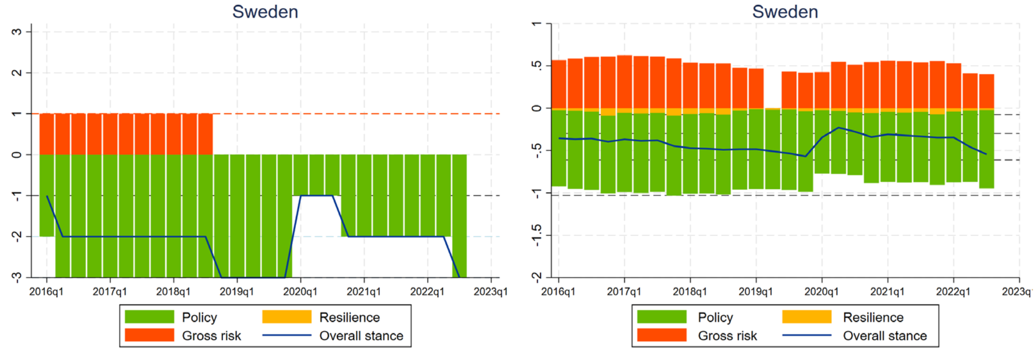

Slovakia
Policy
Resilience
Gross risk
Overall stance


Slovenia
Policy
Resilience
Gross risk
Overall stance


Slovenia
Policy
Resilience
Gross risk
Overall stance


Spain
Policy
Resilience
Gross risk
Overall stance


Spain
Policy
Resilience
Gross risk
Overall stance



Source: Contact Group on Macroprudential Stance.
Notes: Left: Decomposition by funding and collateral risk minus resilience and corresponding policy using ESRB (2021) methodology and using capital for the policy measure as per the current data; Right: Decomposition by risk, resilience and policy calculated using the revised method, including the revised method own funds policy measurement. Note that where the blue line representing the overall stance is not illustrated, certain data are missing for the calculation.

BBM stance indicator: Transition matrices

Table A4 shows the changes resulting from the use of cumulative distributive functions rather than buckets as in ESRB (2021), while keeping the same percentiles as those used in ESRB (2021) for the verbalised assessment (i.e. 14th, 46th, 81st and 82nd).

Table A4
Comparison of results: CDF and bucketing

		CDF approach (same percentiles for verbal assessment as in ESRB 2021)					
		Loose	**Grey-loose**	**Neutral**	**Grey-tight**	**Tight**	**Total**
Bucketing approach (ESRB 2021)	**Loose**	55	2	40			97
	Grey-loose	6	0				6
	Neutral	34	3	130	16	1	184
	Grey-tight			16	135	16	167
	Tight				19	57	76
	Total	**95**	**5**	**186**	**170**	**74**	**530**

Source: Contact Group on Macroprudential Stance.
Note: Green cells correspond to matching verbalised assessments under the two approaches, yellow cells to verbalised assessments differing by one zone, and red cells to assessments differing by two zones.

Table A5 shows the changes resulting from the use of the revised percentiles for the verbalised assessment (10th, 30th, 70th and 90th percentiles).

Table A5

Comparison of results: CDF approach with percentiles from ESRB (2021) and revised percentiles

		CDF approach (revised percentiles for verbal assessment)					
		Loose	**Grey-loose**	**Neutral**	**Grey-tight**	**Tight**	**Total**
CDF approach (same percentiles for verbal assessment as in ESRB 2021)	**Loose**	53	42				95
	Grey-loose		5				5
	Neutral		59	127			186
	Grey-tight			85	85		170
	Tight				21	53	74
	Total	**53**	**106**	**212**	**106**	**53**	**530**

Source: Contact Group on Macroprudential Stance.
Notes: Green cells correspond to matching verbalised assessments under the two approaches, yellow cells to verbalised assessments differing by one zone, and red cells to assessments differing by two zones.

A.3 Rule book for classifying macroprudential measures

During the process of classifying the macroprudential measures, additional columns were added to the ESRB's notification measures database[23]. These new categories include the classifications: (1) legal status, (2) direction of policy, and (3) stepwise quantification of the effect. The first column classifies the measure by its nature; the second classifies the macroprudential measure by its effect, while the third assigns an intensity to the measure with respect to the length of the phase-in or the extent to which the measure has been released. Table 3 lists the values that each of the additional columns contains (as of February 2023[24]). Below the CGS outlines the general and specific guidelines it followed in the classification exercise and briefly discusses the ambiguous entries and notable experiences during the process.

A.3.1 BBM

General guidelines

1. Classification according to legal status. See columns: *Description of measure*; *Related links.*

[23] See the ESRB's **overview of national macroprudential measures**.

[24] There are two further columns in the file dated 20 May 2023 (Problems, Comments I & II) that are dedicated to the discussions on the open issues.

2. Classification according to direction of policy. See columns: *Type of measure*; *Description of measure*; *Related links.*

3. Quantification of the effect according to phase-in length and scope of loosening. See columns: *Description of measure* (certain phase-ins are explicitly stated); and *Relevant dates* (referring to the *Measure becomes active on*, *Decision made on*, and *ESRB notified on* columns).

Specific guidelines

1. Classify as a *Recommendation* if: the *Related links* column includes further clarification in the form of a recommendation (if the link remains valid).

2. Classify as *Other* if:

   (i) in the *Type of measure* column, *Stress test/sensitivity test* is selected and is not described as a *Recommendation*;

   (ii) in the *Description of measure*, the words "*Considered a problem*" are used.

3. Otherwise, classify as *Legally binding*.

4. Classify as *Neutral* when:

   (i) a measure is amended without any change in parameters (look at the columns *Related links* and/or *Description of measure*);

   (ii) in the *Related links* column, the macroprudential authority has used the same announcement as previously or the link contains information confirming that the regulation renews a previous regulation that has expired;

   (iii) in the *Description of measure* column:

   - there is no announcement of a measure, only clarifications;
   - the description is unchanged in parameters as the previous year.

5. Classify as *Loosening* when:

   (i) in the *Description of measure*:

   - an exemption (rate) is introduced or increased compared to previous announcements.

6. Classify as *Tightening* when: *Description of measure* states "*wider application of the borrower-based measure*".

A.3.2 SyRB

General guidelines

1. All measures under this category are classified as *legally binding*.
2. Classification according to legal status. See columns: *Type of measure; Description of measure; Related links.*
3. Classification according to direction of policy. See columns: *Description of measure.*
4. Quantification of effect according to phase-in length and scope of loosening. See columns: *Description of measure*; *Relevant dates* (referring to the *Measure becomes active on*, *Decision made on*, and *ESRB notified on* columns).

Specific guidelines

1. Classify as *Tightening* when:

    (i) in *Description of measure* it is stated:

    - increase in SyRB level.

