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MuSE: a multiple macro-financial scenario simulation engine for stress testing

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Abstract

We design an econometric framework to simulate multiple adverse macro-financial scenarios that can be used in top-down stress tests. First, we create a financial stress index informed by shocks generated via a non-parametric copula estimated on a large dataset of daily financial indicators. Second, we simulate the joint dynamics of macroeconomic indicators conditional on the copula-based financial shocks in a large multi-country Bayesian VAR model. This framework, which we refer to as the **Mu**ltiple macro-financial stress scenario **S**imulation **E**ngine, MuSE, allows us to replicate thousands of macro-financial stress scenarios where adverse shocks generated in the financial sector propagate into the overall economy, triggering significant macroeconomic fluctuations. We demonstrate its functionality by generating a large number of scenarios inspired from past crises capturing stress stemming from financial markets, sovereign debt, and geopolitical tensions. Using a top-down solvency stress test model, based on recent EU-wide stress tests, we project the capital depletion for euro area banks and find that adverse scenarios triggered by stock market and sovereign shocks appear to threaten the resilience of the euro area banking sector the most at this juncture.

Keywords: Macrofinancial Scenario Calibration, Stress Testing, Financial Institutions, Bayesian Techniques, Financial Copulas

JEL codes: C15, G01, G17, G21

1 Non-technical summary

In the aftermath of the Global Financial crisis, solvency stress tests became a cornerstone in financial risk management and prudential policy setting. These tests usually rely on macro-financial scenarios to project forward the profits and losses of financial institutions over a specific horizon. One, or, at most, a few hypothetical scenarios are used to stress the solvency of financial institutions and their calibration can follow a complex process of discussions among many stakeholders. Such discussions may shape the severity of scenarios; in addition, risks can be mismeasured. For these reasons, a single deterministic scenario may not identify relevant risks and vulnerabilities to the required extent (Breuer and Summer, 2020). To address this issue, several authors have recently advocated the use of multiple adverse scenarios instead (Schuermann, 2026; Valderrama, 2026).

We introduce the **Mu**ltiple macro-financial stress scenario **S**imulation **E**ngine (MuSE) which combines several statistical and econometric tools to generate in an efficient, yet economically consistent way, thousands of adverse scenarios with a three-year horizon suitable for stress testing. First, a non-parametric copula is estimated on a large data set of daily financial indicators via the financial shock simulator (FSS). Second, from the FSS we derive an index of financial stress, similar to Holló et al. (2012). Finally, the projected financial stress index is included in a large multi-country Bayesian vector autoregressive (BVAR) model like the one proposed by Angelini et al. (2019). We illustrate the application of this approach by simulating several stress scenarios and plugging them into a top-down[1] stress test model (Caccavaio et al., 2025; Couaillier et al., 2026). We find that, at this juncture, adverse scenarios triggered by stock market and sovereign shocks continue to have the potential to reduce bank and system-level capital ratios the most.

The paper is structured as follows: Section 3 introduces the statistical and econometric framework underpinning MuSE. Section 4 presents the financial stress indices for the euro area and four large countries (Germany, France, Italy and Spain) and the calibrated macroeconomic scenarios. In Section 5 we leverage the information collected in past EU-wide stress test exercises to link scenarios to bank and system-level capital depletion. We then conclude with Section 6.

[1] A *top-down*, or *desktop*, stress test is conducted using statistical or econometric models without involving financial institutions. In the event that a stress test involves entities directly, they are referred to as *bottom-up*.

2 Introduction

In the aftermath of the Global Financial crisis, solvency stress tests became a cornerstone in financial risk management and prudential policy setting, regularly used to assess how well financial institutions cope with financial and economic shocks, with results feeding into the setting of prudential requirements. These tests usually rely on macro-financial scenarios to project forward the profits and losses of banks, insurers, funds or financial institutions over a specific horizon. Adverse scenarios should be severe but plausible (see, for instance, Borio et al. (2014); Baudino et al. (2018); European Banking Authority (2018); Figueres et al. (2025)), should capture both the vulnerabilities evidenced in past macro-financial downturns as well as the latest risk narrative reflecting the actual concerns of prudential authorities. For this reason, stress tests are based on hypothetical scenarios, as no crisis repeats itself, and take current risks and vulnerabilities into account. This means, however, that empirical tools are needed to construct such severe, plausible and economically consistent scenarios.

Modelling a hypothetical adverse macro-financial scenario requires the calibration of a potentially large number of shocks to financial and macroeconomic variables (Farmer et al., 2022). These shocks need to be consistent with each other to generate a scenario of stress that is sufficiently severe on the one hand but also plausible on the other. Therefore, the design of a stress scenario not only needs to depart from historical distributions of macroeconomic and financial variables to capture typical empirical relationships, but also needs to ensure that scenario severity compares with past episodes of financial and macroeconomic stress in a plausible way. The adverse scenarios used in official stress tests are generally designed to capture the materialisation of a systemic stress event.[2] One, or, at most, a few scenarios are used to stress banks' solvency and their calibration can follow a complex process of discussions among many stakeholders. For instance, for the EU-wide stress test exercise for banks, which is coordinated by the European Banking Authority (EBA), the adverse macro-financial scenario is designed by the European Systemic Risk Board (ESRB), with the input of national central banks and supervisors, in close collaboration with the European

[2]To the extent that adverse scenarios reflect hypothetical crisis events, they should not be used in the same way as projections of macroeconomic variables. As such the treatment of uncertainty in the scenario generation context also differs. This conceptual difference is discussed in Section 3.4 .

Central Bank (ECB). It is approved by the ESRB General Board, before it is published by the EBA.[3] The CCAR stress test scenario calibration process in the United States welcomes feedback on the scenario shocks from the private sector and the public via consultations (Federal Reserve, 2025).

As discussions among stakeholders tend to shape the severity of scenarios, and risks can often be mismeasured, a single deterministic scenario may fail to identify relevant risks and vulnerabilities to the required extent (Breuer and Summer, 2020). Using multiple adverse scenarios in official stress tests instead would allow prudential authorities to better assess the resilience of financial entities against a multitude of relevant risks (Schuermann, 2026; Valderrama, 2026) and to calibrate capital buffers against the most severe realisation of these stress test outcomes more effectively (Aikman et al., 2024; Barr, 2023). While it would be very costly to ask financial institutions to run stress tests under more than a few scenarios[4] for policy purposes, interest in tools to generate multiple, internally consistent scenarios for top-down[5] tests has been growing in the financial industry and among policymakers.

Montesi and Papiro (2018) and Montesi et al. (2020) use stochastic scenarios, drawn from Monte Carlo simulations, to assess resilience at bank level or to identify break points in a reverse stress testing approach. While these approaches work well for financial indicators, they leave out a consistent calibration of variables characterising macroeconomic developments for each scenario. Aikman et al. (2024) show how models with structural elements can support the generation of plausible stress test scenarios, although their approach covers a relatively contained number of financial variables that can be stressed. Baes and Schaanning (2023) develop an algorithm that searches systematically for scenarios that maximise contagion effects from asset liquidations under stress.[6] However, their focus is on short term contagion dynamics and does not cover medium-term projections for macroeconomic variables.

[3]See European Systemic Risk Board (2025); Gross et al. (2022).

[4]Running many stress-test scenarios is costly because each scenario requires substantial computational resources, data processing and validation effort.

[5]A *top-down*, or *desktop*, stress test is conducted using statistical or econometric models without involving financial institutions. In the event that a stress test involves entities directly, they are referred to as *bottom-up*.

[6]Under the condition that an institution-specific shock is not too large but generates losses of at least 10 percent of the initial total system equity.

Beyond calibration aspects, multiple scenarios not only need to be sufficiently severe, but also plausible and consistent. Although they should not simply replicate past crises, scenarios that are unlikely to materialize will offer limited insights when used in a stress test. A stress test should not consider a scenario that is implausible nor neglect plausible scenarios (Breuer et al., 2009). Different approaches have been offered to address this issue: focusing on market risk shocks, Flood and Korenko (2015) suggest sampling shocks from a plausible joint probability distribution to enforce the consistency of a scenario. Breuer et al. (2009) propose a method to assess the plausibility and severity of a scenario that does not depend on the number of different risk factors that are stressed but on the outcome of the stress test. Similarly, Barbieri et al. (2022) assess scenario severity and plausibility in terms of capital depletion.

Our approach yields multiple, internally consistent macro-financial scenarios by combining several statistical and econometric models within the **Mu**ltiple macro-financial stress scenario **S**imulation **E**ngine (MuSE). MuSE places at its centre the identification of extreme financial shocks drawn from the correlation of potentially thousands of financial indicators at daily frequency. This is key because financial shocks impact the tail distribution of GDP significantly and generate severe recessions. In contrast to Adrian et al. (2019, 2022), our approach generates multiple macro-financial scenarios covering a large number of macroeconomic and financial variables, triggered by plausible extreme financial shocks. We do not use outcomes to inform our scenario calibration, rather we leverage the correlation of financial variables (similar to Flood and Korenko (2015)) that occurred during past crises to design new plausible scenarios. We ensure, through a macroeconometric model, that variables are not projected stochastically but are economically consistent and, by applying filters, that they are sufficiently severe.

First, we utilise a non-parametric copula estimated on a large set of daily financial indicators to bootstrap paths for financial variables over the horizon of a stress scenario. This tool, which we refer to as the financial shock simulator, was first discussed by Rancoita and Ferreiro (2019). It allows capturing the dynamics of specific historical stress constellations, such as, for instance, a general financial and confidence shock as observed in the Great Financial Crisis, a government debt fragmentation shock as in the euro area government debt crisis, or a disruption in energy commodity markets stemming from geopolitical tensions as observed at the outbreak of Russia's war against Ukraine. The methodology aims at capturing both the univariate characteristics of financial variables in a specific economic environment and their corresponding joint behaviour.

In a second step, the link between the financial sphere and the real economy is analysed by mapping the evolution of the financial variables into an index of financial stress (see Angelopoulou et al. (2014); Hatzius et al. (2010); Chavleishvili et al. (2021); Darracq Paries et al. (2014)). We build on the methodology developed by Holló et al. (2012) for their Composite index of systemic stress (CISS) because of its focus on systemic vulnerabilities that are relevant for financial instability. In addition to Holló et al. (2012), our financial stress index can be projected forward by one year and decomposed into its main shock drivers.

Finally, to generate scenario paths for macroeconomic variables that are consistent with stressed financial variables, we include the projected financial stress index in a large multi-country Bayesian vector autoregressive (BVAR) model similar to the one proposed by Angelini et al. (2019). In that way, we can capture the relationship between macroeconomic indicators, which are available only at quarterly frequency, and a large number of high-frequency financial data in a parsimonious way. The BVAR model is then used to draw scenario paths for macroeconomic variables conditional on the copula-based financial shocks, guaranteeing that the simulated scenarios for the macroeconomy are consistent with the evolution of the financial variables. The BVAR includes the four largest euro area countries (France, Germany, Italy and Spain) in addition to the euro-area aggregate. Moreover, it features t-distributed errors to account for abnormally large fluctuations in the course of the Covid-19 pandemic and the 2022/2023 surge in inflation. We employ Minnesota-type independent Normal-Inverted Wishart priors and use the Metropolis-Hastings-Gibbs sampler to estimate it.

We illustrate the working of this approach by simulating several adverse scenarios with different characterisations of financial stress and investigating the effects on GDP growth, prices and the financial variables themselves. By plugging these adverse scenarios into a top-down stress test model (Caccavaio et al., 2025; Couaillier et al., 2026), which is estimated on bank-level depletion from the latest EU-wide stress tests, we investigate which types of scenarios have the potential to reduce bank and system-level capital ratios the most and thereby weaken banking-sector resilience.

The paper is structured as follows. Section 3 provides background on the copula-based model used to generate financial shocks, the financial stress index, and the BVAR used to expand the financial shocks into adverse paths for a large number of macro-financial variables. Section 4 presents the financial stress indices as well as the yearly distributions of projected macro-financial variables. In Section 5 we link the scenarios to individual bank and system-level capital depletion and investigate the ensuing bank solvency. We conclude in Section 6 while deferring all supplementary material to the Appendices.

3 Modelling a scenario of macro-financial stress

MuSE hinges on three pillars: the Financial Shock Simulator (FSS), the associated financial stress index (FSI), and a multi-country BVAR model used to expand the stressed one-year financial market variables to a three-year horizon. Figure 1 (see Annex) shows a stylised representation of these pillars and provides a list of the variables informing each.

3.1 The Financial Shock Simulator

The Financial Shock Simulator (FSS) projects hundreds of variables jointly and translates a given scenario narrative into shocks to relevant financial variables. It uses the sampling methodology, originally developed by Efron (1992), which is widely used by practitioners due to its convenience and simplicity.

The FSS employs bootstrapping to simulate trajectories of a large number of financial risk factors over a stress test horizon using a high-dimensional empirical copula (Rancoita and Ferreiro, 2019; Gross et al., 2022; Hipp, forthcoming).[7] In this way, it replicates the historical marginal distribution and maintains the observed correlations between variables. These two elements are central for stress testing as the impact of tail events needs to be assessed in conjunction with the simultaneous shocks to multiple, often hundreds, of risk factors.

