EUROPEAN CENTRAL BANK
EUROSYSTEM

Working Paper Series

Cyril Couaillier, Finn Faber, Joana Passinhas,
Costanza Rodriguez d'Acri, Frances Shaw

Monitoring banks' vulnerabilities using stressed depletion indices

No 3295 / October 2026

Disclaimer: This paper should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.

Abstract

We introduce two indicators to track the build-up of vulnerabilities in the euro area banking sector on a quarterly basis by leveraging the information collected in EU-wide solvency stress tests. First, we introduce an indicator of conditional capital depletion, the Stress Vulnerability Index (SVI), which quantifies potential losses under adverse scenarios when tail credit risk is highest. Second, we introduce an indicator of earnings vulnerability, the Profitability Vulnerability Index (PVI), which assesses the capacity of the banking sector to generate capital organically. While the two indices spike synchronously during systemic crises, they can also decouple. We show that this occurs when tail risks to capital subside but earnings remain compressed, or conversely, when recessionary fears mount while current profitability strengthens. These divergences provide actionable signals for macroprudential policy by distinguishing between the accumulation of solvency risks and the impairment of loss absorption capacity. In doing so, the indices support decisions on the activation, build-up, stability or release of prudential buffers. We validate the usefulness of the indicators by showing that both indicators were strongly associated with the probability that euro area banks received state aid in the aftermath of the Great Financial Crisis.

Keywords: Bank capital, Financial stability, Stress test

JEL codes: E61, G01, G21, G28

Non-technical summary

Can the information collected during biennial bank solvency stress tests be transformed into indicators providing regular updates on the build-up of vulnerabilities in the banking sector? In this paper, we introduce two new quarterly indicators to track the build-up of vulnerabilities in banks, leveraging the information collected by prudential authorities during the biennial EU-wide solvency stress tests conducted by the European Central Bank (ECB) and the European Banking Authority (EBA).

The first indicator, the Stress Vulnerability Index (SVI), builds directly on the results of the past EU-wide stress tests, exploiting the elasticities between bank common equity tier 1 depletion and the adverse scenario paths of selected macroeconomic variables, estimated in a Bayesian Model Averaging setting. The SVI simulates capital depletion under adverse scenarios, thus assessing how banks would perform if an adverse scenario were to materialize. The second indicator, the Profitability Vulnerability Index (PVI), relies on the relationship between macroeconomic data and actual bank profitability at the tails as a predictor of bank distress, estimated in a quantile panel-model econometric setting, similar to J. H. Lang & Forletta (2020). The PVI identifies pressures on banks' current earnings capacity by analyzing how macroeconomic conditions affect their profitability, focusing on the left tail of the profitability distribution. By combining these models with quarterly data, either realised or projected (based on the ECB's Staff Macroeconomic Projections Database), we generate time series of simulated bank-level capital depletion and profitability stress. Following Hollo et al., 2012 and Chavleishvili & Kremer, 2025, we transform the series into diffusion indicators to monitor the level of distress of euro area banks.

The indicators successfully capture key periods of banking sector stress. Both show elevated levels during the Global Financial Crisis and European Sovereign Debt Crisis, with the PVI index displaying sharper spikes during acute crisis episodes. However, there are periods during which the indicators point in different directions. We show that this occurs when tail risks to capital subside but earnings remain compressed, or conversely, when tail risk fears mount while current profitability strengthens. The EBA methodology, which underpins the SVI, explicitly focuses on capital depletion through loan losses and risk-weighted asset dynamics over multi-year adverse scenarios, while the PVI approach captures the immediate impact of macroeconomic conditions also on net interest income and operating profitability.

The complementarity of the SVI and PVI, including when the indices diverge, provides actionable signals for macroprudential policy by allowing policy-makers to distinguish between the accumulation of solvency risks and the impairment of absorption capacity. In doing so, the indices support decisions on the activation, build-up, preservation or release of prudential buffers. Notably, the recent decoupling between the two indices where the SVI remains slightly elevated despite improved profitability captured by the PVI validates the cautious approach advocated by macroprudential authorities to preserve existing buffer levels rather than reduce them, even during periods of strong bank profitability, when tail risks and uncertainty remain elevated. The indices therefore support the cautious approach to buffers advocated by the ECB in its recent stress test and macroprudential stress test extensions (see Rodriguez d'Acri & Shaw, 2025).

Finally, we show that both indicators were strongly associated with the probability that euro area banks received state aid in the aftermath of the Great Financial Crisis, with statistically significant positive coefficients for both country-wide and bank-specific recapitalization schemes during high-stress periods. This provides additional evidence that the indicators identify vulnerable banks and countries, and thus to support policymakers in the conduct of macroprudential policy.

1 Introduction

Every two years, the largest European Union (EU) banks undergo a stress test to assess their ability to withstand financial and economic shocks using an adverse scenario and a common methodology.[1] The information collected during the EU-wide stress tests, a major bank solvency stress test exercise in terms of complexity and total bank assets covered, is very rich; it provides transparency on bank solvency risks to market participants and it informs both macro- and microprudential policy; at the same time, its low frequency constrains its usefulness as a regular monitoring tool. This raises a critical question: can the rich information embedded in stress tests be transformed into high(er)-frequency indicators that provide regular updates on bank depletion risks and resilience? In this paper, we introduce two new quarterly indicators that leverage the information collected in EU-wide solvency stress tests to measure distinct but complementary dimensions of banking sector soundness: the Stress Vulnerability Index (SVI) and the Profitability Vulnerability Index (PVI). By transforming low-frequency stress test data into continuous monitoring tools, we provide prudential authorities with a dynamic assessment of bank solvency risks.

With our work we show how to leverage the granular information contained in stress test exercises to develop predictive and coincident bank distress indicators using balance sheet and stress test projection data. Specifically, we develop models that predict bank-level distress in terms of (i) the depletion of Common Equity Tier 1 (CET1) capital under adverse scenarios (SVI), and (ii) left-tail events in bank-level return on assets (ROA), where the chosen percentile is calibrated using past stress test outcomes (PVI), thereby capturing the materialization of profitability losses under severe yet plausible stress scenarios. The predictions of these models are then transformed into distress indices that can be monitored over time at a quarterly frequency to inform on banking vulnerability at the individual or system level.

A central contribution of this paper lies in demonstrating the complementarity of these two indices. While both indices successfully capture periods of acute systemic stress—such as the Global Financial Crisis (GFC) and the European Sovereign Debt Crisis (ESDC)—their dynamics can diverge meaningfully outside of these episodes, reflecting the distinction between stress tail risks and contemporaneous profitability risks. The SVI functions as an indicator of con-

[1] The EU-wide stress tests are conducted with a biennial frequency and is coordinated by the European Banking Authority (EBA) in cooperation with the European Systemic Risk Board (ESRB), the ECB and national competent authorities.

ditional capital depletion, capturing the magnitude of potential losses under adverse scenarios, when the tail risk of credit losses is highest. In contrast, the PVI acts as an indicator of earnings vulnerability, assessing the banking sector's capacity to generate organic capital —its first line of defense. Crucially, these two dimensions do not always co-move. While they spike synchronously during systemic crises, they can decouple during periods where tail risks to capital subside but earnings remain compressed, or conversely, when recessionary fears mount while current profitability strengthens. These divergences provide actionable signals for macroprudential policy by distinguishing between the accumulation of solvency risks and the impairment of capital generation capacity. A divergence between the two indices allows policymakers to assess whether the banking sector faces an acute threat to its capital stock — potentially warranting the accumulation of buffers — or a structural inability to replenish capital through retained earnings, which requires vigilance regarding business model sustainability. In this sense, our indicators help contain the tension identified by Benoit et al. (2017) between indicators that are developed to address regulatory needs but cannot be replicated and more global indicators conceived for market monitoring, which are, however, less useful for regulatory purposes. While relying on data that is broadly available to the public, the SVI and the PVI offer actionable signals to policymakers responsible for the calibration of prudential tools.

Significant strides have been made to measure systemic financial stability risks following the 2007-2008 crisis with indicators capturing the build-up of banking sector distress. Aggregate metrics have been developed to monitor the accumulation of financial imbalances, leverage and asset price misalignments using business and financial cycle indicators (Aikman et al., 2015; Deghi et al., 2018; J. Lang et al., 2019; Schüler et al., 2020). These measures mainly capture aggregate cyclical conditions rather than bank-level vulnerabilities and as such can inform the calibration of broad-based macroprudential tools. They struggle however to provide direct mapping between risk of adverse scenarios and the impact on banks' capital, which would also inform the preemptive build-up of adequate capital buffers. As discussed in detail in this paper, the joint review of the SVI and PVI indices instead provide insights to policymakers about banks' resilience to shocks and the need to build buffers in more comprehensive way than what is provided for by more broad based measures of systemic risk accumulation.

Efforts to predict bank distress have instead focused on deriving the probability of a bank entering a vulnerable state in a forward-looking manner. This provides the necessary lead time to act—for example, by activating or tightening prudential buffers to dampen the financial cycle

or increase resilience. Extending the work of Betz et al. (2014), J. H. Lang et al. (2018) identify macro- and bank-specific risk drivers with the best real-time forecasting properties to signal future distress. Similarly, J. H. Lang & Forletta (2020) identify vulnerable banks by projecting the left tail of the return-on-assets (ROA) distribution three to five years ahead. In these frameworks, banks' vulnerable states are often defined using a binary variable preceding distress events (e.g., state aid, distressed mergers). The SVI complements these approaches by using stress test elasticities to generate a continuous measure of conditional capital depletion. Notably, Philippon et al. (2017) demonstrate that stress test-based sensitivities to macroeconomic factors contain predictive information regarding realised losses, thus providing reliable information on bank resilience. The SVI builds on this insight, creating a vulnerability index that answers how much capital would be depleted if a severe scenario were to occur today.

In parallel to predictive models, efforts to identify systemic financial stress events have led to the development of coincident indicators. Instead of trying to predict future distress, these indices provide information on the current state of the financial system and can be used in real time to assess instability and inform policy action, such as the loosening of macroprudential policy. Most of these popular indicators are composite, designed to capture the multi-faceted nature of financial crises: the CISS for the euro area as a whole (Hollo et al., 2012; Chavleishvili & Kremer, 2025) and the CLIFS for a country-specific approach (Duprey et al., 2017).[2] The PVI aligns with this coincident perspective: by measuring the current risk of compression of the banking sector's earnings capacity, it assesses the system's immediate ability to absorb shocks (profitability vulnerability).

At the same time, several widely used market-based measures of systemic risk rely on bank share price information (Acharya et al., 2017; Brownlees & Engle, 2017; Adrian & Brunnermeier, 2016) to provide real-time information. However, these indicators are only available for listed banks and implicitly assign a significant weight on the risks arising from interconnections between banks.[3] By contrast, we use bank balance sheet information to estimate the PVI and SVI,

[2]They are obtained by normalizing a set of stress indicators using their empirical cumulative distribution in a recursive manner, after initializing the standardization for a fixed period of time. This is done to mitigate the risk of future data signaling financial instability in the past, which would reduce the real-time feature of the approach. It also prevents event reclassification as new data could change previous assessments. Besides aggregating these normalized stress indicators, both the CISS and the CLIFS consider the correlation among the sub-indicators, as systemic financial stress relies on a strong co-movement to extreme stress for all identified dimensions. Results using the CISS display strong explanatory power regarding the left tail of the real growth distribution, strengthening the link between financial stress events and economic crises (Chavleishvili & Kremer, 2025).

[3]Many coincident, share-price based, metrics quantify how much an individual bank is affected by stress in

resulting in an index that is available for more banks, less prone to fluctuations driven by market sentiment, and that also offers a clearer perspective on individual banks' vulnerabilities, as interconnections play a less prominent role. We offer in this way a complementary perspective to approaches that identify an important role for banking sector networks in predicting crises (Minoiu et al., 2013). In addition, our approach allows us to monitor profitability developments for both listed and unlisted banks.

The PVI also connects to a more recent literature that addresses financial stability questions by focusing on the tails of outcome distributions rather than their averages. Beginning with Adrian et al., 2019, the growth-at-risk approach asks how the left tail of future GDP growth varies with current financial conditions. J. H. Lang & Forletta, 2020, Passinhas & Pereira, 2023 and De Nora et al., 2025 extend this approach to bank-level outcomes, projecting the left tail of the return-on-assets distribution or calibrating capital buffers against tail risks. The PVI also sits within this literature, applied directly to the bank level question of profitability vulnerability rather than to aggregate growth outcomes.

We use state-aid interventions as an external validation exercise for our indicators. Specifically, we investigate whether peaks in individual banks' PVI and SVI are associated with the receipt of state-aid packages. If the indicators successfully identify vulnerable institutions, periods of elevated stress should be associated with a higher likelihood of subsequent public support measures. We find that both indices are strongly associated with state-aid events during the crisis period, with statistically significant positive relationships between elevated index values and both country-wide banking sector support schemes and bank-specific recapitalisations.