2. Classify as *Loosening* when the following is stated in *Description of measure*:

    (i) SyRB has been reduced;

    (ii) SyRB has been fully released;

    (iii) if the de minimis limit applies, when none of the banks is assessed to be above that limit.

3. Classify as *Neutral* when in *Description of measure* it is stated that:

    (i) SyRB rate is unchanged;

    (ii) definitions have changed;

    (iii) institution-specific systemic risk buffer has been reassessed.

4. When quantifying the effect of the policy we relied on the following guidelines:

    (i) the measure is classified as *tightening* at the date it is first announced;

    (ii) the number of steps in the buffer increase are determined on the basis of the *Relevant dates* column;

    (iii) announcements of the same measure made afterwards (within the phase-in period) are classified as neutral.

A.3.3 O-SII

General guidelines

1. All measures under this category are classified as *legally binding*.
2. Classification according to legal status. Isee columns: *Description of measure*; *Related links*.
3. Classification according to direction of policy. Isee columns: *Description of measure*.
4. Quantification of effect according to phase-in length and scope of loosening. Isee columns: *Description of measure* (certain phase-ins are explicitly stated); *Relevant dates* (referring to the *Measure becomes active on*, *Decision made on*, and *ESRB notified on* columns).

Specific guidelines

1. Classify as *Tightening* when the measure is first announced (at the beginning of the phase-in).
2. Classify as *Neutral* when the measure is a continuation of one already implemented (all other instances, except *Loosening* instances in the COVID-19 period).
3. Classify as *Loosening* in the COVID-19 period. The loosening (-1) during the COVID-19 period is weighted with the fraction of the number of banks for which the O-SII buffer was released to the total number of identified O-SIIs in the country.
4. Quantification of effect according to phase-in length and scope of loosening:
   - The number of identified O-SIIs is not a criterion for reclassifying the measure as *Tightening*/*Loosening* as it is the same measure. The number of identified O-SIIs is a country-specific characteristic rather than being specific to the measure.
   - For countries that have shared information on the length of the phase-in period (BE, HU, PT and SI), the values of a stepwise increase in the buffer requirements are entered in the *Stepwise* column.

A.3.4 G-SII

General guidelines

1. All measures under this category are classified as legally binding.
2. Classification according to legal status. See columns: *Description of measure*; *Related links.*
3. Classification according to direction of policy. See columns: *Description of measure.*

4. Quantification of effect according to phase-in length and scope of loosening. See columns: *Description of measure* (certain phase-ins are explicitly stated); *Relevant dates* (referring to the *Measure becomes active on*, *Decision made on* and *ESRB notified on* columns).

Specific guidelines

1. Classify as *Tightening* when the measure is first announced (at the beginning of the phase-in).
2. Classify as *Neutral* when the measure is a continuation of one already implemented (all other instances, except *Loosening* instances in the COVID-19 period).
3. Classify as *Loosening:* no instances.
4. Quantification of effect according to phase-in length and scope of loosening:

   (i) The number of identified G-SIIs is not a criterion for reclassifying the measure as *Tightening*/*Loosening* as it is the same measure.

   (ii) For countries that have shared information on the length of the phase-in period (FR, DE and SE), the values are entered in the *Stepwise* column.

A.3.5 CCoB

General guidelines

1. Classification according to legal status. See columns: *Description of measure*.

Specific guidelines

1. Classify as *Tightening* when the *Description of measure* column states that the measure is an "Early introduction at 2.5% level". When a gradual build-up is announced, only the initial announcement is classified as *Tightening* (as a stepwise one).
2. Classify as *Neutral*:

   (i) measures entered after the initial announcement for (during the phase-in period) that do not constitute a change of the measure
   When a decision for an early introduction (without a phase-in) is subsequently amended so that a gradual build-up of the measure is granted, only the initial announcement is classified as a *Tightening* and the following one(s) as *Neutral.*

3. Consider a stepwise increase in the buffer rate when stated as such (for example, the capital conservation buffer was applied from 1 January 2015, it was phased in gradually such that the buffer was 0% in 2015, 0.625% in 2016, 1.25% in 2017, 1.875% in 2018 and 2.5% in 2019).

4. Consider no stepwise increase in buffer rate otherwise or when an early introduction is stated (e.g. early introduction at 2.5% level).

5. Classify as *Other* if an early introduction decision (without a phase-in) was later amended so that a gradual build-up of the measure is granted.

A.3.6 Other measures

General guidelines

1. Classification according to legal status. See columns: *Description of measure*; *Basis in Union law*.

2. Classification according to legal status. See columns*: Description of measure*; *Related links.*

3. Classification according to direction of policy. See columns): *Description of measure*.

4. Quantification of effect according to phase-in length and scope of loosening. See columns: *Description of measure* (certain phase-ins are explicitly stated).

Specific guidelines

1. Classify as a *Recommendation* if the *Basis in Union law* column clarifies that it is indeed a recommendation.

2. Otherwise, classify as *Legally binding*.

3. Classify as *Neutral* when in the *Description of measure* column:

    (i) the authorities have stated that it is a "continuation of practice";

    (ii) it is stated that the entry is an amendment of an existing measure (and the effect of the amendment is unclear);

    (iii) an "acceleration of the gradual increase…" is announced.