For example, take two financial time series, X and Y, with daily observations x_t and y_t for $t \in \{1, \ldots, T\}$, expressed as returns with a marginal and joint empirical cumulative distribution

[7] Ruiz and Pascual (2002) provide an overview of methods used to bootstrap financial time series.

function denoted as F_X, F_Y, and $F_{X,Y}$, respectively.[8,9] In a first step, the FSS bootstraps N alternative future paths by drawing, with replacement, H draws per simulation from the observed x_t and y_t, with H being the horizon over which the scenario unfolds. Then, in the n^{th} simulation, $n \in \{1, \ldots, N\}$, the following steps are performed:

- An index $h_{(i,n)}$ is drawn independently from a discrete uniform distribution $\mathcal{U}(1, T)$, for $i \in \{1, \ldots, H\}$. Each $h_{(i,n)}$ identifies a t (date) which is the same across all time series constituting the FSS sample;

- The cumulated simulated returns for X and Y in simulation n are computed as:

$$s_n^x = \sum_{i=1}^{H} x_{h_{(i,n)}} \tag{1}$$

and

$$s_n^y = \sum_{i=1}^{H} y_{h_{(i,n)}}. \tag{2}$$

Since each draw of $h_{(i,n)}$ refers to the same t for all simulated variables, the FSS tool preserves the historical correlation across variables for the simulated variables over the scenario horizon. The outcome of (1) and (2), repeated N times, is a matrix of simulated values:

$$S = \begin{bmatrix} s_1^x & \cdots & s_N^x \\ s_1^y & \cdots & s_N^y \end{bmatrix}, \tag{3}$$

where the rows of S contain the simulations for X and Y (S^X and S^Y, respectively) cumulated over H.[10] Although each column n of S represents a generic random scenario based on the initial empirical copula, these scenarios do not automatically reflect a certain narrative nor a needed degree

[8] The FSS tool considers returns to preserve stationarity, since in our setting correlation is measured as the comovement in the historical daily deviations of the series from their mean in levels, returns allow us to represent them as a valid empirical copula that captures the true joint distribution of financial shocks. For variables such as stock prices or exchange rates we use log returns, whereas for interest rates differences are considered.

[9] We refer to generic marginal and joint distributions to ease notation instead of a full characterisation of the copula as in Rancoita and Ferreiro (2019).

[10] Each row can be interpreted as the simulated empirical distribution of each cumulated variable.We also interchangeably refer to these distributions as unconditional, as they are the results of the simulation before any features of the narrative are considered.

of severity.

In a second step, the scenarios can be conditioned on specific values of one or more simulated variables, as illustrated in Figure 2. These variables are called "triggers" and represent the narrative that motivates the developments reflected in the scenario. The remaining variables are called response variables, reacting to the trigger as determined by their conditional simulated distribution given the realisation of the trigger variable. In the example above, with X as the trigger variable subject to a minimum shock x^*, and Y as the response, we have the set $S_{X \geqslant x^*} = \{n : s_n^x \geqslant x^*\}$ which contains all the simulations in S conditional on a specific realisation of X.[11] In our setting, the subset of simulations for Y given that the simulation for X exceed the value x^* is called conditional distribution of Y.

However, scenarios for stress testing purposes might require to replicate the behaviour of the economy as observed in past crises, thereby targeting rather uncommon events in the data, such as very severe market turmoil. Moreover, scenarios might target patterns across financial variables that rarely emerge within the available time series. In practice, this boils down to a data problem as specific assumptions regarding the comovement of variables may not be reflected in the data used for sampling or in the observed time series.

One way to overcome these challenges is to constrain simulations to achieve a desired level of correlation between variables while preserving the historical marginal distributions of the full time series. This can be achieved by restricting the correlations between observations. This approach in practice would require two parallel simulations: a standard FSS simulation and an ancillary simulation which determines, *a priori*, the desired correlation, which is then used to adjust the FSS simulation. Appendix B.1 provides further details on this approach.

Alternatively, another approach leverages the intuition of dynamic correlations and importance sampling (see e.g. Hesterberg (1988)), drawing from specific parts of the historical distribution with higher probability. To capture a desired behaviour, one can overweigh the likelihood of (i.e. assign a larger probability to) certain periods over others, considering two sub-periods or even mul-

[11] The methodology is able to handle any direction (sign) of the shocks, both for the trigger and the response variables. With the appropriate adjustments, the formulas to extract the relevant metrics from each simulation allow for creating shocks that target any tail of the variables' distribution.

tiple periods of the time series $\mathcal{T}$. This approach creates simulations that can emphasize peculiar events that occurred rarely in the data sample, hence capturing in a more precise way the specific risks the policy makers are concerned about. A practical example of this approach is provided in Appendix B.2.

Building on the principles of importance sampling, we endow MuSE with a financial stress index (FSI), derived directly from the FSS, which we use to select stress episodes and simulate adverse scenarios for the euro area and selected countries. In addition to a standard implementation of importance sampling, by simulating scenarios using an FSI we can also track its underlying components. This facilitates an assessment of the differentiated stress drivers across crises and allows us to embed specific risk narratives in our toolkit.

3.2 A scenario conditional Financial Stress Index

Many statistical indicators have been designed to measure financial stress, falling under the labels of "financial conditions indices" (FCIs) or "financial stress indices" (FSIs). For a detailed survey of existing indices we refer to the well-known papers of Kliesen et al. (2012); Hatzius et al. (2010), and for a more recent reference to the introduction of Monin (2019) or Section 2 of Chavleishvili et al. (2021). For the purpose of this paper, it is sufficient to note that, on the one hand, FSIs tend to contain information on spreads, correlations, and interest rates, some of which have been aggregated first into subindices and then into the final measure Kliesen et al. (2012). FCIs, on the other hand, tend to use both financial and non-financial variables to measure financial instability. As FSIs generally only use financial measures they are conceptually closer to our approach.

To operate MuSE, we construct five indexes, one for the euro area and the four major European economies (Germany, France, Italy and Spain), that encompass the specific variables simulated in the FSS while, at the same time, adequately capturing the stress episodes highlighted by other indicators. Within MuSE, the FSI is the bridge between the two stages: it condenses the financial shocks generated by the FSS into a single stress measure, through the underlying financial variables, that is then fed into the BVAR to propagate them into the broader macroeconomy. Since tracking developments in the financial sector is difficult, there is still no consensus among experts on the correct way to estimate such indices and on which variables should be included in their calculation. We consider the following indicators as inspiration and benchmark the CISS by Holló et al. (2012), its newer version by Chavleishvili et al. (2021), the sovereign version by Garcia-de Andoain and Kremer (2018), the FCI of Banque de France (Petronevich and Sahuc (2019)) as well as Angelopoulou et al. (2014) and Darracq Paries et al. (2014). When constructing the FSS-derived FSI we take methodological decisions on four building blocks: (1) which variables we include in its construction; (2) how to standardise the data to ensure comparability and aggregability; (3) how to define, construct and calculate its components; and finally (4) how to weight and aggregate these components into a final value and time series. We summarise the different options for the creation of an FSS-derived FSI in Table 1.

The FSS-derived FSIs aggregate 10 financial indicators that capture conditions across the money, bond, equity, and foreign exchange markets (see Table 2 for euro area and Table 3 for the country specific FSIs components). The country-specific indices differ from the euro-area index mainly through the inclusion of a country-specific short-term sovereign risk measure, the 2-year sovereign spread against the 2-year euro swap rate, in line with Garcia-de Andoain and Kremer (2018). This allows us not only to measure whether financial stress is high but also to compare country heterogeneity across the major euro-area economies. The choice of indicators is motivated by several criteria: first, each indicator is available at a daily frequency, which is crucial to capture short-term fluctuations in market conditions. Second, the indicators provide a broad coverage of the principal market segments and channels through which financial stress can propagate. Finally, these variables are widely used in the construction by authorities of macro-financial scenarios.[12]

We construct the indices under the assumption that higher values of a stress indicator correspond to tighter conditions in the respective market segment. To ensure each indicator enters the index as a stationary, comparable, stress measure, we transform the raw series according to their statistical properties before standardisation. Spreads and volatility measures are mean-reverting and enter directly. Equity prices, by contrast, are non-stationary, so equity-market stress is summarised through the maximum cumulative loss over a one-year rolling window(4), yielding a stationary mea-

[12]We do not include a dedicated repo or secured-funding indicator in the money-market block since our framework is designed to generate medium-term macro-financial scenarios for solvency stress testing.

sure of how far equities have fallen below their recent peak. The choice of a one-year horizon reflects the fact that shocks considered in ESRB adverse scenarios typically feature an annual frequency. This measure, originally proposed to identify episodes of severe stock market stress, follows the methodology of Patel and Sarkar (1998) and has subsequently been employed in the construction of different FCI and FSIs, including Holló et al. (2012).

$$\mathrm{CMAX}_t = 1 - \frac{x_t}{\max\{x_i : i = t-252, \ldots, t\}} \tag{4}$$

We standardise raw stress indicators, $x_{i,t}$, into stress factors, $z_{i,t}$, by estimating the empirical cumulative distribution function (CDF). To account for temporal dynamics, avoid look-ahead bias and allow for real-time operational use of the FSI, this standardisation is performed recursively. In this way, we obtain stress factors that are on a common scale $z_{i,t} \in [0,1]$ and follow approximately a uniform distribution.

Formally, we define the standardisation as follows

$$z_{i,t} = \hat{F}(x_{i,t}) := \begin{cases} \frac{1}{T_0 - 1} \sum_{s=1}^{T_0-1} \mathbb{I}(x_{i,s} \leqslant x_{i,t}) & \text{for } t = 1, \ldots, T_0 - 1 \\ \\ \frac{1}{t} \sum_{s=1}^{t} \mathbb{I}(x_{i,s} \leqslant x_{i,t}) & \text{for } t = T_0, \ldots, T \end{cases}$$

where $\mathbb{I}(\cdot)$ denotes the indicator function, T is the total number of observations, and T_0 corresponds to 1$^{\text{st}}$ of January 2002. This threshold T_0 has been deliberately chosen to ensure a few years of data, before starting to calculate the CDF recursively.[13]

The FSI aims to identify periods in which several stress indicators are simultaneously elevated and exhibit heightened time-varying cross-correlations, signalling episodes of systemic financial stress. Formally, the index is defined as:

$$FSI_t = (w \circ z_t)' C_t (w \circ z_t)$$

[13] We use t, T_0 and T to denote both, a date and the number of observations up to and including that date; the two coincide because observations are indexed consecutively from the first one ($s = 1$).

where z_t refers to the vector of standardised stress factors at time t, w the vector of portfolio weights, assumed equal across factors, and C_t the matrix of time-varying cross-correlations across stress factors (5). Aggregating the factors through C_t ensures that the index rises when the stress factors are elevated and increasingly correlated at the same time.

The matrix C_t has unit diagonal entries and off-diagonal entries $\rho_{j_1,j_2,t}$ that measure the comovement between stress factors j_1 and j_2 at time t:

$$C_t = \begin{pmatrix} 1 & \cdots & \rho_{1,10,t} \\ \vdots & \ddots & \vdots \\ \rho_{10,1,t} & \cdots & 1 \end{pmatrix}. \tag{5}$$

These correlations, $\rho_{j_1,j_2,t}$, are not estimated on a fixed window but evolve over time. As in the CISS construction, we track them through a covariance matrix H_t that is updated recursively via an exponentially weighted moving average (EWMA):

$$H_t = \lambda H_{t-1} + (1-\lambda)\,\tilde{z}_t\tilde{z}_t'$$

where $\tilde{z}_{i,t} = z_{i,t} - 0.5$ are the stress factors demeaned and $\lambda = 0.93$ is the decay parameter, with a higher λ yielding more persistent correlations. The pairwise correlations in C_t are then calculated by normalising the off-diagonal entries of H_t by the corresponding variances:

$$\rho_{j_1,j_2,t} = \frac{h_{j_1,j_2,t}}{\sqrt{h_{j_1,j_1,t}\,h_{j_2,j_2,t}}},$$

where $h_{j_1,j_2,t}$ denotes the (j_1, j_2) entry of H_t.

Because the variables underlying the FSI are employed in standard stress test scenarios, such as those calibrated by the ESRB, the FSI enables the identification of the specific financial shocks that drive a financial tightening episode, thereby facilitating a more granular interpretation of scenario narratives and their underlying stress drivers. Formally, we define the contribution of a stress factor to the index at time t as:

$$contribution_{i,t} = (w \circ z_t)_i \cdot (C_t w \circ z_t)_i$$

To assess the validity of our choices and the resulting FSS-derived FSI we use both quantitative and qualitative measures: quantitatively, we compare our index to the CISS (Composite Indicator of Systemic Stress in the financial system, Holló et al. (2012)), thereby treating the CISS as a robustness benchmark given its well established role in the literature. We measure the R^2 between our stressed FSI variants and the CISS. Qualitatively, as usually done when constructing such FSIs (see e.g Holló et al. (2012); Darracq Paries et al. (2014)), we check by visual inspection the time series and find that our FSI indicators distinguish well the historical periods of financial stress compared to calm periods.

