# Stress testing with multiple scenarios: a tale on tails and reverse stress scenarios

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**Abstract**

This paper proposes an operational stress testing approach allowing one to assesses the vulnerability of the banking sector in multiple plausible macro-financial scenarios. The approach further allows to search for scenarios which push the banking system or individual banks toward their worse outcomes and identify macro-financial risk factors which are or particular relevance for the system and institutions. We illustrate this concept by employing a macroprudential stress testing model for the euro area and show how it can complement single-scenario stress test, inform or contribute scenario design and evaluate the risks in the banking system. In that, we also show how one can optimise scenarios and stress tests to accommodate different mandates and instruments, along with evolving risk or regulatory environment and interests of supervisory and macroprudential agencies.

***Keywords:*** macroprudential stress test, multiple scenarios, reverse stress testing, financial stability, banking sector risks, systemic risks

***JEL Classification:*** E37, E58, G21, G28



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# Non-technical summary

In the wake of the global financial crisis (GFC), the world saw a surge in regulatory reforms, including the introduction of stress testing as a vital tool for regulators. But why is stress testing so important? Firstly, it offers a forward-looking perspective that empowers regulators to act swiftly. By examining the financial health of institutions under challenging economic conditions, regulators gain the ability to demand protective measures in advance. Secondly, it simplifies complex information about institutions with intricate business models, hidden exposures, and complex balance sheets into easy-to-understand metrics. This boosts transparency, aids in shaping effective policies, and enhances regulatory credibility.

Real-life stress tests often rely on complex economic scenarios with many variables, attempting to capture real-world financial risks. However, there's a catch: they may not always guarantee scenarios that are realistic, severe and including truly more relevant risks at any time. In other words, the likelihood of their realisation is not known with their impact being then hard to interpret in the policy context. They can leave aside dangerous scenarios which have never been considered and create an illusion of safety. Or they can consider scenarios which are very implausible and create a false sense of alarm. These pitfalls have led to scrutiny of many past stress tests from both regulators and markets.

Our paper introduces a fresh approach to assessing the resilience of the banking sector by considering multiple plausible economic scenarios. Instead of being constrained by historical biases, we explore a wide range of scenarios consistent with past economic shocks. This broad perspective allows us to pinpoint the weakest points of the banking system and individual banks, providing a clear view of their potential vulnerabilities. Additionally, it enables us to identify which macro-financial risk factors are most relevant to these institutions, a process known as reverse stress testing.

We illustrate this concept using a semi-structural model for the euro area, covering individual euro area economies and banks, as well as their interactions. This model, commonly used for macroprudential stress testing, allows us to go beyond assessing bank solvency and examine variables crucial to macro-financial supervisors, such as lending to the non-financial private sector.

Multiple scenario distributional stress testing can add relevant information to post-stress test management actions. We provide examples demonstrating how distributional stress testing can yield various at-risk measures, distinguish between institution-specific and system-wide risks, and offer insights into the evolving risks within the banking system. In each of those application we inspect numerous alternative futures instead of a single set of risks and can keep track of the plausibility of these risks.

Furthermore, our framework allows us to define scenario severity clearly and create scenarios that match desired levels of severity. Reverse stress testing helps identify risks to the banking system and design scenarios that align with supervisory and macroprudential agency goals. It also helps incorporate economic narratives consistent with policymakers' expectations.

In conclusion, our paper advocates for the incorporation of multiple-scenario and reverse stress testing approaches alongside conventional single-scenario stress testing. These methods enrich scenario design, validate supervisory exercise results, and shed light on the diverse distribution of risks among individual institutions within the banking system. Notably, advancements in stress test infrastructure make these approaches increasingly feasible.



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# 1 Introduction

The aftermath of the global financial crisis (GFC) ushered in a wave of regulatory reforms, among them the introduction of stress testing into the regulatory toolkit. Regulatory stress testing offers important benefits. First, it provides a forward-looking perspective that empowers regulators to take prompt action. By scrutinizing the financial solvency of institutions during stylized but challenging economic conditions, regulators gain the ability to demand adequate protective measures ahead of time. The second advantage of stress testing is its ability to distill complex information about institutions with intricate business models, latent exposures, and cryptic balance sheets into easily understandable metrics (see, e.g., Schuermann [2014]). This attribute increases transparency within the financial sector and helps shape effective policies, in addition to easing their communication, both of which ultimately boost regulatory credibility.

The widespread adoption of stress tests created the need for severe, plausible, and meaningful scenarios. Stress testing requires regulators to envision scenarios in which financial institutions could face substantial losses, jeopardizing their solvency. The major regulatory stress tests, therein the Comprehensive Capital Assessment Reviews led by the Federal Reserve, and the EU-wide stress tests led by the European Banking Authority (EBA),[1] involve single hypothetical adverse macro-financial scenarios. They project economic activity, asset prices, and labor markets that mirror financial system risks prevalent at the moment of scenario design, and for a three-year horizon. However, the plausibility, severity, and relevance of these scenarios are often elusive, which causes them to be often challenged by regulators and markets.

This paper proposes to assess the vulnerability of the banking sector by examining multiple plausible macro-financial scenarios. This approach delivers a complete picture of the resilience of the banking system, as it describes the full probability distribution of its or each individual bank's solvency. Moreover, it facilitates reverse stress testing, that is, the search for scenarios that are severe enough to put a significant strain on the financial system or individual institution. We illustrate this concept by employing a macroprudential stress testing model for the euro area to derive the full space of alternative macro-financial scenarios. We demonstrate how the approach can accurately identify risks present in the banking system and their heterogeneous distribution across banks, allow separating institution-specific and systematic components of risks, and select scenarios leading to desirably severe bank outcomes, while perhaps reflecting most policy-relevant narratives.

To derive a complete scenario space, we employ a semi-structural macro-micro Bank Euro Area Stress Test (BEAST) model detailed in Budnik et al. [2023]. The BEAST nests the representation of the individual euro area economies and banks and their two-way interactions. It consists of a macroeconomic block that takes into account cross-country spillovers through trade connections, and a banking block with around 90 individual euro area banks, collectively covering around 70% of the euro area banking sector. The model recognizes the impact of macro-financial aggregates on banks and that of bank-level lending on macroeconomic outcomes. Finally, all model equations are solved jointly, turning all relationships between variables, therein feedback loops, contemporaneously. Together, the model achieves a balance between maintaining the heterogeneity of individual banks while simultaneously offering an aggregate and temporal perspective.

The BEAST is not only a "workhorse model" for risk and scenario analysis, but also a

[1] The annual Comprehensive Capital Assessment Reviews have been conducted annually since 2010, and the EU-wide stress tests, biannually since 2011. For a history and comparison of supervisory stress testing in different jurisdictions, see Cihak [2004] for an early take-aways, and Borio et al. [2014], Baudino et al. [2018] or Pliszka [2021] for post-GFC assessments.



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well-defined stress test infrastructure. As a stress test model, it puts emphasis on modelling the impact of macro-financial scenarios on credit risk, net interest and fee and commission income, and, in the second line, market risk and remaining profitability items. As a macro-prudential infrastructure, it incorporates banks' behavioural reactions and related amplification mechanisms between the banking system and the real economy and between bank solvency and funding costs. It delivers projections related to bank solvency, lending to the non-financial private sector, distinct bank liability components, loan loss provisioning, bank solvency, and maturity mismatches.

Relevantly, the model permits stochastic simulations of macro-financial and bank-level outcomes. The behavioral and risk parameter equations of the model are estimated using a combination of macroeconomic and bank-level data. These supplement other equations that reflect accounting, regulatory, and macro-financial identities. Estimation of core model equations delivers the information on historical shocks and their correlations, and parameter uncertainty. These can be applied to build different combinations of future macro-financial shocks while recognising model parameter uncertainty.[2]

The BEAST stochastic simulations offer scenarios which span all plausible realisations of risks while accounting for model ambiguity. Each scenario is plausible by construction in at least two senses. It is internally consistent thanks to the disciplined construction of a semi-structural model (Flood and Korenko [2015b]), and statistically plausible, as it relies on estimated distributions of shocks and parameters (Studer [1999], Breuer et al. [2009], Breuer and Csiszár [2013], Breuer and Csiszár [2016]). Multiple stochastic simulations employing such distributions ensure that no scenarios are missed and that the scenario space factors in model risks.

We use model simulations to demonstrate three intertwined variants of stress testing. First, we describe and illustrate possible applications of multi-scenario or distributional stress testing. To this end, we look at the full distributions of predicted bank outcomes and, in particular, at their lower tails. In this way, we extract information on evolving tail risks to the banking system and individual banks without taking a position on the type of risk and circumventing the fallacy of overlooking plausible events. We also show that distributional stress testing can be used to establish individual banks' exposure to systemic risks, which we measure as banks' propensity to be undercapitalized when the whole system is undercapitalized akin to Acharya et al. [2017]. Finally, we elaborate on how distributional stress testing can be employed to validate and interpret other stress tests, by comparing our results with the outcomes of the 2023 EBA/SSM stress test.

Next, the availability of well-described solvency distributions allows us to elegantly solve the reverse stress testing problem in a multivariate dynamic set-up. As postulated by Breuer and Csiszár [2013] we systematically inspect alternative macro-financial scenarios to identify those that push the banking system or individual banks below the severity threshold. Sufficiently severe scenarios that are separated from the complete space of plausible realities form mixed scenarios that capture the uncertainty of adverse scenarios themselves.[3] We then discuss that the severity threshold should reflect the ambitions of policy makers for a particular stress test. With bank solvency remaining in the eye of most supervisory agencies, we first disentangle scenarios that correspond to a lower percentile of the system-wide solvency distribution. Then we show how our approach can be tailored to deliver scenarios for macroprudential agencies, which may

[2]See Budnik et al. [2021b] and Budnik et al. [2021d] for the discussion of the application of the model to stochastic simulations in the context of assessing the benefits of resilience-building regulatory policies.

[3]The notion of mixed scenarios has been introduced by Breuer and Csiszár [2013]. They contrast mixed scenarios with single scenarios, which are merely the realizations of distributions spanned by mixed scenarios.



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wish to put more emphasis on bank lending, or the role of amplification mechanisms. We further establish a number of interesting trade-offs between scenario plausibility and severity in relation to scenario horizon.

Lastly, we show how reverse stress testing can be aligned with the desire to incorporate an economic narrative consistent with the expectations of policy makers. To this end, we once again inspect the distribution of scenarios selected with postulated severity metrics. However, this time, we choose the subset of scenarios closest to the postulated narrative. The selected scenarios reflect narratives commonly associated with hypothetical stress test scenario designs. However, in contrast to the latter, the probability of our narrative-based scenarios can be evaluated.

This paper touches on several streams of literature. The first and broadest is the practice of designing stress testing scenarios (Cihak [2004], Quagliariello [2009]). The new element of our approach is to blend the probabilistic scenario design with the merits of the hypothetical approach. We show how to pin down a "hypothetical adverse situation triggered by the materialization of risks" (ESRB [2021]) within the probabilistic setup, where scenarios are based on statistical inference from historical variable distributions, and their likelihood can be established.

The second is stress testing based on multiple scenarios and the closely linked literature on distributional forecast. Both literatures postulate looking at many alternative futures, rather than point forecasts or scenarios. Distributional forecasting evaluates the full distribution of plausible outcomes. The multiple scenario stress test systematically seeks regions of outcome distributions that speak of vulnerabilities in the system or institution (Studer [1999]). Multiple scenario stress testing poses two problems: how to arrive at a distribution of plausible multivariate scenarios and how to identify its areas of severity. Regarding the first challenge, Studer [1999] and Breuer et al. [2009] propose to describe the joint distributions of risks applying the Mahalanobis distance[4], Breuer and Csiszár [2013] and Breuer and Csiszár [2016] use entropy balls[5] and McNeil and Smith [2012] employ the concept of half-space trimming[6] Regarding the definition of severity, Studer [1999], Breuer et al. [2009], Breuer and Csiszár [2013], Breuer and Csiszár [2016] filter scenario distributions looking for those leading to the lowest expected asset payoff and McNeil and Smith [2012] for those offering the minimum net asset value.

Our additions to the discussion of multiple scenario stress tests are two-fold. First, we indicate a possible avenue to deal with the uncertainty inherent in any experiment that uses historical data to project future events. An element is adding structural elements and theoretical postulates to statistical identification, as in the model we use, which ameliorates the scenario uncertainty compared to data-only or reduced-form approaches. Another element is recognizing the uncertainty of the model parameters while generating the scenario space, which can accommodate another share of model risks. A more pronounced innovation, which can initially pass as innocuous, is that we suspend the distinction between risk factors and financial outcomes. Breuer and Summer [2018] start to jointly assess risk factors and financial outcomes and label such scenarios as generalized. Nevertheless, in contrast to us, they still evaluate the

[4]More plausible scenarios are those whose distance from the multi-variate mean is below a certain threshold. Scenarios with a decreasing plausibility level form elipsoids of scenario spaces with increasing distance from the mean of the multivariate risk distributions. A Mahalanobis ellipsoid would be a good choice for risk distributions such as normal or t-Student.

[5]Entropy balls require the a priori knowledge of the reference distribution of risks. The plausibility of scenarios is then judged by the distance to the reference distributions, with increasing distance marking decreasing probability of realisation.

[6]The half-space trimming to construct relevant scenario sets similarly asks for the a priori knowledge the distributions of risks.



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probability of generalised scenarios based solely on the distribution of risk factors. Looking at macro-financial scenarios as joint risk factor-outcome events solves two intricate issues. It accommodates the presence of non-linearities or amplification mechanisms in the impact of risk factors on the financial sector.[7] It allows evaluating scenario adversity along with the intentions of policy makers by looking directly (and only) at the distribution of their focus variable.

Third, our work connects to macro-financial at risk measures and tail-based measures of systemic risks. Following the Adrian et al. [2019] growth-at-risk article, there has been renewed interest in applying the value-at-risk analysis to financial stability problems. For example, Cont et al. [2020] introduces liquidity-at-risk for joint solvency-liquidity stress testing, and Budnik et al. [2022] use bank lending-at-risk to track the evolution of the macroprudential stance. Huang et al. [2009], Adrian and Brunnermeier [2016], Acharya et al. [2017] construct systemic risk indices by looking at tail risks for future bank solvency. Our approach shares with these literature its forward-looking orientation, and nests the derivation of various at-risk measures and indices.

Fourth, and perhaps most obviously, we add to the literature on reverse stress testing. This literature deals with the complexity of reverse stress testing with multivariate scenarios by offering different approaches to identify candidate scenarios. Henry [2021], Glasserman et al. [2015], Flood and Korenko [2015a] look only at a subset of plausible scenarios. Henry [2021] operates with a grid of scenarios derived by arbitrary scaling economically consistent risk factors, Glasserman et al. [2015] inspects risk factors in the vicinity of large historical losses, Flood and Korenko [2015a] randomly checks scenarios selected from a mesh of the distribution of (eliptically distributed) risk factors. Estimation and Approach [2015], Kapinos and Mitnik [2016], Grundke and Pliszka [2018], Traccucci et al. [2019] reduce the dimensionality of the risk factor space by applying the principal component analysis (PCA). Our approach is closest to McNeil and Smith [2012] and Breuer and Summer [2018] who systematically search for relevant scenarios in the full distribution of outcomes. However, we combine their idea with that of Budnik et al. [2021c] and Sarychev [2014] and show how to select scenarios that are not only plausible and severe, but also incorporate a postulated narrative.

This paper is structured as follows. Section 2 introduces the main concepts developed in the paper. Section 3 provides a high-level overview of the macroprudential stress test model. Section 4 presents the simulation setup. Section 5 presents the results corresponding to the full distribution-based stress test for the solvency of the general banking system. Section 6 introduces the reverse stress testing for system-wide bank solvency. Section 7 looks beyond system-wide bank solvency. Finally, Section 8 concludes the paper.

## 2 Exposition

This section lays out the main ideas illustrated in the next parts of the paper. It starts with an exposition of a standard real-life stress test and builds on this example to establish a universal exposition of a stress test. It then expands on the exposition to arrive at the definitions of a distributional and reverse stress test, and explains the principles of selecting scenarios based on multivariate criteria or with a postulated scenario narrative.

[7] The problem of mapping actual non-linearities in the pass-through of risk factors into outcome variables in the context of stress testing has been flagged by Glasserman et al. [2015] who then apply non-parametric estimates of a Maximum Expected Shortfall to address the problem.



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## 2.1 European banking sector stress test

The primary real-life benchmark for our analysis is the European Union (EU)-wide EBA/SSM stress tests.[8] It follows a constrained bottom-up approach that requires each participating bank to (independently) estimate the evolution of a common set of risks (credit, market, counterparty, and operational risk) under the common baseline and a hypothetical adverse scenario.

The building blocks of the scenario design were set up in 2020 and have remained consistent since then. The process begins with the identification of risks to the stability of the EU banking sector by the General Board of the European Systemic Risk Board (ESRB). These risks are then translated into an adverse scenario narrative. The scenario narrative is condensed into a number of shocks to macro-financial aggregates such as country consumption and investment (confidence shocks), output and inflation (productivity shocks), financial variables including bond yields, and foreign exchange rates. Then, these shocks are fed into a multi-country model that approximates the joint dynamics of EU-economies and translated into the final adverse macro-financial scenario (EBA [2021]). Banks then use this scenario to simulate its effects on their balance sheets and calculate resultant solvency metrics.

