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Looking at the evolution of
macroprudential policy stance:
a growth-at-risk experiment with
a semi-structural model

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Abstract

This paper proposes a methodology for measuring the macroprudential policy stance based on a distance-to-tail metric perspective. This approach employs a large-scale semi-structural model reflecting the dynamics of 91 significant euro area banks and 19 euro area economies and is presented through an assessment of the stance evolution for the aggregate euro area economy and for the individual euro area countries. Our results uncover mild tightening of the macroprudential policy stance before the end of 2019. This trend is abruptly interrupted at the onset of the Covid-19 pandemic but reappears at the end of 2020 before picking up again over the first half of 2021. Our assessment also reveals a marginal impact of the macro-financial policies applied, which is particularly notable throughout 2020.

Keywords: macroprudential policy, macroprudential policy stance, distance-to-tail metric, Growth-at-Risk, Lending-at-Risk

JEL codes: E37, E58, G21, G28

Executive summary

Macprudential policies aim to prevent an excessive build-up of risks and to make the financial sector more resilient.

A relevant measure of macroprudential policy stance should capture the balance between macroprudential policy objectives and its instruments, and simultaneously provide a clearer understanding of policy by the public and manage expectations surrounding future macroprudential policy actions. However, constructing such a measure is complex as macroprudential policy involves multiple instruments interacting among each other, each instrument potentially affecting the overall stance in different directions. Moreover, there is no general consensus on how best to measure the ultimate objective of financial stability.

This paper proposes a methodology for measuring macroprudential policy stance based on a risk management approach to controlling and assessing macroprudential policy.

We propose a distance-to-tail metric perspective on the macroprudential policy stance measurement and present the resulting assessment of the stance evolution for the aggregate euro area economy and for the individual euro area countries. The assessment employs a large-scale semi-structural model reflecting the dynamics of 91 significant euro area banks and 19 euro area economies. The model captures the impact of macroprudential policies on bank balance sheets, on their loan supply and on the real economy. The innovative part of the methodology we present is that it focuses on the full distribution of possible outcomes, thus reflecting the uncertainty surrounding future economic developments. Distance-to-tail is defined as a central tendency-corrected tail metric, which implies looking at the difference between a selected lower tail measure, such as Growth-at-Risk (GaR) or expected shortfall (ES), and a central tendency measure (such as mean or median) of the forecast distributions of macro-financial variables to assess the resilience of the system.

The semi-structural approach strikes a middle ground between standard empirical and structural models and offers a high degree of flexibility in incorporating relevant information in its forecasts.

The applied model also allows us to track the interplay between macroprudential and monetary policies and features numerous system-wide and bank-specific capital requirements and buffers as well as leverage requirements, NPL coverage expectations and a shift toward Basel III finalisation. The model is tailored to exhibit sound long-run properties, which help capture the transmission lags in macroprudential policies. The model allows us to build interval forecasts of macroeconomic and banking sector variables and the availability of the full distributions of these outcomes is the key in constructing distance-to-tail type metrics.

Several alternative macroprudential policy stance measures of the distance-to-tail type are considered in this paper.

These alternatives differ by selected macrofinancial variables, sampling schemes, time horizons and both central tendency and tail measures. We present results for two macrofinancial variables

(real GDP and private sector lending), two sampling schemes (benchmark and bootstrapping), five time horizons (one to five years), two central tendency measures (mean and median) and three tail measures (GaR at 5th and 10th percentiles and ES at 10th percentile). Regarding the choice of time horizon, longer horizons are generally preferable as they can accommodate macroprudential policy lags without compromising forecast quality. For a fixed time horizon, the alternative measures are strongly correlated for the most part and while they might differ in the default level of stance, they provide mostly equivalent assessment in terms of dynamics.

As for the results of applying our methodology, a policy exercise tracking the evolution of macroprudential policy stance from 2017 to 2021 reveals a mild tightening of the stance before the end of 2019, reflecting at least partially a coordinated effort of macroprudential and supervisory authorities following the 2008 crisis. This trend is abruptly interrupted at the beginning of 2020 with the onset of the Covid-19 pandemic but reappears at the end of that year before once again increasing notably in the second quarter of 2021. The relative impact of the macro-financial policies applied (including supervisory actions) can be identified from the charts by comparing the two policy options, as the actual policy option reflects the macroprudential policies actually implemented during the reference period while the constant policy option assumes fixed macroprudential policies held at Q4 2017 status. This impact is best observed during 2020, especially for the private sector lending-based stance measure.

The policy exercise also covers the evolution of macroprudential policy stance in selected euro area countries. While the level of stance in general differs across the individual countries, a significant degree of co-movement can be observed across the sample with the dynamics largely reinforcing the findings from the aggregate-level policy exercise. This conclusion holds for both real GDP and private sector lending-based macroprudential policy stance measures.

1 Introduction

A policy stance captures, in relation to a specific point in time and situation, the balance between policy instruments and policy objectives. It puts the stringency of instrument calibration in a broader context of intensity of risks of missing the policy objective. For instance, in the field of monetary policy, tracking the evolution of the real interest rate or its deviations from the Taylor rule (Taylor, 1993) is commonly used to put into perspective choices of monetary policymakers and identify the phase of a monetary policy cycle. Analogously, tracking a measure of macroprudential policy stance should substantiate policy choices, increase their understanding by the public, and manage expectations about future macroprudential policy actions.

The first challenge in measuring macroprudential policy stance is that macroprudential policy involves multiple instruments. Not only is the macroprudential toolbox very broad, including both broad-based and targeted instruments, but also many non-macroprudential instruments can be adapted to macroprudential purposes. To measure the macroprudential policy stance, we must therefore aggregate multiple instruments and account for their interactions among each other and with other policies, including regulatory, supervisory, and monetary.

Another challenge relates to the measurement of the objective of macroprudential policies, i.e. financial stability. Financial stability is a condition in which the financial system – which comprises financial intermediaries, markets, and market infrastructures – is capable of withstanding shocks and the unravelling of financial imbalances.¹ However, there is still no widely accepted approach on how best to measure financial stability and existing approaches differ in their focus and complexity. Furthermore, preserving financial stability often boils down to preventive policies, such as building system resilience against probable but rare events like deep recessions or financial crises. It is relatively straightforward to pinpoint the costs of phasing in such policies, but very difficult to ex ante evaluate their longer-term benefits.

In this paper, we assess the macroprudential policy stance by employing the Growth-at-Risk (GaR) perspective and a semi-structural model. The large-scale semi-structural model captures the joint dynamics of individual banks and euro area economies and it can pin down the transmission channels of capital-based macroprudential and supervisory policies. The model is used to build interval forecasts of output or lending and the macroprudential policy stance is measured by changes in the lower percentile of these forecasts, i.e. Growth-at-Risk, net of the central tendency of the distribution, i.e. mean or median. This approach is illustrated by measuring changes in the macroprudential policy stance in the euro area and in individual euro area countries between 2017 and 2021.

¹ ECB (2021a).

The GaR-based measure of the stance assessment rests on the macro-micro Banking Euro Area Sector Stress Test (BEAST) model.² The model combines the dynamics of 19 euro area countries with the representation of around 90 individual banks jointly covering broadly 70% of euro area banking assets. Each bank is modelled via a rich set of equations mapping macro-financial conditions into bank-level loan-loss provisioning parameters, risk weights or funding costs, and capturing banks' behavioural reactions such as adjustments in lending volumes, interest rates, liability structure and profit distributions. In addition, the model captures two relevant feedback loops: real-financial feedback loop (between the banking sector and the economy) and solvency-funding cost feedback loop.

Banks in the model are subject to system-wide and bank-specific capital requirements and buffers. The model accounts for Pillar I and Pillar II capital requirements, including Pillar II Guidance (P2G) and the full set of macroprudential capital buffers, which include the capital conservation buffer (CCoB), the countercyclical capital buffer (CCyB), the buffers for global and other systemically important institutions (G-SIIs and O-SIIs) and the systemic risk buffer (SyRB). Additionally, the model includes leverage requirements kicking in in 2021, a detailed specification of the NPL coverage expectations entering into force in 2018, and the shift toward Basel III finalisation starting from 2023. These requirements will impact lending and profit distribution decisions among banks.

Banks are also affected by market interest rates, allowing us to track the interplay between prudential and monetary policies. Changes in ECB monetary policy interest rates (i.e. conventional monetary policy) and asset purchases – approximated by the size of the ECB balance sheets – impact the short and long end of the yield curve, correspondingly. These directly affect banks' funding costs, loan pricing and revaluation losses on trading books, which has a direct impact on bank profitability and capitalisation. Simultaneously, they also influence economic activity, credit demand and banks' own incentives to bear risks, which is reflected in the volume and average riskiness of the loans they grant.

The model's semi-structural design allows us to absorb various sources of information available at the point of building macro-financial forecasts. It concerns the most recent realisation of macroeconomic data and detailed information on banks' balance sheets and profit and loss accounts retrieved from supervisory reporting sources. The model also allows us to accommodate forward-looking information, such as ECB staff macroeconomic projections (ECB, 2021b), which are available at the reference date for up to a three-year horizon, as well as information about already announced macroprudential and supervisory policies.