3.3 A multi-country BVAR

To expand the FSS-generated financial shocks into a fully fledged macro-financial scenario we propose a state-space large Bayesian VAR model in a multi-country framework. The main advantage of this framework is that it allows us to simultaneously propagate the simulated financial shocks across a system of macro-financial interactions and thus generate internally consistent scenarios for a large number of indicators.[14] We design a multi-country model setting that builds on the VAR model presented by Angelini et al. (2019). Specifically, we consider a large BVAR endowed with macro-financial indicators at euro area level and at country level for the four major euro area economies, i.e., France, Germany, Italy and Spain. [15]

The recent literature shows that financial conditions are key for forecasting future economic activity during periods of stress; see, among others, Adrian et al. (2019), Brunnermeier et al. (2020)

[14] Notice that in our framework we refer to shocks not in a structural sense but rather as reduced-form deviations used to generate conditional paths for a set of macro-financial indicators.

[15] Specifically, we include the following variables. As for the euro area level indicators: real GDP growth, CPI inflation, residential property prices growth, commercial property prices growth, unemployment rate, oil prices (Brent) growth, stock market prices growth, short-term interest rates, Itraxx, 1-month swap rates, 1-year swap rates, 10-year swap rates, and the Financial Stress Index. As for country level indicators: real GDP growth, CPI inflation, residential property prices growth, commercial property prices growth, unemployment rate, 10-year bond yields, sovereign spread (10-year bond yield minus swap rate), Itraxx, and the Financial Stress Index.

and Figueres and Jarociński (2020). Among this background, we explicitly model macro-financial relationships by including a set of financial variables including the financial stress indices obtained via the Financial Shock Simulation tool (FSS). We employ a state-space Bayesian VAR allowing for errors to have an asymmetric distribution, i.e., t-distributed errors. This model features a number of advantages that allow it to produce sensible forecasts for each variable conditional on different paths. First, the Bayesian VAR (BVAR) model features Minnesota-type priors (see, among others, Bańbura et al. (2015) and Bańbura et al. (2010)) that improve its out-of-sample forecasting performance. Second, the BVAR features t-distributed errors to account for the abnormally large fluctuations related to the Covid-19 shocks. In particular, the specification of the t-distributed errors follows Bańbura et al. (2021). Third, the state-space framework set in the BVAR model can generate projections for each variable conditional on several shocks or assumptions via the Kalman filter (Durbin-Koopman simulator smoother).

The BVAR model features Minnesota-type independent Normal-Inverted Wishart priors. In particular, the prior for the dynamic coefficients features the baseline Minnesota priors by Litterman (1979) as implemented by Bańbura et al. (2010) and two additional priors to account for unit roots and cointegration introduced by Sims (1993) and Doan et al. (1984). Regarding the BVAR estimation, the posterior distribution of coefficients is obtained via the Metropolis-Hastings-Gibbs sampler with 11,000 draws, discarding the first 1,000 draws and generating subsequent 10,000 draws (keeping every 100th draw for inference). The data sample spans from 2000:Q1 till 2024:Q4.

3.4 Treatment of uncertainty in the MuSE framework

It is important to highlight that the treatment of uncertainty when designing hypothetical stress scenarios differs from that considered in typical forecasting exercises. While the latter focuses on measuring the uncertainty surrounding the prediction of the most probable future path of macroeconomic indicators, the former focuses on measuring the dispersion of the distribution of historical macroeconomic fluctuations. This in turn allows the identification of specific plausible events (e.g., tail events describing situations of financial stress) that can be mapped out in a given adverse scenario. In the present paper, the treatment of uncertainty follows this practice. In particular, and differently from a forecasting exercise, we focus on the design of macro-financial stress scenarios.

Our econometric framework accounts for uncertainty in the two main model blocks. The Financial Shock Simulator is based on a non-parametric copula that samples the marginal distributions of a large panel of high-frequency financial variables via bootstrapping over a rather long period spanning from 2000 till 2024. This approach allows us to draw entire distributions, and in particular the tails, while accounting for the uncertainty surrounding cross-correlations across time.[16] Moreover, the multi-country Bayesian VAR allows not only to draw the entire posterior distribution of coefficients, but also the asymmetric distribution of the errors thus accounting for the increase in uncertainty observed during periods of macro-financial stress such as the Covid-19 pandemic or the 2022 energy crisis.

4 Designing scenarios based on past financial stress events

We generate batches of macro-financial internally consistent scenarios that simulate stress events for the euro area using MuSE. We focus on four past stress periods to capture confidence, sovereign and geopolitical risk shocks. More specifically, we turn our attention to the turmoil of the Global Financial Crisis, the Sovereign Debt Crisis, the Russian invasion of Ukraine, and the more recent disruption in French sovereign debt markets. The shocks we generate are consistent with the shock transmission narratives observed during these financial crises.

4.1 Calibrating stress-period specific financial stress indices and macro-financial scenarios

The batches of scenarios for the four different stress periods are generated by drawing annual shocks via the FSS over a one-year horizon. For each scenario, the shocks are applied to the underlying variables of the euro area and country-specific FSIs, using the end of the second quarter of 2025 as the starting point. The FSIs are computed following the methodology described in Section 3.2. This yields FSI paths one year ahead, reaching the end of the second quarter of 2026, resulting in

[16] Notice that the uncertainty related to the sampling of the FSS distributions itself could also be quantified via a re-sampling exercise that simulates several distributions under different assumptions, data samples, etc. Nevertheless such study goes beyond the scope of this paper.

hundreds of adverse FSI paths for each geography.[17] The FSI shock is measured as the difference in index points between the adverse level in the second quarter of 2026 and the initial index value in the second quarter of 2025.

The shocks to the euro area and country-specific FSIs, together with shocks to a selected set of variables (FSS-derived) that characterised each stress period, are used as inputs into the multi-country BVAR. The one-year financial shocks are then propagated over a three-year horizon to obtain adverse (mean) projections for a broad set of macro-financial indicators up to the second quarter of 2028.

4.2 Key scenario features

As discussed in Section 3.2, the FSI serves to identify the drivers underlying an episode in which financial conditions tighten, therefore improving the scenario design process and narrative choice. Different time periods are selected for drawing the FSS annual shocks, reflecting different methodological choices behind the scenario calibration process. Moreover, in order to better gauge the cross-country heterogenous dynamics across different crisis periods, we also include stock market prices and spreads shocks drawn via the FSS (jointly with the FSI shocks) when expanding the scenario using the BVAR model.[18] Below, the different time periods considered for the scenarios are described and a summary can be found in Table 4.

- **Global financial crisis scenarios.** We consider the full year 2008 when drawing annual shocks from the FSS for the Global Financial Crisis scenarios. As illustrated in Figure 4, the euro area FSI experiences its largest recorded increase during 2008, reflecting the severe financial stress associated with the Global Financial Crisis. Figures 4, 5, and 6 further show that a key contributor to this deterioration, both at the euro area level and across individual countries, is the decline in equity prices, represented by the yellow vertical bars.
- **Sovereign debt crisis scenarios.** For the Sovereign Debt Crisis scenarios, the FSS annual

[17] For practical purposes, 300 scenarios per scenario batch have been simulated. A larger or smaller number can also be chosen.

[18] In particular, we jointly draw euro area and country-level shocks for FSI, stock market prices and spreads (country-level only). Additionally, we also include shocks (deviations) for the euro area short-term interest rate to account for the stance of monetary policy during each specific period.

shocks are drawn from the full year 2011. This choice is deliberate: as shown in Figure 4, the euro area FSI exhibits a pronounced increase in 2011, whereas the index begins to ease during the second half of 2012. Furthermore, Figures 5 and 6 highlight that the FSI drivers for Italy and Spain differ from those for Germany and France over the same period. In particular, the two-year sovereign spread (light orange bars) contributes strongly and positively to the FSIs of Italy and Spain, while its contribution for Germany and France is negligible or even negative. This variable is included in the FSI as an indicator of sovereign debt stress, in line with Garcia-de Andoain and Kremer (2018). The differences in magnitude in index levels across countries during this period aligns well with the broader narrative of fragmentation.

- **Geopolitical risk scenarios.** For these scenarios, we draw the FSS shocks from the full year 2022, a period characterised by substantial monetary policy tightening and heightened geopolitical risk following Russia's invasion of Ukraine. As shown in Figure 4, the increase in the euro area FSI during this period is considerable. Among its main drivers, money-market stress indicators, the EUR TED spread (grey) and the 3-month EUR swap-rate volatility (light purple), display contributions above their historical averages.[19]

- **French sovereign debt disruption scenarios.** In a specular way to the sovereign debt scenarios, the 2-year sovereign spreads in these scenarios exhibit a positive and above-average contribution for Germany and, in particular, France, relative to Italy and Spain, starting in the second half of 2024 (Figures 5 and 6). Over the same period, France's FSI begins to display a considerable increase, signalling a deterioration in financial conditions that complements the observed spread dynamics. In line with these developments, we calibrate the annual FSS shocks over the sample spanning from the second half of 2024 through the first half of 2025. This maintains consistency with the one-year sampling horizon applied across all scenarios. Furthermore, this scenario window captures the inversion of the yield curve,

[19] Notice that our flexible framework allows also for drawing oil price shocks jointly with the FSI shocks via the FSS, and then load both shocks into the multi-country BVAR model. This could allow the expanded macro-financial scenarios to better capture the inflation dynamics associated with the energy price shocks materialized during 2022. Nevertheless, since the 2022 energy-related shocks are abnormally large, in the current exercise we opt for a less constrained specification without oil price shocks to guarantee a proper level of comparability across the different scenarios. Alternatively, we model the energy price - headline inflation relationship in the BVAR model that features oil prices as an endogenous variable.

providing additional information regarding market expectations and the re-pricing of term premia.

The different features of each period of financial stress are carried forward into the macro-financial variables as intended. For example, at euro area level, equity prices decline the most for 2008-type scenarios consistent with the stress transmission mechanisms we observed during the Global Financial Crisis; sovereign spreads surge the most for the sovereign debt crisis scenarios, while short-term swap rates are significantly higher for scenarios drawn from the 2022 sample which capture the tightening of financial conditions resulting from geopolitical risk shocks (Figure 7). Analysing the evolution of sovereign spreads across each scenario batch at the country level reveals that the scenarios produced by MuSE successfully replicate the cross-country heterogeneity as intended (Figure 8), with sovereign spreads increasing the most for countries like Italy and Spain for scenarios based on the correlations observed during the sovereign debt crisis. Figures 9, 10, 11 and 12 provide additional details on all the projected macro-financial variables.

4.3 Selecting tail scenarios

To ensure that adverse scenarios are sufficiently severe, that the hypothetical scenarios not only reflect the historical distributions of the underlying variables - thus capturing their typical empirical relationships - but also that the severity of the scenario compares in an appropriate way with past episodes of macroeconomic and financial stress, MuSE allows for the application of an additional conservative layer guided by expert judgement. Before feeding the multiple scenarios into a top-down stress test model discussed in Section 5.1, we apply a number of filters to ensure that the scenarios best match the stress transmission channels characterising the selected stress periods.

For example, we consider the correction in stock market prices, measured in terms of the decline of equity prices, to represent a dominant feature of the 2008-type scenario batch. Accordingly, we only keep the 100 and 50 scenarios in which the stock market correction was most severe. We also only focus on the 100 and 50 most adverse scenarios of the 2011-batch in which the spreads of Italian and Spanish sovereign bonds were widest and the 100 and 50 scenarios in which the inversion of the yield curve was strongest for the 2022-batch. Finally, as the 2025 scenario batch cannot be easily connected to a single variable, we take a sub-sample of scenarios at random.

5 Impact on banks

To assess the impact that different adverse scenarios have on bank resilience, we combine the scenarios described in Section 4 with a top-down stress test model that provides distribution and frequency information on the reduction in common equity tier 1 (CET1) ratios of the largest euro area banks over a period of three years.

5.1 Stress test-based elasticities model

We use the stress-test elasticities model developed by Couaillier et al. (2026) and already used by Caccavaio et al. (2025) to test bank resilience, e.g., the depletion of CET1 capital ratios over a period of three years, under our simulated multiple scenarios. In practice, we use their stress-test elasticities to simulate the losses banks experience under different adverse scenarios.

Couaillier et al. (2026) leverage the information collected by prudential authorities from banks in the context of past EU-wide stress tests to link bank capital losses to the macroeconomic variables of the EBA adverse scenarios using Bayesian model averaging econometric techniques. Elasticities linking bank capital depletion and stress test scenarios are estimated through multiple regression equations that account for combinations of different variable and fixed effects. Changes in Common Equity Tier 1 (CET1) ratios for each bank across both baseline and adverse scenarios serve as the dependent variable. Explanatory variables include macroeconomic variables, bank-specific balance sheet characteristics, and the interactions between these. For each stress test, depletion and starting point balance sheet data for approximately 90 banks are included, covering up to approximately 75% of total assets of all banks supervised under the Single Supervisory Mechanism.

5.2 Identifying tail banks

We then proceed with investigating the resulting capital depletion simulations both from the perspective of system- and bank-level losses, where the system is defined by the universe of banks under the direct supervision by the SSM covered by Couaillier et al. (2026). To do so, we investigate the distributions of system-level and bank-specific losses, as well as their tails, defined by the 95th percentile of each distribution. Focussing on tail observations is not uncommon in the risk management literature, where Value at Risk and Expected Shortfall concepts are used to inform capital requirements in particular for market risk.

Our first finding, presented in Figure 13a, supports our approach: as expected differences in median losses are less pronounced when looking at the 100-worst scenarios than when we move further into the tails of the scenarios and look at the 50-worst scenarios per batch in Figure 13b.