The process of refining the adverse scenario involves several stages of adjusting the calibration of the shocks and incorporating expert insights. Throughout these stages, the overall severity of the scenario can decrease, but there is often a gain in achieving greater consistency in severity across countries. In the refinement stages, the assessment of scenario plausibility is mostly qualitative and there is no systematic assessment of the joint likelihood of risk realisation. Moreover, the ultimate measure of scenario severity becomes evident only as the final outcome of the bottom-up approach (or the top-down ECB macroprudential) stress test.

## 2.2 Traditional supervisory stress test

Each stress test can be described as an exercise in which information available at the time when the exercise is carried out is used to project variables of interest to a policy-maker, putting the emphasis on the realisation of risks. Let us introduce some notation to condense this idea, which we can later use throughout this chapter. $\mathcal{X}$ is going to be all relevant information relevant for the conduct of a stress test exercise available at the time when a stress test is launched. It will include current and historical information on balance sheets of banks, information on current and past macro-financial conditions, and regulatory policies. $\mathcal{Y}$ will be a complete set of results of this exercise available until the end of the horizon $H$ of the stress test.

A stress test exercise should also consider some future events that commonly take the form of future macro-financial scenarios including the realisation of risk factors. They will be contained in $\mathcal{S}$. Finally, $\mathcal{M}$ will be the mapping function:

$$\mathcal{M} : \mathcal{X}|\mathcal{S} \rightarrow \mathcal{Y} \tag{1}$$

For instance, the mapping function will include at minimum the principles of accounting and regulatory rules.

[8] The stress test is run jointly by the European Banking Authority (EBA) and the ECB Banking Supervision (SSM). The EBA develops the overall methodology of the stress test and designs its templates. The EBA stress test focuses on the largest EU banks. The SSM stress test uses the EBA methodology and applies it to all banks under its direct supervision, including those not covered by the EBA sample, with the necessary adjustments for smaller banks to allow proportionate treatment. For more information, visit https://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing.



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A policy maker is usually interested only in a subset of the outcomes of the stress test. We acknowledge this fact by introducing a policy preference function $\mathscr{C}$ which is a simple selection function that narrows the results of a stress test $\mathscr{Y}$ to $K$ variables of interest:

$$\mathscr{C} : \mathscr{Y} \to \mathbb{R}^K \tag{2}$$

The relatively traditional framework of the bottom-up EBA/SSM stress test can be well condensed within the general scenario definition. Information fed into the EBA/SSM stress test is a detailed structure of banks' balance sheets and profit and loss accounts, and they are stressed under two scenarios. Let $B$ be a vector of variables including bank balance sheets and profit and loss accounts, and $r$ be a vector consisting of unique values of the GDP path, interest rates, and other macro-financial variables. For a stress test conducted at time $t$:

$$\begin{aligned} \mathscr{X} &= B_t \\ \mathscr{S} &= \{r^j_{t+1}, \dots, r^j_{t+H}\}^1_{j=0} \end{aligned} \tag{3}$$

where $j = 0$ would be a baseline and $j = 1$ adverse scenario.

Finally, while mapping risk factors in the evolution of their balance sheets, banks will apply (i) the principles of accounting and regulatory rules, (ii) caps, floors, and additional limits imposed by EBA/SSM such as a constant balance sheet assumption, and (iii) their own internal risk models, though under scrutiny of the top-down challenge by the ECB. These elements can be jointly denoted by $M$, which can be imagined as a set of equations that map risk factors into bank balance sheets $M : r \to B$. The outcome of a stress test execution can then be summarized as:

$$M(\mathscr{X}|\mathscr{S}) = \{B^j_{t+1}, \dots, B^j_{t+H}\}^1_{j=0} \tag{4}$$

The EBA/SSM stress test "aims to inform supervisory decisions and increase market discipline" while focusing on the CET1 ratio $CETR$ at the end of the scenario horizon:

$$\mathscr{C}(\{B^j_{t+1}, \dots, B^j_{t+H}\}^1_{j=0}) = CET1R^1_{t+H} \tag{5}$$

The adversity of the stress test is generally evaluated by looking at $CET1R^1_H$ and contrasting it with expectations, while the plausibility of the scenario is mostly evaluated based on the contrast $\{r_{t+1}, \dots, r_{t+H}\}$ with its historical distributions.

## 2.3 Macroprudential stress test

The focus of the ECB macroprudential stress test has consistently centered around assessing the effects of both the same baseline and adverse scenarios as in the EBA/SSM exercise. However, the macroprudential stress test (i) relaxes the assumption of the constant balance sheet in order to study dynamic adjustments of banks' loans and liability structure, (ii) accounts for amplification mechanisms therein the feedback loop between the real economy and the banking sector, and (iii) removes a number of other assumptions such as zero write-offs or recovery rates, or various methodological caps and floors present in the EU-wide supervisory stress test



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exercises. By removing these limitations, the results of the macroprudential stress test enrich our understanding of how adverse macroeconomic developments can spread and highlight systemic risks that may emerge in such scenarios (for a comprehensive review of the role of the macroprudential stress test, refer to Chapter 8 in Budnik et al. [2023]).

The ECB macroprudential stress test, on which we build here, sets the basis for a more general problem statement. To this end, replaces the distinction between macro-financial risk factors and banks' balance sheets, with a more general distinction between endogenous $\mathcal{Y}$, and exogenous or state-dependent variables in $\mathcal{X}$. Among other properties, it recognises the presence of amplification mechanisms and dynamic codependence between the macro-financial and banks' balance sheets.

In terms of the notation already used for the EBA/SSM stress test, the macroprudential stress test will focus on the joint prediction of $\{B_{t+1},\dots,B_{t+H},r_{t+1},\dots,r_{t+H}\}$. State-dependent or exogenous variables will include part realisations of macro-financial and balance sheet variables $\{r_t,r_{t-1},\dots,B_t,B_{t-1},\dots\}$, along with information on future (and known) policy parameters, e.g., already scheduled increases in capital buffers or release of expiring policies $\{p_{t+1},\dots,p_{t+H},\}$.

The set of exogenous variables also includes i.i.d. shocks $\{\nu_t,\dots,\nu_{t+H}\}$ where $\nu$ is a single vector of all relevant shock realisation (see Section 3). The statistical and economic properties of these shocks distinguish them from macro-financial risk factors that are generally auto- and cross-sectionally correlated, or even mean and variance non-stationary. Their distributions are identified based on the combination of data and structural assumptions.

Finally, the mapping function will as before apply (i) the principles of accounting and regulatory rules, but add (ii) behavioural assumptions about banks' adjustments, and (iii) replace banks' internal risk models with the corresponding top-down equations mapping macro-financial variables in risk parameters. The last modification is the recognition of the uncertainty of the model parameters. The stress test is run under different stochastic assumptions on the model parameters $\mathcal{P}$. The latter have known, and empirically informed, distributions and correlation structure (see Section 3). The corollary of equation (1) is then:

$$\mathcal{M}_{\mathcal{P}}:(\mathcal{X},\mathcal{S})\rightarrow\mathcal{Y} \tag{6}$$

It is important to note that $\mathcal{X}$ and $\mathcal{S}$ are in this case independent, so $(\mathcal{X},\mathcal{S}) \iff \mathcal{X}|\mathcal{S}$.

The specificity of the ECB macroprudential stress test is that shocks are intentionally chosen to ensure that, in the absence of amplification mechanisms, they can replicate the macro-financial scenarios provided in the EBA/SSM stress test as in equation (3). Let us denote by $\bar{\mathcal{M}}$ the mapping function where we disable and feedback from the banking sector to the real economy. Then, the corollary of equations (3) and (4) together can be presented as follows:

$$\begin{aligned}
\mathcal{M}_{\mathcal{P}}(\mathcal{X},\mathcal{S}) &= \{\mathbf{B}^j_{t+1},\dots,\mathbf{B}^j_{t+H},\mathbf{r}^j_{t+1},\dots,\mathbf{r}^j_{t+H}\}^1_{j=0}\\
\mathcal{X} &= \{r_t,r_{t-1},\dots,B_t,B_{t-1},\dots\}\\
\mathcal{S} &= \{\nu^j_{t+1},\dots,\nu^j_{t+H}\}^1_{j=0}\\
\{\nu^j_{t+1},\dots,\nu^j_{t+H}\} &= \bar{\mathcal{M}}^{-1}_{\mathcal{P}}(\{r^j_{t+1},\dots,r^j_{t+H}\}|\mathcal{X})\ for\ j\in\{0,1\}
\end{aligned} \tag{7}$$

where thickened symbols indicate stochastic realisations (owing to parameter uncertainty) of the corresponding variables, i.e. $\mathbf{B}\equiv B_{\mathcal{P}}$, $\mathbf{r}\equiv r_{\mathcal{P}}$ and $\nu\equiv \nu_{\mathcal{P}}$.

The main focus variables in the ECB macroprudential stress test are the CET1 ratio, lending to the non-financial private sector, and the strength of the amplification mechanism captured by



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GDP evolution. For convenience, we condense the variables of interest into a vector $c$, which will include $CET1R$, lending $L$, and GDP $Y$. In contrast to the supervisory exercise, the emphasis is put almost equally on the baseline and adverse scenario outcomes and on the dynamics of variables over all scenario horizon. Finally, the uncertainty of the projected variables is evaluated by providing the corresponding uncertainty ranges. This can be captured by the policy preference function:

$$\begin{aligned} \mathscr{C}(\mathscr{Y}_{\mathscr{P}}) = \{E_{\mathscr{P}}(\{\mathbf{c}^0_{t+h}, \mathbf{c}^1_{t+h}\}^H_{h=1}), Q_{\mathscr{P}}(\{\mathbf{c}^0_{t+h}, \mathbf{c}^1_{t+h}\}^H_{h=1})\} \\ c^j_t = \{CET1R^j_t, L^j_t, Y^j_t\} \end{aligned} \tag{8}$$

where $E$ is the expected value and $Q$ selects one of the lower and higher percentiles of the variables distributions.

## 2.4 Multiple scenarios and distributional stress test

With these two real-life examples of stress tests, we can now introduce the general macroprudential stress test as follows:

$$\begin{aligned} \mathscr{M}_{\mathscr{P}} : (\mathscr{X}, \mathscr{S}) \to \mathscr{Y} \\ \mathscr{X} = \{r_t, r_{t-1}, \ldots, B_t, B_{t-1}, \ldots\} \\ \mathscr{S} = \{\nu_{t+1}, \ldots, \nu_{t+H}\} \;\; \nu_t \sim i.i.d. \\ \mathscr{Y} = \{\mathbf{B}_{t+1}, \ldots, \mathbf{B}_{t+H}, \mathbf{r}_{t+1}, \ldots, \mathbf{r}_{t+H}\} \end{aligned} \tag{9}$$

the complete macroprudential stress test relies on multiple stochastic scenarios spanned by a collection of possible values of $\nu$ which we will refer to as scenario uncertainty (and Breuer and Csiszár [2016] dub distributional model uncertainty) and accommodates parameter uncertainty related to possibly incorrect specification (and identification) of the model.

The results of the stress test $\mathscr{Y}$ will be governed by a probability law $\mathbb{P}$ on $\Omega$. Following the conventions of Breuer and Csiszár [2016], $\Omega$ is a state space equipped with a $\sigma$-algebra, with a measure $\mu$. Let $\Phi$ describe the cumulative distribution function of $\mathbb{P}$ and $\phi$ its density function.

The availability of a well-described and dynamically consistent distribution of macro-financial and bank-level outcomes offers the ability to inspect the stress test results for all possible realities. The distributional stress test is down to considering marginal probability functions for the variables of interest contained in $\mathscr{C}(\mathscr{Y})$.

The distribution of $\mathscr{C}(\mathscr{Y})$ is well described by a density function:

$$\phi_{\mathscr{C}}(\mathscr{Y}) := \phi_{\mathscr{C}(\mathscr{Y})}(\mathscr{C}(y)) = \int_{y^{-\mathscr{C}}} \phi_{\mathscr{Y}^{-\mathscr{C}}|\mathscr{C}(\mathscr{Y})}(y^{-\mathscr{C}}|\mathscr{C}(y))\phi_{\mathscr{Y}^{-\mathscr{C}}}(y^{-\mathscr{C}})d\mu(y^{-\mathscr{C}}) \tag{10}$$

where $y \in \mathscr{Y}$ is a vector with a single stress test result, and $y^{-\mathscr{C}}$ is the corresponding result excluding the vector elements selected by $\mathscr{C}(y)$.

This marginal distribution of the stress test results should in general be a $K$-variate and can be further analysed for individual elements of $\mathscr{C}(\mathscr{Y})$ by repeating the marginalisation procedure or selecting conditional distributions of interest.



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## 2.5 Reverse stress test

Reverse stress testing seeks to find plausible scenarios that put the system under stress. What is the most likely event that could create a response exceeding a given threshold or provoke the relevant outcome. In terms of the earlier notation, the interests of reverse stress testing are scenarios $\mathcal{S}^\star \subset \mathcal{S}$ such that $\mathscr{C}$ described on $\mathscr{M}_{\mathscr{P}}(\mathcal{X}, \mathcal{S}^\star)$ meets the postulated sufficient severity criteria.

After Cihak [2004] we consider two approaches to reverse stress testing: one based on threshold values of outcome variables, and one fixing the plausibility of the realisation of an adverse event. Reverse stress testing based on thresholds seeks for scenarios where $\mathscr{C}(\mathcal{Y})$ is below (or above) a certain threshold that we label $\mathscr{C}^\star$. For an example of the EBA/SSM in equation (5) one can, for instance, postulate (which we consider in Section 6) that $CET1R^1_H \leq 10\%$. For now, we assume that $k = 1$ and return to case $k > 1$ shortly afterwards.

Thus, in the threshold approach, we will consider scenarios that meet the following condition:

$$\begin{aligned} \mathcal{S}^\star &: \mathscr{C}(\mathcal{Y}^\star) < \mathscr{C}^\star \\ \mathcal{Y}^\star &:= \mathscr{M}_{\mathscr{P}}(\mathcal{X}, \mathcal{S}^\star) \end{aligned} \tag{11}$$

which will deliver a scenario, or a stress test result space, with the probability of realisation described by the conditional cumulative probability function:

$$\begin{aligned} \Phi_{\mathscr{C}}(\mathcal{Y}^\star) &:= \Phi_{\mathcal{Y}|\mathscr{C}(\mathcal{Y})}(y|\mathscr{C}(y) < \mathscr{C}^\star) \\ = \int_{-\infty}^{\mathscr{C}^\star} \int_{-\infty}^{+\infty} &\phi_{\mathcal{Y}|\mathscr{C}(\mathcal{Y})}(y|\mathscr{C}(y)) d\mu(\mathscr{C}(y)) d\mu(y^{-\mathscr{C}}) \end{aligned} \tag{12}$$

The worst-case scenario approach sets the plausibility of stress scenarios. We can formulate it analogously to the threshold scenario approach in equation (14) by identifying the infimum of a scenario subset described by the scenario selection criteria $\mathscr{C}$ and the postulated plausibility level $p$. The worst-case approach translates into searching for scenarios fulfilling:

$$\mathscr{C}^\star = \inf\{\mathscr{C}(\mathcal{Y}) : \Phi_{\mathscr{C}}(\mathcal{Y}) < p\} \tag{13}$$

## 2.6 Multi-variate severity criteria

For multivariate selection functions $\mathscr{C}(.)$ it is relevant to realise that the sufficient condition for (14) and (13) to apply to multivariate severity criteria is that $\mathscr{C}(\mathcal{Y})$ describes a linear order $\leq_{\mathscr{C}}$ on $\mathcal{Y}$. For example, for $CET1R^1_H$ it will be a natural order on $\mathbb{R}$.

The most straightforward way of interpreting multiple criteria, namely the sequential application of $K$ individual criteria from the selection function $\mathscr{C}$. In such a case, the order $\leq_{\mathscr{C}}$ should correspond to the Leontieff preference (or loss) function of the policy maker with equal weights. Let $\mathscr{C}_k(.)$ denote the $k$-th variable selected by $\mathscr{C}(.)$ and $c_k$ the corresponding element of $\mathscr{C}^\star$. Threshold vector $\mathscr{C}^\star$ will include multiple thresholds for different outcome variables. It can also be saturated with $-\infty$ ($+\infty$) for variables that are not intended to be used in scenario selection. The policy preference which we will later denote as $\mathscr{C}_{[K]}(.)$ would give the following corollary of equation (14):



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$$\mathcal{S}^{\star} : \mathcal{C}_1(\mathcal{Y}^{\star}) < c_1, \ldots, \mathcal{C}_K(\mathcal{Y}^{\star}) < c_K \tag{14}$$

However, as noted by Breuer et al. [2009] the sequential application of multiple criteria triggers the artifact of 'dimensional dependence.' It says that the plausibility of scenarios will depend on the number of criteria. To see this, it suffices to consider equation (16) and notice that:

$$\begin{aligned} &\int_{-\infty}^{c_{k+1}} \int_{-\infty}^{c_k} \cdots \int_{-\infty}^{c_1} \int_{-\infty}^{+\infty} \phi_{\mathcal{Y}|\mathcal{C}_{K+1}(\mathcal{Y})}(y|\mathcal{C}_{K+1}(y)) d\mu(\mathcal{C}_{K+1}(y)) d\mu(y^{-\mathcal{C}_{\mathcal{K}+1}}) \\ &\quad < \int_{-\infty}^{c_k} \cdots \int_{-\infty}^{c_1} \int_{-\infty}^{+\infty} \phi_{\mathcal{Y}|\mathcal{C}_K(\mathcal{Y})}(y|\mathcal{C}_K(y)) d\mu(\mathcal{C}_K(y)) d\mu(y^{-\mathcal{C}_{\mathcal{K}}}) \end{aligned} \tag{15}$$

For the worst-case scenario approach, the tendency of plausibility level to decrease with the number of criteria results directly from the following:

$$p^{c_{k+1}} p^{c_k} \ldots p^{c_1} < p^{c_k} \ldots p^{c_1} \tag{16}$$

even for the highest permissive levels of $p^{c_{k+1}} < 1$.

