EUROPEAN CENTRAL BANK

EUROSYSTEM

Occasional Paper Series

Harun Mirza, Carmelo Salleo, Zoe Trachana

A portfolio perspective on euro area bank profitability using stress test data

No 356

Contents

Abstract

This study assesses euro area banks' profitability using granular stress test data from three EU-wide exercises, coordinated by the European Banking Authority, that took place in 2016, 2018, and 2021. We propose a credit portfolio-level risk-adjusted return on assets for the euro area as a whole and for individual countries to assess the profitability of lending activities among euro area banks. Using banks' own projections under the adverse scenarios of the stress test exercises for a consistent sample of euro area banks, we aim to uncover the effect of severe macroeconomic and financial conditions on the profitability of the various portfolios. We investigate how many country portfolios switch from profitable to loss-making under adverse conditions and show that this number peaks in the 2018 stress test exercise, while the 2021 exercise yields the lowest overall profitability. Overall, around 30% of exposures become unprofitable under stress conditions across the latest two exercises (compared to 20% for the 2016 exercise), mostly concentrated in the non-financial corporations (NFC) segment and, to a lesser extent, in the financial and mortgage portfolios. We also show in a regression analysis that the yield curve is an important determinant of portfolio-level profitability in a stress test setting, while the unemployment rate seems to be relevant in determining portfolio switches and GDP growth seems to influence the change in profitability. The results also point to some portfolio heterogeneity.

JEL classification: G01, G17, G21

Keywords: Bank profitability, net interest income, cost of risk, stress testing, scenario analysis, portfolio analysis

Non-technical summary

We introduce a new methodology for measuring the bank portfolio return on assets under severe but plausible adverse macro-financial scenarios among euro area banks, based on stress test data. Under severe conditions, bank portfolios sustain a significant drop in their profitability. This makes it harder for banks to provision their exposures adequately in response to deteriorating macroeconomic conditions, which may lead to financial stability risk and, most notably, would limit financial institutions in their role as credit providers to the real economy, thus undermining economic growth.

While one strand of research on this matter focuses on banks' overall performance, other academic work considers bank profits or income components and the impact of macroeconomic and financial drivers on bank-level or country-level aggregates, while not looking at portfolio specificities.

This paper proposes an approach to address such specificities by introducing a return on assets (ROA) metric at portfolio level. In doing so, it relies on data from past EBA stress test exercises in the form of bank portfolio-level information on their exposures to financials, consumer credit for households, household real estate and credit to non-financial corporations and sovereigns, among other items. Data from past EBA stress test exercises offer a rich set of granular level information on both the asset and liability side of the balance sheet, using banks' own scenario-dependent projections under pre-defined adverse scenarios.

In order to examine the impact of severe conditions on portfolio performance, we analyse which drivers are key in determining which individual portfolios may migrate from a profitable state under "normal" conditions to loss-making under adverse conditions. The observed dispersion can provide valuable insights into the heterogeneous impact of adverse conditions on different asset classes and allow for a better understanding of potential vulnerabilities under stress. Indeed, we show that the impact of the adverse conditions varies by type of bank portfolio.

Lastly, we use a regression analysis in a bid to capture the main determinants of portfolio dynamics under stress. We show that both macroeconomic and financial factors seem to play a role in determining bank portfolio profitability.

1 Introduction

We propose using granular stress test data to construct a comprehensive measure of return at portfolio level for various adverse economic scenarios. The current study relies on a comprehensive sample of actual bank portfolio-level projections obtained from three stress test exercises in 2016, 2018 and 2021, as conducted by the ECB together with the SSM and coordinated by the European Banking Authority (EBA), to calculate the portfolio-level risk-adjusted return on assets (ROA) for the euro area as a whole and for individual countries. This measure is broader than a net interest margin (NIM) metric, which is calculated at the bank level, to also look at costs associated with holding the related portfolio, such as credit risk and the cost of equity, along with the effective interest rate and funding costs required to obtain the NIM.[1] This new measure can then be used to provide additional insights into the question of how adverse macroeconomic and financial developments covered by different scenarios affect the profitability of bank intermediation. The analysis sheds light on the profitability of specific banking activities, as opposed to the profitability of banks themselves, thus abstracting from certain structural factors such as cost inefficiencies resulting from overheads.

The literature on bank profitability has evolved significantly over the past years. It typically assesses the impact of macroeconomic and financial drivers on bank profits or income components (see, e.g., Ho and Saunders, 1981; Flannery, 1981; Molyneux and Thornton, 1992; Albertazzi and Gambacorta, 2009; Covas, Rump and Zakrajsek, 2014; Genay and Podjasek, 2014; and Claessens, Coleman and Donnelly, 2018) or on profitability measures such as the return on equity (ROE) or the return on assets (ROA), either bank-by-bank or on aggregate (see, e.g., Athanasoglou, Brissimis and Delis, 2008; Albertazzi and Gambacorta, 2009; Goddard, Liu, Molyneux and Wilson, 2011; Coffinet and Lin, 2013; Andersson, Kok, Mirza, Móré and Mosthaf, 2018; and Claessens et al, 2018). Further, the data used for these analyses typically come from bank statements or regular supervisory sources (this is the case for Athanasoglou et al, 2008, Albertazzi and Gambacorta, 2009; Coffinet and Lin, 2013; Covas, Rump and Zakrajsek, 2014; Borio, Gambacorta and Hofmann, 2017; and Altavilla, Boucinha and Peydró, 2018;), from commercial providers (Flannery, 1981; Molyneux and Thornton, 1992; Goddard et al, 2011; and Claessens et al, 2018), or more recently from stress test exercises (see Andersson et al, 2018; and Durrani, Metzler, Michail and Werner, 2022). In the latter case, the authors use stress test data to assess bank profitability, although they use a bank-by-bank approach while also looking at the aggregate return on equity, thus abstracting from portfolio specificities. To the best of our knowledge, this is the first comprehensive study that proposes using granular bank stress test data to construct a country- and portfolio-specific measure of profitability, which allows us to assess

1 The analysis abstracts from other risk drivers such as market risk and other sources of returns, such as fee and commission income, as well as any overhead costs.

which country portfolio pairs are profitable and how resilient they are to macro-financial shocks.[2]

The EU-wide stress test exercises examine the resilience of banks to macro-financial shocks using a common methodology and set of scenarios. The exercises are coordinated by the EBA and conducted for the largest euro area banks by the ECB alongside national competent authorities that are members of the Single Supervisory Mechanism (SSM).[3] Aside from the larger banks included in the sample of the EBA exercise, we also look at certain smaller euro area banks, which are also considered significant institutions -thought not part of the sample of the EBA exercise, and include them in the stress test using the same methodology and scenarios (a few simplifications may apply in light of the proportionality principle). This sample of banks is generally referred to as the SSM or SREP sample. The ECB coordinated the exercise for SSM/SREP banks and quality-assured their submissions. The sample that we use for the analysis in this paper is a consistent set of 61 EBA and SREP banks that took part in all three of the exercises in 2016, 2018 and 2021 and that are located in 12 different euro area countries.[4]

The EU-wide stress test exercises are conducted in a constrained bottom-up fashion using prescribed methodological assumptions and scenarios. Banks must report relevant risk parameters and key financial statement items at the starting point of the exercise (e.g. end-2020 for the most recent 2021 stress test) and project them both under a baseline and an adverse scenario over a horizon of three years. The corresponding quality assurance process for the submissions is conducted by the relevant competent authorities. For banks under the Single Supervisory Mechanism (SSM), this process is largely driven by the ECB together with the national competent authorities.

The availability of comprehensive stress test data collected at various points in time provides a unique opportunity to assess bank profitability using granular portfolio-level information for relevant risk drivers and income sources over time and under different severe macroeconomic scenarios. Importantly, the EBA stress test methodology enforces a static balance sheet such that the scenario projections reflect the changing macro-financial environment rather than any changes in the bank business models. Also, the fact that these datasets have a similar data structure and are available for a relatively large sample of banks supervised by the SSM – covering at least 80% of euro area bank credit exposures – allows for a consistent analysis of profitability over time.[5] This study focuses on the banks' credit business by calculating risk-adjusted returns using the information supplied in the banks' NII and credit risk stress test templates for the five most important bank portfolios in the euro area.

2 The approach is exemplified by Mirza, Mokas, Salleo and Trachana (2020), although they choose to focus on ECB top-down, bank-level projections for pandemic scenarios, as covered by the ECB COVID-19 Vulnerability Analysis. For more details on this ECB exercise, please see https://www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr200728_annex~d36d893ca2.en.pdf.

3 For more details on the EBA EU-wide stress test, please see https://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing.

4 These countries are Austria, Belgium, Cyprus, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Slovenia and Spain. Our sample covers mostly the largest domestic banks in these countries and at least two banks per country.

5 The stress test templates of the 2014 EU-wide exercise have a substantially different structure for the relevant risk drivers and have thus been excluded from the present analysis. In addition, that exercise was run prior to the establishment of the SSM and therefore followed a different quality assurance process.

Using the historical data reported by the banks, we show that retail portfolios command the highest returns across countries followed by exposures to non-financial corporations (NFCs). While the profitability of these portfolios has suffered following the outbreak of the COVID-19 pandemic in 2020, the corresponding risk-adjusted returns remain comfortably above zero. Sovereign portfolios, on the other hand, consistently record close to zero or even negative returns, suggesting that excess liquidity on banks' balance sheets in times of low interest rates would be a drag on profitability. Meanwhile, interbank exposures record low overall returns that barely cover the cost of risk, implying that low interest rates might create a disincentive for banks to allocate funds in the interbank market.