The model can be used to build interval forecasts of macroeconomic and banking sector conditions. The empirical identification of behavioural equations provides estimates of reduced-form shock distributions. These exogenous and uncorrelated shocks in the macro block of the model can be employed to explore and build many alternative and plausible scenarios through repetitive stochastic

² See Budnik et al. (2020) and Budnik et al. (2019) for a description of the model. The model is discussed and developed further within the Macro-Micro (MaMi) workstream of the Working Group on Stress Testing (WGST) of the FSC.

simulations. These scenarios are then reflected in the full distributions of endogenous model variables such as GDP or lending. A recent example of how this approach was applied can be found in Budnik et al. (2021a), where it is used to estimate the impact of Basel III finalisation in the euro area.

The availability of the full distributions of economy-wide outcomes allows us to describe the corresponding Growth-at-Risk (GaR) or even expected shortfall (ES) metrics. Forecasts of GDP or lending rely on actual and announced macroprudential policies providing information about the relative contribution of the latter to risk outlook. Tail events can be measured, for example, by the 10th or 5th percentile of the GDP or lending growth distribution, which allows us to capture sufficiently adverse circumstances while maintaining desirable levels of accuracy.

A so-called distance-to-tail metric calculated as a difference between GaR or ES and mean or median of the distribution is then used to build a measure of the macroprudential policy stance. The relationship between distance-to-tail metric and stance relates to the risk-resilience framework as defined in ESRB (2019). The risk-resilience framework assesses a balance between systemic risk and resilience relative to financial stability objectives, given implemented macroprudential policies. The macroprudential policy stance is then characterised as a metric of the residual systemic risk in the financial system with respect to a neutral risk level defined by the policymaker. In this context, the macroprudential policy can be perceived as a risk management approach, which involves taming risks and vulnerabilities to limit the extreme negative tail realisations (benefits) while at the same time avoiding reductions in the positive parts of the future growth distribution (costs) (Chavleishvili et al., 2021).

This paper contributes to the rapidly growing body of research that advocates the risk management framework as the most appropriate to developing and assessing macroprudential policy. The research typically focuses on how macroprudential policy instruments impact the real GDP growth distribution and in particular its downside risks. Former Bank of England governor Mark Carney, in his UCL speech (Carney, 2020), suggests a macroprudential policy loss function built around the GaR metric. Suarez (2021) explores a potential application of the empirical GaR approach to the design and assessment of macroprudential policies, while Chavleishvili et al. (2021) propose the risk management view to macroprudential policy using a QVAR model to operationalise their GaR approach. Galán (2020) uses quantile regression to assess the impact of macroprudential policy on the left tail of GDP growth distribution. Similarly, recent IMF (Brandao-Marques et al., 2020) and Bank of Canada (Duprey and Ueberfeldt, 2020) working papers employ quantile regression to show how policymakers can manage GDP growth tail risks using both macroprudential and monetary policy instruments.

The proposed semi-structural model approach fortifies the assessment of the macroprudential policy stance with broad data use and narrative building. The semi-structural approach can integrate most recent data and forward-looking information with clear identification of transmission channels. This approach links well to discretionary policy setting, i.e. policy setting considering all relevant information at a point in time rather than following a strict time-invariant rule. It will

also have strong communicational advantages, as any assessment of macroprudential policy stance can be broken down and explained to the policymakers and the public. Last, the approach will also be more informative about the role of banking system heterogeneity in the transmission of macroprudential policies and more robust with regard to structural changes than the time-series Growth-at-Risk methods.

The rest of our report is structured as follows. Section 2 describes the model, highlighting its design, main features and specifications. Section 3 covers individual elements of the macroprudential policy stance assessment, including mapping of the stance in the tails of the distribution and introduces a logic of the policy exercise. Section 4 explores alternative measures of the macroprudential policy stance and presents an evolution of the stance between 2017 and 2021, including country-level results. Lastly, Section 5 contains our conclusions.

2 Model

2.1 Semi-structural design

The BEAST³ is a semi-structural model linking macro and bank-level data and is regularly used by the ECB for macroprudential stress testing⁴ and policy assessment.⁵ Both sides of bank balance sheets are modelled in a high level of detail to reflect their heterogeneity. The asset side of each bank's balance sheet distinguishes between different loan portfolios, equity exposures and securitised portfolios. The liability side distinguishes equity as well as wholesale and retail funding dynamics. For each bank, the developments of profitability and solvency are further broken down into the impact of credit, market and operational risks, net interest income and dividend pay-outs.

A share of model equations maps the pass-through of scenarios into bank balance sheet parameters. The BEAST adapts several micro data-based bank sensitivity equations that capture the impact of macrofinancial variables on flows between the three IFRS 9 asset impairment stages, loss given default and loss rate parameters, risk weights, revaluation losses, funding costs and net fee and commission income (NFCI).

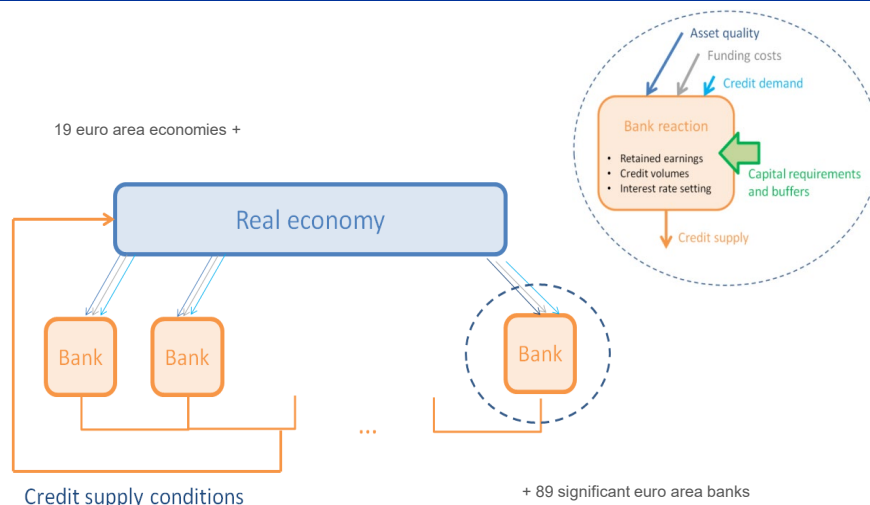
A further set of bank-level equations stipulates banks' behavioural responses. Banks react to changes in general economic conditions, taking account of their own financial situation, and adjust their lending volumes, loan pricing, profit distribution policies and liability structure accordingly (Figure 1). Banks' decisions reflect their empirical reluctance to undercut their capital targets set by a combination of regulatory capital minimum requirements and buffers, along with the quality of their assets, their profitability, and their funding structures.

³ See Budnik et al. (2020).

⁴ See, e.g.: Budnik et al. (2019) or Budnik et al. (2021d).

⁵ See, e.g.: Budnik et al. (2021a), Budnik et al. (2021b) or Budnik et al. (2021c).

Figure 1
Schematic illustration of the BEAST



Source: ECB

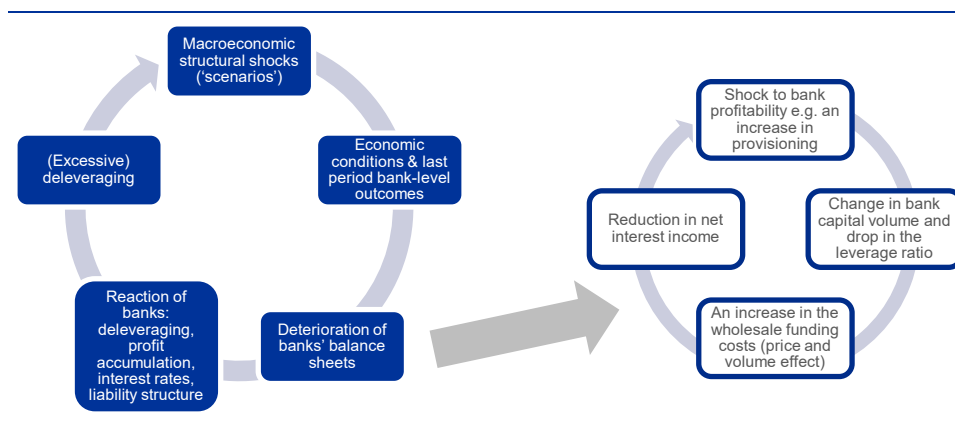
The macroeconomic module captures the dynamics of each euro area economy including intercountry trade spillovers. The dynamics of the individual euro area economies are estimated with a structural panel vector autoregressive (SVAR) model building on Budnik et. al (2020) and employing Bayesian methods with embedded long-run priors to stabilise the long-term dynamics of the system at values consistent with long-term trends and stylised facts. An additional block of cross-country trade spillovers replicates the functioning of Stress Test Elasticities (STEs), regularly employed in the EBA EU-wide stress tests, by linking countries' import volumes to foreign demand variables, and their export prices to foreign price variables. The model puts all macro-financial and bank-level equations together and solves them as a system, thus preserving internal consistency and allowing for simultaneous (same time period) feedback mechanisms.