The alternative proposed by Breuer et al. [2009] is to interpret $\mathcal{C}(\mathcal{Y})$ as a Mahalanobis distance of $y \in \mathcal{Y}$ from the postulated and known distribution $\Gamma$ which ensures that:

$$\mathcal{C}_M : \mathcal{Y}|\Gamma \to \mathbb{R} \tag{17}$$

regardless of the number of criteria. However, there are at least two weaknesses of this approach. First, it asks for knowledge of $\Gamma$, which can be increasingly difficult to specify for the increasing number of variables and/or atypical, e.g., bimodal, distributions. Flood and Korenko [2015b] provides a practical solution to both of these problems in real-life stress test applications. Second, while it reflects the statistical relationship between the variables of interest, it must not well map policy preferences.

Our solution is to specify $\mathcal{C}(.)$ as a set of criteria and weights $\omega$ attributed to those of a policy maker. Then the application of $\leq_{\mathcal{C}}$ proceeds along with a multidimensional nonparametric sorting rank algorithm of Sarychev [2014]. Such $\mathcal{C}_{\omega}(.)$ will map all scenarios in $\mathbb{R}$:

$$\mathcal{C}_{\omega} : \mathcal{Y} \to \mathbb{R} \tag{18}$$

The weighting approach resembles the proposal of Estimation and Approach [2015] or Grundke and Pliszka [2018] but $\omega$ is set by the stress test designer rather than identifying the scenario variables by the Principal Component Analysis (PCA). An appealing additional feature of policy-chosen weights is that they can be applied to variables with any distribution, and not only to those that are approximately normally distributed (as is the case for PCA chosen weights). To recognise the importance of this property, note that scenario distributions may not only have thick tails but also be strongly assymmetric, in the presence of systemic events.

The algorithm is described in detail by Sarychev [2014] and later by Budnik et al. [2021c] and can be summarized as:



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$$
\begin{aligned}
\mathscr{C}_\omega(\mathscr{Y}) = \sum_{k=1}^{K} \omega_k i(\mathscr{C}_K(\mathscr{Y})) \\
i : \mathscr{C}_K(\mathscr{Y}) \to \mathbb{N} \\
i(\mathscr{C}_K(\mathscr{Y})) = index((\mathscr{C}_K(\mathscr{Y}), \leq))
\end{aligned}
\tag{19}
$$

For each variable $k$ included in $\mathscr{C}$ all its scenario realisations are first sorted to create an ordered set $(\mathscr{C}_K(\mathscr{Y}))$ and then the rank of the realisation is aggregated into the joint criteria with weight $\omega_k$.

The algorithm of Sarychev [2014] can accommodate any distribution of criterion variables and offers the flexibility of integrating many, even complex criteria, which are themselves functions of scenario variables.

## 2.7 Incorporating economic narrative

On occasion, policy-makers may aim at a macro-financial scenario that exemplifies a particular economic narrative. Reverse stress test scenarios should already pin down the elements of the economic narrative relevant to ensure sufficient severity of the scenario. However, within the space of plausible and severe scenarios there may still be many alternative realities with different story-lines.

To this end, we modify and adapt the method for selecting plausible scenarios with a postulated narrative by Budnik et al. [2021c]. Let $\mathscr{N}$ be a function described on the space of future scenarios $\mathscr{Y}$ that are scored along with the criteria contained in $A$ and the weights in $w$:

$$
\mathscr{N}_w(\mathscr{Y}, A) \to \mathbb{R} \tag{20}
$$

The criteria contained in $A$ can involve different metrics that can be described in $\mathscr{Y}$. For example, for selecting credit crunch scenarios, there can be a cumulative drop in euro area lending in the medium-term horizon and, for the market freeze scenario, an increase in interest rates on bank wholesale funding in the short-horizon.[9] $w$ would include weights attributed to each criteria and jointly with $A$ pin down desired economic story-line of a scenario. Otherwise, $\mathscr{N}$ is a function of the same type as $\mathscr{C}$ sorting different macro-financial scenarios along with the different criteria in $A$ and weighting their ranks with $w$.

Following the selection of scenarios along with equation (14) we can always apply $\mathscr{N}$ to $\mathscr{Y}^\star$ with probability of realisation $\Phi_{\mathscr{C}}(\mathscr{Y}^\star)$ (as in equation (16)) and sub-select the scenarios from the tail of the resulting distribution:

$$
\begin{aligned}
\mathscr{S}^{\star\star} : \mathscr{N}_w(\mathscr{Y}^\star, A) < \bar{\mathscr{N}} \\
\bar{\mathscr{N}} = \inf\{\mathscr{N}_w(\mathscr{Y}^\star, A) : F(\mathscr{Y}^\star) < p^\star\}
\end{aligned}
\tag{21}
$$

Where $F$ is the cumulative probability function described in the scenario score $\mathscr{N}(\mathscr{Y}^\star)$. The outcome scenarios will have probability $p^\star \times \Phi_{\mathscr{C}}(\mathscr{Y}^\star)$, test the banking system or individual institutions for policy-relevant risks (as the whole space $\mathscr{Y}^\star$) but also emphasise the narrative which, for instance, closest corresponds to market expectations.

[9]See the discussion of such criteria jointly with examples of application in Budnik et al. [2021c].



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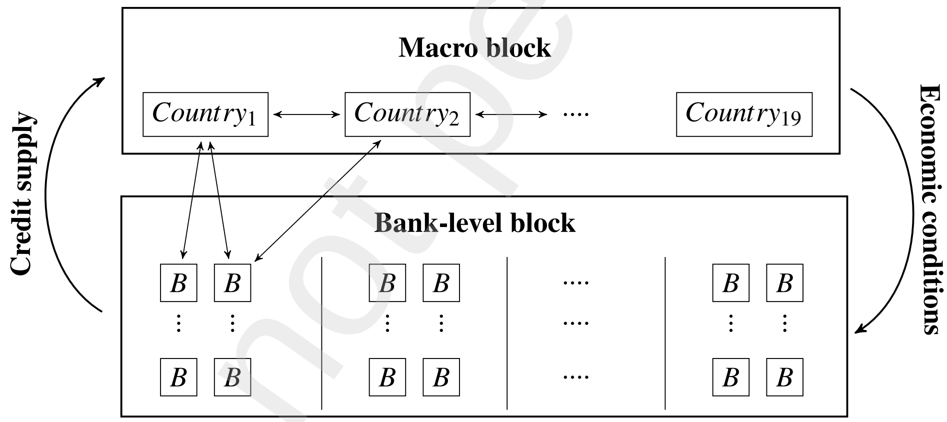
# 3 Model

The BEAST is a widely utilised "workhorse model" deployed for risk and scenario analysis, and evaluating the effects of policies influencing financial stability. Since 2018, the model has built the backbone of the ECB macroprudential stress test (Budnik [2019], Budnik et al. [2019], Budnik et al. [2021a], Budnik et al. [2021a]).

## 3.1 Overview

The model incorporates the representation of 19 individual euro area economies within the macroeconomic block and around 90 of the largest euro area banks represented on a consolidated level within the bank-level block. The economies are interconnected, with cross-border trade spillovers, as depicted in Figure 1. Banks are influenced by economic conditions not only in the country where they are headquartered but also in other countries to which they have exposures or from which they collect funding. Economic conditions can impact various aspects such as the quality of bank assets, credit demand, funding costs, or availability. Simultaneously, the lending decisions of banks, when aggregated at the country level, have an influence on the macroeconomic outlook of that country.

Accordingly, the model incorporates two types of cross-border spillovers: trade spillovers, which directly link the economies, and financial spillovers, which result from the international activities of numerous European banks.




Notes: $Country_1 - Country_1$ represent individual euro area economies, $B$ represents an individual bank. Straight arrows connecting countries highlight the presence of cross-border trade spillovers. Banks headquartered in a country are positioned below the country label. The straight arrows connecting countries and individual banks indicate the two-way interactions between banks and economies, where these banks have exposures or source funding. The two curved arrows on the sides of the figure represent the direction of the two components of the interactions between banks and economies.

**Figure 1:** Basic model structure

The bank's assets consist of holdings in both the banking and trading books, including interest-bearing securities that may be classified in either book (see Table 1). In the banking book, the model specifically tracks loan exposures to the non-financial corporate sector ($NFC$), household loans backed by real estate ($HHHP$), and household credit for consumption purposes ($HHCC$) that can exhibit significantly different dynamics depending on the geographical location. It also considers exposures to sovereigns ($SOV$), the financial sector ($FIN$), and central banks ($CB$) where banks have the ability to adjust the amounts of asset holdings without changing their geographical composition.

On the liability side, a bank's balance sheet comprises equity, sight and term deposits from corporates ($NFC$) and households ($HH$), secured funding through repos, issued collateralised



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debt securities, and unsecured wholesale funding including inter-bank liabilities and debt securities. Banks have the ability to adjust private sector deposits separately for different geographical regions, while the geographical composition of other liabilities remains constant. Finally, banks can adjust their capitalisation through profit retention, while it is assumed that banks are unable to recapitalise or issue new shares.

| Assets | Liabilities |
|---|---|
| Loans NFC | Capital |
| Loans HHHP | |
| Loans HHCC | Sight deposits HH |
| Loans FIN | Sight deposits NFC |
| Loans CB | Term deposits |
| Loans OTHER | Deposits CB |
| | Deposits SOV |
| Equity exposures | Repo |
| Securitized portfolio | Debt securities (secured) |
| | Debt securities (unsecured) |
| Securities SOV | |
| Securities NFC | Wholesale funding (unsecured) |
| Securities FIN | |
| Trading assets | |

**Table 1:** Schematic illustration of bank's balance sheet

Bank net profits take into account impairments resulting from credit risk, net interest income, asset revaluation, and net trading and fee-commission income. Within the model, the flows between the three IFRS9 asset impairment stages – performing, with increased credit risk since initial recognition, and credit-impaired – are monitored for each distinct banking book portfolio. Changes in asset quality are reflected in the corresponding loan loss provisions, which, when aggregated, are included in the profit and loss statement.

Each banking book portfolio has its assigned credit risk weight based on an internal model-based approach (IRB) or a standardised approach (STA). Total risk-weighted amounts are obtained by combining the amounts of credit risk exposure in the banking book with capital charges associated with market and operational risk. These risk-weighted amounts serve as the denominator for calculating the Common Equity Tier 1 (CET1) capital ratio.

Banks in the model operate in monopolistic competition in lending markets while acting as price-takers in funding markets. Accordingly, they have the ability to discriminate between different lending markets in which they operate, and in each, they face a downward-sloping demand curve. Bank lending volumes and pricing are determined by the interplay of loan demand and supply factors. Loan demand primarily depends on macro-financial variables, including the business cycle, GDP, unemployment, inflation dynamics, and market interest rates. On the other hand, the supply of loans is influenced by the specific circumstances of each individual bank, such as its solvency, leverage, profitability, asset quality, and funding costs.

The structure of banks' debt funding depends on the pecking-order principle. Newly issued assets or maturing liabilities are replaced in the first line by retail, sovereign, and central bank funding, which are relatively low-cost sources of funding, but have limited availability. If these sources are not sufficient, banks turn to the wholesale market. Although wholesale funding is unlimited, it comes at a higher cost. In the wholesale market, a bank can choose to secure fund-



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ing by posting collateral, accessing funds close to the risk-free rate, or it can issue unsecured debt, which carries an additional credit spread.

Profit retention is based on a straightforward rule: a bank distributes profits as long as it can maintain its internal target capital ratio. This internal target is determined by a combination of regulatory requirements, buffers, and an additional bank management buffer reflecting the bank's business model and balance sheet characteristics.

Banks are subject to capital requirements, buffers, and liquidity regulation. They attempt to reduce the distance between actual CET1 and leverage ratios to their regulatory thresholds by adjusting their lending and dividend payout policies. There is an important non-linearity in bank responses to a capital shortfall versus surplus in relation to capital requirements and buffers. A bank that faces a CET1 capital shortfall reduces its lending to the non-financial private sector by a greater absolute amount than a bank with the same magnitude surplus increases it. The deviation from the requirements of the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR) affects the composition of bank wholesale funding.

In closing the model, bank lending decisions have an impact on the real economy. This impact is achieved by aggregating a measure of excessive bank deleveraging proportionate to a reduction in lending resulting from capital shortfall in relation to regulatory thresholds, at the country level, and transforming it into a credit supply shock that directly influences the real economy.[10] The model also captures the funding-solvency feedback loop. Deteriorating bank solvency leads to a higher credit spread on unsecured wholesale funding and an increased reliance on wholesale funding overall. The resulting higher average cost of funding reduces bank profitability and may further deplete its existing capital. A solvency-funding costs feedback loop is particularly prone to emerge during adverse macroeconomic conditions when risk margins in wholesale markets are already elevated.

Finally, the model equations are all stacked in one system and solved simultaneously and sequentially for each period of the forecast horizon.

## 3.2 Macroeconomic block

The macroeconomic block includes the representation of individual economies within the euro area[11] and the international environment of the rest of the world.

Each euro area economy is represented by a set of equations derived from the country-level structural vector autoregressive model (SVAR). Each country, denoted as $C$, is characterised by the following:

$$\begin{aligned} Y_t^C &= a_Y^C + \sum_L A_{Y,L}^{Y,C} Y_{t-L}^C + \sum_L B_L^{Y,C} M_{t-L}^{EA} + \sum_L E_L^{Y,C} X_{t-L}^C + \sum_L F_L^{Y,C} Z_{t-L}^C + v_t^{Y,C,+} \\ M_t^C &= a_M^C + \sum_L A_{M,L}^{M,C} Y_{t-L}^C + \sum_L B_L^{M,C} M_{t-L}^{EA} + \sum_L E_L^{M,C} X_{t-L}^C + \sum_L F_L^{M,C} Z_{t-L}^C + v_t^{M,C,+} \\ M_t^{EA} &= \left( \sum_C w^C \times M_t^C > M^\star \right) .+ M^\star \end{aligned} \tag{22}$$

[10]The model can operate with two alternative feedback loops. The first feedback loop, as described in the main text, is employed throughout this paper. The second feedback loop supersedes the dynamics of country-level lending volumes and interest rates with their aggregated bank-level counterparts. Comparative exercises carried out using the two feedback loops have shown that the choice of one of them does not significantly affect the results presented in the paper.

[11]As of 2022, the euro area consists of Belgium, Germany, Ireland, Spain, France, Italy, Luxembourg, the Netherlands, Austria, Portugal, Finland, Greece, Slovenia, Cyprus, Malta, Slovakia, Estonia, Latvia, and Lithuania.



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where $Y_t^C$ is a vector of 10 country-specific endogenous variables, including real GDP, HICP, unemployment rate, the spread between 10-year government bond yield and 3-month EURIBOR, import volume, export price, residential property price, bank loan volumes and lending rate for the non-financial private sector, and equity price index. Vectors $M_t^C$ and $M_t^{EA}$ each include the EURIBOR 3-month rate and the assets of the Eurosystem as a measure of unconventional monetary policy. Vectors $X_t^C$ represent country-specific measures of foreign demand and competitors' export prices, and $Z_t^C$ includes an additional set of variables, including dummies related to the episode of the COVID-19 pandemic and the index of energy prices. $M^\star$ imposes a a floor level of -1.5% on the 3-month EURIBOR and $w^C$ represents the individual country nominal GDP share in the euro area nominal GDP (in 2021). The number of lags, $L$, is set at 2, and $t$ represents the time period. Vectors $a$ and matrices $A$, $B$, $E$, and $F$ contain the estimated coefficients of the model.

Vectors $v^{C,+}$ can be broken down into two components. Let $v_t^{C,+} = [v_t^{Y,C,+'}, v_t^{M,C,+'}]'$ and:

$$v_t^{C,+} = v_t^C + e_i \circ \frac{1}{d_i^C} \times LoansupplyInnov_t^C \tag{23}$$

where $v$ includes reduced-form residuals from the estimation of country-level VARs, assumed to be independent and identically distributed with a mean of zero and a covariance matrix $\Sigma$. $d_i^C$ is the $i$-th element of the matrix $D^C$ that provides the mapping between the vector of reduced-form residuals $v^C$ and orthogonal structural shocks $\varepsilon^C$ along with $v_t^C = D^C \varepsilon_t^C$ where $\varepsilon_t^C \sim \mathcal{N}(0, 1)$.[12] $e_i$ is a vector with all zero elements except unit $i$-th element. $LoansupplyInnov^C$ aggregates bank-level information on excessive deleveraging, defined in a way that $\frac{1}{d_i^C} \times LoansupplyInnov_t^C$ implies a 1% instantaneous change in loan volumes.