Using banks' own scenario projections, we assess the impact of macroeconomic conditions on the profitability of different asset classes under adverse conditions. We focus on the dispersion of the impact of scenarios on the profitability metric across portfolios and on the transition of portfolios between profitability states. This dispersion allows us to better understand the heterogeneous impact of adverse conditions on different asset classes and obtain a clearer picture of potential vulnerabilities. The transition of portfolios from profitable to non-profitable can also inform us about the ability of banks to generate profits from their activities under adverse conditions.

While consumer credit exposures, as well as NFC portfolios, seem to be sensitive to macroeconomic conditions, the profitability of mortgage exposures is relatively resilient to macro-financial shocks. Even though risk-adjusted returns for financial and sovereign exposures are less volatile under the stress test scenario, their profitability does suffer, further implying even more negative returns.

We investigate how many country portfolios switch from profitable to loss-making under adverse conditions and show that this number peaks in the 2018 stress test exercise, while the latest 2021 stress test exercise yields the lowest overall profitability. This implies that, aside from the severity of the adverse scenario, starting-point profitability matters when looking at the impact of macro-financial shocks on the final risk-adjusted returns of the relevant portfolios. The overall share of switching portfolios relative to total exposures is comparable across the two latest exercises, at around 30%, while switches are mostly concentrated in the NFC segment and, to a lesser extent, in the financial and mortgage portfolios. Under stress, significant shares of these exposure classes become unprofitable based on our measure.

We further show that the heterogeneity of the profitability metric decreases under the adverse scenarios, as all portfolio and country exposures seem to be consistently affected by the macro-financial shocks in terms of deteriorating returns. A high correlation across shocks therefore increases the risk for bank profitability, implying lower protection from diversification across portfolios. Therefore, under a regime of low interest rates coupled with a severe recession, more bank portfolios are at risk of becoming unprofitable, which would make it harder for banks to provision their exposures adequately in response to deteriorating macroeconomic conditions, thus leading to financial stability risks, and also to provide credit to the real economy, which could undermine economic growth.

We also use a regression analysis to show that the yield curve is an important determinant of portfolio-level profitability in a stress test setting. The results suggest that the unemployment rate seems to be mostly relevant in determining portfolio switches, while GDP growth seems to generally influence the change in profitability on aggregate. The results also point to some portfolio heterogeneity.

This paper is organised as follows: Section 2 introduces the derivation of the proposed profitability metric. Section 3 describes the data used. Section 4 presents the evolution of the metric over the last half of the decade using historical data reported by banks. Section 5 explores the impact of macroeconomic conditions on profitability and its main drivers using banks' own projections under the adverse scenarios of the three exercises. Lastly, Section 6 concludes.

2 The profitability measure and aggregation methodology

Bank-specific stress test submissions are available for the 2016, 2018 and 2021 EU-wide exercises. The data are aggregated with a view to constructing meaningful country and euro area-wide indicators to obtain a more aggregate view on the profitability of bank intermediation. In this section, we introduce the methodology for deriving the key profitability indicators and the main assumptions used. The analysis relies on the five main portfolios of banks reflecting the main counterparty and collateral categories of bank lending.[6] These exposures account for the lion's share of bank credit exposures. The five portfolios are derived by aggregating the exposures and risk parameters (volume-weighted averages) of several sub-portfolios. The exposures are grouped into Financials (FIN), Households – Consumer credit (HH-CC), Households – Mortgages (HH-HP), Non-financial corporations (NFC) and Sovereigns (SOV).[7] In light of the relevant specificities of the methodology and templates of each individual stress test exercise, in Section 9.2 of the Appendix we describe the technical assumptions we made in each case to ensure an approach that is as consistent as possible across these exercises. We also mention the relevant caveats in each case.

2.1 A measure for portfolio profitability

Based on the stress test data, we perform a profitability analysis at both country- and asset class-level.[8] This profitability assessment reflects three main components: interest earned on assets, the weighted-average cost of capital, and the cost of risk. This study abstracts from any market risk considerations or any type of overhead costs. Further, it disregards additional sources of income potentially related to the portfolios we looked at, such as fee and commission income. Due to data availability constraints and the structure of the underlying dataset, we had to make certain simplifying assumptions that are described below.

Country- and asset class-level profitability is measured as the risk-adjusted return on assets, derived as follows:

$$RoA_{Country}(Asset\ Class) = EIR_{Country}(Asset\ Class) - WACC_{Country} - CoR_{Country}(Asset\ Class) \quad (1)$$

$EIR_{Country}(Asset\ Class)$ is the weighted average effective interest rate for a specific country and asset class across bank exposures to this specific country-portfolio pair; weights are derived from the absolute bank exposures to said country-portfolio pair,

6 These are very close to the six portfolios for which the ECB top-down credit risk stress test models are calibrated; see, e.g., Gross, Georgescu and Hilberg (2017).

7 An exact mapping of these asset classes to the portfolios captured in the EBA credit risk and NII templates is provided in Appendix A.

8 We consider all euro area countries for which comprehensive stress test data coverage is available and also compile aggregates at the euro area-wide level.

in line with the EBA's net interest income template.[9] The derivation of the other two items is described below.

2.2 Calculation of Weighted Average Cost of Capital (WACC)

Weighted average cost of capital is derived from the cost of funding (i.e. related to banks' liabilities), CoF,[10] and the cost of equity, CoE, as follows, where the weights add up to one:

$$WACC_{Country} = CoE_{Country} * w_{Equity,\ Country} + CoF_{Country} * w_{Funding,\ Country} \qquad (2)$$

Profitability is assessed at country and asset class level, so WACC should ideally be estimated at the same level. However, the CoF and CoE metrics cannot be attributed to the asset class level because banks do not hold capital or attract funding one-to-one to hold a particular asset class, but rather to meet regulatory requirements and to fund their asset side. We also lack the information needed to implement a proper Fund Transfer Pricing approach from the stress test and complementary commercial data. Thus, we have to rely on the assumption that both CoE and CoF are consistent across classes within a given country.[11]

The cost of equity (CoE) is derived for each country and portfolio pair from Bloomberg, using country market capitalisation weighted averages for those banks listed on the STOXX Europe 600 index. For countries that do not have a bank present on the index, we rely instead on the euro area weighted average cost of capital. For the scenario projections, we assume that the cost of equity remains constant over the scenario horizon. This is to focus the analysis on how the scenarios influence bank (interest) income-generating activities adjusted for the main risks.

We obtain the cost of funding (CoF) at country level as the weighted average funding costs of all liabilities of banks with exposures to the country concerned and portfolio. The weight is equal to the volume of liabilities of the bank to the total liabilities of banks with exposures to the country and portfolio. We source this information from the net interest income stress test templates.

Next, using the CoE and CoF measures, we construct the weighted average cost of capital (WACC) for each country-portfolio pair. We define the WACC associated with a particular country-portfolio pair as the weighted average of CoF and CoE in line

9 The effective interest rate reflects the weighted average return on existing, maturing and new business.

10 The cost of funding is calculated as the weighted average interest rate paid across a bank's liabilities in a given country.

11 CoE is calculated as a country-specific market capitalisation weighted average of CoE across banks located in the country concerned. CoE and market capitalisation data for individual banks are obtained from Bloomberg using the "WACC_COST_EQUITY" and "CUR_MKT_CAP" time series. CoF is bank-specific and calculated using stress test data. However, at the bank level, funding costs cannot be attributed to the individual portfolios that they finance. Thus, CoF is assumed to be the same for each asset class for a given bank. As a next step, we aggregate the CoF measure to the country-portfolio level by using as weights the share of liabilities of each bank holding these portfolios to all liabilities located in that country. Thus, when aggregating to the country level, CoF will not be exactly equal across portfolios in a given country, as the individual underlying bank exposures have different weights in the different portfolios. Similarly, CoE will not be constant across portfolios within a country.

with equation (2). The weight is a measure of leverage[12] (LEV) for each bank exposed to the corresponding country-portfolio pair. The calculation of the weight introduces a country-portfolio level dependency of the WACC. For each country-portfolio pair, the volume of total exposure can be decomposed into assets of banks with different leverage ratios. We then assume that the weight of equity for any given country and asset class pair is equal to the weighted average leverage of banks holding the particular country-portfolio pair, using as weights their share of holdings of this country-portfolio pair.

2.3 Calculation of Cost of Risk (CoR)

To derive the cost of risk we can, in principle, employ two different approaches. The first and preferred approach builds on actual loan loss provisions by banks, calculated as the difference in the stock of provisions between the start and end of a given year divided by total credit risk exposures at country portfolio level. This provides the most reliable picture of actual provisioning needs among banks both historically and in the projections along the stress test scenario horizon. As such, it indicates the sensitivity of bank credit portfolios to macro-financial shocks, while also reflecting possible changes in their respective provisioning policy. Consequently, it may indicate a positive contribution made by the cost of risk to a bank's profitability in a year where the entity would have drawn down on its stock of provisions.

An alternative would be following an incurred loss approach in spirit (possibly adjusted for legacy assets).[13] This would imply calculating the cost of risk as the sum of gross impairment flows in a given year divided by total credit risk exposure at country portfolio level. This approach would ignore possible reductions in the stock of provisions (perhaps deriving from an improvement in the credit risk characteristics of the loan book or changes in provisioning policy), and would also be more consistent across exercises. We provide more details on the second approach in Section 9.3 of the Appendix.

Under our preferred approach, cost of risk is calculated on the basis of changes in the stock of provisions. This stock represents provisions for all future (lifetime) expected losses under IFRS 9 accounting rules for Stage 2 and 3 exposures and for the next year for Stage 1 exposures, which applies for the stress test exercises in 2018 and 2021. This change in provisions is then divided by the total credit risk exposure at country portfolio level across all three stages. Cost of risk based on stock of provisions is thus derived in the following way:

$$CoR_{Country}(Asset\ Class) = \frac{\Delta Provisions_{Country}(Asset\ Class)}{Exposure_{Country}(Asset\ Class)} \quad (3)$$

12 We source the bank-specific leverage ratio from the CSV_CAP EU-wide stress test templates.

13 Various euro area bank balance sheets suffer from high levels of underperforming or non-performing exposures, often related to the recent financial and sovereign debt crisis. However, asset quality has been steadily improving over the period covered by our analysis; see, for example, the EBA Risk Dashboard from Q4 2020, which is the starting point for the 2021 stress test exercise: https://extranet.eba.europa.eu/sites/default/documents/files/document_library/Risk%20Analysis%20and%20Data/Risk%20dashboard/Q4%202020/972092/EBA%20Dashboard%20-%20Q4%202020%20-%20footnote%20%281%29.pdf?retry=1.