The rest of the paper is organised as follows: Section 2 describes the econometric specifications and data used to model bank distress. Section 3 describes the time evolution of each index and identifies it's main drivers, also showing how the two indices co-move over time. Section 4 shows, as a robustness check, how the indicators could have identified vulnerable banks during the Great Financial Crisis while Section 5 concludes.

another bank or the banking sector as a whole.

2 Designing the two indices

2.1 Stress test based approach

The stress test based approach leverages the elasticities obtained from the EU-wide stress test exercises to project how banks' capital would be depleted under adverse macroeconomic scenarios. This approach captures potential capital vulnerabilities by assessing how simulated adverse developments in key macroeconomic variables would affect bank capital ratios through credit losses and risk-weighted asset dynamics.

2.1.1 Data and variables

The stress test based approach relies on simulated data coming from EU-wide stress test exercises for the years 2018, 2021 and 2023. For each exercise, the European Systemic Risk Board (ESRB), in collaboration with the ECB, produces a baseline and an adverse 3-year scenario; the former is based on the most recent Broad Macroeconomic Projection Exercise (BMPE), i.e. the biannual main forecast exercise of the Eurosystem; the latter simulates "severe yet plausible" adverse scenarios, by assuming the materialization of the main macrofinancial risks identified by the ESRB. In a second stage, banks' balance sheets and profits and losses are projected under both scenarios, with a mix of centralized top-down models and bottom-up projections from banks. The key results are the projected evolution of the CET1 ratio at bank level for each scenario.

For each stress test exercise, we retrieve the 3-year change in macrofinancial variables under both baseline and adverse scenarios, along with bank-level characteristics at the starting point (i.e. the year before the start of the projections), and the 3-year change in CET1 ratio in both scenarios. The macroeconomic drivers we include in the model are unemployment rates (URX), short-term nominal rates (STN), and growth rate of real gross domestic product (GDP) and real estate prices (RPP) - similar to the profitability vulnerability index discussed later. In addition, the iTraxx index is included as a measure of credit default swap rates. We capture sovereign spreads as the difference between 10-year government bond yields and swap rates of the same maturity. The slope of the yield curve is the difference between short- and long-term interest rates. Further, we leverage the detailed balance-sheet information provided by banks to include measures of credit risk, namely bank-level probabilities of default (PD), their total assets, their risk exposure amount (REA), and net interest income (NII), the last two expressed as a ratio to total assets. Our sample includes 93 banks, representing more than 75% of the total assets of

the banks placed under direct supervision by the ECB (the so called *Significant Institutions*). We exclude banks belonging to specific business models (Development/Promotional Lenders, Asset Managers and Custodian Banks) from the estimation sample, as the distinctive nature of their operations makes their quantitative depletion results more challenging to evaluate.

Details on the estimation sample properties' for model variables are included in Table 1. Adverse scenario 3-year CET1 capital depletion is considerable with an average of -5.92% and there is large heterogeneity across banks and exercises. Macroeconomic variables such as real GDP, real-estate prices and unemployment have the expected signs, conditional on the scenario. Projections for short-term rates and the slope of the yield curve reflect different monetary regimes characterising each stress test (e.g. low-for-long in 2018 and rising rates in 2023), and do not show clear tendencies between baseline and adverse scenarios. Finally, bank-level starting points are constant between baseline and adverse scenarios, and show significant cross-sectional variation within the sample.

Table 1: Descriptive statistics used to estimate the stress test based indicator

Scenario	Baseline	Adverse	Baseline	Adverse	Baseline	Adverse	Baseline	Adverse	Baseline	Adverse	Baseline	Adverse	Baseline	Adverse	Baseline	Adverse
Statistic	Mean	Mean	SD	SD	P10	P10	P25	P25	P50	P50	P75	P75	P90	P90	N	N
Δ CET1 (%)	1.08	-5.90	2.64	4.03	-1.00	-9.99	-0.08	-6.64	0.75	-5.19	2.08	-3.85	3.18	-2.62	236	236
GDP (in %)	7.18	-4.02	3.28	1.77	3.29	-6.31	4.19	-5.68	6.27	-3.77	9.91	-2.96	11.93	-1.50	237	237
Real estate prices (%)	8.58	-18.74	4.94	5.89	2.44	-25.84	4.99	-23.02	8.59	-18.75	12.53	-15.09	14.35	-10.55	237	237
Unemployment level (%)	7.14	10.11	3.14	3.45	3.88	6.35	4.84	7.74	6.35	9.46	8.66	11.13	11.60	15.53	237	237
Δ Sovereign Spreads (%)	-0.07	0.53	0.35	0.69	-0.40	-0.21	-0.24	0.10	0.01	0.54	0.14	1.00	0.22	1.62	237	237
Δ iTraxx	1.62	113.32	2.91	61.10	-1.27	19.29	-1.27	19.29	0.00	149.06	5.21	157.23	5.21	157.23	237	237
Δ Short-term rates (%)	0.90	1.53	1.08	1.62	-0.15	-0.16	-0.11	-0.13	0.26	0.74	2.27	3.55	2.35	3.60	237	237
Δ Yield curve slope (%)	-0.40	-0.46	0.93	0.85	-1.63	-1.46	-1.54	-1.39	0.12	-0.36	0.34	0.40	0.46	0.56	237	237
PD (%)	0.82	0.82	1.14	1.14	0.02	0.02	0.25	0.25	0.50	0.50	1.00	1.00	1.76	1.76	236	236
Assets (log)	11.67	11.67	1.30	1.30	10.46	10.46	10.82	10.82	11.41	11.41	12.47	12.47	13.66	13.66	236	236
NII / TA (%)	1.22	1.22	0.62	0.62	0.53	0.53	0.82	0.82	1.14	1.14	1.54	1.54	2.12	2.12	236	236
RWA / TA (%)	38.68	38.68	16.60	16.60	17.28	17.28	29.46	29.46	35.97	35.97	47.65	47.65	59.57	59.57	236	236
Starting point CET1 (%)	18.50	18.50	11.50	11.50	12.04	12.04	13.37	13.37	15.48	15.48	18.58	18.58	24.75	24.75	236	236

Sources: Authors' calculations based on data from Bloomberg, ECB, European Commission, Eurostat, IMF, National Central Banks (through ECB Statistical Data Warehouse) and supervisory data.
Notes: Variables in changes (%) represent change (growth) across three years, except the bank-level variables which are starting points.

2.1.2 Methodology

Estimation of the bank level capital depletion relies on a three-step approach, first letting the data speak through a set of agnostic regressions, then disciplining the results via sign restrictions, finally aggregating the models in a single one, giving more weight to the best performing specifications for each bank.

First, we run a series of regressions, regressing the bank-level 3-year change in CET1 ratio

over the macrofinancial and bank-level variables described earlier.[4] The macrofinancial variables are taken as 3-year change in the relevant scenario and the bank-level variables at starting point of the relevant stress test exercise. The objective of this step is to consider all possible set of relevant right-hand side variables, while avoiding overloading the regression with too many explanatory variables at the same time. For further flexibility, the analysis also considers two regression models: (1) regressions weighted by risk weighted assets (RWA) with business model fixed effects, and (2) regressions weighted by RWA with bank-specific fixed effects. This approach yields a sample of around 1000 regressions.

In a second step, the resulting regressions are disciplined via sign restrictions to ensure robustness and theoretical consistency. In practice, we impose a set of restrictions on the estimated coefficients and any estimated equation that violates these constraints is excluded from the set of candidate models. Those restrictions, reported in the Appendix A.1 are based on the economic literature and ensure that the selected equations display a meaningful economic behavior. The table includes four columns, one for each of the fixed effect and estimator combinations used.

The third and final step consists of aggregating the selected candidate model in a unique equation via a Bayesian Model Averaging (BMA) approach. First, we rank the equations according to their Bayesian Information Criterion (BIC) and select the top equations contributing to 99% of the cumulative model Bayesian weight. This is to avoid the proliferation of explanatory variables coming from equations with negligible weight. Then, we define an average equation for each setting of fixed effects, averaging all remaining equations, with weights assigned according to the Bayesian posterior probabilities. This approach ensures that variables appearing less frequently in the top equations, indicating weaker explanatory power, have proportionally lower contributions to capital change projections, compared to their unweighted coefficients.

Finally, these average equations are combined into one final projection per bank and scenario using a two stage weighting process. For each model, we assign a weight based on its overall goodness of fit (R^2), normalised relative to the other model. Additionally, for each model-bank combination, we assign a weight based on how well that model has historically predicted that

[4]We chose to use the change in CET1 ratio compared to the starting point rather than compared to the baseline for two reasons. First, this is the standard main metrics used in the EU-wide stress test exercise. Second, policymakers primarily care care about whether banks have enough capital to survive a crisis, not about how they would have performed in a world where no crisis occurred. The starting-point comparison is therefore more intuitive and policy-relevant, as it directly measures the capital a bank could lose relative to where it actually stands at the onset of stress. Accordingly, we designed the SVI to inform on actual capital at risk due to its policy objective.

specific bank's outcomes, measured by the root mean squared error (RMSE) and normalised across all banks within each model. The final projection for each bank is a weighted average of the two model projections, where each model's contribution is determined by the product of its overall fit weight and its bank-specific fit weight:

$$\text{Proj}_b = \sum_{m=1}^{2} w_m^{(R^2)} \, w_{m,b}^{(\text{RMSE})} \, \text{Proj}_{m,b} \tag{1}$$

where $w_m^{(R^2)}$ is the weight assigned to model m based on its R^2 relative to the other models (such that the weights sum to one across models), and $w_{m,b}^{(\text{RMSE})}$ is the weight assigned to model m's projection for bank b based inversely on the RMSE of that projection, normalised such that for each model, the RMSE weights across all banks sum to one. This approach accounts for both overall model performance and individual bank-specific predictive accuracy.

2.1.3 Estimation results

Table 2 reports the Bayesian-weighted coefficients from the stress-based model estimated on pooled EBA stress test data (2018, 2021, 2023). The two panels correspond to our alternative specifications: bank fixed effects (left) and business model fixed effects (right). For each variable, we report the posterior-weighted coefficient and the Bayesian weight indicating the share of top-performing models in which the variable appears.

The results show that real economy variables dominate the stress test-based projections, consistent with the importance of credit risk transmission in the EBA methodology and in euro area banks' balance sheets. GDP growth and unemployment emerge as the most robust predictors, with Bayesian weights at or near unity in both specifications. The coefficient on GDP (unemployment) implies that a 1 percentage point deterioration in cumulative GDP growth (unemployment) over the stress horizon is associated with 12–22 (55) basis points of additional CET1 depletion. Real property prices carry substantial explanatory power (Bayesian weight of 0.99–1.00), with coefficients of 0.06–0.12 indicating that real estate corrections amplify capital depletion through collateral valuation effects and mortgage portfolio deterioration. This channel proved particularly salient during the Great Financial Crisis and remains a key vulnerability for European banks with concentrated real estate exposures.[5]

[5]The negative coefficient of the yield curve is likely driven by the methodology of the EU-wide stress test. Notably, it constrains the net interest income to be lower than its starting point in the adverse scenario, offsetting the positive impact of a steepening of the yield curve on NII, while still accounting for the negative impact on

In contrast, financial market variables exhibit lower and more heterogeneous Bayesian weights. Sovereign spreads and the iTraxx index appear in fewer top performing models, suggesting that while these variables contribute marginally to fit, they are less robust predictors of capital depletion than real economy fundamentals. This pattern is consistent with the EBA methodology and euro area banks' focus on credit losses from the loan book rather than mark-to-market effects on securities portfolios.

Bank-level starting points generally receive low Bayesian weights (0.06–0.13), suggesting that once time-invariant bank or business model specific factors are accounted for through fixed effects, the remaining variation in capital depletion is more strongly driven by the severity of the macroeconomic scenario than by the observed bank or business model characteristics. The interaction terms between GDP or unemployment and bank PD also receive negligible weight, suggesting limited evidence of non-linear amplification through initial asset quality in the stress test projections, though this may partly reflect the constrained sample size.

We assess the robustness of those results via in-sample and out-of-sample tests. Since this analysis is based on stress test data, we compare its projections with the stress test outcomes under the adverse scenarios of the exercises used for estimation (2018, 2021, and 2023) for in-sample performance, as well as under the adverse scenario of the most recent exercise not included in the estimation sample (2025) for out-of-sample performance. The results indicate that the model captures the variability of the final stress test outcomes reasonably well in both in-sample and out-of-sample settings, with recent exercises displaying an R^2 above 50% (Appendix A.2). This evidence is reinforced by root mean squared errors that are below—or comparable to—the sample standard deviation in the in-sample and out-of-sample exercises, respectively. To complement those robustness checks performed on stress test data with real work analysis, Section 4 explores the predictive performance of the SVI on actual state-aid interventions during crisis, akin to an additional out-of-sample test.

2.2 Profitability-based approach

The profitability vulnerability index examines the relationship between bank profitability and the current macroeconomic environment in a quantile setting. By focusing on the left tail of the conditional profitability distribution, this approach captures how current macroeconomic conditions compress bank earnings, in particular interest rate dynamics given their impact on

the market value of securities.