Secondly, focussing on these most severe scenarios shows that even at this juncture, scenarios characterised by a 2008-type confidence and financial market shock would prove more disruptive for the euro area banking system despite its increased capitalisation and profitability. Scenarios calibrated using a 2022-type geopolitical risk shock, which triggered an aggressive monetary policy reaction resulting in an inversion of the yield curve, are beneficial for bank profitability and tend to generate lower depletion in the tails compared to 2008- and 2011-scenario types. Scenarios matching the latest disruptions in French sovereign markets transmit less strongly to system level losses, as reflected in the more muted reaction in macro-financial variables described in Section 4.2. Looking at the distribution of bank-level results for all the scenario-batches brings further robustness to this finding. From multiple perspectives (median and tail bank losses, 100- and 50-worse scenarios) 2008-type scenarios prove to be most disruptive for euro area banks (Figures 14a and 14b).

Inspecting these results from the perspective of bank business models offers additional insights (Figure 15). G-SIBs and investment banks, which together account for the larger share of euro area banking sector assets, are most negatively affected under 2008-type scenarios, likely pushing the tails of the system level distribution further to the left. Investment banks are most affected by 2025-type scenarios likely reflecting the exposure of these entities towards securities and fixed income markets of the larger euro area sovereigns, either directly or indirectly through their role as market makers in derivatives or repo markets. By contrast, more traditional lender and universal banks are most affected under 2011-type scenarios, triggered by disruptions in Italian and Spanish sovereign bond markets.

Zooming into bank-level tails offers a final insight: while some banks suffer large losses under all scenario configurations, few appear to fall into the tails of selected scenario batch distributions only (Figure 16). This result echoes the work of Baes and Schaanning (2023) who identify an "Anna Karenina" principle of stress testing given which despite differences in scenarios, every stressful scenario stresses the same (most vulnerable) banks.

6 Conclusions

We develop a Multiple macro-financial stress scenario Simulation Engine (MuSE) to contribute to the increasing need to perform stress tests using multiple scenarios (Breuer and Summer, 2020; Schuermann, 2026; Valderrama, 2026). Compared to existing tools and frameworks (Montesi et al., 2020; Aikman et al., 2024; Baes and Schaanning, 2023), our approach allows for a consistent calibration of many variables characterising macroeconomic developments for each scenario.

We generate multiple, internally consistent macro-financial scenarios, using statistical and econometric models by putting at the centre the identification of extreme financial shocks drawn from the correlation of potentially thousands of high frequency financial indicators. First, we utilise a non-parametric copula estimated on a large data set of daily financial indicators to bootstrap paths for financial variables over the horizon of a stress scenario - the financial shock simulator (FSS). In a second step, the link between the financial sphere and the real economy is analysed by mapping the evolution of the financial variables into an index of financial stress (Angelopoulou et al., 2014; Hatzius et al., 2010; Chavleishvili et al., 2021; Darracq Paries et al., 2014). In addition to Holló et al. (2012), our financial stress index can be projected forward by one year and decomposed into its main shock drivers. Finally, to generate scenario paths for macroeconomic variables that are consistent with stressed financial variables, we include the projected financial stress index in a large multi-country Bayesian vector autoregressive (BVAR) model like the one proposed by Angelini et al. (2019). In that way, we can capture the relationship between macroeconomic indicators available at quarterly frequency with high-frequency financial data in a parsimonious way. We illustrate the working of this approach by simulating several stress scenarios and plugging these adverse scenarios into a top-down stress test elasticity based model (Caccavaio et al., 2025; Couaillier et al., 2026). We identify the types of scenarios that have the potential to reduce banks and system-level capital ratios the most at this juncture.

The scenarios generated by MuSE thus rely on drawing shocks from past crises, are independent of the outcome of a stress test, and their calibration does not depend on the specific portfolio choices of stressed entities. Accordingly, the definition of scenario stress is derived from the data distribution used to calibrate the Financial Stress Index which captures periods of financial instability in Europe. MuSE allows policymakers to focus on the choice of scenario shocks independently from the portfolio choices of financial institutions. Once calibrated, the scenarios highlight which entities are more vulnerable to different adverse shocks and which scenario types have the potential to trigger systemic vulnerabilities. Our thinking therefore differs from *reverse stress testing* for example where the narrative of a scenario is less relevant than the quantification of shocks capable of producing large enough losses. In this way, MuSE is well suited for stress testing conducted to support financial stability and macroprudential policy, complementing tools that identify weaknesses in individual institutions.

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Annex

Tables

Table 1: **Choices for the building blocks in the construction of a financial stress index**

Building block	**Option 1**	**Option 2**	**Option 3**	**Option 4**	**Option 5**
Standardisation	Mean 0, variance 1	Mean 0, variance 1, with purging	PIT	**PIT (time-varying)**	
Market segment aggregation	PCA	Arithmetic average	Static PCA	**No market segment aggregation**	
Overall aggregation	PCA variance share	PCA volatility share	GARCH variance	GARCH volatility	**Portfolio theory (EWMA)**

Note: Bold entries indicate the configuration used in the FSS-derived FSI. Empty cells indicate that the building block has fewer than five options.

Table 2: **Components of the euro area financial stress index**

Market segment	**Component**	**Label in charts**
Money market	Spread between the three-month French sovereign yield and the three-month Euribor	TED Spread EUR
	Volatility of the three-month euro swap rate	3M EUR Swap Vol.
Bond market	iTraxx Europe credit default swap index (overall)	CDS iTraxx EA
	Non-financial corporate bond spread over the ten-year euro swap rate	Corp. Bond Spread NFC EA
	Financial corporate bond spread over the ten-year euro swap rate	Corp. Bond Spread Fin EA
	Ten-year sovereign spread over the ten-year euro swap rate	Sov. Spread 10Y EA
Equity market	Euro area stock market prices, measured as the maximum cumulative loss over a one-year window	Stock Mkt Prices EA
	Implied volatility of euro area equity prices (VSTOXX index)	VSTOXX
Foreign exchange	Euro–US dollar exchange rate	FX EUR/USD
	One-month implied volatility of the euro–US dollar exchange rate	FX EUR/USD 1M Vol.

Note: The three-month euro swap-rate volatility is estimated using a GARCH model, with parameters selected according to the Akaike information criterion. Corporate bond data are obtained by aggregating iBoxx yield data at country level by sector. French spreads are used as the benchmark, following Holló et al. (2012). They represent a liquid core proxy for the euro-area short-term spreads that avoids the safe-haven distortions of German spreads and the credit risk of peripheral ones. Data start in 1998, or when first available.

Sources: Bloomberg, Datastream, Refinitiv, and own calculations.

Table 3: **Components of the country-specific financial stress indices**

Market segment	**Component**	**Label in charts**
Money market	Spread between the three-month French sovereign yield and the three-month Euribor	TED Spread EUR
	Volatility of the three-month euro swap rate	3M EUR Swap Vol.
Bond market	iTraxx Europe credit default swap index (overall)	CDS iTraxx
	Non-financial corporate bond spread over the ten-year euro swap rate	Corp. Bond Spread NFC
	Financial corporate bond spread over the ten-year euro swap rate	Corp. Bond Spread Fin
	Ten-year sovereign spread over the ten-year euro swap rate	Sov. Spread 10Y
	Two-year sovereign spread over the two-year euro swap rate	Sov. Spread 2Y
Equity market	Stock market prices, measured as the maximum cumulative loss over a one-year window	Stock Mkt Prices
Foreign exchange	Euro–US dollar exchange rate	FX EUR/USD
	One-month implied volatility of the euro–US dollar exchange rate	FX EUR/USD 1M Vol.

Note: In the country charts, the country-specific series carry a country code in the label (e.g. "CDS iTraxx DE"); the money-market and foreign-exchange series are common across countries. The three-month euro swap-rate volatility is estimated using a GARCH model, with parameters selected according to the Akaike information criterion. Corporate bond data are obtained by aggregating iBoxx yield data at country level by sector. French spreads are used as the benchmark, following Holló et al. (2012). They represent a liquid core proxy for the euro-area short-term spreads that avoids the safe-haven distortions of German spreads and the credit risk of peripheral ones. Data start in 1998, or when first available.

Sources: Bloomberg, Datastream, Refinitiv, and own calculations.

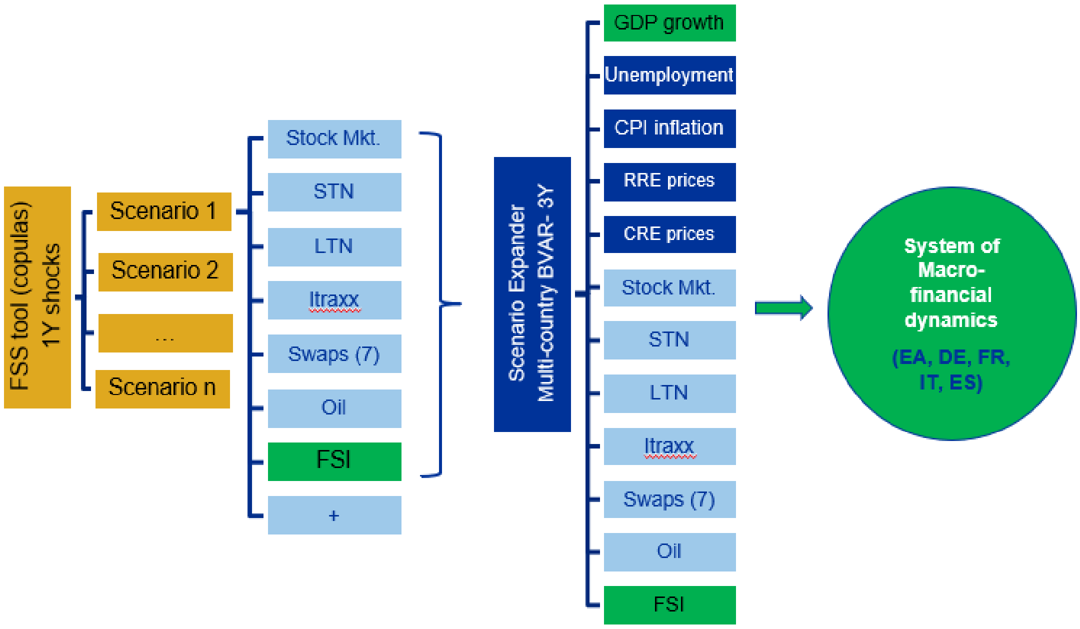
Table 4: **Summary of the four scenario batches**

Scenario	**FSS sampling window**	**Stress narrative**	**Main FSI drivers**
Global financial crisis	Full year 2008	Confidence and broad financial-market shock	Decline in equity prices
Sovereign debt crisis	Full year 2011	Euro-area sovereign fragmentation	Two-year sovereign spread (Italy and Spain)
Geopolitical risk	Full year 2022	Stress in global commodity markets and monetary tightening	Money-market stress (EUR TED spread, three-month EUR swap-rate volatility)
French sovereign debt disruption	H2 2024 – H1 2025	Core (French) sovereign fragmentation	Two-year sovereign spread (Germany and France), yield-curve inversion

Note: Each scenario batch draws FSS annual shocks over a one-year window. The euro area and country-specific FSI shocks, together with the additional FSS-derived variables listed, are used as inputs into the multi-country BVAR to expand the scenarios over a three-year horizon.