When calculating CoR based on the stock of provisions for the years 2015 and 2016 and the projections under the 2016 stress test exercise (at which time IFRS 9 was not yet implemented), one simply has to add the stock of provisions for performing and non-performing exposures. These provisions prior to the introduction of IFRS 9 had a one-year horizon, which represents a discrepancy between the exercises. The change in total provisions is then divided by the sum of performing and non-performing exposures.

The country- and asset class-level CoR measures are linked to the line items of the NII template using the mapping described in Section 9.1 of the Appendix. The bank-specific data are then aggregated to country and asset class level to enter the main equation. It is important to note that for the latest two exercises, we ignore lifetime losses from Stage 1 to Stage 2 (referred to as LRLT1-2) and lifetime losses from Stage 2 to Stage 2 (referred to as LRLT2-2), which are specific to IFRS 9. We do this to ensure consistency with the 2016 exercise, and in any case it has only a negligible impact on the results. Further, it is worth noting that the stress test methodology does not allow for any reversal of provisions on non-performing exposures.

3 Data

We use data from bank-specific stress test submissions delivered under the 2016, 2018 and 2021 EU-wide stress test exercises. This covers historical data for the starting point years, i.e. 2015, 2017 and 2020, respectively, as well as projections under the adverse scenario for the three-year horizon of the respective exercise. In addition, we employ bank-specific data from Bloomberg that we aggregate at country level. Tables 9 and 10 in the Appendix show the respective data series. We do not use any projections under the baseline scenarios given that the focus of our analysis is on how robust the profitability of bank credit intermediation is to severe but plausible macro-financial shocks rather than baseline conditions.

4 Key characteristics of euro area bank credit profitability based on historical data from stress test exercises

Using the above novel profitability metric, we document key facts regarding the profitability of the main bank exposures over the second half of the last decade, a period coinciding with accommodative monetary policy and very low interest rates, but steady growth for most euro area countries. The year 2020, however, was a turning point due to the outbreak of the COVID-19 pandemic.

For this analysis we use historical data as reported by the participating banks for the respective stress test exercises. To begin with, we observe heterogeneous developments across asset classes (see Figure 1 below). From 2015 to 2017, risk-adjusted returns decrease slightly for sovereign credit portfolios but are relatively stable for mortgage and financial exposures, while they improve for consumer credit and NFCs, which are the most profitable asset classes with an adjusted ROA of around 4.1% and 2% in 2017, respectively, at euro area level. Mortgages follow closely behind at 1.6%, while financials remain negative in terms of our profitability metric at -0.2%. At the same time, risk-adjusted returns on sovereign holdings suffer the heaviest deterioration, becoming slightly negative in 2017. The period can be characterised by a broad decline in interest rates (apart from consumer credit), which coincided with a diminishing cost of risk captured by reversals of provisions. Overall, retail portfolios and exposures to non-financial corporations are clearly the most profitable. Returns on sovereign and financial portfolios are the lowest and barely cover the cost of risk. The analysis further abstracts from any overhead costs, so these returns may actually reflect an upper bound.[14] For financial and sovereign exposures it implies that there must be reasons other than profitability for banks to hold them.

Between 2017 and 2020 risk-adjusted returns deteriorated across all asset classes other than financials, which may be attributed to the further decline in interest rates and, specifically in 2020, to the outbreak of the COVID-19 pandemic. The outbreak was followed by a severe recession and a further drop in interest rates. While an increase in credit provisioning is not (yet) visible in view of the existing moratoria[15] and thus cost of risk remains stable in Figure 1, incurred losses for 2020 can already be seen to increase significantly. Retail and NFC portfolios are the most heavily affected by the decline in profitability, with the latter falling by more than 1 percentage point in terms of the risk-adjusted return. Consumer credit suffers a similar drop, at around 0.9 percentage points, while returns on mortgages decrease by around 0.6 percentage points. The profitability of sovereign exposures

14 Other sources of revenue such as net fee and commission income are also ignored, although it tends to be lower than, say, administrative expenses, at bank level. Further, an allocation of such income at portfolio level is not available.

15 See, for example, the letter sent by the chair of the SSM Supervisory Board to significant institutions in April 2020: https://www.bankingsupervision.europa.eu/press/letterstobanks/shared/pdf/2020/ssm.2020_letter_IFRS_9_in_the_context_of_the_coronavirus_COVID-19_pandemic~4cab8e5650.en.pdf?9cd0e8be2f3ab031c0ceaad0bffc8116.

deteriorates further and stands at around -0.4% in 2020. While one might argue that funding costs for sovereigns may also be lower (e.g. in the context of a Fund Transfer Pricing analysis), it stands out as the least profitable asset class based on our metric. The profitability of the financial portfolios remains relatively constant.

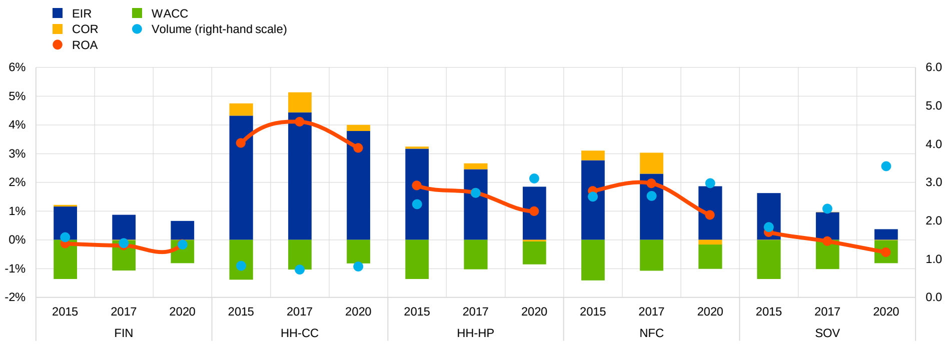
Meanwhile, volumes increased most dramatically for sovereign exposures between 2015 and 2020, making it the largest asset class at close to €4 trillion in our sample in 2020. The large volume of the portfolio combined with low returns weighs on bank profitability. Mortgage and NFC exposures also followed an upward trend and are the next biggest asset classes, at around €3.1 trillion and €3 trillion, respectively, in 2020. Financial and consumer credit exposures are more stable and have significantly smaller volumes, at €1.4 trillion and €0.8 trillion, respectively, at this point in time.

Overall, sovereign exposures largely record returns that barely managed to cover banks' weighted average cost of capital, indicating that portfolios used inter alia for regulatory purposes may be a drag on bank profitability. Exposures to financial institutions even record consistently negative returns at aggregate level, implying that low interest rates might create a disincentive for banks to allocate funds in the interbank market. In summary, this suggests that exposures to households and NFCs are the most profitable, although they also seem to be more sensitive to economic and interest rate conditions than financial exposures. Sovereign exposures are barely profitable throughout and seem to suffer further under adverse economic conditions in a low interest rate environment.

Figure 1

Historical stress-test data – Euro area risk-adjusted ROA components by portfolio

(left-hand scale: percentages per annum; right-hand scale: € trillions per annum)



Sources: 2016, 2018 and 2021 EBA stress test templates. Bloomberg Finance L.P. and authors' calculations.
Notes: COR: cost of risk – change in provisions approach; EIR: weighted average effective interest rate; ROA: weighted average risk-adjusted return on assets; WACC: weighted average cost of capital. FIN: financial corporations; HH-CC: household consumer credit; HH-HP: household mortgages; NFC: non-financial corporations; SOV: sovereigns.

5 The impact of macroeconomic conditions on asset class profitability

As a next step, we explore how adverse macroeconomic conditions and the interest rate environment, as covered under the adverse stress test scenarios, could affect profitability in the euro area. So far, we have used the historically reported data at the starting point in order to document the state of, and trend in, profitability. However, our dataset also includes banks' own projections on the evolution of their interest income and interest expenses on all interest-earning assets and interest-bearing liabilities conditional on the respective adverse macroeconomic scenarios of the three EBA EU-wide stress test exercises, as well as the related provisioning needs. These projections provide a unique opportunity to assess how profitability could be affected by the path taken by key macroeconomic variables and interest rates under adverse conditions, thus shedding light on potential financial stability implications. Under the EBA stress test methodology, banks need to hold their asset allocation constant throughout the scenario horizon, in what is known as the "static balance sheet" assumption[16]. This setting implies that banks are forced ex ante to maintain a fixed asset allocation. Consequently, the projections of interest income, funding costs, as well as credit losses, conditional on the adverse scenario, will not be affected by the ex post behaviour of banks. Further, it is unlikely that on aggregate banks shift the allocation of their assets away from the portfolios that will be the most affected by the adverse scenarios in the short term. Therefore, using the projections under the adverse scenarios, we can obtain estimates on how macroeconomic conditions may affect the performance of the profitability metric that are not the result of a shift in asset allocation either as an ex post response to the impact on profitability or as an ex ante shift in asset allocations in expectation of the impact of macro-financial shocks.[17]

We have a comprehensive dataset using three stress test exercises with an increasing level of severity over time. The scenarios are presented in Table 1 below. The increase in stress severity is illustrated by the larger impact on real GDP growth and the level of unemployment over the scenario horizon, as well as the sharper drop in stock prices. Further, these scenarios incorporate different assumptions regarding the paths of interest rates. In the 2016 and 2018 EU-wide stress test scenarios, interest rates rise, with the increase being particularly pronounced in the case of the 3-month swap rate in the 2018 exercise. In contrast, in the 2021 EU-wide stress test adverse macroeconomic scenario, interest rates are assumed to remain lower for longer, with long-term rates remaining almost flat and short-term rates even falling slightly. In addition, the residential real estate price shocks are of a similar magnitude across the three exercises examined, while for commercial real estate

16 According to the static balance sheet assumption, assets and liabilities that mature or amortise within the time horizon of the exercise should be replaced with similar financial instruments in terms of type, currency, credit quality at date of maturity, and original maturity as at the start of the exercise.