Table 2: Estimated weighted coefficients and Bayesian weight for each model of the stress-based approach

Macro variables	Bank fixed effects		Business model fixed effects	
	Weighted Coefficient	Bayesian weight	Weighted Coefficient	Bayesian weight
ΔSovereign spreads	−0.00054	0.04	−0.00095	0.01
ΔURX	–	–	−0.05823	0.21
ΔSTN	0.00059	0.04	0.21219	0.47
ΔYield curve slope	−0.42793	1.00	−0.27722	0.62
ΔiTraxx	−0.00007	0.02	−0.00752	0.64
GDP	0.21616	1.00	0.12373	0.74
RPP	0.06072	0.99	0.11853	1.00
URX	−0.55084	1.00	–	–
Bank variables				
NII (% Assets)	0.00083	0.06	0.00014	0.10
REA (% Assets)	−0.00009	0.06	0.00001	0.11
PD	0.00071	0.08	−0.01411	0.11
Log Assets	–	–	0.01602	0.13
Interaction terms				
GDP:PD	0.00001	0.00	0.00194	0.02
ΔURX:PD	–	–	0.00657	0.04
URX:PD	−0.00035	0.01	–	–

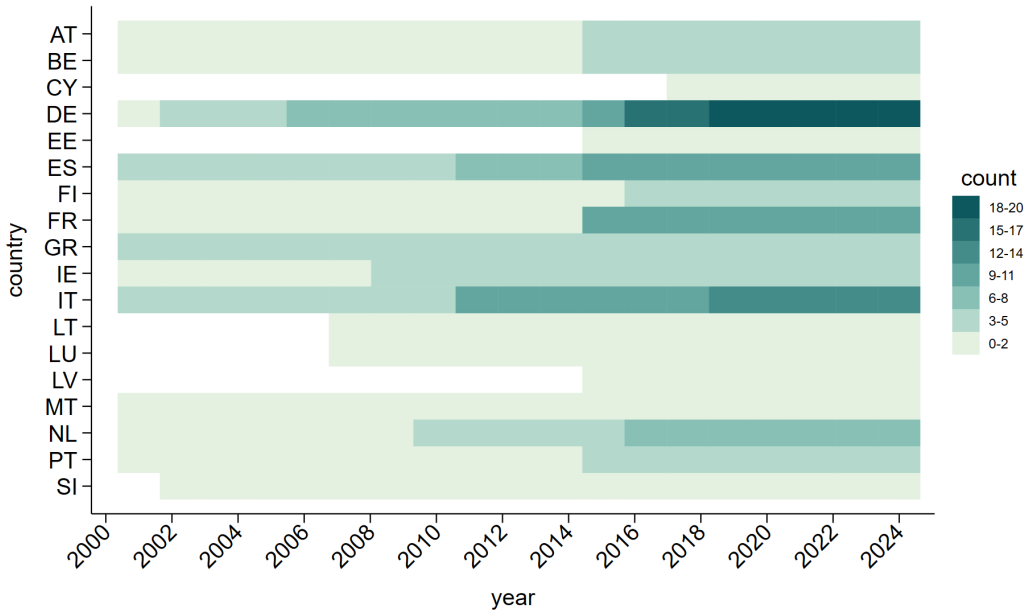
Notes: Regressions consider estimates weighted by REA. Weighted coefficients are obtained by considering each variable average estimated coefficients over the selected equations and then scaled by the Bayesian weights. The list of selected regressors contains the unemployment rate (URX) in level and in first-difference, the short-term nominal rates (STN) in first-difference, the growth rates in the gross domestic product (GDP) and in the real estate prices (RPP), the first-difference in iTraxx index ($\Delta iTraxx$), in slope of the yield curve ($\Delta Yieldcurveslope$) and in sovereign spreads ($\Delta Sovereignspreads$), starting point values of bank-level probabilities of default (PD), their total assets in log ($LogAssets$) and their risk exposure amount and net interest income as a ratio to total assets ($REA(\%Assets)$ and $NII(\%Assets)$ respectively), and the interaction of PD with GDP, URX and ΔURX.

net interest margins.

2.2.1 Data and variables

We employ an unbalanced quarterly panel of 94 EU banks covering the period between 2001Q1 - 2024Q4. We include most banks that participated in the 2025 EU-wide stress tests for which a sufficiently long time-series exists. Our sample includes a total of 5,130 observations, corresponding to more than 75% of the euro area's banking assets located in all euro area countries[6], with coverage increasing over time[7] (see Figure 1). The dataset builds on two different sets of information: i) bank-level data sourced from market data sources and supervisory reporting and ii) macro-financial indicators. To account for different geographical exposures in the balance-sheet, macroeconomic variables are weighted at the bank level using banks' credit risk exposures by geography, which we retrieve from supervisory data.

Figure 1: Number of banks by country and year



Sources: Authors' calculations based on data from Bloomberg, ECB, European Commission, Eurostat, IMF, National Central Banks (through ECB Statistical Data Warehouse) and supervisory data.
Notes: This figure reports the number of banks per country in the estimation sample of the PVI.

The dependent variable is defined as the annualized returns over current assets for each bank

[6]Banks from Germany, France, Italy and Spain account for most observations in the dataset.
[7]From 2014 onward there is a larger sample following the new harmonized framework for the collection of statistical information on consolidated banking data in all Member States of the EU.

at each quarter. The macro-financial variables included in the model are the annual growth in GDP, stock price growth, residential real estate price indices, both short and long-term interest rates, defined as the 3-month interbank market rates and 10-year sovereign yields, respectively. A dummy variable for 2020 controls for this very specific period characterized by the COVID-19 pandemic. Table 3 summarises the statistical properties of the variables. Importantly for our model, a substantial tail of observations showcase weak macrofinancial environment and bank profitability, with banks' ROA and yearly growth in output, equity prices, and house prices being negative for more than 10% of the sample. This confirms the validity of focusing on this (substantial and risky) left tail. Regarding rates, most of the sample period covers the *low-for-long* era of near or below zero policy rates. However, it also covers the rapid monetary tightening of 2022-2023, and as such covers two main types of rate risk for banks: *low-for-long* rates compressing margins, and rapid rate tightening forcing a substantial negative repricing of assets.

Table 3: Descriptive statistics used to estimate the profitability-based indicator

Variable	Mean	SD	P10	P25	P50	P75	P90	N
Return on assets (%)	0.47	0.49	-0.07	0.17	0.41	0.72	1.18	5130
Real GDP growth (%)	1.68	3.30	-2.47	0.51	1.84	3.05	5.08	5130
Equity prices growth (%)	4.89	19.36	-20.16	-7.41	6.03	17.82	27.63	5130
Residential real estate prices growth (%)	3.62	5.61	-2.73	0.71	3.74	6.73	10.44	5130
3-month interbank rate (%)	1.38	1.95	-0.38	-0.23	0.42	2.92	3.99	5130
10-year government yield (%)	2.56	2.18	0.22	0.84	2.53	3.90	4.71	5130

Sources: Authors' calculations based on data from Bloomberg, ECB, European Commission, Eurostat, IMF, National Central Banks (through ECB Statistical Data Warehouse) and supervisory data.
Notes: Growth variables are obtained as 1 year growth rates.

2.2.2 Methodology

We obtain a profitability-based measure of banking stress by using quantile regressions to estimate the relationship between profitability and the macro-financial scenario in an adverse setting, focusing on a low quantile. If the left-tail of a bank's ROA distribution becomes more negative, this signals an increase of downside risk as, with the same probability, it is estimated that the bank would incur more losses. In turn, this would deplete capital which is harder to replace when financing conditions are tighter, which usually happens when a bank is in distress.[8]

[8]This distributional analysis has been explored in the context of macroprudential policy in several papers (J. H. Lang & Forletta, 2020, Passinhas & Pereira, 2023, De Nora et al., 2025).

Quantile regressions capture the possible non-linear relationship between profitability and its drivers when a shock happens, leading to more extreme elasticities than in normal times. To test for this possibility, we conduct a Khmaladze test as proposed in Koenker & Xiao (2002) and find evidence that the variables affect the location, the scale and the shape of the conditional distribution of ROA (Appendix B.1). Technically, we strongly reject both the location and location-scale model.[9] Given these results, and since we have a lagged dependent variable that could give rise to the Nickel bias, we consider the Galvao (2011) method of estimation in which the lagged dependent variable is instrumentalised by its own lag.

The form of the conditional quantile regression used to estimate the relevant quantiles (τ) of each bank i's profitability distribution at time t is given by:

$$Q_{\pi_{i,b,t}}(\tau|\pi_{i,t-4}, \mathbf{X}_{i,t}) = \alpha_b(\tau) + \rho(\tau)\pi_{i,t-4} + \mathbf{X}'_{i,t}\boldsymbol{\beta}(\tau) \tag{2}$$

where $\pi_{i,b,t}$ is the profitability measure, annualized ROA, at time t for bank i of the b business model, $\alpha_b(\tau)$ are business model fixed effects, $\rho(\tau)$ identifies persistence in annualized profitability, $\mathbf{X}_{i,t}$ is the vector of exposure weighted macro-variables as previously defined, and $\boldsymbol{\beta}(\tau)$ is a vector with the quantile effects of the macro-variables.

2.2.3 Estimation results

Results for selected low quantiles and the median are presented in Table 4. Previous profitability is statistically significant and consistently positively affects banks' profitability distribution, although the impact declines at lower quantiles, capturing higher income volatility when banks are under stress. We obtain the expected positive signs for the variables related with the business cycle, as higher real GDP, equity prices, and residential real estate growth signal higher demand for credit and for financial services while supporting credit quality (at least in the short term) and inducing higher monetary policy rates, supporting banks' profitability. While GDP and equity variables have a relatively steady impact across the three tested quantiles of bank's ROA, the impact of residential real estate prices increases at lower quantiles, capturing the impact on housing crises on banks' tail profitability risk. Finally, higher policy rates support banks' profitability via net interest income, while the negative impact of 10-year sovereign yields reflect

[9] To perform these tests, we considered the lagged dependent variable and the variables in Table 3, as well as business models fixed effects. Since we are not considering bank individual fixed effects, and we have enough coverage on the 12 business models employed, results do not suffer from the incidental parameter problem.

the credit spread their capture. The latter impact substantially increases at lower ROA quantiles, again reflecting its tail risk nature.

Table 4: Estimation results for the conditional distribution of annualized ROA

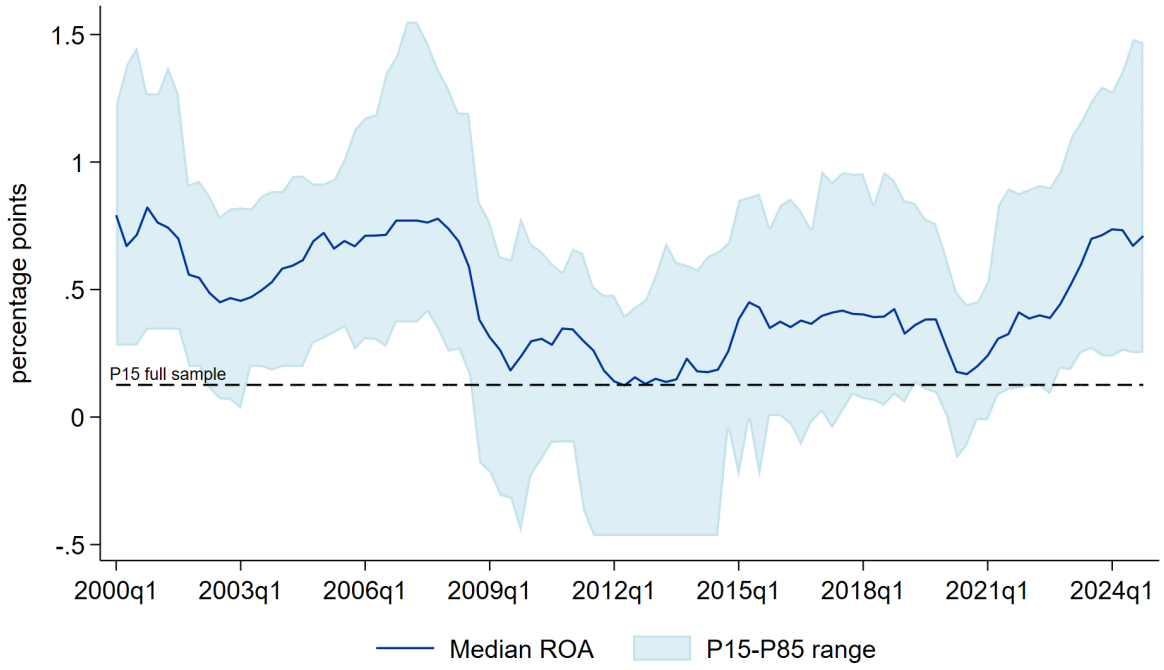
Variables	$\tau = 0.1$	$\tau = 0.15$	$\tau = 0.5$
Return on assets (4-quarter lag)	0.596***	0.637***	0.713***
	(0.053)	(0.043)	(0.048)
Real GDP growth	0.019***	0.016***	0.018***
	(0.004)	(0.004)	(0.003)
Equity prices growth	0.003***	0.004***	0.003***
	(0.001)	(0.001)	(0.0004)
Residential real estate prices growth	0.009**	0.008***	0.003
	(0.003)	(0.002)	(0.002)
3-month interbank rate	0.058***	0.047***	0.030***
	(0.015)	(0.011)	(0.008)
10-year government yield	-0.044***	-0.035***	-0.014**
	(0.014)	(0.010)	(0.007)
Covid-19 dummy (year 2020)	-0.150*	-0.105	-0.006
	(0.088)	(0.064)	(0.032)
Observations	5,130	5,130	5,130

Notes: τ represents the target percentile of the respective quantile estimation. The quantile regression model includes business model fixed effects that vary across quantiles. Bootstrapped (considering 500 replications) standard errors clustered at bank-level are in parenthesis. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

We use the results on 15^{th} percentile to build the profitability-based index for three reasons. First, looking at the period before the Great Financial Crisis, the 15th unconditional percentile before 2008, while positive, would go below zero much faster than the median (Figure 2). This asymmetric behavior emerges again during the European Sovereign Debt Crisis and further confirms the option to look at lower percentiles rather than at the center of the distribution. Second, the 15th percentile of the unconditional ROA distribution, considering the full sample, is positive but close to zero, whereas the 10th percentile would already be negative. This relates to the goal of wanting to establish a stress indicator that signals the start of banking stress before losses emerge, preferable to more extreme percentiles such as the 10th or the 5th. Third,

when comparing tail projections based on the 15th percentile coefficients we are also most able to match the stress test projections reported by banks in the latest stress tests.