4. Classify as *Loosening* or *Tightening* according to the *Description of measure* column.

A.4 GaR net stance assessments over time

Table A6

Net stance from Q4 2019 to Q3 2021 under the bias-corrected model as of Q3 2021

8Q	Q4 2019	Q1 2020	Q2 2020	Q3 2020	Q4 2020	Q1 2021	Q2 2021	Q3 2021
AT	-0.07	0.00	0.00	0.00	0.00	-0.01	0.00	-0.02
BE	-0.20	-0.08	-0.05	-0.03	-0.03	-0.05	-0.05	-0.05
BG	-0.07	-0.07	-0.09	-0.10	-0.09	-0.03	-0.04	-0.06
CY	-0.01	-0.04	-0.07	-0.09	-0.08	-0.03	0.00	-0.03
CZ	-0.13	-0.17	-0.17	-0.19	-0.19	-0.22	-0.20	-0.15
DE	-0.09	-0.03	-0.05	-0.05	-0.04	-0.08	-0.06	-0.07
DK	-0.24	-0.18	-0.20	-0.19	-0.18	-0.19	-0.22	-0.24
ES	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.01	-0.02
FI	-0.10	-0.08	-0.09	-0.10	-0.09	-0.09	-0.08	-0.11
FR	-0.10	-0.03	-0.02	-0.02	-0.02	-0.04	-0.04	-0.06
GR	-0.05	-0.03	-0.04	-0.03	-0.07	-0.04	-0.02	-0.06
HR	-0.13	-0.04	-0.06	-0.05	-0.03	0.00	0.00	0.00
HU	0.01	0.02	0.01	0.04	0.04	0.03	0.07	0.05
IE	-0.01	0.06	-0.01	-0.05	-0.01	-0.01	-0.01	-0.02
IT	-0.15	-0.11	-0.12	-0.09	-0.09	-0.09	-0.09	-0.10
LT	-0.06	-0.05	-0.06	-0.08	-0.07	-0.08	-0.08	-0.08
LU	-0.04	0.00	0.00	-0.03	-0.02	0.00	-0.02	-0.02
LV	-0.07	0.00	-0.02	0.00	-0.01	-0.01	0.00	0.00
MT	-0.12	-0.05	-0.03	-0.03	-0.03	-0.04	-0.05	-0.04
NL	-0.24	-0.20	-0.20	-0.20	-0.20	-0.04	-0.03	-0.02
NO	-0.08	0.00	0.03	0.01	-0.03	-0.08	-0.14	-0.06
PL	-0.09	-0.09	-0.08	-0.12	-0.06	-0.07	-0.07	-0.03
PT	-0.31	-0.27	-0.29	-0.25	-0.25	-0.14	-0.15	-0.06
RO	-0.03	-0.02	-0.03	-0.03	-0.02	-0.03	-0.04	-0.03
SE	-0.25	-0.17	-0.22	-0.20	-0.17	-0.13	-0.07	-0.08
SI	-0.05	-0.01	0.00	-0.01	-0.03	-0.04	-0.04	-0.07
SK	-0.07	-0.02	-0.04	-0.06	-0.05	-0.07	-0.12	-0.12

8Q	Q4 2019	Q1 2020	Q2 2020	Q3 2020	Q4 2020	Q1 2021	Q2 2021	Q3 2021
AT	-0.07	0.00	0.00	0.00	0.00	-0.01	0.00	-0.02
BE	-0.20	-0.08	-0.05	-0.03	-0.03	-0.05	-0.05	-0.05
BG	-0.07	-0.07	-0.09	-0.10	-0.09	-0.03	-0.04	-0.06
CY	-0.01	-0.04	-0.07	-0.09	-0.08	-0.03	0.00	-0.03
CZ	-0.13	-0.17	-0.17	-0.19	-0.19	-0.22	-0.20	-0.15
DE	-0.09	-0.03	-0.05	-0.05	-0.04	-0.08	-0.06	-0.07
DK	-0.24	-0.18	-0.20	-0.19	-0.18	-0.19	-0.22	-0.24
ES	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.01	-0.02
FI	-0.10	-0.08	-0.09	-0.10	-0.09	-0.09	-0.08	-0.11
FR	-0.10	-0.03	-0.02	-0.02	-0.02	-0.04	-0.04	-0.06
GR	-0.05	-0.03	-0.04	-0.03	-0.07	-0.04	-0.02	-0.06
HR	-0.13	-0.04	-0.06	-0.05	-0.03	0.00	0.00	0.00
HU	0.01	0.02	0.01	0.04	0.04	0.03	0.07	0.05
IE	-0.01	0.06	-0.01	-0.05	-0.01	-0.01	-0.01	-0.02
IT	-0.15	-0.11	-0.12	-0.09	-0.09	-0.09	-0.09	-0.10
LT	-0.06	-0.05	-0.06	-0.08	-0.07	-0.08	-0.08	-0.08
LU	-0.04	0.00	0.00	-0.03	-0.02	0.00	-0.02	-0.02
LV	-0.07	0.00	-0.02	0.00	-0.01	-0.01	0.00	0.00
MT	-0.12	-0.05	-0.03	-0.03	-0.03	-0.04	-0.05	-0.04
NL	-0.24	-0.20	-0.20	-0.20	-0.20	-0.04	-0.03	-0.02
NO	-0.08	0.00	0.03	0.01	-0.03	-0.08	-0.14	-0.06
PL	-0.09	-0.09	-0.08	-0.12	-0.06	-0.07	-0.07	-0.03
PT	-0.31	-0.27	-0.29	-0.25	-0.25	-0.14	-0.15	-0.06
RO	-0.03	-0.02	-0.03	-0.03	-0.02	-0.03	-0.04	-0.03
SE	-0.25	-0.17	-0.22	-0.20	-0.17	-0.13	-0.07	-0.08
SI	-0.05	-0.01	0.00	-0.01	-0.03	-0.04	-0.04	-0.07
SK	-0.07	-0.02	-0.04	-0.06	-0.05	-0.07	-0.12	-0.12

8Q	Q4 2019	Q1 2020	Q2 2020	Q3 2020	Q4 2020	Q1 2021	Q2 2021	Q3 2021
AT	0.00	0.02	0.02	0.02	0.02	0.01	0.01	0.00
BE	-0.05	-0.01	0.00	0.01	0.01	0.00	0.00	0.00

BG	0.02	0.01	0.00	0.00	0.03	0.04	0.03	0.03
CY	0.15	0.13	0.14	0.12	0.05	0.01	0.04	0.01
CZ	-0.01	-0.05	-0.06	-0.06	-0.05	-0.06	-0.04	-0.03
DE	0.01	0.02	-0.01	-0.01	0.01	-0.02	0.01	-0.01
DK	0.07	0.03	0.05	0.07	0.07	0.05	0.05	0.02
ES	0.03	0.03	0.02	0.02	0.03	0.02	0.02	0.01
FI	-0.01	-0.02	-0.03	-0.03	-0.03	-0.02	-0.01	-0.02
FR	-0.04	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.03
GR	0.02	0.02	0.00	0.01	0.00	0.03	0.05	0.03
HR	0.03	0.05	0.03	0.03	0.04	0.03	0.04	0.03
HU	0.05	0.06	0.06	0.07	0.06	0.05	0.07	0.05
IE	0.19	0.18	0.13	0.03	0.06	0.04	0.06	0.01
IT	0.03	0.02	0.01	0.02	0.01	0.01	0.01	-0.01
LT	0.02	0.02	0.02	0.03	0.04	0.04	0.04	0.04
LU	-0.01	0.01	0.01	-0.01	0.02	0.06	0.03	0.01
LV	-0.02	0.04	0.03	0.05	0.04	0.02	0.04	0.02
MT	0.08	0.10	0.10	0.10	0.09	0.07	0.05	0.07
NL	0.14	0.13	0.13	0.14	0.15	0.03	0.01	0.02
NO	-0.08	0.02	0.07	0.05	-0.01	-0.06	-0.14	-0.04
PL	0.04	0.03	0.03	-0.01	0.02	0.02	0.02	0.02
PT	0.14	0.14	0.11	0.09	0.07	0.03	0.02	0.03
RO	0.03	0.05	0.03	0.02	0.04	0.03	0.01	0.03
SE	-0.11	-0.05	-0.10	-0.07	-0.05	-0.04	0.01	-0.01
SI	0.07	0.05	0.06	0.05	0.05	0.04	0.04	0.03
SK	-0.02	0.03	0.02	0.00	0.02	0.00	-0.04	-0.05

Source: Contact Group on Macroprudential Stance.