17 Note that projections of interest rate margins for interest-earning assets and interest-bearing liabilities are subject to caps and floors, respectively, imposed by the EBA stress test methodology. Therefore, banks are not allowed to increase their interest rate margin on their assets beyond the cap, and nor are they allowed to project interest rate margins on their liabilities below the floor. The caps and floors are scenario-sensitive and specific to the location of the activity, as they depend on the scenario path of country-specific sovereign yields.

there is a pronounced shock amplification prescribed at euro area level in the most recent exercise.

Table 1

Key variables of macroeconomic scenarios for the stress test exercises

	2016 EBA Adverse	2018 EBA Adverse	2021 EBA Adverse
Euro area GDP	-2.3	-2.9	-3.6
Euro area unemployment	1.5	1.2	4.5
Euro area long-term rates	1.2	1.4	0.1
3-month EUR swap	0.3	0.9	-0.2
Euro area stock prices	-26	-31	-50
Residential real estate prices	-20.2	-16.5	-15.7
Commercial real estate prices	-20.4	-17.7	-30.9

Sources: 2016, 2018 and 2021 ESRB macro-financial scenarios.
Notes: (1) Minimum cumulative growth from the starting point (p.p.); (2) Maximum deviation from the starting point (p.p.); (3) Maximum percentage deviation from the starting point (p.p.); and (4) Cumulative growth from the starting point.

Projections of profitability under the individual stress test scenarios also point to a differing sensitivity of returns for different portfolio types and different drivers. In Figure 2, we show the impact of the scenarios on our profitability measure and its individual components per scenario and asset class, calculated as the difference between the respective variable at the starting point and the predicted annual average over the stress test horizon under the adverse scenario.

While risk-adjusted returns decline in all three scenarios, the largest declines are recorded under the 2018 adverse stress test scenario. However, it is worth noting that bank balance sheet structures and profitability indicators at the starting point have also evolved over time (as shown in Figure 1) and the stress test methodology has been adapted.[18] The most notable change has been the introduction of IFRS 9 as of the 2018 stress test exercise, which first and foremost requires forward-looking provisioning policies for banks' credit risk.

The impact of the 2016 and the 2021 adverse scenarios on our predicted profitability measure is comparable. This may seem surprising, given that the 2021 scenario stands out as the harshest. However, one needs to consider that the 2020 starting point year captures significantly lower levels of profitability, which to some degree may be reflected in the banks' credit risk provisions, some of which may be released as the scenario improves towards the end of the stress test horizon (in line with

18 See the respective EBA stress test methodological notes for the years 2016, 2018 and 2021, which describe the relevant constraints and assumptions governing these exercises. A consistent feature is the assumption of a static balance sheet, implying that total assets per bank and portfolio do not change across the scenario projections. The EU-wide stress test is conducted every two years. However, the 2020 stress test was postponed by one year due to the emergence of the pandemic. For euro area banks, the ECB conducted a vulnerability analysis (VA) relying largely on the EBA methodology. It is also worth noting that EBA stress tests are constrained bottom-up exercises, whereas the ECB VA followed a constrained top-down approach that is quality-assured through interactions with supervisory teams. Therefore, we do not use the VA results in our analysis. For a discussion of ECB stress test quality assurance from a top-down perspective, see Macroprudential Bulletin, ECB, Issue 3, June 2017, Chapter 2.

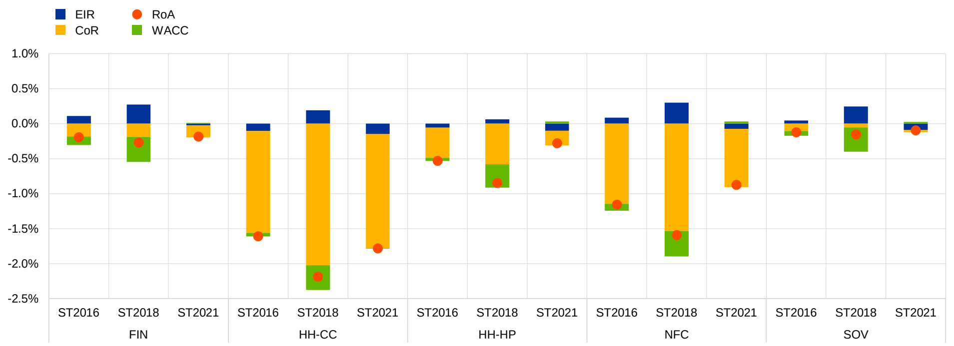
provisioning practices under IFRS 9). Further, the 2021 stress test allowed for a certain number of exceptions also related to COVID-19 specific moratoria.

When inspecting individual portfolios, we can observe the following. Across exercises, returns on the household consumer credit portfolio fall the most – at between 1.6 percentage points in the 2016 exercise and 2.2 percentage points in the 2018 exercise –, followed by exposures to NFCs, which drop by between 0.9 percentage points in the 2021 exercise and more than 1.5 percentage points in the 2018 exercise. These two portfolios happen to be the most profitable historically, while also being the riskiest. Mortgage exposures also exhibit deteriorating profitability dynamics under the three exercises, although the impact is more contained at below 1 percentage point. This may be related, inter alia, to a lower riskiness of the portfolio. Further, and especially in the latest exercise, the drop is very gentle at around 0.3 percentage points. The profitability of sovereigns and financials drops significantly less, at around 10-16 basis points for the former and 19-26 basis points for the latter, depending on the exercise. However, these declines come on top of an already very low or even negative profitability of these exposures.

Figure 2

Change in RoA projections by portfolio under three adverse stress test scenarios

(percentages – annual average per exercise)



Source: Authors' calculations.
Notes: See Figure 1. Change in RoA projections by portfolio from the respective starting point to the annual average under the EBA adverse scenarios for the years 2016-2018, 2018-20 and 2021-23 for the 2016, 2018 and 2021 exercises, respectively.

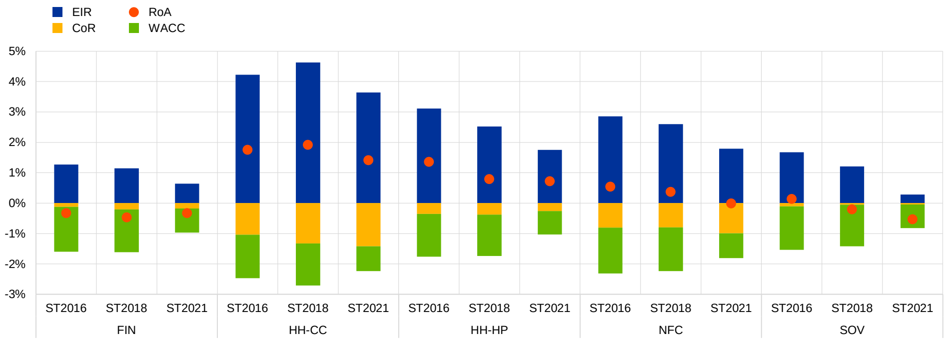
Apart from considering the change in our profitability measure, it is also worth taking a look at the final resulting risk-adjusted returns under the respective adverse scenarios as depicted in Figure 3. It is evident that across asset classes the 2021 exercise yields the lowest predicted returns. This is a result of low starting point profitability coupled with a harsh scenario. While the 2018 exercise features a strong relative impact, in absolute terms predicted profitability levels are higher when compared to 2021.

Interestingly, while consumer credit remains the most profitable portfolio at aggregate level even after stress and despite a sharp deterioration, exposures to NFCs exhibit a slightly negative profitability in the 2021 exercise. Mortgages remain profitable on aggregate across all exercises and therefore seem to be a relatively secure source of revenue, mirroring the findings of the related literature (see, for example, Durrani et al., 2022).

Figure 3

RoA level projections by portfolio under three adverse stress test scenarios

(percentages – annual average per exercise)



Source: Authors' calculations.
Notes: See Figure 2. Average annual RoA projections by portfolio under the EBA adverse scenarios for the years 2016-2018, 2018-2020 and 2021-2023 for the 2016, 2018 and 2021 exercises, respectively.

Next, we examine how the dispersion of the profitability metric is affected by macroeconomic conditions (see Figure 4 below). Historically, heterogeneity seems to be greater for portfolios with higher returns and higher risk. Retail portfolios exhibit the greatest heterogeneity until 2017, followed by exposures to NFCs. However, heterogeneity appears to decrease over time for these portfolios and is especially contained for mortgages in 2020. Heterogeneity among the low profitability and low risk portfolios, i.e. financials and sovereigns, remains relatively contained right from the start of the sample period and decreased further in the case of sovereigns.

Turning to scenario predictions, it would seem that the patterns are similar to the starting points, although heterogeneity is less prevalent when compared with the starting points. In other words, the shocks covered under the adverse scenario seem to reduce the differences in the profitability between the individual country portfolios. There are likely two main reasons for this. First, portfolios are subject to similar adverse conditions (relative to the less consistent economic conditions at the starting point), where all economic indicators across all countries are subject to comparable shocks, and consequently the majority of exposures suffer under stress. Second, the relatively strict methodological constraints of the EBA stress test exercise impose a certain degree of conservatism in the adverse scenarios that may lead to similar responses across portfolios and countries. A notable exception to this pattern would be mortgage exposures in the 2018 exercise, which suffer significant profitability losses under the adverse scenario and seem to have significant outliers on the downside leading to an increase in heterogeneity. This effect may be driven, inter alia, by a large dispersion in the real estate price shocks across countries assumed under this scenario.