Figure 2: ROA unconditional distribution through time



Sources: Authors' calculations based on supervisory data.
Notes: Median, 15th (P15) and 85th (P85) percentiles obtained for each point in time, reflecting bank heterogeneity.

We perform a number of robustness checks to assess the sensitivity of our results to the choice of estimator and to validate the model specification. In particular, we re-estimate the 15th percentile of annualized ROA using three approaches: the quantile via moments estimator of Machado & Silva (2019), the standard quantile regression of Koenker & Bassett Jr (1978), and the IV quantile regression approach based on Galvao (2011) (using the IV quantile regression estimator of Chernozhukov & Hansen (2006)). We confirm that estimates are broadly similar across methods and display the same signs (Appendix B.2). Differences mainly concern the magnitude of the lagged dependent variable and the significance of residential real estate price growth. Despite similar fitted values across estimators, we retain the IV quantile regression due to concerns about Nickell bias and the rejection of the location-scale specification.

We also evaluate how well each estimator targets the 15th percentile by comparing the share of observations below the fitted values across subsamples. All approaches perform reasonably

well, with observed proportions close to the 15% benchmark and similar squared correlations between fitted and actual profitability (Appendix B.2). This suggests that overall fit is comparable across methods. We perform a similar exercise but in an out-of-sample situation, with an expanded estimation window, to infer on the out-of-samples properties of the chosen estimator and conclude it performs well in estimating the 15th percentile, confirming the model's ability to capture future left-tail risks to bank profitability (Appendix B.3).

Finally, we validate the model by analyzing the contribution of each regressor to how well our predictions fit the overall variability of the dependent variable. The full specification achieves a squared correlation above 50%, compared with just above 40% for a simple AR(1) model. Adding macroeconomic variables - such as GDP growth, equity prices, real estate prices, and short-term interest rates—provides modest improvements in fit (Appendix B.3).

2.3 Constructing bank stressed resilience indices

To estimate the Stress Vulnerability Index (SVI), the elasticities obtained from simulated stress test data, are applied to historical bank-level data and projections of macro-financial variables. We retrieve bank-level starting points from COREP and FINREP reporting. To ensure a long historical perspective, we complement this with Bloomberg data for the period prior to 2015, extending balance-sheet information backward where early data points are unavailable. [10]

Projections of macro-financial variables under an adverse scenario are obtained through time by considering its path under the most probable stress scenario relevant to each period and the baseline from the (Broad) Macroeconomic Projection exercise (BMPE):

$$var_t = var_{BMPE} + (var_{adverse} - var_{baseline}) \tag{3}$$

We consider different relevant stress paths for the variables over time by leveraging the exercises used for estimation (2018, 2021, and 2023), as well as the most recent exercise (2025). We also incorporate the narrative shocks from earlier exercises, including the 2014 Comprehensive Assessment (CA) and the 2016 exercise, together with the Pandemic (2020) and Russia–Ukraine (2022) Vulnerability Assessments designed by the ECB. The cumulative three-year changes in real GDP growth, along with the end period used for the index of each scenario, are reported

[10] Most employed bank-variables are available backwards, with different time spans for each bank, as they are in current supervisory data and therefore require no further adjustments. The exception is the probability of default, which is not directly available. To construct this measure, we rely on its relationship with non-performing loans.

in Table 5.

Table 5: Cummulative real GDP growth under different exercises

	2014	2016	2018	2020	2021	2022	2023	2025
Adverse	−2.28%	−2.00%	−2.08%	−7.86%	−3.56%	−4.50%	−5.82%	−6.07%
Adverse–baseline	−7.52%	−8.22%	−9.14%	−13.20%	−13.48%	−12.83%	−10.66%	−11.44%
Scenario used until	2015q3	2017q3	2019q3	2020q3	2021q3	2022q3	2024q3	–

Sources: ECB and EBA data.
Notes: Values are an average considering the set of banks used to obtain SVI and are weighted by their corresponding exposure to different jurisdictions.

This results in a quarterly, bank-level projection of CET1 depletion conditional on the most salient macro-financial risks identified at that point in time. The lower severity of the adverse scenario in earlier stress tests exercises, starting in 2014 and reaching up to the 2018 exercise, affect the SVI until the third quarter of 2019. More stringent scenarios, such as those designed in more recent years, would have produced a higher estimated capital depletion, possibly signaling higher stress during the GFC than in the COVID-19 crisis.

For the profitability vulnerability index (PVI) we don't rely on scenario data. We instead use current macroeconomic data and previous bank-level profitability measures for the estimates of the $15th$ percentile to project tail profitability for each bank.

To construct the normalised SVI and PVI , we transform the bank-level raw projections into two aggregate indices bounded by [0,1], following the approach of Hollo et al. (2012). To do so, we consider, for each index, their underlying pooled sample of bank-level projections $\hat{y} = (\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n)$ with n the total number of observations in the sample (banks $\times$ time periods). The ordered sample is then $(\hat{y}_{[1]}, \hat{y}_{[2]}, \ldots, \hat{y}_{[n]})$ where

$$\hat{y}_{[1]} \leq \hat{y}_{[2]} \leq \ldots \leq \hat{y}_{[n]}$$

with $[r]$ the ranking number such that $\hat{y}_{[n]}$ represents the sample maximum, e.g. the highest level of estimated profitability (in case of the PVI) considering all banks and time periods, and $\hat{y}_{[1]}$ is the minimum projected profitability in the sample. The transformed stress index for bank i at time t ($I_{i,t}$) is computed as the complement of the empirical cumulative distribution function (CDF) $F(\hat{y_{it}})$, as higher profits at the tail would correspond to less stress. This can be defined as:

$$I_{it} = 1 - F(\hat{y}_{it}) := \begin{cases} 1 - \frac{r}{n} & \text{for } \hat{y}_{[r]} \leq \hat{y}_{it} < \hat{y}_{[r+1]}, \quad r = 1, 2, \ldots, n-1, \\ 0 & \text{for } \hat{y}_{it} \geq \hat{y}_{[n]} \end{cases} \tag{4}$$

$$\text{for } t = 1, 2, \ldots, T, \qquad \text{for } i = 1, 2, \ldots, I, \qquad \text{with } n = I \times T.$$

Then, for a particular observation $\hat{y}_{it}$, the index I_{it} will give the share of observations in the sample (across banks and time periods) that were estimated to have higher profitability than bank i in t, in a tail event.

3 Results

3.1 Stress Vulnerability Index

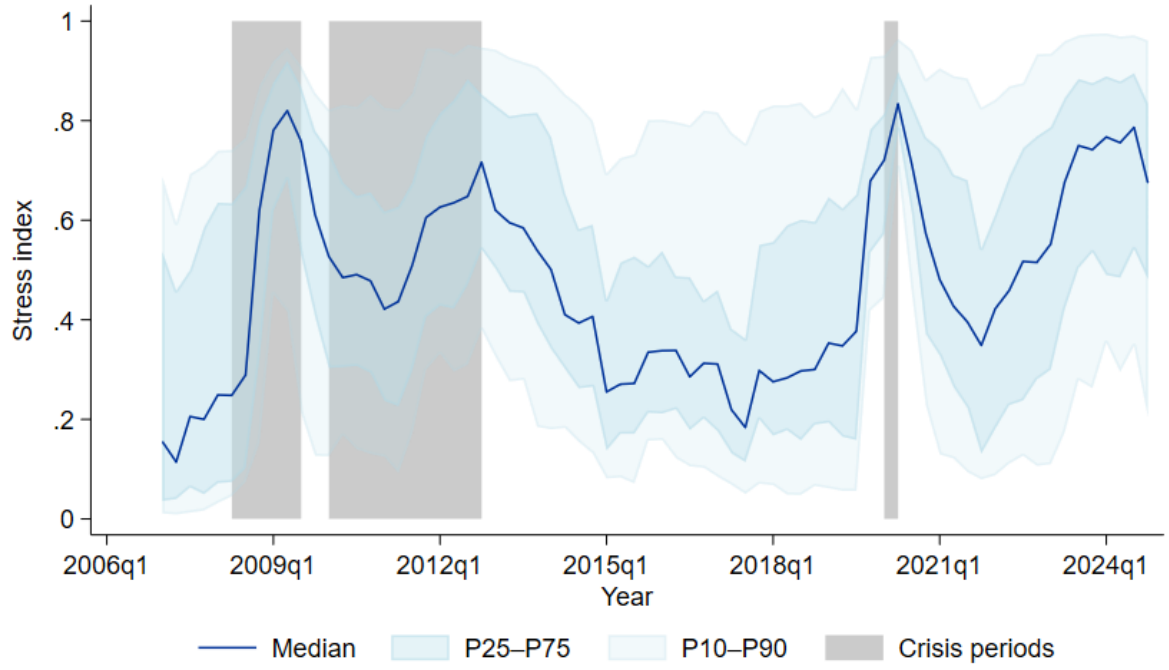
The SVI captures the evolution of prospective banking sector vulnerabilities under adverse macroeconomic scenarios over time (Figure 3). It shows moderate stress levels in the pre-crisis period of 2006-2007, but increases over time, reflecting the building of systemic risks that would materialize during the Great Financial Crisis. Stress rises sharply in 2008-2009 as the crisis unfolds, with the median index reaching values around 0.8, indicating that under adverse conditions, a substantial majority of banks would experience significant capital depletion.

Following the initial crisis peak, the index moderates somewhat in 2010-2011 but remains elevated, consistent with on-going fragility in the banking sector. A second wave of elevated stress emerges during 2011-2013, coinciding with the European Sovereign Debt Crisis (ESDC), where peripheral sovereign spreads and deteriorating macroeconomic conditions threatened bank solvency through both direct sovereign exposures and heightened credit risk. The dispersion across banks, shown by the interquartile and interdecile ranges, widens considerably during crisis periods, indicating heterogeneous vulnerabilities across the sector, with some institutions facing particularly severe capital pressures under adverse scenarios. From 2014 onward, the index gradually declines as macroeconomic conditions stabilize and banks rebuild capital buffers. However, stress increases again, especially in 2020-2021 with the COVID-19 pandemic, reflecting concerns about credit losses and economic contraction under adverse scenarios. The index shows another elevation in 2022-2024, driven by the combination of monetary policy tightening, geopolitical tensions, and concerns about potential recession, though stress levels remain well below crisis-era peaks. In the most recent observation, the stress index decreased slightly, notably

as concerns about the impact of monetary tightening on credit risk eased.

Importantly, the risk of capital loss captured by the SVI must be put into perspective with the evolution of the capital ratio of the banking system. This ratio showcases a substantial increase since the end of the Great Financial Crisis, as banks recovered from the crisis and adjusted to higher capital requirements and tighter market discipline in terms of solvency ratio. This puts the European banking system in a stronger position to withstand external shocks to capital as captured by the SVI.

Figure 3: Stress Vulnerability index - historical evolution



Notes: Median, 10th (P10), 25th (P25), 75th (P75), 90th (P90) percentiles obtained for each point in time, reflecting bank heterogeneity. Crisis periods identify the Great Financial Crisis (2008q2-2009q3), the European Sovereign Debt Crisis (2010q1-2012q4) and the COVID-19 pandemic crisis (2020q1-2020q2).