Table A7

Net stance from Q4 2019 to Q3 2021 under the non-bias-corrected model as of Q3 2021

4Q	Q4 2019	Q1 2020	Q2 2020	Q3 2020	Q4 2020	Q1 2021	Q2 2021	Q3 2021
AT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
BE	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
BG	0.01	0.00	0.01	0.00	0.01	0.01	0.00	0.01
CY	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02
CZ	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DE	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00
DK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ES	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00
FI	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
FR	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
GR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
HR	0.00	0.00	0.01	0.01	0.01	0.01	0.00	0.01
HU	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01
IE	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01
IT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
LU	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01
LV	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.00
MT	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01
NL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NO	0.01	0.02	0.02	0.02	0.01	0.01	0.00	0.01
PL	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RO	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
SI	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
SK	0.03	0.04	0.03	0.04	0.03	0.02	0.02	0.01

8Q	Q4 2019	Q1 2020	Q2 2020	Q3 2020	Q4 2020	Q1 2021	Q2 2021	Q3 2021
AT	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BG	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
CY	-0.03	-0.02	-0.03	-0.04	-0.05	-0.04	-0.04	-0.04
CZ	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DE	0.00	0.00	-0.01	-0.01	-0.01	-0.01	0.00	0.00
DK	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00
ES	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
FI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FR	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01
GR	-0.01	-0.01	-0.02	-0.01	-0.02	-0.01	-0.01	-0.01
HR	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00
HU	0.01	0.01	0.02	0.02	0.01	0.01	0.00	0.01
IE	0.02	0.00	0.00	-0.01	-0.01	0.00	0.01	0.02
IT	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.01
LT	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
LU	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.01
LV	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.01
MT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NL	0.00	0.00	0.00	0.00	0.00	-0.01	-0.02	-0.01
NO	0.01	0.02	0.02	0.02	0.01	0.00	-0.02	0.00
PL	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01
RO	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01
SE	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00
SI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SK	0.03	0.04	0.03	0.03	0.03	0.02	0.02	0.01

Source: Contact Group on Macroprudential Stance.
Notes: The time series of net stance were calculated as of the third quarter of 2021 using the complete available dataset from the contributions to the fitted values. Ideally the time series of net stance would have been calculated using an expanding window, not having perfect foresight. However, expanding window calculations were not used because of the short time series in the panel.

A.5 Technical appendix for growth-at-risk

A.5.1 Variable selection and non-crossing QR

We applied the method put forward by Bondell, Reich & Wang, 2010 to avoid quantile crossing. The method is asymptotically identical to the original quantile regression method.

The original minimisation:

$$\hat{\beta}_\tau = argmin_\beta \sum_{i=1}^{n} \rho_\tau(y_i - z_i^T \beta)$$

$$\rho_\tau\,(u) = u\{\tau - I(u < 0)\}\,, \quad \tau_1, \dots, \tau_q\!: \hat{\beta}_\tau = \left(\hat{\beta}_{\tau_1}^T, \dots, \hat{\beta}_{\tau_q}^T\right)^T$$

The new minimisation:

$$\hat{\beta}_\tau = argmin_\beta \sum_{q=1}^{Q} w_{\tau_q} \sum_{i=1}^{n} \rho_\tau(y_i - z_i^T \beta)$$

Subject to $z^T \beta_{\tau_j} \geq z^T \beta_{\tau_{j-1}},\ x \in D,\ D \subset R^p, j = 2, \dots q$.

We completed our non-crossing frequentist QR method with a Lasso-type variable selection based on Jiang, Wang, Bondell (2014).

Lasso regression performs L1 regularisation via the addition of a penalty equal to the absolute value of the coefficients. Certain coefficients may shrink to zero and may therefore be eliminated from the model. Larger penalties shrink coefficient values closer to zero, which is ideal for achieving simpler models which in turn are easier to interpret and select variables from.

$$min \sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2 + \lambda \sum_{j=2}^{p} |\beta_j|$$

The minimisation is: $min \sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2$ with the constraint $\sum_{j=2}^{p} |\beta_j| \leq s$.

The parameter λ has the following properties:

λ is the tuning parameter,

λ increases imply bias increases,

λ decreases imply variance increases.

We applied the adaptive Lasso method, which further improves the variable selection properties. The final minimisation is:

$$\hat{\beta}(\tau) = argmin_{\beta,\alpha} \sum_{q=1}^{Q} \sum_{i=1}^{n} \rho_{\tau_q} \left(y_i - \alpha_{\tau_q} - x_i^T \beta_{\tau_q}\right)$$

Subject to $\alpha_{\tau_q} + x^T\beta_{\tau_q} \geq \alpha_{\tau_{q-1}} + x^T\beta_{\tau_q-1},\ \ x \in D,\ D \subset R^p,\ j = 2, \dots q.$

$$\sum_{q=1}^{Q}\sum_{k=1}^{K} w_{k,\tau_q}\left|\beta_{k,\tau_q}\right| \leq t^*$$

Where $w_{k,\tau_q} = \left|\theta_{k,\tau_q}\right|^{-1}$ are the estimated coefficients of a regular QR with a full design matrix.

Here, t^* is a global variation parameter, which is non-quantile-specific. A grid search is used to select the optimal t^*. The model with the lowest AIC and BIC will be identified as the optimal model.

A.5.2 Bias in the dynamic panel QR with fixed effects and Galvao type bias correction

The Monte Carlo work of Nerlove (1971) proved that the fixed effects model suffers from a drawback. Standard methods of estimation lead to seriously biased coefficients in dynamic models in cases where there are relatively small numbers of time periods (shallow panels).

Nickell (1981) investigated these biases analytically for the first-order autoregressive case:

$$y_{i,t} = \beta + \rho y_{i,t-1} + \sum_j \beta_j x_{ij,t} + f_i + \varepsilon_{i,t}$$

Subtracting the time mean:

$$y_{i,t} - \bar{y}_i = \beta + \rho\left(y_{i,t-1} - \bar{\bar{y}}_{i,-1}\right) + \sum_j \beta_j\left(x_{ij,t} - \bar{\bar{x}}_{ij}\right) + \left(\varepsilon_{it} - \bar{\varepsilon}_i\right)$$

It is clear that ordinary least squares (OLS) estimates will be biased even if N, the number of individuals, goes to infinity. The main reason for this is that the correlation between $y_{i,t-1}$ and $\bar{\varepsilon}_i$ does not go to zero.