The rest of the world comprises 18 international economies that have the strongest financial links to the euro area.[13] Each country in the rest of the world segment is represented by equations of a reduced-form VAR:

$$\tilde{Y}_t^C = \tilde{a}_{\tilde{Y}}^C + \sum_L \tilde{A}_L^C \tilde{Y}_{t-L}^C + \tilde{v}_t^C \tag{24}$$

with representing a $K^C$-dimensional white noise process characterised by a time-invariant positive definite covariance matrix. Vector $\tilde{Y}$ comprises $K^C$ variables, including real GDP, import volumes, and export prices for each country.

The dynamics of individual euro area economies are influenced by cross-country trade spillovers through foreign demand $FDR$ and competitors' export prices $CXD$ contained in $X_t$. The foreign demand variable reflects the import volumes $MTR$ of a country's trading partners, while the foreign price variable captures the export prices $XTD$ of other countries. In both cases, the foreign demand and price variables are weighted by the counterparty's export or import shares, respectively.

[12] We do not discuss structural representation of shocks to country-level VARs it does not have a direct imprint on the results presented in thsi paper. It identifies and constrains nine shocks through a combination of sign and zero restrictions and the three remaining structural shocks are left unrestricted. The former include a credit supply shock, credit demand, a standard monetary policy and the unconventional monetary policy shock, stock price shock, bond yield shock and a residential property price shock, aggregate demand and aggregate supply shocks.

[13] These are all non euro area European Union economies as of 2020, such as Bulgaria, Czech Republic, Denmark, Croatia, Hungary, Poland, Romania, Sweden, as well as two European Free Trade Association (EFTA) economies, Switzerland and Norway. Furthermore, other regions included in the model are Brazil, China, Japan, Mexico, Russia, Sweden, Turkey, the United Kingdom, and the United States.



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$$
\begin{aligned}
FDR_t^C &= \sum_{T \in \{EA \backslash C, RoW\}} w_{FDR}^T \times MTR_t^T \\
CXD_t^C &= \sum_{T \in \{EA \backslash, RoW\}} w_{CXD}^T \times MTR_t^T
\end{aligned}
\tag{25}
$$

where $w_{FDR}^T$ represents the share of exports from country $C$ to country $T$ in the total exports of country $C$ and $w_{CXD}^C$ represents the share of imports from country $T$ in the total imports of country $C$.

## 3.3 Scenario uncertainty

VAR equations describing the evolution of euro area economies are estimated in a Bayesian panel setup along with the specification:

$$
\begin{aligned}
Y_t^C &= a_Y^C + \sum_L A_L^{Y,C} Y_{t-L}^C + \sum_L B_L^{Y,C} M_{t-L}^C + \sum_L E_{Y,L}^C X_{t-L}^C + \sum_L F_{Y,L}^C Z_{t-L}^C + \nu_t^{Y,C} \\
M_t^C &= a_M^C + \sum_L A_L^{M,C} Y_{t-l}^C + \sum_L B_L^{M,C} M_{t-L}^C + \sum_L E_{M,L}^C X_{t-L}^C + \sum_L F_{M,L}^C Z_{t-L}^C + \nu_t^{M,C}
\end{aligned}
\tag{26}
$$

providing the posterior estimates of the model parameters, historical $\nu$ and $\Sigma$. Analogous information is available for VAR representing non-euro area economies with the recognition that those are estimated individually with a multivariate least squares estimator.

The uncertainty of the scenario is mapped by Monte Carlo (MC) stochastic simulations of $\nu$ and $\tilde{\nu}$ applying the wild block boostrap or estimated parameters of the shock distributions. The former sampling scheme recognises the full cross–correlation structure between the shocks drawn for different economies. The latter assumes that such shocks are uncorrelated.

## 3.4 Parameter uncertainty

Parameter uncertainty refers to the uncertainty regarding the values of coefficients in the model equations. In the BEAST model, it is treated separately for the parameters entering the macro-financial block on the one hand and the banking block on the other. The uncertainty of parameters in macro-financial equations for the euro area is captured by repetitively drawing parameters from their joint posterior distribution estimated for the vector autoregression in equation (26).

Bank-level equations are estimated using frequentist methods, most of the time in a fixed effects panel framework, such as:

$$
y_{i,t} = X_{i,t}\beta + \alpha_i + \varepsilon_{i,t} \tag{27}
$$

where $y_{i,t}$ is the dependent bank variable observed at time $t$ for bank $i$, $X_{i,t}$ is the vector of the regressors, $\beta$ is the vector of parameters, and $\varepsilon_{i,t}$ is the error term.

To evaluate the uncertainty of estimated bank-level equations and the rest of the world's economies, we assume that the Gauss-Markov theorem holds. Resultantly, the estimated parameter vectors and matrices $\hat{\beta}$, $\tilde{a}_{\tilde{Y}}^C$, $\tilde{A}_L^C$ are normally distributed, and we draw parameter coefficients in individual equations from[14]:

[14]The limitation of this framework is that equations estimated separately are considered independently while evaluating the parameter uncertainty. Furthermore, the uncertainty is assessed only for a share of empirical bank level equations most relevant for the mapping of the real economy - banking sector feedback loop (see Chapter 6 in **??** for details.



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$$\hat{\beta} \sim \mathcal{N}(\beta, \sigma^2(X^\top X)^{-1}) \tag{28}$$

# 4 Simulation setup

Model simulations start in 2022 Q4 and expand to the 5-year horizon (2027 Q4). Scenario uncertainty is built for the full set of reduced-form shocks for the euro area and the rest of the world's economies and involves the uncertainty related to the evolution of energy prices. The reduced-form shocks are boostrapped from their historical distributions. Additionally, the simulation considers the parameter uncertainty for all macroeconomic equations and behavioral equations at the bank level. The simulations are unconditional and do not center around any prespecified scenario.[15]

In this setup, we will look at three alternative scenario horizons for stress tests: 1 year ahead, 3 year ahead, and 5 year ahead. We also focus on a subset of variables describing both the macro-financial environment and the banking system. For macro-financial scenarios there are GDP, HICP inflation, 3-month Euribor, Eurosystem assets, 10-year bond yields, unemployment rate, equity, and house prices. These variables generally correspond to the set of variables that enter the design of the EBA / SSM scenario. For the banking sector, we will look at the transitional CET1 ratio as a measure of solvency, the change in the transitional CET1 capital, bank profitability measured by return on assets (ROA) and the nonperforming loan (NPL) ratio as a measure of bank asset quality. Additionally, we look at the average debt funding costs of banks, and their liquidity mismatches measured by the liquidity coiverage ratio (LCR). The evolution of bank lending to the non-financial private sector of the euro area is mapped by the corresponding loan volumes and lending rates. At most instances and if not mentioned otherwise, macro-financial variables are presented as euro-area averages weighted by the nominal GDP (for the unemployment rate they are weighted by country-level labour force. Bank-level variables are weighted accordingly to the definition of a variable, namely the CET1 ratio is weighted by bank-level Risk Weighted Assets, lending volumes, and interest rates to the euro area non-financial system by relative country-level volumes of outstanding and new loans, respectively.

# 5 Looking at the full distribution of events

This section looks at the results of stochastic simulations and evaluates the risk to system-wide bank solvency. It starts by looking at the full distribution of possible futures. Then it presents the results of a distributional stress test for bank solvency bot on the system and bank level.

## 5.1 Macro-financial scenarios

The complete distribution of scenarios is illustrated in Figure 2. In the medium term, the expected growth rate of GDP and inflation return to their longer-term averages of slightly below

[15]The detailed robustness check employed alternative sampling scheme, where macro-financial shocks were drawn from the estimated parametric distributions. With the alternative sampling scheme, the space of future scenarios reflects greater uncertainty. The higher variance of future scenarios translates into higher tail measures (in absolute terms) and more extreme stress scenarios than for the boostraping scheme. However, it has not significantly affected any of the results presented in the following chapters. The results can be provided by the authors on request.



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2%. Expected short-term interest rates, represented by the 3-month EURIBOR, stabilize accordingly. The probability of 3-month EURIBOR falling below the 0% threshold is around 50%, but that of 3-month EURIBOR returning to all time lowest levels observed in the low inflation environment in any of the future quarters is significantly below 10%. The expected level of government bond yields remains more than two percentage points above that of 3-month EURIBOR reflecting the presence of time and risk premium. The euro area stock price index follows an increasing trajectory. The same holds for the house price index, which starts to climb slowly in the medium run.

The expected bank profitability stays positive, translating into an average period ROA of around 0.5% over the simulation horizon. CET1 capital increases over time in line with the expansion of bank assets, therein loans to the non-financial private sector, although as the ratio of risk weighted amounts, it decreases somewhat in the longer horizon compared to the end of 2022. This sliding path of the CET1 ratio in the longer horizon reflects conservative assumptions of the model that do not allow banks to access capital markets, exclude bank recapitalisations, entry of new, more efficient banks, adaptations of their business models or restructurings. The quality of the bank assets deteriorates slightly, which can be partially attributed to model assumptions such as missing sale-offs of assets and partially to the gradual normalization of labour markets predicted at the longer end of the horizon. Lastly, the liquidity coverage ratio stabilizes at the level that is safely above required 100% but below the level in 2022. The latter correction reflects the assumed normalization of monetary policy and the partial pull-out of central bank liquidity support in the medium run.

The estimates of scenario uncertainty are relatively broad and extend over the horizon especially for index and stock variables such as the CET1 ratio or equity indices.

## 5.2 Tails of bank solvency

The distribution of system-wide bank solvency at a chosen horizon comprehensively summarizes solvency risks. Figure 3 zooms in on the distribution of system-wide CET1 ratio. The fanchart of the CET1 ratio becomes flatter and less symmetric with increasing scenario horizon. The outcomes at 1-year horizons are relatively centered around the mean. Over time, an increasing mass of probability corresponds to scenarios involving amplification mechanisms. The left tail of the distribution becomes longer and thicker.

Table 2 selects candidate tail metrics of $10^{th}$, $5^{th}$ and $1^{st}$ percentiles. The mean or median system-wide CET1 ratio remains around 3 percentage points above the projected regulatory requirements and buffers over the medium run. However, the CET1 ratio in the tail systematically decreases over time. The probability of the CET1 ratio dropping 1.5 percentage points below its expected level in one year is firmly below 1%. In a three-year perspective, the banking sector as a whole is likely to fall below the average level of the projected regulatory CET1 threshold with a probability below 5%. The two measures of tail risks jointly speak of the high capacity of the euro area banking system to cope with short- to medium-term stress.

| | Mean | Median | 10 perc | 5 perc | 1 perc |
|---|---|---|---|---|---|
| Starting point | 15.2% | | | | |
| 1-year | 13.2% | 13.2% | 12.7% | 12.5% | 11.8% |
| 3-year | 13.9% | 14.2% | 12.7% | 11.8% | 7.2% |
| 5-year | 12.8% | 13.8% | 11.5% | 9.5% | -3.2% |

**Table 2:** System-wide CET1 outcomes at different horizons



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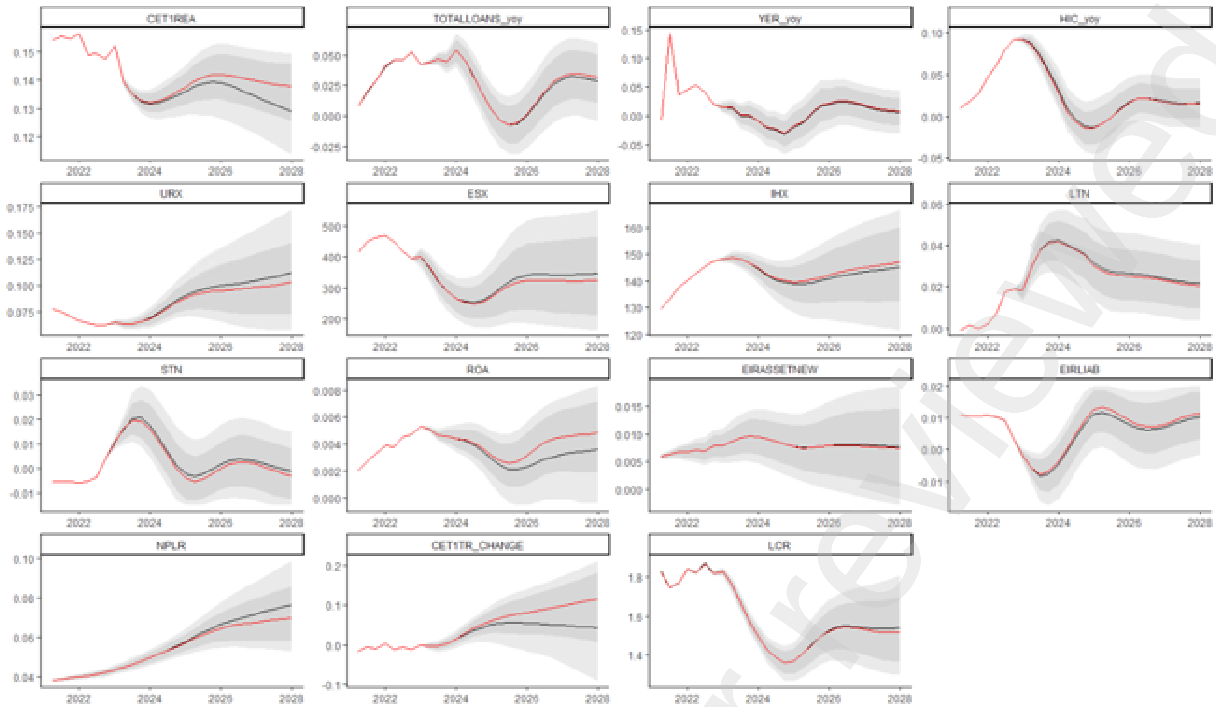
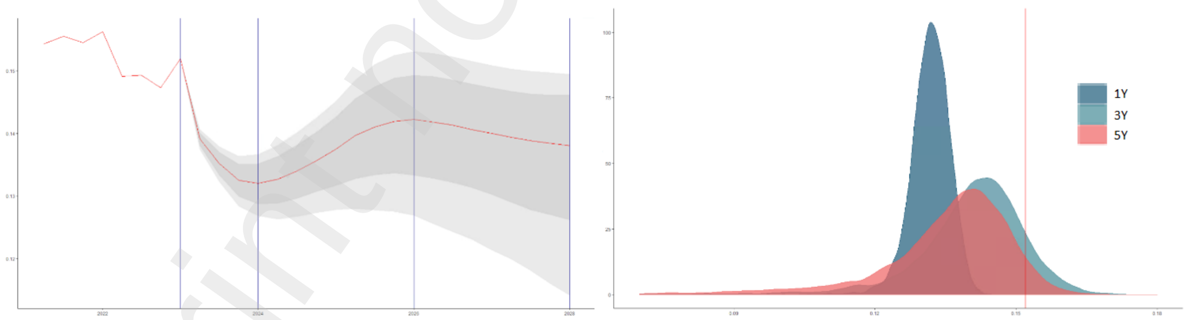



**Figure 2:** Full distribution of plausible scenarios

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW - interest rate on new lending to the non-financial private sector, EIRLIAB - the average debt funding costs, NPLR – NPL ratio, CET1TR_CHANGE - percentage change in CET1 capital compared to the end 2022, LCR - liquidity coverage ratio. Red line: median, black line: mean, dark field 60%, lighter field 80%.




**(a)** CET1 ratio fanchart

**(b)** CET1 ratio at horizons

**Figure 3:** CET1 ratio at three horizons: 1-year, 3-years and 5-years

Notes: LHS chart: red line - median, dark field 60%, lighter field 80% probability span. Blue horizontal lines mark, starting from the left hand side, the starting point (end 2022), 1-year, 3-year and 5-year forecast horizons. RHS chart: red horizontal like - the starting point (end 2022) CET1 ratio.

The longer the horizon, the higher the probability that the banking sector will face significant trouble. These are the tail risks, extremely unlikely but still often underestimated. Inspection of such extreme tails at the horizon beyond common supervisory practice can still provide relevant

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information to regulators.

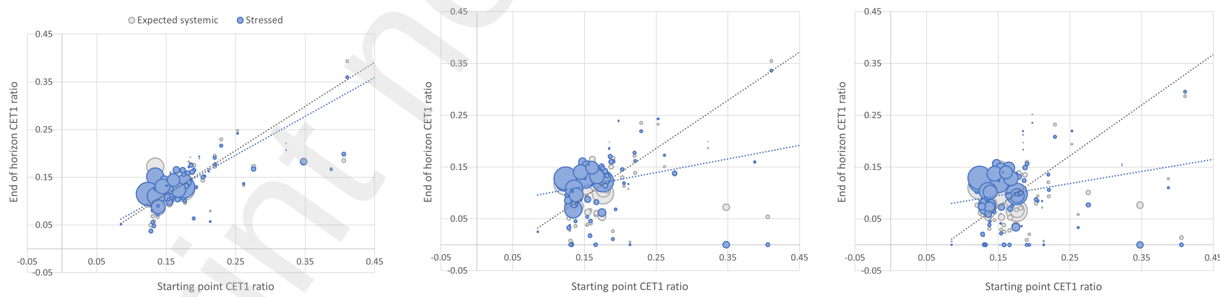
## 5.3 Distributional stress testing in a heterogenous banking system

The tail analysis of risks can detect pockets of vulnerabilities inherent to different types of banks. We present examples of two alternative perspectives that can be followed within distributional stress testing. First, we look at the tails of unconditional bank-level outcomes that have the capacity to uncover their systemic and idiosyncratic vulnerabilities. Second, we look at bank-level outcomes conditional on system-wide distress.