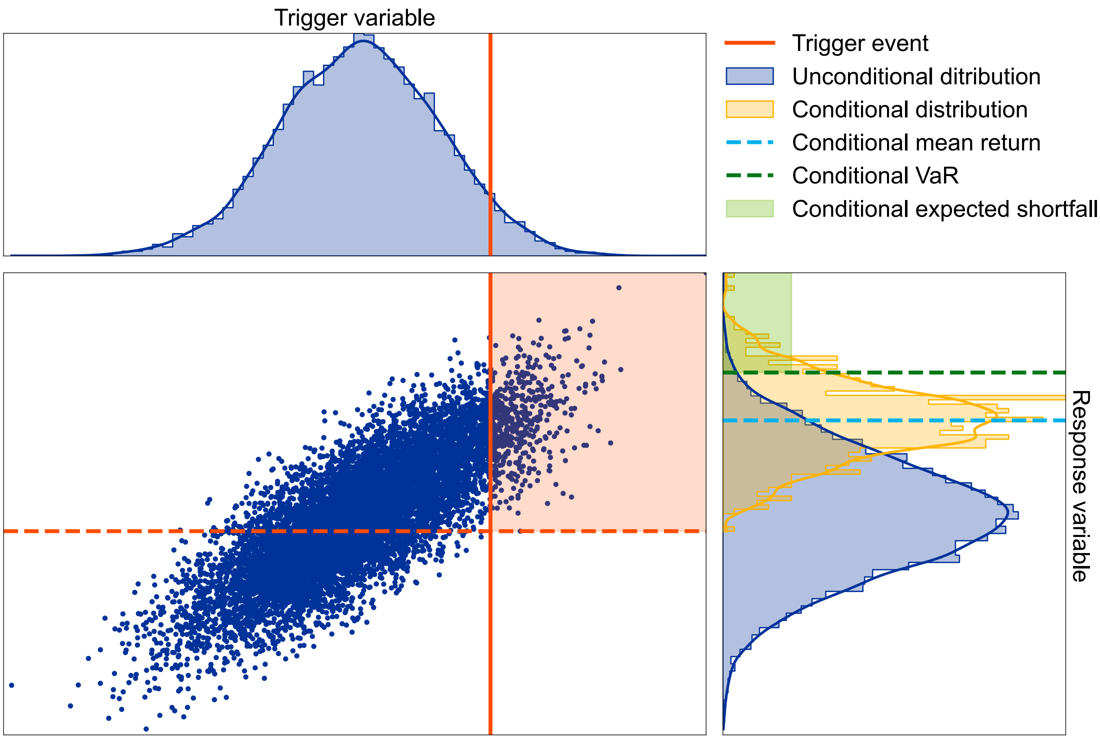
Figures

Figure 1: **Multiple Stress Test Scenarios Engine**



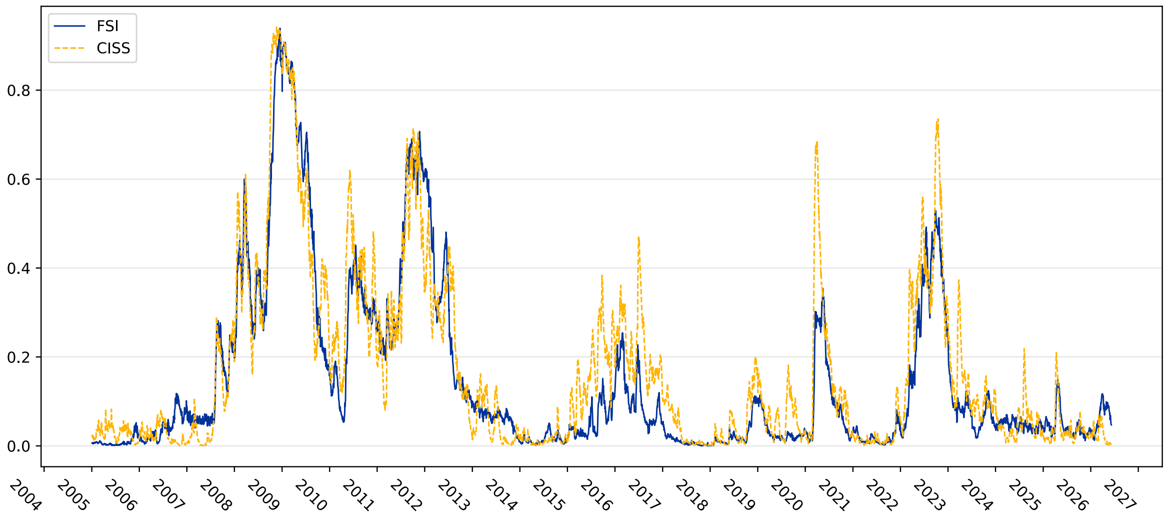
Note: The diagram depicts the econometric framework to simulate multiple macro-financial stress test scenarios driven by financial market shocks. In the first block of the framework multiple adverse financial shocks are generated via the Financial Shock Simulator (FSS) tool based on a multivariate copula. Then, in the second block the Scenario Expander tool expands the stressed financial scenarios into macro-financial indicators. The Scenario Expander tool builds on a multi-country Bayesian VAR model featuring aggregated euro area level indicators and country-level variables for the four major economies including Germany, France, Italy and Spain.

Figure 2: **Stylised representation of the financial shock simulator**



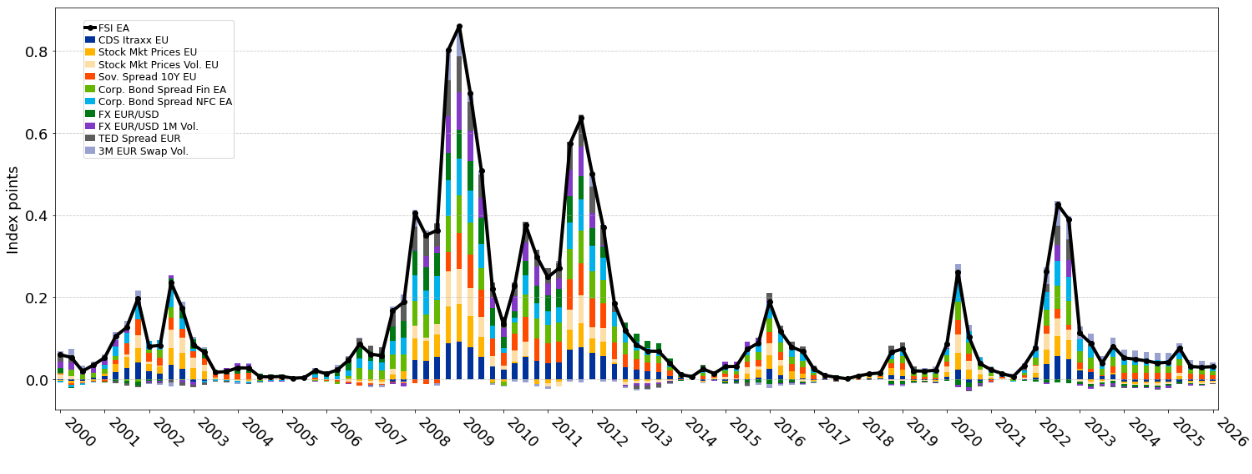
Note: Scatter plot and marginal distributions of two hypothetical variables simulated via the FSS. The vertical red line determines the narrative-dependent trigger of the scenario, conditional on which a new marginal distribution of the response variable can be extracted, in yellow. Three main metrics can be extracted from the latter: the conditional mean return (dotted light blue line), the conditional value-at-risk (dotted green line) and the conditional expected shortfall (tail of the conditional distribution included in the green area).

Figure 3: **Euro Area Financial Stress Index and CISS**



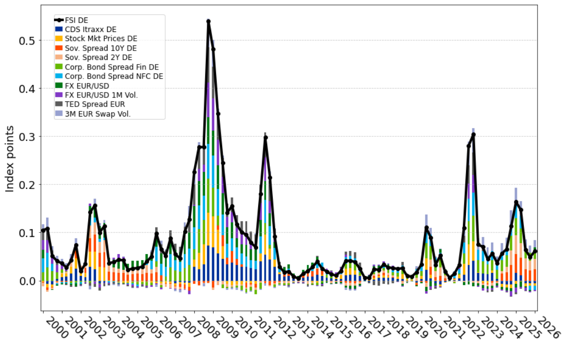
Note: The blue solid line depicts the euro area Financial Stress Index (FSI) constructed using the Financial Shock Simulator (FSS) underlying indicators. The yellow dashed line shows the euro area Composite Indicator of systemic Stress (CISS) by Holló et al. (2012).

Figure 4: **Euro Area Financial Stress Index Historical Drivers**

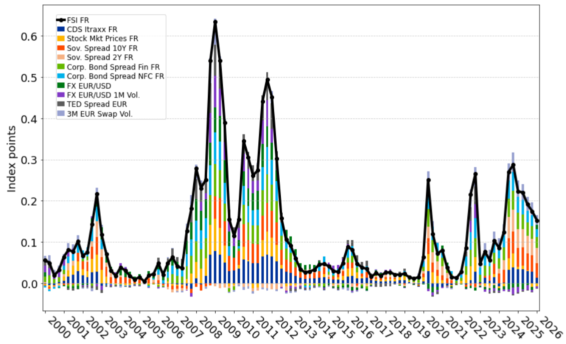


Note: The black solid line shows the euro area Financial Stress Index (FSI). The vertical bars depict the contribution of each underlying financial indicator to fluctuations on the FSI across time.

Figure 5: **Financial Stress Index Historical Drivers for DE and FR**



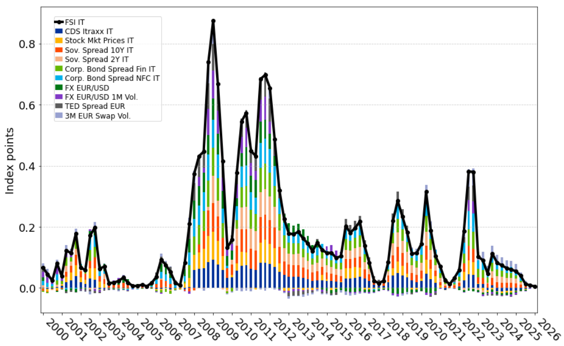
(a) Financial Stress Index Historical Drivers for Germany



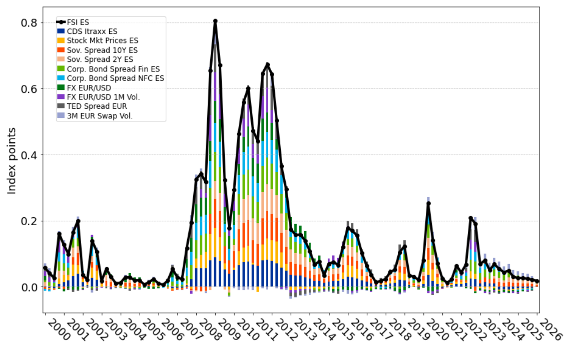
(b) Financial Stress Index Historical Drivers for France

Note: The black solid line shows the Financial Stress Index (FSI) for each country. The vertical bars depict the contribution of each underlying financial indicator to fluctuations on the FSI across time.

Figure 6: **Financial Stress Index Historical Drivers for IT and ES**



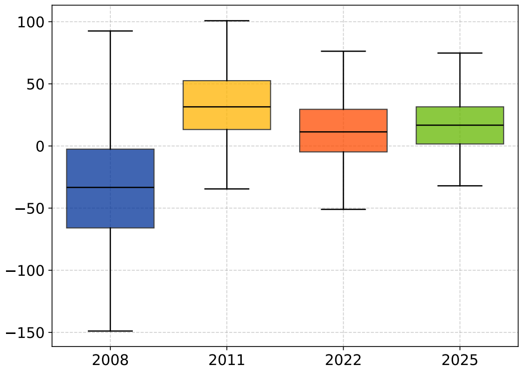
(a) Financial Stress Index Historical Drivers for Italy



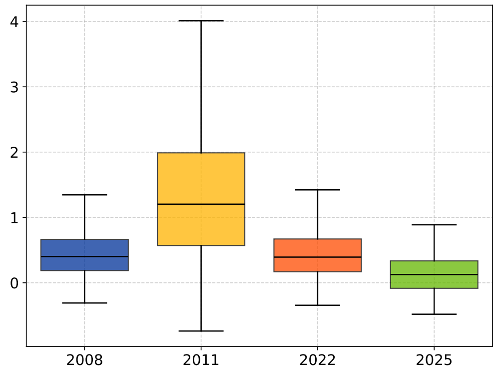
(b) Financial Stress Index Historical Drivers for Spain

Note: The black solid line shows the Financial Stress Index (FSI) for each country. The vertical bars depict the contribution of each underlying financial indicator to fluctuations on the FSI across time.

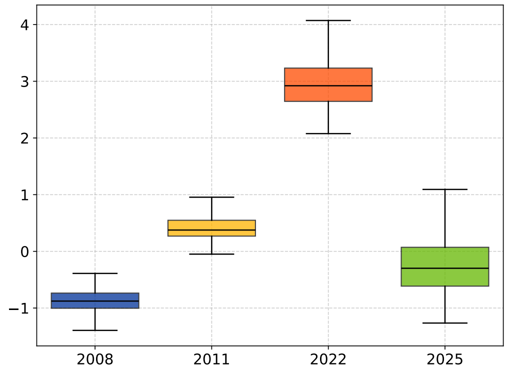
Figure 7: **Comparison of selected variables across the different scenario narratives**



(a) Equity prices



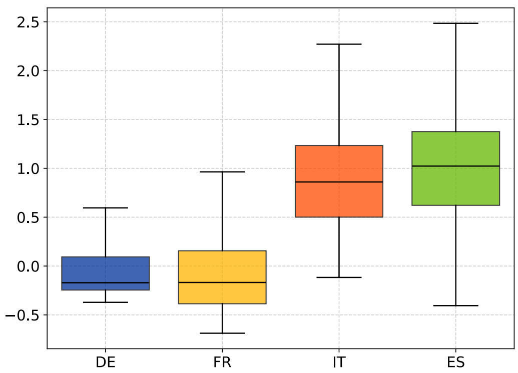
(b) 10-year sovereign spread



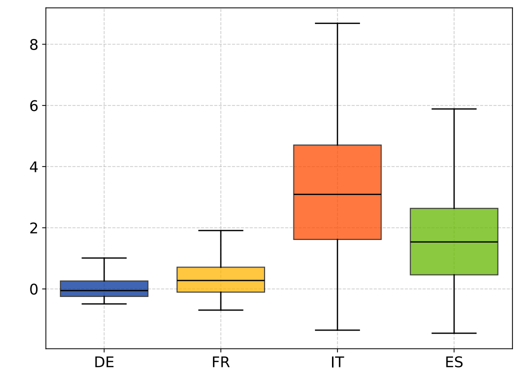
(c) Short-term rates

Note: The box plots show the distributions of shocks for key scenario macro-financial indicators at the euro area level as projected by MuSE for the four scenario batches showcasing the sensitivity of the scenarios to the period-specific narrative. Figures indicate cumulative (panel a) and maximum (panels b and c) deviation from starting point across the 3-year scenario horizon (in percentage points). The different scenario paths are computed conditional on financial market shocks drawn from four samples corresponding to (1) the 2008 sample corresponding to the Great Financial Crisis, (2) the 2011 sample period exhibiting the largest cross-country (long-term) interest rate spread differential related to the Sovereign Debt crisis, (3) the 2022 sample corresponding to the heightening on geopolitical tensions as shown by the Geopolitical Risk Index, and (4) the 2024-2025 sample.