Nickell provides analytical proof for the size of the bias for $\hat{\rho}$ and $\hat{\beta}$.

$$\operatorname*{plim}_{N\to\infty}(\hat{\rho} - \rho) \approx \frac{-(1+\rho)}{T-1}$$

The bias is always negative if $\rho > 0$ and if $T = 10,\ \rho = 0.5$ the bias is -0.167.

The bias on $\hat{\beta}$ depends on the relationship between the exogenous variables and $\bar{y}_{i,-1}$. If an exogenous variable is positively related to $\bar{y}_{i,-1}$ then its coefficient will be upward biased and vice-versa.

Galvao (2011) studies quantile regression dynamic panel models with fixed effects. Panel data fixed effects estimators are typically biased in the presence of lagged dependent variables as regressors, similarly to Nickell's case. To reduce the dynamic bias, Galvao (2011) uses the instrumental variables quantile regression method of Chernozhukov and Hansen (2006) with lagged regressors as instruments. Monte Carlo simulations show that the instrumental variables approach sharply reduces the dynamic bias.

We use Galvao's method to correct the bias in the dynamic panel QR with fixed effects, since the shortest time series in the unbalanced panel is $T = 20$. We use the second lag of GDP growth as an instrument, on the understanding that time lags in the regressor variable set must not

Non-bias corrected model; old MPI; h=4q; perc 0.1	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.217	-0.007	-0.140	-0.034	0.000	0.000	-0.003	0.012	0.001	-0.012
Significance	***	*	***				***	*		*
Standard error	0.037	0.004	0.021	0.022	0.001	0.001	0.001	0.007	0.001	0.007

intersect/overlap.

We also correct for occasional large crossings in resultant fitted values using Chernozhukov et al. (2010) by sorting the fitted values.

Table A8 below compares the old baseline code and the bias-corrected code in terms of coefficients and fit for the old and new versions of the MPI index.

Table A8
Comparison of the old baseline code with the bias-corrected code

Bias corrected model; old MPI; h=4q; perc 0.1	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.995	0.009	-0.012	-0.350	-0.023	0.001	-0.002	-0.001	0.027	0.001
Significance	***			***	***				***	
Standard error	0.092	0.009	0.047	0.052	0.003	0.003	0.002	0.016	0.002	0.016

Non-bias-corrected model; horizon=4q; old MPI	Quantile	QWCRPS
	0.1	0.011
	0.5	0.004
	0.9	0.008

Bias-corrected model; horizon=4q; old MPI	Quantile	QWCRPS
	0.1	0.031
	0.5	0.018
	0.9	0.012

Non-bias corrected model; old MPI; h=8q; perc 0.1	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.110	-0.041	0.085	0.084	-0.001	-0.002	-0.005	0.016	0.000	-0.027
Significance	***	***	***	***			***	**		***
Standard error	0.036	0.004	0.020	0.022	0.001	0.001	0.001	0.008	0.001	0.007

Bias corrected model; old MPI; h=8q; perc 0.1	Yh_lag	SRI	CLIFS	SRIx CLIFS	MPIcap	MPIbbm	SRIx MPIbbm	CLIFSx MPIbbm	SRIxMPI cap	CLIFSx MPIcap
Value	-0.994	-0.043	-0.047	0.016	0.019	0.003	0.000	-0.004	0.014	0.003
Significance	***	***			***				***	
Standard error	0.100	0.010	0.057	0.056	0.003	0.003	0.002	0.019	0.003	0.019

Non-bias-corrected model; horizon=8q; old MPI	Quantile	QWCRPS
	0.1	0.012
	0.5	0.004
	0.9	0.008

Bias-corrected model; horizon=8q; old MPI	Quantile	QWCRPS
	0.1	0.017
	0.5	0.016
	0.9	0.040

Source: Contact Group on Macroprudential Stance.

A.5.3 Back-testing GaR

Back-testing a risk measure involves testing forecasts against realisations. However, distributions do not materialise ex post; only one scenario , i.e. one data point, materialises. A risk measure is said to be back-testable if there exists an observable test statistic that makes it possible to decide whether predictions are over or under-estimated. We consider density forecasts in a time series context that is in an expanding window setup consisting of the past m observations used to fit a density forecast for a future observation that lies k periods ahead.

The comparison typically uses a proper scoring rule. A scoring rule is a loss function $S(f, y)$ with arguments that include the density forecast, f, and the realisation, y, of the future observation Y. It is critically important that a scoring rule be proper in a particular sense:

$$E_f S(f, Y) = \int f(y) S(f, y) dy \leq \int f(y) S(g, y) dy = E_f S(g, Y)$$

Important examples of strictly proper scoring rules are the logarithmic, quadratic, spherical, and continuous ranked probability scores (see Gneiting and Raftery, 2007). We use scoring rules that are negatively oriented penalties, meaning the lower the score, the better. Density forecast methods are then ranked by comparing their average scores. Specifically, if

$$\bar{S}_n^f = \frac{1}{n-k+1} \sum_{t=m}^{m+n-k} S(\hat{f}_{t+k}, y_{t+k})$$

$$\bar{S}_n^g = \frac{1}{n-k+1} \sum_{t=m}^{m+n-k} S(\hat{g}_{t+k}, y_{t+k})$$

then we prefer f if $\bar{S}_n^f \leq \bar{S}_n^g$, and prefer g otherwise.

In our back-tests we use the weighted, proper versions of the continuous ranked probability score (CRPS) (see Gneiting and Raftery, 2007). Any density forecast f induces a probability forecast for the binary event $\{Y \leq z\}$ via the value of the corresponding cumulative distribution function (CDF),

$$F(z) = \int_{-\infty}^{z} f(y) dy$$

at the threshold $z \in R$. It is also coupled with the quantile forecast $F^{-1}(\alpha)$ at the level $\alpha \in (0,1)$. The CRPS is then defined as

$$CRPS = \int_{-\infty}^{\infty} PS(F(z), I\{y \leq z\})\, dz = \int_{-0}^{1} QS(F^{-1}(\alpha), y)\, d\alpha$$

where PS is the probability score:

$$PS(F(z), I\{y \leq z\}) = (F(z) - I\{y \leq z\})^2,$$

and QS is the quantile score:

$$QS(F^{-1}(\alpha), y) = 2(I\{y \leq F(\alpha)\} - \alpha)(F^{-1}(\alpha) - y).$$

We construct weighted versions of the CRPS to emphasise regions of interest. The quantile weighted continuous ranked probability score (QWCRPS) is given by the following expression:

$$S(f, Y) = \int_{-0}^{1} QS(F^{-1}(\alpha), y)\, v(\alpha) d\alpha$$

where $v(\alpha)$ is a nonnegative weight function on the unit interval. In our case for the centre: $v(\alpha) = \alpha(1-\alpha)$; right tail: $v(\alpha) = \alpha^2$; and left tail: $v(\alpha) = (1-\alpha)^2$.