Figure looks at the two tail measures of individual bank solvency compared to the starting point in different scenario horizons. The blue balls represent what we call the stressed CET1 ratio, namely the lower percentile of the bank-level CET1 ratio. Individual banks' stressed CET1 ratios can nest risks and scenarios that are very specific to their portfolios and business models (Flood and Korenko [2015b]). Gray balls represent the expected systemic CET1 ratios, which we define as the mean bank-level CET1 ratio for the lower percentile of the system-wide CET1 ratio. measures bank vulnerability in a systemic crisis. The expected systemic CET1 ratio measures the vulnerability of the banks in a systemic crisis and links to the systemic expected shortfall (SES) proposed by Acharya et al. [2017]. The stressed CET1 ratio amounts to the $10^{th}$ percentile of the bank-specific distribution described in the full space of possible futures. The systemic expected CET1 ratio corresponds to the mean bank-level CET1 conditional on the system-wide CET1 ratio falling in its $10^{th}$ percentile.

It also relates to a classical stress test with macro-financial scenarios where for comparability and along with the desire to treat firms equitably, all institutions face identical scenarios.

Figure looks at the stress (blue balls) and systemic expected (gray balls) CET1 ratios of individual banks compared to the starting point at different horizons. The stressed CET1 ratio amounts to the $10^{th}$ percentile of the bank-specific distribution described on the full space of possible futures. The expected systemic CET1 ratio corresponds to the mean bank-level CET1 conditional on the system-wide CET1 ratio falling in its $10^{th}$ percentile.




**(a)** 1 year **(b)** 3 year **(c)** 5 year

**Figure 4:** CET1 threshold of euro area scenarios

Notes: Blue balls - stressed CET1 ratio for $10^{th}$ percentile, gray balls - systemic expected CET1 ratio for $10^{th}$ percentile. The size of balls corresponds with the size of banks' assets at the end of 2022. The charts zoom in the banks with the initial CET1 ratio (as at the end of 2022) below 45%.

Along with intuition, stressed CET1 ratios are generally below their expected systemic counterpart. The gap between the two measures of bank-level vulnerabilities widens over the scenario horizon, signifying an increasing probability of the emergence of specific and "unlikely" scenarios that pose a strain on a bank with its unique structure of exposures and business



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model, but less so on the overall banking systems. Intuitively, these are also mostly small banks for which the two measures of solvency evolve differently over an increasing scenario horizon.

The expected stressed CET1 ratios relate to a classical stress test in which the desire to treat firms equitably translates into exposing all institutions to the same adverse scenarios. To test this intuition, stressed and expected systemic CET1 ratios are compared with the results of the EBA/SSM stress test 2023.[16] The left hand side chart in Figure 5 reports the change in bank-level CET1 ratios from their starting point for two metrics derived from the distributional stress test against the results of the Europe-wide stress test. The first observation is that the results of the EBA/SSM stress test are, in broad terms, closer to the systemic expected CET1 ratios than to the stressed CET1 ratios. The second is that on average large banks appear to be put under sufficient stress in the EBA/ SSM exercise, at least compared to the two distributional stress test metrics and the 10-$^{th}$ percentile threshold. For smaller banks, the picture is more varied. This again reflects a proportionately greater focus put on larger banks in the supervisory exercise.


**(a)** CET1 ratio

**(b)** CET1 capital

**Figure 5:** Distributional stress test versus EBA/SSM stress test changes in CET1 ratio and capital over 3-year horizon

Notes: Blue balls - stressed CET1 ratio for 10$^{th}$ percentile, gray balls - systemic expected CET1 ratio for 10$^{th}$ percentile. The size of balls corresponds with the size of banks' assets at the end of 2022. In the macroprudential stress test capital losses over 100% of the initial CET1 capital are possible, as the stress test incorporates capital transformation triggers for AT1 and T2 instruments.

When comparing the results of a constant balance sheet and macroprudential exercise, it is also interesting to contrast changes in capital. Such changes measure actual losses carried by banks' investors or, in the case of a bailout, states, and they tend to be systematically understated in stylised stress tests where banks neither expand nor shrink their balance sheets. Consistent with this expectation, the graph on the right side of Figure 5 shows much larger capital losses measured in macroprudential stressed and expected systemic CET1 capital compared to the results of the EBA/SSM exercise, although there are some banks that experience capital gains at least as compared to the starting point. In general, capital losses of large versus small banks show a pattern similar to changes in the CET1 ratios. These are mainly small banks, which appear more vulnerable to tail idiosyncratic and systemic risks than could be captured in the EU-wide stress test.

The comparison illustrates one of the possible applications of distributional stress test, as ex

[16]In this we use the fact that the starting points of our and the EBA/SSM stress test are congruent, although the latter stress test accommodates morte comprehensive update of banks' balance sheet results at the end of 2022.



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ante or ex post evaluation metrics of bottom-up exercises. It also signifies which banks can be understressed in the exercise and where additional supervisory scrutiny may be needed while both interpreting the stress test results and applying bank-specific capital charges.

# 6 Reverse stress testing

This chapter shows how to delineate plausible scenarios with the desired severity. The concept of reverse stress testing is straightforward to implement for a single risk factor and a single outcome variable. It requires a simple inversion of the function to map risks into outcomes. However, such an inversion becomes very complex for real-life scenarios, with multiple macro-financial factors, multiperiodicity, and possibly nonlinear transmission of risks into balance sheets of institutions.

We implement two examples of a reverse stress test to illustrate the flexibility of our approach. Furthermore, we note how reverse stress testing based on multiple scenarios can inform policy choices about scenario severity. An early assessment of the plausibility of different scenarios ensures that later calibrated severity thresholds warrant scenarios with good interpretability. The chapter closes with an example of selection of plausible and severe scenarios with a desired economic narrative.

## 6.1 Worst-case scenarios

Figure 6 illustrates the macro-financial scenarios corresponding to 10% worst-case scenarios for the CET1 ratio at the system level and for the horizon of one year. The red line represents the median of the full distribution of scenarios, while blue fancharts and the blue line summarise the distribution and median of the worst-case scenarios, respectively.

A strong reduction in bank solvency on a short horizon emerges in scenarios with lower economic growth, combined with a significant pick-up in inflation. High inflation triggers a monetary policy response, sharp increases in bond yields, and pronounced corrections in asset prices. The plunging asset prices of stocks and bonds lead to revaluation losses and shrinking bank capital. At the same time, high inflation fuels an increase in nominal bank lending. Although loan volumes in real terms to the non-financial private sector are firmly below the median of the full scenario distribution, their expansion in nominal terms contributes to weak CET1 ratio by inflating its denominator.

Short-term worst-case scenarios for bank solvency bear some resemblance to the evolution of the euro area economy at the exit from the COVID-19 pandemics. Fragile economic growth, sharply increasing inflation, and first steps in monetary policy normalisation that led to corrections of prices in financial markets.

The medium-term risks to the bank's solvency reflect a classical recession. The 10% worst-case scenarios for the CET1 ratio in the 3-year horizon are illustrated in Figure 6.4. They depict a sustained contraction in output, an increase in unemployment, low inflation but a strong correction in asset prices. Bank funding costs increase on the back of their deteriorating balance sheets and increasing risk premia, and banks struggle to pass through these increases into lending rates. Bank lending and profitability drop, and asset quality deteriorates.

In the long run, most prevalent solvency risks relate to a lasting black swan recession. The risks summarised in Figure 8 are qualitatively similar to medium-term risks and yet reflect a recession that lasts not 3 but 5 years, with monetary policy becoming with high probability bounded by zero interest rate friction. Bank capital is continuously depleted, leading to very adverse outcomes at the system level.



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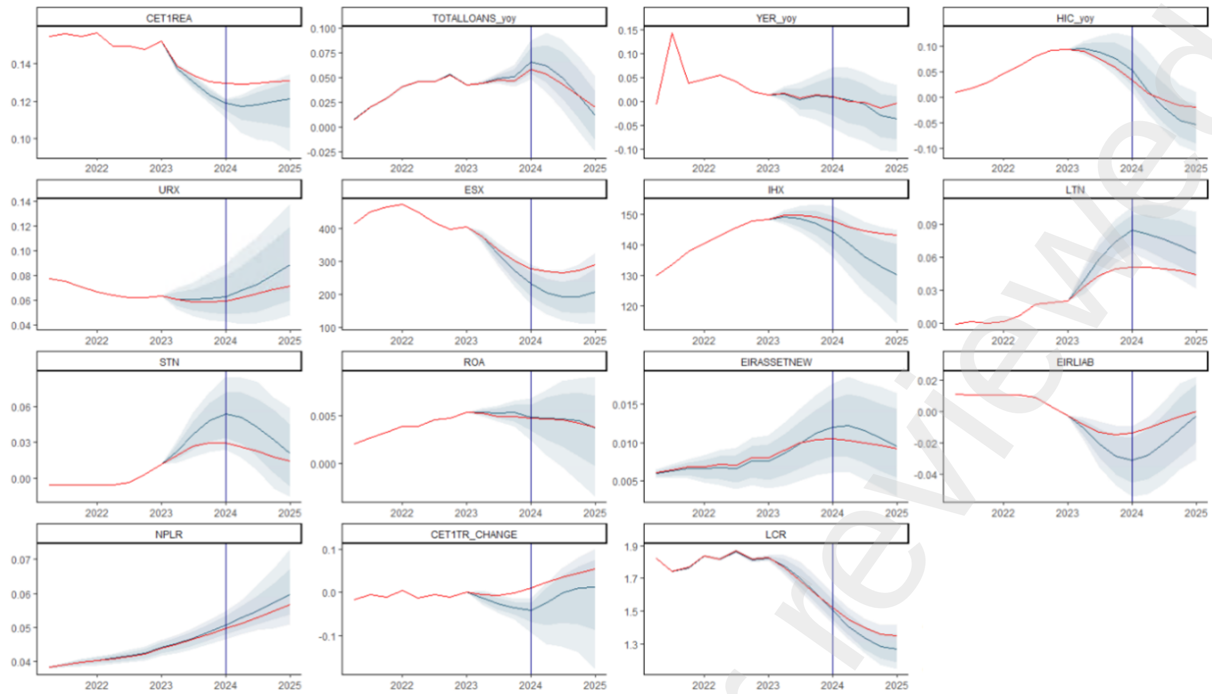

**Figure 6:** Worst-case scenarios for system-wide CET1 ratio at 1-year horizon

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - percentage change in CET1 capital compared to the end 2022, LCR - liquidity coverage ratio. Red line: median for the full distribution of events, blue line: median of relevant worst-case scenarios, blue darker field 60%, blue lighter field 80%. The navy blue vertical line marks the end of the scenario horizon.

## 6.2 Threshold scenario severity

The alternative avenue to ensure sufficient severity of the scenario is to select scenarios with a postulated maximum level of the CET1 ratio. Figure 9 illustrates the outcome of such selection that asks the system-wide CET1 ratio to not be higher than 10% in three alternative stress test horizons.

The short- to long-term risks to bank solvency identified with this approach are qualitatively similar to those uncovered by the corresponding worst-case scenarios. Short-term risk scenarios are those with a sudden acceleration of inflation and a decisive reaction of monetary policy. In the medium to long term, bank solvency is prone to risks characteristic of a recessionary environment. The threshold severity scenarios or 3-year and 5-year-forward bank solvency reflect a reduction in economic output and asset prices, with an impact on bank asset quality and loan demand.

There is a clear and intuitive difference between the depth and duration of recession that threatens bank solvency in the medium and long term. The recession that could bring bank solvency below 10% in the 3 year horizon must be deeper and commensurate with sharper corrections in asset prices.

However, extreme macro-financial development necessary to bring the CET1 ratio below 10% on the one-year horizon has a minuscule probability of realization of 0.2%. So low plau-



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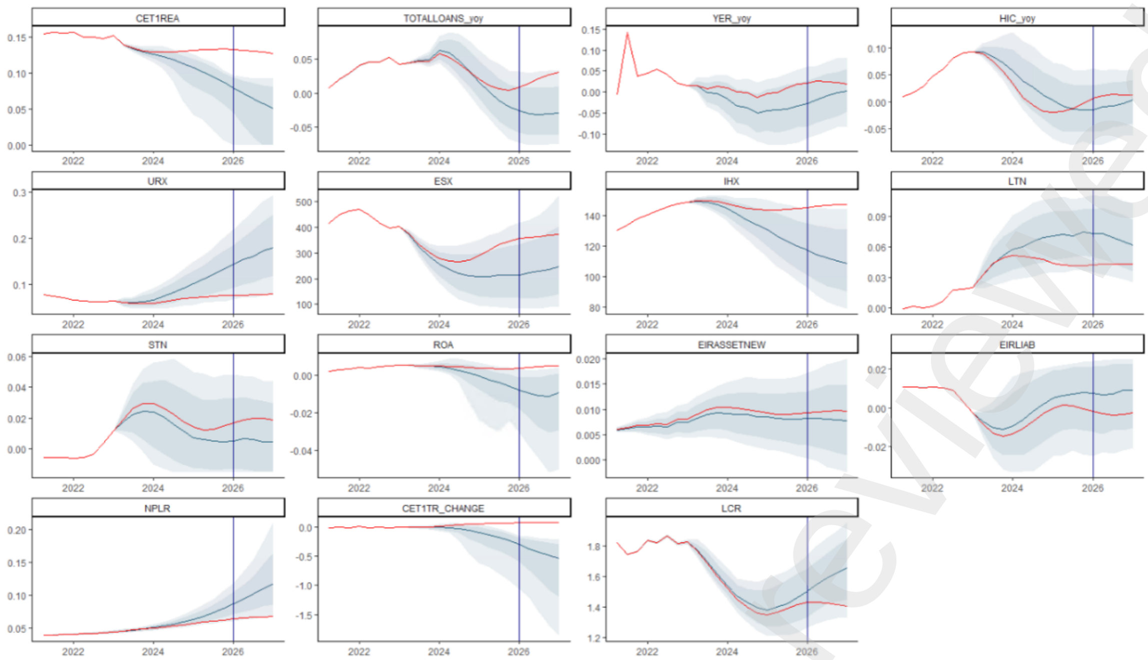


**Figure 7:** Worst-case scenarios for system-wide CET1 ratio at 3-year horizon

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - percentage change in CET1 capital compared to the end 2022, LCR - liquidity coverage ratio. Red line: median for the full distribution of events, blue line: median of relevant worst-case scenarios, blue darker field 60%, blue lighter field 80%. The navy blue vertical line marks the end of the scenario horizon.

sibility of the scenarios prevents their meaningful quantitative, and to a degree also qualitative, interpretation. The probability of the CET1 ratio falling below 10% in the 3 year horizon is already 2.8%, and in the 5 year horizon 9%.

The trade-offs present in the analysis of threshold scenarios are the plausibility of the scenarios and are illustrated in Figure 10. The probability of scenarios with a CET1 ratio below a threshold and with fixed scenario horizon increases exponentially from low thresholds in the left corner of the chart to high thresholds in the right corner of the chart. Selected scenarios illustrating the effect of changes in the threshold level at the same scenario horizon are placed in Appendix A. This intuitive property is directly related to approximately mean stationary properties of the CET1 ratio. For a given threshold, the plausibility of scenarios increases with the horizon of the scenario, along with the increasing uncertainty of the CET1 ratio.

These properties of threshold scenarios should not be overlooked when designing a stress test. For any preferred scenario horizon, the threshold must still be informed by the distribution of the variable of interest. One practical take away is that, in any stress test exercise, including the EBA/SSM process, the ambitions regarding the impact on banks could be informed and scaled according to the outcomes of distributional stress test, with implications on the postulated shape of adverse macro-financial scenarios.



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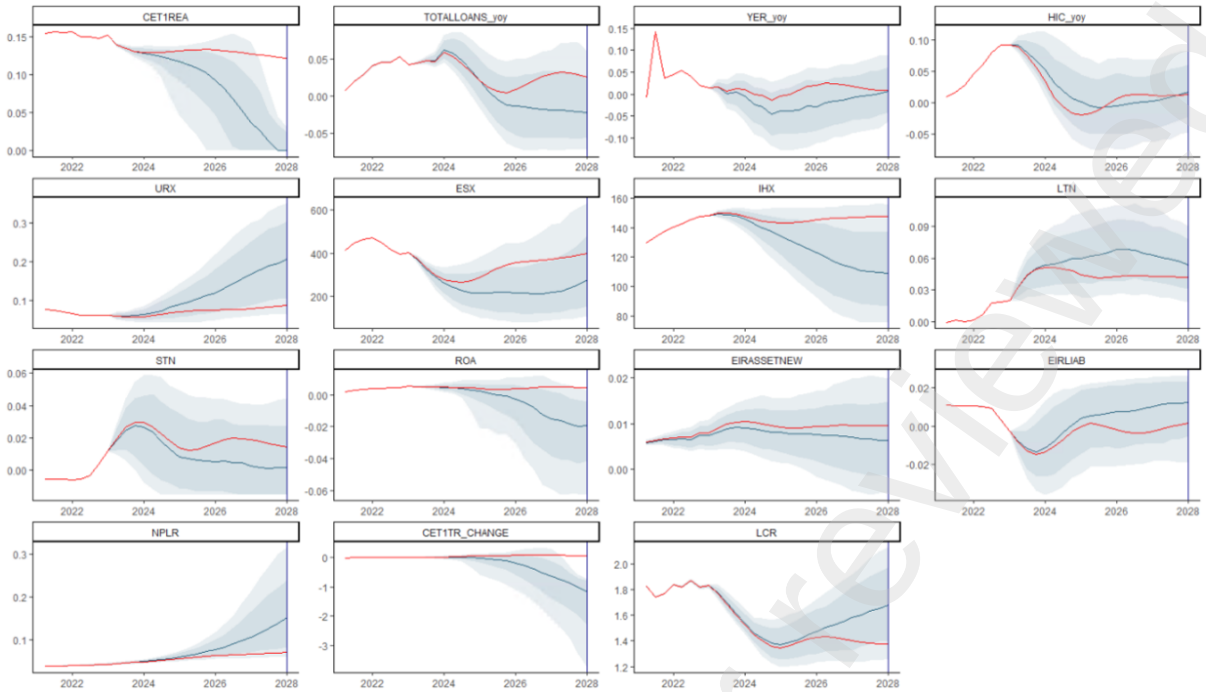


**Figure 8:** Worst-case scenarios for system-wide CET1 ratio at 5-year horizon

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - percentage change in CET1 capital compared to the end 2022, LCR - liquidity coverage ratio. Red line: median for the full distribution of events, blue line: median of relevant worst-case scenarios, blue darker field 60%, blue lighter field 80%. The navy blue vertical line marks the end of the scenario horizon.