Solving all equations jointly enables a comprehensive modelling of amplification mechanisms, therein the feedback loop between the banking sector and the real economy. In normal times, banks adjust their credit volumes and interest rates largely in line with the evolution of aggregate credit demand. In adverse conditions, banks attempt to restore eroded capitalisation and credit supply factors become more relevant. Actions among individual banks aimed at repairing their capital levels lead to a negative credit supply shock disrupting the macro economy. Figure 2, left-hand side panel, sketches the functioning of the feedback loop.

A further amplification mechanism represents the interaction between solvency and funding costs. A solvency shock reflected in an increase of bank leverage leads to an increase in bank wholesale funding costs. Decreasing bank solvency makes the institution more vulnerable to default and this risk is priced into the unsecured funding costs of banks. This, in turn, has an adverse effect on bank capital by eroding net interest income. Last, impaired solvency further aggravates bank funding conditions (Figure 2, right-hand side panel). The two amplification

mechanisms interrelate: a deterioration in the cost of funding would be reflected in bank lending rates, which would in turn affect the supply of credit to the real economy.

Figure 2
Schematic illustration of the feedback loops



Source: ECB

2.2 Modelling uncertainty

The SVAR model represents each euro area economy and includes a dozen macro-financial variables that can significantly affect banks' balance sheets. It includes real GDP, HICP, unemployment rate, short-term interest rate, long-term interest rate, Euro System balance sheet, import volumes, export prices, residential property prices, bank lending rates, bank loan volumes, equity price index and two exogenous variables – foreign demand and competitors' prices. Short-term interest rates and the size of the ECB balance sheet can capture monetary policy developments along both conventional and unconventional angles.

Each euro area economy is also exposed to a dozen structural or reduced-form shocks. Panel estimates of countries' VARs deliver the empirical (multi-normal) distributions of structural shocks such as aggregate demand, aggregate supply, standard and unconventional monetary policy shocks, housing demand and equity price shocks. These distributions can be then used to generate many alternative scenarios via repetitive (Monte-Carlo) simulations. Panel estimates of the corresponding reduced-form countries VARs and time series of reduced-form shocks allow us to apply bootstrapping methods to generate analogous scenarios.

Additionally, the uncertainty of future outcomes is related to parameter uncertainty in the macro block of the model. Stochastic simulations within the model involve the full distributions of VAR model parameters.

2.2.1 Benchmark specification

A reduced-form panel VAR for 19 euro area economies has the following form:

$$Y_{i,t} = c_i + \sum_{j=1}^p A_{i,j} Y_{i,t-j} + B_i X_{i,t} + D_i \varepsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ is a vector of endogenous variables for a country i , c_i is a vector of country-specific intercepts, $X_{i,t}$ is a vector of exogenous variables, $A_{i,j}$ is a country-specific matrix of autoregressive coefficients for a lag j , p is a number of lags, B_i is a matrix of coefficients for exogenous variables, D_i is a matrix providing the mapping between a vector of reduced form residuals $\varepsilon_{i,t} \sim N(0, \Sigma)$ and the orthogonal structural shocks $\varepsilon_{i,t} \sim N(0,1)$, such that $\varepsilon_{i,t} = D_i \varepsilon_{i,t}$.

The estimation procedure follows the Bayesian approach proposed by Jarocinski (2010). While the vectors of parameters $A_{i,j}$ and B_i can differ between countries, they are sampled from distributions with similar mean and variance. As a result, some degree of homogeneity is preserved between countries. The vector c_i incorporates steady-state priors following Villani (2009). We assume lag order of $p = 2$ and apply a Gibbs sampler to arrive at the full posterior distribution of parameter draws.

The structural representation D_i of the panel VAR model is derived by combining a set of zero and sign restrictions. The identification approach pursues the same strategy as in Budnik et al. (2020) and follows the methodology of Arias et al. (2018). There are nine structural shocks pinned down by a set of zero and sign restrictions on impact: aggregate supply, aggregate demand, monetary policy, credit supply, credit demand, bond yield, housing demand, unconventional monetary policy, and stock prices shock.

Alternative macro-financial scenarios are generated by creating series of draws from the joint posterior distribution of structural shocks $\varepsilon_{i,t} \sim N(0,1)$. The related Monte Carlo simulations follow a two-step procedure to also account for parameter uncertainty: (i) drawing from the posterior distribution of the panel VAR parameters c_i , $A_{i,j}$, B_i , D_i , and (ii) drawing a sequence of the structural shocks from $\varepsilon_{i,t} \sim N(0,1)$ of the length corresponding to the horizon of the simulation.

2.2.2 Bootstrapping

Bootstrapping eliminates any ex ante parametrical assumptions about the reduced-form residuals ε_t in the VARs. It does so by carefully sampling the shock process $\hat{\varepsilon}_t$ from the set of historical residuals $\{\varepsilon_t, t \in 1, \dots, n\}$, where n is the size of the historical sample. In the VAR setting, each ε_t is a vector; therefore, the residuals for each variable are sampled jointly.

The bootstrapping method applied in this paper is the geometric block bootstrap, which recognises the time-series nature of the model. It is named block bootstrap because instead of sampling a single data point, it samples whole blocks of consecutive residuals and can thus preserve the time correlation present in the original data. For each block i , the starting point t_i is drawn uniformly in $\{1, \dots, n\}$. For example, t_1 denotes the starting point of the first block.

The designation geometric is derived from the length of each block being drawn according to a geometric distribution. The length l of a block follows

$$P(l = k) = p(1 - p)^{k-1},$$

where p is the parameter of the geometric distribution. The parameter p is chosen such that the average block length, $l_{avg} = 1/p$, corresponds to the optimal block size as defined in Politis and White (2006). For instance, assume l_1 to be a length of the first block following a geometric distribution. The first block is therefore $\{\hat{\epsilon}_1, \hat{\epsilon}_2, \dots, \hat{\epsilon}_{l_1}\} = \{\epsilon_{t_1}, \epsilon_{t_1+1}, \dots, \epsilon_{t_1+l_1-1}\}$. The bootstrap procedure continues to generate blocks in this manner until the required total length is reached or exceeded; the last block is truncated if necessary. In contrast to the benchmark specification, bootstrapping allows for a time-varying variance.

2.2.3 Replicating historical distributions

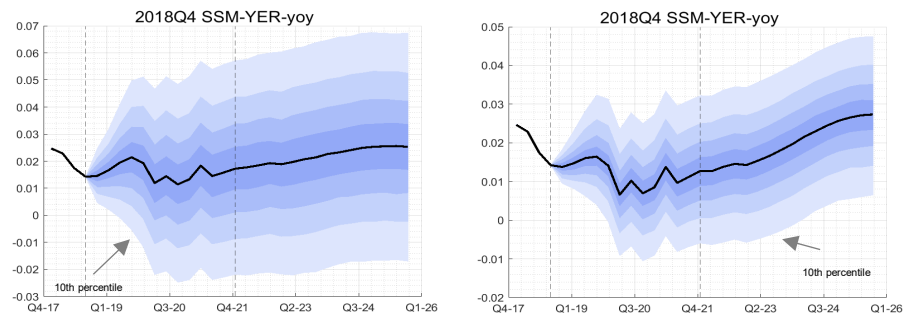
Chart 1 shows the forecast GDP growth distribution for the benchmark specification and the bootstrapping approach defined above. The two vertical lines lay out the maximum five-year horizon used in the analysis. The shades of the blue ranges spreading around the mean projection (represented by the black line) show individual deciles of the future GDP growth distribution. The tail events are defined for the purpose of macroprudential policy stance assessment as e.g. the 10th percentile of the distribution and they are thus represented by the lowest bound of the fan chart.

The model captures asymmetry in the distribution of output growth forecasts based on the non-linearities of bank behaviour. For instance, banks will deleverage most aggressively when they breach regulatory capital requirements. This feature allows for a meaningful interpretation of changes in the lower tails of the growth distribution.

Chart 1
Euro area GDP growth distribution fan charts

Mean and individual deciles of the future GDP growth distribution

Year-on-year GDP growth rate; benchmark (left) and bootstrapping (right)



Source: ECB.

Note: The first vertical line represents the reference period (in this case 2018Q4). The second vertical line marks the three-year horizon from the reference period. The black line shows the mean forecast and the ranges correspond to the individual deciles of the distribution.

3 Assessment of stance

This chapter introduces individual elements of the macroprudential policy stance assessment. First, it explains how the stance is mapped onto the tails of the GDP distribution using the Growth-at-Risk approach. Then it shows how information from different sources can be incorporated into the assessment, therein macroeconomic forecasts, bank-level data and current and announced policy instruments. Lastly, it describes the assessment of the euro area macroprudential policy stance performed in the next chapter.

3.1 Mapping of the stance in the tails of growth distribution

The macroprudential policy stance establishes a relationship between macroprudential actions by policymakers and the objective of financial stability (ESRB, 2019). However, developing a framework for assessing the macroprudential policy stance is inherently challenging due to the multi-dimensional nature of the exercise and predicaments regarding the measurement of both the risks and the instruments.