The decomposition of the index into its macroeconomic drivers (Figure 4) graphically reveals the important role played by real economy drivers, compared to financial ones.[11] Throughout

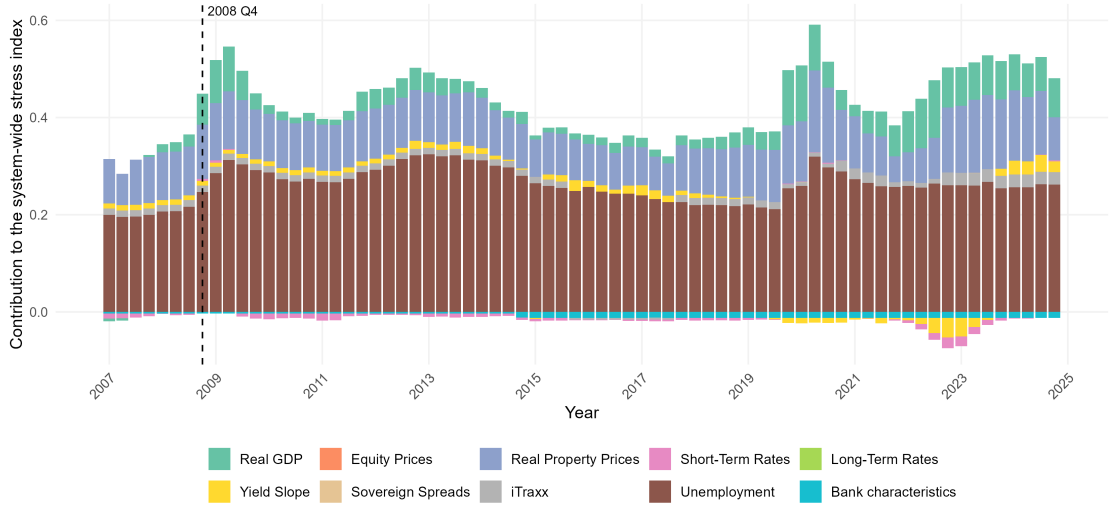
[11]Since the CDF transformation does not allow for a linear representation of the contribution of the macro-financial variables on the index, we explore the first-order Taylor expansion to obtain a linear approximation of $F(\hat{y_{it}})$:

$$F(\hat{y}) \approx F(0) + F'(0) \times \hat{y} = F(0) + F'(0) \times (\hat{\beta}_1 x_1 + ... + \hat{\beta}_p x_p) \quad (5)$$

where $F(0)$ is the cumulative probability of a non-positive fitted value of the underlying variable, $F'(0)$ is the density at zero and $\hat{\beta}_j$ and x_j with $j = 1, ..., p$ are the estimated coefficients and variables from the regressions, respectively.

most of the sample period, unemployment appears as the main risk driver, capturing its impact on credit risk through both the direct rise in household loan delinquencies, and the indirect impact on the macroeconomy. By the same token, adverse real GDP growth contributes substantially to stress, reflecting the importance of a potential economic contraction in driving loan losses in stress test scenarios. The contribution of unemployment rises notably during crisis periods, consistent with its role in retail credit deterioration. Real estate prices play an important role as well throughout the period, with a notable increase in 2022 when monetary policy tightening triggered a reduction in residential real estate prices, sparking concerns over the credit quality of housing loans. On the contrary, financial variables, i.e. rates, spreads and equity prices, have a very contained impact on this indicator, confirming its focus on the real economy, through the credit risk channel mainly, compared to banks' income, mostly driven by interest rates and financial market activities.

Figure 4: Decomposition of the SVI through time



Notes: Weighted average over time obtained using total assets. Only time-varying components included. Unemployment considers both the variable in levels and in changes. Impact of interaction terms of a macro-variable with a bank characteristic are attributed to the macro-variable.

Then we can decompose the linear approximation into its drivers by expanding $\hat{y_{it}}$. Since the stress index is just the complement of Equation (5), we get:

$$I = 1 - F(\hat{y_{it}}) \approx 1 - F(0) - F'(0) \times (\hat{\beta}_1 x_1 + ... + \hat{\beta}_p x_p) \tag{6}$$

with $-F'(0) \times \hat{\beta}_i x_i$ as the scaled impact of each variable on the stress of the bank i at time t.

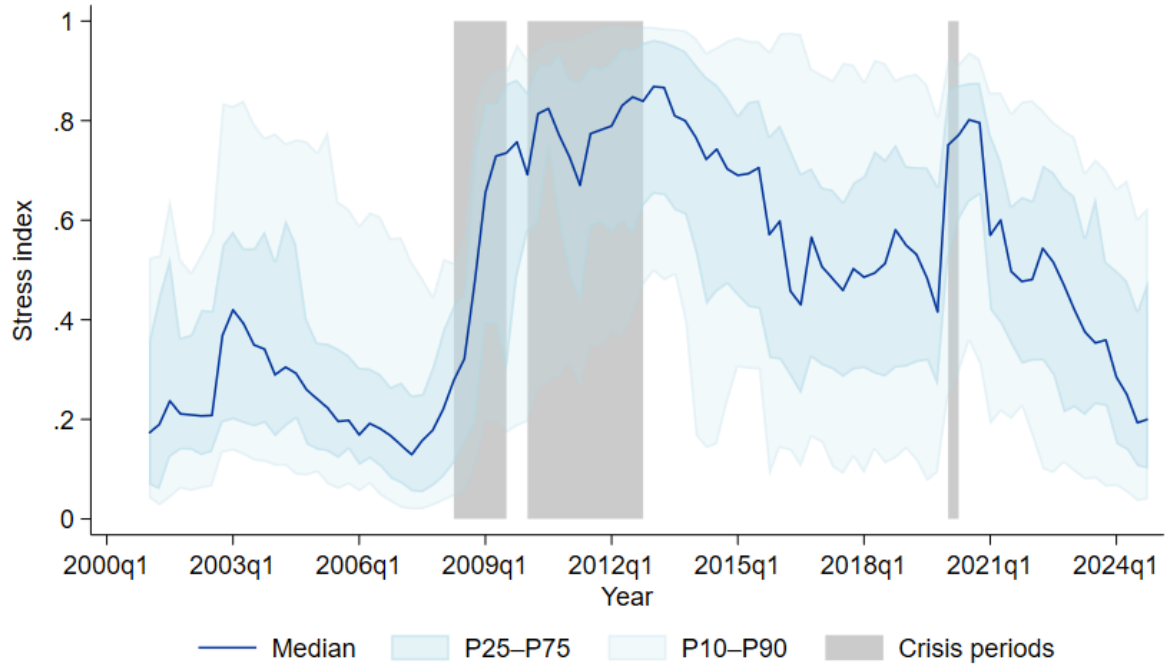
3.2 Profitability vulnerability index

The PVI exhibits a sharp increase in the stress index in the fourth quarter of 2008 as the US subprime crisis affected European banks (Figure 5). The levels of stress then varied but remained high between 2009 and 2014, as the GFC progressed, leading to the ESDC. After 2013, the index displays a downward trend, with some spikes in 2016 and during the initial phase of the COVID-19 crisis, remaining at low levels of stress since 2023.

The profitability focus of this index is evident in its sharp reaction to crisis events that immediately compressed earnings. The index jumps from relatively moderate levels below 0.4 in mid-2008 to peaks above 0.6 by the end of the year, directly reflecting the collapse in equity markets, the freezing of interbank markets, and the sharp deterioration in economic growth that immediately compressed bank profitability. The subsequent volatility through 2009-2014 captures the ongoing instability, with elevated stress persisting as banks worked through legacy losses, faced sovereign debt market turbulence, and operated in an environment of weak economic growth and low profitability.

The dispersion across banks, shown in the interquartile and interdecile ranges, is particularly wide during 2009-2014, indicating substantial heterogeneity in how banks' profitability responded to the stressed macroeconomic environment. Some banks maintained relatively resilient profitability (lower PVI values), while others faced severe profitability compression reflected in PVI values approaching 0.9-1.0. This heterogeneity reflects differences in business models, geographical exposures, funding structures, and legacy asset quality across institutions. The period from 2014 onward shows a gradual normalization, as banks recovered from the GFC and ESDC. However, the PVI remained in medium to high levels, capturing the downward pressure of *low-for-long* rates on banks' profitability. The COVID-19 related stress in 2020 is visible but relatively muted and short-lived compared to the GFC & ESDC period, reflecting both initial severe market correction and important concerns regarding asset quality, then the rapid and massive policy intervention supporting economic activity and the public credit guarantee programs. By 2023-2024, the index declined to levels below 0.3 for the median bank, indicating that the left tail of the profitability distribution has improved substantially. This reflects the combination of higher net interest margins in the rising rate environment and improved asset quality with declining default rates. The relatively narrow dispersion in recent periods suggests more homogeneous resilience across the sector compared to the post-crisis years.

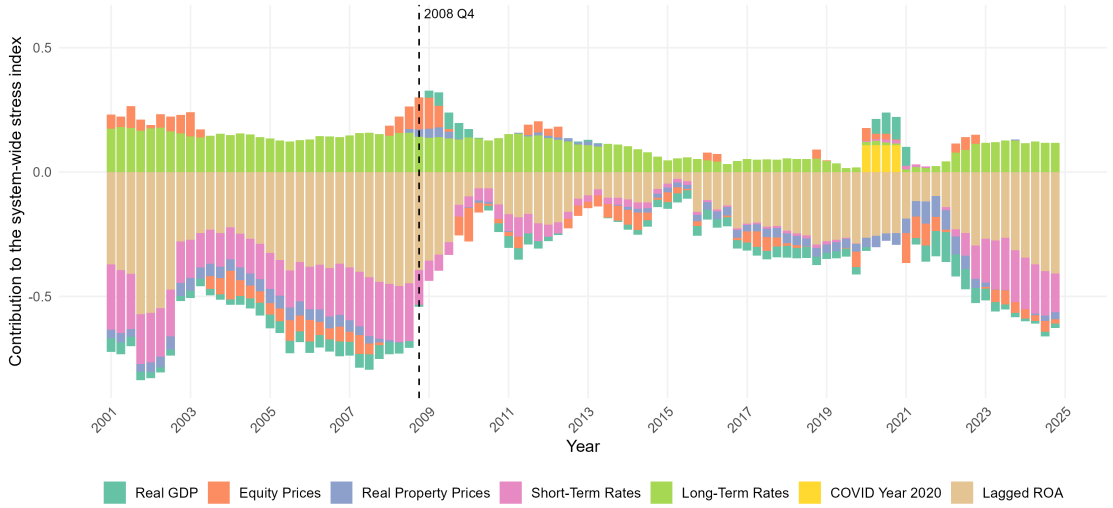
Figure 5: Profitability Vulnerability index - historical evolution



Notes: Median, 10th (P10), 25th (P25), 75th (P75), 90th (P90) percentiles obtained for each point in time, reflecting bank heterogeneity. Crisis periods identify the Great Financial Crisis (2008q2-2009q3), the European Sovereign Debt Crisis (2010q1-2012q4) and the COVID-19 pandemic crisis (2020q1-2020q2).

The decomposition analysis (Figure 6) provides insight into which macrofinancial factors drove stress at different times. Lagged profitability plays a stabilizing role throughout most of the sample, with higher past ROA supporting current resilience (lower index). This contribution diminishes during crisis peaks as consecutive periods of losses erode this buffer. Real GDP growth shows its expected positive contribution to stress during economic contractions, with particularly notable spikes during 2008-2009 and 2011-2013 when recession conditions directly compressed profitability through loan loss provisions and weak lending volumes. Real estate prices add to stress particularly from 2008-2013, as market corrections threatened collateral values and drove credit losses.

Figure 6: Decomposition of the PVI through time



Notes: Weighted average over time obtained using total assets. Only time-varying components included.

In contrast to the SVI, financial variables play a key role in the evolution of the PVI, as they drive banks' net interest income. The contribution of short-term rates shifts dramatically over the sample period: initially reducing stress (supporting profitability) pre-crisis, the contribution becomes negligible as rates fall to the zero lower bound between 2009 and 2021. From 2022 onward, as rates rise rapidly, short-term rates again contribute significantly to reducing stress (via higher NII).The contribution of long-term government yield captures complex dynamics. During the sovereign debt crisis, rising peripheral yields added substantially to stress through sovereign exposure losses and funding market fragmentation. During the subsequent low-rate period, very low long-term rates supported lending volumes (reducing stress) but compressed margins. Finally, since the 2022 monetary tightening, this component has turned positive again, capturing renewed financial risks. Finally, equity market conditions contribute sharply to stress during market crashes, reflecting both direct mark-to-market effects and the broader risk appetite and funding cost implications of equity market turbulence.

3.3 Combined indices: complementary views on banks' solvency drivers?

Comparing the SVI and the PVI reveals both commonalities and instructive differences regarding the mechanics of systemic risk (Figure 7). Both indices identify the GFC and the ESDC as

periods of acute systemic fragility, confirming that both approaches successfully capture the materialisation of banking stress. However, their dynamics outside these crisis episodes diverge, reflecting the distinction between potential capital depletion under stress and the profitability vulnerability in the current environment.

The SVI demonstrates higher sensitivity to acute macro-financial deterioration. It spikes sharply during the onset of the GFC in 2008, the peak of the sovereign debt crisis in 2011–2012, and the monetary tightening cycle of 2022–2023. This dynamic captures the conditional tail risk facing the banking sector, where tightening financial conditions and deteriorating economic outlooks signal a potential erosion of capital through credit losses and risk-weighted asset inflation. Proxying the magnitude of the shock the system would need to absorb if a severe scenario materialized.