## 6.3 Non-linearities and amplification mechanisms

In the discussion of scenario severity, the salient rule of thumb is that to increase the severity of stress test one must aim at more adverse macro-financial conditions. Especially in the approach in which macro-financial scenario design is decoupled from the assessment of the target variable, it is often the only yardstick available. Its reflections are present in, e.g. Henry [2021], who scales macro-financial risk factors with a set of scalars to arrive at a grid of scenarios with different severity.

However, the pass-through of macro-financial variables, or risk factors, into bank variables is not linear. We show it by sequentially identifying scenarios with progressing severity defined for system-wide CET1 ratio outcomes. Figure 11 summarises the result of this exercise, where, for the change in the CET1 ratio threshold, we look at the cumulative change in GDP normalised by its expected value for different stress test horizons.

In the ranges where the banking sector would be seen as resilient, marginal changes in the CET1 ratio demand measurably worse GDP outcomes. Around the CET1 thresholds of 11% to 13% for the 3-year horizon, which can still be considered too permissive for real-life stress test exercises, the marginal impact of macro-financial outlook on the banking sector is very low. A moderate economic slowdown does not have a pronounced impact on bank solvency. However, for progressively low CET1 ratios, falling in ranges which one sees in real-life stress tests, the



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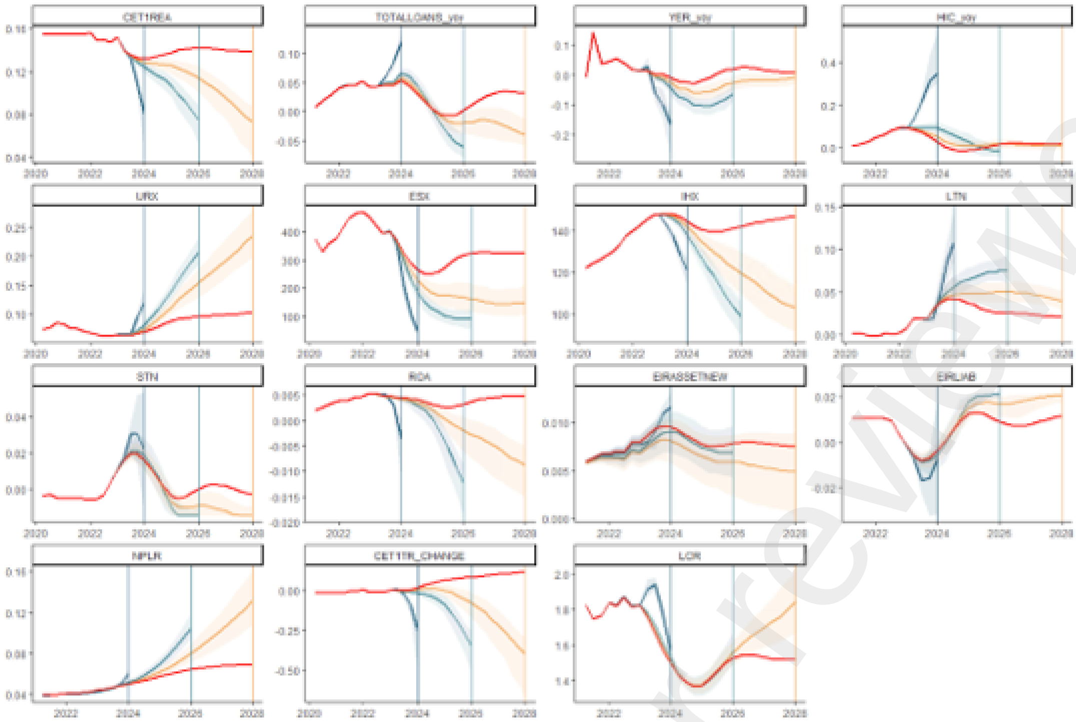
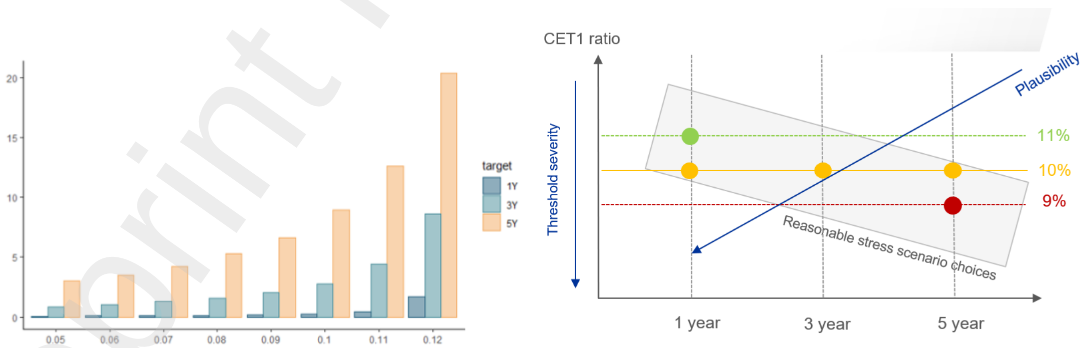



**Figure 9:** Macro-financial scenarios with 10 perc CET1 ratio for 1-year, 3-year and 5-year horizon

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - percentage change in CET1 capital compared to the end 2022, LCR - liquidity coverage ratio. Red line: median for the full distribution of events, dark blue line: median for threshold scenarios with 10% CET1 ratio in one year, lighter blue line: median for threshold scenarios with 10% CET1 ratio in three years, yellow line: median for threshold scenarios with 10% CET1 ratio in five years. The fan charts span 40% for the corresponding threshold scenarios. The vertical lines mark the end of each scenario horizon.




**(a)** Probability for horizons and thresholds

**(b)** Trade-offs

**Figure 10:** Plausibility versus CET1 threshold of euro area scenarios

pass-through of economic conditions starts increasing. Moreover, there is a break-even point when even slightly worse macro-financial scenario triggers substantial further deterioration in bank solvency.



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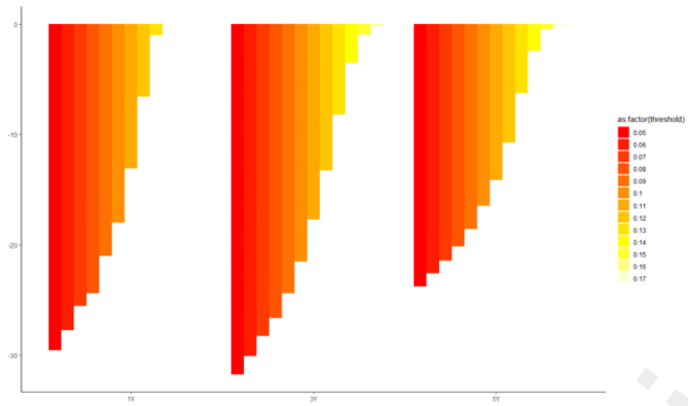

**Figure 11:** Mean euro area GDP fall in the scenario horizon per scenario severity threshold for the CET1 ratio

Notes: OY-axis represents the mean deviation of cumulative euro area GDP change from the beginning until the end of stress scenario horizon from its expected value (based on the full distribution of outcomes).

## 6.4 Selecting a desired narrative

On occasion, we are interested in a macrofinancial scenario that exemplifies a particular economic narrative. To this end, we can comb through projected results to identify scenarios that emphasise risks and vulnerabilities in the narrative. To this end, it suffices to translate the scenario narrative into criteria that can be applied to scenario evaluation. Here, we consider a simple example where a scenario designer, next to ensuring scenario plausibility and severity, may wish to emphasise relatively loose or tight monetary policy.

Figure 12 and 13 contrast the worst-case scenarios with different monetary policy stances. Each family of scenarios is characterized by similar adversity measured by the system-wide CET1 ratio, and has a probability of 5% realization. They cut the space spanned in Figure 6.4 into two equal slices and differ in the three-year average level of the real interest rate.

Relatively loose monetary policy emerges in stagflation scenarios with high inflation and low GDP growth, while relatively tight policy emerges in scenarios with a more positive economic outlook. Although not visible in the figures, more accommodating monetary policy scenarios also involve a stronger expansion of the ECB balance sheet, signifying a looser unconventional tools' calibration. Scenarios with tighter monetary policy and lower inflation appear to put less pressure on the real economy. Unemployment is lower, asset prices, and real lending to the non-financial private sector higher, than in scenarios with lower real interest rates. With the two alternatives at hand, the results suggest that it is too loose a future monetary policy that formed a higher risk to the euro area macro-financial system rather than too tight at the beginning of 2023. And last, such space of scenarios can be cut further, seeking scenarios with narrower narratives, such as co-emerging fragmentation risks or labor market deterioration.



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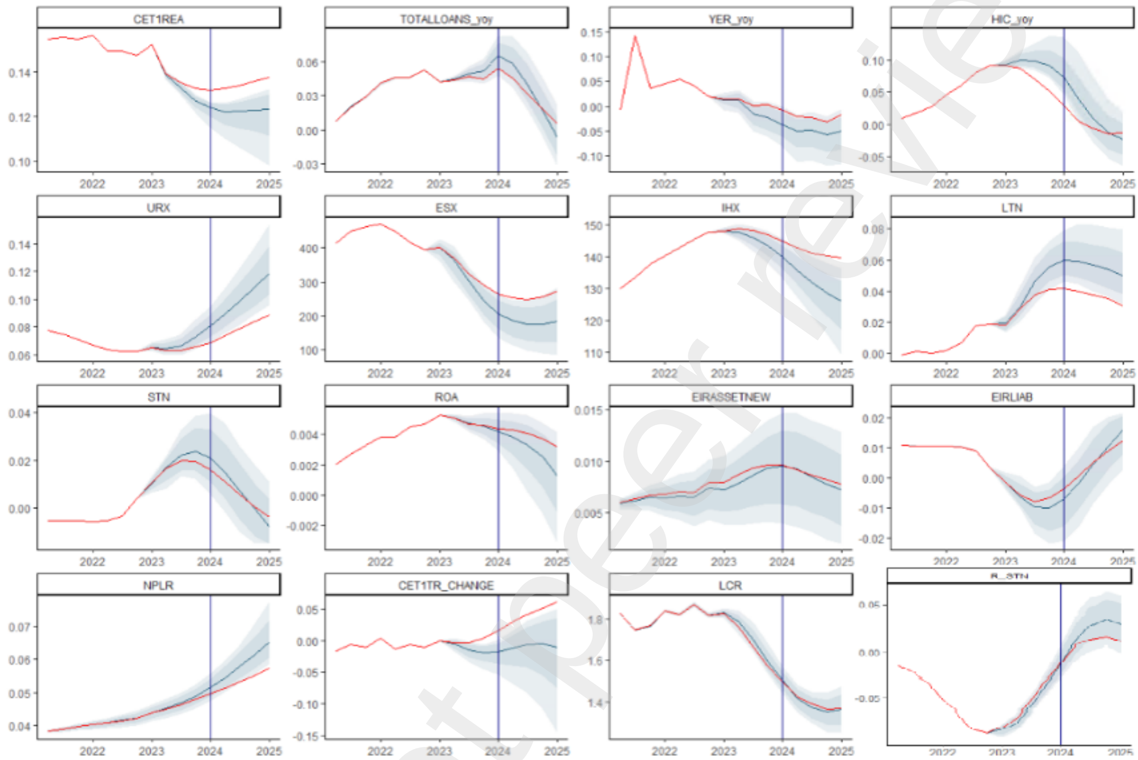


**Figure 12:** Worst-case scenarios for system-wide CET1 ratio at 3-year horizon with looser monetary policy

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - percentage change in CET1 capital compared to the end 2022, LCR - liquidity coverage ratio, R_STN - 3-month EURIBOR minus HICP inflation rate. Looser monetary policy corresponds to the period average real interest rate (EURIBOR minus HICP inflation rate) below its median for the worst case scenarios with 10% plausibility. Red line: median for the full distribution of events, blue line: median of relevant worst-case scenarios with looser monetary policy, blue darker field 60%, blue lighter field 80%.



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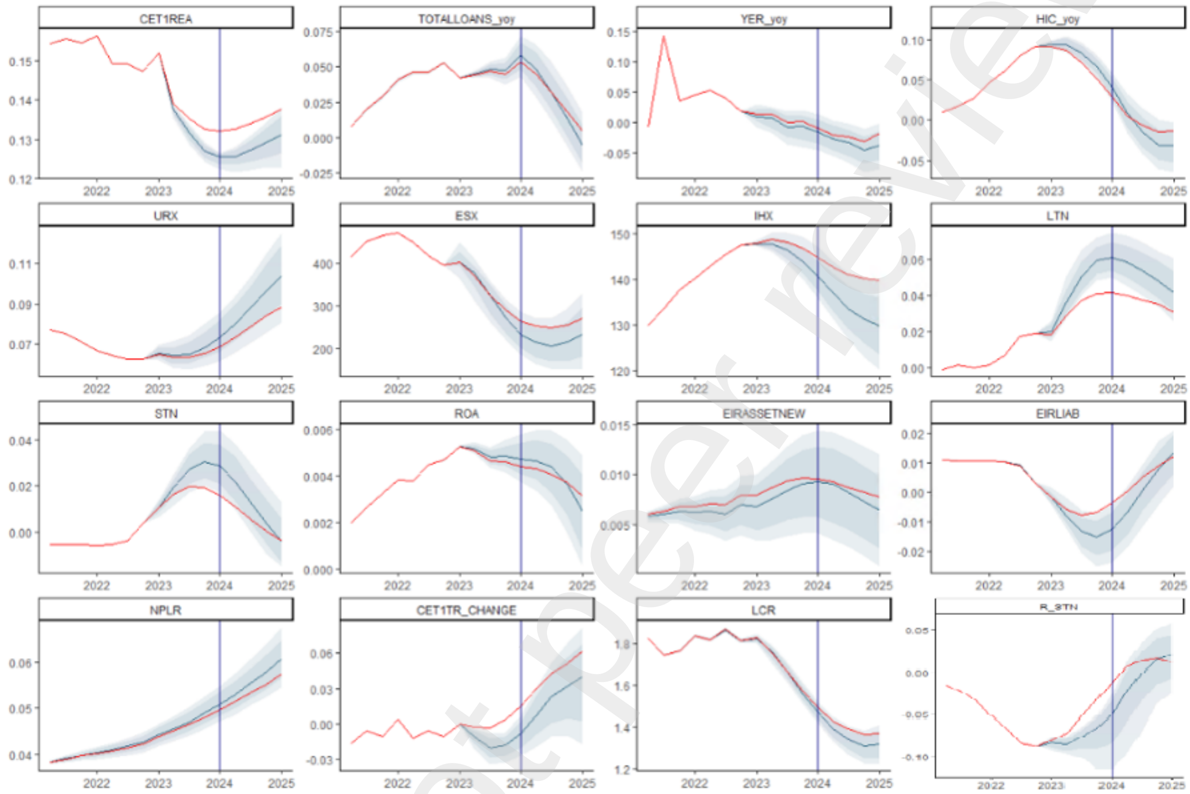


**Figure 13:** Worst-case scenarios for system-wide CET1 ratio at 3-year horizon with tighter monetary policy

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - percentage change in CET1 capital compared to the end 2022, LCR - liquidity coverage ratio, R_STN - 3-month EURIBOR minus HICP inflation rate. Tighter monetary policy corresponds to the period average real interest rate (EURIBOR minus HICP inflation rate) above its median for the worst case scenarios with 10% plausibility. Red line: median for the full distribution of events, blue line: median of relevant worst-case scenarios with tighter monetary policy, blue darker field 60%, blue lighter field 80%.



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# 7 Looking beyond system-level solvency

This chapter elaborates on the application of concepts discussed in previous chapters to stress test exercises, which, due to circumstantial or institutional reasons, aim to look at the resilience of the financial system in a more holistic manner. The first example concerns the application of these concepts to stress tests that focus on bank solvency and lending simultaneously. The second example looks at a stress test, emphasizing the emergence of endogenous financial stability risks. Additionally, Appendix B discusses the design of a joint solvency liquidity stress test.