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A.5.4 Quantile regression and machine learning

Machine learning (ML) methods can also be used to develop advanced economic models and policy analyses in addition to the classic econometric models. Thanks to their enhanced predictive power, ML techniques can make traditional economic models more accurate, though not always. This could lead to better simulations of economic scenarios, more accurate policy recommendations, and a deeper understanding of economic dynamics. Therefore, we compared various ML techniques with quantile regression (QR) and ordinary least squares (OLS) using 40 rolling windows for one quarter ahead of out-of-sample forecasts. We analysed 1,755 rows without missing values from a total of 26 countries, all after 1 January 1999. In other words, we employed a panel data model with fixed effects, including dummy variables, using one for each country except Germany, which was kept out as a basis group.

To evaluate the predictive accuracy, we used the classic metrics of root mean square error (RMSE) and mean absolute deviation (MAD). These goodness-of-fit measures indicate how close the predicted values are to the actual values; the smaller the better, as presented in Table A9 in ascending order. We list only those ML methods outperform OLS. Note that QR performs better than the ML methods. The k-nearest neighbour method (KNN), with k=3, which is the closest to QR, probably selects three neighbours among the most recent observations from the same country. Based on these results, the Expert Group on Macroprudential Stance views QR as the most appropriate model.

Table A9

Comparison of estimation methods by 40 rolling windows for out-of-sample forecasts, one quarter ahead

(dependent variable: average annualised real GDP over eight quarters ahead, n=1599)

Method	RMSE	MAD
Quantile regression (q=0.5)	0.0223	0.0132
KNN (k=3)	0.0223	0.0140
Random forest (RFQR)	0.0226	0.0146
Gradient boosting	0.0241	0.0162
Bayesian ridge	0.0267	0.0183
OLS	0.0272	0.0186

Source: Contact Group on Macroprudential Stance.
Note: RMSE: root mean square error; MAD: mean absolute deviation; OLS: ordinary least squares; RFQR: random forest quantile regression; KNN: K-nearest neighbour.

As QR appears to be the most suitable method, looking at the above results, we re-ran the primary model keeping only the significant variables for q=0.1 and q=0.5. Table A10 below shows the significant estimates with p-values in parentheses using a manual backward stepwise elimination method based on p-values. The Bank Concentration (Herfindahl-Hirschman Index, HHI) variable was not used on its own as it causes multicollinearity problems due to its correlation with the country dummy variables. The capital-based MPI variable and its interactions with SRI and CLIFS significantly affect future GDP for the median QR model (q=0.5). However, the same variables are not significant for the QR model, with q=0.1. The borrower-based MPI variable and its interactions with SRI and CLIFS significantly affect future GDP for the QR model, with q=0.1. For the median QR model (q=0.5), only the interaction between the borrower-based MPI variable and CLIFS is significant. The interactions make the models non-linear, and we interpret the coefficients accordingly:

In the QR-(q=0.1) model, the marginal effect of the borrower-based MPI depends on SRI and CLIFS:

$$\frac{dGDP}{dMPI\text{-}B} = -0.0014 - 0.0030 \times SRI + 0.0092 \times CLIFS.$$

In the QR-(q=0.5) model, the marginal effect of the borrower-based MPI depends on CLIFS:

$$\frac{dGDP}{dMPI\text{-}B} = 0.0088 \times CLIFS,$$

and the marginal effect of the capital-based MPI depends on SRI and CLIFS:

$$\frac{dGDP}{dMPI\text{-}C} = 0.0008 - 0.0013 \times SRI - 0.0162 \times CLIFS.$$

Evaluating SRI and CLIFS at their mean values of -0.00668 and 0.126, respectively, the above three marginal effects are equal to -0.00022, 0.0011 and -0.0012, respectively. That is, a unit increase in capital-based MPI, ceteris paribus, is expected to reduce GDP growth by 0.12% on average.

Table A10

Quantile regression coefficient estimates and p-values in parentheses under estimates

(dependent variable: average annualised real GDP over eight quarters ahead)

		10th percentile	Median
Risk and stress	SRI	-.0068** (.042)	-.0041*** (0.000)
Macroprudential policy	Borrower-based MPI	-.0014** (0.021)	
	Borrower-based MPI x SRI	-.0030*** (0.000)	
	Borrower-based MPI x CLIFS	.0092* (0.085)	.0088*** (0.000)
	Capital-based MPI		.0008*** (0.000)
	Capital-based MPI x SRI		-.0013*** (0.000)
	Capital-based MPI x CLIFS		-.0162*** (0.000)
Structural variables	Bank concentration (HHI) x SRI	-.0644** (0.020)	
Control variables	Real GDP growth rate	-.1393*** (0.000)	
	Lagged real GDP growth rate	-.1510*** (0.000)	-.0464*** (0.001)
Number of observations - n		**1755**	**1755**
Pseudo R2		**0.21**	**0.14**

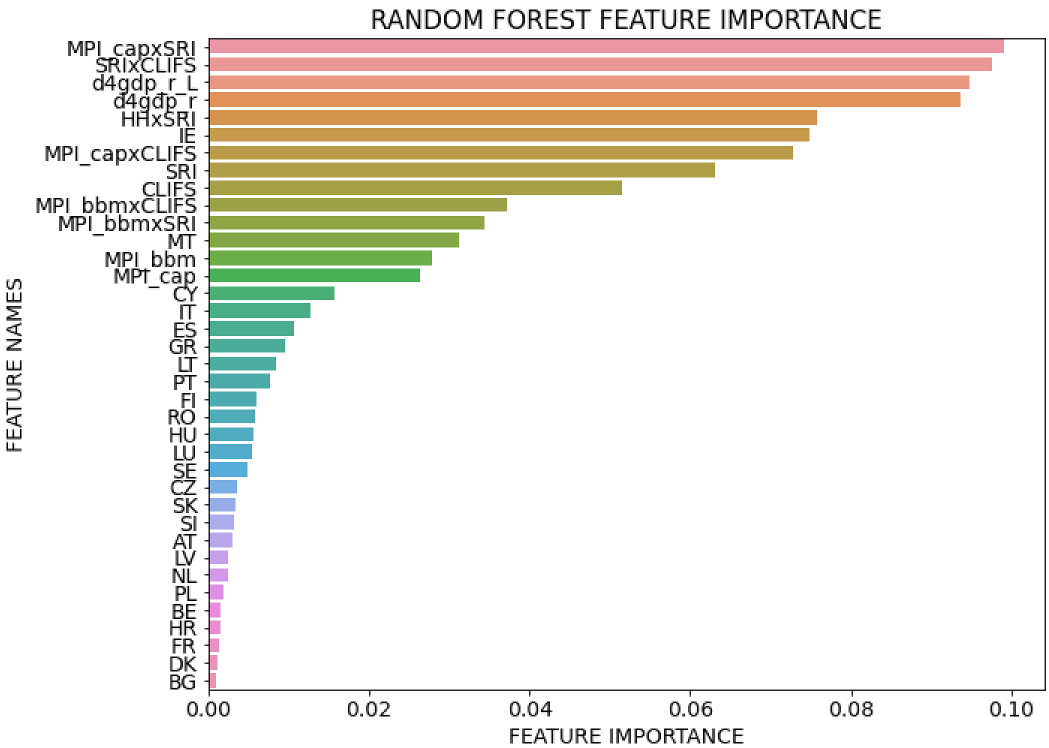
Source: Contact Group on Macroprudential Stance.
*Note: Significance levels of *10%, **5% and ***1%. The figures shown in parentheses are the p-values of the coefficient tests.*