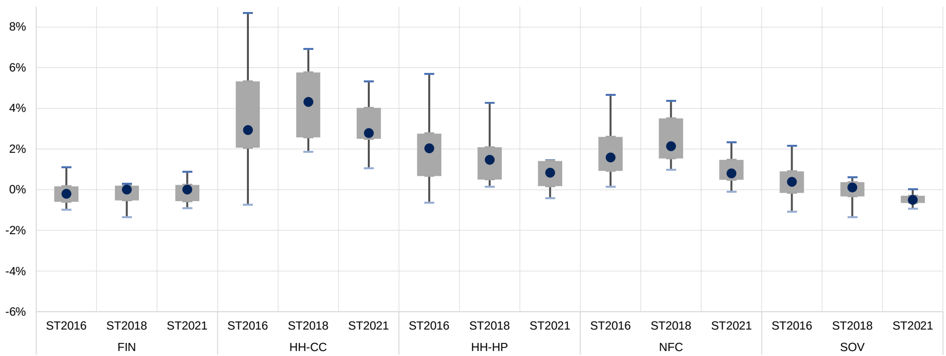
Overall, the distributions of returns shift downward in the adverse scenarios, in line with the results presented in Figure 2. The lower ranges of the box plots indicate that most portfolios in many countries are barely profitable or even loss-making, in the sense of a negative adjusted return under the adverse scenarios.

Figure 4

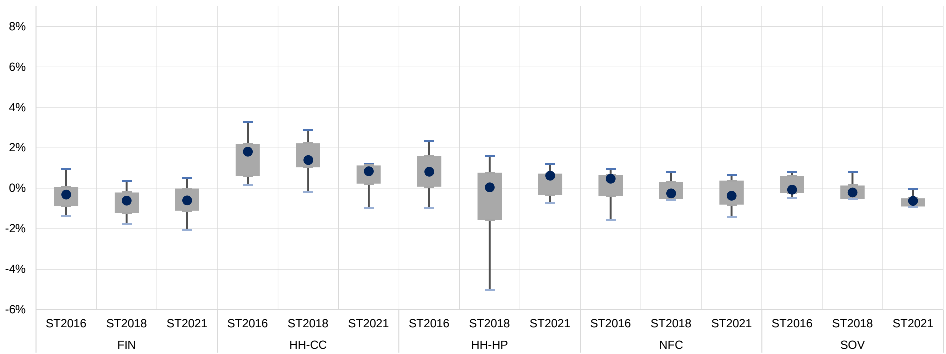
Heterogeneity of profitability projections across countries and portfolios – starting points and scenario projections from the 2016, 2018 and 2021 EBA stress test exercises

(percentages per annum)

a) Starting points



b) Scenario projections (annual average) over scenario horizon



Source: Authors' calculations.
Note: See Figure 1.

From the above analysis, we can observe that the adverse scenarios affect not only the level of profitability across countries and portfolios, but also the dispersion of the metric. In what remains of this section, we examine which country portfolios transition from being profitable to unprofitable, and vice versa. We define a portfolio as profitable when the adjusted return is positive and as unprofitable when the same metric is negative. For each scenario, we assess whether the portfolios switch between these two states.

In Figure 5, we plot the average of the adjusted return on assets metric over the adverse scenario of each exercise against its value at the beginning of each exercise for each country-portfolio pair. The various portfolios are shown in different colours. We can also divide the charts into four areas. The upper right quadrant shows those portfolios that were profitable at the start of the exercise and remained so throughout the horizon, while the bottom left quadrant shows those portfolios that were already unprofitable right from the start of the exercise and remained so throughout. The upper left and lower right quadrants are the transition areas, showing those portfolios that switched from unprofitable to profitable and from profitable to unprofitable, respectively.

While we can observe a strong trend across all asset classes, indicating that the profitability metric is persistent, some portfolios do transition from being profitable to unprofitable. The least profitable (but not yet loss-making) portfolios at the beginning of the exercises are typically those, which also record more frequent transitions to a non-profitable state.

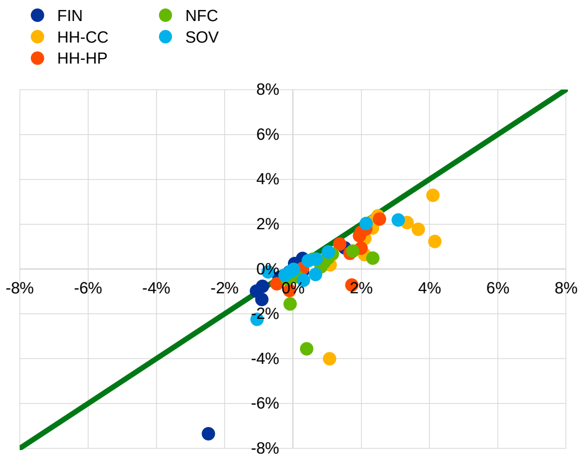
For all exercises, most of the country-portfolio pairs are located below the 45-degree line, indicating a worsening in their respective profitability. Turning to portfolio switches in the lower right quadrant, we can observe that, while the number is rather limited at nine (out of 60 country-portfolio pairs) for the adverse scenarios of the 2016 exercise, it increases significantly to 23 for the 2018 exercise and remains relatively high under the 2021 adverse stress test adverse at 17. This is in line with the results presented in Figures 2 to 4 above and also relates to the fact that in 2020 a significant number of country-portfolio pairs are already loss-making (lower left quadrant). Further, we notice that the initial level of profitability plays an important role in the transitions, as expected, where portfolios with low but positive levels of profitability at the starting point seem more likely to switch to loss-making.

Figure 5

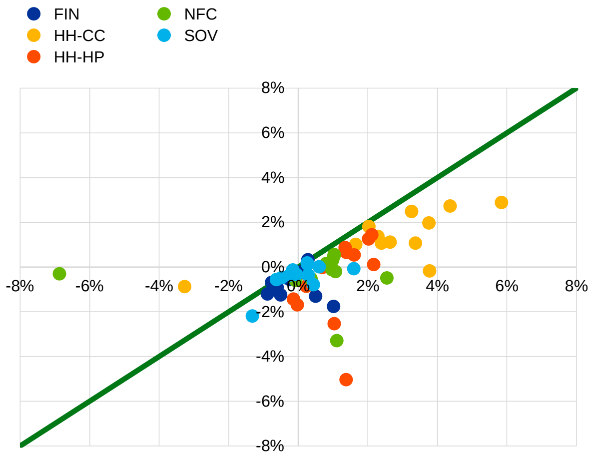
Switches in portfolio profitability under different adverse stress test scenarios

(percentages per annum)

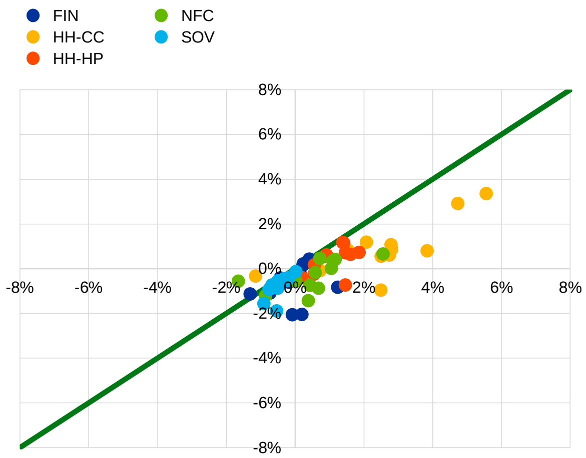
a) **2016 stress test exercise (x-axis = RoA end-2015; y-axis = RoA adverse)**



b) 2018 stress test exercise (x-axis = RoA end-2017; y-axis = RoA adverse)



c) 2021 stress test exercise (x-axis = RoA end-2020; y-axis = RoA adverse)



Source: Authors' calculations.
Note: See Figure 1.

We also investigate the share of portfolios relative to the total outstanding credit in our bank sample that switch to loss-making under the respective adverse scenarios. In this regard, see Table 2 below, which depicts this share both within an asset class and across all asset classes. We find that across the exercises significant amounts of exposures switch to loss-making, at around 20% overall in the 2016 exercise and around 30% in both the 2018 and 2021 exercises. Focusing on the last two exercises, the main impact comes from exposures to NFCs, which account for 20% of the total share of exposures switching to loss-making under the 2021 exercise, and 12% under the 2018 exercise. This is followed by exposures to financials (at 5% and 7%, respectively) and to mortgages (at 2% and 6%, respectively).

We also consider the share of exposures that switch to loss-making by asset class. It turns out that a significant share of the exposures is affected, at 77% and 45% under the 2021 and 2018 exercises, respectively, for the NFC portfolio, followed by financials at 46% and 50%, respectively. For the mortgage portfolios also, 11% and 23% of exposures switch to loss-making under the last two exercises. Under the

2016 exercise, the financial and sovereign portfolios are the most affected, with more than 30% of exposures switching to loss-making in both cases.

To summarise, under stress conditions a significant volume of exposures switches from profitable to loss-making at the aggregate level. On top of that, almost all individual portfolio classes become unprofitable across the euro area under the adverse scenario.