Growth-at-Risk (GaR) is widely regarded as a promising approach for assessing the macroprudential policy stance.⁶ GaR emphasises the relative importance of risks embedded in the lower tail of the growth distribution. Macroprudential policymakers aim to prevent or mitigate the systemic risks or counteract excessively detrimental effects of financial imbalances. Hence, they attempt to reduce downside risks to the economy and control the lower tail of the growth distribution.

ESRB (2021) recommends the distance-to-tail as a stance metric that focuses on the relative importance of risks embedded in the lower tail of the growth distribution, relative to its central tendency. The distance-to-tail stance metric is independent of parallel shifts in the growth distribution that symmetrically affect both its tails and central tendency. Such shifts are likely to depend on factors outside the remit of macroprudential policy, such as structural changes or reforms. Macroprudential policy focuses, instead, on reducing downside risks, desirably without negatively affecting the expected growth.

3.2 Elements of stance assessment and policy discretion

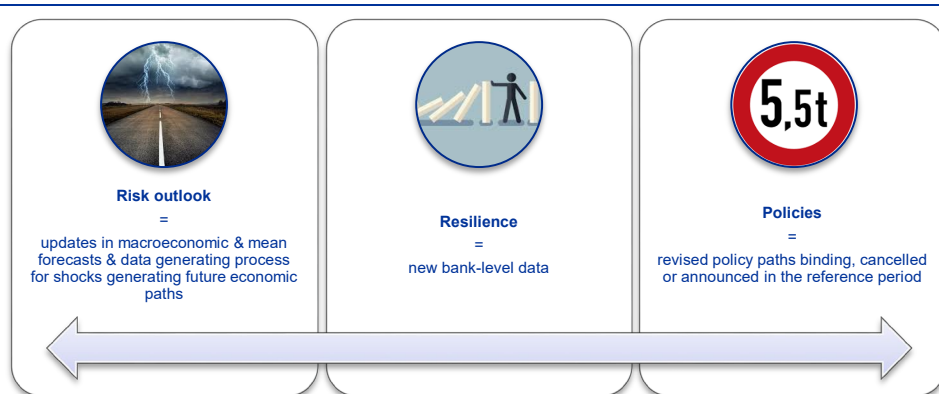
The Growth-at-Risk approach to the macroprudential policy stance assessment can be pursued with different models. The semi-structural approach

⁶ See Box 3 in ESRB (2019).

has the advantage of explaining transmission channels of risks and policies. Yet other advantage is its ability to incorporate many sources of relevant information.

The BEAST model can provide a comprehensive risk outlook, while accounting for system resilience along with active or planned policies at a point in time. A macrofinancial forecast for each time point relies on all available historical data and updated information regarding the shock-generating process influencing the distribution of future economic scenarios (see Figure 3, left-hand side panel). The exact way of updating the shock-generating process depends already on the stochastic simulation setup. For applications employing bootstrapping, the set of residuals used for shock generation will each time include more and more observations accommodating the most recent data realisations.

Figure 3
Mapping updates of the information to stance assessment



Source: ECB.

The central tendency of the forecasted distribution of variables can be anchored on projections derived from models best tuned to this purpose. In our application, we anchor the mean paths of country-level macrofinancial variables on Eurosystem and ECB staff macroeconomic projections, which are published four times a year (in March, June, September and December).⁷ This information is supplemented by the forecast of the ECB balance sheet incorporating the information on existing unconventional monetary policy programmes with a similar cut-off date to the ECB staff macroeconomic projections. Outside of the horizon pinned down in the Eurosystem and ECB staff exercise (up to three years), the model follows its endogenous dynamics.

The information on banking system resilience rests on the most recent data on individual banks' balance sheets sourced from FINREP and COREP frameworks. The supervisory reporting is used to update the information on banking, trading books, bank liabilities, components of bank profitability and own funds.

Last, the model can encapsulate a complete picture of macroprudential, supervisory and regulatory policies. The model focuses on capital-based policies.

⁷ ECB (2021b).

The set of instruments from the macroprudential toolbox that feed into the assessment includes CCyB, CCB, SRB and O-SII/G-SII. The assessment will each time incorporate all known paths of each instrument. For example, it will allow for the effect of a CCyB that is announced to become binding only at some point in the future. This information is supplemented with detailed bank-level information on Pillar II requirements and buffers. The model replicates the fact that trespassing macroprudential buffers trigger restrictions on Maximum Distributable Amounts. Additionally, model formulas allow us to incorporate the effects of profit distribution restrictions (if binding).

The interactions between macroprudential and regulatory policies appear relevant as several regulatory reforms have been phased-in in recent years or are being planned for the years ahead. Figure 4 summarises this information, including announcement dates. First is Basel III finalisation, initially scheduled to be introduced in 2021 but postponed until 2022 in response to Covid-19. This aspect will translate into higher effective capital requirements and buffers (including those macroprudential) and affect the distribution of risks in the system (by selectively targeting IRB banks).⁸ Second are supervisory coverage expectations introduced as an element of the NPL guidance over 2018, which will have a substantial bearing on banks' capacity to build up capital buffers in the years to come.⁹ Third, we have changes resulting from CRD5/CRR2, partially front-loaded to 2020, which have a direct impact on capital requirements by for changing the composition of Pillar II minima, among other effects.

Figure 4
Relevant regulatory changes in 2018-2020



Source: ECB.

The final key policy element incorporated in the model are Covid-19 mitigation policies not directly targeting but having a very pronounced effect on the banking sector. These policies take the form of public guarantees and public moratoria introduced in most of the jurisdictions during 2020. The model thoroughly replicates the workings of the two schemes, their introduction and extension dates, and country specificities. For example, public guarantees will directly impact bank loan supply and demand, pricing of loans and risk weighting of exposures, with an indirect impact on longer term solvency and the profitability outlook of banks.¹⁰

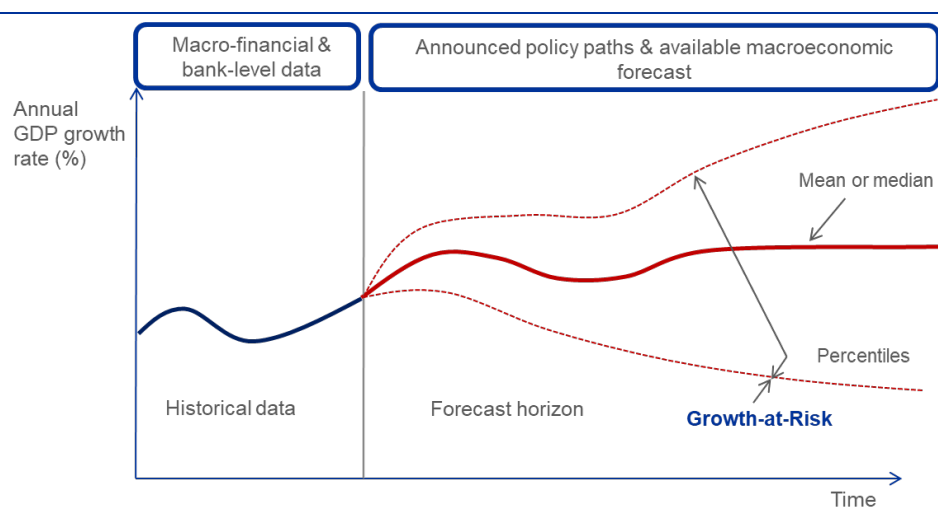
⁸ See Budnik et al. (2021a).

⁹ See Budnik et al. (2021b).

¹⁰ See Budnik et al. (2021c).

Figure 5 summarises the essence of the stance assessment. The data and the forward-looking information available at a point in time are fed into the model, which is then used to run multiple stochastic simulations, tracking the evolution of economies and banks under thousands of alternative but plausible scenarios. Stochastic simulations allow us to derive full distributions of all endogenous variables, including GDP and lending. The measures of the distribution relevant for the stance assessment are then read out at the horizon of interest.

Figure 5
Schematic illustration of the stance assessment



Source: ECB.