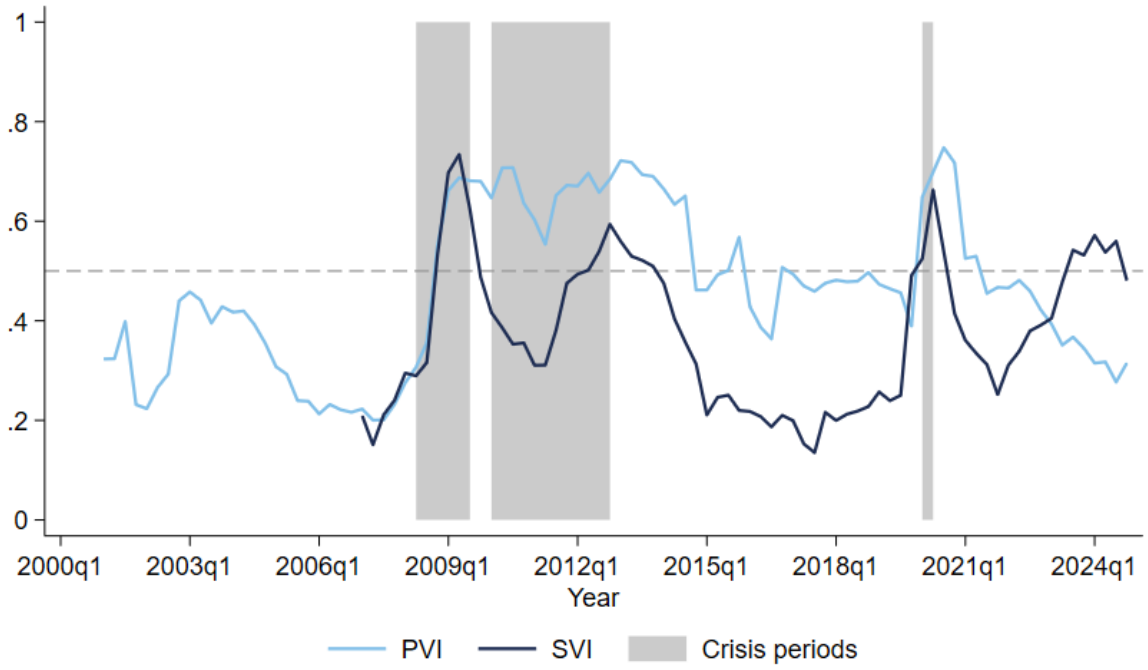
The PVI, by contrast, gauges the banking sector's first line of defense, namely its ability to generate capital through retained earnings. It exhibits greater persistence during periods of structural earnings compression, notably remaining elevated throughout the low-for-long interest rate environment (2014–2019), even as the SVI subsided. From a resilience perspective, this metric captures the flow of revenue available to absorb shocks. When the PVI is high, the sector's ability to replenish or build capital buffers is impaired.

A particularly notable divergence emerges during the recent monetary tightening cycle (2022–2023). The PVI declined, driven by the recovery in net interest margins on the back of the sharp rise in interest rates, while the SVI rose substantially, driven by concerns regarding borrower solvency and recession risks due to the same monetary contraction. This decoupling underscores the complementarity of the two indices, capturing how the flow of earnings improved even as the conditional risk to the capital intensified (but ultimately did not materialise). In such conditions, policymakers need to consider both the immediate improvement in banks' *actual* profitability and capital position and the accumulation of *potential risk*.

These observed divergences reflect the distinct focuses of the two approaches. The SVI, drawing on EBA stress test methodology, emphasizes credit risk-driven solvency assessment through detailed modeling of loan loss provisions, risk-weighted asset evolution, and capital adequacy over multi-year adverse scenarios. It explicitly addresses the question: how would banks' capital positions evolve under severe but plausible stress? The PVI, in contrast, focuses on current earnings capacity by capturing how realized macroeconomic conditions affect the left tail of the profitability distribution. This naturally emphasises near-term profitability drivers

such as net interest income dynamics with rate changes, equity market effects, and immediate provisioning needs.

Figure 7: The two stress indices



Notes: PVI is the Profitability Vulnerability Index, while SVI is the Stress Vulnerability Index. Weighted average over time obtained using total assets. Dashed line at 0.5 marks median stress environment. Crisis periods identify the Great Financial Crisis (2008q2-2009q3), the European Sovereign Debt Crisis (2010q1-2012q4) and the COVID-19 pandemic crisis (2020q1-2020q2).

The complementarity of the two approaches becomes clear from this comparison. The SVI is most valuable for informing medium-term macroprudential policy decisions about capital buffer requirements, as it assesses capital depletion under adverse scenarios. The PVI is more valuable for assessing current earnings pressures and for decisions about whether current conditions warrant consideration of buffer releases to support credit supply. Together, they provide a more complete picture of banking sector resilience than either could alone: the SVI answering 'how vulnerable is the sector if conditions deteriorate substantially?' and the PVI answering 'how stressed is the sector right now?'

A divergence where the SVI rises while the PVI remains subdued—as observed in the recent tightening—provides a robust signal for buffer activation or at minimum, for preserving existing buffer levels, as the forward-looking risk environment does not warrant a reduction in resilience.

It indicates that while tail risks are building and warrant higher buffers, the banking sector possesses the internal profitability to accumulate this capital. Conversely, a high PVI environment implies weak internal capital generation, suggesting that the sector would struggle to replenish capital following a shock, regardless of the immediate credit risk outlook.

The variable decompositions reinforce these distinctions. The stress test index shows larger contributions from variables that drive loan losses and procyclical amplification in adverse scenarios—notably unemployment, property price corrections, and recession depth. The profitability index shows larger contributions from interest rate variables that immediately affect net interest margins and from equity market conditions that affect trading income and funding costs.

This analysis therefore suggests that periods where they point in different directions are not failures of either measure but rather informative signals about the nature of banking sector vulnerabilities at that moment. Furthermore, the median stress threshold of 0.5 provides a useful reference point: both indices above this level suggest significant level of stress requiring policy attention, while both below it indicates generally more benign conditions. Finally, it is key to put those indices in perspective of the banks' capital ratio. While the former inform on the risk of negative capital shock, the latter informs on the capital buffer they can use to absorb this shock, thus giving a full picture of banks' solvency resilience.

4 Validation Using State-Aid Interventions

We use state-aid interventions as an external validation exercise for the proposed indicators. While the aggregate SVI and PVI capture major episodes of banking sector stress, it is also important to assess whether the underlying bank-level indicators identify institutions that subsequently experience severe distress.[12] State-aid interventions provide a natural benchmark for this purpose, as they represent observable manifestations of severe banking sector stress.

We focus on the GFC and later the ESDC, which together provide a particularly informative setting because they were characterised by the build-up and materialisation of vulnerabilities within the banking system and ultimately resulted in widespread recapitalisations and public

[12] As such, this analysis can be interpreted as an out-of-sample test for the SVI, which is based on stress test data while the state aid data is historical. Also, since both SVI and PVI are not designed to capture specific period of times identified as dummies (e.g. crisis/no crisis), the usual performance indicators such as AUROC are not suited. This analysis implicitly play this role

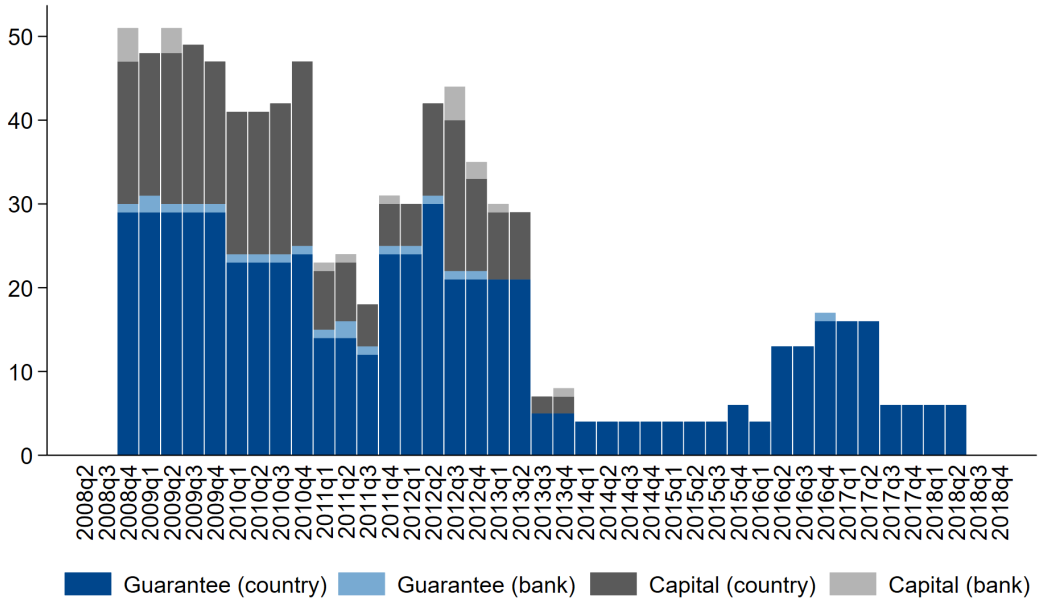
support measures across Europe. By contrast, crises triggered by exogenous shocks, such as the COVID-19 pandemic, are less suitable for validation purposes because the resulting stress originates outside the financial system and is therefore less directly linked to the vulnerabilities that the SVI and PVI are designed to capture. We therefore examine whether elevated values of the bank-level SVI and PVI are associated with a higher likelihood of subsequent state-aid interventions during the GFC.

To this end, we build a dataset focused on aid in the form of state guarantees (to the liability side), liquidity measures and capital injections, in the spirit of Betz et al., 2014 and J. H. Lang et al., 2018, distinguishing between country-wide schemes and bank-specific aid. Because state-aid interventions during the GFC were implemented through both bank-specific measures and country-wide support schemes, we consider both forms of intervention in the validation exercise. Our analysis is based on a memo from the European Commission (EC) on state aid decisions to financial institutions between 2008 and 2016 (European Commission, 2016). We complement this information by including EC decisions to not object to additional extensions of existing aid schemes after 2016.

We consider the date of the support announcement and all further extensions and prolongations. Since each extension and prolongation constitutes a new decision by the European Commission, involving reassessment of appropriateness and sometimes modifications to the original scheme, we treat each measure as an independent state-aid decision.

The first impact of the transmission of the subprime crisis to European banks was in the form of liquidity shocks and capital losses, which were addressed through country-wide guarantee schemes and capital support (Figure 8). Many of these schemes were extended until end-2010, with a small number of them continuing into the first three quarters of 2011. With the onset of the ESDC, some countries extended both guarantee and capitalisation schemes from Q4 2011 to mid-2013. Some bank capitalisations occurred outside country-wide schemes, particularly in Q4 2008 following the initial impact of the subprime crisis, and again in the second half of 2012 during the peak of the ESDC.

Figure 8: Number of banks with some type of state-aid available in each period



Source: Authors' calculations based on European Commission, 2016.

Notes: Values represent the number of banks that had, in each quarter, access to some type of state-aid, either country-wide or bank-specific.

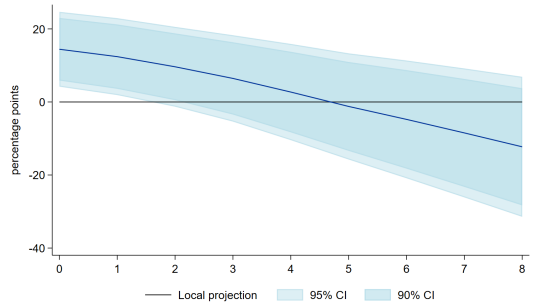
We relate this state aid database with results aggregated by country, focusing on the periods where banks were at their highest stress, choosing values of 0.85 or higher of the PVI. Results show that countries with the highest overall share of banks in high stress throughout the time period in focus, such as Portugal and Greece, had prolonged country-wide guarantee and recapitalization schemes, reflecting both liquidity and solvency issues (Figure 11 in Appendix C).

To investigate the relationship between stress and state aid, we assess the probability that state-aid schemes are activated when stress is high, both contemporaneously and in subsequent quarters. To do so, we estimate the effect of the indices on country-wide state aid schemes (excluding bank-specific aid), over an 8 quarter horizon (i.e. $t+h$ with $h=0,...,8$) using local projections (Jordà, 2005). We also include bank fixed effects to account for unobserved factors that may differentially affect the probability of a bank being exposed to state aid scheme. [13]

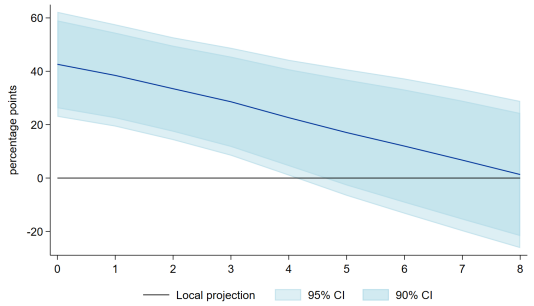
[13] Estimations considering, individually, bank-specific aid through guarantees/liquidity aid or recapitalisations yield small and less precisely estimated effects. This reflects the systemic nature of the crises during this period, when elevated stress levels and subsequent state aid were not confined to a limited number of banks.