Table 2

Number and share of portfolios with negative profitability switches per exercise under the adverse scenario

		Switches	EA share within portfolio class	EA share across portfolio classes
ST2016	FIN	1	34%	6%
	HH-CC	0	0%	0%
	HH-HP	2	13%	3%
	NFC	3	17%	5%
	SOV	3	33%	6%
	Total	9	N/A	20%
ST2018	FIN	5	50%	7%
	HH-CC	1	0%	0%
	HH-HP	6	23%	6%
	NFC	8	45%	12%
	SOV	3	13%	3%
	Total	23	N/A	29%
ST2021	FIN	3	46%	5%
	HH-CC	3	3%	0%
	HH-HP	3	11%	3%
	NFC	7	77%	20%
	SOV	1	6%	2%
	Total	17	N/A	30%

Source: Authors' calculations.
Note: The table includes cases where portfolios with positive returns in "normal" times moved into negative territory in terms of the adjusted RoA metric.

6 Regression Analysis

We analyse the effect of different drivers of bank profitability under stress. In doing do, we rely on two complementary approaches: (i) an analysis of the probability of a certain portfolio moving from a profitable state to a non-profitable (loss-making) state and how this is influenced by macro-financial drivers and other structural indicators under adverse conditions, and (ii) an analysis of the change in profitability under the adverse scenario with respect to the reference year and of which drivers affect such a change.

6.1 Estimating the probability of switching to a loss-making state

We employ a logit regression for a set of different specifications:

$$Y_i = P(Y_i = 1) + e_i = \beta_0 + \beta_1 x_{i1} + e_i \qquad (4)$$

where the left-hand side variable is the switch dummy on our risk-adjusted return on assets as a binary variable that takes the value of 1 whenever there is a change in the state of any country portfolio from profitable to loss-making. The explanatory variables are included in x_{i1} and differ, depending on the specification. In this way we can assess the effect of a change in one of the selected macro-financial drivers on the probability of a country portfolio switching from a profitable to a loss-making state.

As macro-financial variables, we use the shock to GDP growth in our baseline approach (see Table 3) and the change in the unemployment rate in an alternative approach (see Table 4), as well as the slope of the yield curve in both cases. We also include exercise dummies for 2018 and 2021 to capture fixed effects that could derive from changes in the methodology or regulation. We estimate different specifications for each approach, including also either the NPL ratio (as a proxy for asset quality), the real estate price shock, or a dummy for portfolios which exhibit an adjusted ROA of close to zero (defined as less than 10 bps) and which may, therefore, be close to the switch line.

6.2 Estimating what drives the change in profitability

We also estimate a panel fixed effects regression model to determine what generally drives changes in bank portfolio profitability:

$$Y_{it} = a_i + \beta X_{it} + \delta_t + u_i + e_{it} \qquad (5)$$

where the left-hand side variable denoted by Y_{it} is the risk-adjusted return on assets at country portfolio level, a_i denotes the intercept for each portfolio, X_{it} refers to the vector consisting of the explanatory variables, δ_t is the coefficient for the time regressors (t), and $u_i + e_{it}$ are the within-entity error terms and overall error terms, respectively. In this way we can assess the effect of a change in one of the selected macro-financial drivers on the actual profitability of the country portfolios in question.

As macro-financial variables, we use once again the shock to GDP growth in our baseline approach (see Table 5) and the change in the unemployment rate in an alternative approach (see Table 6), as well the slope of the yield curve in both cases. We also include exercise dummies for 2018 and 2021 to capture any fixed effects that may derive from methodological or regulatory changes, among other factors. For each approach, we also estimate different specifications, including either the NPL ratio, the real estate price shock or the border switch dummy.

6.3 Regression results

The estimation results based on the logit model shown in Tables 3 and 4 provide evidence that a change in the yield curve reduces the probability of portfolio switches. In other words, a steeper yield curve is conducive to the profitability of bank credit exposures. For this model, the unemployment rate seems to work better than GDP growth as a predictor across specifications and, as expected, a higher unemployment rate increases the probability of portfolio switches to a loss-making state. The 2018 stress test exercise implies a higher probability of switching, as indicated by a positive and significant coefficient on the fixed effect. The coefficient in the 2021 exercise is negative and borderline significant (at the 10% level), indicating a lower probability of switching under that exercise, at least in the baseline specification. The variables included in the other specifications (NPL ratio, real estate price shock, border switch dummy) do not appear to be significant. The baseline model is our preferred specification, in view also of the highest log likelihood and the chi-square test, allowing us to reject a null hypothesis of jointly insignificant coefficients.

In principle, it would be interesting to investigate whether there are differences across portfolios with respect to the factors influencing the probability of a portfolio switching from profitable to loss-making. However, in view of the limited number of observations, we can only successfully estimate such a logit model for the mortgage portfolio based on the GDP growth specification. While the results are as expected in terms of signs and significance (both a steeper yield curve and higher GDP growth would lower the probability of switching to a loss-making state), they do not allow for any strong conclusions to be made, as the null hypothesis that all coefficients are jointly zero may not be rejected (see Table 11 in the Appendix for the results).

Table 3

Logit regression on portfolio switches – Baseline model including GDP

	Yield curve	GDP	Specification	ST2018 dummy	ST2021 dummy	Log-likelihood	Observations	χ^2 statistic
Baseline	-12.99**	-6.12		0.07	-0.12**	-17.43	64	11.39
	0.02	*0.47*		*0.40*	*0.02*			*0.02*
NPL	-13.75	-6.22	0.07	0.08	-0.12**	-17.42	64	11.40
	0.13	*0.49*	*0.91*	*0.46*	*0.02*			*0.03*
RRE	-14.72	-6.73	-0.00***	0.07	-0.14	-17.40	64	11.44
	0.11	*0.50*	*-0.05*	*0.41*	*0.17*			*0.04*
Border switch	-14.05***	-11.00	1.34	0.07	-0.15***	-14.68	64	16.89
	0.01	*0.20*	*1.00*	*0.28*	*0.00*			*0.00*

Source: Authors' calculations.
Notes: The table shows the results of a logit regression based on the model depicted in equation (5), where the variable of interest is a dummy variable taking the value of 1 when there is a change in ROA from profitable to loss-making across the three years of the stress horizon. The first row presents the margins of the estimated coefficients under the baseline specification, i.e. the logit regression including the yield curve calculated as the delta between the 10-year long-term interest rate in Germany and the short-term interest rate in any given country, the shock to GDP growth and exercise time dummies. Different specifications are shown in the three rows below and include an additional macro-financial variable with respect to the baseline model, namely the NPL ratio, the residential real estate price shock or a binary variable indicating whether any country portfolio is close to the border of switching, defined as a distance from 0 of less than 10 basis points. The log likelihood of each specification is also presented in the table next to the number of observations available. The final column provides the chi-square statistic, allowing us to test the joint null hypothesis that all of the regression coefficients (other than the constant term) are zero.

Table 4

Logit regression on portfolio switches – Baseline model including UR

	Yield curve	UR	Specification	ST2018 dummy	ST2021 dummy	Log-likelihood	Observations	χ^2 statistic
Baseline	-27.72*	4.56**		0.30***	-0.27*	-17.02	64	12.20
	0.06	*0.03*		*0.00*	*0.09*			*0.02*
NPL	-25.51*	4.92**	-0.47	0.28**	-0.29*	-16.97	64	12.30
	0.10	*0.01*	*0.74*	*0.01*	*0.06*			*0.03*
RRE	-26.57	4.39**	-0.01	0.27*	-0.29	-17.00	64	12.24
	0.10	*0.04*	*-0.84*	*0.06*	*0.10*			*0.03*
Border switch	-23.65**	5.23***	2.35	0.26	-0.29*	-14.33	64	17.60
	0.02	*0.00*	*1.00*	*0.28*	*0.09*			*0.00*

Source: Authors' calculations.
Notes: The table shows the results of a logit regression based on the model depicted in equation (5), where the variable of interest is a dummy variable taking the value of 1 when there is a change in ROA from profitable to loss-making across the three years of the stress horizon. The first row presents the margins of the estimated coefficients under an alternative specification, i.e. the logit regression including the yield curve calculated as the delta between the 10-year long-term interest rate in Germany and the short-term interest rate in any given country, the change in the unemployment rate and exercise time dummies. Different specifications are shown in the three rows below and include an additional macro-financial variable with respect to the baseline model, namely the NPL ratio, the residential real estate price shock or a binary variable indicating whether any country-portfolio is close to the border of switching defined as a distance from 0 of less than 10 basis points. The log likelihood of each specification is also presented in the table next to the number of observations available. The final column provides the chi-square statistic, allowing us to test the joint null hypothesis that all of the regression coefficients (other than the constant term) are zero.

The estimation results based on the panel fixed effect model indicate that the baseline specification including GDP growth seems to work better than the one with the unemployment rate, as shown in Tables 5 and 6 below. As expected, higher GDP is associated with improved profitability of bank credit exposures, all else being equal. Conversely, in a crisis setting, lower GDP growth implies lower profitability. All other coefficients are shown to be insignificant. At the same time, the relatively low R2 of around 0.10 indicates that the model does not perform particularly well, albeit with a much larger number of observations when compared with the logit model.

Once again, we are interested in potential differences across portfolios with respect to the drivers of portfolio profitability. In this case, we can estimate results only for the NFC portfolio and the specification with GDP growth (see Table 8 in the Appendix for the results). The model seems to perform much better when compared with the results based on all portfolios. The R2 of the baseline specification is 0.46 and all coefficients are shown to be significant. However, surprisingly the coefficient on the slope of the yield curve is estimated to be negative, implying that a steeper yield curve would actually lower bank profitability. This finding merits further attention and efforts should be made to ascertain whether it is specific to the NFC portfolio. It is important to note though that this behaviour may be attributed, among other factors, to the methodology underpinning the EBA stress test exercises. Indeed, in the context of pass-through constraints, methodological prescriptions imply asymmetric behaviour, where higher interest rate paths translate more directly to higher interest expenses when compared with interest income.

These results indicate that there may be significant differences across portfolios when comparing the estimation results of the panel model for the NFC portfolio with the results based on all portfolios. Apart from differences in coefficients, the fact that the R2 is much lower for the latter points to some heterogeneity across portfolios. Additional research will be required to further investigate this.