3.3 Policy exercise

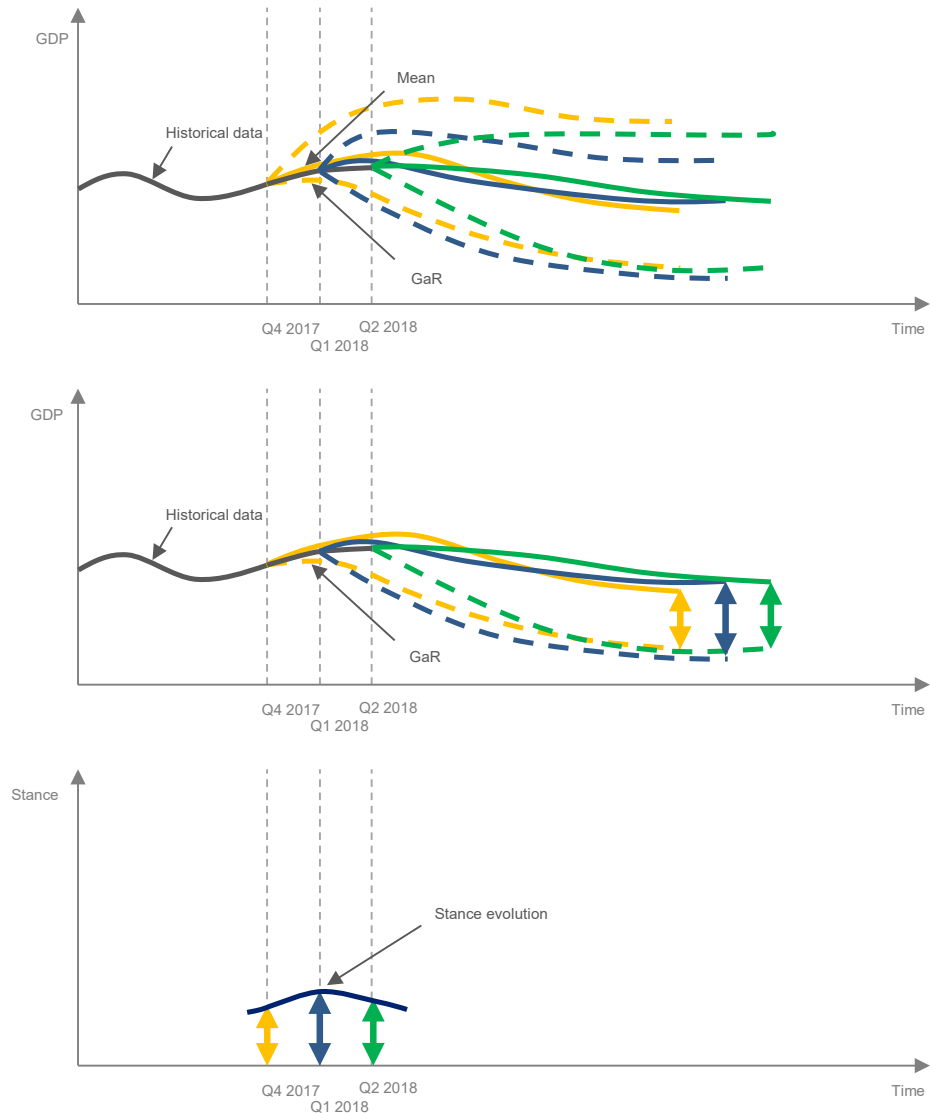
In order to illustrate the methodology, the model was used to assess the macroprudential policy stance evolution in the euro area from 4Q 2017 to 3Q 2021. We ran period-by-period recursive out-of-sample forecasts, where the emphasis was put on the full distribution rather than only on a mean of the endogenous variables. At each reference period, the assessment of stance includes only the information available until that point in time. The exercise also fully respects information lags, such as bank-level data being typically available with a lag of around two quarters and national accounts with a lag of around one quarter. Each simulation includes 36,000 different scenarios from which less than 0.1% is discarded (pruned) due to numerical instabilities.¹¹

Figure 6 illustrates the concept of the exercise. For each quarter, we derive a forecast of the real GDP (or alternatively private sector lending) distribution at a pre-selected horizon. In Figure 6, the reference quarters for the stylised forecasts are 4Q 2017 and 1Q-2Q 2018. We keep track of a central tendency (e.g. mean as in Figure 6, or median) and tails (e.g. individual percentiles as in Figure 6, or expected

¹¹ In non-linear models a fraction of simulations will tend to become highly unstable and fall out of the scope of plausible scenarios due to issues such as repetitively dividing by an extremely small number.

shortfall) measured at the end of the horizon. We aim to derive quarter-by-quarter evolution of the distance-to-tail metric as illustrated in the bottom panel of Figure 6 for the lower tail of the distribution (GaR) and the distribution's mean.

Figure 6
Schematic illustration of multi-period stance assessment



Source: ECB

Chart 2 includes the empirical counterpart of measures that can be read out from the upper panel of Figure 6. The left-hand side panel shows the mean one to five years ahead of the compound annual real GDP growth rate forecast. The expected euro area GDP growth was above 0.5% for one year ahead, and above 1% annually for five years ahead on average in 2018-2019. The mean GDP growth for one year and two years ahead in 2020 reflects the expected rebound in economic activity following the sharp contraction in the first half of 2020 (the beginning of the Covid-19 pandemic). The increase in expected three- to five-year ahead annualised

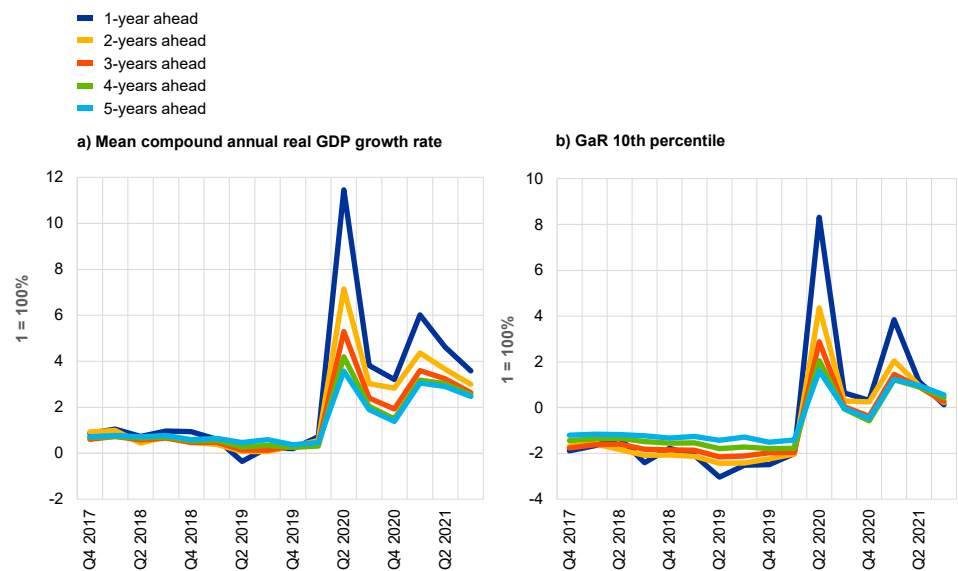
GDP growth rate in 2020 is already lower, reflecting the forecast convergence of GDP growth to its long-term trend following the rebound.

There is a strong co-movement between the mean and the tail of the forecast GDP growth over time, signifying the empirical relevance of shifts in the overall forecast distribution. The right-hand side panel of Chart 2 shows the 10th percentile of the compound annual real GDP growth rate forecast distribution one to five years ahead. The correlation coefficient between the mean and the 10th percentile for each forecast horizon is above 95%. It justifies the focus on measuring the distance between the mean and the relevant percentile of the future GDP distribution (i.e. distance-to-tail) to capture the evolution of macroprudential policy stance.

Chart 2

Euro area mean (LHS) and GaR 10th percentile (RHS) compound annual real GDP growth rate one to five years ahead

Substantial co-movement of stance measures at different time horizons



Source: ECB.

4 Results

This chapter explores alternative measures of the macroprudential policy stance and presents an evolution of the stance between 2017 and 2021, including country-level results.

The first section discusses various alternative stance measures. The following part looks at the evolution of macroprudential policy stance between Q4 2017 and Q3 2021 for two different policy options – constant and actual policy trajectories. Lastly, a development of stance across selected euro area countries is presented focusing on both real GDP and private sector lending-based stance measures.

4.1 Exploring alternative measures of stance

Several stance measures can be defined building on the principles described in the last section.

The first possible choice is the sampling scheme, i.e. benchmark simulations based on multiple draws from the distributions of structural shocks (see Section 2.2.1), or bootstrap simulations based on multiple draws from actual reduced-form residuals (see Section 2.2.2). Another selection is the horizon at which the stance is measured. The last choice is the measurement of tails (GaR versus expected shortfall and a selection of percentile) and the central tendency (mean versus median).

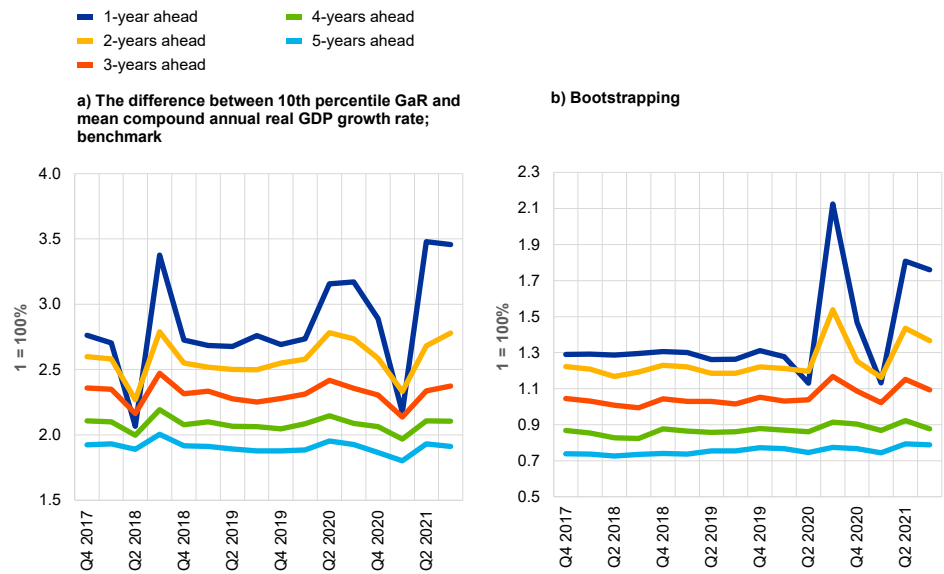
The choice of the horizon should, among other factors, reflect transmission lags of macroprudential policies and persistence of macro-financial risks.