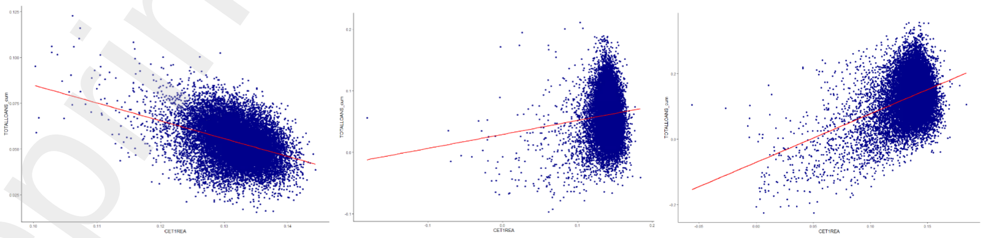
## 7.1 Macroprudential trade-offs: solvency and lending

So far, all examples of the application of our methodology have referred to solvency criteria. However, from a macroprudential viewpoint, bank lending is an equivalently relevant outcome of a stress test. A macroprudential policy maker would like to know whether in adverse circumstances banks will be in a position to maintain their lending to the economy. The policy maker can proceed with designing an adverse scenario with sufficient level of scenario severity. Table 3 presents the moments of cumulative change distributions of lending analogous to those presented in Table 2 for bank solvency (see also Appendix A for the related figures).

| | Mean | Median | 10 perc | 5 pec | 1 perc |
|---|---|---|---|---|---|
| 1-year | 5.4 | 5.4 | 4.1 | 3.7 | 3.1 |
| 3-year | 6.1 | 6.1 | 1.5 | 0.1 | -2.8 |
| 5-year | 12.6 | 13.1 | 3.8 | -0.1 | -12.1 |

**Table 3:** Cumulative change in euro area bank lending to the non-financial private sector

Figure 14 points out that the system-wide solvency and lending outcomes are generally correlated. Interestingly, this correlation changes over the stress test horizon. In the short term, it is negative (the correlation coefficient is close to 0.2, with the p-value of zero) reflecting primarily a denominator effect for the CET1 ratio. A strong expansion of lending in good times is likely to bring CET1 ratios of banks at least temporarily down, as bank assets in the denominator of CET1 ratio go up. On the contrary, in bad times, banks are likely to reduce lending to preserve their solvency. The longer the horizon, the clearer the positive relationship between bank solvency and the ability to provide credit to the economy. In the five-year horizon, the correlation coefficient is close to 0.8, with a p-value of zero.



**(a)** 1 year **(b)** 3 year **(c)** 5 year

**Figure 14:** Correlation of system-wide CET1 and euro area lending in different futures

Notes: Observations in the graphical representation are filtered using Cook's distance for better readability.

A joint stress test of bank solvency and lending involves policy preferences on the relative relevance of factors. In our example we take an ambivalent stance and assign system-wide



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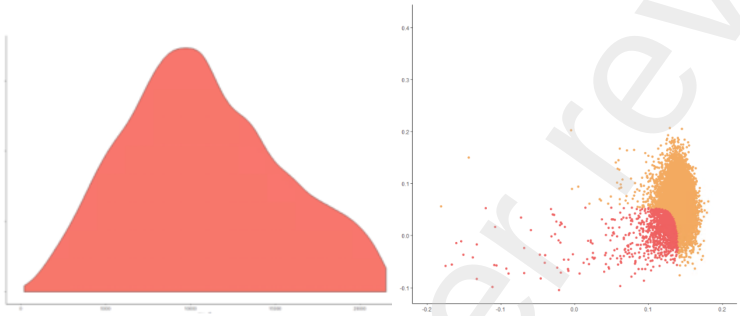
solvency and lending outcomes equal weights. However, a conservative policy maker in benign times can aim at a higher weight assigned to solvency versus lending, while a crisis situation may ask for higher weight being placed on lending. Weights can also be distributed among more variables of interest, such as the number of corporate defaults, lending rates, and bank profitability.

Next, all simulations are sorted along with the relative emphasis placed on both policy criteria. This step produces a univariate distribution of the severity of the scenario illustrated in Figure 15 in the panel on the left side. Finally, we choose the severity threshold, for example, the 10 percentile as in the right panel in Figure 15. The outcome is a selection of scenarios that guarantee a sufficient level of stress for both bank lending and solvency, with a joint probability of realisation of 10%.



**(a)** Loss function at 3-year horizon (equal weights)

**(b)** Worst-case selection for CET1 ratio and cumulative lending change

**Figure 15:** Loss function and scenario selection for the joint CET1 ratio and lending growth stress test

The results of such a stress test are illustrated in Figure **??**, and contrasted with two reference stress tests, which aim at 10 percentile of bank solvency and bank lending separately. The scenarios stressing the macroprudential combination of bank resilience measures are somewhere in-between those stressing each of the individual factors. The solvency outcomes are generally better than that in the worst-case solvency stress test with the same plausibility level, but weaker than in the worst-case solvency stress test for lending. The reverse holds true for lending to the non-financial private sector.

Risk to bank solvency and lending in the medium term are again related to an economic recession, the same as that to bank solvency. This could be expected from the correlation of the two criteria. Inflation initially overshoots as compared to the median of the full scenario distribution but goes down toward the end of the horizon. The interesting realization when comparing these three sets of results is that unemployment and asset prices emerge as a risk factor for bank solvency, but to a lesser extent for bank lending. Lending, in turn, appears to be more sensitive to monetary policy stance, with respect to the level of real interest rates and the expansion of the ECB assets.[17]

Appendix A also reports the outcome of a similar scenario selection for a one-year horizon. At this horizon, the reported correlation between bank lending and solvency is moderately negative and trade-offs between sufficiently adverse lending versus CET1 ratio outcomes are more

[17]It should be noted that, in general, this approach will provide a different assessment of risks than the sequential application of the two criteria in the spirit described in Section 6.4. The latter prioritises the severity described along with the first criteria, such as bank solvency. And will use the second criterion to strengthen the narrative of the scenario.



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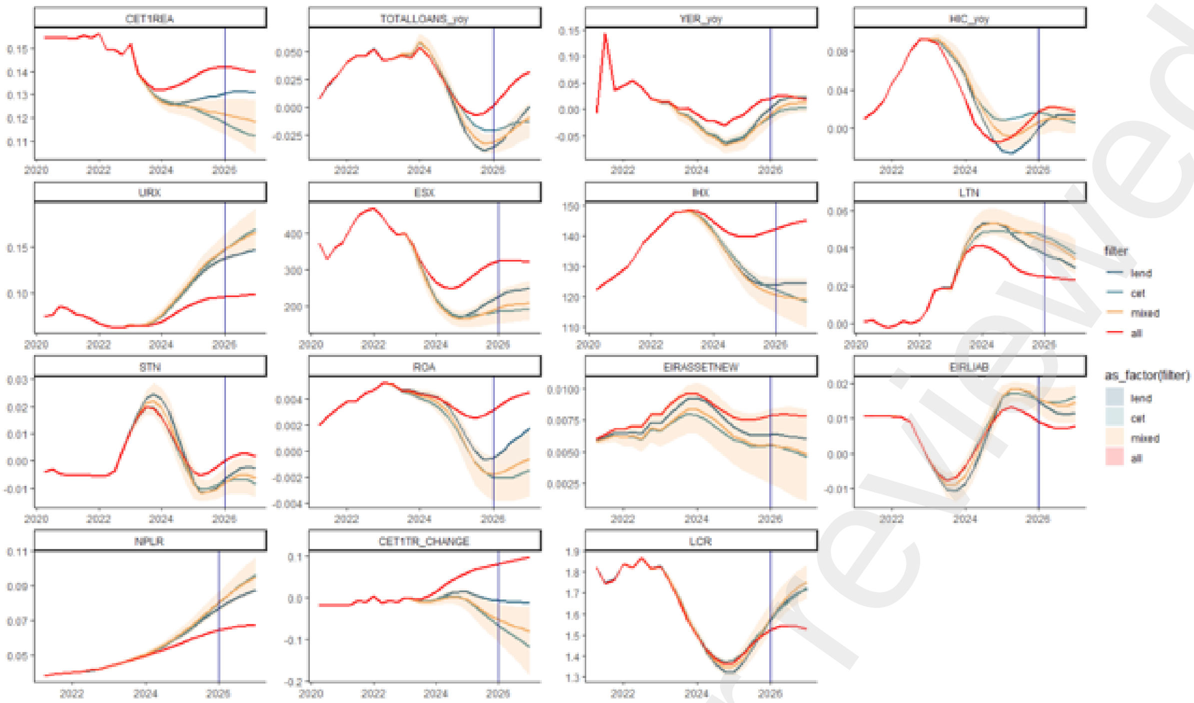


**Figure 16:** Worst-case scenarios for bank solvency and lending

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - the cumulative change in CET1 capital, LCR - liquidity coverage ratio. Red line: median for the full distribution of events, dark blue line: median of worst-case scenarios for lending growth, light blue line: median of worst-case scenarios for CET1 ratio, yellow: median of worst-case scenarios for CET1 and lending growth jointly. Fancharts mark 40% probability for the worst-case scenarios for CET1 and lending growth jointly.

conspicuous. It turns out that the economic slowdown necessary to stress the two criteria jointly would need to be deeper than the one needed to stress each of them separately.

## 7.2 Systemic risks

An alternative approach to thinking of a macroprudential stress test is to put to the front the ability of the banking system to absorb rather than amplify macro-financial shocks. One may wish for scenarios that trespass the ability of the banking system to sponge up changes in the external environment, and release coordination failures. Such scenarios can uncover hidden vulnerabilities with potentially pronounced effect on the economy as a whole that go under the radar of stress tests focused on adversity of particular banking sector metrics. Moreover, it can be used to cross-check the outcomes of more straightforward scenario designs or, when monitored over time, to deliver information about evolving resilience of the banking sector.

The selection of scenarios that emphasize systemic amplification of risks in the banking sector focuses on the measure of negative lending supply feedback from the banking sector to the real economy. The measure is placed in the lower left corner of Figure 17 and amounts to the appropriately country weighted sum of negative loan supply shocks entering the macro-financial block of the model as a result of non-linear adjustments of individual banks. Figure 17 further contrasts the worst-case 10% amplification scenarios with the worst-case solvency and



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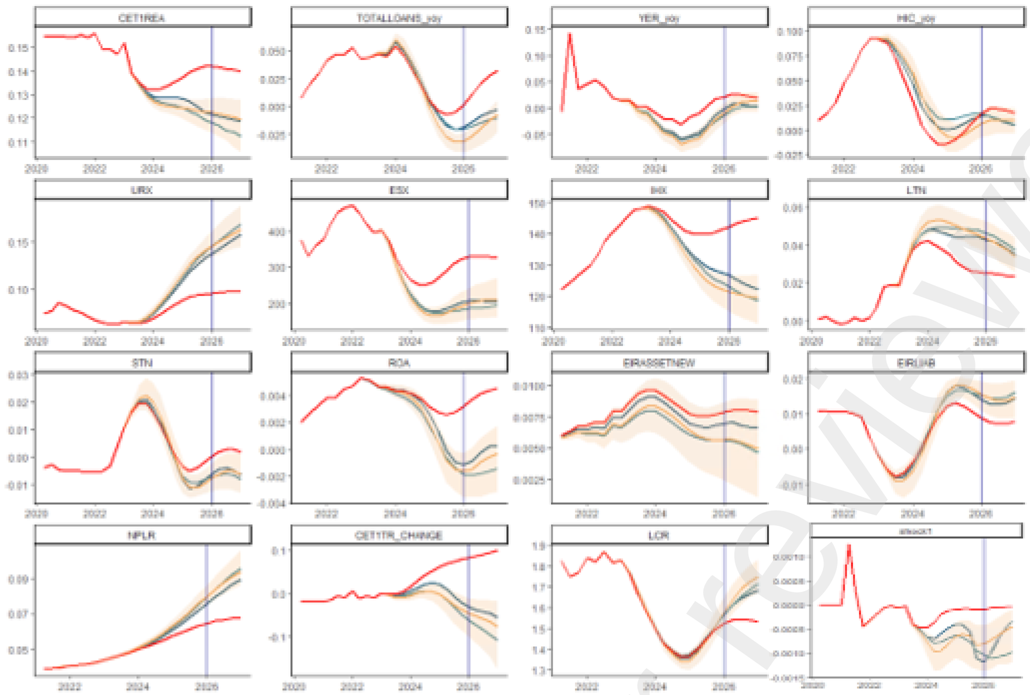


**Figure 17:** Worst-case scenarios for system-wide amplification

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - the cumulative change in CET1 capital, LCR - liquidity coverage ratio, Shock1 - loan supply shock resulting from the banking sector developments. Red line: median for the full distribution of events, dark blue line: median of worst-case scenarios for amplification, light blue line: median of worst-case scenarios for CET1 ratio, yellow: median of worst-case scenarios for CET1 and lending growth jointly. Fancharts mark 40% probability for the worst-case scenarios for CET1 and lending growth jointly.

the solvency and lending scenarios.

Amplification mechanisms emerge in scenarios with weak economic activity and when banks experience low profitability and capital losses.[18] In general, reasonably similar scenarios can be derived based on two simple solvency and lending severity metrics. However, the joint solvency and lending stress test appears to instill a higher negative loan demand component, reflected in a relatively strong contraction in loan volumes and interest rates. On the contrary, the stress test that uncovers the worst-case amplification mechanism hangs to a stronger degree on loan supply channels.

# 8 Conclusions

Real-life stress test scenarios commonly rely on complex macro-financial scenarios with many variables and economic narratives that reflect economic relationships. Nevertheless, their method-

[18]Both selection design (the choice of the measure of negative lending supply feedback from the banking sector to the real economy as a relevant selection metrics) and its results are necessarily specific to the model. However, we still aim to emphasize the most universal aspect of such a selection. By focusing on the magnitude of the amplification mechanism (in any model), macroprudential policy makers can receive scenarios at the core of their mandate.



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ology may not guarantee scenarios that are simultaneously plausible, severe, and capable of capturing the most critical risks at any given moment (Breuer and Summer [2018]).

The challenges are numerous. There are often trade-offs between designing statistically plausible scenarios and anticipating the future described in the risk narrative. The concept of "sufficient severity" can also be misleading. In the case of stress tests, such as assessing banking system solvency, the focus often shifts away from the ultimate goal, and severity becomes a metric attributed to macro-financial outcomes. While this focus on the severity of risk factors may be justified in linear environments, where their impact on the financial system is always proportional, this is hardly the case in reality. Furthermore, adverse scenario narratives, while comprehensive, are susceptible to human biases, including overlooking plausible realities or overestimating the likelihood of improbable events.

The paper presents a conceptually neat approach that can help many of the regulatory stress test challenges. The necessary step is to start the stress test design by inspecting the full distribution of possible future realities. This distribution should have three desirable properties. First, it should be derived from a model or models that can instill different narratives of economic scenarios. Reduced-form, data-only approaches cannot project futures that do not reflect past correlations, and the scenarios they provide miss the economic interpretation. Our proposal is to use models that combine statistical analysis with structural identification. We apply the semi-structural macroprudential stress test model to illustrate the advantages of the approach. Such semi-structural setups can also be adapted to include additional indicators or policy beliefs increasing the discretionary interpretation of their outcomes.

Our paper introduces a conceptually neat approach that addresses many of the challenges faced in regulatory stress tests. The essential step is to initiate stress test design by examining the full distribution of potential future scenarios. This distribution should possess three crucial attributes.

First, it should be derived from models capable of incorporating various economic scenario narratives. Unlike reduced-form, data-driven approaches, these models can provide scenarios with economic interpretations. We propose the use of models combining statistical analysis with structural identification, exemplified by the semi-structural macroprudential stress test model. These semi-structural setups can also accommodate additional indicators or policy beliefs, enhancing the interpretability of their outcomes.

Then, the scenario space should encompass a wide range of scenario risks, including model uncertainty. While our application addresses parameter uncertainty in generating scenario spaces, similar outcomes can be achieved by combining results from different models, each emphasizing different frictions or utilizing different datasets.

And finally, the scenario space should encompass all risk factors and outcome variables of the stress test, such as banks' CET1 ratios. This completeness allows for an accurate description of the severity of the desired scenario and, consequently, the stress test itself.

Our framework facilitates the conduct of multiple scenario distributional stress tests, reverse stress tests, and the design of scenarios for bottom-up exercises. We provide examples illustrating how multiple scenario distributional stress testing can yield various at-risk measures, differentiate between idiosyncratic institution-specific and system-wide systemic risks, and comprehensively depict the evolution of risks within the banking system. Our reverse stress test bypasses the need for complex models of banks and economies, seeking and selecting sufficiently adverse scenarios within a space of candidate scenarios. The examples we provide demonstrate how reverse stress testing can yield scenarios tailored to meet supervisory, macroprudential, or broader policy objectives.

While our primary contribution is methodological, we also contrast some of our results with



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those of the EBA/SSM stress test in 2023. We confirm certain intuitions about the exercise. Although the stress test is presented as focusing on testing the solvency of individual banks, its design often leads to outcomes better interpreted as testing individual banks' resilience in the face of system-wide solvency strains. It has limited ability to assess idiosyncratic risks specific to smaller banks' business models and balance sheets. It underscores that the EBA/SSM stress test is just one component considered when determining bank capital requirements and buffers, with other bank-specific information playing a substantial role. Additionally, while the EBA/SSM stress test aims to challenge bank solvency, it is also relevant for assessing the banking system's ability to provide lending to the real economy, akin to the ECB macroprudential stress test.