Table 5

Panel regression of change in ROA – Baseline including GDP

	Yield curve	GDP	Specification	ST2018 dummy	ST2021 dummy	R^2	Observations	F-stat
Baseline	-0.03	0.16**		-0.01	0.01	0.11	180	4.15
	0.97	*0.01*		*0.13*	*0.23*			*0.01*
NPL	0.18	0.17**	0.03	0.00	-0.01*	0.06	180	4.09
	0.84	*0.01*	*0.68*	*0.28*	*0.30*			*0.00*
RRE	0.01	0.19***	0.00	-0.01	-0.02	0.12	180	4.65
	0.99	*0.01*	*-0.55*	*0.16*	*0.22*			*0.00*
Border switch	-0.07	0.17***	0.01	-0.01	-0.01	0.12	180	3.35
	0.95	*0.01*	*0.30*	*0.13*	*0.20*			*0.01*

Source: Authors' calculations.
Notes: The table shows the results of a panel fixed effects regression based on the model depicted in equation (6), where the variable of interest is the delta of ROA between the average value of the three-year adverse scenario with respect to the starting point value. The first row represents the baseline specification, which consists of a panel regression including the yield curve calculated as the delta between the 10-year long-term interest rate in Germany and the short-term interest rate in any given country, GDP growth and exercise time dummies. Different specifications are shown in the three rows below and include an additional macro-financial variable with respect to the baseline model, namely the NPL ratio, the residential real estate price shock or a binary variable indicating whether any country portfolio is close to the border of switching, defined as a distance from 0 of less than 10 basis points. The R2 of each specification is also presented in the table next to the number of observations available. The final column provides an F statistic allowing us to test the joint null hypothesis that all of the regression coefficients (other than the constant term) are zero.

Table 6

Panel regression of change in ROA – Baseline including UR

	Yield curve	UR	Specification	ST2018 dummy	ST2021 dummy	R^2	Observations	F-stat
Baseline	0.25	-0.03		0.00	0.07	0.04	180	5.04
	0.80	*0.79*		*0.25*	*0.49*			*0.00*
NPL	0.19	-0.02	-0.01	0.00	-0.05	0.05	180	4.61
	0.85	*0.84*	*0.92*	*0.24*	*0.58*			*0.00*
RRE	0.18	-0.06	0.00	0.00	0.01	0.11	180	5.28
	0.86	*0.65*	*0.56*	*0.52*	*0.46*			*0.00*
Border switch	0.24	-0.03	0.00	0.00	0.01	0.04	180	51.38
	0.81	*0.80*	*0.61*	*0.25*	*0.50*			*0.01*

Source: Authors' calculations.
Notes: The table shows the results of a panel fixed effects regression based on the model depicted in equation (6), where the variable of interest is the delta of ROA between the average value of the three-year adverse scenario with respect to the starting point value. The first row represents an alternative specification, which consists of a panel regression including the yield curve calculated as the delta between the 10-year long-term interest rate in Germany and the short-term interest rate in any given country, the unemployment rate and exercise time dummies. Different specifications are shown in the three rows below and include an additional macro-financial variable with respect to the baseline model, namely the NPL ratio, the residential real estate price shock or a binary variable indicating whether any country portfolio is close to the border of switching, defined as a distance from 0 of less than 10 basis points. The R2 of each specification is also presented in the table next to the number of observations available. The final column provides an F statistic allowing us to test the joint null hypothesis that all of the regression coefficients (other than the constant term) are zero.

7 Conclusions and ongoing work

This study shows that stress test data may be useful in allowing conclusions to be drawn not only for bank capital projections but also for their profitability under stress. We derive risk-adjusted returns of bank credit exposures at portfolio level. Using this new measure, we are able to document the level of, and trend in, bank profitability between 2015 and 2020, a period coinciding with monetary accommodation in the euro area and a period of extremely low interest rates. In addition, we exploit banks' own projections under different adverse scenarios as covered by the three EU-wide stress test exercises conducted in 2016, 2018 and 2021.

We use our metric to investigate how many country portfolios switch from profitable to loss-making under adverse conditions and show that this number peaks in the 2018 stress test exercise, while the latest 2021 stress test exercise yields the lowest overall profitability. A significant share of exposures (around 30%) become unprofitable under stress conditions across the two most recent exercises, mostly concentrated in the NFC segment and, to a lesser extent, in financial and mortgage portfolios. Overall, retail portfolios remain the most robust under stress and on aggregate continue to exhibit positive returns even in a crisis scenario.

The regression results suggest that the yield curve is an important driver of bank portfolio profitability in a stress test setting, while the results are less clear-cut for GDP growth and the unemployment rate. The results further point to significant heterogeneity across portfolios, which deserves further investigation.

8 References

Altavilla, C., Boucinha, M. & Peydró, J.L. (2018), “Monetary policy and bank profitability in a low interest rate environment”, *Economic Policy*, 33(96), pp. 531-586.

Albertazzi, U. & Gambacorta, L. (2009), “Bank profitability and the business cycle”, *Journal of Financial Stability*, 5(4), pp. 393-409.

Andersson, M., Kok, C., Mirza, H., Móré, C. & Mosthaf, J. (2018), “How can euro area banks reach sustainable profitability in the future?”, *ECB Financial Stability Review Special Feature A*, November

Athanasoglou, P.P., Brissimis, S.N. & Delis, M.D. (2008), “Bank-specific, industry-specific and macroeconomic determinants of bank profitability”, *Journal of International Financial Markets, Institutions and Money*, 18(2), pp. 121-136.

Borio, C., Gambacorta, L. and Hofmann, B. (2017), “*The influence of monetary policy on bank profitability*”, International Finance, 20(1), pp. 48-63.

Claessens, S., Coleman, N. & Donnelly, M. (2018), “‘Low-For-Long’ interest rates and banks’ interest margins and profitability: Cross-country evidence”, *Journal of Financial Intermediation*, 35 (A), pp. 1-16.

Coffinet, J. & Lin, S. (2013), “Stress-Testing Banks’ Profitability: The Case of French Banks”, *Journal of Financial Perspectives*, 1(2), pp. 67-80.

Covas, F.B., Rump, B. & Zakrajšek, E. (2014), “Stress-testing US bank holding companies: A dynamic panel quantile regression approach”, *International Journal of Forecasting*, 30(3), pp. 691-713.

Durrani, A., Metzler, J., Michail, N.A. & Werner, J.G. (2022), “Bank lending rates and the remuneration for risk: evidence from portfolio and loan level data”, *ECB Working Paper Series*, No 2753.

ECB (2015), *Financial Stability Review – May 2015, Box 5 – Measuring the cost of equity in the euro area*, pp. 61-63.

Flannery, M.J. (1981), “Market interest rates and commercial bank profitability: An empirical investigation”, *The Journal of Finance*, 36(5), pp. 1085-1101.

Genay, H. and Podjasek, R. (2014), “What is the impact of a low interest rate environment on bank profitability?”, *Chicago Fed Letter*, July.

Goddard, J., Liu, H., Molyneux, P. & Wilson, J.O. (2011), “The persistence of bank profit”, *Journal of Banking & Finance*, 35(11), pp. 2881-2890.

Gross, M., Georgescu, O. & Hilberg, B. (2017), "Credit risk satellite models", in Dees, S., Henry, J. and Martin, R. (eds.), *STAMP€: Stress-Test Analytics for macroprudential Purposes in the euro area*, ECB, Frankfurt am Main.

Ho, T.S.Y. & Saunders, A. (1981), "The determinants of bank interest margins: theory and empirical evidence", *The Journal of Financial and Quantitative Analysis*, 16 (4), pp. 581-600.

Mirza, H., Mokas, D., Salleo, C. & Trachana, Z. (2020) "A portfolio perspective on bank profitability using (post-)pandemic stress-test scenarios", *ECB Financial Stability Review Box A*, November.

Mirza, H. & Zochowski, D. (2017) "Stress test quality assurance from a top-down perspective", *ECB Macroprudential Bulletin*, Issue 3, June.

Molyneux, P. & Thornton, J. (1992), "Determinants of European bank profitability: A note", *Journal of banking & Finance*, 16(6), pp. 1173-1178.

9 Appendix

9.1 Mapping granular stress test credit risk portfolios

Below we show the mapping from the stress test asset classes to our five portfolios of interest, both from the NII available and credit risk sub-portfolios. The mapping refers to the EBA Template granularity of stress test exercises for 2018 and 2021. For the 2016 exercise, minor mapping adjustments due to differences in granularity have been taken into account.

Table 7

Mapping granular stress test portfolios

Portfolio	Regulatory Approach	Asset class
SOV	IRB	Central banks and central governments
NFC	IRB	Corporates. Other. Not secured by real estate property
NFC	IRB	Corporates. Other. Secured by real estate property
NFC	IRB	Corporates. SME. Not secured by real estate property
NFC	IRB	Corporates. SME. Secured by real estate property
NFC	IRB	Corporates. Specialised lending. Not secured by real estate property
NFC	IRB	Corporates. Specialised lending. Secured by real estate property
FIN	IRB	Institutions
HH_CC	IRB	Retail. Other. Non-SME
HH_CC	IRB	Retail. Other. SME
HH_CC	IRB	Retail. Qualifying revolving
HH_HP	IRB	Retail. Secured by real estate property. Non-SME
HH_HP	IRB	Retail. Secured by real estate property. SME
SOV	STA	Central governments or central banks
NFC	STA	Corporates. Non-SME
NFC	STA	Corporates. SME
FIN	STA	Institutions
SOV	STA	Regional governments or local authorities
HH_CC	STA	Retail. Non-SME
HH_CC	STA	Retail. SME
HH_HP	STA	Secured by mortgages on immovable property. Non-SME
HH_HP	STA	Secured by mortgages on immovable property. SME

Source: Authors' calculations.
Note: IRB may be either the A-IRB or F-IRB approach.