The CGS applied the random forest quantile regression (RFQR) method in Python. The variable importance in Table A10above differs from the significance of the estimates in Table 2. Note that the most important variable is capital-based MPI × SRI in both cases (q=0.1 and q=0.5). In general, we can conclude from the two tables that both the capital-based MPI and the borrower-based MPI make a much smaller contribution to the model than the interactions capital-based MPI × SRI, SRI × CLIFS and HHI × SRI, the risk and stress indices SRI and CLIFS, and also the interactions borrower-based MPI × CLIFS and borrower-based MPI × SRI. The countries displaying the strongest country effects are IE and MT.

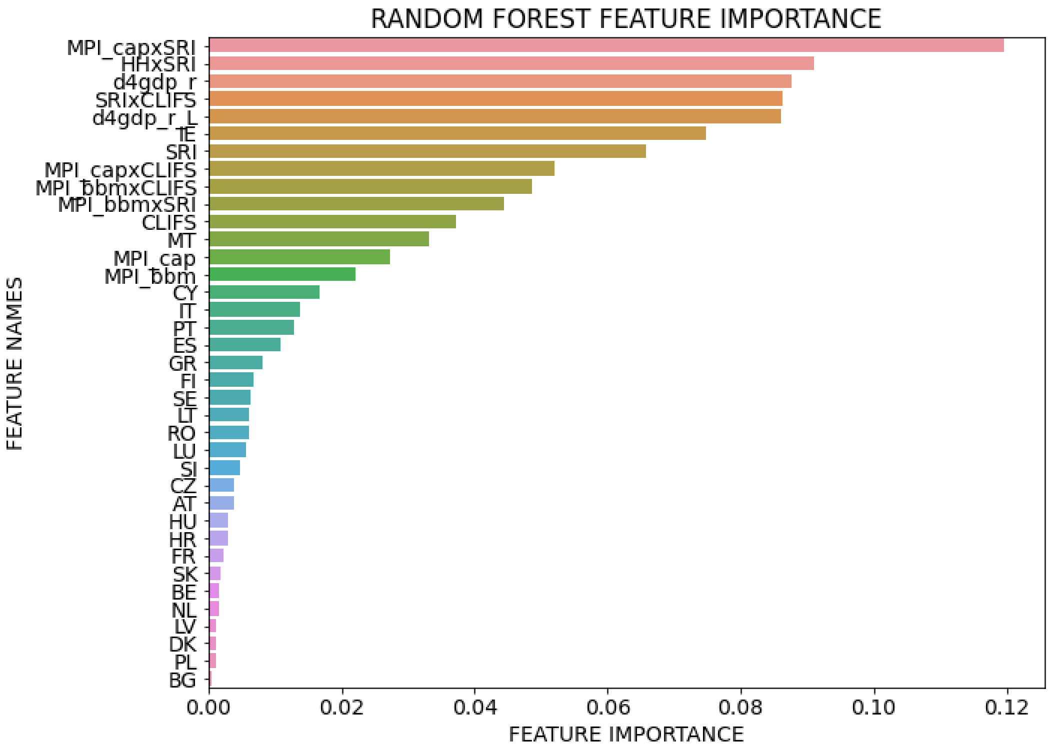
Forecasts for the dependent variable (annualised real GDP over eight quarters ahead) in the third quarter of 2021 for 22 EU countries are presented in Table A11 for the methods QR(q=0.1 & 0.5), RFQR(q=0.1 & 0.5), KNN and OLS.

Chart A2

Random forest quantile (q=0.1)



Random forest quantile (q=0.5)



Source: Contact Group on Macroprudential Stance.
Notes: The stance classification in the example is based on percentiles of the MTD series. The 10th, 25th, 75th and 90th percentiles have been selected as thresholds.

Table A11

Forecasts for the dependent variable in Q3 2021 for 22 EU countries

(dependent variable: average annualised real GDP over eight quarters ahead)

Country	QR(q=0.5)	RFQR(q=0.5)	QR(q=0.1)	RFQR(q=0.5)	OLS	KNN(k=3)
AT	0.019	0.013	-0.005	-0.005	0.012	0.012
BE	0.023	0.016	0.012	0.020	0.021	0.032
BG	0.025	0.025	-0.010	0.011	0.018	0.026
CY	0.017	0.006	-0.025	-0.021	0.021	0.003
CZ	0.020	0.000	0.000	-0.004	0.018	0.032
DE	0.015	0.015	-0.004	-0.003	0.012	0.039
ES	0.023	0.003	-0.012	-0.025	0.020	0.044
FI	0.023	0.016	-0.006	0.015	0.021	0.039
FR	0.020	0.014	-0.007	-0.016	0.012	0.020

Country	QR(q=0.5)	RFQR(q=0.5)	QR(q=0.1)	RFQR(q=0.5)	OLS	KNN(k=3)
GR	0.019	0.012	-0.068	-0.001	0.015	-0.011
HU	0.025	0.016	-0.024	0.005	0.017	-0.022
IT	0.004	-0.016	-0.021	-0.021	0.000	-0.026
LT	0.033	0.033	0.003	0.012	0.025	0.033
LU	0.031	0.026	0.010	0.015	0.031	0.048
LV	0.028	0.019	-0.020	0.013	0.022	0.027
MT	0.057	0.026	-0.001	-0.028	0.045	0.008
NL	0.018	0.027	-0.011	0.006	0.017	0.022
PL	0.036	0.025	0.025	-0.004	0.038	0.039
PT	0.012	0.011	-0.025	-0.020	0.008	-0.004
RO	0.038	0.037	0.011	0.016	0.035	0.016
SE	0.028	0.025	0.004	0.017	0.024	0.022
SK	0.025	0.016	0.013	0.003	0.024	0.012

Source: Contact Group on Macroprudential Stance.
Note: QR: quantile regression; RFQR: random forest quantile regression; KNN: K-nearest neighbour.