Figure 9: Stress indices impact on the probability of future country-wide state-aid by measure

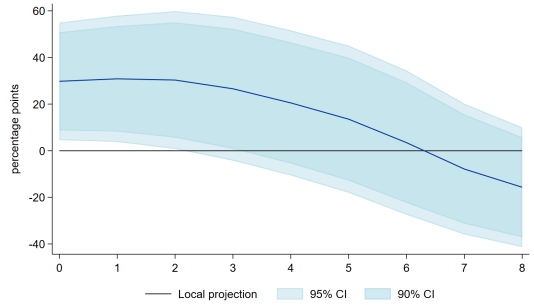
(a) PVI - Capital injection



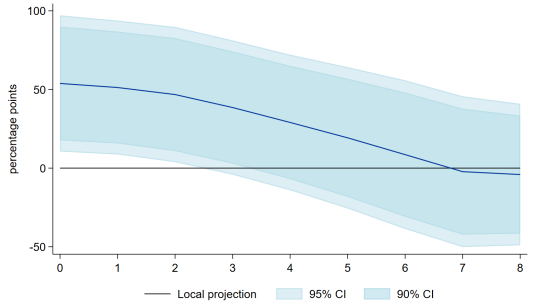
(b) PVI - Guarantee scheme



(c) SVI - Capital injection



(d) SVI - Guarantee scheme



Notes: Estimated considering bank fixed effects. Each projection horizon h relates state-aid at time $t+h$ and stress indices at time t. Confidence intervals considers Driscoll-Kraay robust standard errors (Driscoll & Kraay, 1998), addressing potential cross-sectional dependence (spatial correlation), autocorrelation, and heteroskedasticity.

The local projection reveal that an increase in both indices is significantly associated with a higher probability of state aid schemes, with guarantees having the highest magnitude (Figure 9). This may reflect the fact that most capital injections through a country-wide scheme were done at the same time a guarantee country-wide scheme was in place, while the reverse is not true. The contemporaneous effect is particularly strong, coinciding with periods in which state aid is activated, but the effects remain statistically significant for 2 quarters ahead (capital injections, panels a and c) and 3-4 quarters ahead (guarantee schemes, panels b and d). Focusing on the guarantee schemes (panel b), a one-unit increase in stress as measured by the PVI is associated with roughly 40 percentage points higher probability of country-wide guarantee schemes being in place contemporaneously, with this effect declining gradually but remaining around 20 percentage points even 4-5 quarters ahead. This makes intuitive sense: banking sector

stress that triggers state aid implementation tends to be prolonged, with schemes extended until conditions normalize. The SVI (panel d) shows similar patterns though with somewhat less span over time. As most measures were put in place to absorb losses, they are more related with stress from compressed profitability than with future potential credit risk materialisation. The contemporaneous effect is around 50 percentage points, declining to roughly 25 percentage points by quarter 4.

These results provide additional evidence that the indices capture meaningful dimensions of banking sector vulnerability. The indices not only correlate with state aid contemporaneously but also contain information about future interventions, suggesting they capture persistent vulnerabilities rather than transitory noise. For policymakers, this suggests that elevated index values should be interpreted as signals of potentially prolonged stress requiring sustained policy attention. The gradual decay in the local projection coefficients further suggests that the information contained in the indices is most relevant during periods of acute stress and naturally diminishes as financial conditions stabilise.

5 Conclusion

This paper develops two complementary indices to monitor euro area banking sector resilience through the lens of capital depletion risk: SVI that exploits elasticities from biennial EU-wide stress tests to assess capital vulnerability under adverse scenarios, and PVI based on quantile regression of banks' profitability on macrofinancial conditions to reflect current earnings pressures. By transforming detailed supervisory stress test data and historical profitability relationships into quarterly time series and then into diffusion indices, we create tools that provide regular updates on banking sector vulnerabilities to fill the information gaps between the biennial stress test exercises.

Our main findings demonstrate that both indices successfully identify periods of banking sector stress, with each offering distinct insights reflecting their methodological foundations. The SVI, drawing on EBA stress test methodology, puts the emphasis on credit risk-driven capital depletion under adverse scenarios, due to weakening macroeconomic conditions: it provides insights into capital adequacy under stress. Instead, the PVI focuses on how current macroeconomic conditions affect earnings, particularly through net interest income as the main channel: in practice it captures banks' current earnings capacity.

The complementarity between the indices reflects the multifaceted nature of banking sector resilience, offering policy insights both when they comove, as well as when they decouple. When the SVI signals elevated concerns relative to the PVI, this indicates vulnerabilities under adverse scenarios that would materialise despite currently adequate earnings, i.e. precisely the situation where building macroprudential buffers is appropriate, as banks have capacity through retained earnings to build capital. When the profitability index is elevated relative to the stress test index, risks in the real economy may be subdued, but downward pressure on profitability indicates that banks have weak internal capital generation capacity, and would thus struggle to make up for negative capital shock.

This dual perspective enhances supervisory capacity to monitor banking sector conditions continuously, providing timely information to support both microprudential supervision and macroprudential policy decisions. The recent divergence between the indices demonstrates that strong current profitability does not automatically warrant buffer reductions as tail risks remain elevated, highlighting the importance of maintaining adequate resilience even during periods of robust bank earnings. As banking systems face ongoing structural changes and evolving risks, such continuous monitoring tools will become increasingly valuable for maintaining financial stability.

References

Acharya, V., L.H., P., Thomas, P., & M., R. (2017). Measuring systemic risk. *The Review of Financial Studies*, *30*(1), 2-47.

Adrian, T., Boyarchenko, N., & Giannone, D. (2019, April). Vulnerable growth. *American Economic Review*, *109*(4), 1263-1289. Retrieved from https://ideas.repec.org/a/aea/aecrev/v109y2019i4p1263-89.html doi: None

Adrian, T., & Brunnermeier, M. (2016). Covar. *American Econoic Review*, *106*(7), 1705-1741.

Aikman, D., Haldane, A. G., & Nelson, B. D. (2015, 06). Curbing the credit cycle. *The Economic Journal*, *125*(585), 1072-1109. Retrieved from https://doi.org/10.1111/ecoj.12113 doi: 10.1111/ecoj.12113

Benoit, S., Colliard, J.-E., Hurlin, C., & Pérignon, C. (2017, 03). Where the risks lie: A survey on systemic risk*. *Review of Finance*, *21*(1), 109-152. Retrieved from https://doi.org/10.1093/rof/rfw026 doi: 10.1093/rof/rfw026

Betz, F., Oprică, S., Peltonen, T. A., & Sarlin, P. (2014). Predicting distress in european banks. *Journal of Banking & Finance*, *45*, 225–241.

Brownlees, C., & Engle, R. (2017). Srisk: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies*, *30*(1), 48-79.

Chavleishvili, S., & Kremer, M. (2025). Ciss of death: measuring financial crises in real time. *Review of Finance*, *29*(3), 685–710.

Chernozhukov, V., & Hansen, C. (2006). Instrumental quantile regression inference for structural and treatment effect models. *Journal of Econometrics*, *132*(2), 491–525.

Deghi, A., Welz, P., & Żochowski, D. (2018). A new financial stability risk index to predict the near-term risk of recession. *Financial Stability Review*, *1*(May).

De Nora, G., Pereira, A., Pirovano, M., & Stammwitz, F. (2025). *From losses to buffer - calibrating the positive neutral ccyb rate in the euro area*. ECB Working Paper.

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of economics and statistics*, *80*(4), 549–560.

Duprey, T., Klaus, B., & Peltonen, T. (2017). Dating systemic financial stress episodes in the eu countries. *Journal of Financial Stability*, *32*, 30–56.

European Commission. (2016). *State aid: Overview of decisions and on-going in-depth investigations of Financial Institutions in Difficulty.* https://www.ft.dk/samling/20161/aktstykke/aktstk.114/spm/18/svar/1415483/1771410.pdf. ([Online; accessed 07-July-2025])

Galvao, A. F. (2011). Quantile regression for dynamic panel data with fixed effects. *Journal of Econometrics*, *164*(1), 142–157.

Hollo, D., Kremer, M., & Lo Duca, M. (2012). *Ciss-a composite indicator of systemic stress in the financial system.* ECB Working paper.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review*, *95*(1), 161–182.

Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. *Econometrica*, 33–50.

Koenker, R., & Xiao, Z. (2002). Inference on the quantile regression process. *Econometrica*, *70*(4), 1583–1612.

Lang, J., Izzo, C., Fahr, S., & Ruzicka, J. (2019). Anticipating the bust: a new cyclical systemic risk indicator to assess the likelihood and severity of financial crises. *ECB Occasional Paper 219*.

Lang, J. H., & Forletta, M. (2020). *Cyclical systemic risk and downside risks to bank profitability* (No. 2405). ECB Working Paper.

Lang, J. H., Peltonen, T., & Sarlin, P. (2018). *A framework for early-warning modeling with an application to banks* (No. 2182). ECB working paper.

Machado, J. A., & Silva, J. S. (2019). Quantiles via moments. *Journal of econometrics*, *213*(1), 145–173.

Minoiu, C., Kang, C., Subrahmanian, V., & Berea, A. (2013). Does financial connectedness predict crises? *IMF Working Papers*.

Passinhas, J., & Pereira, A. (2023). *A macroprudential look into the risk-return framework of banks' profitability.* Banco de Portugal Working Paper.

Philippon, T., Pessarossi, P., & Camara, B. (2017). *Backtesting european stress tests* (Tech. Rep.). National Bureau of Economic Research.

Rodriguez d'Acri, C., & Shaw, F. (2025). Beyond the single bank: macroprudential insights from the 2025 eu-wide stress test and its extensions. *Macroprudential Bulletin*, *32*(November).

Schüler, Y. S., Hiebert, P. P., & Peltonen, T. A. (2020). Financial cycles: Characterisation and real-time measurement. *Journal of International Money and Finance*, *100*, 102082. Retrieved from https://www.sciencedirect.com/science/article/pii/S0261560619301597 doi: https://doi.org/10.1016/j.jimonfin.2019.102082

A Stress Vulnerability Index (SVI)

A.1 Sign restrictions in the SVI estimation

Macro variables	
GDP	+
RPP	+
Δ URX	-
URX	-
Δ Sovereign Spreads	-
Δ iTraxx	-
Δ Short-term rates	
Δ Yield curve slope	

Micro variables
Assets (log)
NII (% Assets)
PD
Starting point CET1
REA (% Assets)

Interaction variables	
GDP:PD	
ΔURX:PD	
PD:URX	
NII (% Assets):ΔYield curve slope	+

A.2 In-sample and out-of-sample performance

In order to test the in-sample and out-of-sample properties of the estimated risk-based index, we compare its projection with the stress test results in the adverse scenario of the exercises used for estimation (2018, 2021 and 2023) and the most recent exercise which is not in the estimation

sample (2025).

Results show that our model captures fairly well the variability of the final stress test results both in-sample and out-of-sample, with recent exercises having a R^2 above 50% (Table 6). These results are further confirmed by root mean squared errors below (comparable) the standard deviation of the sample in the in-sample (out-of-sample) exercise.

Table 6: In-sample and out-of-sample model performance

	In-sample			Out-of-sample
Metric	**2018**	**2021**	**2023**	**2025**
R^2	31.7%	42.2%	58.9%	52.2%
RMSE	2.2	1.9	1.7	2.7
Standard deviation (sample)	2.4	2.3	2.7	2.55

Notes: Assessment made by comparing our individual bank results with the ones from the 2018, 2021, 2023 (in-sample) and 2025 (out-of-sample) EBA stress test results.

B Profitability Vulnerability Index (PVI)

B.1 Khmaladze tests for location and location-scale models

To assess the validity of the location-scale model and of the location model, which would imply no need for quantile regressions, we conducted two Khmaladze tests as proposed in Koenker & Xiao (2002). Results in Table 7 show that the joint tests, considering all variables and business model fixed effects, highly reject the null hypothesis that the variables either shift the conditional distribution of profitability through a location shift or through a location-scale shift (which could be estimated using the quantile via moments of Machado & Silva, 2019). The variables that contribute the most to the rejection of the tests are the AR(1) component and short-term rates, meaning they probably also affect the shape of the conditional distribution.