Table 8
Mapping granular stress test net interest income portfolios

	2016 EBA Adverse
FIN	Debt securities. Credit institutions and other financial corporations
NFC	Debt securities. Non-financial corporations
SOV	Debt securities. Central banks and general governments
FIN	Loans and advances. Credit institutions and other financial corporations
HH_CC	Loans and advances. Households. Credit for consumption
HH_CC	Loans and advances. Households. Other
HH_HP	Loans and advances. Households. Residential mortgage loans
NFC	Loans and advances. Non-financial corporations. Other
NFC	Loans and advances. Non-financial corporations. Small and medium-sized enterprises
SOV	Loans and advances. Central banks and general governments

Source: Authors' calculations.

9.2 Technical assumptions to ensure consistency across results

This section lists the relevant assumptions that have been made in order to ensure consistency across the results of the individual exercise. This is necessary due to the fact that the three exercises differ somewhat in terms of the methodology and the reporting templates that have been used by the participating banks.

9.2.1 2016 Stress Tests

The credit risk template is missing maturities. To be able to calculate the cost of risk as described in Section 2.3, we map the corresponding maturities reported in the NII template to the relevant credit risk exposures.

For the sake of simplicity, we ignore relevant reporting fields to correct for interest income from non-performing exposures, after verifying that this has no significant impact on the results.

9.2.2 2018 Stress Tests

The historical data at the starting point of the exercise, i.e. in 2017, for NII total volumes are reported as yearly averages, whereas the scenario data refer to year-end. We correct for this by scaling average volumes for that year to end-year volumes (which are subject to the static balance sheet assumption), keeping a constant ratio of maturing, existing and new exposures, respectively.

9.2.3 2021 Stress Tests

The EBA NII template for the 2021 exercise maintains total reported performing volumes constant in the scenario projections, while non-performing exposures grow. This is done to simplify other calculations and there is a correction for this at the total NII level by asset class to avoid violating the static balance sheet assumption. To ensure constant total exposure volumes in our analysis, we correct for this at the volume level by keeping the ratio of maturing, existing and new exposures, respectively, constant.

9.3 Calculation of cost of risk – Gross impairment flows

Cost of risk may also be calculated using within-year flows of provisions, captured by the so-called gross impairment flows (GIF) in the stress testing templates. For the exercise in 2018 and subsequent years, which are subject to the IFRS 9 accounting standards, this implies taking into account gross impairment flows from Stage 1 to Stage 3 (performing assets to non-performing assets) and the corresponding flows from Stage 2 to Stage 3 (underperforming assets to non-performing assets)[19]. When adding gross impairment flows from Stage 3 to Stage 3, i.e. additional losses on already non-performing exposures, we scale this number by the remaining maturity in order to avoid a possible strong effect of legacy assets, which may require additional provisions in a specific year of the stress test scenarios. Gross impairment flows are aggregated across bank submissions according to the country of exposure and the asset class:[20]

$$CoR_{Country}(Asset\ Class) = \frac{\mathrm{GIF13}+GIF23+GIF33/maturity}{Exposure(S1)+\ Exposure(S2)+Exposure(S3)} \quad (6)$$

The country and asset class level cost of risk measures are also mapped to the line items of the NII template via the mapping described in Table 9 below. The bank-specific data are then aggregated to country and asset class level to enter equation 3. For the 2016 stress test, for which the IFRS 9 accounting standards were not yet in force, we replace the numerator in equation (3) with the sum of gross impairment flows from performing assets and the net impairment flows from non-performing

19 Under IFRS 9 accounting standards, assets at amortised cost must be accounted for as Stage 2 if they have undergone a significant increase in credit risk since initial recognition, but are still performing. In this study we consider such assets as “underperforming”.

20 For simplicity, the country, asset-class subscripts are dropped on the right-hand side of the equation as well as the summation symbol for the exposures in the denominator.

assets scaled by maturity (gross impairment flows are not reported). Likewise, the denominator is the sum of performing and non-performing exposures in this case.

As under the stock-based approach, for the two most recent exercises we ignore lifetime losses from Stage 1 to Stage 2 (referred to as LRLT1-2) and lifetime losses from stage 2 to stage 2 (referred to as LRLT2-2), which are specific to IFRS 9. This is to ensure consistency with the 2016 exercise and in any case has only a negligible impact on the results.

9.4 Data

Table 9
Stress test data series

	2016 EBA – Adverse
CoR	End of year stock of provisions
CoR	Beginning of year stock of provisions
CoR	End of year non-performing exposures (or default stock)
CoR	End of year performing exposures (or stock of non-defaulted assets)
CoR	Within year gross impairment flow (S1-S3)
CoR	Within year gross impairment flow (S2-S3)
CoR	Within year gross impairment flow (S3-S3)
CoR	Average maturity (in years)
EIR	EIR component on existing business – margin (annual rate in %)
EIR	EIR component on maturing business – margin (annual rate in %)
EIR	EIR component on new business – margin (annual rate in %)
EIR	EIR component on existing business – reference rate (annual rate in %)
EIR	EIR component on maturing business – reference rate (annual rate in %)
EIR	EIR component on new business – reference rate (annual rate in %)

Source: Authors' calculations.

Table 10
Other commercial and banking data

Variable	Definition	Source
NPL	Country-level non-performing loans	EBA Risk Dashboard
WACC_COST_EQUITY	Cost of Equity	Bloomberg
CUR_MKT_CAP	Current market cap	Bloomberg

Source: Authors' calculations.

9.5 Portfolio regression results

Table 11

Logit regression results on mortgage portfolio switches

	Yield curve	GDP	Specification	ST2018 dummy	ST2021 dummy	Log-likelihood	Observations	χ^2 statistic
Baseline	-14.99***	-20.37***		-0.01	-0.19**	-4.80	18	3.58
	0.00	*0.09*		*0.89*	*0.02*			*0.47*
NPL	-13.76	-18.82***	0.00	0.00	-0.18	-4.79	18	3.60
	0.09	*0.21*	*0.86*	*1.00*	*0.14*			*0.61*

Source: Authors' calculations.
Notes: The table shows the results of a logit regression based on the model depicted in equation (5), where the variable of interest is a dummy variable taking the value of 1 when there is a change in ROA from profitable to loss-making across the three years of the stress horizon. The first row presents the margins of the estimated coefficients under the baseline specification, i.e. the logit regression including the yield curve calculated as the delta between the 10-year long-term interest rate in Germany and the short-term interest rate in any given country, the shock to GDP growth and exercise time dummies. Different specifications are shown in the row below and include an additional macro-financial variable with respect to the baseline model, namely the residential real estate price shock. The log likelihood of each specification is also presented in the table next to the number of observations available. The final column provides the chi-square statistic, allowing us to test the joint null hypothesis that all of the regression coefficients (other than the constant term) are zero.

Table 12

Panel regression results on non-financial corporations portfolio change in ROA

	Yield curve	UR	Specification	ST2018 dummy	ST2021 dummy	R^2	Observations	F-stat
Baseline	-2.19**	0.41***		-0.022*	-0.05**	0.46	36	156.97
	0.05	*0.00*		*0.10*	*0.02*			*0.00*
NPL	-0.89	0.49***	0.19	-0.01	-0.03*	0.32	36	44.27
	0.67	*0.00*	*0.38*	*0.56*	*0.08*			*0.00*
RRE	-2.05*	0.49**	0.00	-0.02	-0.06	0.43	36	98.71
	0.09	*0.01*	*0.60*	*0.11*	*0.11*			*0.00*
Border switch	-2.19*	0.41***	0.00	-0.02*	-0.05**	0.46	36	156.97
	0.05	*0.00*	-	*0.10*	*0.02*			*0.01*

Source: Authors' calculations.
Notes: The table shows the results of a panel fixed effects regression based on the model depicted in equation (6), where the variable of interest is the delta of ROA between the average value of the three-year adverse scenario with respect to the starting point value. The first row represents an alternative specification which consists of a panel regression including the yield curve calculated as the delta between the 10-year long-term interest rate in Germany and the short-term interest rate in any given country, the unemployment rate and exercise time dummies. Different specifications are shown in the three rows below and include an additional macro-financial variable with respect to the baseline model, namely the NPL ratio, the residential real estate price shock or a binary variable indicating whether any country portfolio is close to the border of switching, defined as a distance from 0 of less than 10 basis points. The R2 of each specification is also presented in the table next to the number of observations available. The final column provides an F statistic, allowing us to test the joint null hypothesis that all of the regression coefficients (other than the constant term) are zero.

Acknowledgements
We are grateful to Dimitris Mokas and Dionysios Mylonas for related work on the topic and discussions. We would also like to thank John Fell, Spyros Palligkinis, Sebastian Scheffler and Tamarah Shakir for their useful comments and suggestions, as well as seminar participants at Banca d'Italia, at the ECB DG/MF Seminar Series and at the 10th EBA Annual Research Workshop, and especially the discussant Inês Drumond. We also thank Marija Deipenbrock, Anca Dinita and Alexandros Kouris for their outstanding research support.

Harun Mirza
European Central Bank, Frankfurt am Main, Germany; email: Harun.Mirza@ecb.europa.eu

Carmelo Salleo
European Central Bank, Frankfurt am Main, Germany; email: Carmelo.Salleo@ecb.europa.eu

Zoe Trachana
European Central Bank, Frankfurt am Main, Germany; email: Zoi.Trachana@ecb.europa.eu

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

This paper can be downloaded without charge from the ECB website, 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 Occasional Paper Series can be found on the ECB's website.

PDF ISBN 978-92-899-6424-1, ISSN 1725-6534, doi:10.2866/362002, QB-AQ-24-020-EN-N