A.6 CLIFS vs CISS

Topic: Country-Level Index of Financial Stress (CLIFS) versus Composite Indicator of Systemic Stress (CISS).

Conclusion: in the out-of-sample comparison, CLIFS and CISS perform roughly the same (CISS slightly outperforming CLIFS).

Table A12

CLIFS versus CISS by in-sample comparison using pseudo R-square

(dependent variable: average annualised real GDP growth over h quarters ahead at 10th percentile and median)

Quantile regression	Q=0.5	Q=0.1
One quarter ahead (h=1) – n=1715	Pseudo R2	
CLIFS	0.0282	0.2871
CISS	0.0279	0.2895
One year ahead (h=4) – n=1637		
CLIFS	0.1337	0.1973
CISS	0.1670	0.2773
Two years ahead (h=8) – n=1533		
CLIFS	0.1975	0.2601
CISS	0.2265	0.2719
Three years ahead (h=12) – n=1429		
CLIFS	0.2979	0.3529
CISS	0.3314	0.3552
Four years ahead (h=16) – n=1325		
CLIFS	0.3742	0.4378
CISS	0.4196	0.4562
Five years ahead (h=20) – n=1221		
CLIFS	0.3962	0.4813
CISS	0.4381	0.4994

Source: Contact Group on Macroprudential Stance.
Note: RMSE: root mean square error; MAD: mean absolute deviation; OLS: ordinary least squares; RFQR = random forest quantile regression; KNN = K-nearest neighbour.

Table A13

CLIFS versus CISS by 40 rolling windows for out-of-sample forecasts, one quarter ahead

(dependent variable: average annualised real GDP over h quarters ahead)

Quantile regression	Q=0.5	
One quarter ahead (h=1) – n=1715	RMSE	MAD
CLIFS	0.3526	0.2477
CISS	0.3560	0.2500
One year ahead (h=4) – n=1637		
CLIFS	0.0377	0.0222
CISS	0.0395	0.0230
Two years ahead (h=8) – n=1533		
CLIFS	0.0303	0.0192
CISS	0.0306	0.0197
Three years ahead (h=12) – n=1429		
CLIFS	0.0235	0.0159
CISS	0.0231	0.0152
Four years ahead (h=16) – n=1325		
CLIFS	0.0193	0.0134
CISS	0.0182	0.0122
Five years ahead (h=20) – n=1221		
CLIFS	0.0170	0.0119
CISS	0.0167	0.0115

Source: Contact Group on Macroprudential Stance.
Note: RMSE: root mean square error; MAD: mean absolute deviation; OLS: ordinary least squares; RFQR: random forest quantile regression; KNN: K-nearest neighbour.

A.7 COVID-19 period analysis

Topic: Comparison of GaR using data before COVID-19 (until the fourth quarter of 2019) and using COVID-19 period data (until the fourth quarter of 2021), choosing GaR four and eight quarters ahead (using the new MPI index).

Table A14

Quantile regression coefficient estimates and standard errors for GaR 10th percentile, four quarters ahead

		Without COVID-19 data	With COVID-19 data	With COVID-19 data and dummies	With COVID-19 data and GEOVOL
Risk and stress	SRI	-0.010*** (0.002)	-0.007** (0.004)	-0.004 (0.004)	-0.011*** (0.004)
	CLIFS	-0.17*** (0.012)	-0.15*** (0.020)	-0.14*** (0.020)	-0.16*** (0.022)
	SRI x CLIFS	-0.0367*** (0.012)	-0.0037 (0.020)	-0.0287 (0.022)	0.0002 (0.021)
Macroprudential policy	Borrower-based MPI	-0.0006 (0.001)	-0.0026*** (0.001)	-0.0026** (0.001)	-0.0024** (0.001)
	Borrower-based MPI x SRI	-0.0012* (0.001)	-0.0038*** (0.001)	-0.0038*** (0.001)	-0.0034*** (0.001)
	Borrower-based MPI x CLIFS	0.014*** (0.005)	0.015** (0.007)	0.016** (0.008)	0.014*** (0.007)
	Capital-based MPI	0.0010* (0.001)	-0.0001 (0.001)	0.0001 (0.001)	0.0013 (0.001)
	Capital-based MPI x SRI	0.0001 (0.001)	-0.0018** (0.001)	-0.0016*** (0.001)	-0.0006*** (0.001)
	Capital-based MPI x CLIFS	-0.0018 (0.004)	-0.0037 (0.006)	-0.0058 (0.007)	-0.0072 (0.007)
Control variables	Lagged real GDP growth rate	-0.016 (0.024)	-0.228*** (0.037)	-0.165*** (0.042)	-0.224*** (0.037)
Other variables	Dummy of Q2 2020			0.08*** (0.018)	
	Dummy of Q3 2020			0.04** (0.018)	
	GEOVOL				0.03*** (0.007)

Source: Contact Group on Macroprudential Stance.
*Notes: Significance levels of *10%, **5%, ***1%. The figures shown in parentheses are the standard errors of the coefficients.*

Table A15

Quantile regression coefficient estimates and standard errors for GaR 10th percentile, eight quarters ahead

		Without COVID-19 data	With COVID-19 data	With COVID-19 and GEOVOL
Risk and stress	SRI	-0.018*** (0.002)	-0.017*** (0.002)	-0.018*** (0.002)
	CLIFS	0.049*** (0.013)	0.045*** (0.012)	0.061*** (0.012)
	SRI x CLIFS	0.022* (0.012)	0.020 (0.012)	0.023* (0.012)
Macroprudential policy	Borrower-based MPI	-0.0004 (0.001)	-0.0005 (0.001)	-0.0006 (0.001)
	Borrower-based MPI x SRI	-0.0028*** (0.001)	-0.0029*** (0.001)	-0.0030*** (0.001)
	Borrower-based MPI x CLIFS	0.0028 (0.005)	0.0027 (0.004)	0.0028 (0.004)
	Capital-based MPI	0.0004 (0.001)	-0.00002 (0.001)	0.0001 (0.001)
	Capital-based MPI x SRI	0.0000 (0.001)	0.0001 (0.001)	0.0000 (0.000)
	Capital-based MPI x CLIFS	-0.010** (0.004)	-0.008** (0.004)	-0.010*** (0.004)
Control variables	Lagged real GDP growth rate	0.39*** (0.035)	0.37*** (0.031)	0.37*** (0.027)
Other variables	GEOVOL			-0.01*** (0.004)

Source: Contact Group on Macroprudential Stance.
*Notes: Significance levels of *10%, **5% and ***1%. The figures shown in parentheses are the standard errors of the coefficients.*

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