Or, looking from a practitioner view, the choice of the horizon should reflect how far ahead macroprudential policymakers look when assessing the policy setting. For instance, a standard stress test exercise will reach up to three years ahead. Chart 3 presents the assessment of macroprudential policy stance based on the compound annual real GDP growth rate distance-to-tail measured between mean and GaR at 10th percentile at horizons ranging from one to five years. The left-hand side panel shows simulation results with the benchmark specifications and the right-hand side panel shows bootstrapping results. For example, the below 2% level of five-year ahead macroprudential policy stance in 2018 in the left-hand side panel means that the lower tail of the compound annual real GDP growth rate between 2018 and 2023 would be 2 pp below the expected compound annual real GDP growth rate over the same period. The higher the level of the stance indicator, the more pronounced the tail risks, or equivalently a looser macroprudential policy stance.

Chart 3

Euro area compound annual real GDP growth rate distance-to-tail –10th percentile GaR vs mean one to five years ahead

Substantial co-movement of stance measures at different time horizons



Source: ECB.

The level and time-variation of the stance indicator generally decreases with the length of the horizon. Additionally, the level of stance is generally higher for the benchmark specification for any forecast horizon. The higher level of the stance indicator in the benchmark compared to the bootstrapping results reflects the on average almost five times higher variance of the benchmark compared to the bootstrapped forecasts. The pattern has increasing tendency with growing time horizon as the ratio is around 3.7 for the one-year horizon and grows to over 6 for the five-year horizon. Last, the decreasing volatility of the stance indicator with the length of the forecast horizon reflects the propensity of the model and economies to return to their long-term growth paths over the medium run.

A correlation analysis of co-movements between the stance measures based on different horizons reveals that they move together closely, though the relationship between them weakens with an increasing gap between reference time horizons. An average correlation between adjacent $t \pm 1$ horizons (e.g. for two-years horizon correlation with one-year and three-years horizons) is almost 92%. The average correlation steadily decreases with time gap to around 84% and 73% for $t \pm 2$ and $t \pm 3$, respectively. For $t \pm 4$ (i.e. the correlation between the one-year and five-year horizon), it decreases even further to roughly 68%, which represents a drop of almost 24 pp when compared to the adjacent horizons. In general, no significant dependency of co-movement tightness on the time horizon was identified, i.e. an average correlation between short-end and long-end horizons is roughly similar. Thus, there is no clear horizon preference stemming from the correlation analysis alone. However, the longer horizons are generally preferable due to empirical evidence on significant transmission lags of macroprudential policies.

Another dimension of comparison concerns the usage of different risk measures, based on GaR at 10th percentile versus GaR at 5th percentile, GaR versus expected shortfall (ES), and mean versus the median of the forecast distributions. First, we explore sensitivity of the macroprudential policy stance measure on the selected percentile of the forecast distribution.

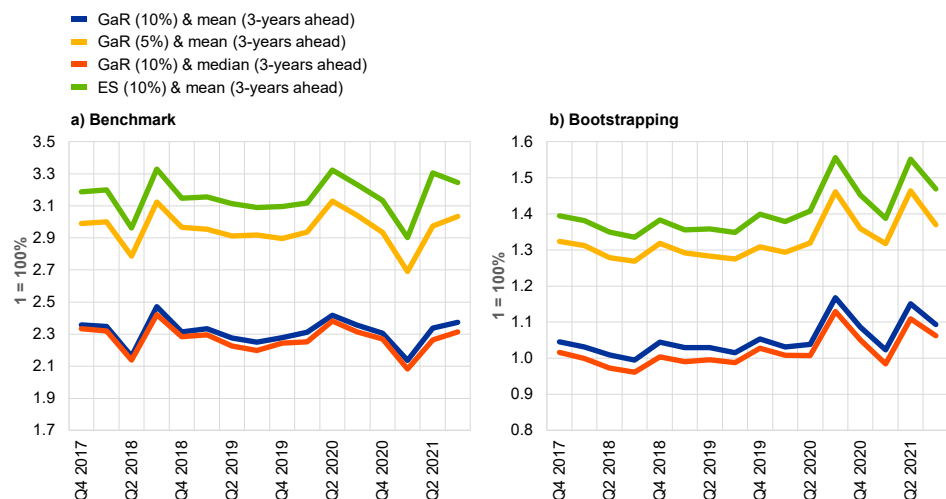
A comparison between the measures based on three-year ahead 10th percentile and 5th percentile GaR can be examined in Chart 4, revealing a strong average correlation of almost 98%. Thus, while a default level of stance would change, using 5th instead of 10th percentile GaR would otherwise lead to a similar assessment in terms of dynamics. The expected shortfall (ES) measure of macroprudential policy stance relies on the difference between the mean and ES rather than GaR at 10th percentile. It is contrasted for a three-year ahead forecast horizon with its GaR counterpart in Chart 4. The two measures correlate well, with average correlation close to 97% and thus, analogically to the previous case, using ES instead of GaR would lead to a shift in the stance level, but to a very similar assessment in terms of dynamics. Lastly, Chart 4 also shows the measurement for the three-year horizon based on the difference between GaR at 10th percentile and the median. The average correlation between the measures based on mean and based on median is very high, reaching 99%. Hence, using a median- instead of mean-corrected tail measure would lead to an equivalent assessment of stance both in terms of level and dynamics.¹²

Chart 4

Euro area compound annual real GDP growth rate distance-to-tail – comparison of alternative stance measured three years ahead

Alternative measures of macroprudential policy stance based on different measures of tails and central tendency

Comparison between 10th percentile GaR vs. mean compound annual real GDP growth rate, 5th percentile GaR vs. mean compound annual real GDP growth rate, 10th percentile GaR vs. median compound annual real GDP growth rate and 10th percentile ES vs. mean compound annual real GDP growth rate



Source: ECB.

¹² The strength of co-dependency with the default measure based on mean and GaR at 10th percentile is essentially independent of the time horizon for all the alternatives examined, with average correlation across time horizons of almost 97% for both 5th percentile and ES and almost 99% for median.

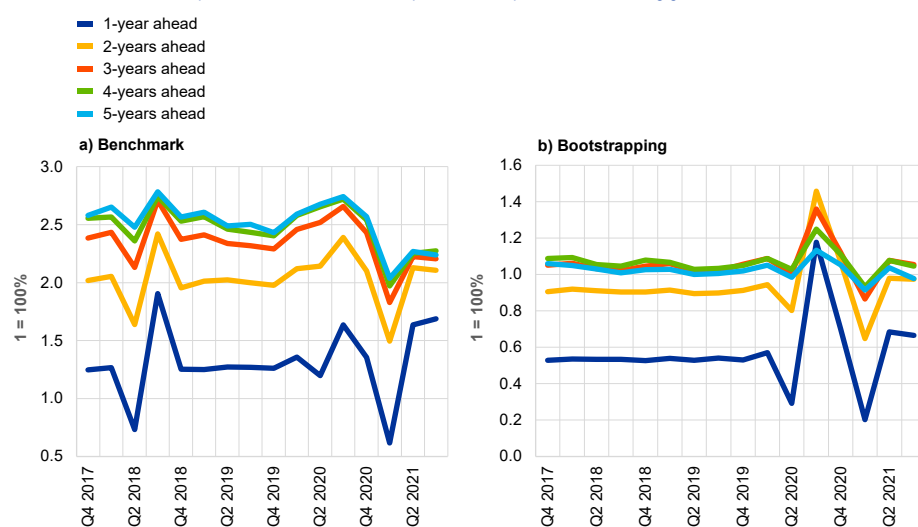
To complement the analysis, we also explored approaches based on non-GDP measures, especially private sector lending, as shown in Chart 5. In this case, the measurement for each time horizon is based on compound annual private sector lending growth rate distance-to-tail measured between mean and the so-called Lending-at-Risk (LaR) at 10th percentile. The left panel shows simulation results with the benchmark specifications, while the right panel presents the bootstrapping results. While the level of stance indicator increases with the length of the horizon, its time variation tends to decrease as the horizon lengthens. Similarly to the GDP-based measure, the level of stance is generally higher for the benchmark specification for any forecast horizon due to on average more than five times higher variance of benchmark compared to bootstrapped forecasts.¹³ Also in terms of the correlation analysis, similar conclusions can be made as with the GDP-based measure, since the dependencies between the time horizons are comparable between the two measures. Lastly, comparing correlations between GDP- and lending-based stance measures reveals that while the average correlation is solid (approximately 70%), there is a clear decreasing pattern as the time horizon lengthens, as the average correlation is close to 90% for the one-year horizon, but gradually fades to slightly over 40% for the five-year horizon.