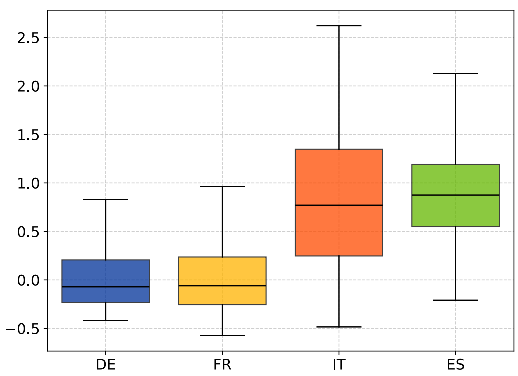
Figure 8: **Scenario heterogeneity across countries and scenario narratives: focus on sovereign spreads**



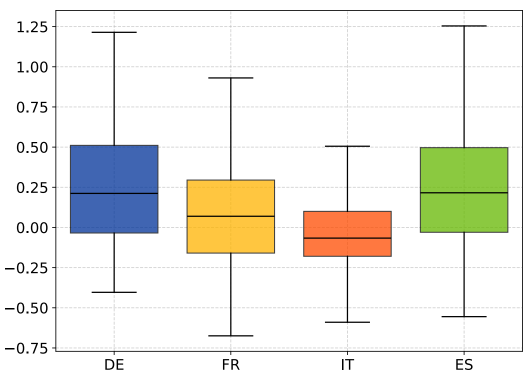
(a) GFC-type scenarios



(b) SDC-type scenarios



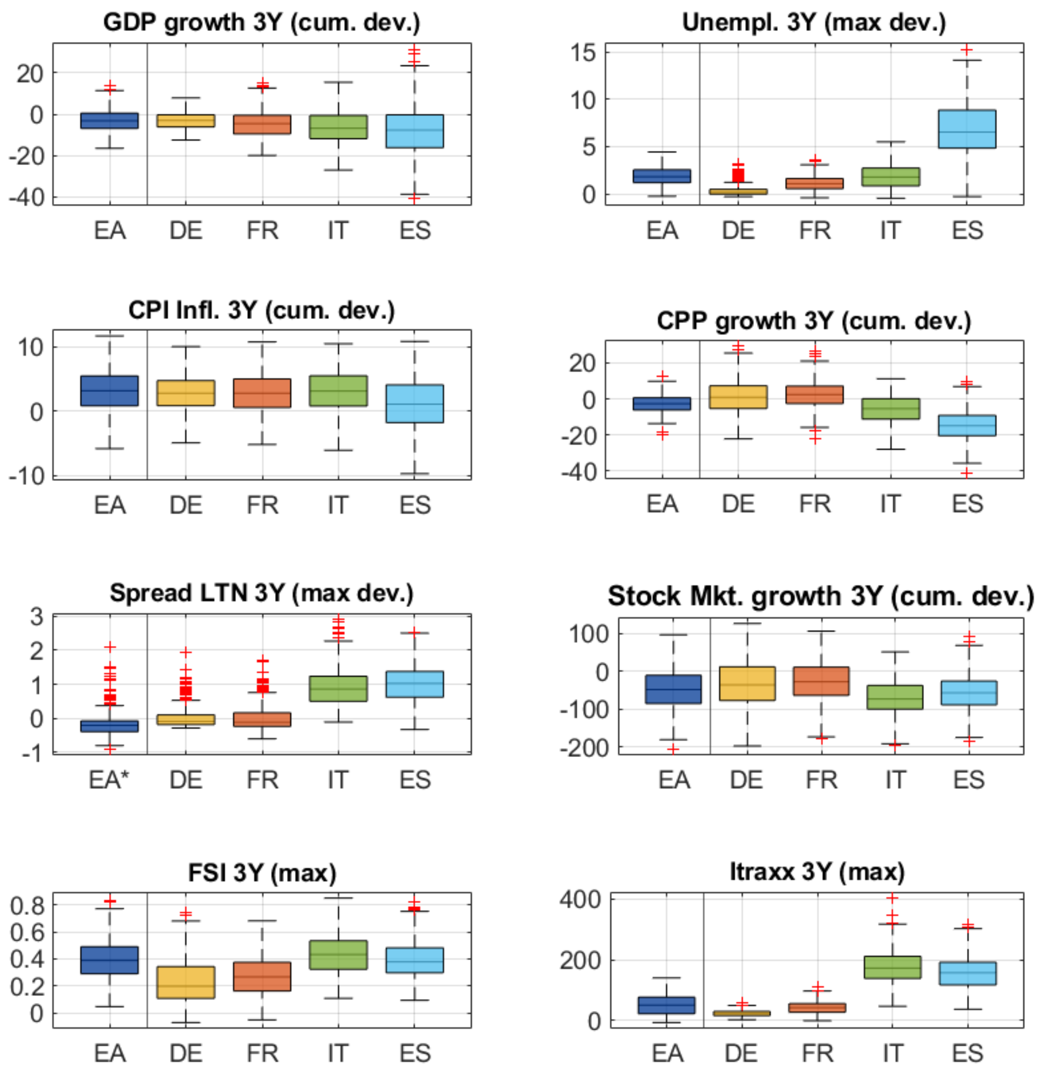
(c) Geopolitical risk-type scenarios



(d) Fragmentation-type scenarios

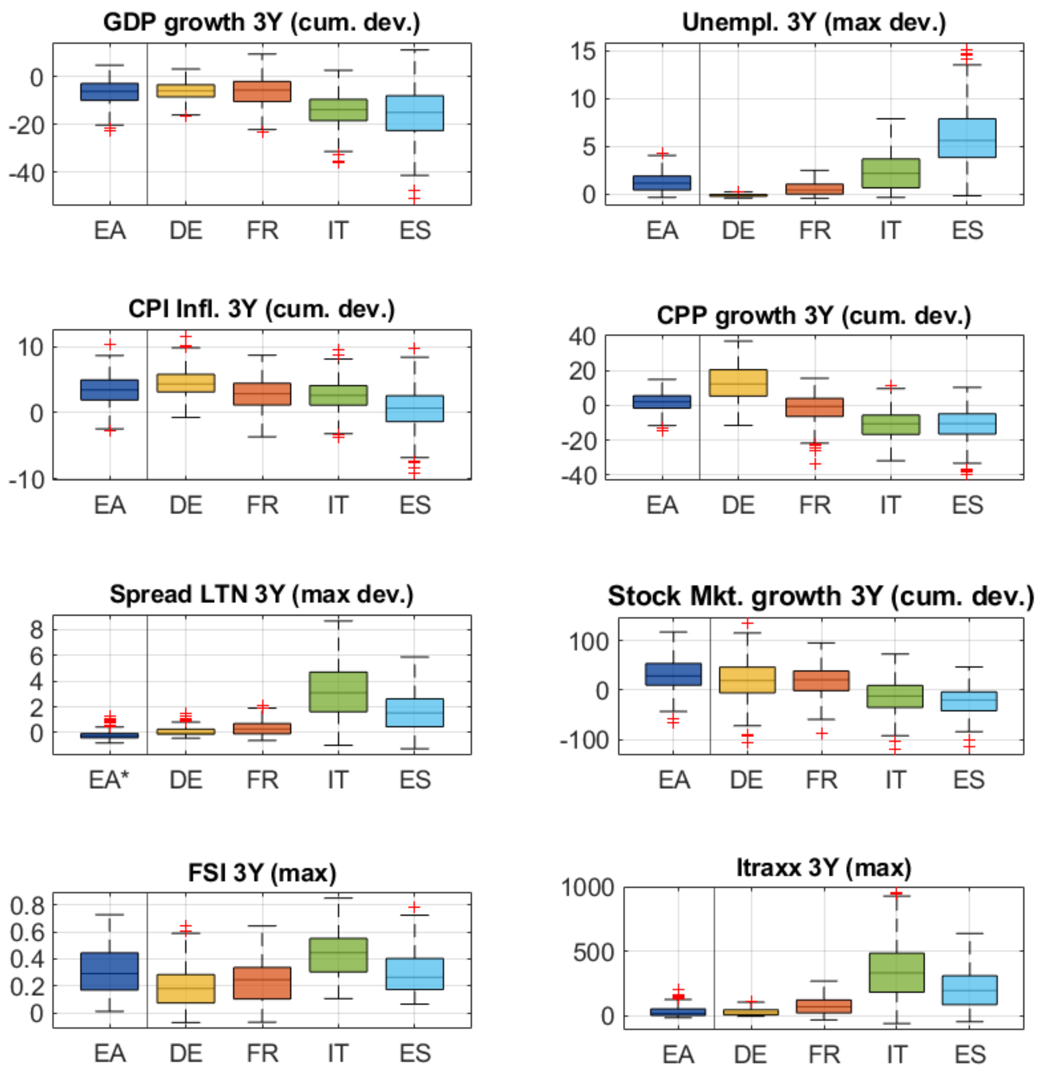
Note: The box plots show the distributions for sovereign spread shocks at country level projected by MuSE for the four scenario batches showcasing cross-country heterogeneity that varies across stress episodes. Figures indicate maximum deviation from starting point across the 3-year scenario horizon (in percentage points). The different scenario paths are computed conditional on financial market shocks drawn from four samples corresponding to (a) the 2008 sample corresponding to the Great Financial Crisis (GFC-type scenario), (b) the 2011 sample period exhibiting the largest cross-country (long-term) interest rate spread differential (SDC-type scenarios), (c) the 2022 sample corresponding to the heightening on geopolitical tensions as shown by the Geopolitical Risk Index (Geopolitical risk-type scenario), and (d) the 2024-2025 sample (Fragmentation-type scenario).

Figure 9: **Scenario Distribution for Great Financial Crisis Shocks**



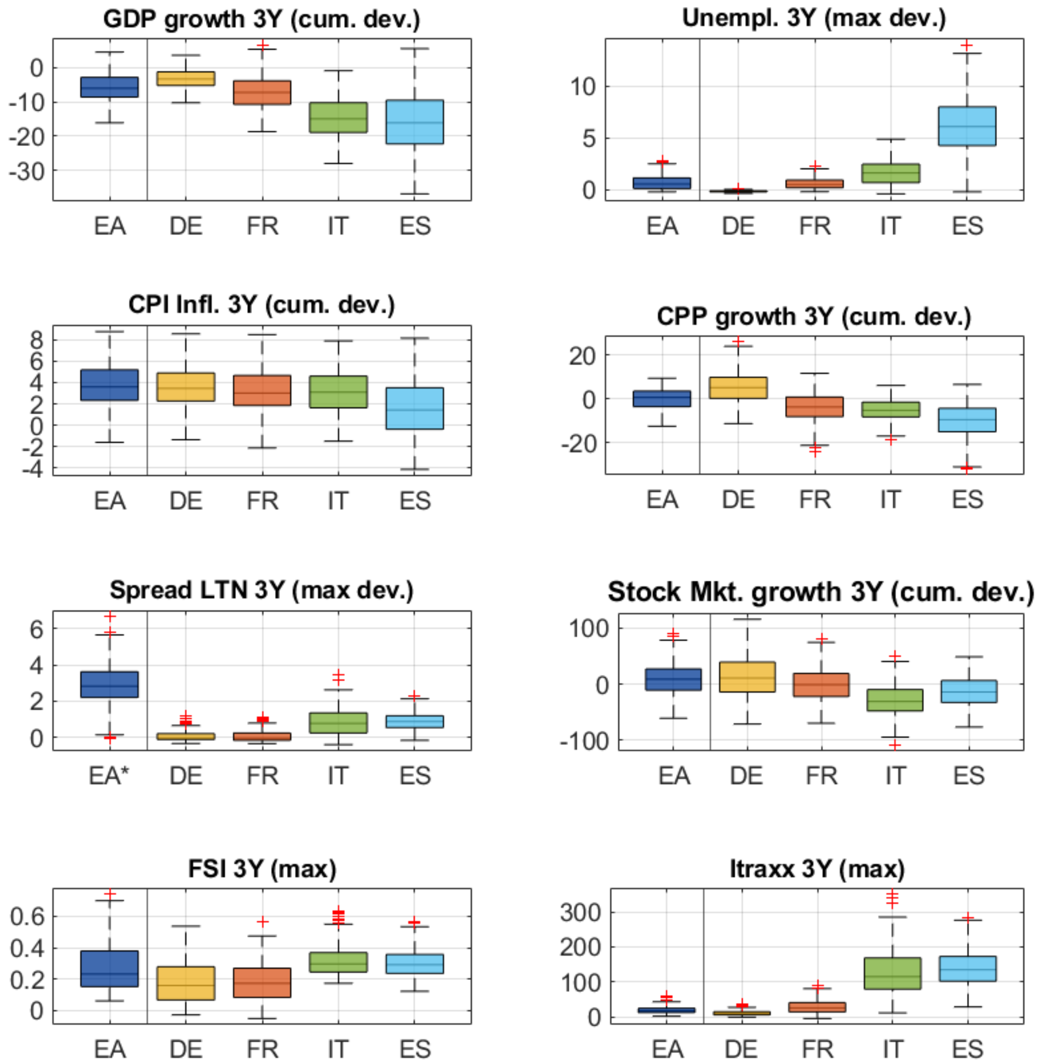
Note: The box plots show the distributions for key scenario macro-financial indicators at euro area and country level. Figures indicate cumulative deviation from starting point across the 3-year scenario horizon (in percentage points). The different scenario paths are computed conditional on financial market shocks drawn from the 2008 sample corresponding to the Great Financial Crisis.