B.2 Estimates using different estimators

In order to further inspect the differences between using alternative estimators we estimate the 15th percentile using the quantile via moments of Machado & Silva (2019), standard quantile regression estimator of Koenker & Bassett Jr (1978) and the estimator we employ throughout the

Table 7: Khmaladze tests for location and location-scale models

Joint effect	
	test statistic
location	52.96^{***}
location-scale	28.40^{***}

Marginal effects		
	location	**location-scale**
AR(1)	2.79^{***}	2.55^{***}
Real GDP growth	0.93	1.37
Equity prices growth	0.78	0.64
Residential property prices growth	1.63	0.96
Short-term rates	3.99^{***}	2.57^{***}
Long-term rates	1.26	0.41
Covid-19 (2020)	1.96	1.01

Critical values		
	joint	**marginal**
1%	18.49	2.420
5%	16.78	1.923
10%	15.83	1.664

N=5,130 p=18

Notes: The Khmaladze test is used to test the location and location-scale models. The test statistics and critical values are provided for the joint test (considering all variables) and for the marginal test (considering each variable). These are obtained using KhmaladzeTest in R and we used 0.25 as the trimming value. N is the number of observations in the sample and p the number of variables, including the business model fixed effects. Asymptotic critical values are from Koenker & Xiao (2002). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

paper based on the approach of Galvao (2011) which uses the IV quantile regression estimator of Chernozhukov & Hansen (2006) to address potential bias when the regressors contain a lag of the dependent variable and fixed effects.

Results in Table 8 show that all estimates have the same sign and most estimates are similar across estimators. The exceptions are the lag dependent variable, which is higher in the IV quantile regression, and the residential real estate prices growth which is less significant when the location-scale model is not considered.

Table 8: Estimation results for the 15th percentile of the conditional distribution of annualized ROA across estimators

Variables	**Quantile via moments**	**Standard quantile estimator**	**IV quantile regression**
Return on assets (4-quarter lag)	0.589***	0.622***	0.637***
	(0.049)	(0.021)	(0.043)
Real GDP growth	0.016***	0.016***	0.016***
	(0.004)	(0.005)	(0.004)
Equity prices growth	0.003***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)
Residential real estate prices growth	0.010***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)
3-month interbank rate	0.051***	0.047***	0.047***
	(0.011)	(0.006)	(0.011)
10-year gov yield	-0.030***	-0.035***	-0.035***
	(0.008)	(0.009)	(0.010)
Covid-19 dummy (year 2020)	-0.114**	-0.108**	-0.105
	(0.049)	(0.044)	(0.064)
Observations	5,130	5,130	5,018

Notes: The models include business model fixed effects that vary across quantiles. Bootstrapped standard errors clustered at bank-level are in parenthesis. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

In order to assess if the chosen estimator is appropriate to estimate the 15th percentile of banks' profitability, we obtain the fitted values using three different quantile estimate approaches and divide the fitted sample in four subsamples using the quartiles of the fitted values. In each of these subsamples we obtain the percentage of observations equal to or below the fitted value and compare it with the expected value of 15%. We do this for our IV quantile approach based on the Galvao (2011) approach and two other competing estimators: the quantile via moments of Machado & Silva (2019) and the standard quantile regression estimator of Koenker & Bassett Jr (1978).

Results in Table 9 show that the three estimators are reasonably good to estimate the 15th percentile of the profitability distribution. Moreover, the correlation between fitted and actual profitability, considering the squared correlation, is comparable across estimators.

Table 9: Estimator robustness across estimators

	Estimator		
Subsample	**Quantile via moments**	**Standard quantile estimator**	**IV quantile regression**
Sample 1	0.18	0.18	0.18
Sample 2	0.15	0.15	0.15
Sample 3	0.12	0.12	0.12
Sample 4	0.15	0.15	0.15
Squared correlation	0.535	0.537	0.529

Notes: Each sample contains a quarter of the whole sample. Each collumn has the proportion of observations in the original sample that are equal to or below the fitted values obtained with each estimator. The target proportion is 0.15 as we estimated the 15th percentile. The squared correlation is obtained to check for the fit in a similar fashion as the regression to the mean uses the R^2.

However, due to the rejection of the location-scale model and due to the potential Nickell bias of having a lagged dependent variable in the regressors in a fixed effects model, we do not use the quantile via moments or the standard quantile regression estimator. Although the fitted values would be similar across estimators, the drivers behind would be different, especially the role of the lagged dependent variable as can be seen in the Appendix B.3.

B.3 Model validation

Out-of-sample performance

To test how well the model is able to estimate the 15th percentile of banks' profits even when the available data is not used to estimate the coefficients, we estimate the model recursively from 2017 to 2020, adding one year of data every time, and compare the fitted values of the testing window (from end date of estimation to 2024). The choice for this window was made in order to have sufficient observations in both the training and testing windows (in 2017 they are evenly split at around 2500 observations). Again, as in the in-sample exercise, we expect to see that the percentage of observations equal to or below the fitted value in the testing window is around 15%. This type of out-of-sample exercise is especially important as the future use of the stress index depends on the reliability of the estimated coefficients. Results confirm that the model is

reliable to estimate future left-tail realizations of banks' profitability, as the values obtained are between 15.8% and 18.8%.

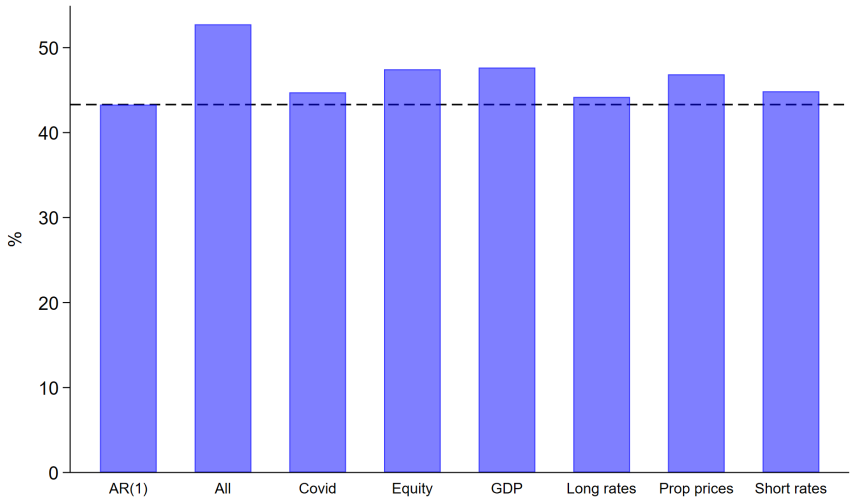
Selected regressors

In order to study how each regressor contributes to the correlation between fitted and actual profitability, we consider the squared correlation (to check the fit in a similar fashion as the regression to the mean use the R^2) between the fitted values considering each variable and the lagged dependent variable in comparison with observed profitability. When comparing these squared correlations with the one that is obtained by simply estimating the regressions using the lag dependent variable (our baseline AR(1)), we can make sense of which variables of the macro scenario are the most relevant.

Figure 10 shows the overall fit considering i) the final specification (under "All"), ii) just using the lagged dependent variable (AR(1)) and iii) adding each macro to the AR(1) specification.

The overall fit for the final specification is 53%, as presented in Table 9. When only considering the AR(1) component, it already puts the squared correlation with observed profitability at slightly above 40%. Adding equity prices, real GDP growth or real property prices growth prove that each variable contributes to increasing the fit relatively to the simplest model of just considering the lagged component.

Figure 10: Overall R^2 and contribution by variable

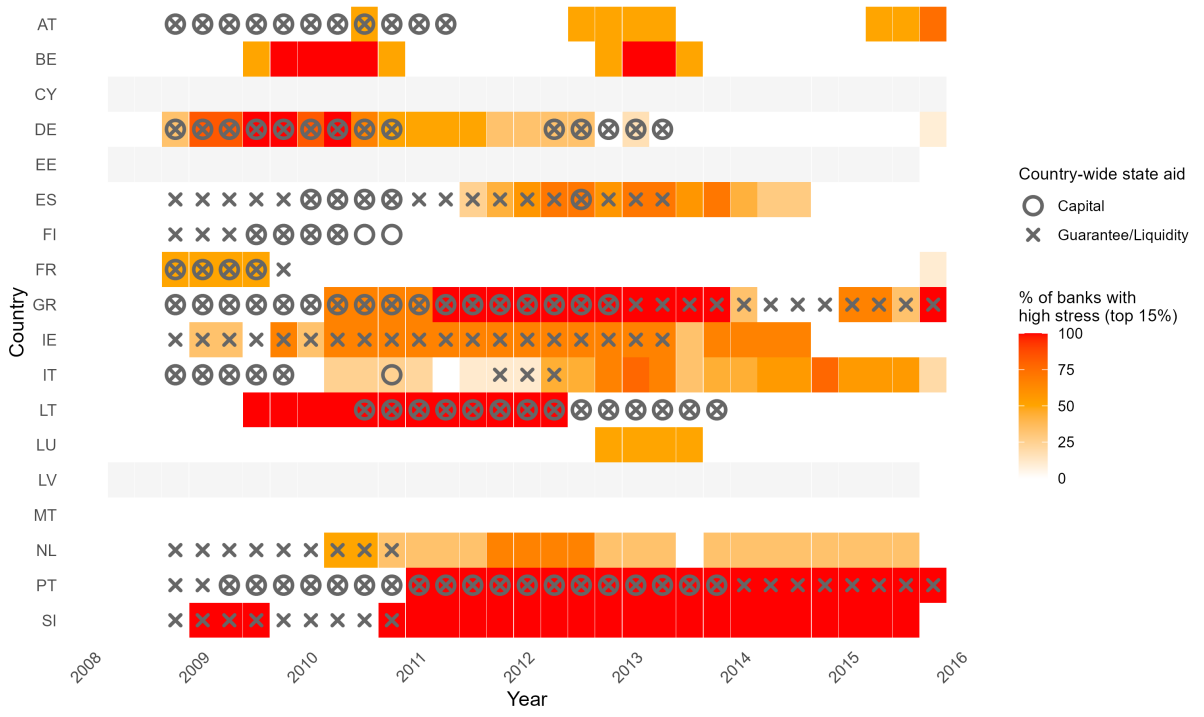


Notes: The squared correlation is obtained to check for the fit in a similar fashion as the regression to the mean uses the R^2. Dashed line indicates the value for the baseline specification AR(1) which only includes the lagged dependent variable. Other bars consider each variable in addition to the AR(1).

C State aid

We relate the state aid database with results aggregated by country, focusing on the periods where banks were at their highest stress, based on the PVI, choosing the top 15% of stress. We can do this by limiting our assessment to banks and periods where the index is greater than 0.85. When we do that, we see that the first high stress banks identified were from Germany and France at the end of 2008 (Figure 11). The countries with the highest overall share of banks in high stress throughout the time period in focus, such as Portugal and Greece, had prolonged country-wide guarantee and recapitalization schemes, reflecting both liquidity and solvency issues.

Figure 11: Percentage of banks within each country at the top 15% of stress



Source: Authors' calculations based on European Commission, 2016.

Notes: High stress measured as periods where a bank had a PVI equal or above to 0.85. Grey areas represent periods with no data.

Acknowledgements

We thank A. Abbondanza, T. Ferriere, T. Garcia, O. M. Georgescu, T. O'Connor for their inputs to the first versions of the models. The paper benefits from comments and suggestions from K. Assenmacher, M. Behn, S. Ben Hadj, G. Cappelletti, I. Dahak, C. Kok, D. Mylonas, A. Petropolous, C. Salleo, J. Santos Silva as well as from the members of the ECB's Advisory Group on Stress Testing and the Stress Testing Operational Board and Operational Steering Board. Comments from an anonymous referee have helped to strengthen the paper's contribution. C. Cascini provided outstanding research assistance. M. Juselius, A. Ponte Marques, N. Tarashev kindly provided access to data that allowed us to kickstart the work while M. Grodzicki and colleagues from the Systemic Risk and Financial Institutions Division at the ECB provided the data to finalise the work. The dataset used in this paper contains confidential statistical information. Its use for the purpose of the analysis described in the text has been approved by the relevant European Central Bank (ECB) decision making bodies. All the necessary measures have been taken during the preparation of the analysis to ensure the physical and logical protection of the information.
The views expressed are those of the authors and do not necessarily reflect those of the ECB or the Eurosystem. All errors and omissions are our own.

Cyril Couaillier
European Central Bank, Frankfurt am Main, Germany; Banque de France, Paris, France; email: cyril.couaillier@ecb.europa.eu

Finn Faber
European Central Bank, Frankfurt am Main, Germany; email: finn.faber@ecb.europa.eu

Joana Passinhas
European Central Bank, Frankfurt am Main, Germany; Banco de Portugal, Lisbon, Portugal; email: jpassinhas@bportugal.pt

Costanza Rodriguez d'Acri
European Central Bank, Frankfurt am Main, Germany; email: costanza.rodriguez@ecb.europa.eu

Frances Shaw
Central Bank of Ireland, Dublin, Ireland; email: frances.shaw@centralbank.ie

© European Central Bank, 2026

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

All rights reserved. Any reproduction, publication and reprint in the form of a different publication, whether printed or produced electronically, in whole or in part, is permitted only with the explicit written authorisation of the ECB or the authors.

This paper can be downloaded without charge from www.ecb.europa.eu, from the Social Science Research Network electronic library or from RePEc: Research Papers in Economics. Information on all of the papers published in the ECB Working Paper Series can be found on the ECB's website.

PDF ISBN 978-92-899-8026-5 ISSN 1725-2806 doi:10.2866/5823461 QB-01-26-233-EN-N