Chart 5

Euro area compound annual private sector lending growth rate distance-to-tail – 10th percentile LaR versus mean one to five years ahead

Private sector lending-based assessment of macroprudential policy stance for different time horizons

The difference between 10th percentile LaR and mean compound annual private sector lending growth rate



Source: ECB.

¹³ Also in this case the pattern has increasing tendency as the time horizon lengthens – the ratio is around 4.5 for the one-year horizon and grows to over 6 for the five-year horizon.

4.2 The evolution of macroprudential policy stance between 2017 and 2021

Chart 5 depicts the evolution of the semi-structural GaR-based macroprudential stance measure for the three-year ahead compound annual real GDP growth rate forecast for the euro area. The assessment is intentionally based on the longer-horizon forecasts, which can accommodate policy lags¹⁴ without compromising forecast quality. As in the previous section, the metrics are compared between the benchmark and the bootstrapping approach. The results are presented for two alternative policy options – actual and constant policy. The actual policy option reflects the macroprudential policies implemented and planned during the period. By contrast, the constant policy option assumes no policy change from Q4 2017 onwards.

A few important take-aways can be derived from investigating the evolution of the semi-structural GaR macroprudential policy stance between 2017 and 2021. First, the exercise indicates a mild tightening of the stance before 2020 as the actual policy distance between the tail and the mean of the GDP distribution was, until the end of 2019, generally below its level at the end of 2017. Second, even though the distance-to-tail increases abruptly at the onset of the Covid-19 pandemic, it trends to normalisation towards the end of the year, caused, among other factors, by progress in vaccine developments. In the second quarter of 2021, we can again observe a loosening of the stance, mainly due to the uncertainty fanned by successive waves of infections and novel virus variants. These conclusions would also be supported by the alternative metrics, which might show different absolute values of the macroprudential policy stance but depict similar trends.

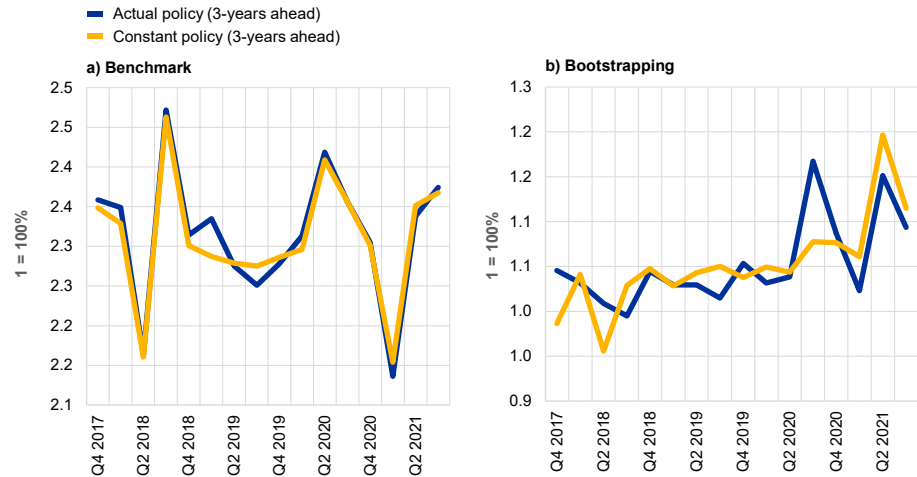
¹⁴ See e.g. Budnik and Ruenstler (2020), who document substantial macroprudential policy lags in the United States.

Chart 6

Euro area compound annual real GDP growth rate distance-to-tail – comparison of alternative policy options three years ahead

GDP-based assessment of macroprudential policy stance three years ahead for actual and constant policy

The difference between 10th percentile GaR and mean compound annual real GDP growth rate



Source: ECB.

The relative impact of macro-financial policies can be best illustrated by the underlying trends in the distance-to-tail of private sector lending growth.

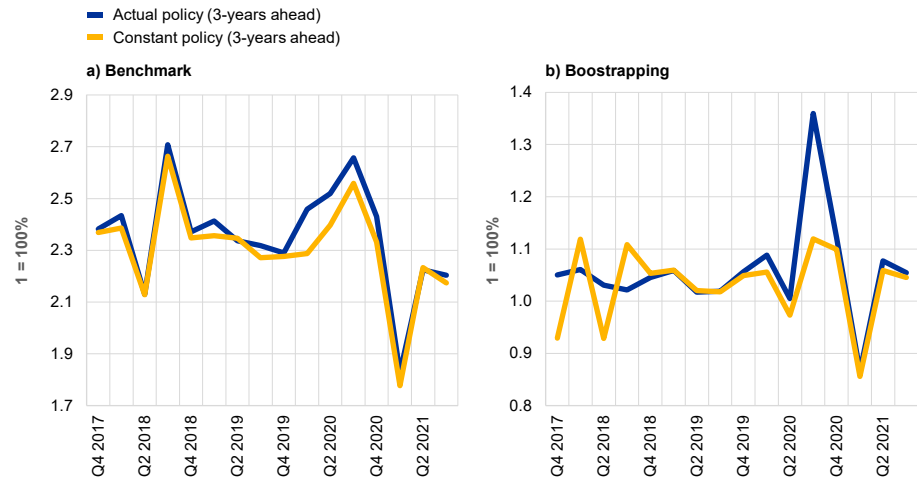
Private sector lending dynamics are not only often seen as an intermediary target of macrofinancial policies but are also more directly influenced by these policies than the economic output. Chart 7 summarises the information on the LaR metric for the compound annual lending of banks to the non-financial private sectors growth rate. Similarly to the GDP semi-structural GaR stance metrics, there is a slow downward trend in the series, marking increased resilience of the banking system and the economy, which is interrupted at the beginning of 2020 but reappears at the end of the year before increasing again most notably in the second quarter of 2021. The relative impact of the macro-financial policies applied (including supervisory actions) is far clearer in this perspective, especially during 2020.

Chart 7

Euro area compound annual private sector lending growth rate distance-to-tail – comparison of alternative policy options three years ahead

Private sector lending-based assessment of macroprudential policy stance three years ahead for actual and constant policy

The difference between 10th percentile LaR and mean compound annual private sector lending growth rate; benchmark (left) and bootstrapping (right)



Source: ECB.

4.3 Country-level results

The semi-structural GaR stance measure across selected euro area countries is signified by a high degree of co-movement. The differences in the period average levels of stance across countries typically relate to the relative output variability, with higher level of stance in smaller countries such as Greece, Ireland, or Slovenia, and lower in larger economies such as Germany or France (see Chart 8). The most informative, however, are country-level changes, with a very general trend toward strengthening of stance before the Covid-19 pandemic, at least partially reflecting a coordinated effort by macroprudential and supervisory authorities following the 2008 crisis. At the end of 2020, the stance in many countries returned to pre-Covid levels, only to increase again in 2021 across a majority of euro area countries. Chart 9 captures the stance developments across the selected countries based on private sector lending and largely reinforces the findings above.

Chart 8

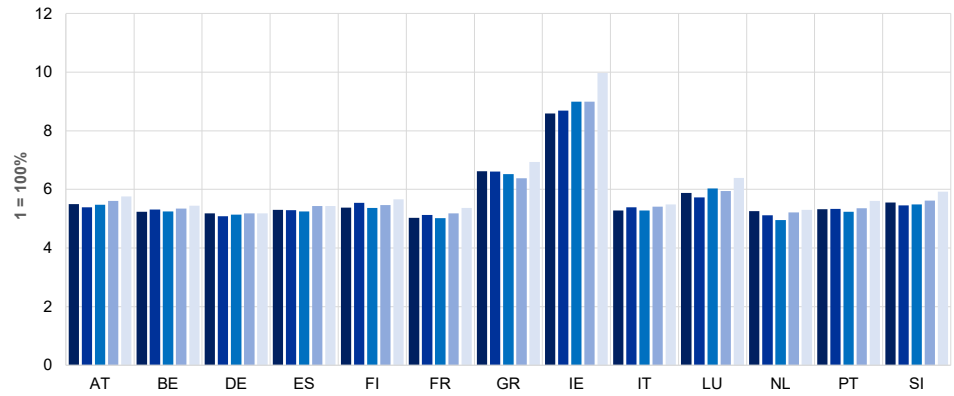
Euro area countries compound annual real GDP growth rate distance-to-tail – mean versus the 10th percentile GaR three years ahead