Figure 10: **Scenario Distribution for Sovereign Debt Crisis Shocks**



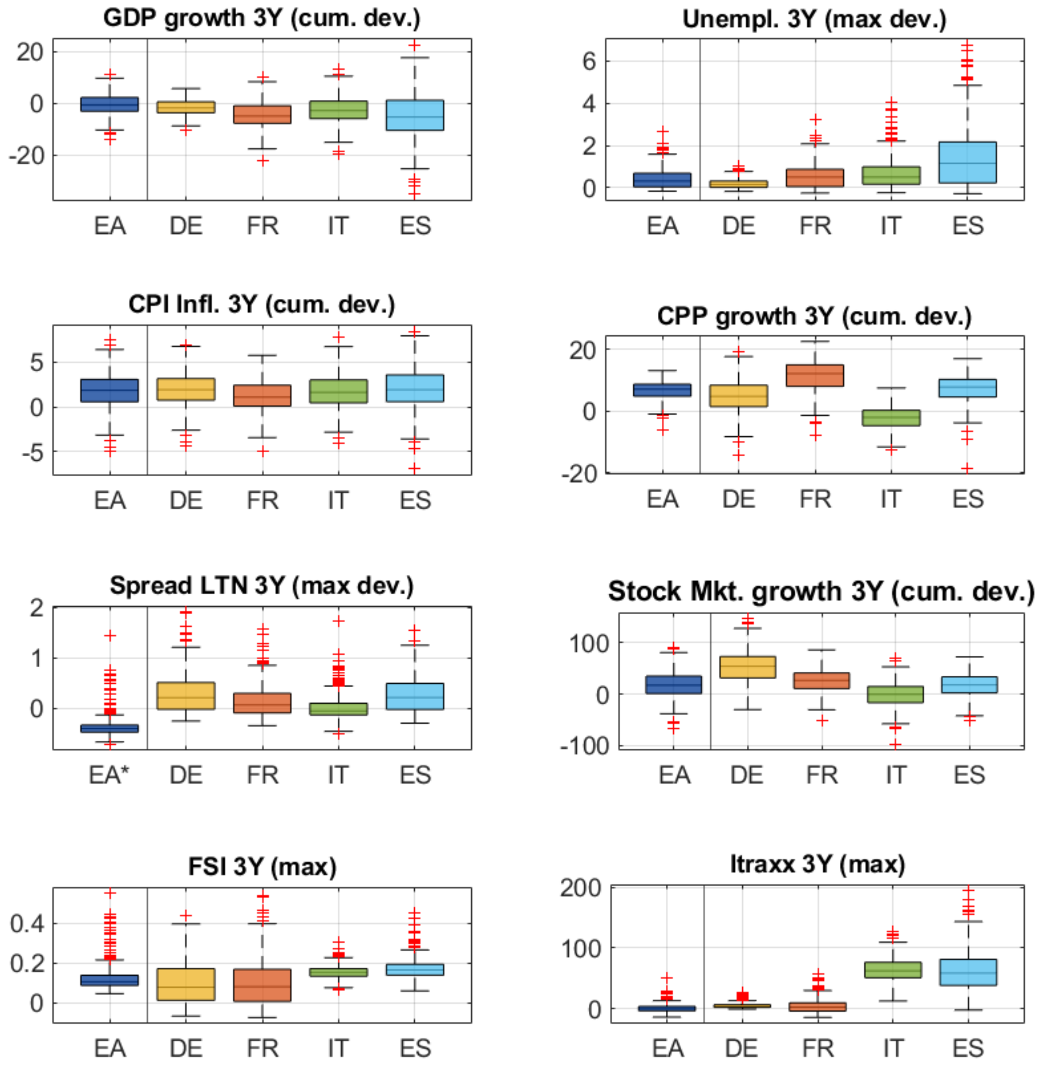
Note: The box plots show the distributions for key scenario macro-financial indicators at euro area and country level. Figure indicates cumulative deviation from starting point across the 3-year scenario horizon (in percentage points). The different scenario paths are computed conditional on financial market shocks drawn from the 2011 sample period exhibiting the largest cross-country (long-term) interest rate spread differential.

Figure 11: **Scenario Distribution for Geopolitical Risk Shocks**



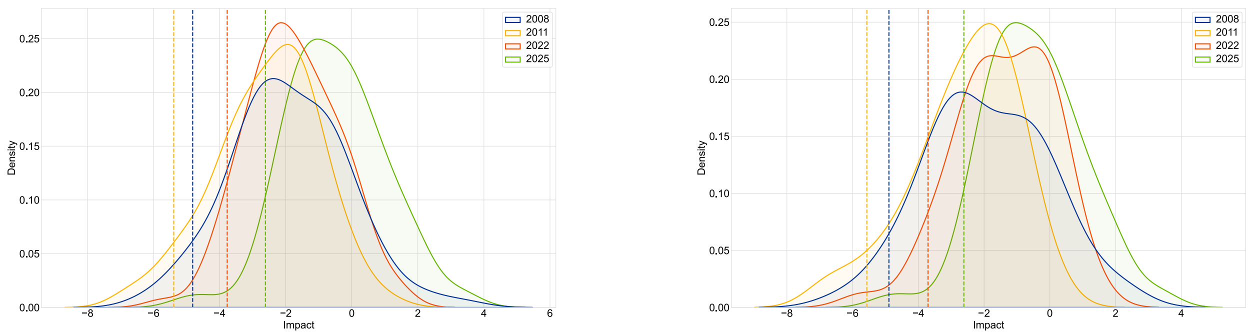
Note: The box plots show the distributions for key scenario macro-financial indicators at euro area and country level. Figures indicate cumulative deviation from starting point across the 3-year scenario horizon (in percentage points). The different scenario paths are computed conditional on financial market shocks drawn from the 2022 sample corresponding to the heightening on geopolitical tensions as shown by the Geopolitical Risk Index.

Figure 12: **Scenario Distribution for Fragmentation Shocks**



Note: The box plots show the distributions for key scenario macro-financial indicators at euro area and country level. Figures indicate cumulative deviation from starting point across the 3-year scenario horizon (in percentage points). The different scenario paths are computed conditional on financial market shocks drawn from the 2024-2025 sample.

Figure 13: **System-level capital depletion**



(a) Worst 100 scenarios per bucket

(b) Worst 50 scenarios per bucket

Note: Distribution of CET1 ratio depletion at system level by scenario batch and simulation. The system value is the weighted average of bank-level results, where the weights are the bank's RWA. The dotted lines indicate the 5^{th} percentile of each distribution.

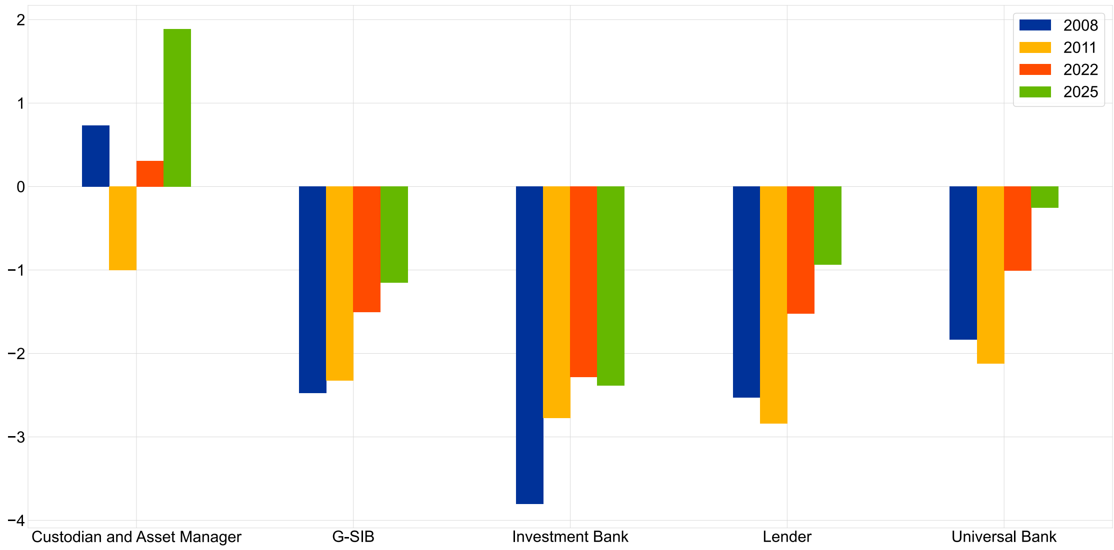
Figure 14: **Bank-level capital depletion**

(a) Worst 100 scenarios per bucket

(b) Worst 50 scenarios per bucket

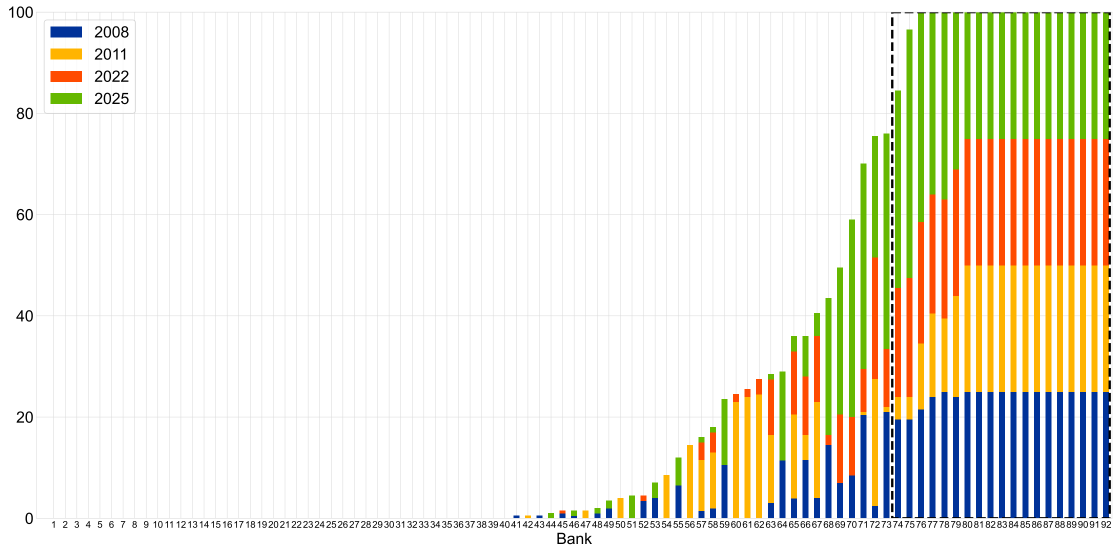
Note: Distribution CET1 ratio depletion at bank level by scenario batch and simulations. The dotted lines indicate the 5^{th} percentile of each distribution.

Figure 15: **Median impact by business model**



Note: Per each business model (x-axis) the chart displays the median depletion across banks and scenario bucket.

Figure 16: **Worst performing banks by scenario**



Note: Per each bank (x-axis) the chart displays the percentage of times the bank has been in the quartile (y-axis), across banks, displaying the highest depletion. Per each scenario, a bank always being in the worst quartile will have a value of 25% in the chart, making a maximum of 100% across the four scenarios' buckets. The dotted rectangle indicates the banks that are in the tails of the depletion distribution more than 80% of the times, across all scenarios.

Appendix of the paper "MuSE: a multiple macro-financial scenario simulation engine for stress testing"

A FSS metrics

To derive a relevant metric for Y in a certain scenario, multiple approaches can be pursued, depending on the variables' relevance in the exercise and on the appropriate level of severity for the projections. The FSS tool incorporates three options: the first one is the sample mean of the conditional distribution, the so-called conditional mean return (CMR):

$$\begin{aligned} CMR_{S_Y|S_X \geqslant x*} &= \mathbb{E}[S^Y|S^X \geqslant x^*] = \frac{\mathbb{E}[S^Y \cap \mathbf{1}_{S^X \geqslant x*}]}{\mathbb{P}(S^X \geqslant x^*)} \\ &= \frac{1}{\frac{|S_{X \geqslant x*}|}{N}} \frac{1}{N} \sum_{n=1}^{N} s_n^y \mathbf{1}_{\{s_n^x \geqslant x*\}} = \frac{1}{|S_{X \geqslant x*}|} \sum_{n=1}^{N} s_n^y \mathbf{1}_{\{S_{X \geqslant x*}\}}. \end{aligned} \tag{6}$$

The second option is based on a specific percentile, i.e. a confidence level, α of the conditional distribution of S^Y, called conditional value-at-risk ($CoVaR$).[20] Implicitly it is defined as:

$$\mathbb{P}(S^Y \leqslant CoVaR^{\alpha}_{S_Y|S_X \geqslant x*}|S^X \geqslant x^*) = \alpha. \tag{7}$$

Explicitly, the $CoVaR$ can be expressed as:

$$\begin{aligned} CoVaR^{\alpha}_{S_Y|S_X \geqslant x*} &= \inf\left\{z : F_{S^Y|S^X \geqslant x*}(z) \geqslant \alpha\right\} \\ &= \inf\left\{z : \mathbb{P}(S^Y \leqslant z|S^X \geqslant x^*) \geqslant \alpha\right\} \\ &= \inf\left\{z : \frac{\mathbb{P}(\{S^Y \leqslant z\} \cap \{S^X \geqslant x^*\})}{\mathbb{P}(S^X \geqslant x^*)} \geqslant \alpha\right\} \\ &= \inf\left\{z : \frac{|\{n : s_n^y \leqslant z \wedge s_n^x \geqslant x^*\}|}{|S_{X \geqslant x*}|} \geqslant \alpha\right\}, \end{aligned} \tag{8}$$

where $F_{S^Y|S^X \geqslant x*}(\cdot)$ is the cumulative distribution function of S^Y conditional on $S^X \geqslant x^*$. Therefore, the $CoVaR$ provides the lowest value of the simulation for Y conditional on observing $S^X \geqslant x^*$,

[20] See Adrian and Brunnermeier (2016).

with probability α.