Together, we intend to add new arguments to the discussion advocating the supplementation of conventional single-scenario stress testing with multiple-scenario and reverse stress testing approaches. In summary, we contribute to the literature advocating the supplementation of conventional single-scenario stress testing with multiple-scenario and reverse stress testing approaches. Both approaches support scenario design, validate supervisory exercise results, and accurately identify the diverse distribution of risks within the banking system among individual institutions. Importantly, and reflecting a pronounced evolution of stress test infrastructures over the last years, they also become increasingly achievable.

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# A Appendix: Supplementary information

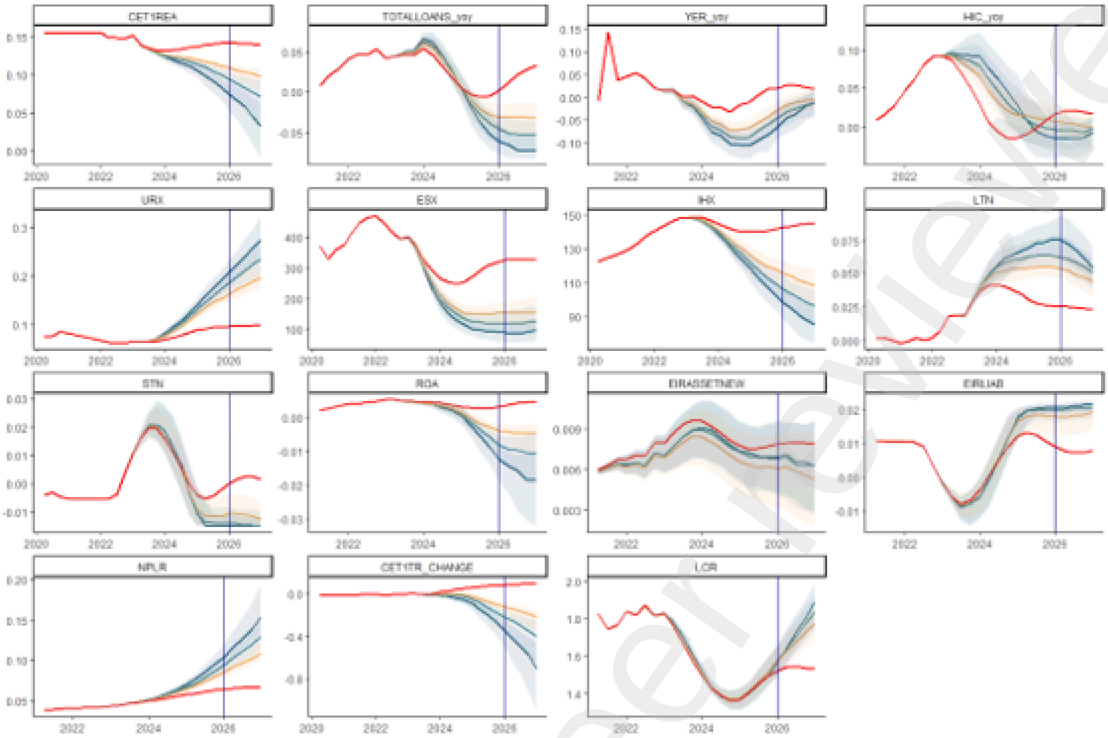


**Figure 18:** Macro-financial scenarios with 10, 11 and 12 perc CET1 ratio for 3-year horizon

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - percentage change in CET1 capital compared to the end 2022, LCR - liquidity coverage ratio. Red line: median for the full distribution of events, dark blue line: median for threshold scenarios with 10% CET1 ratio in three years, lighter blue line: median for threshold scenarios with 11% CET1 ratio in three years, yellow line: median for threshold scenarios with 12% CET1 ratio in three years. The fan charts span 40% for the corresponding threshold scenarios. The vertical navy blue line marks the end of each scenario horizon.

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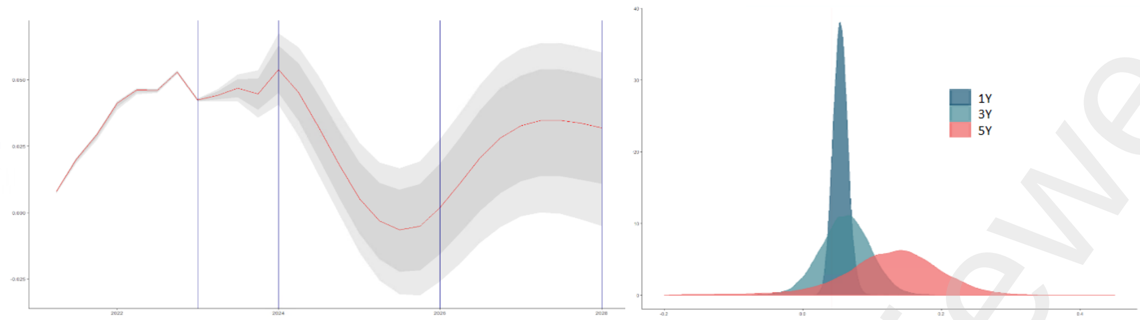


**(a)** Loans y-o-y fanchart **(b)** Loans at horizons

**Figure 19:** Lending volumes to the non-financial private sector at three horizons: 1-year, 3-years and 5-years

Notes: LHS chart: bank loan volumes to the non-financial private sector y-o-y. Red line - median, dark field 60%, lighter field 80% probability span. Blue horizontal lines mark, starting from the left hand side, the starting point (end 2022), 1-year, 3-year and 5-year forecast horizons. RHS chart: cumulative lending from the end 2022.

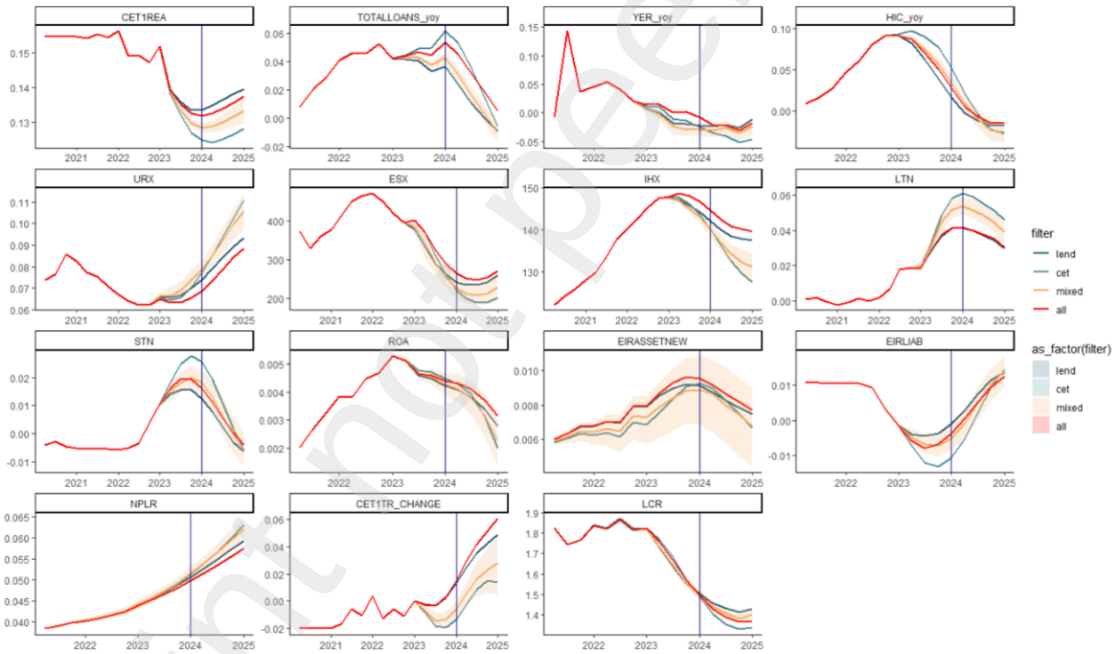


**Figure 20:** Worst-case scenarios ($10^{th}$ percentile) for bank solvency and lending in one year horizon

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - the cumulative change in CET1 capital, LCR - liquidity coverage ratio. Red line: median for the full distribution of events, dark blue line: median of worst-case scenarios for lending growth, light blue line: median of worst-case scenarios for CET1 ratio, yellow: median of worst-case scenarios for CET1 and lending growth jointly. Fancharts mark 40% probability for the worst-case scenarios for CET1 and lending growth jointly.

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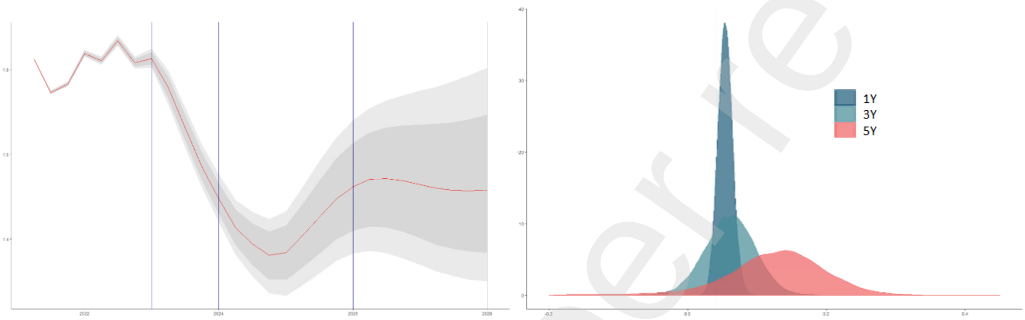
# B Appendix: Joint liquidity and solvency stress testing

This Appendix expands on the ideas discussed in Chapter 7 by illustrating the case of joint liquidity and solvency stress testing. We add this discussion to illustrate how stress testing and reverse stress testing can add to the discussion of interactions between bank liquidity and solvency. Its placement in an appendix recognises that although the model we use includes a comprehensive representation of bank liquidity, its quarterly frequency, and relatively stronger focus on the real economy than on financial markets make it still the model best fitted to study bank solvency, profitability, or lending and their interrelations with macroeconomies.

Figures 21 and Table 4 zoom in on the evolution of system-wide LCR over the three alternative scenario horizons. An interesting difference compared to the CET1 ratio or even bank lending is the general symmetry of the distribution, which persists even in the longer horizons.




**(a)** LCR fanchart **(b)** LCR at horizons

**Figure 21:** Euro area banking sector LCR at three horizons: 1-year, 3-years and 5-years

Notes: LHS chart: Red line - median, dark field 60%, lighter field 80% probability span. Blue horizontal lines mark, starting from the left hand side, the starting point (end 2022), 1-year, 3-year and 5-year forecast horizons.

| | Mean | Median | 10 perc | 5 pec | 1 perc |
|---|---|---|---|---|---|
| 1-year | 1.50 | 1.50 | 1.44 | 1.43 | 1.39 |
| 3-year | 1.52 | 1.52 | 1.37 | 1.32 | 1.25 |
| 5-year | 1.54 | 1.52 | 1.30 | 1.25 | 1.16 |

**Table 4:** Euro area bank LCR

We should focus on one year horizon, which is most meaningful for stress testing LCR. At this horizon, the correlation between the system-wide CET1 ratio and LCR is positive, as illustrated in Figure 22. There is also a positive correlation between LCR and NSFR.[19]

Figure 23 plots stress scenarios for the CET1 ratio and LCR considered jointly and with equal weights. It contrasts them with scenarios with the same 10% probability but stressing either bank solvency or liquidity.

Liquidity tensions can emerge even in a solvent banking system along with a modest economic slowdown, as long as they are accompanied by a relatively high level of real interest rates. In comparative terms, solvency stress involves a more significant deterioration in asset prices and unemployment. The combined stress test hits the middle field, placing similar strain

[19] In the longer horizons, the correlation between the CET1 ratio and LCR gradually turns moderately negative, while remaining positive for the CET1 ratio and NSFR. This is an intuitive result very closely related to structural similarities between the CET1 ratio solvency and the long-term liquidity mismatch measures of the NSFR.



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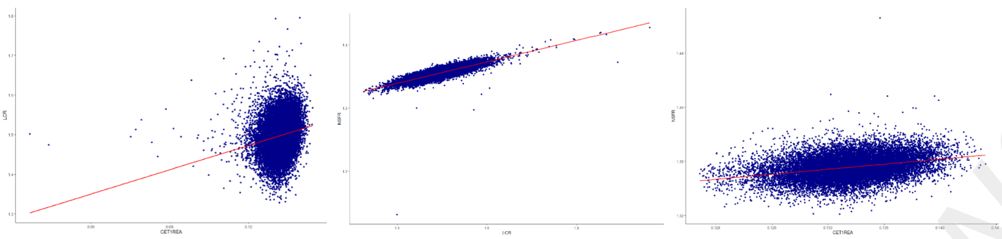

**(a)** CET1 ratio vs. LCR **(b)** LCR vs. NSFR **(c)** CET1 vs. NSFR

**Figure 22:** Correlation of system-wide CET1 ratio, LCR and NSFR at 1 year horizon

Notes: Observations in the graphical representation are filtered using Cook's distance for better readability.

on bank maturity mismatches as the solo liquidity stress test, but involving lower capital losses than the stress test designed to evaluate banks' CET1 ratios.

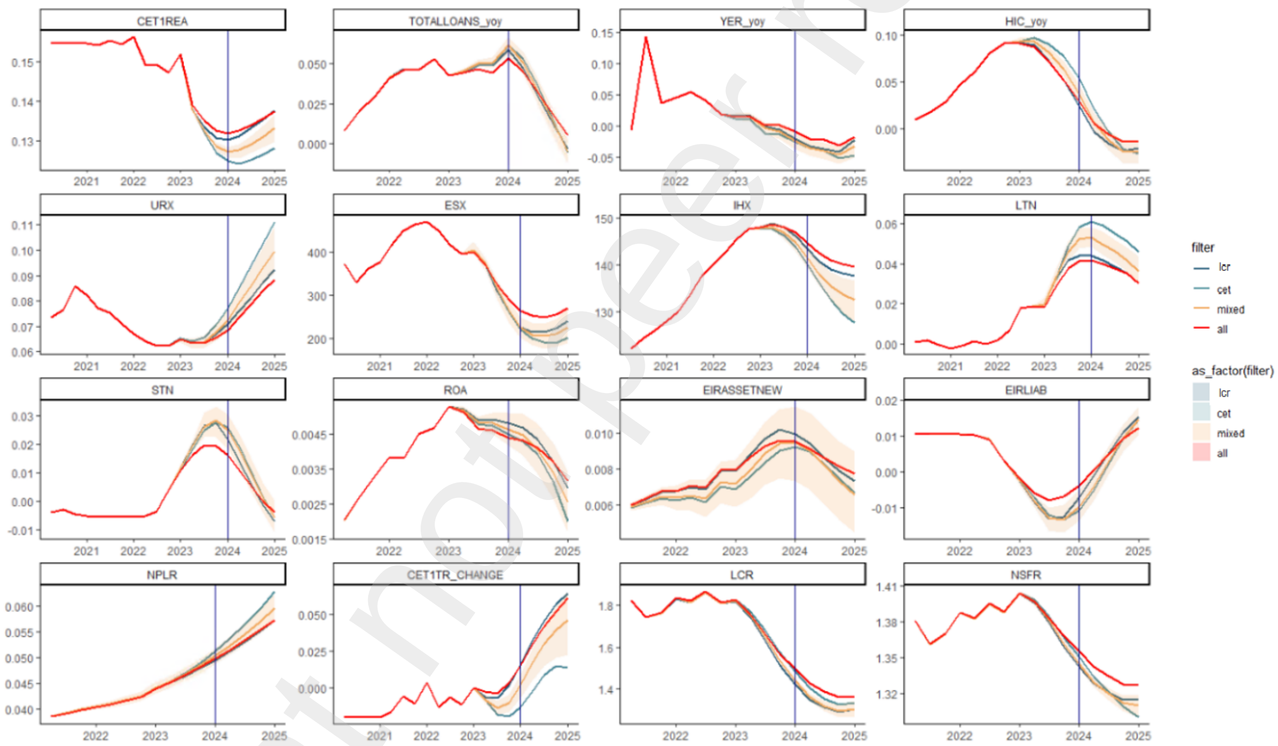


**Figure 23:** Worst-case scenarios ($10^{th}$ percentile) for bank solvency and liquidity in one year horizon

Notes: CET1REA – CET1 ratio, TOTALLOANS_yoy – annual bank lending volumes to the non-financial private sector growth rate, YER_yoy – annual GDP growth rate, HIC_yoy – HICP inflation, URX – unemployment rate, ESX – equity price index, IHX – house price index, LTN – 10-year bond yields, STN – 3-month EURIBOR, ROA – return on assets, EIRASSETNEW – interest rates on new lending to the non-financial private sector, EIRLIAB - the average cost of debt funding, NPLR – NPL ratio, CET1TR_CHANGE - the cumulative change in CET1 capital, LCR - liquidity coverage ratio, NSFR - net stable funding ratio. Red line: median for the full distribution of events, dark blue line: median of worst-case scenarios for LCR, light blue line: median of worst-case scenarios for CET1 ratio, yellow: median of worst-case scenarios for CET1 and LCR jointly. Fancharts mark 40% probability for the worst-case scenarios for CET1 and LCR jointly.



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