Country examples for semi-structural GaR stance between 2017 and 2021

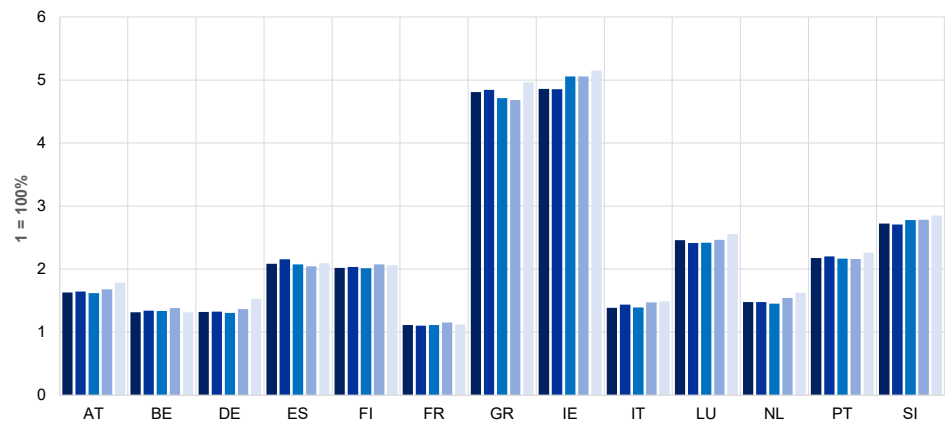
The difference between 10th percentile GaR and mean compound annual real GDP growth rate

- Q4 2017
- Q4 2018
- Q4 2019
- Q4 2020
- Q3 2021

a) Benchmark



b) Bootstrapping



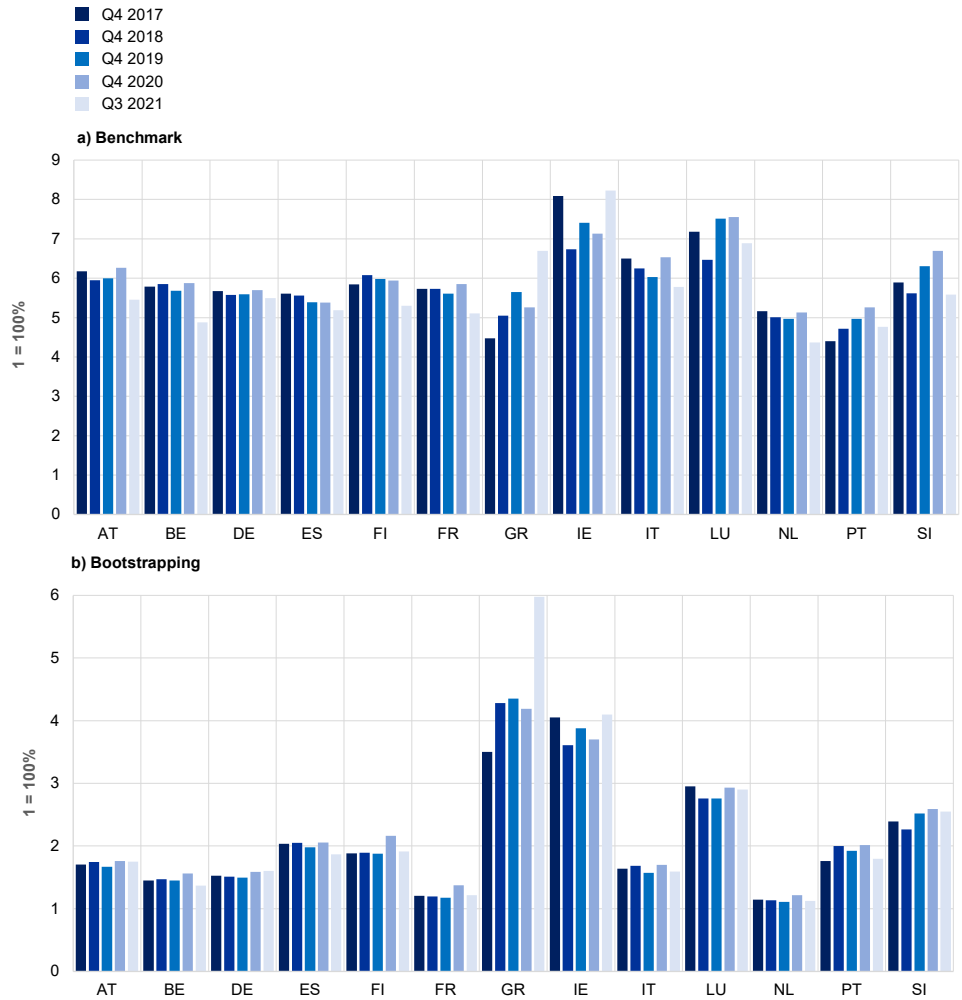
Source: ECB.

Chart 9

Euro area countries compound annual private sector lending growth rate distance-to-tail – mean versus the 10th percentile LaR three years ahead

Country examples for semi-structural LaR stance between 2017 and 2021

The difference between 10th percentile LaR and mean compound annual private sector lending growth rate; benchmark (top) and bootstrapping (bottom)



Source: ECB.

5 Conclusions

This paper presents a possible way of measuring macroprudential policy stance by applying a mean-corrected GaR perspective and a large-scale semi-structural model. This model strikes a middle ground between standard empirical and structural models. Semi-structural models, in comparison to other approaches, offer ample flexibility in incorporating relevant information in a forecast. It makes them a popular choice in monetary policy forecasting, where the aim is to build forecasts encapsulating the information derived from satellite models and expert intuition, while preserving the ability to decompose and economically justify the end result. The model has sound long-run properties, ensured by tailored estimation techniques, and can be used to build longer horizon conditional forecasts. These long-term properties help capture transmission lags in macroprudential policies or the persistency of systemic risks.

The semi-structural approach can accommodate the interplay between macroprudential and monetary and supervisory policies. Additionally, the semi-structural BEAST model can explore a very rich information set, including the information about current and future policies, detailed information about the banking sector at any juncture, and the relevant forecasts of macrofinancial variables from Eurosystem projections. Including the latter binds the assessment of the macroprudential policy stance even closer to monetary policy stance, with the same forecasts informing monetary policy decisions.

Additionally, the merits of the semi-structural approach can be exploited based on other models already available to Member States. By exploring alternative structural models, policymakers may be able to emphasise other transmission channels, introduce more country specificities or re-use infrastructures already supporting central bank monetary policy.

The analysis shows a strong co-movement between the mean and the lower tail of the forecast distribution of the macrofinancial variables considered. This justifies the focus on the distance-to-tail metric, which measures the distance between a central tendency and a relevant sufficiently low percentile of the forecast distribution to capture the evolution of macroprudential policy stance. In particular, we focused on two macrofinancial variables: real GDP as a measure of the overall economic output and private sector lending as an often cited intermediary target of macroprudential policies.

Through the prism of the distance-to-tail metric, we explored multiple alternative stance measures. These alternatives differ by sampling schemes and both central tendency and tail measures. The correlation analysis reveals a generally high degree of co-movement and thus while the default level of stance might change across the alternative measures, they otherwise lead to a very similar assessment in terms of dynamics. The alternatives also differ by the time horizon they consider and there is no clear horizon preference stemming from the correlation analysis alone.

However, longer horizons are generally preferable as they can accommodate macroprudential policy lags without compromising forecast quality.

The policy exercise we conducted tracks the evolution of macroprudential policy stance from 2017 to 2021 for two different policy options, focusing on both real GDP and private sector lending-based stance measures on a three year horizon. The stance dynamics reveal mild tightening of the stance before the end of 2019, at least partially reflecting a coordinated effort by macroprudential and supervisory authorities following the 2008 crisis. This trend is abruptly interrupted at the beginning of 2020 with the onset of the Covid-19 pandemic but reappears at the end of the year before increasing most notably in the second quarter of 2021 due to further uncertainty caused by successive waves of the virus and novel virus variants. The relative impact of the macrofinancial policies applied (including supervisory actions) can be observed most notably during 2020 and is more significant in the private sector lending perspective.

The policy exercise also focuses on the evolution of country-level macroprudential policy stance measure for selected euro area countries. While the level of stance might differ among the individual countries, there is a significant degree of co-movement across the sample. The observed dynamics largely reinforce the findings from the aggregate-level policy exercise described above for both real GDP and private sector lending-based results.

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List of abbreviations

BEAST	Banking Euro Area Sector Stress Test (model)
CCoB	Capital Conservation Buffer
CCyB	Countercyclical Capital Buffer
COREP	Common Reporting Framework
CISS	Composite Indicator of Systemic Stress
CRD	Capital Requirements Directive
CRR	Capital Requirements Regulation
EBA	European Banking Authority
ECB	European Central Bank
ES	Expected Shortfall
ESRB	European Systemic Risk Board
EU	European Union
FINREP	Financial Reporting Framework
FSC	Financial Stability Committee
GaR	Growth-at-Risk
GDP	Gross Domestic Product
G-SIIs	Global Systemically Important Institutions
HICP	Harmonised Index of Consumer Prices
IFRS	International Financial Reporting Standards
IMF	International Monetary Fund
IRB	Internal Ratings Based (approach)
LaR	Lending-at-Risk
MaMi	Macro-Micro (workstream)
NFCI	Net Fee and Commission Income
NPL	Non-Performing Loans
O-SIIs	Other Systemically Important Institutions
P2G	Pillar II Guidance
pp	Percentage Points
QVAR	Quantile Vector Autoregressive (model)
SSM	Single Supervisory Mechanism
STEs	Stress Test Elasticities
SVAR	Structural Panel Vector Autoregressive (model)
SyRB	Systemic Risk Buffer
UCL	University College London
VAR	Vector Autoregressive (model)
WGST	Working Group on Stress Testing

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