Finally, if we consider the tail of $F_{S^Y|S^X \geqslant x*}(\cdot)$ at α probability, we can derive a further measure similarly to the CMR, the conditional expected shortfall ($CoES$):

$$\begin{aligned}
CoES^{\alpha}_{S_Y|S_X \geqslant x*} &= \mathbb{E}[S^Y | S^Y \leqslant CoVaR^{\alpha}_{S_Y|S_X \geqslant x*}, S^X \geqslant x^*] \\
&= \frac{\mathbb{E}[S^Y \cap \mathbf{1}_{S^Y \leqslant CoVaR^{\alpha}_{S_Y|S_X \geqslant x*}} \cap \mathbf{1}_{S^X \geqslant x*}]}{\mathbb{P}(\{S^Y \leqslant CoVaR^{\alpha}_{S_Y|S_X \geqslant x*}\} \cap \{S^X \geqslant x^*\})} \\
&= \frac{1}{|\{n : s^y_n \leqslant CoVaR^{\alpha}_{S_Y|S_X \geqslant x*} \wedge s^x_n \geqslant x^*\}|} \sum_{n=1}^{N} s^y_n \mathbf{1}_{\{s^y_n \leqslant CoVaR^{\alpha}_{S_Y|S_X \geqslant x*}\}} \mathbf{1}_{\{s^x_n \geqslant x*\}}.
\end{aligned} \tag{9}$$

Hence, the $CoES$ calculates the expected value of the simulations for Y that exceed the value of $CoVaR^{\alpha}_{S_Y|S_X \geqslant x*}$, conditional on $S^X \geqslant x^*$.

B Additional details on scenario selection

B.1 Restricting correlations

To illustrate how the FSS tool can restrict correlations, consider four variables simulated via FSS (a, b, c, and d) and two variables simulated via the ancillary method (a and c) — see Figure 17. In the first step, both simulations are performed. The FSS simulation uses the standard bootstrap method, while the ancillary simulation involves generating random realizations from a multivariate normal distribution $\mathcal{N}(\mathbf{0}, \Sigma)$, where the variance of each variable is set to 1, and the correlation structure is imposed as desired. This correlation can either reflect historical observations or be otherwise specified. A direct correspondence between the variables a and c in both simulations is assumed. In the second step, the results for each variable are grouped separately. The FSS results for a given variable (a and c) are then reordered so as to maximise their rank correlation with the corresponding ancillary simulation results. This sorting ensures consistency with the cumulative distribution function approach typically applied when constructing copulas[21]. Importantly, the sorting of the remaining FSS variables (e.g. b and d) must follow the ordering of the variables associated with the ancillary simulation (e.g. a or c). Economically, this step assumes that the correlation between other variables (b and d) and those included in the ancillary simulation (a and c) reflects the relationships observed in the historical data and reproduced via bootstrap sampling.[22] It is reasonable to assume that the fundamental correlation structures within certain markets remains unchanged while, instead, the ones across markets may shift under stress. Finally, after the sorting processes are completed, the FSS simulations are recombined. The variables simulated by the FSS retain their historical marginal distributions while incorporating the desired correlation structure derived from the ancillary simulation.

B.2 Dynamic correlation and importance sampling

An example of correlations that vary in sign depending on the periods of choice is provided by looking at the returns displayed by the Eurostoxx 600 and the 10-year euro SWAP rate. From 2000 onward it is close to zero when computed on the overall sample (Figure 18). Nonetheless, different metrics[23] which capture the dynamic nature of correlations between financial variables reveal that it can suddenly swing from highly positive to highly negative values.

Figure 19 illustrates how the FSS tool can address such problem using either a weighting scheme or by imposing specific correlations, as detailed in Appendix B.1. The figure contains three charts that show the conditional projections of the Eurostoxx 600, given a trigger event defined by the 10-year euro SWAP rate. As expected, the standard FSS simulation (right chart) projects a distribution of the Eurostoxx 600 values hovering around zero, in line with the very low overall historical correlation between the two time series. In contrast, the weighting scheme method (middle chart) and the correlation-restriction method (left chart) can produce projections that reflect a negative correlation between the trigger event and the conditional variable. The weighting scheme

[21] See Nelsen (2006).

[22] For instance, if a and c represent the 10-year EUR SWAP rate and the EUROSTOXX 600, respectively, then b and d could correspond to the 7-year EUR SWAP rate and the EUROSTOXX 50. Therefore, in the example we are implicitly assuming that the relevant correlation between b and a and between d and c is the historical one.

[23] The model used here to capture dynamic correlation is the DCC-GARCH from Engle (2002). In the literature there are also alternative approaches, such as the exponential weighted moving average (EWMA). Alternatively, one could simply calculate the sample correlation choosing a (daily) rolling window.

method implies that the Eurostoxx 600 conditional distribution remains predominantly bounded by the historical observations of the sub-period overweighted by the sampling process. The correlation-restriction method, instead, makes sure that the conditional distribution of the stock prices is in line with their historical marginal distribution.

Figure 17: **Stylised workflow to impose correlations to FSS simulations**

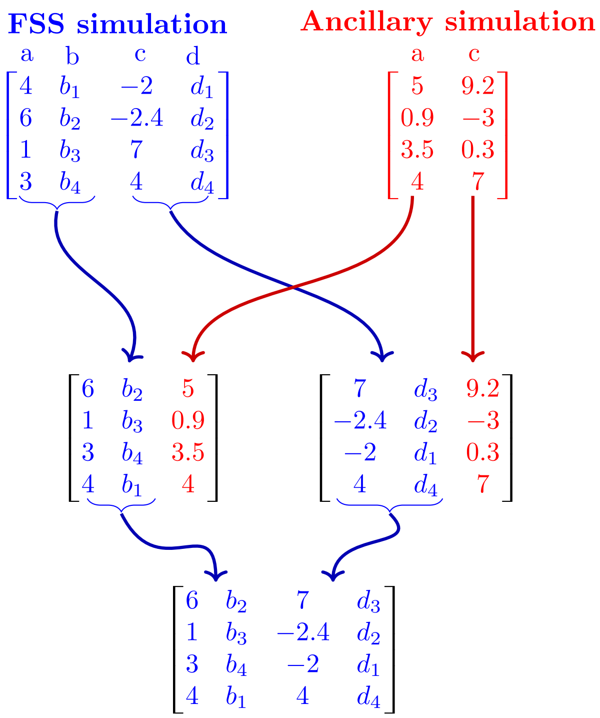
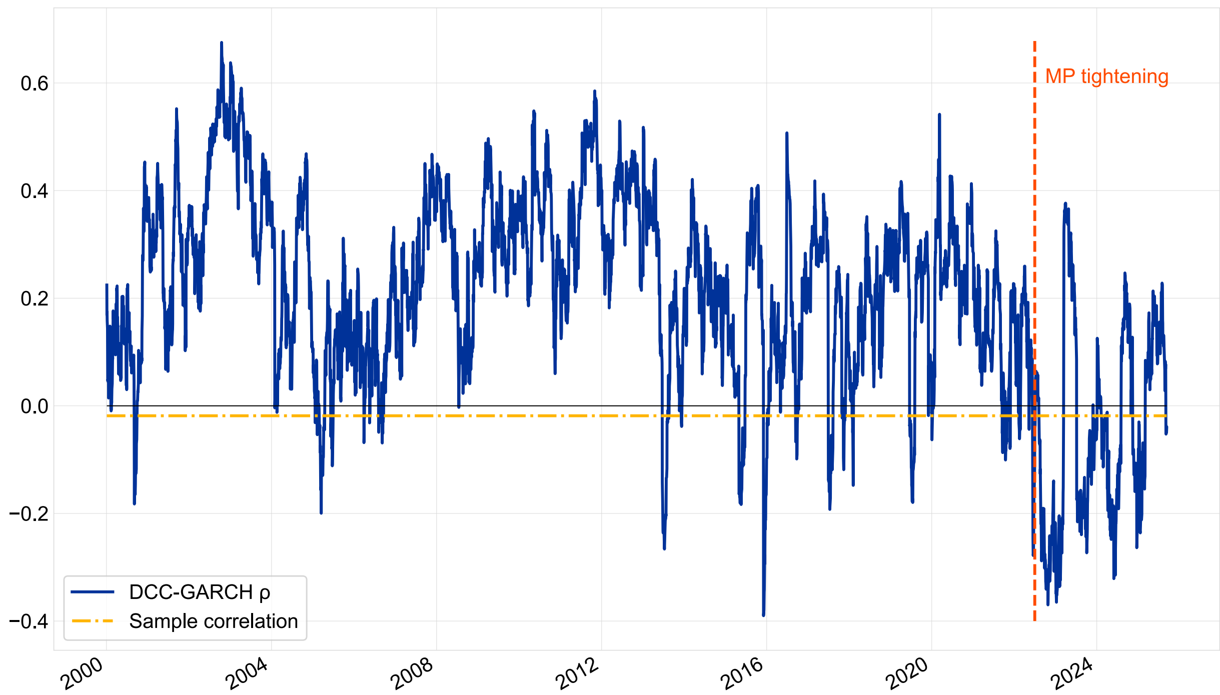
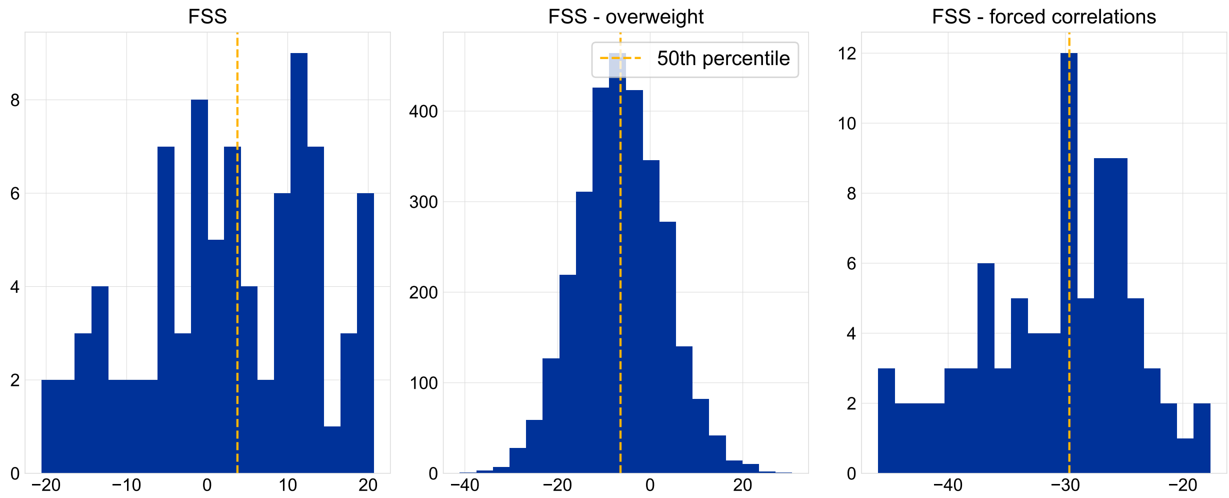


Figure 18: **Dynamic conditional correlation between 10-year euro SWAP rate and Eurostoxx 600**



Note: The blue solid line represents the dynamic correlation between the 10-year euro SWAP rate and Eurostoxx 600 computed via the DCC-GARCH as per Engle (2002). The yellow dotted line represents the sample correlation between the two series, while the vertical red dotted line marks the beginning of the 2022 ECB monetary policy tightening.

Figure 19: **Eurostoxx 600 conditional distributions under different FSS methodologies**



Histogram of the Eurostoxx 600 returns conditional marginal distributions, given a 200 basis points shock to the 10-year euro SWAP rate. The yellow dotted line represents the 50th percentile of each distribution. The left chart has been computed via the standard FSS approach. The middle chart has been computed via a weighting scheme for the data sampling in the FSS tool, with 95% probability associated with the 2022 sample and 5% with the reminder. The chart on the right has been computed via the FSS tool with forced correlations, assuming a −80% Pearson's correlation between the Eurostoxx 600 quarterly returns and the 10-year euro SWAP rate quarterly returns.

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